A Causal Mediation Model on the Valuation Effects of Cross-Listings*

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Abstract

A company's decision to cross-list its stock on multiple exchanges has historically been associated with higher valuation. Since cross-listing also impacts a firm's stock price informativeness, which itself affects firm valuation, a causal mediation model is applied to study the direct and indirect effects of cross-listing on valuation through informativeness as a mediator variable. Linear regressions at the cross-section and aggregated across a multi-year period indicate that a log-transformed version of Tobin's q may be the most suitable valuation metric to model. Using robust standard errors and quasi-Bayesian Monte Carlo simulations, a significant positive average direct effect and total effect are identified in mediation analysis both within each year and pooled across multiple years. The average indirect effect of cross-listing on valuation through informativeness tends to be negative and smaller in magnitude, but still significant; it is present at the aggregated level and in some years. Therefore, in the absence of a causal mediation model, the positive direct effect of cross-listing may be under-estimated.

Keywords: Causal mediation analysis, cross-listing, stock price informativeness, valuation
JEL Codes: C49, G15, G30

1 Introduction

In an increasingly integrated global economy, publicly traded companies face decisions on whether to list their stocks on home exchanges, foreign ones, or both. Many foreign companies that cross-list in the United States do so through American depositary receipts (ADRs), which are equivalent to a specified number of shares of securities trading on the home market. Such cross-listing is associated with positive average abnormal return, lower cost of capital, and higher Tobin's q ratios relative to non-cross-listed peers (Foerster and Karolyi, 1999; Hail and Leuz, 2009; Doidge, Karolyi, and Stulz, 2004). Additionally, Lang, Lins, and Miller (2003) find that non-American firms listed on US exchanges receive greater analyst coverage and have more accurate forecasts. Cross-listing can also function as a signal that firms care about minority shareholders or as a defense against hostile takeovers (Coffee, 1999; Kastiel and Libson, 2019).

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However, it is noteworthy that certain effects of cross-listing differ based on a firm's choice of cross-listing exchange, as well as its country of origin. Previous literature has studied stock price informativeness, which is an idiosyncratic volatility measure that captures how much variation in excess firm return is not explained by excess US or local market return. Fernandes and Ferreira (2008) find that following US cross-listings, firms from developed markets see an improvement in stock price informativeness, whereas firms from emerging markets observe a decrease in such informativeness. Given the theoretical work of Foucault and Gehrig (2008) demonstrating how stock price informativeness can help a company more efficiently allocate its capital, this has ramifications on a firm's long-term valuation and prospects. Higher values of informativeness indicate that the firm's stock price displays enough variation to be an informative signal to firm managers regarding the quality of their capital allocation decisions. As another example of how choice of listing country matters, Doidge, Karolyi, and Stulz (2009) find that premiums associated with listing in the United States are higher than those for the United Kingdom, despite their similarities as developed markets. Bianconi and Tan (2010) add that the United Kingdom's financial disclosure regulations are less stringent than those of the United States, so American cross-listings may reap more benefits associated with informativeness and disclosure. There exists an extensive literature on how a firm's origin and its listing choice impact factors such as price informativeness, liquidity, and valuation. These are further addressed in the literature review.

Causal mediation analysis seeks to model how a regressor (exposure) variable can impact the ultimate response variable both directly and through an intermediate (mediator) variable. A decomposition of the effect of cross-listing on company valuation both directly and through change in informativeness will be examined. Specifically, this thesis views cross-listing as the exposure variable and stock price informativeness as the mediator variable. Since previous research has documented how the decision to cross-list stock can impact stock price informativeness, this thesis seeks to combine prior literature on the relationship between cross-listing and informativeness with the potential relationship between informativeness and company valuation. This work also aims to examine the exact causal linkage between cross-listing and valuation, decomposing the total effect into direct and indirect channels. Such decomposition tests the hypothesis from Foucault and Gehrig (2008) that increased informativeness can improve the clarity of the signal that firm prices provide regarding how firm managers are allocating capital.

The rest of this thesis is organized as follows. Section 2 is devoted to a literature review of the hypotheses behind why a firm may cross-list and the implications of doing so. Section 3 reviews the causal mediation model, and Section 4 explicitly frames the models used in this paper. Section 5 discusses the data. Results and conclusions are presented in Sections 6 and 7, respectively.

2 Literature Review

2.1 Hypotheses Behind Motivation to Cross-List

Extensive literature summarizes the reasons that a firm may want to cross-list in a foreign exchange. Mittoo (1992) reports that managers see many benefits to listing in the United States, including reduced cost of capital, increased access to (foreign) capital, further stock liquidity, and firm exposure. Such benefits have been substantiated by prior research (Ahearne, Griever, and Warnock, 2004; Alexander, Eun, and Janakiramanan, 1987; Doidge, Karolyi, and Stulz, 2004; Foerster and Karolyi, 1999; Melvin and Valero-Tonone, 2003; Miller, 1999). Additionally, there are different hypotheses regarding the main reasons why a firm may choose to cross-list in a foreign exchange.

The market segmentation hypothesis posits that firms will cross-list in order to circumvent a separation of markets. Under a partial or complete segmentation of domestic and foreign markets, Alexander, Eun, and Janakiramanan (1987) show that domestic investors require that foreign firms have higher returns than their domestic counterparts. When such foreign firms cross-list, they eliminate some investment frictions for domestic investors, which broadens their shareholder population and spreads out risk. In theory, this results in a lower cost of capital for cross-listed firms. However, there is mixed support for the market segmentation hypothesis. For example, abnormal returns have been observed even for firms from well-integrated markets (Foerster and Karolyi, 1999). Furthermore, given the move towards a more integrated global economy, the market segmentation hypothesis predicts fewer cross-listings. In reality, the opposite phenomenon is observed: Karolyi (2006) observes that the volume of international listings has grown over time.

The statistically significant share price movements of non-US companies following their US listing documented by Foerster and Karolyi (1999) do, however, support the investor recognition hypothesis. According to Merton (1987), investors are willing to pay a premium for more familiar assets. When a foreign company cross-lists in the US, it becomes more exposed and familiar to American investors, so the "unfamiliarity discount" fades away. Subsequently, the firm's stock price rises. Dodd (2013) embraces a similar notion, reporting that familiarity with a firm's country of origin provides additional information to investors, who then are more willing to trade the firm's stock.

It is also possible that firms seeking to increase their operational foreign activity will pursue cross-listing in various exchanges. This has been named the global business strategy hypothesis. In a survey of managers, Bancel and Mittoo (2001) note that global firms who maintain sizable operations abroad are more likely to cross-list. Such firms may also desire to improve investor recognition, ease of access to their products, and their own ability to raise capital (Bancel and Mittoo, 2001; Pagano, Roell, and Zechner, 2002; Saudagaran, 1988). Pagano, Roell, and Zechner (2002) found that increasing the degree of internationalization is an effective way for corporations to achieve such goals.

Firms might also cross-list in order to improve the liquidity of their stock. Increased liquidity reduces the bid-ask spread faced by stock traders, which can result in greater trading volume. Under the aptly named liquidity hypothesis, firms desiring to increase the liquidity and trading activity of their stock may pursue cross-listings. Mittoo (1992) surveyed managers of non-US companies, 28% of whom included liquidity as a primary decision variable in their choice to cross-list. Given that cross-listing occurs on new exchanges, firms can broaden their investor base and further increase trading volume. Foerster and Karolyi (1998) study stocks from the Toronto Stock Exchange that cross-list on American exchanges, and they find that spreads decrease following the additional listing. Additionally, Smith and Sofianos (1997) provide empirical evidence of trading activity, reporting that the trading volume for non-US stocks increased by 42% following cross-listing on the NYSE. Despite the extensive data consistent with the liquidity hypothesis, such an explanation fails to account for why some foreign firms still have not cross-listed. After all, if cross-listing clearly results in more liquidity—reducing spreads and the cost of capital—one might expect far more foreign firms to engage in cross-listing. Yet numerous publicly traded firms still do not engage in such a practice.

Alternatively, firms based in countries with weak protections for minority shareholders may cross-list in markets more protective of such minority shareholders in order to assuage minority shareholder concerns of exploitation. Coffee (1999) and Stulz (2009) coin the term bonding hypothesis, where a firm "bonds" itself to the more stringent regulations of the country in which it cross-lists. Such a signal increases the firm's access to capital, which then reduces costs of capital and augments firm valuation. Reese and Weisbach (2002) identify empirical support for such a hypothesis: after cross-listing in the United States, firms from countries with weaker investor protections are able to raise more equity capital in home markets. They observe that equity issues increase after all cross-listings, even for those with weak shareholder protections. Notably, such increases are most prominent for firms originating in countries with the weakest regulations in defense of minority investors. This result exists outside of event studies too. Doidge (2004) studies internationally domiciled firms and their relationship between cross-listing and voting premiums. The author examines the private benefits of control in two cases when such benefits are directly measurable: when a control block is sold and the firm has more than one class of publicly traded shares with differing voting rights, and when a firm has two class shares differentiated only by voting rights. The author finds that non-US firms cross-listed on US exchanges have lower voting premiums than their non-cross-listed counterparts. When a US listing is first announced, all share classes benefit, but low-voting class shares benefit more than high-voting share classes. Such evidence supports the bonding hypothesis' prediction that by improving protection of minority investors, private benefits of control are reduced.

Foucault and Gehrig (2008) pioneer the theoretical work explaining how firm managers can learn from their stock prices following a cross-listing. Additionally, Lang, Lins, and Miller (2003) find that analyst coverage and forecast accuracy improves for stocks following a cross-listing. They state that these cross-listed firms have higher valuations, implying that an improved informational environment may increase valuations. Foucault and Frésard (2012) extend the stock price learning model to include peer valuations, and they call the notion that firms may cross-list to improve stock price informativeness, and subsequently valuation, the learning hypothesis of cross-listing. Firm managers can employ information from stock prices in the efficient allocation of capital. Empirical evidence from Ghosh and He (2015) observes that cross-listed firms dedicate more money to research and development and conduct better acquisitive activity (as demonstrated by a better bidder's abnormal return surrounding deal announcement). There are multiple candidate explanations for how cross-listing may change how informative a stock price is. Baker, Nofsinger, and Weaver (2002) cite the increased visibility through analyst and media coverage as a potential driver behind increased informativeness. Alternatively, Lang, Lins, and Miller (2003) point towards the stricter SEC listing and reporting requirements, which result in companies disclosing more financial details, as improving the amount of information priced into shares. However it is also possible, as Fernandes and Ferreira (2008) explain, that stock price informativeness can decrease after cross-listing, particularly if a firm is classified into a broader industry in the country where it cross-lists and does not receive individual coverage. Abdallah and Abdallah (2019) ultimately find that firms cross-listed in the U.S. improve their investment efficiency following the additional listing if informativeness rises, in support of the learning hypothesis.

More recently, Kastiel and Libson (2019) present cross-listing as a method by which firms can protect, or insulate, against hostile takeovers. Under the insulation hypothesis, firms may treat cross-listing as an anti-takeover device since direct fees make it far more costly for an acquirer to pursue tender offers in both foreign and domestic exchanges. Additionally, the legal complications of adhering to a new jurisdiction's laws can make a takeover even more unappealing. Even if a hopeful acquirer can amass enough shares in the domestic market to take over the firm, cross-listing increases the number of domestic shares such an acquirer must buy. Tsang, Yang, and Zheng (2022) employ a hostile takeover probability measure from Cain, McKeon, and Solomon (2017) and find that there exists a significant positive relation between existence of threats to corporate control and likelihood of a firm cross-listing. If firms cross-list in an attempt to evade hostile takeovers, they may seek to complicate their hopeful acquirer's efforts by choosing exchanges that differ significantly in accounting requirements from US GAAP. Again, Tsang, Yang, and Zheng (2022) find empirical support that firms facing control threats are more likely to choose exchanges with host countries that maintain large accounting differences from US standards. This is a more nascent area of research than prior hypotheses and is still developing.

2.2 Implications of Cross-Listing

Foreign firms that list in the United States experience a valuation premium relative to their non-cross-listed counterparts. In a seminal work, Doidge, Karolyi, and Stulz (2004) (the three authors are hereafter referred to as DKS) find that the Tobin's q ratio is significantly higher for foreign companies with US cross-listings than for non-cross-listed peers. The 16.5% difference in q ratios grows to 37% when the cross-listed population is restricted to companies on dominant U.S. exchanges. Such valuation benefits associated with cross-listing also hold for London markets. In a more focused study, Bianconi and Tan (2010) observe a subset of companies based in the Asia-Pacific region and observe the statistically significant cross-listing premium for cross-listings both in the United States and the United Kingdom. However, there exists mixed literature on the difference between a US and UK listing premium: Bianconi and Tan (2010) find that the statistical significance of the difference in such a premium is not robust under a treatment effect methodology. However, DKS (2009) conduct a broader analysis of the London to New York valuation premium and find that between the two established markets, stocks cross-listed in the U.S. maintain a higher valuation premium than those cross-listed in the United Kingdom.

To some extent, such positive effects also apply to additional cross-listings. Ghadhab and Hellara (2016) observe that a substantial number of firms maintain multiple cross-listings. Ghadhab and M'rad (2018) find that companies with U.K. cross-listings who then choose to add a US listing receive a marginal positive valuation impact.

Certain consequences of cross-listing can differ by the firm's home country. As discussed in the explanation of the bonding hypothesis for cross-listing, the information environment of a stock changes upon cross-listing. Fernandes and Ferreira (2008) use firm-specific stock return variation (which French and Roll (1986) show is closely related to price informativeness) in their findings that after a cross-listing, price informativeness improves for firms coming from developed countries but decreases for firms from emerging markets. This thesis aims to augment the existing literature on the hypotheses and consequences of cross-listing by combining the learning hypothesis first introduced by Foucault and Gehrig (2008) with the work done on stock price informativeness by Fernandes and Ferreira (2008) under a mediation model.

3 Causal Mediation Models

Baron and Kenny (1986) propose causal mediation models to examine the mechanisms by which a treatment (exposure) variable influences an outcome both directly and indirectly through intermediate variables (mediators). Conti, Heckman, and Pinto (2016) and Chernozhukov, Kasahara, and Schrimpf (2021) apply such models to research in economics and finance. Additionally, there exists some literature extending causal mediation analysis to econometrics (Heckman and Pinto, 2015). Huber (2020) and Celli (2022) offer comprehensive surveys of the use of mediation analysis in economics and econometrics. To provide another concrete example in finance, one might consider that a firm's industry sector affects its financial performance, which then flow through to influence stock returns. The mediation model could be applied to study the indirect (mediation) effects of financial metrics that result in an additional impact to stock return. The exposure variable would be the industry sector, the mediator would be financial performance metrics, and the response variable would be stock returns. Guo et al. (2023) employed a high-dimensional mediation model to study stock reactions to the COVID-19 pandemic in a similar manner. They studied the mediation effects of the financial performance values that connected a company's sector to its stock return using data.

In this paper, the exposure variable is a binary cross-listing variable and there is one mediator (stock price informativeness). The response variable of interest is a company's valuation, calculated in this paper as Tobin's q.

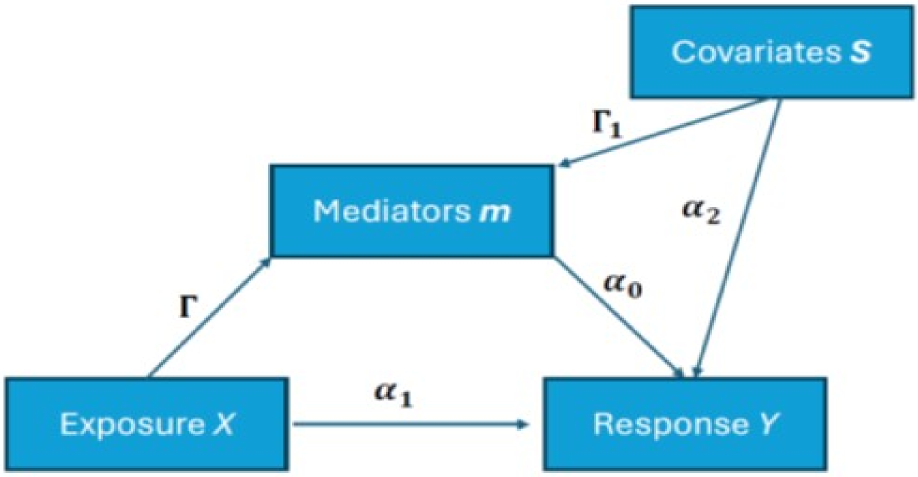

Figure 1: Diagram of Mediation Model

To formalize the causal mediation model, let Y be the outcome, $\boldsymbol{m}$ be the p-dimensional mediator, $\boldsymbol{x}$ be the q-dimensional exposure variable and $\boldsymbol{s}_1$ and $\boldsymbol{s}_2$ be the r_1 and r_2-dimensional covariates, where $\boldsymbol{s}_1$ and $\boldsymbol{s}_2$ are allowed to overlap and even be the same, but are not necessarily identical. The mediation model is defined as

$$Y = \boldsymbol{\alpha}_0'\boldsymbol{m} + \boldsymbol{\alpha}_1'\boldsymbol{x} + \boldsymbol{\alpha}_2'\boldsymbol{s}_1 + \varepsilon_1, \tag{1}$$

$$\boldsymbol{m} = \Gamma'\boldsymbol{x} + \Gamma_1'\boldsymbol{s}_2 + \boldsymbol{\varepsilon}, \tag{2}$$

where $\boldsymbol{\alpha}_0$, $\boldsymbol{\alpha}_1$ and $\boldsymbol{\alpha}_2$ are p-, q- and r_1-dimensional regression coefficient vectors, and Γ and Γ_1 are $q \times p$ and $r_2 \times p$ coefficient matrices, respectively. It is typically assumed in the literature that ε_1 and $\boldsymbol{\varepsilon}$ are independent random errors with $\mathrm{Var}(\varepsilon_1) = \sigma_1^2$ and $\mathrm{Cov}(\boldsymbol{\varepsilon}) = \Sigma$; ε_1 is independent of $\boldsymbol{m}$ and $\boldsymbol{x}$; and $\boldsymbol{\varepsilon}$ is independent of $\boldsymbol{x}$. Plugging (2) into (1) then yields

$$y = (\boldsymbol{\beta} + \boldsymbol{\alpha}_1)'\boldsymbol{x} + \boldsymbol{\alpha}_2'\boldsymbol{s}_1 + (\Gamma_1\boldsymbol{\alpha}_0)'\boldsymbol{s}_2 + \varepsilon_1 + \varepsilon_2 = \boldsymbol{\gamma}'\boldsymbol{x} + \boldsymbol{\alpha}_2'\boldsymbol{s}_1 + (\Gamma_1\boldsymbol{\alpha}_0)'\boldsymbol{s}_2 + \varepsilon_3, \tag{3}$$

where $\boldsymbol{\beta} = \Gamma\boldsymbol{\alpha}_0, \varepsilon_2 = \boldsymbol{\alpha}_0^T\boldsymbol{\varepsilon}$ with $\mathrm{Var}(\varepsilon_2) = \sigma_2^2 = \boldsymbol{\alpha}_0^T\Sigma\boldsymbol{\alpha}_0, \boldsymbol{\gamma} = \boldsymbol{\beta} + \boldsymbol{\alpha}_1$, and $\varepsilon_3 = \varepsilon_1 + \varepsilon_2$ is the total random error. In the literature, $\boldsymbol{\beta}$ is referred to as the indirect effect of $\boldsymbol{x}$ on y mediated by $\boldsymbol{m}$ (Imai, Keele, and Tingley, 2010). Additionally, $\boldsymbol{\alpha}_1$ is called the direct effect and $\boldsymbol{\gamma} = \boldsymbol{\alpha}_1 + \boldsymbol{\beta}$ is the total effect.

Figure 1 above displays a diagram of the mediation model. Visually, the mediation model decomposes the total effect of the exposure variables X on the response variable into indirect effects (through mediators) and direct effects. Guo et al. (2023) interprets $\boldsymbol{\alpha}_1$ and $\boldsymbol{\beta} = \Gamma\boldsymbol{\alpha}_0$ as the average natural direct effect and average natural indirect effect, respectively, of a one unit change in the exposure variable $\boldsymbol{x}$. This thesis aims to determine whether there exist mediators through which cross-listing influences corporate valuation and, if so, how the total effect separates into indirect and direct components.

The parameter vectors $(\boldsymbol{\alpha}_0, \boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2)$ and parameter matrices (Γ, Γ_1) can be estimated by the corresponding least squares estimates based on models (1) and (2), respectively. Denote the least squares estimate of Γ and $\boldsymbol{\alpha}_0$ to be $\widehat{\Gamma}$ and $\hat{\boldsymbol{\alpha}}_0$, respectively. Then a natural estimator of $\boldsymbol{\beta}$ is

$$\hat{\boldsymbol{\beta}} = \widehat{\Gamma}\hat{\boldsymbol{\alpha}}_0.$$

In this thesis, we focus on the setting in which $p = 1$ and $q = 1$. That is, there is only one exposure variable and only one mediator. Thus, $\boldsymbol{\beta}$, Γ and $\boldsymbol{\alpha}_0$ are scalar. Of interest is to test

$$H_0 : \boldsymbol{\beta} = 0 \quad \text{versus} \quad H_1 : \boldsymbol{\beta} \neq 0.$$

Under certain regularity conditions, $\widehat{\Gamma}$ and $\hat{\boldsymbol{\alpha}}_0$ asymptotically follow a joint normal distribution. By using the delta method, we may further derive the asymptotic normal distribution of $\hat{\boldsymbol{\beta}}$ when either Γ or $\boldsymbol{\alpha}_0$ does not equal 0. However, when both Γ and $\boldsymbol{\alpha}_0$ equal 0, we cannot use the delta method to derive the limiting distribution of $\hat{\boldsymbol{\beta}}$ since the gradient of $\Gamma\boldsymbol{\alpha}_0 = 0$ when $\Gamma = 0$ and $\boldsymbol{\alpha}_0 = 0$. The null hypothesis H_0 implies that Γ or $\boldsymbol{\alpha}_0$ equals 0. Thus, the limiting normal distribution derived by using the delta method cannot be used to calculate the critical value for testing H_0. In this thesis, we employ quasi-Bayesian methods to calculate p-values and confidence intervals of causal effects including direct and indirect effects by directly using the **mediation** R package (Tingley et al., 2014).

4 Model

4.1 Cross-Sectional Models of Valuation

Following DKS (2004) who employ a cross-sectional approach, this paper begins with regressing Tobin's q on previously studied covariates, subject to availability of the variables. First, Tobin's q is calculated as

$$\frac{\text{(Total Assets - Book Equity) + Market Capitalization}}{\text{Total Assets}}$$

For each year t, the following initial cross-sectional analysis is run across all stocks i.

$$Q_{it} = \beta_0 + \beta_1 CL_{it} + \beta_2 Turnover_{it} + \beta_3 SalesGrowth_{it} + \beta_4 Size_{it} + \beta_5 IndustryQ_t + \varepsilon_{it} \qquad (4)$$

The dependent variable Q_{it} is firm i's Tobin's q in year t. CL_{it} is a binary indicator for whether firm i was cross-listed in year t, and $Turnover_{it}$ is a liquidity measure that is calculated by dividing the last available daily volume of stock i traded in a year t by the total number of shares outstanding on that same day. $SalesGrowth_{it}$ is the two-year annual compounded growth rate of total revenue for firm i as of the end of year t. This paper proxies firm $Size$ by taking log(Market Capitalization) for market capitalization in dollars. This variable is included following the work of Fernandes and Ferreira (2008), who treat size as a covariate in predicting stock price informativeness. It is included here primarily to ensure that variables appearing in the mediator equation (which predicts stock price informativeness using a set of covariates) also appear in the outcome equation (which predicts Tobin's q). Finally, $IndustryQ_t$ is the median global Tobin's q for a certain industry in a given year.

After estimating the above $\boldsymbol{\beta}$ coefficients using a linear model, stock price informativeness is added as a covariate on the right side of (4). The model then becomes

$$Q_{it} = \beta_0 + \beta_1 CL_{it} + \beta_2 Turnover_{it} + \beta_3 SalesGrowth_{it} + \beta_4 Size_{it} \\ + \beta_5 IndustryQ_t + \beta_6 Informativeness_{it} + \varepsilon_{it} \tag{5}$$

Following Fernandes and Ferreira (2008), stock price informativeness for a given firm-year observation (for fixed i and t) is calculated first by projecting a stock's excess return on market factors for each firm-year combination:

$$r_{itw} = \delta_{0i} + \delta_{1it} r_{mtw} + \delta_{2it} r_{UStw} + e_{itw} \tag{6}$$

across various w values for weekly return data within that year, with $\mathrm{E}(e_{itw}) = \mathrm{Cov}(r_{mtw}, e_{itw}) = \mathrm{Cov}(r_{UStw}, e_{itw}) = 0$. Here, r_{itw} is stock i's return for week w in year t in excess of the risk-free rate; r_{mtw} is the value-weighted excess regional market return for week w in year t ; and r_{UStw} is the value-weighted excess U.S. market return for week w in year t . After running such a regression for each firm-year combination, the firm-specific return variation is calculated by taking the ratio of idiosyncratic volatility to total volatility $\sigma^2_{ite}/\sigma^2_{it}$. Such a ratio is captured by $1 - R^2_{it}$ of equation (6). Since R^2 values are bounded by 0 and 1, Fernandes and Ferreira (2008) conduct their analyses using a logistic transformation of $1 - R^2_{it}$. The same procedure is applied here.

$$Informativeness_{it} = \log\left(\frac{1 - R^2_{it}}{R^2_{it}}\right) = \log\left(\frac{\sigma^2_{ite}}{\sigma^2_{it} - \sigma^2_{ite}}\right) \tag{7}$$

Consequently, the formulation of this stock price informativeness variable quantifies how much the firm's stock return varies relative to marketwide movements. In other words, it captures the degree to which stock prices do not comove with the broader regional and US markets to which a company might belong. Informativeness is scaled by the total variation in returns because firms in some countries may be more sensitive to broader economic shocks than others. Therefore, firm-specific events could be similarly more intense. This procedure aligns not only with the work done by Fernandes and Ferreira (2008), but it also makes these results comparable to Morck, Yeung, and Yu (2000).

This work also models a fuller version of (5) by adding log(Assets) as a covariate. Such an inclusion is substantiated by DKS (2009) which find that log(Assets) is a highly significant predictor in a firm's decision to cross-list. Sales growth and median industry q, which are already included as regressors in equation 5, are also significant predictors of a firm's decision to list on multiple exchanges. Therefore, the fullest version of the cross-section model analyzing Tobin's q across firms in a given year t is:

$$Q_{it} = \beta_0 + \beta_1 CL_{it} + \beta_2 Turnover_{it} + \beta_3 SalesGrowth_{it} + \beta_4 Size_{it} \\ + \beta_5 IndustryQ_t + \beta_6 Informativeness_{it} + \beta_7 \log(\text{Assets})_{it} + \varepsilon_{it} \tag{8}$$

The above specifications in equations (4), (5), and (8) all model Tobin's q as a linear function of the right-hand side. However, Bianconi and Tan (2010) take their dependent variable to be the transformed log (Tobin's q). After analyzing the distribution of Tobin's q in the multi-period sample, it is clear that the distribution of Tobin's q values has a long right tail. Therefore, equations (4), (5), and (8) are repeated with the log-transformed Tobin's q as the dependent variable. Taking $q_{it} = \log(Q_{it})$, the log-transformed regressions are as follows:

$$q_{it} = \beta_{l0} + \beta_{l1}CL_{it} + \beta_{l2}Turnover_{it} + \beta_{l3}SalesGrowth_{it} + \beta_{l4}Size_{it} + \beta_{l5}IndustryQ_t + \varepsilon_{it} \quad (9)$$

$$\begin{aligned} q_{it} = \beta_{l0} + \beta_{l1}CL_{it} + \beta_{l2}Turnover_{it} + \beta_{l3}SalesGrowth_{it} + \beta_{l4}Size_{it} \\ + \beta_{l5}IndustryQ_t + \beta_{l6}Informativeness_{it} + \varepsilon_{it} \end{aligned} \quad (10)$$

$$\begin{aligned} q_{it} = \beta_{l0} + \beta_{l1}CL_{it} + \beta_{l2}Turnover_{it} + \beta_{l3}SalesGrowth_{it} + \beta_{l4}Size_{it} \\ + \beta_{l5}IndustryQ_t + \beta_{l6}Informativeness_{it} + \beta_{l7}\log(Assets)_{it} + \varepsilon_{it} \end{aligned} \quad (11)$$

4.2 Causal Mediation Model

Given the multi-year nature of the data used (which is described in section 5), causal mediation analysis can both be run for each year individually and for the aggregated firm-year observations across the entire sample. As specified in section 3, the mediation model can be defined as:

$$\begin{aligned} Q_{it} = \alpha_t + \beta_1 CL_{it} + \beta_2 Turnover_{it} + \beta_3 SalesGrowth_{it} + \beta_4 Size_{it} \\ + \beta_5 IndustryQ_t + \beta_6 Informativeness_{it} + \beta_7 \log(Assets)_{it} + \varepsilon_{it} \end{aligned} \quad (8)$$

$$Informativeness_{it} = \gamma_0 + \gamma_1 CL_{it} + \gamma_2 Turnover_{it} + \gamma_3 SalesGrowth_{it} + \gamma_4 Size_{it} + u_{it} \quad (12)$$

The first equation—where Tobin's q is the dependent variable—can be replaced with any of the iterations in equations (4), (5), (9), (10), 11) depending on whether one desires to analyze the non-transformed or log-transformed version using a fuller or sparser model. The model captured by the two above equations will recover the average direct effect of cross-listing on Tobin's q (β_1) and the average indirect effect of cross-listing on Tobin's q through informativeness ($\gamma_1 \cdot \beta_6$). For the log-transformed equivalent of the mediation model using the fullest linear model, equation 8 can be replaced by equation 11, in which case the average direct effect would be β_{l1} and the average indirect effect would be $\gamma_1 \cdot \beta_{l6}$.

Equation 12 models stock price informativeness as a linear function of a cross-listing dummy variable, stock turnover, two-year compounded annual sales growth, and size of the company, all of which are inspired by Fernandes and Ferreira (2008). Noticeably, it uses covariates already included in the equation predicting Tobin's q, but it excludes the median industry q and the log(Assets) variables.

Since there are multiple years in the data used, this work will aim to identify both the average direct and indirect effects at the cross-sectional level but also aggregated across years. In particular, the question of interest in this work is whether cross-listing influences valuation through modifying unexplained stock price return volatility. If such a causal linkage exists, the question then centers around what proportion of the average total effect ($\beta_1 + (\gamma_1 \cdot \beta_6)$ and $\beta_{l1} + (\gamma_1 \cdot \beta_{l6})$ in the original and log-transformed values of Tobin's q, respectively) is represented by the indirect channel.

Given that the firm-year data used in this thesis follows many of the same firms over multiple years, one might anticipate the usage of panel data methods. However, the usage of fixed and random effects in conjunction with mediation models has not been extensively studied, primarily due to the complexities of mediation effects within and across years. More specifically, mediation analysis is typically not combined with longitudinal data methods since—in multi-period data—each explanatory variable influences the outcome both through within-period and between-period effects. The within-period effects of a covariate can mediate both within- and between-period causal relationships of a *different* explanatory variable with the dependent variable of interest.

This problem also exists for between-period effects of any given covariate. This results in the potential causal paths growing as a combinatorial function of the number of mediators. Therefore, this paper opts to use a simpler pooled estimation approach to calculate coefficients in order to be compatible with the mediation model.

5 Data

5.1 Identifying Control and Cross-Listed Firms

The data consists of 18,194 firm-year observations from 2015-2019. For cross-listed firms, a list of firm names and their cross-listing status in a given year was taken from Citibank's database on active and inactive American depositary receipts. For the purposes of this work, a company is only classified as cross-listed in a year if it is cross-listed on a major American stock exchange (NYSE or Nasdaq) for at least four months or its entire active life within a given year. Some companies do list on over-the-counter markets, but such markets are less regulated and do not adhere to the same informational disclosures that larger stock exchanges impose. Therefore, only American depositary receipts on the NYSE and Nasdaq are considered as official cross-listings.

To select a set of control firms, for each country with at least three representative cross-listed firms in the data, the index constituent list of the country's market index was taken as of the first market trading day in 2015. All countries across these indices that were not cross-listed at any point within the 2015-2019 period are treated as a control set of companies. Index constituent lists were taken from Datastream.

5.2 Stock Price Informativeness

To calculate stock price informativeness, weekly data was gathered on stock price returns, regional market returns, US market returns, and the risk-free rate. Stock prices for firms were pulled from Capital IQ, and weekly returns were calculated from the first to last market trading day of each week. Regional market index values were supplied by Datastream, accessed through Wharton Research Data Services, and weekly returns were calculated from the first to last active trading day of each week. US market returns were supplied by the Center for Research in Security Prices. In order to calculate returns in excess of the risk-free rate, a normalized weekly excess return was subtracted from each of the above weekly returns. To calculate the corresponding risk-free rate, data on 30-day treasury bill yields was taken from FRED. These treasury bill returns were then normalized by raising the 30-day yields to the 7/30 so as to correspond to a full week.

For each firm-year observation, stock price informativeness was calculated as the log value of the amount of unexplained variation in excess firm return divided by total variation in excess firm return. Further details can be found in section 4.1. In order to calculate excess regional market return for each of these firm-year regressions, all firms were assigned a regional market index that corresponded to their countries of origin. See table 23 for the comprehensive list; three countries (China, Japan, Australia) were designated as their own regions due to unique growth trends against the landscape of neighboring countries (or in the case of Australia, its ability to stand alone as its own geographical class). Assignments of regional indices are provided in the appendix (table 24).

5.3 Firm-Level Data

The main source of firm-level financial data for the following analysis was Capital IQ. Industry assignment is taken from Capital IQ as the global industry classification standard (GICS). The following variables were all provided by Capital IQ: total assets, outstanding shares, book value per share, market capitalization, trading volume, and two-year compounded annual revenue growth. For firms that disappeared from the dataset in later years, dummy variables (for disappearances related to acquisition or bankruptcy) are encoded. If a firm disappears from the dataset due to acquisition by or merger into another company within the 2015-2019 period, the *Acquired* dummy variable receives value 1. If a firm disappears from the dataset due to bankruptcy or forcible delisting (where the exchange mandates that the firm must de-list due to regulatory or financial concerns), the *Bankrupt* dummy variable is set to 1. The *Acquired* and *Bankrupt* binary variables are manually encoded using research on Capital IQ and various search engines.

Tobin's q is calculated as total assets minus (book value per share · shares outstanding) plus market capitalization all over total assets. Any observations with zero values for total assets, outstanding shares, book value per share or market capitalization are excluded. Additionally, the distribution of Tobin's q is noted below in tables 1 and 2.

Table 1: Descriptive Statistics for Tobin's Q

	Min	1st Quartile	Median	Mean	3rd Quartile	Max
2015	0.130	0.997	1.358	15.583	2.321	27990.410
2016	0.165	0.997	1.305	18.237	2.121	24252.5
2017	0.218	1.012	1.323	24.500	2.053	39753.9
2018	0.209	0.953	1.121	28.234	1.643	57565.89
2019	0.119	0.953	1.140	35.234	1.710	41470.280
All	0.118	0.981	1.234	24.242	1.960	57565.89

Table 2: Distribution of Tobin's Q Across Time

	2015	2016	2017	2018	2019	All
$0 \leq 1$	952	935	859	1273	1222	5241
$1 \leq 2$	1648	1746	1842	1667	1665	8568
$2 \leq 5$	832	744	727	500	493	3287
$5 \leq 10$	180	150	127	90	101	658
$10 \leq 100$	77	68	57	44	46	292
$100 \leq 1{,}000$	31	28	28	29	31	147
$1{,}000 \leq 5{,}000$	3	4	4	2	2	15
$5{,}000 \leq 10{,}000$	1	1	1	3	1	7
$\geq 10,000$	1	2	2	1	4	10
All	3,721	3,671	3,640	3,603	3,558	18,193

Clearly, there is a long right tail of the distribution of Tobin's q values in the sample. To restrict the effect of these extreme outliers, data items with Tobin's q greater than 1,000 are excluded from all following analysis. This only removes between five and seven observations per year, and it does not substantially reduce sample size. Table 3 shows the updated descriptive statistics after such a removal. The mean has shifted dramatically lower for all cross-sections, although there is still a right tail to the data. To address the concerns of a non-normal underlying distribution of Tobin's

q, analysis will first be conducted for the original Tobin's q values, and it will be replicated for log-transformed Tobin's q. A table of descriptive statistics for log-transformed values by year is also included below (see table 4).To be comprehensive, the appendix includes the regressions of Tobin's q and causal mediation analysis—both at yearly cross-sections and aggregated across the sample—replicated with the inclusion of outliers.

Table 3: Descriptive Statistics for Cleaned Tobin's Q

	Min	1st Quartile	Median	Mean	3rd Quartile	Max
2015	0.130	0.997	1.355	4.561	2.314	824.477
2016	0.165	0.997	1.302	4.468	2.105	706.651
2017	0.218	1.012	1.322	5.181	2.047	954.777
2018	0.209	0.952	1.120	4.873	1.641	901.782
2019	0.119	0.952	1.140	4.894	1.706	820.344
All	0.118	0.981	1.234	4.793	1.955	954.777

Table 4: Descriptive Statistics for Log Tobin's Q

	Min	1st Quartile	Median	Mean	3rd Quartile	Max
2015	−2.037	−0.003	0.304	0.515	0.840	6.715
2016	−1.804	−0.003	0.264	0.468	0.744	6.561
2017	−1.522	0.011	0.279	0.473	0.716	6.861
2018	−1.563	−0.049	0.113	0.324	0.495	6.804
2019	−2.133	−0.049	0.131	0.340	0.534	6.710
All	−2.133	−0.019	0.210	0.425	0.670	6.861

6 Results

The following results are reported first using Tobin's q as the valuation measure of interest in order to be comparable to the most seminal research done in this area. Regressions of Tobin's q in each annual cross-section are reported, and causal mediation analysis is conducted both within each year and across all firm-year observations.

Given the heavily skewed distribution of Tobin's q in the data, the above analysis is repeated using the natural log of the Tobin's q values. The linear models using the log-transformed values for each year have greater explanatory power than their non-log counterparts, so the causal mediation analysis is repeated using the log value of Tobin's q as the valuation measure.

6.1 Analysis for Tobin's Q as Outcome Variable

6.1.1 Linear Cross-Sectional Models

For comparability reasons (relative to DKS (2004)), Tobin's q is first regressed in multiple cross-sections at the end of each year from 2015 to 2019. Table 5 replicates the most basic regression from the seminal paper by testing for the significance of cross-listing as a predictor of Tobin's q without controlling for any other variables. While the R^2 found by DKS (2004) in their analysis of the 1997 cross-section is very low (only 0.01), it was still non-zero. Here, the R^2 in each of the 2015 through 2019 cross-sections is essentially zero. More importantly, a major difference between DKS (2004) and the results displayed below is that in the original 2004 work, cross-listing was an extremely significant predictor of company valuation. However, cross-listing alone is not a significant predictor of Tobin's q for any of the years in this dataset. Furthermore, the sign on the cross-listing variable β_1 here is negative. DKS (2004) found that cross-listed companies had *higher* Tobin's q than their non-cross-listed counterparts. In all their cross-sectional regressions, DKS identified a positive sign on the coefficient of the cross-listing dummy. This suggests that cross-listing might have lost some of its significant positive impact on company valuation between 1997 and 2015. However, to avoid hasty conclusions, more covariates are included in the results in table 6.

Table 5: Regressing Tobin's Q on Cross-Listed Indicator

	Tobin's Q				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	4.579***	4.483***	5.199***	4.899***	4.897***
	(0.504)	(0.506)	(0.668)	(0.677)	(0.668)
Cross-Listed	−0.363	−0.305	−0.362	−0.507	−0.055
	(2.313)	(2.292)	(3.013)	(3.012)	(2.937)
N	3,721	3,671	3,640	3,603	3,558
R^2	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.000	0.000	0.000	0.000	0.000

Notes: ***Significant at the 1 percent level.

For each year, we now regress Tobin's q on the binary cross-listing variable, turnover, sales growth, size, and median industry q. Cross-listing is not significant in any of the cross-sections, but size is significant at the 1 percent level in every year. This is a stark departure from the results obtained by DKS (2004), which find that cross-listing is significant in every one of their analyses—including both fuller and sparser models—of the 1997 sample. R^2 values are also lower in the more modern analyses; the explanatory power of the model in equation 4 hovers around 0.01. Similar models in DKS (2004) have R^2 of around 0.08. Unfortunately, some of the covariates employed by DKS (2004) are not accessible, either due to an absence of recently updated values or an omission of the variable value for China (where many firms in the sample are based). However, since cross-listing was significant in every one of the various regressions in DKS (2004), the lack of significance associated with cross-listing still appears to be a departure from what the original authors found, even if the exact regression was not replicated on the 1997 sample. Intriguingly, none of the other covariates—turnover, sales growth, or median industry q—are statistically significant. This also diverges from findings in DKS (2004), which observes turnover, sales growth, and median industry q as statistically significant in all regressions including those variables. The difference in regression results observed between the 2004 paper and the 2015-2019 data points suggests that the factors—

not just cross-listing alone—that influence a company's valuation may have shifted between 1997 and 2015. Again, we observe an insignificant but slightly negative coefficient on cross-listing in this regression, which disagrees with the previously studied positive relationship between cross-listing and valuation.

Table 6: Regressing Tobin's Q on Cross-Listed Indicator and Previously Studied Covariates

	Tobin's Q				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	−6.452**	−6.964***	−10.419***	−10.918***	−10.346***
	(2.505)	(2.531)	(3.347)	(3.265)	(3.278)
Cross-Listed	−1.026	−1.031	−1.191	−1.198	−0.658
	(2.326)	(2.304)	(3.036)	(3.043)	(2.956)
Turnover	−27.804	−28.821	−77.580	−44.529	−31.857
	(28.631)	(35.172)	(56.430)	(42.763)	(31.837)
Sales Growth	−0.216	−0.410	−0.065	0.120	0.049
	(0.338)	(0.617)	(0.682)	(1.087)	(0.636)
Size	0.930***	0.997***	1.423***	1.466***	1.387***
	(0.181)	(0.183)	(0.239)	(0.235)	(0.237)
Industry Q	1.279	1.030	0.903	0.822	0.871
	(0.993)	(0.994)	(1.313)	(1.332)	(1.289)
N	3,721	3,671	3,640	3,603	3,558
R^2	0.008	0.009	0.010	0.011	0.010
Adjusted R^2	0.006	0.007	0.009	0.010	0.009

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.

Next, informativeness is added as a covariate to the regression in table 7 (equation 5 is the model here). In every cross-section, informativeness is significant at the one percent level. The coefficient on informativeness implies that a unit increase in the firm-specific stock return variation would be associated with an increase in Tobin's q of 1.329, 1.084, 2.189, 1.526, and 2.119 in the years 2015, 2016, 2017, 2018, and 2019, respectively. All of these counterfactual increases have magnitude greater than one. As observed in descriptive statistics of Tobin's q in the dataset (see table 3), a one unit increase of Tobin's q is a large effect given the range of values observed. Justifiably, this might raise concerns about a disproportionately large coefficient due to remaining outliers, so we proceed with caution. Later results will replicate these regressions with the log-transformed Tobin's q as the dependent variable to mitigate concerns about the skew and effect of outliers.

Interestingly, the cross-listing dummy is still not a significant predictor of valuation in any year. This set of cross-sections gives rise to the motivation behind why stock price informativeness is chosen as the mediator of interest. It is possible that cross-listing's contemporary impact on Tobin's q may occur through an indirect channel, given the significance of a potential mediator but not of the exposure variable itself. Other than firm size, none of the other covariates are statistically significant predictors of valuation, so they do not stand out as candidates for potential mediation channels.

Table 7: Regressing Tobin's Q on Previously Studied Covariates and Informativeness

	Tobin's Q				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	-10.456^{***}	-9.472^{***}	-19.475^{***}	-17.035^{***}	-17.705^{***}
	(2.709)	(2.661)	(4.055)	(3.759)	(3.665)
Cross-Listed	0.140	−0.730	−0.822	−0.203	1.276
	(2.342)	(2.304)	(3.032)	(3.054)	(2.980)
Turnover	−33.862	−30.446	−88.376	−42.315	(−40.105)
	(28.622)	(35.137)	(56.384)	(42.711)	(31.808)
Sales Growth	−0.210	−0.454	−0.127	0.079	−0.036
	(0.337)	(0.617)	(0.681)	(1.086)	(0.635)
Size	1.013^{***}	1.046^{***}	1.628^{***}	1.670^{***}	1.575^{***}
	(0.182)	(0.183)	(0.244)	(0.243)	(0.240)
Industry Q	1.015	0.884	1.076	0.880	0.268
	(0.993)	(0.995)	(1.312)	(1.331)	(1.292)
Informativeness	1.329^{***}	1.084^{***}	2.189^{***}	1.526^{***}	2.119^{***}
	(0.345)	(0.359)	(0.556)	(0.466)	(0.477)
N	3,721	3,671	3,640	3,603	3,558
R^2	0.012	0.011	0.015	0.014	0.016
Adjusted R^2	0.010	0.009	0.013	0.012	0.014

Notes: ***Significant at the 1 percent level.

The next iteration of the regression includes log(Assets) as a covariate, a choice inspired by DKS (2009) and their work on determinants of a firm's likelihood to cross-list. The model equation is equation 8:

$$Q_{it} = \beta_0 + \beta_1 CL_{it} + \beta_2 Turnover_{it} + \beta_3 SalesGrowth_{it} + \beta_4 Size_{it} + \beta_5 IndustryQ_t + \beta_6 Informativeness_{it} + \beta_7 \log(Assets)_{it} + \varepsilon_{it}$$

In table 8, the inclusion of log(Assets) raises R^2 substantially from around 0.01 to around 0.20 for each year. When the below regressions control for the log value of a firm's total assets, some of the previously insigificant regressors become statistically significant. Noticeably, cross-listing becomes more significant in the earlier years of the cross-section (from 2015 to 2017). Additionally, the sign on the cross-listing dummy is positive, which aligns with DKS (2004) and differs from previous iterations of this regression equation (table 6). For example, in the year 2015, a cross-listed firm would be expected to have—on average—a Tobin's q that is 4.805 units higher than its parallel non-cross-listed counterpart.

Similar to concerns in the previous set of cross-sectional regressions, the magnitude of this coefficient is large relative to the distribution of Tobin's q values in the data. In fact, the statistically significant coefficients on turnover, size, median industry q, and log(Assets) are all of large magnitude relative to the q values in the data. The intercept term is disproportionately large, which suggests that the model form may not be accurate (e.g. it may be overfitting to the specific data or otherwise be unable to capture the true effect of changing a regressor's value). To be comparable to previous research, we proceed with further analysis using Tobin's q, but later regressions will examine whether using the log-transformed Tobin's q is a truer model.

6.1.2 Causal Mediation in the Cross-Section

We now turn to producing causal mediation models intended to decompose the total effect of cross-listing on valuation for each year separately. Within each year, the causal mediation model requires one equation predicting Tobin's q and one equation predicting stock price informativeness. Since each year's regression is run separately, we treat year t as fixed. For the former, we use equation 8:

$$\begin{aligned} Q_{it} = \beta_0 + \beta_1 CL_{it} + \beta_2 Turnover_{it} + \beta_3 SalesGrowth_{it} + \beta_4 Size_{it} \\ + \beta_5 IndustryQ_t + \beta_6 Informativeness_{it} + \beta_7 \log(Assets)_{it} + \varepsilon_{it} \end{aligned}$$

and for the latter we employ equation 12:

$$Informativeness_{it} = \gamma_0 + \gamma_1 CL_{it} + \gamma_2 Turnover_{it} + \gamma_3 SalesGrowth_{it} + \gamma_4 Size_{it} + u_{it}$$

Table 9 displays the regression results of stock price informativeness as a linear function of a cross-listing dummy, stock turnover, sales growth, and firm size. Cross-listing is significant in every cross-section at the five percent level, and in 2015, 2018, and 2019, it is significant at the one percent level. For every year, the coefficient on cross-listing is negative. This suggests that cross-listing on a regulated US stock exchange decreases stock price informativeness (the firm-specific return variation). For example, in 2015, the average firm that is cross-listed in the United States will observe a decline in firm-specific return variation of 0.824. Such a result is consistent with part of the Fernandes and Ferreira (2008) finding, specifically their results that observe stock price informativeness is lower when firms from less developed countries cross-list in the United States.

Figure 2 visualizes the direct and indirect relationships between cross-listing CL_{it} and Tobin's q Q_{it}. The average direct effect α_1 in the figure corresponds to β_1 in the above regression, and the average indirect effect $\Gamma\alpha_0$ corresponds to $\gamma_1\beta_6$ in the above set of equations. The cross-listing dummy is the exposure variable, the mediator is stock price informativeness, and the response variable is Tobin's q.

Sales growth is not a statistically significant predictor for informativeness in this regression, and turnover varies between being highly significant and not at all across years. Firm size is consistently significant at the one percent level. The negative coefficient on size indicates that smaller firms will have more firm-specific return variation. The magnitude of the cross-listing coefficient is much

Table 8: Regressing Tobin's Q on Previously Studied Covariates, Informativeness, and Log(Assets)

	Tobin's Q				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	13.487***	11.146***	11.949***	23.833***	19.492***
	(2.588)	(2.494)	(3.764)	(3.624)	(3.521)
Cross-Listed	4.805**	3.873*	5.398**	4.469	3.957
	(2.125)	(2.078)	(2.714)	(2.734)	(2.674)
Turnover	−132.672***	−110.476***	−101.881**	−81.159**	−48.989*
	(26.122)	(31.726)	(50.331)	(38.201)	(28.521)
Sales Growth	−0.140	−0.631	−0.492	−1.642*	−0.225
	(0.305)	(0.555)	(0.608)	(0.972)	(0.569)
Size	10.763***	10.964***	15.561***	15.051***	14.523***
	(0.377)	(0.375)	(0.507)	(0.495)	(0.490)
Industry Q	−10.369***	−9.968***	−14.298***	−14.631***	−13.916***
	(0.982)	(0.968)	(1.275)	(1.296)	(1.255)
Informativeness	0.317	0.768**	1.044**	0.008	0.191
	(0.314)	(0.323)	(0.498)	(0.420)	(0.432)
Log(Assets)	−9.976***	−10.058***	−14.188***	−14.100***	−13.378***
	(0.347)	(0.342)	(0.466)	(0.469)	(0.454)
N	3,721	3,671	3,640	3,603	3,558
R^2	0.191	0.200	0.215	0.212	0.209
Adjusted R^2	0.190	0.198	0.214	0.211	0.207

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

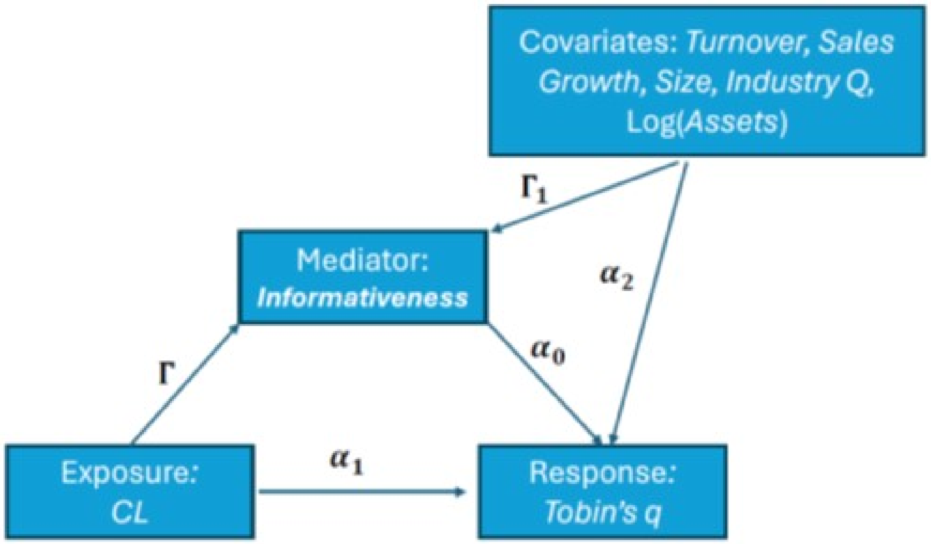

Figure 2: Diagram of Mediation Model for Tobin's q

larger than the coefficient on size though, which indicates that cross-listing may have a stronger effect on informativeness. The below equations are then directed into the mediation model for each year. Results for the causal mediation model applied within each year are provided in table 10.

For each application of causal mediation analysis below, the average causal mediated effect (ACME), average direct effect (ADE), total effect, and proportion of the total effect that is mediated are reported. In all causal mediation analyses in this work, we employ robust standard errors and run 5000 simulations. Tingley et al. (2014) describe 1000 simulations—which are quasi-Bayesian Monte Carlo simulations—as sufficient for most estimated parameters to converge, but we opt for a higher number of simulations due to variation in parameter estimates observed when there are only 1000 simulations. Additionally, lower and upper bounds on a 95 percent confidence interval are given. In every year, the average direct effect and total effect are statistically different from zero at the five percent level. The 2016 year is the only cross-section where the average causal mediated effect is statistically significant, and it is negative. The values reported imply that when a representative company from the 2016 data set cross-lists, such a choice influences stock price informativeness in a way that will—on average—reduce Tobin's q by 0.181. Cross-listing alone has an average direct effect of increasing Tobin's q by 3.853. The statistical significance of the average direct effect may be surprising given that the cross-sections in table 8 do not show that cross-listing is significant in every year. Since point estimates and confidence intervals are produced using quasi-Bayesian Monte Carlo simulations based on normal approximation, it is possible that the skewing effect of outliers in the data is magnified. This is another motivation for the replication of these analyses using a log-transformed Tobin's q as the dependent variable instead, but the below results are presented for comparability to previous literature.

The coefficients reported for the average direct effect (ADE) face the same interpretability issues as the coefficients on cross-listing in the cross-section as a linear regression, where the magnitude of a given coefficient is particularly large relative to the range of Tobin's q values observed. However, the negative sign of the indirect effect (ACME) results in the total effect of cross-listing on valuation being smaller than the direct effect. This is broadly true across all years: the total effect is still

Table 9: Cross-Sectional Analysis of Stock Price Informativeness

	Stock Price Informativeness				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	3.334***	2.534***	4.007***	3.949***	3.930***
	(0.092)	(0.089)	(0.077)	(0.089)	(0.090)
Cross-Listed	−0.824***	−0.239**	−0.193**	−0.663***	−0.822***
	(0.110)	(0.105)	(0.090)	(0.108)	(0.103)
Turnover	4.790***	1.552	4.885***	−1.480	3.719***
	(1.359)	(1.618)	(1.681)	(1.526)	(1.123)
Sales Growth	−0.004	0.041	0.028	0.026	0.041*
	(0.016)	(0.028)	(0.020)	(0.039)	(0.022)
Size	−0.068***	−0.049***	−0.091***	−0.133***	−0.095***
	(0.009)	(0.008)	(0.007)	(0.008)	(0.008)
N	3,721	3,671	3,640	3,603	3,558
R^2	0.037	0.012	0.050	0.077	0.059
Adjusted R^2	0.036	0.011	0.049	0.075	0.058

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 10: Cross-Sectional Causal Mediation Analysis of Tobin's Q

	Estimate	Lower CI Bound	Upper CI Bound	P-Value
		2015 Cross-Section		
ACME	−0.269	−0.861	0.302	0.358
ADE	4.840***	1.700	7.925	0.003
Total Effect	4.571**	1.540	7.514	0.004
Proportion Mediated	−0.058	−0.253	0.088	0.358
		2016 Cross-Section		
ACME	−0.181**	−0.444	−0.003	0.042
ADE	3.853***	1.147	6.585	0.007
Total Effect	3.672***	0.971	6.393	0.008
Proportion Mediated	−0.046**	−0.203	−0.000	0.049
		2017 Cross-Section		
ACME	−0.202	−0.582	0.034	0.125
ADE	5.375***	1.696	8.967	0.006
Total Effect	5.163***	1.529	8.788	0.009
Proportion Mediated	−0.034	−0.182	0.010	0.134
		2018 Cross-Section		
ACME	−0.006	−0.637	0.618	0.990
ADE	4.476**	1.022	7.970	0.013
Total Effect	4.470**	1.049	7.901	0.013
Proportion Mediated	−0.000	−0.225	0.205	0.992
		2019 Cross-Section		
ACME	−0.155	−1.199	0.866	0.782
ADE	3.953**	0.265	7.673	0.036
Total Effect	3.798**	0.224	7.342	0.039
Proportion Mediated	−0.039	−0.677	0.478	0.790

Notes:

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

positive and significant, but it is smaller than the average direct effect. The lack of statistical significance of the indirect effect in the years 2015, 2017, 2018, and 2019 suggests that stock price informativeness may not be a statistically important mediation channel through which cross-listing impacts Tobin's q.

6.1.3 Causal Mediation Across Years

We now move to examining causal mediation analysis aggregated across all data points and time periods. The regression coefficients presented in table 11 reflect a pooled estimation approach on the following equations across firms i and years t:

$$\begin{aligned} Q_{it} = \beta_0 + \beta_1 CL_{it} + \beta_2 Turnover_{it} + \beta_3 SalesGrowth_{it} + \beta_4 Size_{it} \\ + \beta_5 IndustryQ_t + \beta_6 Informativeness_{it} + \beta_7 \log(Assets)_{it} + \varepsilon_{it} \end{aligned}$$

$$Informativeness_{it} = \gamma_0 + \gamma_1 CL_{it} + \gamma_2 Turnover_{it} + \gamma_3 SalesGrowth_{it} + \gamma_4 Size_{it} + u_{it}$$

For the first equation, we see that cross-listing, turnover, informativeness, size, median industry q, and log(Assets) are all statistically significant at the 1 percent level. Both cross-listing and informativeness have positive coefficients. The decision to cross-list is associated with a 4.624 increase in Tobin's q, and a one unit increase in firm-specific stock return variation is associated with a 0.497 increase in firm valuation. Again, the coefficient magnitude on some of these regressors, particularly cross-listing and turnover, may be alarmingly large. It is worth noting that the cross-listing dummy takes on values 0 and 1, and the turnover variable takes on extremely small values (median across data points is 0.002).

The second equation, which predicts informativeness, has cross-listing, turnover, sales growth, and firm size as statistically significant predictors. Notably, cross-listing and larger firm size are associated with lower levels of firm-specific return variation, whereas higher turnover and sales growth are positively related to informativeness. On average for a given firm-year observation, going from being a non-cross-listed firm to a cross-listed one is associated with a 0.537 decrease in informativeness. Given that cross-listing is associated with less informative stock prices, and informativeness is positively associated with Tobin's q, it is unsurprising that the indirect effect (ACME) reported in table 12 is negative.

We observe that when we run the causal mediation model across all data points, there is a statistically significant indirect effect, direct effect, total effect, and proportion of the total effect mediated at the one percent value. There is a negative sign on the ACME value, which indicates that the indirect effect influences the dependent variable in a direction opposite that of the direct effect. The positive ADE is significantly larger in magnitude than the negative ACME, so the total effect is still significantly positive. In the absence of the mediation model, one might have concluded that cross-listing's true impact on valuation was a smaller positive number (4.357) than it truly was (4.630). Due to the decomposition of the total effect into direct and indirect components, it is possible to note that–if cross-listing did not negatively impact stock price informativeness or informativeness did not influence valuation–there would be an even larger total positive impact of cross-listing on valuation. On average across all firm-year observations, cross-listing reduces stock price informativeness in a way that lowers Tobin's q by 0.273. However, the sheer magnitude of the average direct effect (4.630) relative to the distribution of the Tobin's q values observed suggests that further analysis should transform the underlying distribution of q values to be more normal.

Table 11: Informativeness (Mediator) and Tobin's Q (Outcome) Models in Multi-Year Period

	Informativeness	Tobin's Q
	(1)	(2)
Constant	3.536***	15.223***
	(0.041)	(1.408)
Cross-Listed	−0.547***	4.624***
	(0.048)	(1.111)
Turnover	3.133***	−96.900***
	(0.650)	(14.868)
Sales Growth	0.022**	−0.346
	(0.010)	(0.235)
Size	−0.086***	13.137***
	(0.004)	(0.201)
Industry Q		−12.462***
		(0.521)
Informativeness		0.497***
		(0.170)
Log(Assets)		−12.091***
		(0.186)
N	18,193	18,193
R^2	0.038	0.200
Adjusted R^2	0.037	0.199

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.

Table 12: Causal Mediation Analysis for Tobin's Q Across Years

	Estimate	Lower CI Bound	Upper CI Bound	P-Value
ACME	−0.273***	−0.505	−0.053	0.010
ADE	4.630***	3.139	6.135	0.000
Total Effect	4.357***	2.900	5.818	0.000
Proportion Mediated	−0.062***	−0.133	−0.012	0.010

Notes: ***Significant at the 1 percent level.

6.2 Analysis for Log Tobin's Q as Outcome Variable

All following analysis employs the log-transformed Tobin's q, denoted q_{it} instead of Q_{it}, as the dependent variable. As described in table 4, the distribution of the log values of Tobin's q appears more normally distributed than the distribution of non-transformed q values. Issues originating from the heavily skewed distribution of Tobin's q values include overly large magnitudes of coefficient values, low R^2, and the potentially magnified effects of outliers in the quasi-Bayesian Monte Carlo methods. Therefore, all following regressions adopt a different functional model, where we instead model $q_{it} = \log Q_{it}$.

6.2.1 Linear Cross-Sectional Models of Log Tobin's Q

Below in table 13, the simplest regression of valuation on the cross-listing dummy is replicated, holding year t fixed in the cross-section:

$$q_{it} = \alpha_t + \beta_{l1} CL_{it} + \varepsilon_{it}$$

For most years, the regression results parallel those of the same regression run with non-transformed Tobin's q on the right-hand side: the cross-listing is not statistically significant, there is an insignificant negative coefficient on the cross-listing dummy, and R^2 is essentially zero. In 2018 and 2019, cross-listing gains explanatory power. The coefficient $\beta_{l1} = 0.168$ obtained in the 2019 cross-section can be interpreted as cross-listing being associated with a 0.168 increase in log(Tobin's q).

Table 13: Regressing Log(Tobin's Q) on Cross-Listed Indicator

	Log(Tobin's Q)				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	0.518***	0.469***	0.471***	0.318***	0.331***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)
Cross-Listed	−0.076	−0.012	0.055	0.108*	0.168***
	(0.064)	(0.061)	(0.061)	(0.059)	(0.060)
N	3,721	3,671	3,640	3,603	3,558
R^2	0.000	0.000	0.000	0.001	0.002
Adjusted R^2	0.000	0.000	0.000	0.001	0.002

Notes: ***Significant at the 1 percent level.
*Significant at the 10 percent level.

Below, q_{it} is fitted in a linear regression within each cross-section to previously studied covariates, including the cross-listing dummy, turnover, sales growth, size, and median industry q. The model is given by equation 9 holding year t fixed within each regression. Relative to the non-log counterpart of the equation, the log-transformed model has much larger R^2. In table 6, the R^2 values ranged from 0.008 to 0.011. Here, the R^2 values are between 0.098 and 0.133.

$$q_{it} = \beta_{l0} + \beta_{l1} CL_{it} + \beta_{l2} Turnover_{it} + \beta_{l3} SalesGrowth_{it} + \beta_{l4} Size_{it} + \beta_{l5} IndustryQ_t + \varepsilon_{it} \quad (9)$$

Table 14: Regressing Log(Tobin's Q) on Cross-Listed Indicator and Previously Studied Covariates

	Log(Tobin's Q)				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	−0.488***	−0.332***	−0.414***	−0.646***	−0.597***
	(0.064)	(0.064)	(0.064)	(0.061)	(0.064)
Cross-Listed	−0.191***	−0.134**	−0.109*	−0.050	0.011
	(0.060)	(0.058)	(0.058)	(0.057)	(0.057)
Turnover	5.922***	4.579***	−0.004	0.534	0.261
	(0.735)	(0.889)	(1.081)	(0.796)	(0.619)
Sales Growth	−0.001	0.008	0.009	0.033	0.008
	(0.009)	(0.016)	(0.013)	(0.020)	(0.012)
Size	0.018***	0.010**	0.017***	0.031***	0.025***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
Industry Q	0.564***	0.487***	0.517***	0.470***	0.489***
	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
N	3,721	3,671	3,640	3,603	3,558
R^2	0.133	0.100	0.105	0.098	0.101
Adjusted R^2	0.132	0.098	0.103	0.097	0.100

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

In the non-log counterpart to this regression, neither cross-listing nor median industry q were significant in any of the cross-sections from 2015 to 2019. However, the dummy for cross-listing has a statistically significant negative coefficient value in 2015 and 2016 at the 5 percent level. Interestingly, the cross-listing coefficient takes on a weak and insignificant positive value in 2019. The median industry q variable has a statistically significant positive coefficient in each cross-section, which is a departure from the lack of significance in any of the non-log cross-sections. Turnover is also statistically significant in the first two years of the sample with a positive sign whereas it is not statistically significant in any of the non-log cross-sectional regressions. The dramatically higher R^2 suggests that the usage of $q_{it} = \log(Q_{it})$ may more accurately model the relation between valuation and cross-listing, among other covariates.

The next set of cross-sections in table 15 includes informativeness as a covariate and follows equation 10, holding year t fixed within the cross-section. The explanatory power of the model explaining the log-transformed Tobin's q values is significantly higher than the linear regression of the original Tobin's q values. The R^2 values range from 0.1 to 0.147 in the below cross-sections, whereas they were between 0.011 and 0.016 before the log transformation of the dependent variable.

$$\begin{aligned} q_{it} = \beta_{l0} + \beta_{l1}CL_{it} + \beta_{l2}Turnover_{it} + \beta_{l3}SalesGrowth_{it} + \beta_{l4}Size_{it} \\ + \beta_{l5}IndustryQ_t + \beta_{l6}Informativeness_{it} + \varepsilon_{it} \end{aligned} \tag{10}$$

The informativeness variable is a statistically significant predictor of valuation in all years except 2016. It is unclear why 2016 is an anomaly, but it indicates there is some variation between years on how cross-listing and informativeness impact valuation metrics. In 2015, a one unit increase in informativeness would be associated with, on average, a 0.07 increase in log(Tobin's q) which corresponds to an $e^{0.07} \approx 1.073$ increase in Tobin's q. This is smaller in magnitude than the positive coefficient on informativeness in 7, which is 1.329, but still highly statistically significant. Similar to the prior regression before the inclusion of informativeness as an independent variable, cross-listing and turnover are significant in earlier years, and size and median industry q are positive and highly significant in all years. The coefficient on cross-listing is still significantly negative in the earlier years of the data, but it becomes insignificant and weakly positive in some years. This suggests either a changing relationship between cross-listing and log(Tobin's q) or the variation of a covariate.

Table 16 includes log(Assets) as a control variable; the results of the non-log counterpart of this model can be referenced in table 8. The model for this equation is given by:

$$\begin{aligned} q_{it} = \beta_{l0} + \beta_{l1}CL_{it} + \beta_{l2}Turnover_{it} + \beta_{l3}SalesGrowth_{it} + \beta_{l4}Size_{it} \\ + \beta_{l5}IndustryQ_t + \beta_{l6}Informativeness_{it} + \beta_{l7}\log(Assets)_{it} + \varepsilon_{it} \end{aligned} \tag{12}$$

The inclusion of log(Assets) leads to the cross-listing dummy to be significantly positive at the one percent level in every year. The previously observed variation in the sign of the β_{l1} coefficient on cross-listing obtained separately in each cross-section may have coincidentally picked up on variation in log(Assets), which is included in the richest model here. The β_{l1} coefficient in each cross-section, take 2018 for example, can be interpreted as cross-listing being associated with a 0.148 increase in the log value of Tobin's q. This corresponds to a $e^{0.148} \approx 1.160$ increase in Tobin's q. Separately, the 2018 β_{l6} coefficient on informativeness can be interpreted as the potential effect, on average, of a one unit increase in firm-specific return variation being a 0.021 increase in the log value of Tobin's q, which is a $e^{0.021} \approx 1.021$ increase in Tobin's q. Informativeness is statistically significant in every cross-section except in 2017, but its coefficient actually varies in sign. It is (weakly) positive in every year except 2016, in which it is significant and negative. This could be an indication of potential heterogeneity in how informativeness influences valuation.

Similar to the equivalent regression for non-log Tobin's q, log(Assets) is negative and significant in every year. Interestingly, median industry q maintains the same coefficient sign (negative) as in the non-log counterparts, but it is less significant in the regressions with the log-transformed dependent variable. Size is still positively related and highly significant for every year. Turnover is no longer a significant predictor in any year.

The explanatory power of the richest model for the log-transformed valuation measure is much higher than any other set of equations so far. R^2 hovers around 0.70 for each year, which is not only much larger than the $R^2 \approx 0.10$ values seen before the log(Assets) term was included, but also the corresponding non-log model, which had $R^2 \approx 0.20$ in each year. This lends strong support to the usage of the log-transformed Tobin's q as the dependent variable, which is also what Bianconi and Tan (2010) choose to model.

Table 15: Regressing Log(Tobin's Q) on Previously Studied Covariates and Informativeness

	Log(Tobin's Q)				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	-0.698^{***}	-0.338^{***}	-0.587^{***}	-0.929^{***}	-0.884^{***}
	(0.069)	(0.067)	(0.078)	(0.069)	(0.071)
Cross-Listed	-0.130^{**}	-0.134^{**}	-0.102^{*}	-0.004	0.086
	(0.060)	(0.058)	(0.058)	(0.056)	(0.057)
Turnover	5.605^{***}	4.576^{***}	-0.211	0.636	-0.060
	(0.730)	(0.889)	(1.080)	(0.789)	(0.613)
Sales Growth	-0.001	0.008	0.008	0.031	0.004
	(0.009)	(0.016)	(0.013)	(0.020)	(0.012)
Size	0.022^{***}	0.011^{**}	0.021^{***}	0.040^{***}	0.032^{***}
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
Industry Q	0.550^{***}	0.487^{***}	0.520^{***}	0.473^{***}	0.466^{***}
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Informativeness	0.070^{***}	0.002	0.042^{***}	0.070^{***}	0.082^{***}
	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)
N	3,721	3,671	3,640	3,603	3,558
R^2	0.147	0.100	0.108	0.114	0.121
Adjusted R^2	0.146	0.098	0.107	0.113	0.120

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.

Table 16: Regressing Log(Tobin's Q) on Previously Studied Covariates, Informativeness, and Log(Assets)

	Log(Tobin's Q)				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	0.512***	0.651***	0.528***	0.407***	0.419***
	(0.039)	(0.039)	(0.044)	(0.046)	(0.045)
Cross-Listed	0.106***	0.087***	0.119***	0.148***	0.180***
	(0.032)	(0.033)	(0.032)	(0.034)	(0.034)
Turnover	0.612	0.739	−0.690	−0.634	−0.371
	(0.395)	(0.500)	(0.593)	(0.480)	(0.365)
Sales Growth	0.003	−0.000	−0.005	−0.025**	−0.002
	(0.005)	(0.009)	(0.007)	(0.012)	(0.007)
Size	0.515***	0.486***	0.515***	0.478***	0.485***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Industry Q	−0.025*	−0.033**	−0.026*	−0.034**	−0.031*
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
Informativeness	0.018***	−0.013**	0.001	0.021***	0.015***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
Log(Assets)	−0.504***	−0.482***	−0.504***	−0.461***	−0.468***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
N	3,721	3,671	3,640	3,603	3,558
R^2	0.755	0.717	0.732	0.672	0.690
Adjusted R^2	0.754	0.717	0.731	0.672	0.689

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

6.2.2 Causal Mediation on Log Tobin's Q in the Cross-Section

The below figure 3 visually shows how the cross-listing exposure variable directly impacts the response variable through α_1, but also indirectly through the mediator variable of informativeness via $\Gamma\alpha_0$.

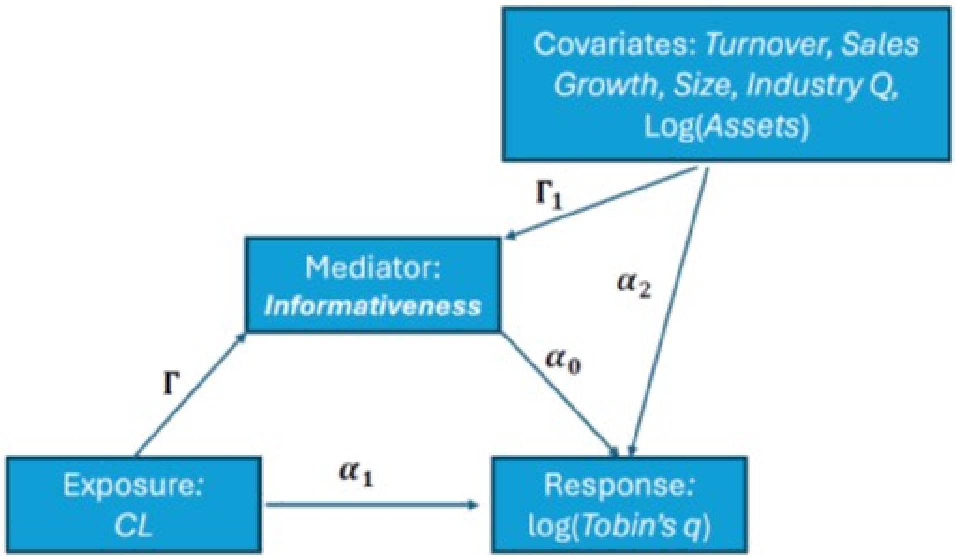

Figure 3: Diagram of Mediation Model for log(Tobin's q)

For each year, we apply the above causal mediation model, using the same equation predicting stock price informativeness for fixed year t. The other equation models log-transformed Tobin's q using the richest model possible. The regression coefficients for each of the below equations are provided in tables 9 and 16, respectively. The exposure variable here is CL_{it}, the mediator is $Informativeness_{it}$, and the response is q_{it}.

$$Informativeness_{it} = \gamma_0 + \gamma_1 CL_{it} + \gamma_2 Turnover_{it} + \gamma_3 SalesGrowth_{it} + \gamma_4 Size_{it} + u_{it} \tag{12}$$

$$\begin{aligned} q_{it} = \beta_{l0} + \beta_{l1} CL + \beta_{l2} Turnover_{it} + \beta_{l3} SalesGrowth_{it} + \beta_{l4} Size_{it} \\ + \beta_{l5} IndustryQ_t + \beta_{l6} Informativeness_{it} + \beta_{l7} \log(Assets)_{it} + \varepsilon_{it} \end{aligned} \tag{11}$$

Table 18 displays the results of causal mediation analysis per the **mediate** package in R for each year's data points (Tingley et al., 2014). P-values and 95 percent confidence intervals are calculated using robust standard errors, and each year's analysis involved the running of 5000 quasi-Bayesian Monte Carlo simulations. It is apparent that both the average direct effect and average causal mediated (indirect) effect are statistically significant in most years, often at the five or one percent level. Both the average direct and indirect effects are significant in 2015, 2016, 2018, and 2019. It is unclear why only the average direct effect is significant in 2017, which is the same year where informativeness was not a significant predictor in the richest iteration of the log-transformed model. In all years examined, the average direct effect and average indirect effect of cross-listing on log-transformed Tobin's q is positive and statistically significant. In years where the average indirect effect is significant, it is negative except for in 2016, where it is 0.003.

These results reflect that—in the majority of years contained in the data—cross-listing has a direct positive impact on log(Tobin's q) and an indirect negative impact by reducing stock price

Table 17: Cross-Sectional Causal Mediation Analysis of Log(Tobin's Q)

	Estimate	Lower CI Bound	Upper CI Bound	P-Value
		2015 Cross-Section		
ACME	-0.015^{***}	-0.024	-0.007	0.000
ADE	0.106^{***}	0.031	0.183	0.007
Total Effect	0.091^{**}	0.017	0.167	0.020
Proportion Mediated	-0.164^{**}	-0.726	-0.052	0.020
		2016 Cross-Section		
ACME	0.003^{**}	0.000	0.007	0.032
ADE	0.086^{**}	0.013	0.158	0.024
Total Effect	0.089^{**}	0.017	0.161	0.021
Proportion Mediated	0.031^{*}	-0.000	0.161	0.052
		2017 Cross-Section		
ACME	-0.000	-0.004	0.003	0.859
ADE	0.119^{***}	0.048	0.190	0.003
Total Effect	0.118^{***}	0.048	0.190	0.003
Proportion Mediated	-0.001	-0.038	0.027	0.861
		2018 Cross-Section		
ACME	-0.014^{***}	-0.023	-0.006	0.000
ADE	0.149^{***}	0.072	0.224	0.000
Total Effect	0.135^{***}	0.058	0.211	0.000
Proportion Mediated	-0.101^{***}	-0.274	-0.038	0.000
		2019 Cross-Section		
ACME	-0.012^{**}	-0.024	-0.002	0.022
ADE	0.179^{***}	0.104	0.256	0.000
Total Effect	0.166^{***}	0.094	0.243	0.000
Proportion Mediated	-0.073^{**}	-0.188	-0.009	0.022

Notes: ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

informativeness, which is positively related to log(Tobin's q). For the year 2016, stock price informativeness was a significant negative covariate for log(Tobin's q), which explains why the indirect effect that year was positive. Cross-listing still reduced stock price informativeness, but since informativeness negatively impacted valuation for data points in that year, such a cross-listing change had an overall positive impact on log(Tobin's q). This suggests not only some heterogeneity in the relationships between cross-listing, informativeness, and this log-transformed valuation metric across different years, but also lends motivation as to why decomposing the total effect into direct and indirect components is necessary. Elsewise, it is difficult to specify the causal impact of cross-listing without knowing how it influences informativeness, and whether the least squares estimate is under- or over-estimating the true direct effect.

6.2.3 Causal Mediation for Log Tobin's Q Across Years

When data points across years are combined together, the causal mediation model can be applied to all the data at once. Table 18 displays the regression coefficients for the below equations, calculated across all years t:

$$Informativeness_{it} = \gamma_0 + \gamma_1 CL_{it} + \gamma_2 Turnover_{it} + \gamma_3 SalesGrowth_{it} + \gamma_4 Size_{it} + u_{it} \tag{12}$$

$$\begin{aligned} q_{it} = \beta_{l0} + \beta_{l1} CL_{it} + \beta_{l2} Turnover_{it} + \beta_{l3} SalesGrowth_{it} + \beta_{l4} Size_{it} \\ + \beta_{l5} IndustryQ_t + \beta_{l6} Informativeness_{it} + \beta_{l7} \log(Assets)_{it} + \varepsilon_{it} \end{aligned} \tag{11}$$

Using the log-transformed version of Tobin's q as the dependent variable makes the coefficient $\beta_{l1} = 0.121$ on cross-listing calculated across years much more interpretable than the $\beta_1 = 4.624$ produced using the original Tobin's q values. The Tobin's q values in the data, excluding outliers, have first quartile value 0.981, median value 1.234, and third quartile value 1.955 across all years. The 4.624 value reflects the effects of extremely high outliers. Using the log transform reduces the outlier impact, and a 0.121 impact on log(Tobin's q) as a result of cross-listing is not unreasonable when the first quartile, median, and third quartile values for log(Tobin's q) across years are -0.019, 0.210, and 0.670, respectively.

This model no longer has turnover as a statistically significant predictor, but cross-listing, informativeness, size, median industry q, and log(assets) all retain their statistical significance and sign relative to the corresponding non-log equations run across all data points. The β_{l6} coefficient can be interpreted as cross-listing having, on average, a positive impact of 0.007 on log(Tobin's q) which implies an $e^{0.07} \approx 1.073$ increase in Tobin's q. The R^2 of the model for q_{it} across years is much higher (0.715) than the R^2 for the corresponding non-log model across time (0.200).

Causal mediation analysis across all data points yields results shown in table 19. The indirect effect is statistically significant and negative, while the direct effect is statistically significant and positive, with greater magnitude. Therefore, the total effect is significant and positive. The proportion of the total effect mediated by stock price informativeness is roughly 3% and is negative. While 3% is a very small proportion of the total effect, it is still statistically significant. If one did not account for the mediator's influence, the direct effect may have been incorrectly identified as 0.117 instead of 0.121, underplaying the positive impact of cross-listing on valuation. These results are all significant at the one percent level.

6.3 Robustness

One might be concerned that companies that exit the dataset over time, usually due to bankruptcy or acquisition, might have intrinsically different characteristics from companies that remain in the

Table 18: Informativeness (Mediator) and Tobin's Q (Outcome) Models in Multi-Year Period

	Informativeness	Log(Tobin's Q)
	(1)	(2)
Constant	3.536***	0.520***
	(0.041)	(0.019)
Cross-Listed	−0.547***	0.121***
	(0.048)	(0.015)
Turnover	3.133***	0.032
	(0.650)	(0.198)
Sales Growth	0.022**	−0.003
	(0.010)	(0.003)
Size	−0.086***	0.498***
	(0.004)	(0.003)
Industry Q		−0.031***
		(0.007)
Informativeness		0.007***
		(0.002)
Log(Assets)		−0.486***
		(0.002)
N	18,193	18,193
R^2	0.038	0.715
Adjusted R^2	0.037	0.715

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.

Table 19: Causal Mediation Analysis for Log(Tobin's Q) Across Years

	Estimate	Lower CI Bound	Upper CI Bound	P-Value
ACME	−0.004***	−0.007	−0.001	0.006
ADE	0.121***	0.088	0.154	0.000
Total Effect	0.117***	0.085	0.151	0.000
Proportion Mediated	−0.031***	−0.061	−0.009	0.006

Notes: ***Significant at the 1 percent level.

dataset for all five years. To account for such potential differences in the companies, I create an "Acquired" dummy variable (which takes on value 1 if the company disappears from the dataset due to acquisition, and is 0 otherwise) and a "Bankrupt" dummy variable (which takes on value 1 if the company disappears from the dataset due to bankruptcy, and is 0 otherwise). As a robustness check, in tables 20, 21, and 22, I replicate the regression results and causal mediation analysis including the dummy variables for acquisition and bankruptcy disappearance on the multi-year data.

The results are nearly identical to those obtained when omitting the disappearance-related indicator variables. Very similar results (minimally different coefficients, no chance in the significance of regressors) are obtained when these disappearing firms are excluded altogether from these regressions, although those results are not explicitly included as a table in this work. This suggests that our results are not only robust when using robust standard errors and a large number of quasi-Bayesian Monte Carlo simulations, but also that the results may be robust relative to a small degree of heterogeneity in firm characteristics within the dataset due to disappearance-related characteristics. One could feasibly imagine that companies that are performing well and rapidly grabbing market share may be acquired by their competitors or larger firms, and companies facing bankruptcy may have characteristics reflective of their financial situation.

In table 20, there are positive coefficients on both the acquisition- and bankruptcy-related dummy variables, both in the regression using the original Tobin's q and the log-transformed Tobin's q. All coefficients are significant except the coefficient on the acquisition dummy variable in the Tobin's q linear regression. The positive coefficient on the acquisition dummy may be expected if firms that are acquired possess characteristics that make them more highly valued. However, the positive and significant coefficient on the bankruptcy dummy variable is less easily explained. In any case, there are only a very smaller number of observations that represent the firms disappearing at some point in the sample years. Specifically, there are 214 and 86 firm-year observations that have a non-zero value for the acquisition and bankruptcy dummies, respectively. This is a very small portion of the data, and the below causal mediation results show that there is minimal change if we account for such disappearances relative to the model that ignores them. Given such minimal differences, I treat the model *not* including these acquisition and bankruptcy variables as the default, under the understanding that the inclusion of the two disappearance-related dummies may lead to overfitting given how few firms within the dataset have nonzero values.

Table 20: Informativeness and Valuation Models in Multi-Year Period

	Informativeness	Tobin's Q	Log(Tobin's Q)
	(1)	(2)	(3)
Constant	3.536***	15.074***	0.516***
	(0.041)	(1.409)	(0.019)
Cross-Listed	−0.547***	4.386***	0.115***
	(0.048)	(1.114)	(0.015)
Turnover	3.133***	−96.798***	0.036
	(0.650)	(14.865)	(0.198)
Sales Growth	0.022**	−0.340	−0.002
	(0.010)	(0.235)	(0.003)
Size	−0.086***	13.183***	0.499***
	(0.004)	(0.202)	(0.003)
Industry Q		−12.491***	−0.032***
		(0.521)	(0.007)
Informativeness		0.493***	0.007***
		(0.170)	(0.002)
Log(Assets)		−12.122***	−0.487***
		(0.186)	(0.002)
Acquired		1.343	0.078***
		(2.207)	(0.029)
Bankrupt		10.630***	0.226***
		(3.474)	(0.046)
N	18,193	18,193	18,193
R^2	0.038	0.200	0.715
Adjusted R^2	0.037	0.200	0.715

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.

Table 21: Causal Mediation Analysis for Log(Tobin's Q) Across Years

	Estimate	Lower CI Bound	Upper CI Bound	P-Value
ACME	-0.268^{**}	-0.496	-0.052	0.015
ADE	4.389^{***}	2.888	5.838	0.000
Total Effect	4.121^{***}	2.614	5.565	0.000
Proportion Mediated	-0.064^{***}	-0.137	-0.012	0.015

Notes: ***Significant at the 1 percent level.

Table 22: Causal Mediation Analysis for Log(Tobin's Q) Across Years, Employing Acquisition and Bankruptcy Disappearance Dummies

	Estimate	Lower CI Bound	Upper CI Bound	P-Value
ACME	-0.004^{***}	-0.007	-0.001	0.009
ADE	0.115^{***}	0.082	0.147	0.000
Total Effect	0.111^{***}	0.078	0.144	0.000
Proportion Mediated	-0.033^{***}	-0.066	-0.009	0.009

Notes: ***Significant at the 1 percent level.

7 Conclusion

Given the extensive literature on how cross-listing influences a company's valuation, the exact causal relationships between cross-listing and valuation measures merit greater consideration. Mediation analysis is one such method to do so, especially since stock price informativeness not only is influenced by a company's cross-listing status, but informativeness itself can impact valuation. This paper adds to the existing literature by noting the positive association between increased firm-specific stock return variation and Tobin's q, which lends empirical support to Foucault and Gehrig's (2008) learning hypothesis, and observing the average negative impact that cross-listing in the United States has on firm-specific return variation adds to Fernandes and Ferreira (2008).

This paper uses the log value of Tobin's q as the evaluative valuation measure, both due to the skewed distribution of Tobin's q in the data and the improved explanatory power of models using the log-transformed value as the dependent variable. When mediation analysis is conducted across all firm-year observations, the model finds that a small but statistically significant proportion of the total effect is attributed to the indirect effects that cross-listing has on valuation through stock price informativeness. This indirect effect is negative, which counters the large positive direct effect, leading to the magnitude of the total effect being slightly smaller but still overwhelmingly positive. The absence of a mediation model would have resulted in an under-estimation of the direct effect of cross-listing on company valuation.

As mentioned in the models section of this paper, panel data methods are omitted from this work. It is possible that the pooled estimation coefficients calculated in this work may not asymptotically converge to the desired population parameters. Such econometric methods were not used here due to the many potential avenues for mediation effects, since within-period effects of a regressor can mediate both within- and between-period causal relationships of other regressors with the valuation measure used. Between-period effects of independent variables face the same issue. Given that potential causal paths grow combinatorically as a function of the number of mediators, this thesis opts for simpler pooled estimation techniques. However, further research in this area could introduce such fixed and random effects with caution to identify the desired direct and indirect effects.

Another potential avenue of research involves variable selection. There are extensive works on what the determinants of company valuation are; this work uses a restricted set of covariates as inputs. However, further work could include more predictors in the model predicting firm valuation. For example, firm indicators accounting for any disappearances from the data across years could identify biases due to acquisition or bankruptcy of the firm across the cross-sections. Other potential applications to stock data are numerous. As Hull (2003) observes, financial markets have grown increasingly complex, adding further nuance to the topics of optimal portfolio allocation, asset pricing, and risk management. A stock's price not only co-moves with its past prices, but it also depends on the prices of any bonds and derivatives issued by the same firm. Furthermore, Graham and Harvey (2001) provide survey evidence that corporate executives employ the valuation of peer companies in capital budgeting decisions, which affect the firm's future value. Thus a firm's share price also depends on the prices of peers and their derivatives, in addition to macroeconomic conditions.

Variable selection could be applied to select the most relevant determinants of valuation to ensure that a sparse but effective model of potential covariates is then fed into the mediation analysis. Classical variable selection criteria such as C_p, the Akaike information criterion, and the Bayesian information criterion (Akaike, 1974; Mallows, 1973; Schwarz, 1978) as well as modern variable selection procedures such as Lasso (Tibshirani, 1996) and SCAD (Fan and Li, 2001; Zou and Li, 2008) could be used to select significant covariates. As is evident, there exists a huge set of variables that may influence a security's price, and a statistical challenge exists in determining which variables are truly impactful. Thus, it may be valuable for future research to extend modern variable selection procedures for analyzing stock data.

Additionally, another potential extension of this thesis could involve model diagnostics by using semiparametric regression techniques. The models applied in this work—see equations (1), (8), and (11) for example—assume that the true model through which cross-listing and other covariates impact corporate valuations is linear. However, it may be that the true relationship is nonlinear. Machine learning methods can be used to diagnose whether the linear regression models employed in examining the effects of cross listing on valuation are appropriate. A natural alternative to the linear model is a partially linear model, in which the effect of cross-listing is linear (since it is a binary categorical variable), whereas covariates are not restricted to such a linear relationship. That is, all covariates are assumed to have some unknown nonlinear relationship with the response variable; therefore, a nonparametric function represents such a relationship. Thus, a natural extension of model (1) is the following partially linear model

$$Y = \boldsymbol{\alpha}_0' \boldsymbol{m} + \boldsymbol{\alpha}_1' \boldsymbol{x} + \boldsymbol{\alpha}_2(\boldsymbol{s}_1) + \varepsilon_1, \tag{13}$$

where $\boldsymbol{\alpha}_2(\boldsymbol{s}_1)$ is an unspecified (i.e. nonparametric) function of $\boldsymbol{s}_1$. This model is called a partially linear model, which with one-dimensional $\boldsymbol{s}_1$ has been extensively studied in prior literature and was first proposed by Engle et al. (1986). Hardle, Liang and Gao (2000) provide a systematical account on partially linear models. Most existing literature employs a one-dimensional $\boldsymbol{s}_1$ to address the curse of dimensionality, since traditional smoothing methods such as local linear regression and spline smoothing methods can only be applied to low-dimensional variables (Fan and Gijbels, 1996; Eilers and Marx, 1996). For multidimensional $\boldsymbol{s}_1$, prior research typically imposes certain model structures on the nonparametric functions. For instance, Cai et al. (2022) requires the baseline function follow an additive model structure. However, modern deep neural networks (DNN) may be a powerful tool in estimating $\boldsymbol{\alpha}_2(\cdot)$ when $\boldsymbol{s}_1$ is multidimensional or even high-dimensional. Instead of imposing particular model structures on these functions, one would consider the estimation of such these functions using techniques related to DNNs. Within a DNN, the input layer reads in all the data, and each hidden layer (of which there can be multiple) applies an activation function to a linear combination of the previous layer's nodes. The most common activation functions are the hyperbolic tangent, rectified linear unit, and sigmoid. Such activation functions enable DNNs to incorporate nonlinear components and craft more complex covariates. Therefore, a DNN can be applied to see if covariates often assumed to have linear relationships with valuation are actually better modeled through a nonlinear form. It would be interesting to explore how to use nonparametric smoothing techniques and DNNs to estimate the partially linear model (13), which is an exciting area for future research.

All above items considered, the research on how to model corporate valuations and the influence of cross-listing is far from complete. This piece contributes to the literature on the exact causal relationship that cross-listing has with valuation, but it leaves open further questions relating to complex mediator relationships in panel data, the usage of richer models, and the allowance of nonparametric forms.

8 Appendix

8.1 Definitions and Data Classification

Table 23: Country Assignments to Region

Country	Region	Country	Region
Argentina	Latin America	Israel	Middle East
Australia	Australia	Italy	Europe
Belgium	Europe	Japan	Asia
Chile	Latin America	Korea	Asia
China	China	Luxembourg	Europe
Colombia	Latin America	Mexico	Latin America
Denmark	Europe	Netherlands	Europe
Finland	Europe	Norway	Europe
France	Europe	Philippines	Asia
Germany	Europe	Spain	Europe
Greece	Europe	Sweden	Europe
Hong Kong	Asia	Switzerland	Europe
India	Asia	Turkey	Middle East
Indonesia	Asia	United Kingdom	Europe
Ireland	Europe		

Table 24: Index Assignments to Region

Region	Index
Asia	S&P Pan Asia Excluding Japan Broad Market Index
Australia	S&P / ASX All Australian 200
China	Shanghai SE Composite
Europe	FTSE Developed Europe
Japan	Nikkei 225 Stock Average
Latin America	FTSE Latin America
Middle East	FTSE Middle East & Africa

8.2 Outputs for Analysis of Tobin's Q Using Dataset with Outliers

The below table 25 replicates table 5 but with the inclusion of outliers in Tobin's q in the dataset. That is, the below regression coefficients reflect the impact of keeping Tobin's q outliers with value above 1,000 for each cross-sectional regression.

Table 25: Regressing Tobin's Q on Cross-Listed Indicator, Outliers Included

	Tobin's Q				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	16.149**	18.956**	25.515**	29.500*	36.888**
	(8.023)	(7.783)	(11.980)	(16.804)	(15.239)
Cross-Listed	−11.934	−14.778	−20.677	−25.108	− − 32.047
	(36.809)	(35.282)	(54.075)	(74.828)	(67.075)
N	3,726	3,678	3,647	3,609	3,565
R^2	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.000	0.000	0.000	0.000	0.000

Notes: **Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 26 corresponds to table 6 but with the inclusion of outliers. Some coefficients, notably that on cross-listing, differ dramatically in magnitude, reflecting the impact of high Tobin's q outliers.

Table 26: Regressing Tobin's Q on Cross-Listed Indicator and Previously Studied Covariates, Outliers Included

	Tobin's Q				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	-76.762^{*}	-96.024^{**}	-146.317^{**}	-187.803^{**}	-213.847^{***}
	(39.920)	(38.972)	(60.143)	(81.269)	(74.864)
Cross-Listed	−13.776	−18.478	−26.453	−39.188	−31.580
	(37.101)	(35.523)	(54.647)	(75.836)	(67.613)
Turnover	−196.144	−255.261	−499.556	−381.682	−214.858
	(456.589)	(542.291)	(1,015.600)	(1,065.875)	(728.232)
Sales Growth	−2.237	−4.483	6.257	36.082	0.987
	(5.385)	(9.517)	(12.270)	(27.030)	(14.520)
Size	9.798^{***}	11.982^{***}	17.595^{***}	22.561^{***}	26.385^{***}
	(2.879)	(2.806)	(4.281)	(5.844)	(5.405)
Industry Q	−4.068	−4.531	−6.606	−10.412	−14.203
	(15.835)	(15.334)	(23.640)	(33.207)	(29.475)
N	3,726	3,678	3,647	3,609	3,565
R^2	0.003	0.005	0.005	0.005	0.007
Adjusted R^2	0.002	0.004	0.004	0.003	0.006

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 27 corresponds to table 7, adding informativeness as a regressor to the linear regression run in table 26. Again, this is included for comparative purposes on how the inclusion of outliers skews coefficients and their magnitudes. Note that no regressors except firm size (which is proxied by the log-transformed market capitalization) are statistically significant.

Table 27: Regressing Tobin's Q on Previously Studied Covariates and Informativeness, Outliers Included

	Tobin's Q				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	-96.959^{**}	-118.159^{***}	-193.120^{***}	-235.240^{**}	-245.921^{***}
	(43.224)	(40.982)	(72.849)	(93.694)	(83.945)
Cross-Listed	−7.873	−15.770	−24.493	−31.459	−23.181
	(37.414)	(35.547)	(54.671)	(76.215)	(68.348)
Turnover	−226.636	−269.397	−555.113	−364.441	−250.642
	(457.245)	(542.202)	(1,016.731)	(1,066.005)	(729.500)
Sales Growth	−2.206	−4.860	5.931	35.749	0.620
	(5.384)	(9.517)	(12.273)	(27.032)	(14.527)
Size	10.214^{***}	12.406^{***}	18.630^{***}	24.139^{***}	27.201^{***}
	(2.899)	(2.816)	(4.377)	(6.046)	(5.492)
Industry Q	−5.406	−5.832	−5.700	−9.961	−16.817
	(15.872)	(15.348)	(23.652)	(33.209)	(29.639)
Informativeness	6.718	9.632^{*}	11.373	11.841	9.201
	(5.516)	(5.531)	(9.990)	(11.638)	(10.927)
N	3,726	3,678	3,647	3,609	3,565
R^2	0.004	0.006	0.005	0.005	0.007
Adjusted R^2	0.002	0.005	0.004	0.003	0.006

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.

However, controlling for log(Assets) as done in table 28 yields statistically significant coefficients on turnover (in some years), size, median industry q, and log(Assets). Additionally, compared to table 8 which is the same regression run on the data *excluding* outliers, the R^2 for the model run on the data including outliers is much lower.

Table 28: Regressing Tobin's Q on Previously Studied Covariates, Informativeness, and Log(Assets), Outliers Included

	Tobin's Q				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	84.498*	63.236	115.501	238.672**	300.665***
	(44.748)	(41.476)	(73.802)	(98.726)	(86.027)
Cross-Listed	26.994	23.900	34.257	24.532	18.249
	(36.757)	(34.569)	(53.263)	(74.654)	(65.517)
Turnover	−934.569**	−910.185*	−620.290	−765.467	−350.486
	(451.474)	(527.462)	(987.777)	(1,042.858)	(698.873)
Sales Growth	−1.547	−5.768	2.509	12.956	−3.249
	(5.275)	(9.229)	(11.925)	(26.492)	(13.918)
Size	81.008***	93.550***	143.047***	171.857***	206.733***
	(6.319)	(5.969)	(9.446)	(12.899)	(11.332)
Industry Q	−88.496***	−95.330***	−144.819***	−182.654***	−215.016***
	(16.901)	(15.993)	(24.839)	(35.131)	(30.480)
Informativeness	−1.079	6.024	−1.421	−5.456	−18.120*
	(5.439)	(5.369)	(9.744)	(11.460)	(10.579)
Log(Assets)	−73.083***	−83.354***	−128.590***	−157.670***	−188.322***
	(5.828)	(5.453)	(8.717)	(12.237)	(10.529)
N	3,726	3,678	3,647	3,609	3,565
R^2	0.044	0.066	0.062	0.049	0.089
Adjusted R^2	0.042	0.064	0.060	0.047	0.088

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 29 shows the regression coefficients for the mediator variable (stock price informativeness) as a linear function of cross-listing, turnover, sales growth, and size. The differences between this table and table 9 reflect the impact of including outliers.

Table 29: Cross-Sectional Analysis of Stock Price Informativeness, Outliers Included

	Stock Price Informativeness				
	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)
Constant	3.326***	2.519***	3.985***	3.946***	3.931***
	(0.092)	(0.089)	(0.077)	(0.088)	(0.089)
Cross-Listed	−0.825***	−0.243**	−0.197**	−0.664***	−0.823***
	(0.110)	(0.105)	(0.090)	(0.108)	(0.103)
Turnover	4.770***	1.521	4.838***	−1.485	3.715***
	(1.359)	(1.619)	(1.685)	(1.525)	(1.123)
Sales Growth	−0.005	0.039	0.028	0.027	0.041*
	(0.016)	(0.028)	(0.020)	(0.039)	(0.022)
Size	−0.067***	−0.047***	−0.089***	−0.132***	−0.095***
	(0.009)	(0.008)	(0.007)	(0.008)	(0.008)
N	3,726	3,678	3,647	3,609	3,565
R^2	0.036	0.012	0.048	0.077	0.059
Adjusted R^2	0.035	0.010	0.047	0.076	0.058

Notes: ***Significant at the 1 percent level.
*Significant at the 10 percent level.

Below, in table 30, causal mediation analysis is run with the equations in tables 28 and 29. We observe that nearly all the causal effects observed in the mediation are insignificant. This is a departure from the results obtained in table 12.

Table 30: Cross-Sectional Causal Mediation Analysis of Tobin's Q, Outliers Included

	Estimate	Lower CI Bound	Upper CI Bound	P-Value
	2015 Cross-Section			
ACME	0.899	−1.602	3.399	0.476
ADE	27.0578	−9.755	63.744	0.154
Total Effect	27.956	−10.096	65.655	0.152
Proportion Mediated	0.031	−0.251	0.303	0.468
	2016 Cross-Section			
ACME	−1.456	−4.260	0.494	0.154
ADE	23.916	−6.093	53.699	0.114
Total Effect	22.459	−6.507	50.902	0.121
Proportion Mediated	−0.057	−0.349	0.148	0.173
	2017 Cross-Section			
ACME	0.325	−5.204	6.098	0.896
ADE	34.280	−8.757	77.662	0.123
Total Effect	34.605	−12.036	80.759	0.142
Proportion Mediated	0.012	−0.535	0.471	0.777
	2018 Cross-Section			
ACME	3.664	−0.773	8.563	0.108
ADE	24.456	−23.480	72.243	0.328
Total Effect	28.120	−20.675	76.917	0.270
Proportion Mediated	0.098	−1.064	1.257	0.312
	2019 Cross-Section			
ACME	14.989*	−0.565	31.304	0.064
ADE	18.299	−32.372	68.530	0.481
Total Effect	33.288	−19.175	86.100	0.205
Proportion Mediated	0.371	−2.686	3.824	0.238

Notes: *Significant at the 10 percent level.

Tables 31 and 32 show the regression coefficients of the equatoins fed into the mediation model and the causal mediation analysis, respectively, across all data points including outliers. We observe that the average direct effect and total effect are both statistically significant and positive, but neither the indirect effect nor the proportion mediated are significant.

Table 31: Informativeness (Mediator) and Tobin's Q (Outcome) Models Across Years, Outliers Included

	Informativeness	Tobin's Q
	(1)	(2)
Constant	3.527***	141.071***
	(0.040)	(31.230)
Cross-Listed	−0.548***	31.970
	(0.048)	(24.655)
Turnover	3.117***	−844.977**
	(0.650)	(329.964)
Sales Growth	0.022**	0.157
	(0.010)	(5.218)
Size	−0.085***	137.232***
	(0.004)	(4.263)
Industry Q		−143.946***
		(11.474)
Informativeness		−2.063
		(3.773)
Log(Assets)		−123.704***
		(3.946)
N	18,225	18,225
R^2	0.037	0.056
Adjusted R^2	0.037	0.056
Notes:	***Significant at the 1 percent level.	
	**Significant at the 5 percent level.	

Table 32: Causal Mediation Analysis for Tobin's Q Across Years, Outliers Included

	Estimate	Lower CI Bound	Upper CI Bound	P-Value
ACME	1.133	−1.244	3.521	0.346
ADE	31.998***	12.418	51.566	0.002
Total Effect	33.131***	13.166	53.212	0.002
Proportion Mediated	0.034	−0.053	0.127	0.347

Notes: ***Significant at the 1 percent level.

References

[1] Abdallah, Abed, and Wissam Abdallah. 2019. "Does cross-listing in the US improve investment efficiency? Evidence from UK firms." *The Quarterly Review of Economics and Finance* 72: 215-231.

[2] Ahearne, Alan G., William L. Griever, and Francis E. Warnock. 2004. "Information costs and home bias: an analysis of US holdings of foreign equities." *Journal of International Economics* 62, no. 2: 313-336.

[3] Akaike, Hirotugu. 1974. "A new look at the statistical model identification." *IEEE Transactions on Automatic Control* 19, no. 6: 716-723.

[4] Alexander, Gordon J., Cheol S. Eun, and Sundaram Janakiramanan. 1987. "Asset pricing and dual listing on foreign capital markets: A note." *The Journal of Finance* 42, no. 1: 151-158.

[5] Baker, H. Kent, John R. Nofsinger, and Daniel G. Weaver. 2002. "International cross-listing and visibility." *Journal of Financial and Quantitative Analysis* 37, no. 3: 495-521.

[6] Bancel, Franck, and Cusha Mittoo. 2001. "European managerial perceptions of the net benefits of foreign stock listings." *European Financial Management* 7, no. 2: 213-236.

[7] Baron, Reuben M., and David A. Kenny. 1986. "The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations." *Journal of Personality and Social Psychology*, 51, no. 6: 1173.

[8] Bianconi, Marcelo and Liang Tan. 2010. "Cross-listing premium in the US and the UK destination." *International Review of Economics & Finance* 19, no. 2: 244-259.

[9] Cai, Xizhen, Yeying Zhu, Yuan Huang, and Debashis Ghosh. 2022. "High-dimensional causal mediation analysis based on partial linear structural equation models." *Computational Statistics & Data Analysis*. 174.

[10] Cain, Matthew D., Stephen B. McKeon, and Steven Davidoff Solomon. 2017. "Do takeover laws matter? Evidence from five decades of hostile takeovers." *Journal of Financial Economics* 124: no. 3, 464-485.

[11] Celli, Viviana. 2022. "Causal mediation analysis in economics: Objectives, assumptions, models." *Journal of Economic Surveys*, 36: 214 - 234.

[12] Chernozhukov, Victor, Hiroyuki Kasahara, and Paul Schrimpf. 2021. "Causal impact of masks, policies, behavior on early COVID-19 pandemic in the US." *Journal of Econometrics*, 220, no. 1: 23-62.

[13] Coffee Jr, John C. 1999. "Future as history: The prospects for global convergence in corporate governance and its implications." *Northwestern University Law Review* 93: 641-708.

[14] Conti, Gabriella, James J. Heckman, and Rodrigo Pinto. 2016. "The effects of two influential early childhood interventions on health and healthy behaviour." *The Economic Journal*, 126, no. 596: F28 - F65.

[15] Dodd, Olga. 2013. "Why do firms cross-list their shares on foreign exchanges? A review of cross-listing theories and empirical evidence." *Review of Behavioural Finance* 5, no. 1: 77-99.

[16] Doidge, Craig. 2004. "US cross-listings and the private benefits of control: evidence from dual-class firms." *Journal of Financial Economics* 72, no. 3: 519-553.

[17] Doidge, Craig, G. Andrew Karolyi, and René M. Stulz. 2009. "Has New York become less competitive than London in global markets? Evaluating foreign listing choices over time." *Journal of Financial Economics* 91, no. 3: 253-277.

[18] Doidge, Craig, G. Andrew Karolyi, and René M. Stulz. 2004. "Why are foreign firms listed in the US worth more?." *Journal of Financial Economics* 74, no. 2: 205-238.

[19] Engle, Robert F., Clive WJ Granger, John Rice, and Andrew Weiss. 1987. "Semiparametric estimates of the relation between weather and electricity sales." *Journal of the American Statistical Association*, 81, no. 394: 310-320.

[20] Eilers, Paul HC, and Brian D. Marx. 1996. "Flexible smoothing with B-splines and penalties." *Statistical Science* 11, no. 2: 89-121.

[21] Fan, Jianqing and Irene Gijbels. 1996. *Local Polynomial Modelling and Its Applications*. Chapman and Hall, London.

[22] Fan, Jianqing and Runze Li. 2001. "Variable selection via nonconcave penalized likelihood and its oracle properties." *Journal of the American Statistical Association* 96, no. 456: 1348-1360.

[23] Fernandes, Nuno, and Miguel A. Ferreira. 2008. "Does international cross-listing improve the information environment." *Journal of Financial Economics* 88, no. 2: 216-244.

[24] Foerster, Stephen R., and G. Andrew Karolyi. 1998. "Multimarket trading and liquidity: a transaction data analysis of Canada-US interlistings." *Journal of International Financial Markets, Institutions, and Money* 8, no. 3-4: 393-412.

[25] Foerster, Stephen R., and G. Andrew Karolyi. 1999. "The effects of market segmentation and investor recognition on asset prices: Evidence from foreign stocks listings in the United States." *The Journal of Finance* 54, no. 3: 981-1013.

[26] Foucault, Thierry, and Laurent Frésard. 2012. "Cross-listing, investment sensitivity to stock price, and the learning hypothesis." *The Review of Financial Studies* 25, no. 11: 3305-3350.

[27] Foucault, Thierry, and Thomas Gehrig. 2008. "Stock price informativeness, cross-listings, and investment decisions." *Journal of Financial Economics* 88, no. 1: 146-168.

[28] French, Kenneth R., and Richard Roll. 1986. "Stock return variances: The arrival of information and the reaction of traders." *Journal of Financial Economics* 17, no. 1: 5-26.

[29] Ghadhab, Imen, and Slaheddine Hallara. 2016. "Cross-listing and value creation." *Journal of Multinational Financial Management* no. 37: 1-11.

[30] Ghadhab, Imen, and Mouna M'rad. 2018. "Does US cross-listing come with incremental benefit for already UK cross-listed firms." *The Quarterly Review of Economics and Finance* no. 69: 188-204.

[31] Ghosh, Chinmoy, and Fan He. 2015. "Investor Protection, Investment Efficiency and Value: The Case of Cross-Listed Firms." *Financial Management* 44, no. 3: 499-546.

[32] Graham, John R., and Campbell R. Harvey. 2001. "The theory and practice of corporate finance: Evidence from the field." *Journal of Financial Economics* 60, no. 2-3: 187-243.

[33] Guo, Xu, Runze Li, Jingyuan Liu, and Mudong Zeng. "Statistical Inference for Linear Mediation Models with High-dimensional Mediators and Application to Studying Stock Reaction to COVID-19 Pandemic." *Journal of Econometrics* 235, no. 1: 166-179.

[34] Hail, Luzi, and Christian Leuz. 2009. "Cost of capital effects and changes in growth expectations around US cross-listings." *Journal of Financial Economics* 93, no. 3: 428-454.

[35] Härdle, Wolfgang, Hua Liang, and Jiti Gao. 2000. *Partially linear model.* Springer Science & Business Media.

[36] Heckman, James J., and Rodrigo Pinto. 2015. "Econometric mediation analyses: Identifying the sources of treatment effects from experimentally estimated production technologies with unmeasured and mismeasured inputs." *Econometric reviews* 34, no. 1-2: 6-31.

[37] Huber, Martin. 2020. "Mediation analysis." *Handbook of Labor, Human Resources and Population Economics*: 1 - 38.

[38] Hull, John. 2003. *Options, Futures, and Other Derivatives* (5th ed.). Prentice Hall, Upper Saddle Review, NJ.

[39] Imai, Kosuke, Luke Keele, and Dustin Tingley. 2010. "A general approach to causal mediation analysis." *Psychological Methods* 15, no. 4: 309.

[40] Kastiel, Kobi, and Adi Libson. 2019. "Global antitakeover devices." *Yale Journal on Reg.* 36: 117-164.

[41] Karolyi, G. Andrew. 2006. "The world of cross-listings and cross-listings of the world: Challenging conventional wisdom." *Review of Finance* 10, no. 1: 99-152.

[42] Lang, Mark H., Karl V. Lins, and Darius P. Miller. 2003. "ADRs, analysts, and accuracy: Does cross listing in the United States improve a firm's information environment and increase market value?." *Journal of Accounting Research* 41, no. 2: 317-345.

[43] Mallows, Colin L. 1973. Some comments on C_p. *Technometrics* 15: 661-675.

[44] Melvin, Michael, and Magali Valero-Tonone. 2003. "The effects of international cross-listing on rival firms." AFA 2004 San Diego Meetings.

[45] Merton, Robert C. 1987. "A simple model of capital market equilibrium with incomplete information." *Journal of Finance* 42: 483-510.

[46] Morck, Randall, Bernard Yeung, and Wayne Yu. 2000. "The information content of stock markets: why do emerging markets have synchronous stock price movements?." *Journal of Financial Economics* 58, no. 1 and 2: 215-260.

[47] Miller, Darius P. 1999. "The market reaction to international cross-listings: evidence from Depositary Receipts." *Journal of Financial Economics* 51, no. 1: 103-123.

[48] Mittoo, Usha R. 1992. "Managerial perceptions of the net benefits of foreign listing: Canadian evidence." *Journal of International Financial Management & Accounting* 4, no. 1: 40-62.

[49] Pagano, Marco, Ailsa A. Roell, and Josef Zechner. 2002. "The geography of equity listing: why do companies list abroad?." *The Journal of Finance* 57, no. 6: 2651-2694.

[50] Reese Jr, William A., and Michael S. Weisbach. 2002. "Protection of minority shareholder interests, cross-listings in the United States, and subsequent equity offerings." *Journal of Financial Economics* 66, no. 1: 65-104.

[51] Saudagaran, Shahrokh M. 1988. "An empirical study of selected factors influencing the decision to list on foreign stock exchanges." *Journal of International Business Studies* 19: 101-127.

[52] Schwarz, Gideon. 1978. "Estimating the dimension of a model." *The Annals of Statistics*, 6: 461-464.

[53] Smith, Katherine, and George Sofianos. 1997. "The impact of an NYSE listing on the global trading of non-US stocks." 97. New York Stock Exchange.

[54] Stulz, René M. 2009. "Globalization, corporate finance, and the cost of capital." In *Global Corporate Governance* 106-134. Columbia University Press.

[55] Tibshirani, Robert. 1996. "Regression shrinkage and selection via the LASSO." *Journal of the Royal Statistical Society Series B: Statistical Methodology* 58, no. 1: 267-288.

[56] Tingley, Dustin, Teppei Yamamoto, Kentaro Hirose, Luke Keele, and Kosuke Imai. 2014. "Mediation: R package for causal mediation analysis."

[57] Tsang, Albert, Nan Yang, and Lingyi Zheng. 2022. "Cross-listings, antitakeover defenses, and the insulation hypothesis." *Journal of Financial Economics* 145, no. 1: 259-276.

[58] Zou, Hui and Runze Li. 2008. "One-step sparse estimates in nonconcave penalized likelihood models. *Annals of Statistics*. 36, no. 4: 1509-1566.