Inconsistency in the Equity Market: Evidence from Large Cross-Holdings *

Marius Savatier†

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Abstract

I study publicly traded firms that hold a large stake in another publicly traded firm. In a frictionless market, the parent's value should move one-for-one with the value of its stake. In the data, it moves only 38 cents on the dollar. This underreaction appears after isolating price movements specific to the subsidiary. The sample covers 187 U.S. parent–subsidiary pair-years between 1999 and 2024. When the parent holds no other assets, the estimated transmission rate is close to one. When the parent holds other assets, the transmission rate falls. The evidence points to a fundamental limit to arbitrage: when replication is imperfect, mispricing becomes harder to detect and hedge.

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†Phd Candidate at Paris Dauphine-PSL; email: marius.savatier@dauphine.psl.eu

1. Introduction

Publicly traded firms sometimes hold large stakes in other publicly traded firms. I call the holding firm the parent and the held firm the subsidiary. In a frictionless market, the value of the parent equals the value of its stake plus the value of its other assets. Because the parent's other assets are not separately traded, this relation cannot be tested directly in prices. Instead, it implies a testable restriction in returns: changes in the value of the stake should transmit one-for-one to the parent.

I estimate the transmission rate by regressing daily parent returns on the daily return of the subsidiary stake. To isolate variation specific to the subsidiary, I control for returns of a large set of other firms. Across the sample of 187 U.S. parent–subsidiary pair-years between 1999 and 2024, the average transmission rate is 0.38. The underreaction shows little reversal in subsequent days. In placebo tests, I replace each subsidiary with the most correlated firm not owned by the parent. The average transmission rate is about zero.

The key cross-sectional determinant of transmission rates is the parent's variance not spanned by the subsidiary. This non-spanned variance is attributable to the parent's other assets. As it increases, the transmission rate falls. When the parent holds no other assets, even if it has liabilities, the transmission rate is close to one. This pattern is consistent with a traditional risk-based limit-to-arbitrage mechanism in which imperfect hedging interacts with limited risk-bearing capacity. First, non-fundamental movements in the stake price or investor inattention create a tendency toward underreaction. Second, as non-spanned variance increases, hedgeability declines, limiting the ability of arbitrageurs to counteract the underreaction.

A separate limit to arbitrage arises from informational frictions. If the subsidiary's value increases by x while the parent increases by only $0.38x$, the gap may reflect offsetting changes in the value of the parent's other assets. Eliminating the underreaction therefore requires forming beliefs about those other assets, which are not independently priced. When arbitrageurs must learn about the value of the parent's other assets from prices,

even risk-neutral arbitrageurs cannot fully eliminate the underreaction. I formalize this mechanism in a model.

The underreaction could reflect a systematic discount on the shares held within the parent, for instance due to double taxation or agency problems. When the parent holds a majority of voting rights, which mitigates these concerns, the transmission rate tends to be higher but remains well below one. Other potential explanations, such as liquidity or limited subsidiary float, do not explain the underreaction. A time-varying discount rate could mechanically match the underreaction if subsidiary-specific price movements induced large changes in the parent's required return. Such a discount rate is difficult to reconcile with standard utility-based models.

Related Literature. The risk-based mechanism has a direct counterpart in the limits-to-arbitrage literature. Gromb and Vayanos (2010) study arbitrage between imperfectly correlated assets under limited risk-bearing capacity, showing that arbitrage fully offsets non-fundamental demand only when a perfect hedge is available.[1] Limited risk-bearing capacity implies predictable returns. Li et al. (2016) and Chang et al. (2022) document such cross-asset predictability in parent–subsidiary structures using portfolio strategies based on subsidiary performance. This evidence is consistent with the slow incorporation of fundamental information. When underreaction instead reflects non-fundamental movements in the subsidiary, predictability takes the form of mean reversion in the subsidiary itself. Long-horizon reversals are documented in Fama and French (1988); Poterba and Summers (1988); Campbell and Shiller (1989). Campbell and Kyle (1993) provide a model in which non-fundamental demand and limited risk-bearing generate mean reversion.

The information-based mechanism described above builds on the noisy rational expectations literature initiated by Grossman (1976); Hellwig (1980); Diamond and Verrecchia (1981). These models show that prices can aggregate dispersed information only if they remain noisy, without necessarily implying predictable returns.[2] In a related argument, Black (1986) conjectures that because arbitrageurs cannot perfectly distinguish noise

[1] See Merton (1987) on incomplete information and limited diversification.

[2] See Vives (2010) for a review. Empirically, Dávila and Parlatore (2025) show that equity price changes are consistent with substantial noise in prices, while Dávila and Parlatore (2023) show that idiosyncratic volatility can reflect noise.

from information, noise can accumulate in prices. Brav and Heaton (2002, 2003); Brav et al. (2004) emphasize that difficulty in verifying mispricing is itself a limit to arbitrage.

Both risk-based and informational frictions appear in the literature on negative stub values, which arise when a publicly traded parent is worth less than the market value of its stake in a publicly traded subsidiary. Mitchell et al. (2002) examine 82 negative stub values using long-parent/short-subsidiary positions and show that arbitrage positions expose investors to fundamental risk related to the parent's other assets and that convergence is bumpy and uncertain. A negative stub does not constitute definitive evidence of mispricing, since the apparent gap may reflect a negative net value of the parent's other assets. This ambiguity leads them to conclude that the impossibility of knowing whether mispricing is present may itself impede arbitrage.[3] To make mispricing harder to dismiss, Lamont and Thaler (2002) study five equity carve-outs with subsequent spin-offs during the Internet bubble and conclude that limited float of the subsidiary's shares generated short-sale constraints.[4]

An example of readily verifiable equity mispricing is the twin stocks anomaly. Firms entitled to identical cash flows have exhibited large deviations from parity across international markets (Rosenthal and Young (1990)), which Froot and Dabora (1999) attribute to international market segmentation. As the near-one transmission rates in cases where the parent has no other assets show, mispricing is typically small when redundant claims trade on the same market.[5]

The rest of the paper is structured as follows. Section 2 introduces the transmission rate. Section 3 describes the data. Section 4 presents the estimation framework. Section 5 reports the empirical results. Section 6 discusses possible mechanisms for the underreaction. Section 7 develops a theoretical model that describes the information-friction mechanism. Section 8 concludes.

[3]Let $MV_{parent} = MV_{stake} + MV_{other} - MV_{liabilities}$. A negative stub, $MV_{parent} < MV_{stake}$, implies mispricing only if $MV_{other} > MV_{liabilities}$, a condition that is often difficult to verify.

[4]Lamont and Thaler (2002) also note that Bergstresser and Karlan (2000) independently documented underreaction of parents to movements in their subsidiaries' values; the manuscript is not publicly available. See also Cornell and Liu (2001).

[5]See Schultz and Shive (2010) for evidence from dual-class shares.

2. Transmission Rate

In a frictionless market, no arbitrage implies that the value of a portfolio equals the sum of the values of its components. For a publicly traded parent holding a stake in a publicly traded subsidiary, this implies

$$P_t^p = P_t^s + P_t^o, \tag{1}$$

where P_t^p denotes the parent's market value, P_t^s the value of its stake in the subsidiary, and P_t^o the value of its other net assets. Equation (1) implies that the parent's return equals the value-weighted return of its components:

$$r_t^p = r_t^{ws} + r_t^{wo}, \tag{2}$$

where $r_t^{ws} \equiv w_{t-1} r_t^s$ and $r_t^{wo} \equiv (1 - w_{t-1}) r_t^o$ denote the weighted returns of the subsidiary stake and of the parent's other assets, respectively, and $w_{t-1} = \frac{P_{t-1}^s}{P_{t-1}^p}$ is the beginning-of-period equity weight of the subsidiary stake.

Neither equation (1) nor equation (2) can be verified directly because the parent's other assets are not publicly traded as a stand-alone security, rendering P_t^o and r_t^o unobservable. A testable implication is provided by the transmission rate, defined as the sensitivity of the parent's return to the weighted return of its subsidiary stake:

$$\tau \equiv \frac{\partial r_t^p}{\partial r_t^{ws}}. \tag{3}$$

Under the frictionless benchmark in equation (2), this sensitivity equals one, so $\tau = 1$. Intuitively, this means that when the market value of the subsidiary stake increases by \$x, the market value of the parent should also increase by \$x.

When all components of the parent are tradable, arbitrage can enforce equation (1) through perfect replication. When the parent's other assets are not separately traded, risk-free arbitrage by outside investors instead requires hedging systematic risks and diversifying idiosyncratic risks. The parent itself can act: if its market value exceeds the combined value of its subsidiary stake and its other assets, it can issue equity and acquire

additional shares in the subsidiary; if it falls short, it can sell shares in the subsidiary and repurchase its own stock. Both mechanisms assume the absence of information frictions: outside arbitrageurs know the distribution of returns, and the parent knows the value of its other assets and does not need to infer it from prices.

More broadly, if arbitrage is understood as trade by risk-bearing speculators who exploit advantageous opportunities, the conventional asset-pricing view holds that such trading leads prices to behave as if they were set by a rational representative agent who values assets as discounted conditional expectations of future cash flows. Because the expectation operator is linear, equations (1) and (2) hold, implying $\tau = 1$ (see Appendix A). Intuitively, when new information changes the valuation of the stake, the representative agent adjusts valuations consistently both inside and outside the parent.

Identifying the transmission rate requires separating subsidiary-specific movements from common factors that also affect the parent's other assets. Let the subsidiary's return admit the following structure:

$$r_t^s = F_t\gamma + e_t^s, \tag{4}$$

where F_t captures common factors potentially correlated with movements in the parent's other assets, and e_t^s is a subsidiary-specific innovation orthogonal to those movements. The transmission rate is estimated through the following regression:

$$r_t^p = \tau r_t^{ws} + F_t^w\beta + u_t, \tag{5}$$

where $r_t^{ws} = w_{t-1}r_t^s$ denotes the weighted return of the stake, $F_t^w = w_{t-1}F_t$ are the corresponding weighted common factors, and u_t is a residual orthogonal to both r_t^{ws} and F_t^w. The transmission rate is identified from the weighted subsidiary-specific innovation $w_{t-1}e_t^s$ (see Appendix A for the derivation).

Estimating (5) requires F_t, which is unobservable. The guiding principle of the empirical strategy is that common factors can be proxied by the returns of other firms. The transmission rate is therefore identified from the component of the subsidiary's return

that is not explained by the returns of other firms. A placebo procedure, in which the subsidiary is replaced by its most correlated firm not owned by the parent, serves as a falsification test of the identification strategy. The cross-section of estimated transmission rates across parent–subsidiary pairs is then used to study what drives variation in these rates.

3. Data

The sample consists of 73 publicly traded parent–subsidiary pairs between 1999 and 2024, yielding 187 pair–year observations. All firms are headquartered in the United States and listed on either the NYSE or NASDAQ.[6] Table 1 reports summary statistics. On average, the subsidiary and parent have market capitalizations of $12 billion and $17 billion, respectively, and the average stake is $6.5 billion, corresponding to a mean portfolio weight of 50% and a mean economic interest of 46%. In 56% of cases, the parent holds a majority of the subsidiary's voting rights. Appendix B reports the time-series evolution and sectoral composition of the sample. About one third of the pairs belong to the Energy sector (Fama–French 48: Oil and Gas, Utilities, and Transport), with the remainder distributed across many industries.

I construct the number of shares held by the parent in the subsidiary from Schedule 13D/G filings. Acquirers of more than 5% of a public company must normally file Schedule 13D, disclosing both their stake and intentions regarding control. Passive investors may instead use the shorter Schedule 13G, which some parent firms, despite holding large stakes, were permitted to file when planning to sell or spin off the subsidiary. A drawback of Schedule 13G is that it is updated only annually, while Schedule 13D must be amended within 10 days of any change.[7] I therefore cross-check ownership using Form 3 and Form 4 filings, which since 2004 require insiders, including investors holding more than 10%, to disclose ownership and report changes promptly.

The number of shares outstanding for the parent is obtained from Compustat. Because

[6]The dataset is stored in SQL with an interactive interface and will be made available for replication.

[7]Since October 2023, Schedule 13D amendments are due within two business days, and most 13G amendments within 45 days after quarter-end, with faster deadlines in some cases.

this figure may be inaccurate when multiple classes of common shares are outstanding, I cross-check shares outstanding using 10-Q and 10-K filings. Stock prices, returns, bid and ask quotes, and trading volumes are obtained from CRSP. For control variables, I supplement these data with returns from Compustat not available in CRSP, primarily for exchange-traded funds (ETFs). The CPI is obtained from the U.S. Bureau of Labor Statistics, and the Fama–French factors are obtained from Kenneth French's website.

I divide the sample into parent–subsidiary pairs observed over one-year periods (252 trading days), excluding financial firms. To be included, a pair must satisfy several criteria: the subsidiary's market value exceeds \$1 billion (January 2000 dollars, deflated using the Consumer Price Index), the portfolio weight exceeds 10%, the average share price of both firms exceeds \$5, and the average daily trading volume of each exceeds \$5 million (January 2000 dollars).

Table 1: Summary Statistics. All variables are averaged over the one-year estimation period. Sub MV is the subsidiary's market value; Parent MV is the parent's market value; Ownership is the proportion of economic interest held by the parent in the subsidiary; Weight is the average ratio of Stake MV to Parent MV; #Trades is the number of trades (some values are missing in CRSP); Mid-quote is $(\text{Ask}_{i,t} - \text{Bid}_{i,t})/\big(\frac{1}{2}(\text{Ask}_{i,t} + \text{Bid}_{i,t})\big)$; Amihud is $|r_i|/\text{DollarVol}_i$; Dollar Volume is price times trading volume; Turnover is daily volume divided by shares outstanding.

Variable	N	Mean	Median	SD	Min	Max
Sub MV	187	11,604	5,493	18,470	1,001	122,669
Parent MV	187	16,960	8,235	21,914	307	161,141
Stake MV	187	6,583	2,748	9,133	136	54,908
Ownership %	187	0.467	0.496	0.229	0.050	0.935
Weight	187	0.504	0.364	0.421	0.102	1.955
# Trades Sub	70	11,792	9,052	9,452	243	35,041
# Trades Parent	61	18,311	10,825	30,503	339	216,902
Mid-Quote Sub	187	0.002	0.001	0.003	0.000	0.023
Mid-Quote Parent	187	0.002	0.001	0.004	0.000	0.023
Dollar Vol Sub	187	81	32	127	5	745
Dollar Vol Parent	187	162	72	214	3	1,404
Amihud Sub	187	2.062	0.778	6.463	0.016	75.296
Amihud Parent	187	0.942	0.245	2.928	0.011	27.271
Turnover Sub	187	0.009	0.006	0.010	0.001	0.077
Turnover Parent	187	0.012	0.009	0.009	0.001	0.085

Note: Dollar values are in millions; Amihud in billions of USD^{-1}.

4. Estimation Framework

4.1. Specifications

To estimate the transmission rate defined in Section 2, I approximate the unobservable factors F_t using proxies constructed from the returns of other assets. Let X_t denote the set of controls used to approximate the common factor structure. The empirical specification is

$$r_t^p = \tau r_t^{ws} + X_t^w \beta + u_t, \tag{6}$$

where $X_t^w = w_{t-1} X_t$. The contents of X_t depend on the specification, but always include $1/w_{t-1}$ and a constant. I consider three specifications.

(1) No Controls. The parent's simple return is regressed on a constant, the previous period's portfolio weight, and the weighted simple return of the subsidiary. Formally,

$$X_t = [\, 1/w_{t-1},\ 1\,].$$

(2) FF5 + Sector. This specification adds the five Fama–French factors and the sector portfolio (Fama 48 sectors). Formally,

$$X_t = \big[\, 1/w_{t-1},\ 1,\ MKT_t,\ SMB_t,\ HML_t,\ RMW_t,\ CMA_t,\ SECTOR_t \,\big].$$

(3) Post-Double-Lasso. This specification uses lasso regression as a selection device. First, I select the 100 assets most correlated with the subsidiary. After removing these, I select the 100 most correlated with the parent, yielding 200 distinct preselected assets. These 200 returns are then augmented with the first 100 principal components computed from these 200 preselected assets. Next, on these 300 potential controls, I run two lasso regressions: one selecting controls most predictive of the subsidiary's return and another selecting controls most predictive of the parent's return. The union of these selected controls is then used in a simple post-lasso regression. Formally, let $\mathcal{I}_s$

and $\mathcal{I}_p$ denote the sets of indexes selected by the lasso for the subsidiary and the parent, respectively. The set of controls is given by $\mathcal{I} = \mathcal{I}_s \cup \mathcal{I}_p$, so that

$$X_t = \left[1/w_{t-1},\ 1,\ \{x_{j,t}\}_{j \in \mathcal{I}} \right].$$

This double-lasso procedure follows Belloni et al. (2014), who propose both the double-selection method and a theoretically grounded penalty for the lasso. It relies on the assumption of sparsity, that among the potential controls only a small number are sufficient. The procedure runs two lasso regressions: one selecting controls most predictive of the dependent variable and another selecting controls most predictive of the variable of interest. The union of the controls selected in these two steps is then used in the final regression, which helps mitigate omitted-variable bias.

The preselection of the 200 most correlated assets is performed on the combined universe of CRSP and Compustat firms in North America, requiring that no selected asset has a correlation above 0.70 with an already selected one. Running the lasso on the full universe yields essentially the same set of controls but at a substantially higher computational cost. Because the factors are unobservable due to the presence of asset-specific returns, augmenting the returns of these 200 most correlated assets with principal components can improve their ability to approximate the underlying common factor structure.[8]

In sum, the no-controls specification provides a benchmark for the bias when not controlling, the FF5 + sector model reflects the standard approach in asset pricing, and the post-double-lasso specification offers a data-driven method designed to approximate the factor structure with greater realism.

4.2. Testing the Transmission Benchmark

For each parent–subsidiary pair-year (hereafter, pair), I estimate one transmission rate. Under the frictionless benchmark of equation (2), each estimate can be written as

$$\hat{\tau}_i = 1 + \varepsilon_i, \tag{7}$$

[8]Lasso regression often selects the first component but generally prefers to select firm returns directly.

where i indexes the parent–subsidiary pair and ε_i captures finite-sample noise.

Letting n denote the number of parent–subsidiary pairs, the cross-sectional average is

$$\bar{\tau} = \frac{1}{n} \sum_{i=1}^{n} \hat{\tau}_i, \tag{8}$$

which estimates $E[\hat{\tau}_i]$. Appendix A.5 shows under which orthogonality conditions we obtain $E[\varepsilon_i \varepsilon_{i'}] = 0$ for $i \neq i'$. The asymptotic normality of $\bar{\tau}$ then follows from the central limit theorem as $n \to \infty$. If the frictionless benchmark holds, the following hypothesis should not be rejected:

$$H_0^s : E[\hat{\tau}_i] = 1, \qquad H_1^s : E[\hat{\tau}_i] \neq 1,$$

where the subscript s refers to the parent–subsidiary sample.

4.3. Placebo Tests

To assess whether the specification adequately removes common factors, I conduct placebo estimations in which the subsidiary's return is replaced by the return of another publicly traded firm not held by the parent. If the proxies capture the factors shared by the placebo firm and the parent, the placebo's firm-specific return should not transmit to the parent, implying a transmission rate of $\tau = 0$. A nonzero estimate would therefore indicate that the specification fails to remove shared factors. To approximate the ideal case where the placebo and the subsidiary share the same factor structure, I replace each subsidiary with its most correlated asset.[9]

Formally, the placebo regression is

$$r_t^p = \tau r_t^{wpl} + X_t^w \beta + u_t, \tag{9}$$

where $r_t^{wpl} = w_{t-1} r_t^{pl}$ and r_t^{pl} denotes the simple return of the placebo asset. For the

[9] One might worry that, in finite samples, replacing the subsidiary with its most correlated asset could overfit by chance. In large samples this should be negligible, and if anything, it makes the placebo test slightly too demanding.

Post-Double-Lasso specification, the full selection procedure is repeated on the parent–placebo pairs, so that the set of selected controls may differ from those obtained for the parent–subsidiary pairs. Under a correctly specified model, the estimated transmission rate in the placebo sample should satisfy

$$H_0^{pl} : E[\hat{\tau}_i] = 0, \qquad H_1^{pl} : E[\hat{\tau}_i] \neq 0,$$

where the subscript pl refers to the parent–placebo sample. Failure to reject this hypothesis provides evidence that the specification adequately removes common factors.

4.4. Determinants of the Transmission Rate

Parent–subsidiary pairs differ in how closely the parent resembles a pure claim on the subsidiary. In some cases, the parent holds little besides the subsidiary stake, while in others it owns substantial additional assets. When a larger share of the parent's return variance comes from such assets, arbitrage positions become harder to hedge and mispricing becomes more difficult to detect. If investor inattention or noise in the subsidiary's share price causes the parent to underreact to movements in the subsidiary, arbitrageurs have an incentive to trade against this mispricing. When the parent is less redundant with the subsidiary, however, arbitrage becomes more difficult and the corrective force weakens. Underreaction should therefore be stronger in pairs where the parent contains more unspanned assets.

To test this prediction, I estimate cross-sectional regressions of the form

$$\hat{\tau}_i = \beta_0 + \beta_1 \log(\widehat{\mathrm{UVR}}_i) + Z_i'\gamma + \varepsilon_i, \tag{10}$$

where $\hat{\tau}_i$ denotes the estimated transmission rate for pair i, $\widehat{\mathrm{UVR}}_i$ is the estimated Unspanned Variance Ratio, a measure of the share of the parent's return variance not spanned by the subsidiary stake, and Z_i is a vector of control variables capturing alternative mechanisms affecting transmission rates across pairs.

Formally, the Unspanned Variance Ratio is given by

$$\widehat{\text{UVR}}_i = \frac{Var(r_t^{p\perp s})_i}{Var(r_t^{ws})_i}, \tag{11}$$

where $Var(r_t^{p\perp s})_i = (1 - R^2_{\text{No Control},i})Var(r_t^p)_i$. The term $R^2_{\text{No Control},i}$ denotes the share of the parent's return variance explained by the weighted return on the subsidiary stake when no controls are included. Thus, $\widehat{\text{UVR}}_i$ measures the parent's variance unexplained by the subsidiary stake relative to the total variance of the subsidiary stake. A value of $\widehat{\text{UVR}}_i = 1$ means that the parent contains as much unspanned variance as variance coming from the subsidiary stake. Section 7 introduces the corresponding theoretical object, UVR_i.

A natural alternative proxy for the amount of unspanned variance is $(1-R^2_{\text{No Control},i})$, the share of the parent's return variance unexplained by the subsidiary. However, this measure relies directly on the parent's variance, which mechanically depends on the transmission rate through the return decomposition and could therefore introduce a mechanical link between the two variables. For this reason, the baseline specification uses the Unspanned Variance Ratio defined above. As a robustness check, I also construct an alternative UVR in which $R^2_{\text{No Control},i}$ is replaced by the R^2 obtained after including controls. Both alternative measures yield similar results (see Appendix D.2).

The estimates of $\hat{\tau}_i$ and $\widehat{\text{UVR}}_i$ rely on the same time-series sample within each pair and may therefore share finite-sample noise. To avoid potential mechanical correlation, I implement a cross-fitting procedure. The sample of trading days is split into two folds: fold A contains every other day and fold B the remaining days. For each pair, I estimate two transmission rates and two sets of statistics $\{R^2_{\text{No Control},i}, Var(r_t^p)_i, Var(r_t^{ws})_i\}$ from which $\widehat{\text{UVR}}_i$ is constructed. Each transmission rate is then regressed on the $\widehat{\text{UVR}}_i$ estimated using the opposite fold. This procedure doubles the number of cross-sectional observations, and standard errors are clustered at the pair level.

The vector Z_i contains several control variables capturing alternative explanations for the underreaction. FLOAT_i measures the share of the subsidiary's stock available for trading after deducting the parent's holdings. Limited float can make it difficult for

arbitrageurs to locate shares to short, as documented by Lamont and Thaler (2003).

I also include a dummy MC_i for majority control, equal to one when the parent holds more than 50% of the subsidiary's voting rights. If the parent wastes the subsidiary's cash flows, the shares embedded within the parent should trade at a discount. If the parent controls the subsidiary, this discount should be minimal because the mismanagement would affect all shares of the subsidiary. Control also reduces potential double taxation of the subsidiary's cash flows. When the parent controls the subsidiary, it can influence payout policy, for instance by encouraging the subsidiary to repurchase its own shares rather than distribute dividends when these are tax-inefficient. Repurchases increase the parent's ownership stake and may eventually allow the parent to execute a tax-free spin-off under Section 355 of the IRS Code. Other mechanisms also exist to minimize taxes.[10]

Liquidity frictions may also influence transmission rates through trading costs or price-measurement errors. I therefore include two standard liquidity measures: $\textsc{Turnover}_i$, defined as average daily trading volume relative to shares outstanding, and $\textsc{Amihud}_i$, the price-impact measure proposed by Amihud (2002). To avoid multicollinearity, these variables are averaged across the parent and the subsidiary, yielding one value per pair. I further include $\log(\textsc{Size}_i)$, the logarithm of the combined market capitalization of the parent and the subsidiary, as firm size may affect investor attention and the informativeness of stock prices. Finally, I include a dummy variable $\textsc{Post2002}_i$, equal to one for observations after the internet bubble.

5. Empirical Results

5.1. The Average Transmission Rates

For each of the 187 parent–subsidiary pairs, and for the corresponding parent–placebo pairs, I estimate transmission rates under the three specifications introduced above, yield-

[10]Under U.S. tax law, corporations receiving dividends from other corporations benefit from the dividends-received deduction, which depends on the ownership stake: 50% if ownership is below 20%, 65% if between 20% and 80%, and 100% if above 80% (prior to 2018: 70%, 80%, and 100%, but with a 35% corporate tax rate instead of 21%).

ing six distributions in total.

Turning first to the parent–subsidiary pairs, Panel A of Table 2 shows that, without controls, the mean transmission rate is 192% (s.e. 12.6%). Adding the Fama–French factors plus a sector factor lowers it to 84.8% (s.e. 6.9%), significantly below one ($t = -2.20$). With the Post-Double-Lasso specification, the mean transmission rate falls further to 38.1% (s.e. 3.6%). This estimate is far below the frictionless benchmark $\tau = 1$ implied by value additivity. The hypothesis $H^s : \tau = 1$ is rejected with a large margin ($t = -19.2$), although the mean remains significantly above zero ($t = 10.56$), indicating that the market partially recognizes the special relation between the two firms. Economically, this implies that only about one third of the subsidiary's return is transmitted to the parent's return.[11] On average, the controls explain only 45.9% of the subsidiary's return variance, leaving more than half as subsidiary-specific returns.[12]

Panel B of Table 2 reports the placebo estimates. As discussed in Section 4, a correctly specified model should yield a placebo transmission rate of zero. Only Post-Double-Lasso satisfies this condition: its placebo mean is –2.2% (s.e. 4.4%, $p = 0.611$), statistically indistinguishable from zero, with a median of 2.3%. By contrast, No Controls and FF5+Sector yield large and significantly positive placebo means of 183% (s.e. 13.9) and 61% (s.e. 7.9), with medians of 133% and 29%. These large placebo means indicate that insufficient controls generate strong upward bias. Because the placebo is chosen as the asset most correlated with the subsidiary, it shares similar sector-level exposures with the parent. When controls are weak, these common exposures remain in the data, causing the placebo to inherit the same positive bias.

From this point on, I focus on transmission rates estimated using Post-Double-Lasso. Figure 1 shows their distribution for parent–subsidiary and parent–placebo pairs. The rest of the paper asks why the empirical mean ($\bar{\tau} = 0.38$, blue line) falls so far short of

[11] The corresponding t-statistics are -2.20 for FF5+Sector $((0.848 - 1)/0.069)$ and -19.2 for Post-Double-Lasso $((0.327 - 1)/0.035)$.

[12] For the same period, the 46.8% R^2 is slightly above the mean R^2 across all US stocks in Peters (2024), which is not surprising since R^2 tends to be higher for larger firms. The 33.6% for FF5+Sector can be compared to Roll (1988), who report about 20%. Aggregate R^2 declined until the early 2000s and has since started to increase, as documented by Campbell et al. (2001); Chiah et al. (2020); Campbell et al. (2023).

the theoretical mean ($E[\tau_i] = 1$ under H_0^s, red line). Before turning to an explanation, I examine whether this underreaction reverses in subsequent days.

Table 2: The Mean Transmission Rates. This table reports mean transmission rates across six distributions (three models × two samples: parent–subsidiary and parent–placebo). *Simple* uses no controls. *FF5+Sector* uses the Fama–French five factors plus 48 sectors. *Post-Double–Lasso* selects controls via Lasso on both parent and subsidiary returns. Avg. R^2 is the mean R^2 across estimations; R^2 (sub) is the share of subsidiary return variance explained by the controls.

	No Controls	FF5+Sector	Post-Double-Lasso
Panel A: Parent–Subsidiary Pairs ($n = 187$)			
mean τ	1.922^{***}	0.848^{***}	0.381^{***}
SE of mean τ	(0.126)	(0.069)	(0.036)
t-stat	15.247	12.231	10.560
p-value	0.000	0.000	0.000
median τ	1.227	0.578	0.387
Avg R^2	0.385	0.581	0.684
Avg R^2 (sub)	–	0.336	0.459
Panel B: Parent–Placebo Pairs ($n = 187$)			
mean τ	1.826^{***}	0.607^{***}	−0.022
SE of mean τ	(0.139)	(0.079)	(0.044)
t-stat	13.114	7.638	−0.509
p-value	0.000	0.000	0.611
median τ	1.327	0.290	0.023
Avg R^2	0.293	0.491	0.628
Avg R^2 (sub)	–	0.501	0.589

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5.2. Short-Term Reversal

For each parent–subsidiary pair, I regress the parent's return on the weighted subsidiary return and the controls selected by Double-Lasso, including four lags of the weighted subsidiary return and one lag of the parent return. Panel A of Table 3 shows that the contemporaneous transmission rate ($\bar{\tau} = 0.386$) remains virtually unchanged, still significantly below one and above zero. The $t-1$ lag is 4.2% (s.e. 1.9%) and is marginally significant at $p < 0.05$, suggesting a slight delayed reaction of the parent to subsidiary news. The $t-2$ lag is 2.6% (s.e. 1.5%) and is not significant at the 10% level, while the

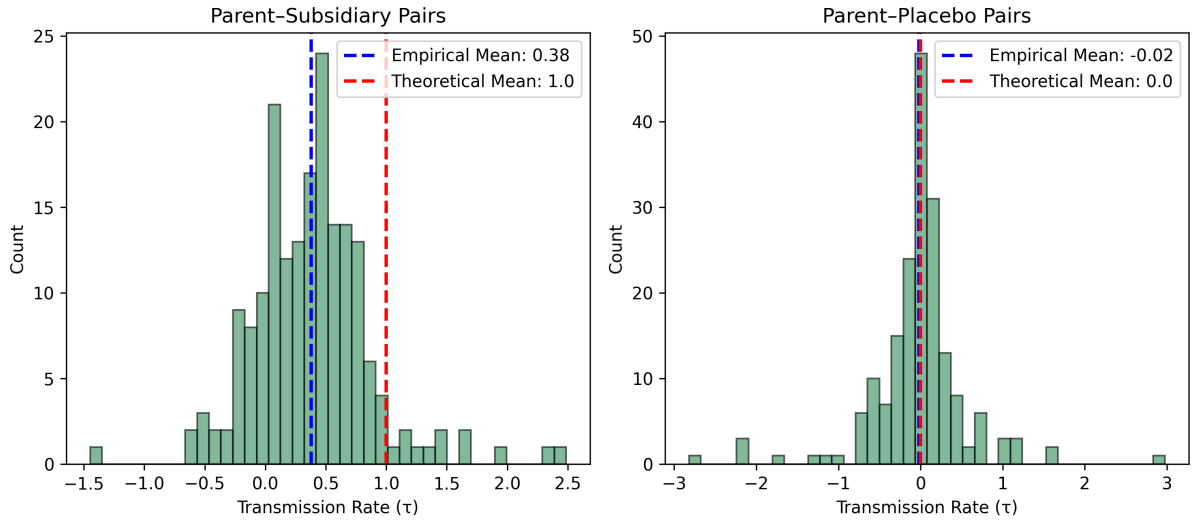


Figure 1: Distribution of estimated transmission rates using Post Double-Lasso. On the left-hand side, the distribution for parent–subsidiary pairs should be centered at 1 (red vertical line), but is instead centered near 0.38 (blue vertical line). On the right-hand side, the transmission rates are estimated for parent–placebo pairs, where the subsidiary is replaced by the most correlated return. If the controls capture common factors, the distribution should be centered at 0, so the red and blue lines overlap, which is approximately the case.

two remaining lags have negative and insignificant coefficients. Summing all transmission rates yields a weekly cumulative transmission rate of 42.4% (s.e. 5%).[13]

The cumulative transmission rate remains highly significantly below one. Short-term reversal is small and disappears after two days. This result does not rule out predictability in parent–subsidiary structures. Using large portfolio strategies, Chang et al. (2022); Li et al. (2016) show that buying parents whose subsidiaries had the highest returns over the previous months and selling those whose subsidiaries had the lowest yields excess returns. If the underreaction is driven by long-term fading noise, predictability may emerge only over longer horizons, consistent with the long-run return predictability documented in Fama and French (1988); Poterba and Summers (1988); Campbell and Shiller (1989).

Panel B of Table 3 reports the placebo estimates. Adding lags and the parent's lagged

[13]The standard error of the sum is computed as

$$\mathrm{SE}\left(\sum_{k=0}^{4}\hat{\tau}_{i,t-k}\right) = \sqrt{\sum_{k=0}^{4}\mathrm{Var}(\hat{\tau}_{i,t-k}) + 2\sum_{k<k'}\mathrm{Cov}(\hat{\tau}_{i,t-k},\hat{\tau}_{i,t-k'})}.$$

If subsidiary returns are serially uncorrelated, the cumulative transmission rate corresponds to the transmission rate obtained from a regression at the lower frequency.

return barely changes the contemporaneous transmission rate, which remains very close to zero at -1.7% (s.e. 4.2%). Since the placebo's specific return should not predict the parent's return, the lag coefficients provide a useful benchmark. The first three lags are insignificant, and only the fourth lag is significant at $p < 0.05$, which is consistent with a false positive arising from multiple tests.

Table 3: Transmission Rates at Contemporaneous and Lagged Horizons. Within each pair, transmission rates are estimated using

$$r_t^p = \tau_0 \tilde{r}_t^s + \tau_1 \tilde{r}_{t-1}^s + \tau_2 \tilde{r}_{t-2}^s + \tau_3 \tilde{r}_{t-3}^s + \tau_4 \tilde{r}_{t-4}^s + \gamma r_{t-1}^p + \tilde{X}_t \beta + u_t,$$

where $\tilde{r}_t^s$ is the subsidiary's weighted return. The table reports the cross-sectional averages of $\hat{\tau}_0, \hat{\tau}_1, \hat{\tau}_2, \hat{\tau}_3, \hat{\tau}_4$ for parent–subsidiary pairs and parent–placebo pairs.

	t	t-1	t-2	t-3	t-4
Panel A: Parent–Subsidiary Pairs ($n = 187$)					
mean τ	0.386^{***}	0.042^{**}	0.026^{*}	-0.020	-0.010
SE of mean τ	(0.038)	(0.019)	(0.015)	(0.017)	(0.014)
z-stat	10.248	2.234	1.798	-1.195	-0.687
p-value	0.000	0.026	0.072	0.232	0.492
median τ	0.359	0.045	0.014	-0.006	0.002
Panel B: Parent–Placebo Pairs ($n = 187$)					
mean τ	-0.017	0.006	0.000	-0.005	-0.033^{**}
SE of mean τ	(0.042)	(0.021)	(0.015)	(0.017)	(0.016)
z-stat	-0.394	0.261	-0.004	-0.293	-2.091
p-value	0.694	0.794	0.996	0.770	0.037
median τ	0.023	0.018	0.005	-0.003	-0.002

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors are HC0.

5.3. Explaining the Cross-sectional Variation in Transmission Rates

Table 4 reports the cross-sectional regressions using weighted least squares (WLS), while Table 5 reports the corresponding equal-weighted (OLS) specification. The WLS regression uses the inverse squared standard errors of $\hat{\tau}_i$, estimated in the first stage using Post-Double-Lasso, as weights. This assigns greater weight to more precisely estimated transmission rates, improving statistical efficiency, while the OLS specification treats each pair equally and provides a useful benchmark.

The baseline WLS specification includes only $\log(\widehat{\mathrm{UVR}}_i)$ as a regressor. The coeffi-

cient is -0.110 with a standard error of 0.016, yielding a t-statistic of -6.875 and a p-value of 1.3×10^{-10}. Economically, this estimate implies that doubling the Unspanned Variance Ratio is associated with a decrease of about 7.5 percentage points in the transmission rate.[14]

The baseline OLS regression yields a smaller coefficient of -0.064 (s.e. 0.016, $t = -4$, $p = 6.3 \times 10^{-5}$), but the relation remains highly significant. Figure 2 plots $\hat{\tau}_i$ against $\log(\widehat{\mathrm{UVR}}_i)$ and shows that the relation visibly flattens at high levels of $\log(\widehat{\mathrm{UVR}}_i)$. These high values are also associated with noisier estimates of transmission rates. In the WLS regression, these noisier observations receive less weight, which explains why the estimated coefficient is further from zero. The same uncertainty about the parent's other assets that makes mispricing difficult to detect in real time also makes transmission rates difficult to estimate precisely ex post.

Including the full set of controls leaves the coefficient on $\log(\widehat{\mathrm{UVR}}_i)$ largely unchanged in both WLS and OLS specifications. In the WLS regression, the R^2 increases from 0.292 to 0.627, while in the OLS regression it rises from 0.058 to 0.105. Thus, $\log(\widehat{\mathrm{UVR}}_i)$ alone accounts for roughly half of the explained variation in transmission rates, making it the dominant explanatory variable in the specification. As a sanity check, Appendix D.1 reports the same regressions for placebo transmission rates, which show no meaningful relation. Appendix D.2 repeats the analysis using an idiosyncratic version of the UVR constructed from residual returns after partialling out the selected controls; the results are similar.

Among the control variables, $\log(\textsc{Size})_i$ is significantly negatively related to transmission rates in the WLS specification, suggesting that larger parent–subsidiary pairs tend to exhibit lower transmission. However, this effect interacts with $\textsc{Amihud}_i$ and the $\textsc{Post2002}_i$ dummy. When these variables are excluded, the size coefficient becomes statistically insignificant. The interaction with $\textsc{Amihud}_i$ indicates that among firms of similar size, higher price impact is associated with lower transmission rates. The interaction with $\textsc{Post2002}_i$ indicates that among internet carve-outs, larger subsidiaries

[14] A doubling of $\widehat{\mathrm{UVR}}_i$ implies $\Delta\hat{\tau}_i = -0.11 \times \log(2) \approx -0.076$.

are associated with lower transmission rates, reflecting that some subsidiaries reached extremely high valuations that did not transmit to the parent, generating negative stub values. In several cases $Var(r_t^{ws}) > Var(r_t^p)$, meaning that the variance of the subsidiary's portfolio-weighted return exceeds that of the parent. These observations appear in Figure 2 as outliers with low $\log(\widehat{\text{UVR}}_i)$ but transmission rates close to zero. In contrast, FLOAT_i and TURNOVER_i show little explanatory power in either specification.

The majority-control dummy MC_i is not significant in the WLS regression but becomes significant at the 5% level in the OLS specification. When the parent controls the subsidiary, the transmission rate increases by about 18%. This pattern is consistent with the possibility that agency frictions or tax considerations interacting with control create a discount on the subsidiary stake embedded in the parent, as discussed in Section 4.4.

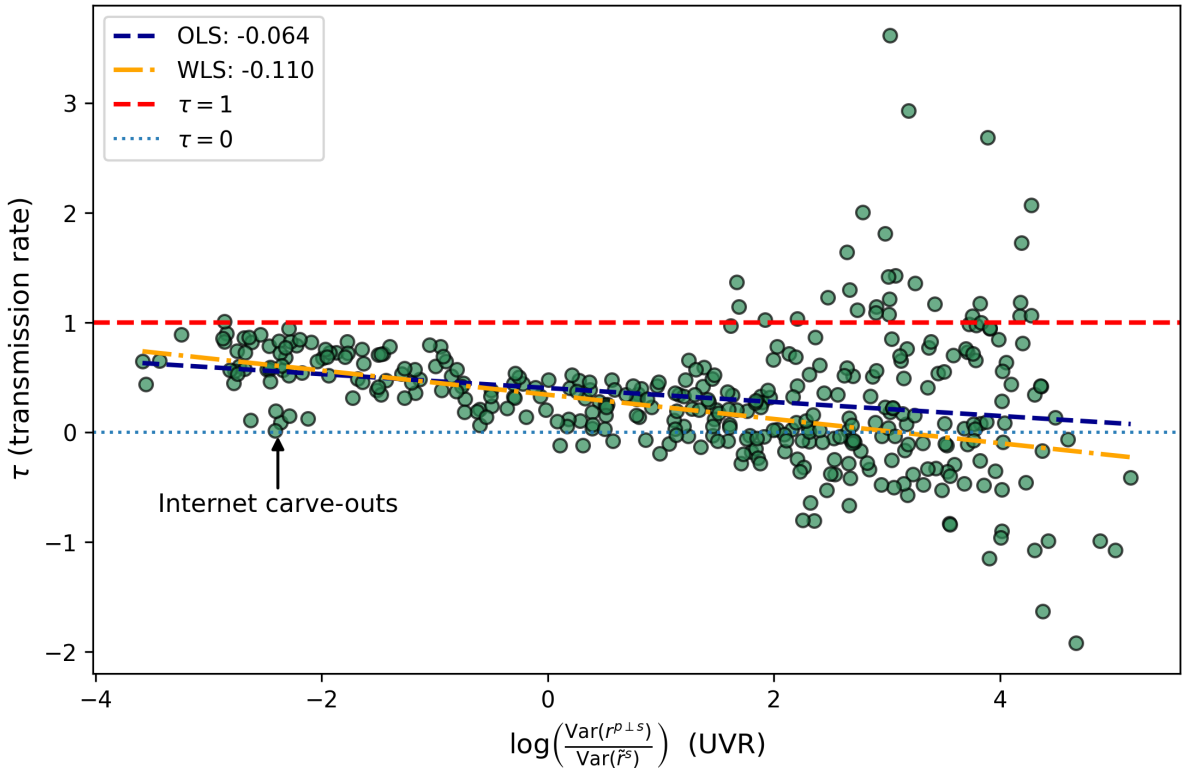


Figure 2: Cross-fitting scatter plots of τ against R^2.

Table 4: Explaining Transmission Rates Using Weighted Least Squares (WLS) and Cross-Fitting. The regression is

$$\hat{\tau}_i = \beta_0 + \beta_1 \log(\widehat{\mathrm{UVR}}_i) + \beta_2 \textsc{Float}_i + \beta_3 \mathrm{MC}_i + \beta_4 \textsc{Turnover}_i + \beta_5 \textsc{Amihud}_i + \beta_6 \log(\textsc{Size}_i) + \beta_7 \textsc{Post2002}_i + \varepsilon_i.$$

i denotes a parent–subsidiary pair observed over one year. The dependent variable is the cross-fitted transmission rate $\hat{\tau}_i$, estimated via Post-Double Lasso. $\log(\widehat{\mathrm{UVR}}_i)$ measures the ratio of the parent's unspanned variance to the subsidiary's variance, capturing uncertainty about the parent's other assets. $\textsc{Float}_i$ is the share of the subsidiary's stock available for trading after deducting the parent's holdings. MC_i is a dummy equal to one when the parent controls more than 50% of the voting rights. $\textsc{Turnover}_i$ is the average daily trading volume relative to shares outstanding, and $\textsc{Amihud}_i$ is the average price impact of trading, computed as the absolute return divided by the dollar volume. $\log(\textsc{Size}_i)$ is the logarithm of the combined market value of the parent and subsidiary, and $\textsc{Post2002}_i$ equals one for observations after the internet bubble. Cross-fitting ensures that $\log(\widehat{\mathrm{UVR}}_i)$ and $\hat{\tau}_i$ are estimated on separate folds. Standard errors are clustered by pair (HC3), and WLS weights are the inverse squared standard errors of $\hat{\tau}_i$.

	Parent–Subsidiary (WLS)				
Variable	Baseline	Full	No Post-2002	No Amihud	–P02, –Am
Constant	0.342***	0.422***	0.474***	0.281**	0.244
	(0.023)	(0.137)	(0.158)	(0.134)	(0.202)
log(UVR)	−0.110***	−0.112***	−0.100***	−0.112***	−0.094***
	(0.016)	(0.017)	(0.026)	(0.018)	(0.031)
Float	–	0.077	0.254	0.027	0.228
	–	(0.223)	(0.379)	(0.229)	(0.431)
MC	–	−0.078	0.062	−0.052	0.157
	–	(0.121)	(0.144)	(0.125)	(0.142)
Turnover	–	−6.306*	−4.073	−5.493	−1.857
	–	(3.575)	(3.615)	(3.400)	(3.837)
Amihud	–	−0.179*	−0.279**	–	–
	–	(0.100)	(0.135)	–	–
log(Size)	–	−0.108***	−0.092***	−0.084***	−0.043
	–	(0.020)	(0.026)	(0.021)	(0.035)
Post-2002	–	0.352***	–	0.422***	–
	–	(0.134)	–	(0.131)	–
R^2	0.292	0.627	0.525	0.591	0.424
df	372	366	367	367	368

Notes: Weighted least squares (WLS) estimates with weights $1/\mathrm{SE}(\hat{\tau}_i)^2$. Standard errors are clustered by pair (HC3). Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Explaining Transmission Rates Using Ordinary Least Squares (OLS) and Cross-Fitting. The regression is

$$\hat{\tau}_i = \beta_0 + \beta_1 \log(\widehat{\mathrm{UVR}_i}) + \beta_2 \textsc{Float}_i + \beta_3 \mathrm{MC}_i + \beta_4 \textsc{Turnover}_i + \beta_5 \textsc{Amihud}_i + \beta_6 \log(\textsc{Size}_i) + \beta_7 \textsc{Post2002}_i + \varepsilon_i.$$

i denotes a parent–subsidiary pair observed over one year. The dependent variable is the cross-fitted transmission rate $\hat{\tau}_i$, estimated via Post-Double Lasso. $\log(\widehat{\mathrm{UVR}_i})$ measures the ratio of the parent's unspanned variance to the subsidiary's variance, capturing uncertainty about the parent's other assets. $\textsc{Float}_i$ is the share of the subsidiary's stock available for trading after deducting the parent's holdings. MC_i is a dummy equal to one when the parent controls more than 50% of the voting rights. $\textsc{Turnover}_i$ is the average daily trading volume relative to shares outstanding, and $\textsc{Amihud}_i$ is the average price impact of trading, computed as the absolute return divided by the dollar volume. $\log(\textsc{Size}_i)$ is the logarithm of the combined market value of the parent and subsidiary, and $\textsc{Post2002}_i$ equals one for observations after the internet bubble. Cross-fitting ensures that $\log(\widehat{\mathrm{UVR}_i})$ and $\hat{\tau}_i$ are estimated on separate folds. Standard errors are clustered by pair (HC3).

	Parent–Subsidiary (OLS)				
Variable	Baseline	Full	No Post-2002	No Amihud	–P02, –Am
Constant	0.402***	0.170	0.199	0.098	0.120
	(0.024)	(0.158)	(0.158)	(0.145)	(0.146)
log(UVR)	-0.064***	-0.057***	-0.055***	-0.056***	-0.053***
	(0.016)	(0.017)	(0.017)	(0.017)	(0.016)
Float	–	0.220	0.240	0.228	0.266
		(0.170)	(0.166)	(0.168)	(0.164)
MC	–	0.173**	0.182**	0.176**	0.194***
		(0.078)	(0.075)	(0.078)	(0.073)
Turnover	–	6.003	6.212	6.464	7.008
		(5.509)	(5.435)	(5.485)	(5.379)
Amihud	–	-0.078	-0.096	–	–
		(0.075)	(0.075)		
log(Size)	–	-0.045	-0.044	-0.035	-0.028
		(0.029)	(0.029)	(0.027)	(0.026)
Post-2002	–	0.059	–	0.090	–
		(0.071)		(0.067)	
R^2	0.058	0.105	0.104	0.103	0.100
df	372	366	367	367	368

Notes: Standard errors clustered by pair (HC3). Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6. Discussion of Possible Mechanisms

The mean transmission rate estimated with the double-lasso is $\tau = 0.38$. The selected controls explain about 50% of the variance of the subsidiary return, so that the transmission rate is identified from the remaining half of subsidiary-specific variation. To explain the underreaction without invoking mispricing, any alternative mechanism must operate at the level of individual parent–subsidiary pairs and explain why a \$1 increase in the value of the subsidiary stake is associated with roughly a 60-cent loss in the parent's valuation.

A time-varying discount rate could mechanically rationalize the underreaction. The relevant question is whether the implied discount factor corresponds to a plausible economic model of preferences. Matching the observed transmission rate would require the discount rate to adjust daily. A \$1 increase in the value of the subsidiary stake would have to make the parent risky enough that its valuation falls by roughly 60 cents. Moreover, because the transmission rate is identified from the subsidiary's specific return, the discount rate would need to price diversifiable risk.

A fixed discount could also explain the underreaction. Large conglomerates were found to be valued less than comparable standalone firms operating in the same industries. Agency problems within conglomerates, often manifesting through inefficient internal capital allocation, were frequently proposed as explanations for this valuation discount (Lang and Stulz (1994); Berger and Ofek (1995); Servaes (1996)).[15] However, in this paper the valuation comparison does not occur between the subsidiary and a comparable standalone firm, but between the shares of the subsidiary traded directly in the market and the same shares embedded in the parent. Two frictions can still lead to a discount on the shares embedded in the parent: the parent may waste the subsidiary's cash flows, and an additional layer of taxation within the parent may warrant a discount. Both frictions are less likely when the parent controls the subsidiary (see Cornell and Liu (2001)). The

[15]See also Lamont and Polk (2002), who show that conglomerates have higher expected returns, consistent with potential mispricing, and Villalonga (2004), who argues that measurement errors in segment data can account for the discount.

coefficient on the majority-control dummy is about 18% and statistically significant in the equal-weighted regression, consistent with the presence of such a discount. The WLS regression yields more mixed results.

Measurement errors in prices could also attenuate the transmission rate.To minimize this concern, the sample is restricted to pairs where both the parent and the subsidiary have at least \$5M in average daily dollar trading volume (January 2000 dollars) and a market capitalization of at least \$1B, limiting microstructure noise. Moreover, Float, Size, Turnover, and Amihud illiquidity explain little of the variation in transmission rates. When the transmission rate is estimated at weekly frequency, the mean transmission increases only slightly, suggesting that price-measurement errors are unlikely to account for the results.

If we allow either the parent to underreact to information about the subsidiary, or the subsidiary price to contain non-fundamental movements that do not transmit to the parent in the absence of arbitrage, limited arbitrage may explain the underreaction. The most natural friction that can limit arbitrage in this setting is deviations from perfect redundancy. The more the parent holds other uncertain assets, the more difficult it becomes to hedge the position. If arbitrageurs have limited risk-bearing capacity, they will trade less aggressively against the underreaction when the parent holds a large amount of other assets. The UVR measure captures the uncertainty surrounding the parent's other assets. Consistent with this mechanism, it is the single best explanatory variable of the transmission rate.

Moreover, even if arbitrageurs are risk-neutral, information frictions can still limit arbitrage. When arbitrageurs do not observe fundamental value and must infer it from prices, identifying mispricing becomes more difficult as the UVR increases, leading to a negative correlation between this ratio and the transmission rate. This idea is formalized in the next section.

7. Limits to Arbitrage under Information Frictions

In this section, I present a short theoretical model showing how higher levels of $\widehat{\text{UVR}}_i$ can limit arbitrage, even for risk-neutral arbitrageurs. I assume that arbitrageurs learn from prices about fundamentals. Noise in the subsidiary's price creates a natural force toward underreaction. When the parent has no other assets, any underreaction leads to a sure profit, as the mispricing is fully observable, so in equilibrium prices must align. When the parent holds other untraded assets, the underreaction can persist because arbitrageurs are not able to perfectly infer the amount of noise. An increase of \$1B in the value of the subsidiary stake while the parent increases by only \$500M can be justified by a decrease in the parent's other assets, for which no price is observed. The difficulty of inferring the amount of noise is governed by the Unspanned Variance Ratio (UVR), introduced above, which captures the uncertainty surrounding the parent's unspanned assets relative to its spanned asset.

7.1. Settings

The model is deliberately simplified to isolate its core mechanism. I assume three periods, $t = 0, 1, 2$. At time $t = 0$, the parent, denoted by p, buys or carves out a stake s, with the following initial market value:

$$P_0^p = P_0^s + P_0^o, \tag{12}$$

where P_0^p is the market value of the parent, P_0^s is the market value of the stake (shares held $\times$ share price), and P_0^o is the value of the parent's other net assets (net of liabilities).

At times $t = 1, 2$, the data-generating process of the stake is given by

$$\Delta P_1^s = v_1^s + n_1^s, \qquad \Delta P_2^s = v_2^s - n_1^s, \tag{13}$$

so that $P_2^s = P_0^s + v_1^s + v_2^s$. Here, v_t^s and n_t^s are mean-zero processes, where v_1^s represents price changes driven by persistent fundamentals, while n_1^s denotes noise that does not

transmit to the parent and vanishes at the terminal date. Without altering the model, it may also represent an informed change that does not vanish at $t = 2$ but still fails to transmit to the parent in the absence of arbitrage.[16] I assume that the market value of the stake is taken as given. Relaxing this assumption would not change the results of the model. I also set expected returns to zero, consistent with a risk-neutral economy, and assume arithmetic (rather than geometric) price changes for simplicity.[17]

At the terminal date $t = 2$, the market value of the parent is

$$P_2^p = v_1^s + v_2^s + v_1^o + v_2^o, \tag{14}$$

which can be interpreted as the long-horizon accumulation of fundamental value.

The endogenous variable of the model is the parent's market value at $t = 1$, given by

$$\Delta P_1^p = v_1^s + v_1^o + f_1 \;\Leftrightarrow\; \Delta P_1^p = \Delta P_1^s - n_1^s + v_1^o + f_1, \tag{15}$$

where f_1 is the dollar amount invested collectively by arbitrageurs in the parent company. To remove unnecessary complication, I assume no noise on the parent, that is, $n_1^p = 0$. So in the absence of arbitrage ($f_1 = 0$), the market value of the parent at $t = 1$ reflects the change in the value of the stake minus the noise, as well as the change in the value of its other untraded assets.

7.2. Arbitrageurs Optimization Problem

Arbitrageurs buy or sell the long-parent/short-subsidiary position. They are risk-neutral and therefore optimize

$$\max_{f_1} E\left[f_1 \frac{(P_2^p - P_2^s) - (P_1^p - P_1^s)}{(P_1^p - P_1^s)} \mid \mathcal{F}_1 \right], \tag{16}$$

[16] This second interpretation of the noise term, as information that is not consistently transmitted, connects to the literature on investors' limited attention. See Bernard and Thomas (1989); Hirshleifer and Teoh (2003); DellaVigna and Pollet (2009).

[17] The model can be restated in geometric returns, with the only difference that the notation becomes heavier. Log returns, however, are not suitable for studying additivity, as the log return of a sum is not equal to the sum of the log returns of its parts.

taking prices as given. $\mathcal{F}_1 = \{P_0^p, P_0^s, P_0^o, P_1^p, P_1^s\}$ is the information set at $t = 1$ and contains the current public prices.

The first-order condition yields

$$E[(P_2^p - P_2^s) - (P_1^p - P_1^s) \mid \mathcal{F}_1] = 0, \tag{17}$$

$$\Leftrightarrow \quad f_1 = E[n_1^s \mid \mathcal{F}_1], \tag{18}$$

This means that arbitrageurs buy or sell the long-p/short-s portfolio in an amount such that the expected profit on this position is zero, implying that they invest an amount equal to the expected noise in the stake market value.

Arbitrageurs have no further information on fundamentals than observed prices. However, being rational statistical thinkers, they use the current observed prices to infer the amount of noise. This yields:

$$E[n_1^s \mid \mathcal{F}_1] = \beta_1 \Delta P_1^s + \beta_2 (\Delta P_1^s - \Delta P_1^p). \tag{19}$$

And $\{\beta_1, \beta_2\}$ depend on arbitrageurs' knowledge of the moments of $\{\Delta P_1^s,\ \Delta P_1^s - \Delta P_1^p\}$, but from the properties of optimal (mean-square) prediction we know that

$$E\big[E[n_1^s \mid \mathcal{F}_1]^2\big] \leq \sigma_{ns}^2, \tag{20}$$

where σ_{ns}^2 denotes the unconditional variance of the noise. If arbitrageurs are rational, the variance of their noise prediction cannot exceed the actual variance of the noise.

7.3. The Transmission Rate

To keep things simple, let us assume that all variables in the model are orthogonal to each other. At time $t = 1$, this implies $E[n_1^s v_1^s] = E[v_1^s v_1^o] = E[n_1^s v_1^o] = 0$. The transmission

rate is then defined as

$$\tau = \frac{\mathrm{Cov}(r_1^p, r_1^{ws})}{\mathrm{Var}(\tilde{r}_1^s)} = \frac{\mathrm{Cov}(\Delta P_1^p, \Delta P_1^s)}{\mathrm{Var}(\Delta P_1^s)} \tag{21}$$

$$= \tau_{\mathrm{n}} + (1 - \tau_{\mathrm{n}})R^2, \tag{22}$$

$$\text{where} \quad \tau_{\mathrm{n}} = \frac{\sigma_{vs}^2}{\sigma_{vs}^2 + \sigma_{ns}^2}, \qquad R^2 = \frac{E\big[\, E[n_1^s \mid \mathcal{F}_1]^2 \,\big]}{\sigma_{ns}^2} \tag{23}$$

The subscript n stands for *natural*: τ_{n} is the transmission rate in the absence of arbitrage. The quantities σ_{vs}^2 and σ_{ns}^2 denote the variances of v_1^s and n_1^s, respectively. The term R^2 measures how much of the noise component n_1^s is predictable from the information set $\mathcal{F}_1$.

Without making further assumptions, $\tau = 1$ arises only in three corner cases. First, when $\sigma_{ns}^2 = 0$, in which case $\tau_{\mathrm{n}} = 1$ and arbitrage is not required. Second, when $\sigma_{vs}^2 = 0$, that is, when there is no transmission before arbitrage takes place; in this case, $\beta_1 = 1$ and $\beta_2 = 0$. Third, when $\sigma_{vo}^2 = 0$, that is, when the parent has no other net assets, or their value does not change; in this case, $\beta_1 = 0$ and $\beta_2 = 1$.

In all other cases, by the properties of optimal prediction stated in Equation (20), we have $R^2 < 1$, which implies $\tau < 1$. Intuitively, what limits arbitrage is that the system the arbitrageurs face is underdetermined: they have one constraint, the return additivity, but two unknowns, the amount of noise and the movement coming from the parent's other assets.

In the model arbitrageurs have deep pockets, and if they knew fundamental values they would trade away any deviation. Since fundamental values satisfy additivity, we would then not observe the underreaction. Ultimately, what limits arbitrage is that they cannot observe the fundamental value of the parent's other assets, and therefore cannot perfectly distinguish noise from information. As a result, transmission remains incomplete, despite expected returns being zero in equilibrium.

7.4. The Unspanned Variance Ratio (UVR)

Let us assume a best-case informational setting in which arbitrageurs know the second moments of all variables involved, namely σ^2_{ns}, σ^2_{vs}, and σ^2_{vo}. Then the attainable R^2 is

$$R^2 = \frac{\sigma^2_{ns}\,(\sigma^2_{vs} + \sigma^2_{vo})}{\sigma^2_{ns}\,(\sigma^2_{vs} + \sigma^2_{vo}) + \sigma^2_{vs}\,\sigma^2_{vo}}. \tag{24}$$

Consistent with the above section, if $\sigma^2_{vs} = 0$ or $\sigma^2_{vo} = 0$, we have $R^2 = 1$ and therefore $\tau = 1$.

Now let us take the derivative of R^2 with respect to σ^2_{vo}:

$$\frac{\partial R^2}{\partial \sigma^2_{vo}} = -\frac{\sigma^2_{ns}\sigma^4_{vs}}{\left[\sigma^2_{ns}\,(\sigma^2_{vs} + \sigma^2_{vo}) + \sigma^2_{vs}\,\sigma^2_{vo}\right]^2}, \tag{25}$$

which is strictly negative, and therefore implies that $\partial\tau/\partial\sigma^2_{vo} < 0$. In other words, holding other sources of uncertainty fixed, an increase in the uncertainty surrounding the parent's other net assets will always reduce the transmission rate τ, and it does so at a diminishing marginal rate. Accordingly, across parent–subsidiary pairs, the transmission rate should decline with the fraction of the parent's variance unspanned by the subsidiary's return:

$$\mathrm{UVR}_i = \frac{\sigma^2_{vo,i}}{\sigma^2_{ns,i} + \sigma^2_{vs,i}}. \tag{26}$$

UVR_i above is defined ex ante, before arbitrage occurs at $t = 1$, whereas the data are ex post. The ratio I estimate in the paper is

$$\widehat{\mathrm{UVR}_i} \;=\; \frac{\mathrm{Var}\big(r^{p\perp s}\big)_i}{\mathrm{Var}(r^{ws})_i} \;=\; \frac{\sigma^2_{vo,i} + g(.)_i}{\sigma^2_{ns,i} + \sigma^2_{vs,i}}, \tag{27}$$

where $r^{p\perp s}$ denotes the component of the parent return orthogonal to the weighted subsidiary return.[18] and

$$g(R^2, \sigma^2_{vs}, \sigma^2_{ns}) \;= \sigma^2_{ns}\tau(1 - R^2). \tag{28}$$

[18]To derive this expression, write $r^p_1 = \tau r^{ws}_1 + r^{p\perp s}_1$, where $\tau = (r^p_1, r^{ws}_1)/(r^{ws}_1)$. Then $(r^{p\perp s}_1) = (r^p_1) - \tau^2(r^{ws}_1)$. Using $\Delta P^p_1 = v^s_1 + v^o_1 + E[n^s_1 \mid \mathcal{F}_1]$, $\Delta P^s_1 = v^s_1 + n^s_1$, orthogonality, and $E[E[n^s_1 \mid \mathcal{F}_1]^2] = R^2\sigma^2_{ns}$, one obtains $(r^{p\perp s}_1) = \sigma^2_{vo} + \sigma^2_{ns}\tau(1 - R^2)$.

Even though $\partial g/\partial \sigma_{vo}^2 > 0$ implies that the covariance between $\widehat{\text{UVR}}_i$ and τ_i becomes more negative, the variance of $\widehat{\text{UVR}}_i$ increases by even more, making the slope slightly less steep in absolute value.

To examine the relationship between τ_i and $\widehat{\text{UVR}}_i$ when the mechanism of the model is absent, consider first the simpler case where there is no noise ($\sigma_{ns,i}^2 = 0$) and variation in τ_i reflects different discounts of the stake within the parent. In that case, $g_i = 0$ and $\widehat{\text{UVR}}_i = \text{UVR}_i = \sigma_{vo,i}^2/\sigma_{vs,i}^2$. One should therefore not expect any systematic relation between τ_i and uncertainty about the parent's other untraded assets.

In contrast, suppose that noise is present but the degree of correction at $t = 1$ is driven by other limits to arbitrage, such as capital constraints. Setting $R_i^2 = 0$ deactivates the model's arbitrage mechanism, implying $\tau_i = \tau_{\text{n},i}$, where $\tau_{\text{n},i}$ is the transmission rate exogenous to the mechanism. We then have $g_i = \sigma_{ns,i}^2 \tau_{\text{n},i}$, and therefore $\widehat{\text{UVR}}_i = \text{UVR}_i + \tau_{\text{n},i}(1 - \tau_{\text{n},i})$. The derivative $\partial \widehat{\text{UVR}}(\tau_{\text{n},i})/\partial \tau_{\text{n},i} = 1 - 2\tau_{\text{n},i}$ is positive for $\tau_{\text{n},i} \in [0, 0.5)$ and negative for $\tau_{\text{n},i} \in (0.5, 1]$, implying that $\tau_{\text{n},i}$ should increase with $\widehat{\text{UVR}}_i$ at low values and decrease at high values. In Figure 2, which plots $\widehat{\text{UVR}}_i$ on the x-axis, this would correspond to a hump-shaped relationship. No such pattern is observed. Moreover, it is reasonable to expect that $Var(\text{UVR}_i) \gg Var(\tau_{\text{n},i}(1 - \tau_{\text{n},i}))$, since the ex-ante share of noise, or of other limits if $\tau_{\text{n},i}$ is driven by factors other than noise, likely varies much less across pairs than the large disparity in parents' balance sheets.

As in the data, the model generates a declining marginal effect of UVR on the transmission rate: a sharp drop when moving from no uncertainty about the parent's other assets to a small amount, followed by progressively smaller decreases as uncertainty rises further. While this pattern matches the data qualitatively, the model cannot generate transmission rates as low as those observed empirically. In the model, the transmission rate is bounded above at 0.75, a bound reached when $\sigma_{vs}^2 = \sigma_{ns}^2$ and $UVR \to \infty$. Explaining the extent of the observed underreaction ($\tau = 0.38$) therefore requires additional ingredients, such as risk aversion or relaxing the assumption that arbitrageurs know the statistical moments.

8. Conclusion

Fundamental value is unobservable, so mispricing can only be tested when assets are replicable. For this reason, empirical research has focused on settings where replication is feasible, such as closed-end funds, twin stocks, or dual-class shares. These cases sometimes reveal striking mispricings, but they also draw attention to the specific frictions they expose. Yet most assets are only partially replicable by other traded assets.

This paper studies situations of partial replication, where a publicly traded firm holds a large stake in another listed firm while also owning other assets. Using 187 parent–subsidiary pairs, I estimate how changes in the value of the stake transmit to the parent's market value. On average, the parent's value rises by only \$0.38 on the dollar. This transmission rate is significantly below the theoretical benchmark of one, with no reversal over the following days.

Across pairs, the transmission rate declines with the degree of partial replication: the greater the variance attributable to the parent's other assets relative to the variance spanned by the subsidiary's return, the weaker the transmission. The simplest interpretation is that orthogonal noise attenuates price transmission, while uncertainty about the parent's untraded assets prevents arbitrageurs from perfectly hedging and observing the mispricing.

Parent–subsidiary structures therefore provide a rare window into mispricing when replication is only partial and cannot be verified in real time. As the setting departs from perfect redundancy, the resulting mispricing becomes larger. This pattern may reflect limited risk-bearing capacity, but it also points to a deeper constraint: the same inability to detect mispricing that leads researchers to focus on perfect-replication settings also constrains the speculators who should correct it.

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A. Transmission Rate: Proofs

A.1. Deriving Value Additivity

Let an asset with payoff stream $\{x_{t+k}\}_{k\geq 1}$ be priced according to the standard linear pricing relation

$$P_t = \mathbb{E}(m_{t+1}x_{t+1} \mid \mathcal{F}_t)\,, \tag{29}$$

where m_{t+1} is the stochastic discount factor and $\mathcal{F}_t$ the information set at time t. Iterating (29) forward yields the infinite-horizon valuation formula

$$P_t = \mathbb{E}\left(\sum_{k=1}^{\infty} M_{t,t+k}\, d_{t+k} \;\middle|\; \mathcal{F}_t\right), \tag{30}$$

where d_{t+k} is the cash flow at $t+k$ and $M_{t,t+k} = m_{t+1}m_{t+2}\cdots m_{t+k}$ is the cumulative discount factor.

For a publicly traded parent firm whose total payoff stream is the sum of the payoff from its subsidiary stake and the payoff from its other net assets,

$$d^p_{t+k} = d^s_{t+k} + d^o_{t+k}. \tag{31}$$

Substituting (31) into (30) gives

$$P^p_t = \mathbb{E}\left(\sum_{k=1}^{\infty} M_{t,t+k}(d^s_{t+k} + d^o_{t+k}) \;\middle|\; \mathcal{F}_t \right). \tag{32}$$

By linearity of expectation and conditioning on the same information set,

$$\begin{aligned} P^p_t = \mathbb{E}&\left(\sum_{k=1}^{\infty} M_{t,t+k} d^s_{t+k} \;\middle|\; \mathcal{F}_t \right) \\ &+ \mathbb{E}\left(\sum_{k=1}^{\infty} M_{t,t+k} d^o_{t+k} \;\middle|\; \mathcal{F}_t \right). \end{aligned} \tag{33}$$

Recognizing each term as the market value of the corresponding payoff stream gives

$$P^p_t = P^s_t + P^o_t. \tag{34}$$

Thus, when assets are priced by a common discount factor conditional on the same information set, value additivity holds: the market value of the parent equals the sum of the market value of its subsidiary stake and the market value of its other net assets.

A.2. Deriving Return Additivity

Start with value additivity in levels,

$$P^p_t = P^s_t + P^o_t, \tag{35}$$

$$\Delta P^p_t = \Delta P^s_t + \Delta P^o_t, \tag{36}$$

$$\frac{\Delta P^p_t}{P^p_{t-1}} = \frac{P^s_{t-1}}{P^p_{t-1}} \frac{\Delta P^s_t}{P^s_{t-1}} + \frac{P^o_{t-1}}{P^p_{t-1}} \frac{\Delta P^o_t}{P^o_{t-1}}, \tag{37}$$

$$r^p_t = w_{t-1} r^s_t + (1 - w_{t-1}) r^o_t, \tag{38}$$

where $w_{t-1} = P^s_{t-1}/P^p_{t-1}$. By defining $r^{ws}_t = w_{t-1} r^s_t$ and $r^{wo}_t = (1 - w_{t-1}) r^o_t$, we obtain

$$r^p_t = r^{ws}_t + r^{wo}_t. \tag{39}$$

Thus, the return of any portfolio of assets is the value-weighted sum of the returns of its components. Value additivity implies return additivity. The reverse, however, does not hold: prices may move consistently while still violating value additivity.

On the other hand, Section 7 shows that when price changes are used as signals about fundamentals in a dispersed-information market, return additivity may fail. After conditioning on the latest price change, however, value additivity can hold in equilibrium with risk-neutral speculators.

A.3. Regression with Common Factors

Let us assume that each simple return can be decomposed into two parts: (i) a component driven by common factors, consisting of a constant and factors shared across assets, and (ii) an idiosyncratic term. Formally,

$$r^j_t = F_t \beta^j + e^j_t, \qquad j \in J, \quad \{s, o\} \subseteq J, \tag{40}$$

where F_t is the row vector of common factors (including a constant), β^j is the column vector of associated factor loadings, and e^j_t is the idiosyncratic component of the return. The index set J denotes the universe of assets under consideration and includes in particular the subsidiary and the parent's other net assets.

The idiosyncratic component is defined to satisfy mean-independence conditions:

$$E[\, e^j_t \mid \mathcal{H}_t \,] = 0, \qquad \text{with } \mathcal{H}_t = \{\Omega_{t-1},\ F_t,\ e^{j'}_t\ (j' \neq j)\}. \tag{41}$$

That is, each idiosyncratic return e^j_t has zero conditional mean given the current common factors and the contemporaneous idiosyncratic returns of other assets. The information set Ω_{t-1} includes at least past prices and therefore contains w_{t-1}.

A.4. From Return Additivity to a Regression Specification

Starting from return additivity and plugging in the factor structure,

$$r_t^p = r_t^{ws} + r_t^{wo}, \tag{42}$$

$$r_t^p = w_{t-1} r_t^s + (1 - w_{t-1}) r_t^o, \tag{43}$$

$$r_t^p = w_{t-1}(F_t \gamma + e_t^s) + (1 - w_{t-1})(F_t \beta^o + e_t^o), \tag{44}$$

$$e_t^p = e_t^{ws} + e_t^{wo}, \tag{45}$$

where $e_t^{ws} = w_{t-1} e_t^s$ and $e_t^{wo} = (1 - w_{t-1}) e_t^o$. By (41),

$$E[e_t^{ws} e_t^{wo}] = E[E[e_t^{ws} e_t^{wo} \mid \mathcal{H}_t]] = E[w_{t-1}(1 - w_{t-1}) E[e_t^s e_t^o \mid \mathcal{H}_t]] = 0.$$

The equation $e_t^p = e_t^{ws} + e_t^{wo}$ is what results from partialling out r_t^p and r_t^s with respect to F_t. By the Frisch–Waugh–Lovell theorem, estimating τ with

$$e_t^p = \tau e_t^{ws} + e_t^{wo} \tag{46}$$

is equivalent to estimating τ with

$$r_t^p = \tau r_t^{ws} + F_t^w \beta + e_t^{wo}. \tag{47}$$

The issue with this specification is that $F_t^w = w_{t-1} F_t$ changes only slowly. However, it is sufficient to estimate

$$r_t^p = \tau e_t^{ws} + v_t, \tag{48}$$

where $v_t = F_t(\beta^o - w_{t-1}\beta) + e_t^{wo}$ and, by (41),

$$E[e_t^{ws} v_t] = E[E[e_t^{ws} v_t \mid \mathcal{H}_t]] = 0.$$

This shows that it is enough to partial out the regressor of interest, a result known as

the *regression anatomy theorem* Angrist and Pischke (2009). Equivalently,

$$r_t^p = \tau r_t^{ws} + F_t^w \beta + u_t, \tag{49}$$

where $u_t = F_t\beta^o - F_t^w\beta + e_t^{wo}$ and β is chosen such that $E[F_t^w u_t] = 0$, which in turn implies that u_t is orthogonal to r_t^{ws}, since τ is identified only from the orthogonal component e_t^{ws}.

A.5. Convergence to Normality of $\bar{\tau}$

For each pair i (one-year window),

$$\hat{\tau}_i = \tau + \varepsilon_i, \qquad \varepsilon_i = (\tilde{F}_i'\tilde{F}_i)^{-1}\tilde{F}_i' u_i, \qquad u_{i,t} = F_t\beta_i^o - \tilde{F}_t\beta_i + \tilde{e}_{i,t}^o, \tag{50}$$

with $\tilde{F}_t = w_{t-1}F_t$ and $\tilde{F}_i$ stacking $\tilde{F}_t$ for $t \in T_i$. Under H_0^s, $\tau = 1$, so $\hat{\tau}_i = 1 + \varepsilon_i$. Define

$$\bar{\tau} = \frac{1}{n}\sum_{i=1}^{n} \hat{\tau}_i. \tag{51}$$

A central limit theorem for $\bar{\tau}$ follows once $E[\varepsilon_i\varepsilon_{i'}] = 0$ for $i \neq i'$ and second moments are bounded.

Non-overlapping windows. Assume $T_i \cap T_{i'} = \varnothing$. Let $\mathcal{H}_t$ denote the filtration up to time t, including past factors and weights. Since

$$\varepsilon_i = (\tilde{F}_i'\tilde{F}_i)^{-1}\tilde{F}_i' u_i = \sum_{t\in T_i} a_{i,t}u_{i,t}, \tag{52}$$

where $a_{i,t}$ is the t-th element of $(\tilde{F}_i'\tilde{F}_i)^{-1}\tilde{F}_i'$, I have from (41) that

$$E[a_{i,t}u_{i,t} \mid \mathcal{H}_t] = 0 \quad \text{for all } i, t. \tag{53}$$

For any $t \in T_i$ and $t' \in T_{i'}$, conditioning on the later sigma-field $\mathcal{H}_{\max(t,t')}$ gives

$$E[a_{i,t}u_{i,t}\, a_{i',t'}u_{i',t'}] = E\big[E[a_{i,t}u_{i,t}\, a_{i',t'}u_{i',t'} \mid \mathcal{H}_{\max(t,t')}]\big] = 0, \tag{54}$$

and therefore

$$E[\varepsilon_i \varepsilon_{i'}] = 0. \tag{55}$$

Overlapping windows. When $T_i \cap T_{i'} \neq \varnothing$, I fix the current common information $\mathcal{H}_t$. It is sufficient that the factor-adjusted components be conditionally orthogonal across pairs on overlapping dates:

$$E\Big[(F_t\beta_i^o - \tilde{F}_t\beta_i)\,(F_t\beta_{i'}^o - \tilde{F}_t\beta_{i'}) \mid \mathcal{H}_t\Big] = 0 \quad \text{for } t \in T_i \cap T_{i'}. \tag{56}$$

Because $\tilde{F}_t = w_{t-1}F_t$ and w_{t-1} varies slowly within a year,

$$F_t\beta_i^o - \tilde{F}_t\beta_i = F_t(\beta_i^o - w_{t-1}\beta_i) \tag{57}$$

is typically small. I assume that any remaining deviations are orthogonal across pairs as in (56). Under this condition and bounded moments, the same linear-combination argument yields

$$E[\varepsilon_i \varepsilon_{i'}] = 0. \tag{58}$$

With $E[\varepsilon_i \varepsilon_{i'}] = 0$ for $i \neq i'$ and finite second moments, a central limit theorem gives

$$\sqrt{n}\,(\bar{\tau} - E[\hat{\tau}_i]) \xrightarrow{d} \mathcal{N}(0, \sigma^2), \qquad \sigma^2 = \mathrm{Var}(\hat{\tau}_i). \tag{59}$$

B. Supplementary Information on the parent-subsidiary pairs data

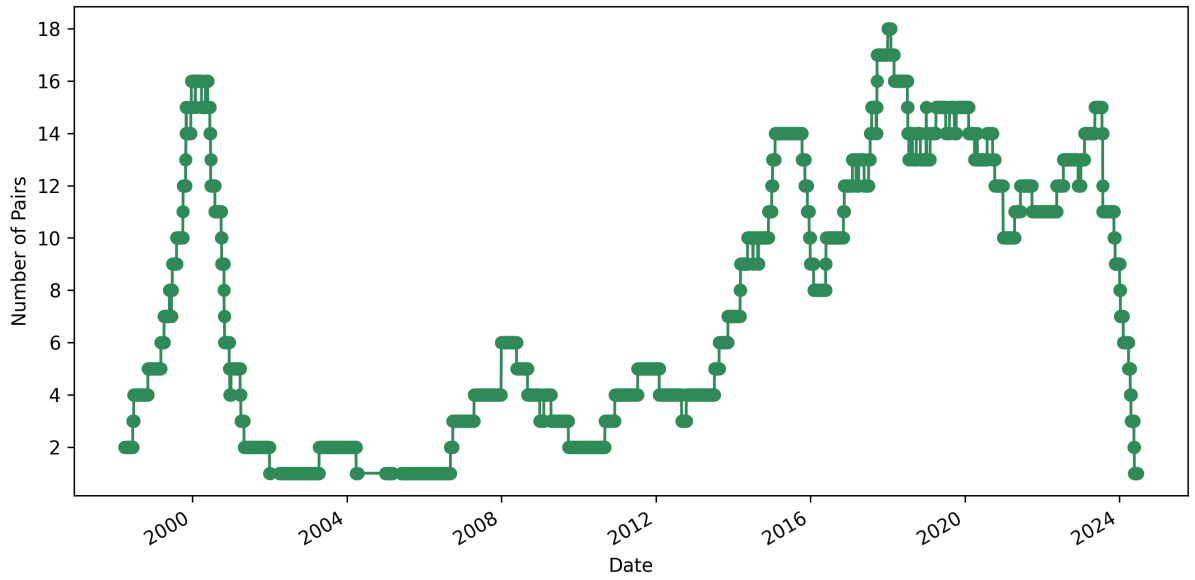


Figure 3: Time-series of the number of parent-subsidiary pairs across time.

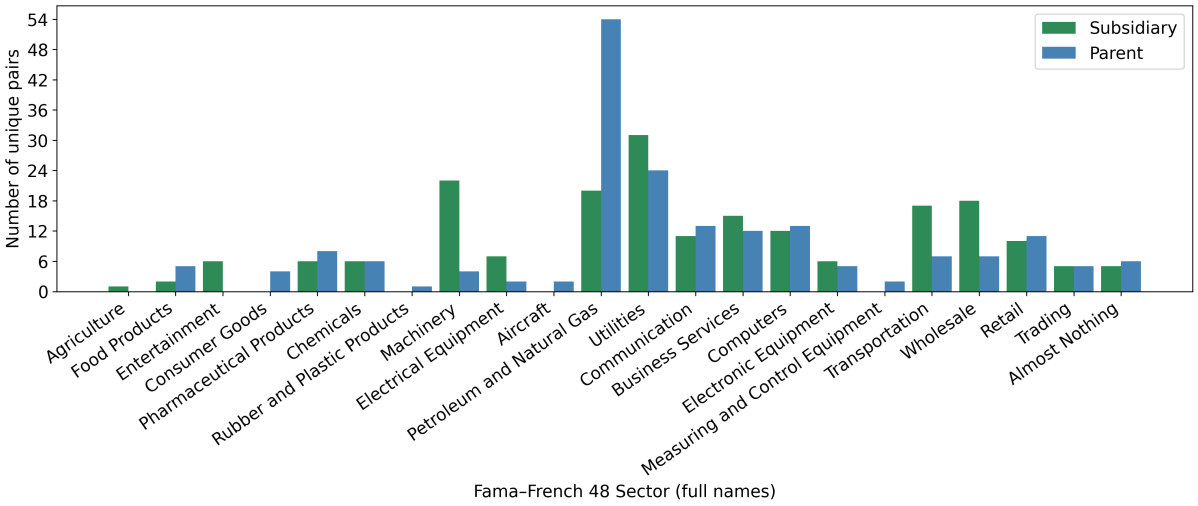


Figure 4: Parent–subsidiary pairs across Fama–French 48 sectors. Most utilities are oil and gas companies with some regulated operations.

C. Average Transmission Rates × characteristics

Table 6: Mean transmission rates estimated by Post-Double-Lasso for All (1999–2024), split by first pair start date.

	All	First<2002	First≥2002
Panel A: Subsidiary Pairs			
n	187	27	160
mean τ	0.381^{***}	0.262^{***}	0.401^{***}
SE of mean τ	(0.036)	(0.040)	(0.041)
z-stat	10.560	6.564	9.675
p-value	0.000	0.000	0.000
median τ	0.387	0.191	0.419
Avg R^2	0.684	0.565	0.704
Avg R^2 (selection on sub)	0.459	0.364	0.475
Panel B: Placebo Pairs			
n	187	27	160
mean τ	−0.022	0.066	−0.037
SE of mean τ	(0.044)	(0.069)	(0.050)
z-stat	−0.509	0.954	−0.746
p-value	0.611	0.349	0.457
median τ	0.023	−0.006	0.026
Avg R^2	0.628	0.515	0.647
Avg R^2 (selection on sub)	0.589	0.463	0.610

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: Mean transmission rates by excluding energy-related subsidiary sectors. Columns report statistics for the full sample and after successively excluding subsidiaries in Utilities, then Utilities+Oil, then Utilities+Oil+Transportation (FF sector short names). Sample sizes by column are $n = \{187, 156, 137, 120\}$.

	All	No Util	No Util+Oil	No Util+Oil+Trans
Panel A: Parent–Subsidiary Pairs				
n	187	156	137	120
mean τ	0.381^{***}	0.367^{***}	0.394^{***}	0.428^{***}
SE of mean τ	(0.036)	(0.032)	(0.034)	(0.035)
z-stat	10.560	11.421	11.617	12.311
p-value	0.000	0.000	0.000	0.000
median τ	0.387	0.397	0.413	0.435
Avg Adj. R^2	0.667	0.662	0.667	0.657
Avg R^2	0.684	0.680	0.684	0.674
Avg R^2 (sub)	0.459	0.456	0.457	0.452
Panel B: Parent–Placebo Pairs				
n	187	156	137	120
mean τ	−0.022	−0.003	0.018	0.023
SE of mean τ	(0.044)	(0.046)	(0.044)	(0.049)
z-stat	−0.509	−0.062	0.407	0.469
p-value	0.611	0.951	0.684	0.640
median τ	0.023	0.026	0.026	0.029
Avg Adj. R^2	0.607	0.593	0.590	0.574
Avg R^2	0.628	0.614	0.611	0.596
Avg R^2 (sub)	0.589	0.600	0.598	0.591

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 8: Regression of transmission rates on Weight only (placebo pairs). When common factors between parent and subsidiary returns are controlled poorly, a spurious negative correlation arises between portfolio weight and transmission rates. In $\tilde{r}_t^s = w_{t-1} r_t^s$, the same amount of omitted common factor inflates the estimated transmission rate when w_{t-1} is small. In the placebo regressions this negative correlation disappears with Post-Double-Lasso, providing additional support for this specification.

Variable	Simple	FF5+Sector	Post Double-Lasso
Constant	3.084^{***}	0.955^{***}	-0.048
	(0.229)	(0.151)	(0.088)
Weight	-2.494^{***}	-0.689^{***}	0.051
	(0.265)	(0.154)	(0.090)
R^2	0.304	0.071	0.001
df	185	185	185

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *HC3 heteroskedasticity-consistent standard errors in parentheses.*

D. Explaining the Cross-Sectional Variation in Transmission Rate

D.1. Placebo Regressions

As a sanity check, I report the same tables and plot for the placebo transmission rates. For the WLS regression, $\log(\widehat{\text{UVR}_i})$ has a coefficient of -0.013 with a standard error of 0.008, and for the OLS the coefficient is -0.050 with a standard error of 0.028. The relation is almost flat, but placebo pairs with small UVR tend to have slightly higher transmission rates. This is not surprising if we assume that a relatively homogeneous small positive bias remains in the transmission rates: it becomes more visible where the transmission rate is higher, that is, for small UVR.

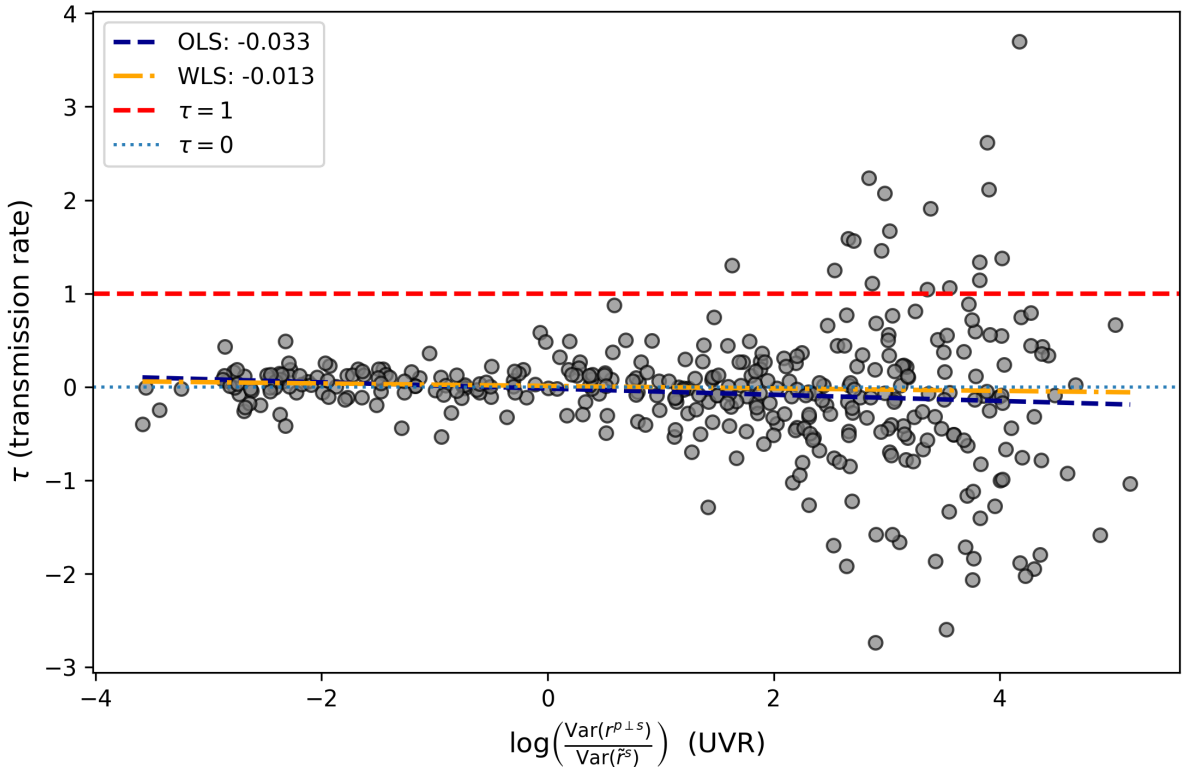


Figure 5: Cross-fitting scatter plots of τ against UVR.

D.2. Idiosyncratic and UVR Regressions

Table 9: Explaining Placebo Transmission Rates Using Weighted Least Squares (WLS) and Cross-Fitting. The regression is

$$\hat{\tau}_i = \beta_0 + \beta_1 \log(\widehat{\mathrm{UVR}_i}) + \beta_2 \textsc{Float}_i + \beta_3 \mathrm{MC}_i + \beta_4 \textsc{Turnover}_i + \beta_5 \textsc{Amihud}_i + \beta_6 \log(\textsc{Size}_i) + \beta_7 \textsc{Post2002}_i + \varepsilon_i.$$

i denotes a parent–placebo pair observed over one year. The dependent variable is the cross-fitted transmission rate $\hat{\tau}_i$, estimated via Post-Double Lasso. $\log(\widehat{\mathrm{UVR}_i})$ measures the ratio of the parent's unspanned variance to the subsidiary's variance, capturing uncertainty about the parent's other assets. $\textsc{Float}_i$ is the share of the subsidiary's stock available for trading after deducting the parent's holdings. MC_i is a dummy equal to one when the parent controls more than 50% of the voting rights. $\textsc{Turnover}_i$ is the average daily trading volume relative to shares outstanding, and $\textsc{Amihud}_i$ is the average price impact of trading, computed as the absolute return divided by the dollar volume. $\log(\textsc{Size}_i)$ is the logarithm of the combined market value of the parent and subsidiary, and $\textsc{Post2002}_i$ equals one for observations after the internet bubble. Cross-fitting ensures that $\log(\widehat{\mathrm{UVR}_i})$ and $\hat{\tau}_i$ are estimated on separate folds. Standard errors are clustered by pair (HC3), and WLS weights are the inverse squared standard errors of $\hat{\tau}_i$.

	Parent–Placebo (WLS)				
Variable	Baseline	Full	No Post-2002	No Amihud	–Am, –P02
Constant	0.011	0.134**	0.128**	0.119**	0.108**
	(0.016)	(0.057)	(0.057)	(0.049)	(0.049)
log(UVR)	-0.013*	-0.025**	-0.022**	-0.024**	-0.021**
	(0.008)	(0.010)	(0.009)	(0.010)	(0.010)
Amihud	–	-0.012	-0.016	–	–
		(0.038)	(0.038)		
Turnover	–	-5.007**	-4.671**	-4.842**	-4.400**
		(2.211)	(2.168)	(2.169)	(2.097)
Free Float	–	-0.077	-0.060	-0.081	-0.062
		(0.054)	(0.044)	(0.050)	(0.043)
log(Size)	–	-0.015	-0.011	-0.012	-0.006
		(0.014)	(0.015)	(0.012)	(0.012)
Control	–	-0.041	-0.026	-0.039	-0.020
		(0.030)	(0.028)	(0.031)	(0.028)
Post-2002	–	0.033	–	0.036	–
		(0.040)		(0.036)	
R^2	0.012	0.046	0.043	0.045	0.042
df	372	366	367	367	368

Notes: Weighted least squares (WLS) estimates with weights $1/\mathrm{SE}(\hat{\tau}_i)^2$. Standard errors are clustered by pair (HC3). Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10: Explaining Placebo Transmission Rates Using Ordinary Least Squares (OLS) and Cross-Fitting. The regression is

$$\hat{\tau}_i = \beta_0 + \beta_1 \log(\widehat{\mathrm{UVR}_i}) + \beta_2 \textsc{Float}_i + \beta_3 \mathrm{MC}_i + \beta_4 \textsc{Turnover}_i + \beta_5 \textsc{Amihud}_i + \beta_6 \log(\textsc{Size}_i) + \beta_7 \textsc{Post2002}_i + \varepsilon_i.$$

i denotes a parent–placebo pair observed over one year. The dependent variable is the cross-fitted transmission rate $\hat{\tau}_i$, estimated via Post-Double Lasso. $\log(\widehat{\mathrm{UVR}_i})$ measures the ratio of the parent's unspanned variance to the subsidiary's variance, capturing uncertainty about the parent's other assets. $\textsc{Float}_i$ is the share of the subsidiary's stock available for trading after deducting the parent's holdings. MC_i is a dummy equal to one when the parent controls more than 50% of the voting rights. $\textsc{Turnover}_i$ is the average daily trading volume relative to shares outstanding, and $\textsc{Amihud}_i$ is the average price impact of trading, computed as the absolute return divided by the dollar volume. $\log(\textsc{Size}_i)$ is the logarithm of the combined market value of the parent and subsidiary, and $\textsc{Post2002}_i$ equals one for observations after the internet bubble. Cross-fitting ensures that $\log(\widehat{\mathrm{UVR}_i})$ and $\hat{\tau}_i$ are estimated on separate folds. Standard errors are clustered by pair (HC3).

	Parent–Placebo (OLS)				
Variable	Baseline	Full	No Post-2002	No Amihud	–Am, –P02
Constant	0.018	-0.004	-0.090	-0.041	-0.080
	(0.024)	(0.202)	(0.213)	(0.185)	(0.192)
log(UVR)	-0.050*	-0.035	-0.042	-0.035	-0.043
	(0.028)	(0.028)	(0.027)	(0.028)	(0.027)
Float	–	0.166	0.112	0.170	0.109
		(0.195)	(0.184)	(0.196)	(0.185)
CC	–	0.179*	0.152	0.181*	0.150*
		(0.099)	(0.092)	(0.098)	(0.090)
Turnover	–	3.183	2.605	3.416	2.510
		(8.290)	(8.206)	(8.312)	(8.150)
Amihud	–	-0.040	0.012	–	–
		(0.090)	(0.067)		
log(Size)	–	-0.034	-0.039	-0.029	-0.040
		(0.048)	(0.047)	(0.044)	(0.041)
Post-2002	–	-0.173	–	-0.157	–
		(0.110)		(0.105)	
R^2	0.017	0.038	0.033	0.038	0.033
df	372	366	367	367	368

Notes: Standard errors clustered by pair (HC3). Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 11: Explaining Transmission Rates Using Weighted Least Squares (WLS) and Cross-Fitting. The regression is

$$\hat{\tau}_i = \beta_0 + \beta_1 \log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i}) + \beta_2 \textsc{Float}_i + \beta_3 \mathrm{MC}_i + \beta_4 \textsc{Turnover}_i + \beta_5 \textsc{Amihud}_i + \beta_6 \log(\textsc{Size}_i) + \beta_7 \textsc{Post2002}_i + \varepsilon_i.$$

i denotes a parent–subsidiary pair observed over one year. The main regressor is the log Idiosyncratic UVR,

$$\log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i}) = \log\left(\frac{\mathrm{Var}(e_i^o)}{\mathrm{Var}(\tilde{e}_i^s)}\right),$$

where both e_i^o and $\tilde{e}_i^s$ are residualized with respect to the same set of controls, ensuring comparability. Cross-fitting ensures that both $\hat{\tau}_i$ and $\log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i})$ are estimated on separate folds. Standard errors are clustered by pair (HC3).

	Parent–Subsidiary (WLS)				
Variable	Baseline	Full	No Post-2002	No Amihud	–Am, –P02
Constant	0.380***	0.391***	0.446***	0.260**	0.225
	(0.025)	(0.134)	(0.155)	(0.126)	(0.193)
$\log(\mathrm{UVR}_{\mathrm{idiosyn.}})$	-0.118***	-0.118***	-0.100***	-0.119***	-0.095**
	(0.022)	(0.019)	(0.032)	(0.021)	(0.039)
Float	–	0.098	0.278	0.050	0.251
		(0.202)	(0.357)	(0.207)	(0.408)
CC	–	-0.052	0.091	-0.029	0.181
		(0.112)	(0.143)	(0.115)	(0.140)
Turnover	–	-5.117	-2.820	-4.416	-0.762
		(3.158)	(3.477)	(3.011)	(3.854)
Amihud	–	-0.167	-0.269**	–	–
		(0.104)	(0.136)		
log(Size)	–	-0.099***	-0.083***	-0.077***	-0.037
		(0.020)	(0.026)	(0.020)	(0.034)
Post-2002	–	0.357***	–	0.424***	–
		(0.126)		(0.120)	
R^2	0.223	0.575	0.471	0.544	0.378
df	372	366	367	367	368

Notes: Weighted least squares (WLS) estimates with weights $1/\mathrm{SE}(\hat{\tau}_i)^2$. Standard errors are clustered by pair (HC3). Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12: Explaining Transmission Rates Using Ordinary Least Squares (OLS) and Cross-Fitting. The regression is

$$\hat{\tau}_i = \beta_0 + \beta_1 \log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i}) + \beta_2 \textsc{Float}_i + \beta_3 \mathrm{MC}_i + \beta_4 \textsc{Turnover}_i + \beta_5 \textsc{Amihud}_i + \beta_6 \log(\textsc{Size}_i) + \beta_7 \textsc{Post2002}_i + \varepsilon_i.$$

i denotes a parent–subsidiary pair observed over one year. The dependent variable is the cross-fitted transmission rate $\hat{\tau}_i$, estimated via Post-Double Lasso. The main regressor is the log Idiosyncratic UVR, defined as

$$\log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i}) = \log\left(\frac{\mathrm{Var}(e_i^o)}{\mathrm{Var}(\tilde{e}_i^s)}\right),$$

where e_i^o and $\tilde{e}_i^s$ are the residual returns of the parent and subsidiary after partialling out the same set of controls. This construction isolates the component of the parent's risk that is orthogonal to the subsidiary. Cross-fitting ensures that both $\hat{\tau}_i$ and $\log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i})$ are estimated on separate folds. Standard errors are clustered by pair (HC3).

	Parent–Subsidiary (OLS)				
Variable	Baseline	Full	No Post-2002	No Amihud	–Am, –P02
Constant	0.390***	0.126	0.146	0.061	0.078
	(0.024)	(0.156)	(0.157)	(0.142)	(0.144)
$\log(\mathrm{UVR}_{\mathrm{idiosyn.}})$	-0.053**	-0.045**	-0.043**	-0.044**	-0.042**
	(0.020)	(0.021)	(0.020)	(0.021)	(0.020)
Float	–	0.244	0.256	0.252	0.278*
		(0.163)	(0.158)	(0.162)	(0.157)
CC	–	0.191**	0.197**	0.194**	0.207***
		(0.080)	(0.076)	(0.080)	(0.075)
Turnover	–	7.571	7.690	7.977	8.345
		(5.196)	(5.141)	(5.184)	(5.104)
Amihud	–	-0.071	-0.082	–	–
		(0.076)	(0.073)		
log(Size)	–	-0.042	-0.041	-0.033	-0.028
		(0.030)	(0.030)	(0.027)	(0.027)
Post-2002	–	0.038	–	0.066	–
		(0.073)		(0.067)	
R^2	0.031	0.084	0.083	0.082	0.081
df	372	366	367	367	368

Notes: Standard errors clustered by pair (HC3). Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13: Explaining Placebo Transmission Rates Using Weighted Least Squares (WLS) and Cross-Fitting. The regression is

$$\hat{\tau}_i = \beta_0 + \beta_1 \log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i}) + \beta_2 \textsc{Float}_i + \beta_3 \mathrm{MC}_i + \beta_4 \textsc{Turnover}_i + \beta_5 \textsc{Amihud}_i + \beta_6 \log(\textsc{Size}_i) + \beta_7 \textsc{Post2002}_i + \varepsilon_i.$$

i denotes a parent–placebo pair observed over one year. The dependent variable is the cross-fitted transmission rate $\hat{\tau}_i$, estimated via Post-Double Lasso. The main regressor is the log Idiosyncratic UVR, defined as

$$\log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i}) = \log\left(\frac{\mathrm{Var}(e_i^o)}{\mathrm{Var}(\tilde{e}_i^s)}\right),$$

where e_i^o and $\tilde{e}_i^s$ are the residual returns of the parent and subsidiary after partialling out the same set of controls. This construction isolates the component of the parent's risk that is orthogonal to the subsidiary. Cross-fitting ensures that both $\hat{\tau}_i$ and $\log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i})$ are estimated on separate folds. Standard errors are clustered by pair (HC3).

	Parent–Placebo (WLS)				
Variable	Baseline	Full	No Post-2002	No Amihud	–Am, –P02
Constant	0.018	0.134**	0.122*	0.109*	0.092*
	(0.013)	(0.068)	(0.066)	(0.059)	(0.054)
$\log(\mathrm{UVR}_{\mathrm{idiosyn.}})$	-0.022*	-0.039*	-0.029	-0.037*	-0.026
	(0.013)	(0.022)	(0.018)	(0.021)	(0.018)
Float	–	-0.074	-0.043	-0.079	-0.047
		(0.060)	(0.057)	(0.055)	(0.054)
CC	–	-0.036	-0.008	-0.032	-0.001
		(0.034)	(0.030)	(0.035)	(0.029)
Turnover	–	-4.887**	-4.182*	-4.580**	-3.788*
		(2.429)	(2.260)	(2.309)	(2.097)
Amihud	–	-0.021	-0.025	–	–
		(0.060)	(0.059)		
log(Size)	–	-0.020	-0.011	-0.014	-0.003
		(0.019)	(0.019)	(0.019)	(0.016)
Post-2002	–	0.069	–	0.072*	–
		(0.045)		(0.043)	
R^2	0.020	0.054	0.045	0.052	0.042
df	372	366	367	367	368

Notes: Weighted least squares (WLS) estimates with weights $1/\mathrm{SE}(\hat{\tau}_i)^2$. Standard errors are clustered by pair (HC3). Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 14: Explaining Placebo Transmission Rates Using Ordinary Least Squares (OLS) and Cross-Fitting. The regression is

$$\hat{\tau}_i = \beta_0 + \beta_1 \log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i}) + \beta_2 \textsc{Float}_i + \beta_3 \mathrm{MC}_i + \beta_4 \textsc{Turnover}_i + \beta_5 \textsc{Amihud}_i + \beta_6 \log(\textsc{Size}_i) + \beta_7 \textsc{Post2002}_i + \varepsilon_i.$$

i denotes a parent–placebo pair observed over one year. The dependent variable is the cross-fitted transmission rate $\hat{\tau}_i$, estimated via Post-Double Lasso. The main regressor is the log Idiosyncratic UVR, defined as

$$\log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i}) = \log\left(\frac{\mathrm{Var}(e_i^o)}{\mathrm{Var}(\tilde{e}_i^s)}\right),$$

where e_i^o and $\tilde{e}_i^s$ are the residual returns of the parent and subsidiary after partialling out the same set of controls. This construction isolates the component of the parent's risk that is orthogonal to the subsidiary. Cross-fitting ensures that both $\hat{\tau}_i$ and $\log(\widehat{\mathrm{UVR}}_{\mathrm{idiosyn.},i})$ are estimated on separate folds. Standard errors are clustered by pair (HC3).

	Parent–Placebo (OLS)				
Variable	Baseline	Full	No Post-2002	No Amihud	–Am, –P02
Constant	-0.002	-0.009	-0.100	-0.043	-0.085
	(0.022)	(0.203)	(0.215)	(0.188)	(0.195)
$\log(\mathrm{UVR}_{\mathrm{idiosyn.}})$	-0.044	-0.029	-0.035	-0.029	-0.036
	(0.027)	(0.027)	(0.026)	(0.027)	(0.026)
Float	–	0.158	0.101	0.162	0.096
		(0.197)	(0.185)	(0.197)	(0.186)
CC	–	0.176*	0.146	0.177*	0.144
		(0.099)	(0.092)	(0.099)	(0.090)
Turnover	–	3.395	2.827	3.605	2.685
		(8.325)	(8.256)	(8.350)	(8.204)
Amihud	–	-0.037	0.018	–	–
		(0.088)	(0.065)		
log(Size)	–	-0.035	-0.040	-0.031	-0.043
		(0.048)	(0.047)	(0.044)	(0.041)
Post-2002	–	-0.180*	–	-0.165	–
		(0.108)		(0.103)	
R^2	0.016	0.037	0.031	0.037	0.031
df	372	366	367	367	368

Notes: Standard errors clustered by pair (HC3). Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

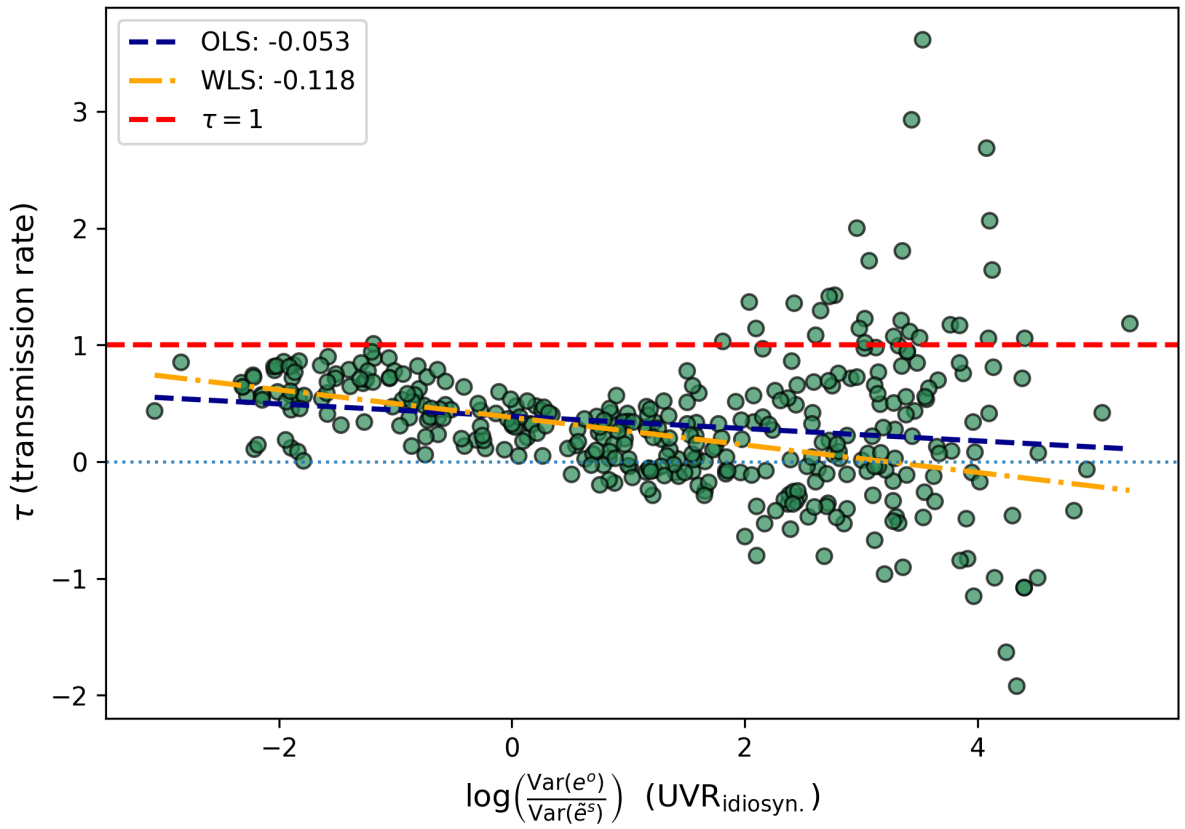


Figure 6: Cross-fitting scatter plots of τ against UVR.

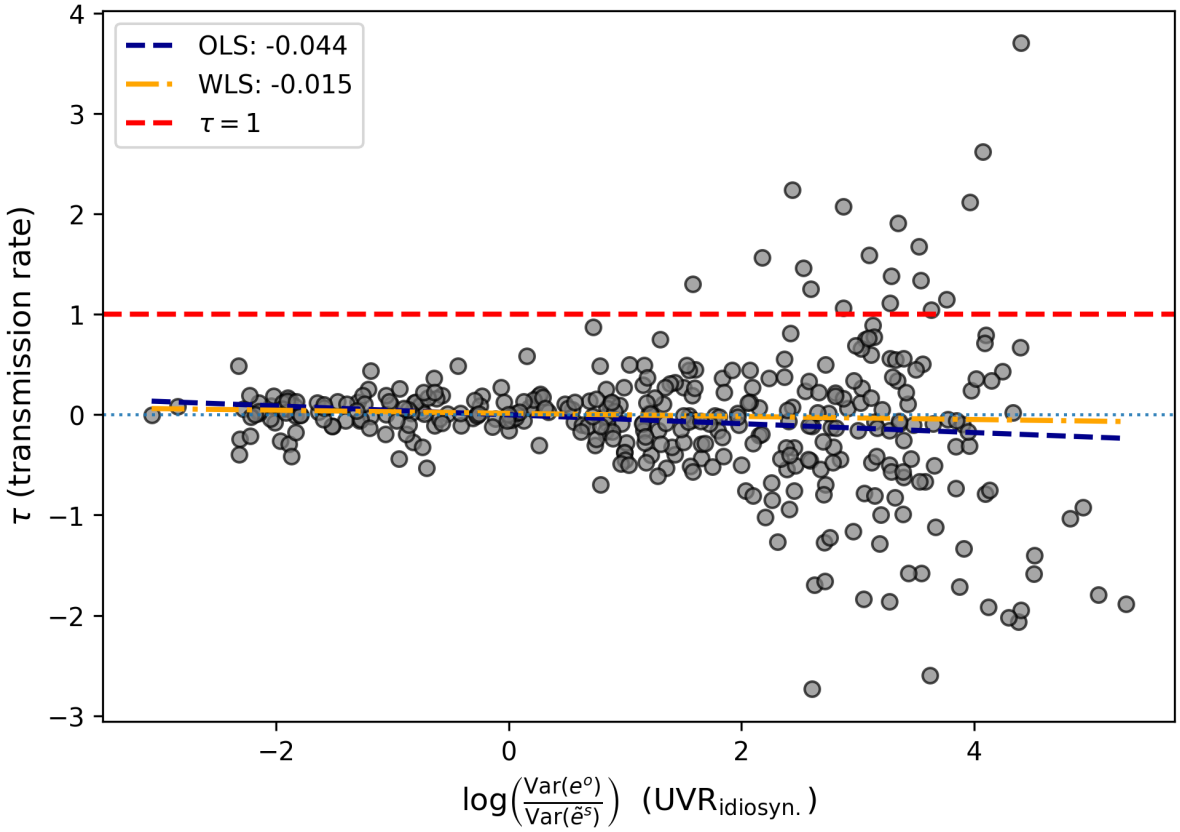


Figure 7: Cross-fitting scatter plots of τ against UVR.

E. Theoretical Model Proofs

E.1. The Transmission Rate

$$\tau = \frac{\text{Cov}(r_1^p, \tilde{r}_1^s)}{\text{Var}(\tilde{r}_1^s)} \tag{60}$$

$$= \frac{\text{Cov}\left(\frac{\Delta P_1^p}{P_0^p},\ \frac{P_0^s}{P_0^p}\frac{\Delta P_1^s}{P_0^s}\right)}{\text{Var}\left(\frac{P_0^s}{P_0^p}\frac{\Delta P_1^s}{P_0^s}\right)} \tag{61}$$

$$= \frac{\frac{1}{(P_0^p)^2}\text{Cov}(\Delta P_1^p, \Delta P_1^s)}{\frac{1}{(P_0^p)^2}\text{Var}(\Delta P_1^s)} = \frac{\text{Cov}(\Delta P_1^p, \Delta P_1^s)}{\text{Var}(\Delta P_1^s)}. \tag{62}$$

Now substitute the model:

$$\Delta P_1^p = v_1^s + v_1^o + f_1, \qquad \Delta P_1^s = v_1^s + n_1^s.$$

And to keep things simple, I assume that all variables in the model are orthogonal: $E[n_1^s v_1^s] = E[v_1^s v_1^o] = E[n_1^s v_1^o] = 0$.

$$\tau = \frac{\text{Cov}(v_1^s + v_1^o + f_1,\ v_1^s + n_1^s)}{\text{Var}(v_1^s + n_1^s)} \tag{63}$$

$$= \frac{\text{Cov}(v_1^s + v_1^o + E[n_1^s \mid \mathcal{F}_1],\ v_1^s + n_1^s)}{\text{Var}(v_1^s + n_1^s)}. \tag{64}$$

Compute numerator and denominator:

$$\tau = \frac{E[(v_1^s)^2] + E[E[n_1^s \mid \mathcal{F}_1]^2]}{E[(v_1^s)^2] + E[(n_1^s)^2]} \tag{65}$$

$$= \frac{\sigma_{vs}^2}{\sigma_{vs}^2 + \sigma_{ns}^2} + \frac{\sigma_{ns}^2}{\sigma_{vs}^2 + \sigma_{ns}^2}\frac{E[E[n_1^s \mid \mathcal{F}_1]^2]}{\sigma_{ns}^2}. \tag{66}$$

Recognizing

$$\tau_{\text{n}} = \frac{\sigma_{vs}^2}{\sigma_{vs}^2 + \sigma_{ns}^2}, \qquad R^2 = \frac{E[E[n_1^s \mid \mathcal{F}_1]^2]}{\sigma_{ns}^2},$$

we obtain

$$\tau = \tau_{\mathrm{n}} + (1 - \tau_{\mathrm{n}})R^2. \tag{67}$$

E.2. Computing the R^2

Starting from the fact that the conditional expectation of the noise is given by the following linear projection,

$$E[n_1^s \mid \mathcal{F}_1] = \beta_1 \Delta P_1^s + \beta_2(\Delta P_1^s - \Delta P_1^p), \tag{68}$$

and assuming that arbitrageurs know the moments of the distribution, they can compute β_1 and β_2 exactly, which allows us to derive R^2.

Given the variables n_1^s, v_1^s, and v_1^o with variances σ_{ns}^2, σ_{vs}^2, and σ_{vo}^2, and given that all variables have zero mean and are mutually independent, we now express R^2 in terms of these variances.

The variances are:

$$\sigma_{ns}^2 = E[(n_1^s)^2], \qquad \sigma_{vs}^2 = E[(v_1^s)^2], \qquad \sigma_{vo}^2 = E[(v_1^o)^2]. \tag{69}$$

Define the regressors:

$$X_1 = \Delta P_1^s = v_1^s + n_1^s, \qquad X_2 = \Delta P_1^s - \Delta P_1^p = v_1^o - n_1^s. \tag{70}$$

Their variances and covariance are:

$$\mathrm{Var}(X_1) = \sigma_{vs}^2 + \sigma_{ns}^2, \tag{71}$$

$$\mathrm{Var}(X_2) = \sigma_{vo}^2 + \sigma_{ns}^2, \tag{72}$$

$$\mathrm{Cov}(X_1, X_2) = -\sigma_{ns}^2. \tag{73}$$

The covariances of n_1^s with the regressors are:

$$\mathrm{Cov}(n_1^s, X_1) = \sigma_{ns}^2, \tag{74}$$

$$\mathrm{Cov}(n_1^s, X_2) = -\sigma_{ns}^2. \tag{75}$$

To find the regression coefficients β_1 and β_2, we use

$$\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} = \begin{pmatrix} \mathrm{Var}(X_1) & \mathrm{Cov}(X_1, X_2) \\ \mathrm{Cov}(X_1, X_2) & \mathrm{Var}(X_2) \end{pmatrix}^{-1} \begin{pmatrix} \mathrm{Cov}(n_1^s, X_1) \\ \mathrm{Cov}(n_1^s, X_2) \end{pmatrix}. \tag{76}$$

Substituting the variances:

$$\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} = \begin{pmatrix} \sigma_{vs}^2 + \sigma_{ns}^2 & \sigma_{ns}^2 \\ \sigma_{ns}^2 & \sigma_{vo}^2 + \sigma_{ns}^2 \end{pmatrix}^{-1} \begin{pmatrix} \sigma_{ns}^2 \\ -\sigma_{ns}^2 \end{pmatrix}. \tag{77}$$

The determinant is:

$$D = \sigma_{vs}^2 \sigma_{vo}^2 + \sigma_{ns}^2(\sigma_{vs}^2 + \sigma_{vo}^2). \tag{78}$$

Thus the inverse matrix is:

$$\frac{1}{D} \begin{pmatrix} \sigma_{vo}^2 + \sigma_{ns}^2 & \sigma_{ns}^2 \\ \sigma_{ns}^2 & \sigma_{vs}^2 + \sigma_{ns}^2 \end{pmatrix}. \tag{79}$$

Multiplying yields:

$$\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} = \frac{1}{D} \begin{pmatrix} \sigma_{ns}^2 \, \sigma_{vo}^2 \\ -\sigma_{ns}^2 \, \sigma_{vs}^2 \end{pmatrix}. \tag{80}$$

Hence:

$$\beta_1 = \frac{\sigma_{ns}^2 \sigma_{vo}^2}{D}, \qquad \beta_2 = -\frac{\sigma_{ns}^2 \sigma_{vs}^2}{D}. \tag{81}$$

Next, compute the variance of the conditional expectation:

$$\mathrm{Var}(E[n_1^s \mid \mathcal{F}_1]) = \beta_1^2 \, \mathrm{Var}(X_1) + 2\beta_1\beta_2 \, \mathrm{Cov}(X_1, X_2) + \beta_2^2 \, \mathrm{Var}(X_2), \tag{82}$$

Finally, substituting yields the closed-form:

$$R^2 = \frac{\sigma_{ns}^2(\sigma_{vs}^2 + \sigma_{vo}^2)}{\sigma_{ns}^2(\sigma_{vs}^2 + \sigma_{vo}^2) + \sigma_{vs}^2\sigma_{vo}^2}. \tag{83}$$