Underreaction in Publicly Traded Cross-Holdings *

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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 U.S. parent–subsidiary pairs 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 greater the uncertainty surrounding the parent's other assets, the stronger the underreaction. This evidence is consistent with a limits-to-arbitrage mechanism in which non-fundamental demand shocks affecting the subsidiary price create a tendency toward underreaction, while uncertainty surrounding the parent's non-hedgeable other assets limits arbitrageurs' ability to trade against this force. I formalize this mechanism in a theoretical model.

JEL Codes: G12, G14, G32, G40

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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 value-weighted return of the subsidiary stake. To isolate variation specific to the subsidiary, I control for returns of a large set of other firms. The sample is restricted to cases where the subsidiary stake represents at least 10% of the parent's value, yielding 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 close zero.

The key cross-sectional determinant of transmission rates is the parent's variance not spanned by the subsidiary, which proxies uncertainty about the payoffs generated by the parent's other assets. As this non-spanned variance 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. Non-fundamental movements in the stake price creates a tendency toward underreaction. As non-spanned variance increases, hedgeability declines, limiting the ability of arbitrageurs to counteract this underreaction. I formalize this mechanism in a theoretical 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.

The limits-to-arbitrage model developed to generate this underreaction is in the spirit of the framework discussed by Gromb and Vayanos (2010), where imperfect correlation between assets limits arbitrageurs' ability to absorb non-fundamental demand shocks. The key difference here is market segmentation: parent investors only trade the parent, subsidiary investors only trade the subsidiary, while arbitrageurs can trade both assets. This assumption is essential. In an otherwise similar setting where all investors can trade both assets, non-fundamental demand shocks are fully transmitted to the parent price, implying a transmission rate equal to one. Similar segmentation assumptions are also present in Gromb and Vayanos (2002) and Gromb and Vayanos (2018).

Limited risk-bearing capacity can also generate predictable returns. Non-fundamental demand shocks affecting the subsidiary price can induce long-horizon mean reversion, as documented in Fama and French (1988); Poterba and Summers (1988); Campbell and Shiller (1989). Campbell and Kyle (1993) develop a model in which non-fundamental demand and limited risk-bearing generate mean reversion. However, longer-horizon risk-adjusted predictability is beyond the scope of this paper.

On shorter horizons, I test whether subsidiary returns predict the parent's return over the following days. They do not. In contrast, Chang et al. (2022) document such cross-asset predictability in parent–subsidiary structures using broad cross-sections of ownership-linked firms and portfolio strategies that buy or sell the parent depending on the subsidiary's performance over the previous month.[1] They interpret this evidence as reflecting the slow incorporation of fundamental information related to the parent's internal capital market. Their sample consists of a large number of ownership-linked firms across the world, without restricting attention, as in this paper, to the relatively rare cases where the subsidiary stake represents a large fraction of the parent's market

[1] See also Li et al. (2016) for evidence among US parent–subsidiary firms.

value.

The paper relates to the literature on negative stub values, where the market value of a parent firm is lower than the market value of its stake in a subsidiary, implying a negative value for the parent's other net assets. A negative net value for the parent's other assets is not impossible. It simply requires the value of the parent's other assets to be lower than its liabilities. Therefore, while negative stub values may appear suspicious, they generally do not completely falsify value additivity.[2] This paper approaches the problem from another angle by estimating a transmission rate between the stake and the parent's market value. This approach allows the analysis to extend beyond extreme negative stub value cases. The cross-sectional variation in transmission rates also makes it possible to test mechanisms driving price transmission across parent–subsidiary pairs.

To make mispricing in negative stub values harder to dismiss, Lamont and Thaler (2002) study five equity carve-outs with subsequent spin-offs during the Internet bubble. In only one case, 3Com and Palm, did the negative stub value persist after the spin-off announcement, making mispricing difficult to dismiss. They argue that the limited float of Palm shares generated short-sale constraints.[3] See also Cornell and Liu (2001), who conclude from a case study of negative stub values that mechanisms commonly used to explain conglomerate or closed-end fund discounts do not apply well to publicly traded parent–subsidiary structures, and that non-fundamental demand combined with limited subsidiary float are the main drivers of the apparent mispricings.

However, the percentage of subsidiary shares floating does not explain transmission rates in the data. Instead, transmission rates are explained by uncertainty related to the parent's other assets. Mitchell et al. (2002) examine negative stub values using long-parent/short-subsidiary positions and show that arbitrage strategies expose investors to fundamental risk related to the parent's other assets, making convergence bumpy and uncertain. They suggest that this uncertainty limits arbitrage aggressiveness. Thus,

[2] For example, Mitchell et al. (2002) explicitly recognize this issue and consider alternative definitions of negative stub values.

[3] Lamont and Thaler (2002) also note that Bergstresser and Karlan (2000) independently documented underreaction of parents to movements in their subsidiaries' values, although the manuscript does not appear to be publicly available.

their findings would naturally lead one to expect transmission rates to decrease as uncertainty related to the parent's other assets increases, which is confirmed in the data. See Cherkes (2012) for a review of the literature on closed-end fund arbitrage and its proposed mechanisms.

When the parent has few or no other assets, and potentially only liabilities at the parent level, the transmission rate is close to one. In one pair, the parent is even perfectly redundant with its stake, such that the Law of One Price should apply. Indeed, it does, and the transmission rate is equal to one. At first sight, this may appear to contradict the famous twin stocks anomaly, where firms entitled to identical cash flows exhibited large deviations from parity across international markets (Rosenthal and Young (1990)). Froot and Dabora (1999) argue that these deviations are explained by international market segmentation, as twin stocks are highly correlated with their respective local markets.[4] By contrast, the parent–subsidiary pairs in my sample are traded on the same market. Likewise, the comparison with closed-end fund discounts (or premiums) also has limits. Arbitrage on closed-end funds requires trading a broad portfolio rather than simply two assets.

Brav et al. (2010) empirically test whether the data match predictions derived from limited arbitrageur risk-bearing capacity. In particular, Shleifer and Vishny (1997) argue that arbitrageurs must specialize, limiting diversification and making idiosyncratic risk relevant for arbitrage. Brav et al. (2010) find little support for the idea that idiosyncratic volatility explains positive-return anomalies such as value stocks and small stocks, but strong support for the idea that idiosyncratic volatility explains negative-return anomalies such as growth stocks. As the underreaction in this paper is identified through idiosyncratic movements in the stake, the evidence is consistent with the idea that arbitrageurs remain averse to risk even when that risk is potentially diversifiable.

The central mechanism in Shleifer and Vishny (1997) is that performance-based financial constraints can weaken arbitrageurs precisely when arbitrage opportunities become larger. Related mechanisms arise through investor withdrawals (Hombert and Thesmar

[4]See also de Jong et al. (2009), who show that arbitrage strategies involving twin stocks do not generate large Sharpe ratios.

(2014)), margin constraints (Gromb and Vayanos (2002)), liquidity spirals (Brunnermeier and Pedersen (2009)), and dynamic convergence risk (Kondor (2009)). Gromb and Vayanos (2018) further show that when arbitrageurs allocate capital across many convergence trades, they can propagate shocks across markets.[5] In the limits-to-arbitrage model developed in this paper, the ratio of risk aversion between arbitrageurs and parent investors that best matches the data is large: arbitrageurs must behave as substantially more risk-averse than local parent investors, potentially reflecting the presence of financial and institutional limits to arbitrage.

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 goes through possible mechanisms behind the underreaction. Section 7 develops a limits-to-arbitrage model generating the underreaction. Section 8 concludes.

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-

[5] See also Davila et al. (2024), who show that arbitrage gaps are a sufficient statistic for the marginal social value of arbitrage.

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^P 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:

$$\mathcal{T} \equiv \frac{\partial r_t^P}{\partial r_t^{wS}}. \tag{3}$$

Under the frictionless benchmark in equation (2), this sensitivity equals one, so $\mathcal{T} = 1$. 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 and the parent knows the value of its other assets.

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 $\mathcal{T} = 1$ (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.

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 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

[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.

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 $(\text{Ask}_{i,t} - \text{Bid}_{i,t})/\left(\frac{1}{2}(\text{Ask}_{i,t} + \text{Bid}_{i,t})\right)$; 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

Identifying the transmission rate requires separating subsidiary-specific movements from common factors that also affect the parent's other assets. Suppose the subsidiary's return admits 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 both F_t and the return on the parent's other assets. If the factor structure were observable, the transmission rate could be estimated through the following regression:

$$r_t^P = \mathcal{T} r_t^{wS} + F_t^w \beta + u_t, \tag{5}$$

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

In practice, however, the factor structure F_t is unobservable. The guiding principle of the empirical strategy is therefore that common factors can be approximated using 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 assets. A placebo procedure, in which the subsidiary is replaced by its most correlated non-owned firm, serves as a falsification test of the identification strategy.

A natural alternative would be to instrument subsidiary returns using shocks plausibly unrelated to the parent's other assets, such as earnings surprises or ownership-flow shocks. I do not follow this approach because parent–subsidiary structures are rare and observed over relatively short windows, making strong and comparable instruments difficult to construct across pairs. Moreover, instrumental-variable estimation would identify transmission from a narrower subset of subsidiary price movements and discard a large share of the variation. Importantly, the most natural omitted-variable concern biases transmission rates upward rather than downward, since closely related parent–subsidiary pairs tend to comove positively. Consistent with this concern, the placebo tests show that insufficient controls generate upward-biased transmission rates. The cross-section of transmission rates is then used to test mechanisms that may explain the observed underreaction.

Let X_t denote the set of controls used to approximate the common factor structure. The empirical specification is

$$r_t^P = \mathcal{T} r_t^{wS} + X_t^w \beta + u_t, \tag{6}$$

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

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

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

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

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

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

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

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

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

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

where $r_t^{wpl} = w_{t-1} r_t^{pl}$ and r_t^{pl} denotes the simple return of the placebo asset. For the Post-Double-Lasso specification, the full selection procedure is repeated on the parent–

[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.

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

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

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

$$\hat{\mathcal{T}}_i = \beta_0 + \beta_1 \log(\widehat{\mathrm{UVR}}_i) + Z_i'\gamma + \varepsilon_i, \tag{10}$$

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 $\mathcal{T} = 1$ implied by value additivity. The hypothesis $H^s : \mathcal{T} = 1$ 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 **??**, 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 ($\bar{\mathcal{T}} = 0.38$, 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 ($E[\mathcal{T}_i] = 1$ 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 $\times$ 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 ($\bar{\mathcal{T}} = 0.386$) 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

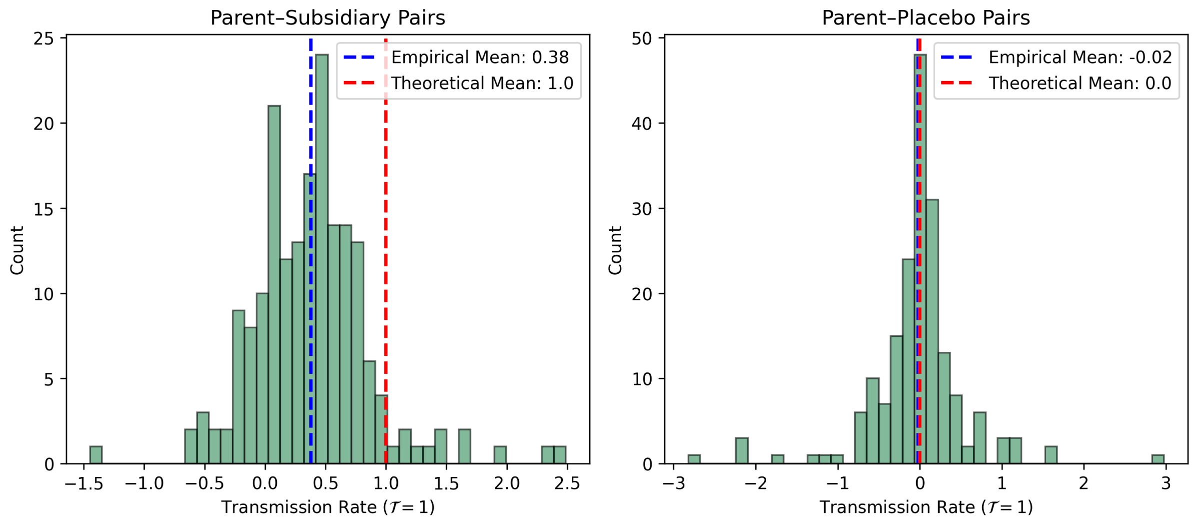

Figure 1: Distribution of estimated transmission rates using Post Double-Lasso. On the left-hand side, the distribution for parent–subsidiary pairs should be centered at 1 (red vertical line), but is instead centered near 0.38 (blue vertical line). On the right-hand side, the transmission rates are estimated 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

$$r_t^P = \mathcal{T}_0 r_t^{wS} + \mathcal{T}_1 r_{t-1}^{wS} + \mathcal{T}_2 r_{t-2}^{wS} + \mathcal{T}_3 r_{t-3}^{wS} + \mathcal{T}_4 r_{t-4}^{wS} + \gamma r_{t-1}^P + X_t^w \beta + u_t,$$

where r_t^{wS} is the subsidiary's weighted return. The table reports the cross-sectional averages of $\hat{\mathcal{T}}_0, \hat{\mathcal{T}}_1, \hat{\mathcal{T}}_2, \hat{\mathcal{T}}_3, \hat{\mathcal{T}}_4$ 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 $\mathcal{T}$	0.386^{***}	0.042^{**}	0.026^{*}	-0.020	-0.010
SE of mean $\mathcal{T}$	(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 $\mathcal{T}$	0.359	0.045	0.014	-0.006	0.002
	Panel B: Parent–Placebo Pairs ($n = 187$)				
mean $\mathcal{T}$	-0.017	0.006	0.000	-0.005	-0.033^{**}
SE of mean $\mathcal{T}$	(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 $\mathcal{T}$	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 $\hat{\mathcal{T}}_i$, 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 coefficient 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 $\log(\widehat{\mathrm{UVR}_i})$ but transmission rates close to zero. In contrast, $\textsc{Float}_i$ and $\textsc{Turnover}_i$ 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.

Overall, Float, Size, Turnover, and Amihud illiquidity explain little of the variation in transmission rates. Combined with the fact that estimating the transmission rate at weekly frequency only slightly increases the mean transmission rate, this suggests that price-measurement errors are unlikely to explain the overall underreaction.

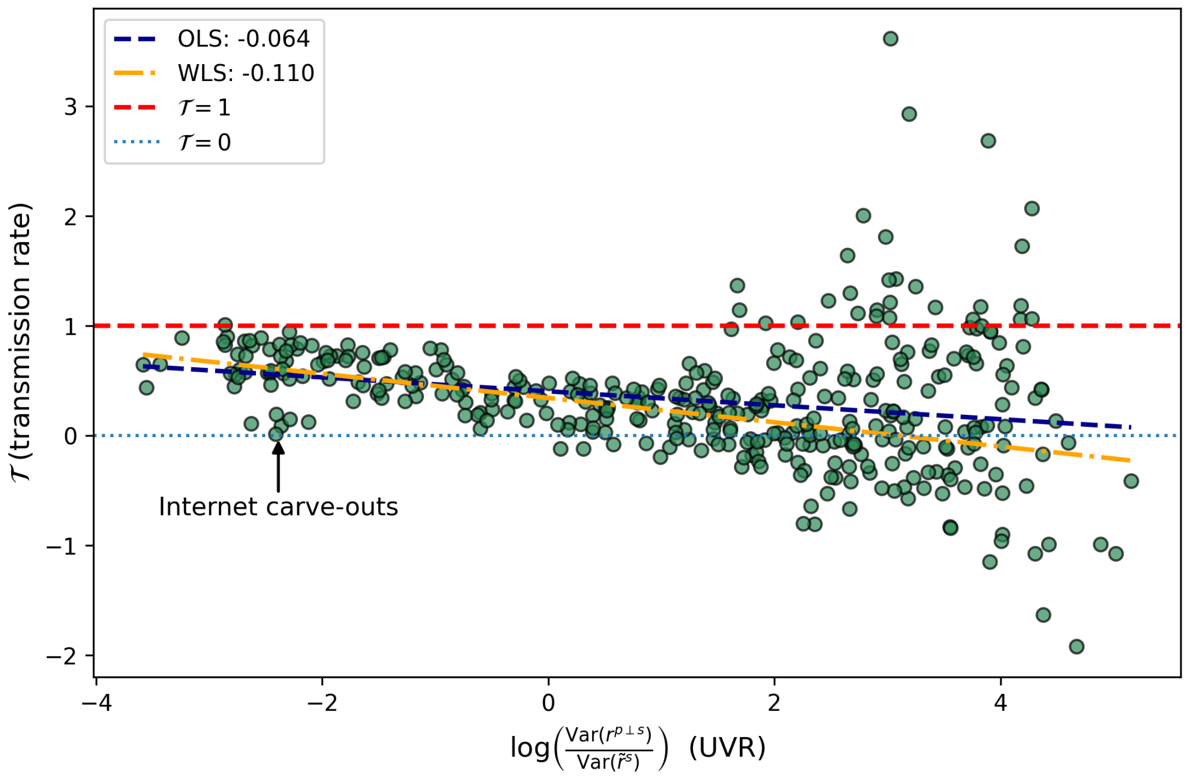

Figure 2: Cross-fitting scatter plots of τ against R^2.

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

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

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

$$\hat{\mathcal{T}}_i = \beta_0 + \beta_1 \log(\widehat{\mathrm{UVR}_i}) + \beta_2 \mathrm{F{\scriptsize LOAT}}_i + \beta_3 \mathrm{MC}_i + \beta_4 \mathrm{T{\scriptsize URNOVER}}_i + \beta_5 \mathrm{A{\scriptsize MIHUD}}_i + \beta_6 \log(\mathrm{S{\scriptsize IZE}}_i) + \beta_7 \mathrm{P{\scriptsize OST}2002}_i + \varepsilon_i.$$

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. $\mathrm{F{\scriptsize LOAT}}_i$ 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. $\mathrm{T{\scriptsize URNOVER}}_i$ is the average daily trading volume relative to shares outstanding, and $\mathrm{A{\scriptsize MIHUD}}_i$ is the average price impact of trading, computed as the absolute return divided by the dollar volume. $\log(\mathrm{S{\scriptsize IZE}}_i)$ is the logarithm of the combined market value of the parent and subsidiary, and $\mathrm{P{\scriptsize OST}2002}_i$ equals one for observations after the internet bubble. Cross-fitting ensures that $\log(\widehat{\mathrm{UVR}_i})$ and $\hat{\mathcal{T}}_i$ are estimated on separate folds. Standard errors are clustered by pair (HC3).

	Parent–Subsidiary (OLS)				
Variable	Base	Full	No P02	No Ami.	–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. Explaining the Underreaction

Let $\theta_{P,1}$, $\theta_{S,1}$, and $\theta_{O,1}$ denote the terminal-date payoffs at $t = 1$ of the parent, the stake, and the parent's other assets, respectively, where $t = 0$ denotes the current date, and where, for simplicity, we assume no intermediary payoffs. The ownership structure implies that

$$\theta_{P,1} = \theta_{S,1} + \theta_{O,1}.$$

Under standard asset pricing theory, the current market value of the parent should satisfy

$$p_{P,0} = E[m_0 \theta_{P,1} \mid \mathcal{I}_0] = E[m_0 \theta_{S,1} \mid \mathcal{I}_0] + E[m_0 \theta_{O,1} \mid \mathcal{I}_0],$$

where $\mathcal{I}_0$ denotes the information currently available and m_0 is the stochastic discount factor reflecting investors' preferences. Let u_0 denote the subsidiary-specific movement in the stake price $p_{S,0}$, after removing all other measurable stock-market movements. The transmission rate is then

$$\mathcal{T} = \frac{Cov(p_{P,0}, u_0)}{Var(u_0)} = \frac{Cov(E[m_0 \cdot \theta_{S,1} \mid \mathcal{I}_0], u_0)}{Var(u_0)} + \frac{Cov(E[m_0 \cdot \theta_{O,1} \mid \mathcal{I}_0], u_0)}{Var(u_0)},$$

where we should have

$$\frac{Cov(E[m_0 \cdot \theta_{S,1} \mid \mathcal{I}_0], u_0)}{Var(u_0)} = 1 \qquad \text{and} \qquad \frac{Cov(E[m_0 \cdot \theta_{O,1} \mid \mathcal{I}_0], u_0)}{Var(u_0)} = 0,$$

such that $\mathcal{T} = 1$. Empirically, however, we obtain $\frac{Cov(p_{P,0}, u_0)}{Var(u_0)} \approx 0.38$. I discuss three mechanisms that can explain the underreaction.

First, the stake embedded within the parent may itself be discounted. This corresponds to the case where

$$\mathcal{T} = \frac{Cov(E[m_0 \theta_{S,1} \mid \mathcal{I}_0], u_0)}{Var(u_0)} < 1,$$

so that $Cov(E[m_0 \theta_{S,1} \mid \mathcal{I}_0], u_0) < Var(u_0)$, and the transmission rate reflects this discount. This interpretation may appear related to the conglomerate discount literature, where large conglomerates were found to trade at lower valuations than comparable standalone firms operating in the same industries (Lang and Stulz (1994); Berger and Ofek (1995); Servaes (1996)).[15] Agency problems and inefficient internal capital allocation arising from the management of multiple unrelated activities have often been proposed as a potential explanation for the conglomerate discount. However, in the setting considered here, the comparison is between shares embedded within another firm and the same shares traded directly on the market. Two frictions can still specifically affect the shares embedded within 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 to explain the underreaction when the parent controls the subsidiary, as it also controls the subsidiary's cash flows, and any wasteful behavior is more plausibly applied to all of the subsidiary's cash flows, not only to the shares held by the parent (Cornell and Liu (2001)). Similarly, taxes can be minimized when the parent controls the subsidiary's distribution policy (Cornell and Liu (2001)). The 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.

Second, good (bad) subsidiary-specific news may be correlated with bad (good) news about the parent's other assets. This corresponds to the case

$$\frac{Cov(E[m_0 \cdot \theta_{O,1} \mid \mathcal{I}_0], u_0)}{Var(u_0)} < 0, \tag{12}$$

where, through the information set $\mathcal{I}_0$, a \$1 subsidiary-specific increase (decrease) destroys (creates) roughly \$0.60 of value in the parent's other assets. This mechanism would require a firm-specific factor causing the parent and subsidiary to systematically react in opposite directions. Most stocks are positively correlated, and this is even more true for parent–subsidiary pairs, which generally operate in the same sector. Consistent

[15]See also Lamont and Polk (2001), 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.

with this intuition, improving the controls in the empirical analysis decreases the transmission rate rather than increasing it. Moreover, placebo firms selected to be the most correlated with the subsidiary were found to have firm-specific returns uncorrelated with the parent, implying that such a factor would need to exist specifically at the parent–subsidiary level while remaining absent from other related firms. The existence of such a factor systematically affecting the parent and subsidiary in opposite directions would itself constitute a nontrivial empirical regularity requiring explanation.

Third, price changes can always be mechanically decomposed into payoff news and discount-rate news (Campbell and Shiller (1989)), such that one can always construct, ex post, a stochastic discount factor m_0 in Equation (12) capable of generating the underreaction. For example, one could assume investor preferences such that increases in the value of the stake make the parent's other assets appear more risky. However, this would imply that investors adjust their pricing of idiosyncratic risk on a daily basis, even though such risk is usually assumed to be diversifiable and therefore largely unrelated to discount rates in standard asset-pricing models. Section 7 instead develops a model in the tradition of the limits-to-arbitrage literature, where discount-rate variation emerges from non-fundamental demand shocks and arbitrageurs' limited risk-bearing capacity. The model generates the underreaction.

7. A Limits-to-Arbitrage Model

In this section, I develop a limits-to-arbitrage model in which non-fundamental demand shocks affecting the subsidiary generate underreaction when arbitrageurs have limited risk-bearing capacity and the parent holds additional assets subject to payoff uncertainty. The model also explains the negative relation observed in the data between uncertainty surrounding the parent's other assets and the transmission rate.

7.1. Environment

There are two periods, $t = 0, 1$. The market consists of one risk-free asset and two risky assets, P and S. Asset P denotes the parent company. I assume that the parent holds half of the subsidiary's outstanding shares. Asset S denotes the remaining floating subsidiary shares.

The gross risk-free rate is equal to one. The two risky assets, P and S, are traded at $t = 0$. The terminal payoff of S at $t = 1$ is

$$\theta_{S,1} \sim N(\mu_S, \tau_{\theta,S}^{-1}),$$

where μ_S denotes the expected payoff of S, and $\tau_{\theta,S}$ its precision, that is, the inverse of the payoff variance. Because the parent holds half of the subsidiary's shares, the payoff of the parent's stake is also $\theta_{S,1}$. The terminal payoff of the parent at $t = 1$ is

$$\theta_{P,1} = \theta_{S,1} + \theta_{O,1}, \qquad \theta_{O,1} \sim N(\mu_O, \tau_{\theta,O}^{-1}),$$

where $\theta_{O,1}$ denotes the payoff generated by the parent's other assets, μ_O its expected payoff, and $\tau_{\theta,O}$ its precision.

I assume that $\theta_{S,1}$ and $\theta_{O,1}$ are independent, reflecting the fact that the model is formulated at the firm-specific level.[16] Under this assumption,

$$\theta_{P,1} \sim N\left(\mu_S + \mu_O, \tau_{\theta,S}^{-1} + \tau_{\theta,O}^{-1}\right).$$

The payoffs $\theta_{P,1}$, $\theta_{S,1}$, and $\theta_{O,1}$ should be interpreted broadly as the terminal economic values relevant for investors and arbitrageurs. They may reflect future cash flows, liquidation values, or future market valuations. For example, $\theta_{S,1}$ and $\theta_{O,1}$ may capture the future values of the stake and the parent's other assets following a spin-off of the stake.

7.2. Parent- and Subsidiary- investors

Markets are segmented, with two non-overlapping continua of unit mass investors: the P-investors only invest in the parent and the risk-free asset, while the S-investors only invest in the remaining floating subsidiary shares and the risk-free asset.

[16] The results extend to the case where correlation is allowed.

Each group of investors $k \in \{P, S\}$ has CARA preferences with risk-aversion parameter γ_k, and terminal wealth $W_{k,1}$. Because they are atomistic, they take prices as given. They solve

$$\max_{q^i_{k,0}} E\left[-e^{-\gamma_k W_{k,1}}\right]$$

subject to

$$W_{k,1} = W_{k,0} + q^i_{k,0}(\theta_{k,1} - p_{k,0}),$$

where $W_{k,0}$ is initial wealth, $q^i_{k,0}$ is the number of shares held, and $p_{k,0}$ is the price of asset k at $t = 0$. From CARA-normality, the demand of investors k is

$$q^i_{k,0} = \frac{\tau_{\theta,k}}{\gamma_k}(\mu_k - p_{k,0}),$$

7.3. Arbitrageurs

There is a unit mass continuum of arbitrageurs who can invest in both assets P and S. They have CARA preferences with risk-aversion parameter ξ, and terminal wealth $W_{\text{arb},1}$. Because they are atomistic, they take prices as given. They solve

$$\max_{q^i_{\text{arb},0}} E\left[-e^{-\xi W_{\text{arb},1}}\right]$$

subject to

$$W_{\text{arb},1} = W_{\text{arb},0} + (q^i_{\text{arb},0})'(\theta_1 - p_0),$$

where $W_{\text{arb},0}$ denotes initial wealth, and

$$q^i_{\text{arb},0} = \begin{pmatrix} q^i_{\text{arb},P,0} \\ q^i_{\text{arb},S,0} \end{pmatrix}, \qquad \theta_1 = \begin{pmatrix} \theta_{P,1} \\ \theta_{S,1} \end{pmatrix}, \qquad p_0 = \begin{pmatrix} p_{P,0} \\ p_{S,0} \end{pmatrix},$$

respectively denote the vector of arbitrage positions, terminal payoffs, and prices.

From CARA-normality, arbitrageur demand is

$$q^i_{\text{arb},0} = \frac{\Sigma_\theta^{-1}}{\xi}(\mu - p_0),$$

where

$$\mu = \begin{pmatrix} \mu_P \\ \mu_S \end{pmatrix}, \qquad \Sigma_\theta = \begin{pmatrix} \tau_{\theta,S}^{-1} + \tau_{\theta,O}^{-1} & \tau_{\theta,S}^{-1} \\ \tau_{\theta,S}^{-1} & \tau_{\theta,S}^{-1} \end{pmatrix}$$

is the variance–covariance matrix of the parent and subsidiary payoffs. This gives

$$q^i_{\text{arb},0} = \frac{1}{\xi} \begin{pmatrix} \tau_{\theta,O} \left(\mu_O - (p_{P,0} - p_{S,0})\right) \\ -\tau_{\theta,O} \left(\mu_O - (p_{P,0} - p_{S,0})\right) + \tau_{\theta,S}(\mu_S - p_{S,0}) \end{pmatrix}. \tag{13}$$

Arbitrageur demand in Equation (13) can be decomposed into two trades. The first allows arbitrageurs to access the payoff generated by the parent's other assets by taking a position in the parent, $\frac{\tau_{\theta,O}}{\xi} \left(\mu_O - (p_{P,0} - p_{S,0})\right)$, while hedging the payoff uncertainty associated with the stake through the opposite position in the stake, $-\frac{\tau_{\theta,O}}{\xi} \left(\mu_O - (p_{P,0} - p_{S,0})\right)$. The lower the uncertainty surrounding the payoff generated by the parent's other assets, that is, the greater $\tau_{\theta,O}$, the more aggressively arbitrageurs trade this long-parent, short-stake portfolio. Independently, arbitrageurs also take a position in the stake of $\frac{\tau_{\theta,S}}{\xi} \left(\mu_S - p_{S,0}\right)$.

7.4. Equilibrium

I assume that both assets are in zero net supply, so that aggregate positions sum to zero in equilibrium. Assuming positive supply would only add a constant discount term to equilibrium prices to compensate investors for bearing aggregate risk, and therefore does not affect the transmission rate. The market-clearing condition for asset P is

$$\int_0^1 q^i_{P,0}\, di + \int_0^1 q^i_{\text{arb},P,0}\, di = 0$$

$$\frac{\tau_{\theta,P}}{\gamma_P}(\mu_P - p_{P,0}) + \frac{\tau_{\theta,O}}{\xi} \left(\mu_O - (p_{P,0} - p_{S,0})\right) = 0 \tag{14}$$

The market-clearing condition for asset S is

$$\int_0^1 q_{S,0}^i \, di + \int_0^1 q_{\text{arb},S,0}^i \, di + n_{0,S} = 0$$

$$\frac{\tau_{\theta,S}}{\gamma_S}(\mu_S - p_{S,0}) - \frac{\tau_{\theta,O}}{\xi}(\mu_O - (p_{P,0} - p_{S,0})) + \frac{\tau_{\theta,S}}{\xi}(\mu_S - p_{S,0}) + n_{0,S} = 0, \tag{15}$$

where $n_{0,S}$ denotes non-fundamental demand shocks affecting the subsidiary shares.

Solving the system formed by Equations (14) and (15), the equilibrium prices are

$$p_{P,0} = \mu_P + \frac{\tau_{\theta,O}\gamma_P\gamma_S\xi}{\tau_{\theta,P}\tau_{\theta,S}\gamma_S\xi + \tau_{\theta,P}\tau_{\theta,S}\xi^2 + \tau_{\theta,P}\tau_{\theta,O}\gamma_S\xi + \tau_{\theta,S}\tau_{\theta,O}\gamma_P\gamma_S + \tau_{\theta,S}\tau_{\theta,O}\gamma_P\xi} n_{0,S},$$

$$p_{S,0} = \mu_S + \frac{\gamma_S\xi\left(\tau_{\theta,P}\xi + \tau_{\theta,O}\gamma_P\right)}{\tau_{\theta,P}\tau_{\theta,S}\gamma_S\xi + \tau_{\theta,P}\tau_{\theta,S}\xi^2 + \tau_{\theta,P}\tau_{\theta,O}\gamma_S\xi + \tau_{\theta,S}\tau_{\theta,O}\gamma_P\gamma_S + \tau_{\theta,S}\tau_{\theta,O}\gamma_P\xi} n_{0,S}.$$

Before computing transmission rates, two limiting cases help clarify the mechanism of the model. First, when arbitrageurs are risk-neutral, $\xi \to 0$, or investors in the stake are risk-neutral, $\gamma_S \to 0$, the non-fundamental demand shock is fully absorbed and prices coincide with fundamentals:

$$p_{P,0} = \mu_P, \qquad p_{S,0} = \mu_S. \tag{16}$$

Second, when investors in the parent become infinitely risk-averse, $\gamma_P \to \infty$, equilibrium prices satisfy

$$p_{P,0} = \mu_P + \frac{\gamma_S\xi}{\tau_{\theta,S}(\gamma_S + \xi)} n_{0,S},$$

$$p_{S,0} = \mu_S + \frac{\gamma_S\xi}{\tau_{\theta,S}(\gamma_S + \xi)} n_{0,S}.$$

Therefore, both prices move one-for-one in response to the demand shock, and the transmission rate is one. When $\gamma_P \to \infty$ and $\xi < \infty$, arbitrageurs freely set the relative price of the parent such that the transmission rate remains equal to one. Generating underreaction therefore requires $\gamma_P < \infty$, such that arbitrageurs trade against parent investors solving a different optimization problem. This underlies the market-segmentation assumption of the model, as without segmentation arbitrageurs and investors would collapse into a single group and the transmission rate would be equal to one.

7.5. Transmission Rate

Using the definition of the transmission rate introduced in Section 2, we obtain

$$\begin{aligned} \mathcal{T} &= \frac{\partial p_{P,0}}{\partial p_{S,0}} = \frac{\partial p_{P,0}/\partial n_{0,S}}{\partial p_{S,0}/\partial n_{0,S}} \\ &= \frac{\tau_{\theta,O}\gamma_P}{\tau_{\theta,P}\xi + \tau_{\theta,O}\gamma_P}, \end{aligned} \tag{17}$$

where $\tau_{\theta,P} = (\tau_{\theta,S}^{-1} + \tau_{\theta,O}^{-1})^{-1}$.

The transmission rate $\mathcal{T}$ is a function of the payoff precision of the parent's other assets, $\tau_{\theta,O}$, the payoff precision of the stake embedded in $\tau_{\theta,P}$, and the risk-aversion parameters of parent investors, γ_P, and arbitrageurs, ξ. The risk aversion of subsidiary investors, γ_S, does not determine the transmission rate directly; it only ensures that the demand shock is reflected in prices. As shown in Equation (16), if $\gamma_S \to 0$, subsidiary investors become risk-neutral and fully absorb the demand shock.

The transmission rate converges to one in four corner cases. As shown in Section 7.4, when parent investors become infinitely risk-averse, $\gamma_P \to \infty$, arbitrageurs effectively determine relative prices, and the transmission rate converges to one. When $\xi \to 0$, arbitrageurs become risk-neutral and absorb the demand shock entirely, while simultaneously enforcing consistency between the parent and the stake, so the transmission rate converges to one. When all uncertainty associated with the parent's other assets vanishes, $\tau_{\theta,O} \to \infty$, hedging becomes perfect, the Law of One Price applies, and the transmission rate converges to one. Lastly, when the uncertainty associated with the stake becomes arbitrarily large, $\tau_{\theta,S} \to 0$, the uncertainty associated with the parent's other assets becomes negligible in relative terms, and the transmission rate converges to one.

The partial derivative of $\mathcal{T}$ with respect to $\tau_{\theta,O}^{-1}$ is

$$\frac{\partial \mathcal{T}}{\partial \tau_{\theta,O}^{-1}} = -\frac{\gamma_P \xi \tau_{\theta,S} \tau_{\theta,O}^2}{\left(\gamma_P(\tau_{\theta,O} + \tau_{\theta,S}) + \tau_{\theta,S}\xi\right)^2} \leq 0. \tag{18}$$

Holding all other parameters fixed, an increase in the uncertainty associated with the parent's other assets decreases the transmission rate. The UVR introduced in Section 4.4, by proxying the ratio $\tau_{\theta,S}/\tau_{\theta,O}$, allows us to test how the transmission rate evolves when uncertainty about the parent's other assets increases while uncertainty about the stake is held fixed. Holding the uncertainty of the stake fixed is important because $\mathcal{T}$ also increases with $\tau_{\theta,S}^{-1}$, such that it is really the ratio $\tau_{\theta,S}/\tau_{\theta,O}$ that yields an unambiguous prediction across parent–subsidiary pairs.

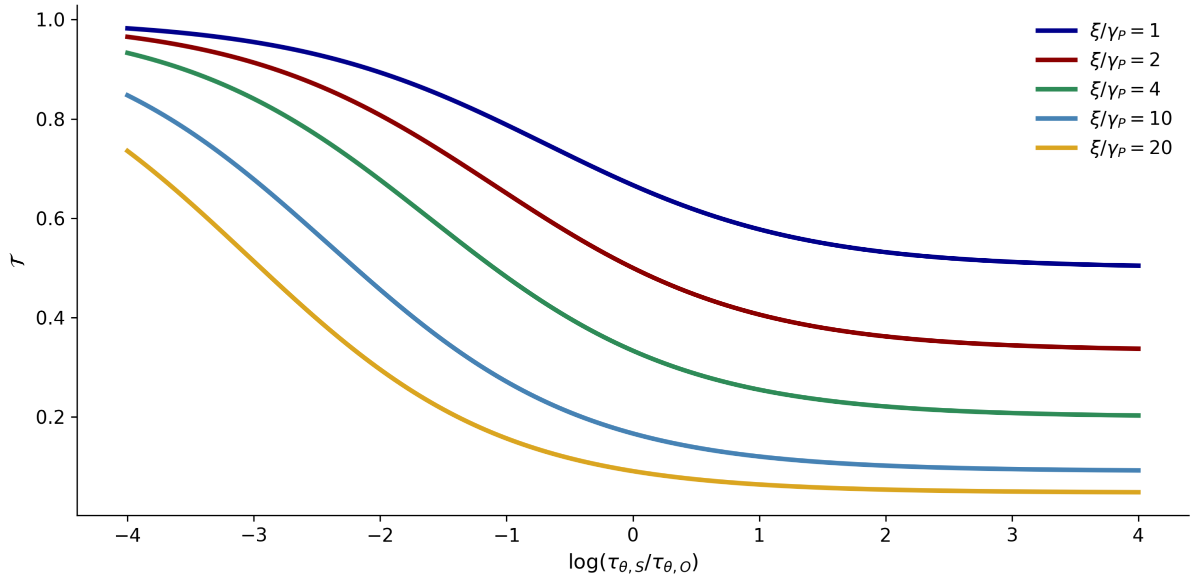

Figure 3: Transmission rate as a function of $\log(\tau_S/\tau_O)$.

Figure 3 is the theoretical counterpart of Figure 2. As $\log(\frac{\tau_{\theta,S}}{\tau_{\theta,O}})$ increases, the transmission rate decreases. In Figure 2 the relation between the transmission rate and the $\log(\widehat{\text{UVR}}_i)$ becomes flatter for high values of the UVR. Similarly, as $\log\left(\frac{\tau_{\theta,S}}{\tau_{\theta,O}}\right)$ increases, the relationship between the transmission rate and $\log\left(\frac{\tau_{\theta,S}}{\tau_{\theta,O}}\right)$ also becomes flatter. In both cases, the inflection point is around zero, that is, when the uncertainty associated with the parent's other assets becomes as large as the uncertainty associated with the stake. In level form rather than log form, both imply a decrease of about 5–10% in the transmission rate when the uncertainty associated with the parent's other assets relative to the stake doubles. In sum, when the parent has no other assets, the transmission rate is equal to one. As uncertainty associated with the parent's other assets progressively increases, the transmission rate initially falls sharply, but the marginal effect becomes smaller as uncertainty accumulates. Analytically, we can see from Equation (18) that the partial derivative of the transmission rate with respect to the payoff uncertainty associated with the parent's other assets decreases as uncertainty increases.

The ratio of risk-aversion parameters $\frac{\xi}{\gamma_P}$ that best matches the empirical relationship in Figure 2 is approximately 10, implying that arbitrageurs behave as if they were substantially more risk-averse than investors in the parent. The fact that the empirical relationship is better matched by such a parametrization may reflect the presence of additional limits to arbitrage beyond limited risk-bearing capacity alone. In particular, while the model allows arbitrageurs to short both assets freely, short selling in practice requires capital to be posted as margin and involves additional stock-borrowing fees.

8. Conclusion

This paper studies publicly traded parent firms holding large stakes in publicly traded subsidiaries. In a frictionless market, changes in the value of the subsidiary stake should transmit one-for-one to the parent's market value. Empirically, however, the transmission rate is substantially below one. After isolating subsidiary-specific price movements, I estimate an average transmission rate of 38 cents on the dollar across U.S. parent–subsidiary pairs between 1999 and 2024.

The key cross-sectional determinant of transmission rates is the parent's variance not spanned by the subsidiary stake, which proxies uncertainty surrounding the parent's other assets. When the parent holds few or no other assets, the transmission rate is close to one. As uncertainty surrounding the parent's other assets increases, the transmission rate falls. This pattern is difficult to reconcile with explanations based solely on limited subsidiary float, liquidity frictions, or broad discount-rate variation. Instead, it is consistent with a limits-to-arbitrage mechanism in which non-fundamental demand shocks affecting the subsidiary generate a tendency toward underreaction, while imperfect hedgeability limits arbitrageurs' ability to trade against this force.

To formalize this intuition, the paper develops a segmented-markets limits-to-arbitrage model in which parent investors and subsidiary investors trade separately, while arbitrageurs can trade both assets. In the model, non-fundamental demand shocks affecting the subsidiary price are only partially transmitted to the parent when arbitrageurs have limited risk-bearing capacity and the parent holds additional non-hedgeable assets. The model also matches the negative relation observed in the data between transmission rates and the uncertainty surrounding the parent's other assets.

More broadly, parent–subsidiary structures provide a natural laboratory for testing empirical predictions of the limits-to-arbitrage literature. The evidence is consistent with assumptions commonly made in the limits-to-arbitrage literature, such as risk-averse arbitrageurs, non-fundamental demand shocks, and market segmentation.

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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

$$P_t = \mathbb{E}(m_{t+1}x_{t+1} \mid \mathcal{F}_t)\,, \tag{19}$$

where m_{t+1} is the stochastic discount factor and $\mathcal{F}_t$ the information set at time t. Iterating (19) forward yields the infinite-horizon valuation formula

$$P_t = \mathbb{E}\left(\sum_{k=1}^{\infty} M_{t,t+k}\, d_{t+k} \;\middle|\; \mathcal{F}_t\right), \tag{20}$$

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,

$$d^p_{t+k} = d^s_{t+k} + d^o_{t+k}. \tag{21}$$

Substituting (21) into (20) gives

$$P^p_t = \mathbb{E}\left(\sum_{k=1}^{\infty} M_{t,t+k}(d^s_{t+k} + d^o_{t+k}) \;\middle|\; \mathcal{F}_t\right). \tag{22}$$

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

$$\begin{aligned} P^p_t = {} & \mathbb{E}\left(\sum_{k=1}^{\infty} M_{t,t+k}d^s_{t+k} \;\middle|\; \mathcal{F}_t\right) \\ & + \mathbb{E}\left(\sum_{k=1}^{\infty} M_{t,t+k}d^o_{t+k} \;\middle|\; \mathcal{F}_t\right). \end{aligned} \tag{23}$$

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

$$P_t^p = P_t^s + P_t^o. \tag{24}$$

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,

$$\begin{align}
P_t^p &= P_t^s + P_t^o, \tag{25}\\
\Delta P_t^p &= \Delta P_t^s + \Delta P_t^o, \tag{26}\\
\frac{\Delta P_t^p}{P_{t-1}^p} &= \frac{P_{t-1}^s}{P_{t-1}^p}\frac{\Delta P_t^s}{P_{t-1}^s} + \frac{P_{t-1}^o}{P_{t-1}^p}\frac{\Delta P_t^o}{P_{t-1}^o}, \tag{27}\\
r_t^p &= w_{t-1} r_t^s + (1 - w_{t-1}) r_t^o, \tag{28}
\end{align}$$

where $w_{t-1} = P_{t-1}^s / P_{t-1}^p$. By defining $r_t^{ws} = w_{t-1} r_t^s$ and $r_t^{wo} = (1 - w_{t-1}) r_t^o$, we obtain

$$r_t^p = r_t^{ws} + r_t^{wo}. \tag{29}$$

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,

$$r_t^j = F_t \beta^j + e_t^j, \qquad j \in J, \quad \{s, o\} \subseteq J, \tag{30}$$

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_t^j 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:

$$E[\, e_t^j \mid \mathcal{H}_t \,] = 0, \qquad \text{with } \mathcal{H}_t = \{\Omega_{t-1},\ F_t,\ e_t^{j'}\ (j' \neq j)\}. \tag{31}$$

That is, each idiosyncratic return e_t^j 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,

$$r_t^p = r_t^{ws} + r_t^{wo}, \tag{32}$$

$$r_t^p = w_{t-1} r_t^s + (1 - w_{t-1}) r_t^o, \tag{33}$$

$$r_t^p = w_{t-1}(F_t \gamma + e_t^s) + (1 - w_{t-1})(F_t \beta^o + e_t^o), \tag{34}$$

$$e_t^p = e_t^{ws} + e_t^{wo}, \tag{35}$$

where $e_t^{ws} = w_{t-1} e_t^s$ and $e_t^{wo} = (1 - w_{t-1}) e_t^o$. By (31),

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

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

$$e_t^p = \tau e_t^{ws} + e_t^{wo} \tag{36}$$

is equivalent to estimating τ with

$$r_t^p = \tau r_t^{ws} + F_t^w \beta + e_t^{wo}. \tag{37}$$

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

$$r_t^p = \tau e_t^{ws} + v_t, \tag{38}$$

where $v_t = F_t(\beta^o - w_{t-1}\beta) + e_t^{wo}$ and, by (31),

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

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,

$$r_t^p = \tau r_t^{ws} + F_t^w \beta + u_t, \tag{39}$$

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),

$$\hat{\tau}_i = \tau + \varepsilon_i, \qquad \varepsilon_i = (\tilde{F}_i' \tilde{F}_i)^{-1} \tilde{F}_i' u_i, \qquad u_{i,t} = F_t \beta_i^o - \tilde{F}_t \beta_i + \tilde{e}_{i,t}^o, \tag{40}$$

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

$$\bar{\tau} = \frac{1}{n}\sum_{i=1}^{n} \hat{\tau}_i. \tag{41}$$

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

$$\varepsilon_i = (\tilde{F}_i' \tilde{F}_i)^{-1} \tilde{F}_i' u_i = \sum_{t \in T_i} a_{i,t} u_{i,t}, \tag{42}$$

where $a_{i,t}$ is the t-th element of $(\tilde{F}_i' \tilde{F}_i)^{-1} \tilde{F}_i'$, I have from (31) that

$$E[a_{i,t} u_{i,t} \mid \mathcal{H}_t] = 0 \quad \text{for all } i, t. \tag{43}$$

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

$$E[a_{i,t} u_{i,t}\, a_{i',t'} u_{i',t'}] = E\big[E[a_{i,t} u_{i,t}\, a_{i',t'} u_{i',t'} \mid \mathcal{H}_{\max(t,t')}]\big] = 0, \tag{44}$$

and therefore

$$E[\varepsilon_i \varepsilon_{i'}] = 0. \tag{45}$$

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:

$$E\Big[(F_t \beta_i^o - \tilde{F}_t \beta_i)\,(F_t \beta_{i'}^o - \tilde{F}_t \beta_{i'}) \mid \mathcal{H}_t\Big] = 0 \quad \text{for } t \in T_i \cap T_{i'}. \tag{46}$$

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

$$F_t \beta_i^o - \tilde{F}_t \beta_i = F_t(\beta_i^o - w_{t-1}\beta_i) \tag{47}$$

is typically small. I assume that any remaining deviations are orthogonal across pairs as in (46). Under this condition and bounded moments, the same linear-combination argument yields

$$E[\varepsilon_i \varepsilon_{i'}] = 0. \tag{48}$$

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

$$\sqrt{n}\,(\bar{\tau} - E[\hat{\tau}_i]) \xrightarrow{d} \mathcal{N}(0, \sigma^2), \qquad \sigma^2 = \mathrm{Var}(\hat{\tau}_i). \tag{49}$$

B. Supplementary Information on the parent-subsidiary pairs data

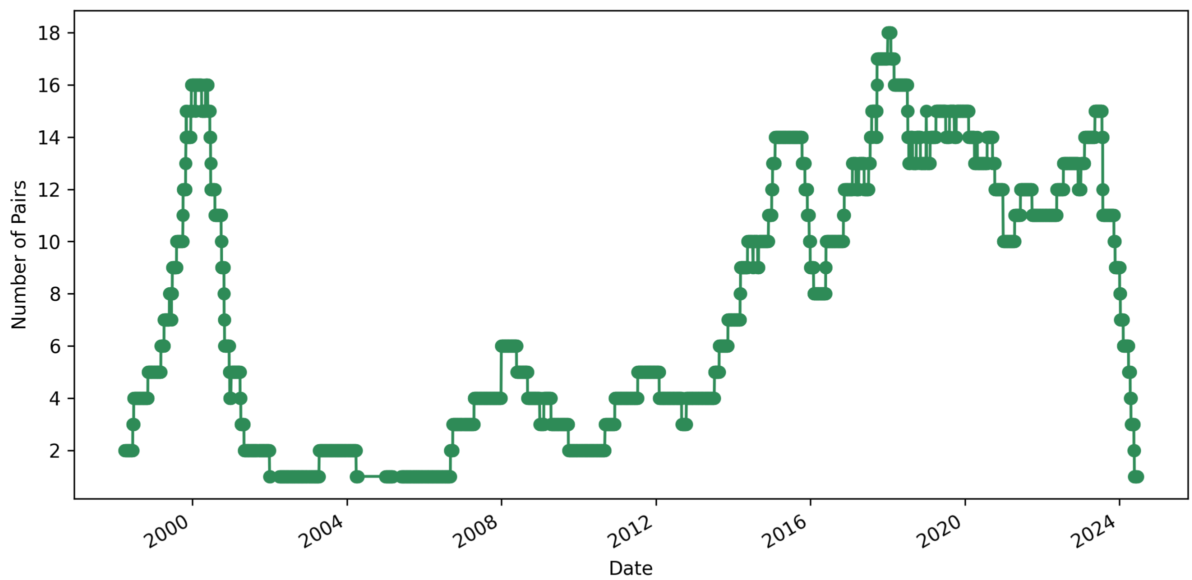

Figure 4: Time-series of the number of parent-subsidiary pairs across time.

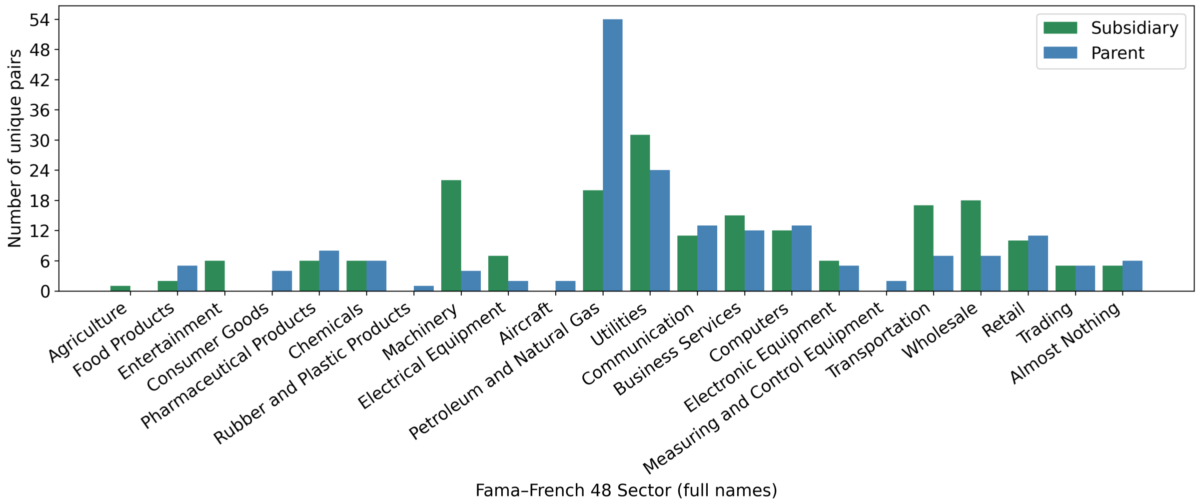

Figure 5: Parent–subsidiary pairs across Fama–French 48 sectors. Most utilities are oil and gas companies with some regulated operations.

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 $\tilde{r}^s_t = w_{t-1} r^s_t$, 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, $\log(\widehat{\mathrm{UVR}}_i)$ 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.

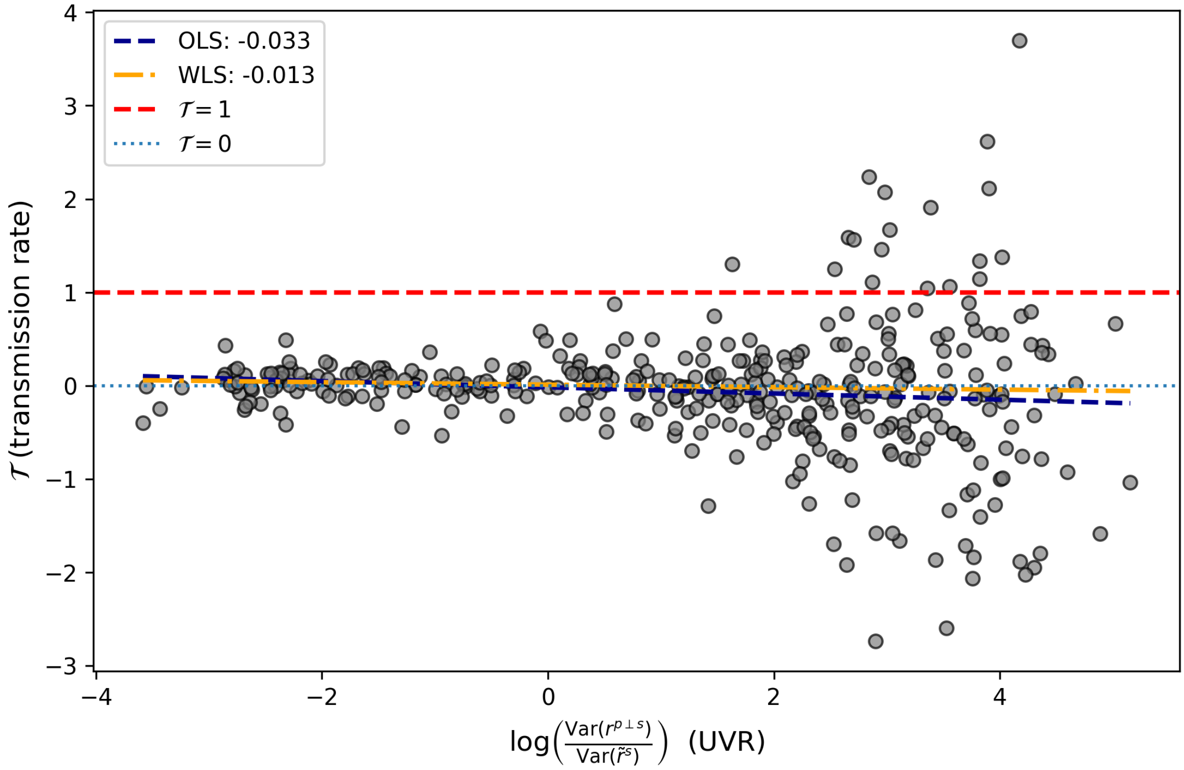

Figure 6: Cross-fitting scatter plots of τ against UVR.

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

$$\hat{\tau}_i = \beta_0 + \beta_1 \log(\widehat{\text{UVR}}_{\text{idiosyn.},i}) + \beta_2 \text{F}\small{\text{LOAT}}_i + \beta_3 \text{MC}_i + \beta_4 \text{T}\small{\text{URNOVER}}_i \\ + \beta_5 \text{A}\small{\text{MIHUD}}_i + \beta_6 \log(\text{S}\small{\text{IZE}}_i) + \beta_7 \text{P}\small{\text{OST}}2002_i + \varepsilon_i.$$

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

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

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 $\log(\widehat{\text{UVR}}_{\text{idiosyn.},i})$ 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)
$\log(\text{UVR}_{\text{idiosyn.}})$	-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 $1/\text{SE}(\hat{\tau}_i)^2$. 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

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

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

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

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 $\log(\widehat{\text{UVR}}_{\text{idiosyn.},i})$ 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)
$\log(\text{UVR}_{\text{idiosyn.}})$	-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

$$\hat{\tau}_i = \beta_0 + \beta_1 \log(\widehat{\text{UVR}}_{\text{idiosyn.},i}) + \beta_2 \text{FLOAT}_i + \beta_3 \text{MC}_i + \beta_4 \text{TURNOVER}_i \\ + \beta_5 \text{AMIHUD}_i + \beta_6 \log(\text{SIZE}_i) + \beta_7 \text{POST2002}_i + \varepsilon_i.$$

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

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

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 $\log(\widehat{\text{UVR}}_{\text{idiosyn.},i})$ 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)
$\log(\text{UVR}_{\text{idiosyn.}})$	-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: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

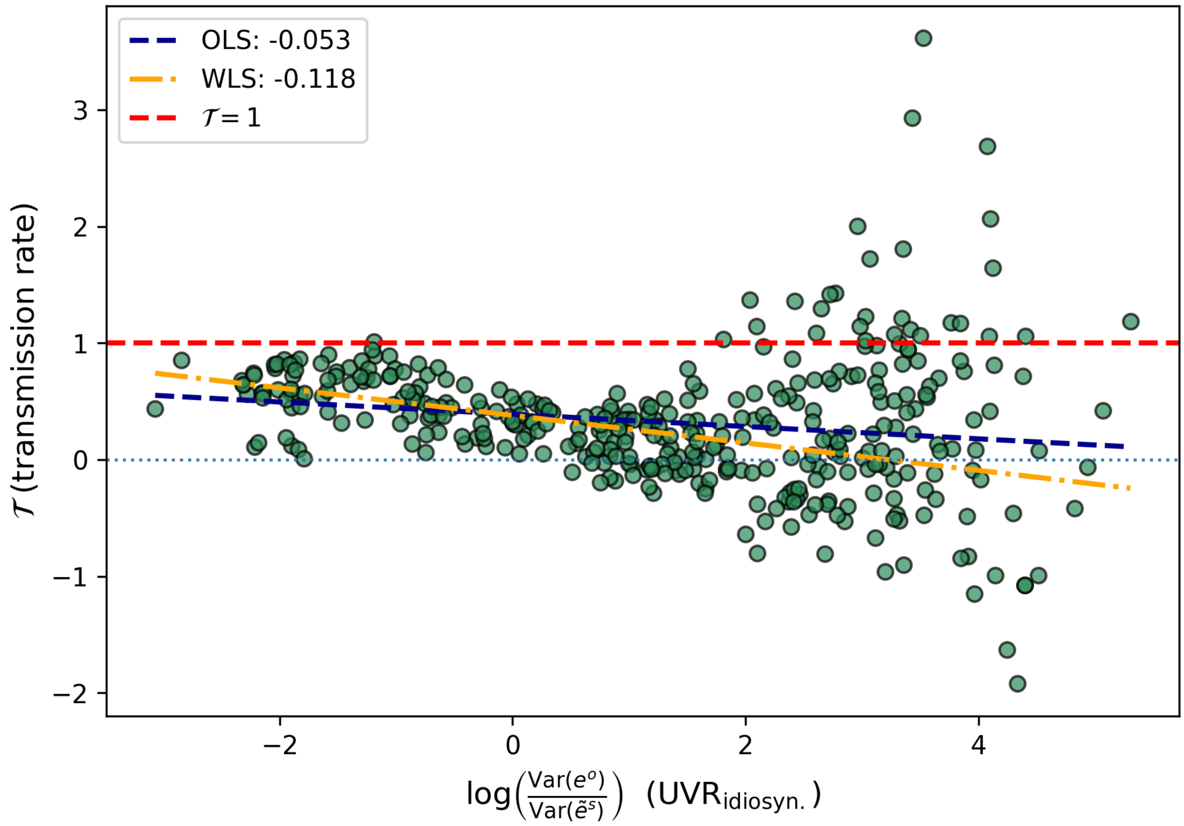

Figure 7: Cross-fitting scatter plots of τ against UVR.

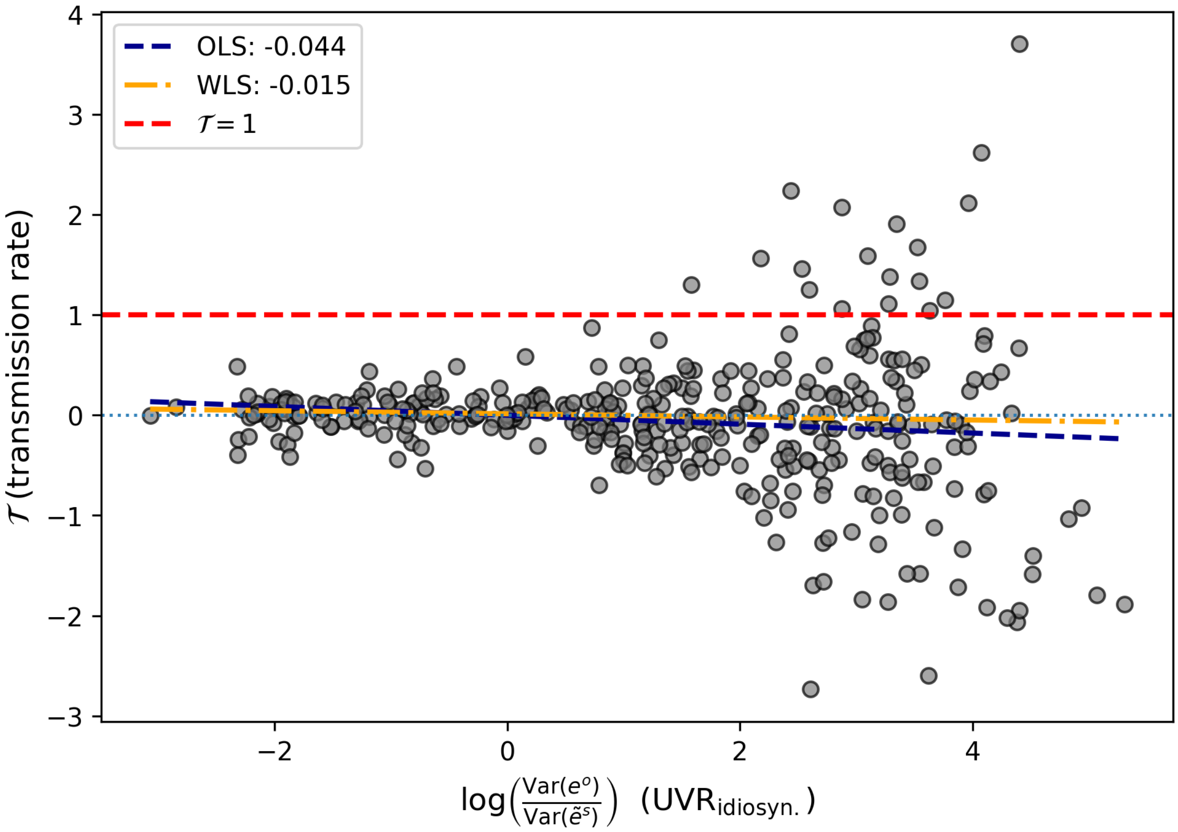

Figure 8: Cross-fitting scatter plots of τ against UVR.

E. Theoretical Model Proofs

E.1. The Transmission Rate

$$\tau = \frac{\mathrm{Cov}(r_1^p, \tilde{r}_1^s)}{\mathrm{Var}(\tilde{r}_1^s)} \tag{50}$$

$$= \frac{\mathrm{Cov}\left(\frac{\Delta P_1^p}{P_0^p}, \frac{P_0^s}{P_0^p}\frac{\Delta P_1^s}{P_0^s}\right)}{\mathrm{Var}\left(\frac{P_0^s}{P_0^p}\frac{\Delta P_1^s}{P_0^s}\right)} \tag{51}$$

$$= \frac{\frac{1}{(P_0^p)^2}\mathrm{Cov}(\Delta P_1^p, \Delta P_1^s)}{\frac{1}{(P_0^p)^2}\mathrm{Var}(\Delta P_1^s)} = \frac{\mathrm{Cov}(\Delta P_1^p, \Delta P_1^s)}{\mathrm{Var}(\Delta P_1^s)}. \tag{52}$$

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: $E[n_1^s v_1^s] = E[v_1^s v_1^o] = E[n_1^s v_1^o] = 0$.

$$\tau = \frac{\mathrm{Cov}(v_1^s + v_1^o + f_1,\ v_1^s + n_1^s)}{\mathrm{Var}(v_1^s + n_1^s)} \tag{53}$$

$$= \frac{\mathrm{Cov}(v_1^s + v_1^o + E[n_1^s \mid \mathcal{F}_1],\ v_1^s + n_1^s)}{\mathrm{Var}(v_1^s + n_1^s)}. \tag{54}$$

Compute numerator and denominator:

$$\tau = \frac{E[(v_1^s)^2] + E[E[n_1^s \mid \mathcal{F}_1]^2]}{E[(v_1^s)^2] + E[(n_1^s)^2]} \tag{55}$$

$$= \frac{\sigma_{vs}^2}{\sigma_{vs}^2 + \sigma_{ns}^2} + \frac{\sigma_{ns}^2}{\sigma_{vs}^2 + \sigma_{ns}^2}\frac{E[E[n_1^s \mid \mathcal{F}_1]^2]}{\sigma_{ns}^2}. \tag{56}$$

Recognizing

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

we obtain

$$\tau = \tau_\mathrm{n} + (1 - \tau_\mathrm{n})R^2. \tag{57}$$

E.2. Computing the R^2

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

$$E[n_1^s \mid \mathcal{F}_1] = \beta_1 \Delta P_1^s + \beta_2(\Delta P_1^s - \Delta P_1^p), \tag{58}$$

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:

$$\sigma_{ns}^2 = E[(n_1^s)^2], \qquad \sigma_{vs}^2 = E[(v_1^s)^2], \qquad \sigma_{vo}^2 = E[(v_1^o)^2]. \tag{59}$$

Define the regressors:

$$X_1 = \Delta P_1^s = v_1^s + n_1^s, \qquad X_2 = \Delta P_1^s - \Delta P_1^p = v_1^o - n_1^s. \tag{60}$$

Their variances and covariance are:

$$\mathrm{Var}(X_1) = \sigma_{vs}^2 + \sigma_{ns}^2, \tag{61}$$

$$\mathrm{Var}(X_2) = \sigma_{vo}^2 + \sigma_{ns}^2, \tag{62}$$

$$\mathrm{Cov}(X_1, X_2) = -\sigma_{ns}^2. \tag{63}$$

The covariances of n_1^s with the regressors are:

$$\mathrm{Cov}(n_1^s, X_1) = \sigma_{ns}^2, \tag{64}$$

$$\mathrm{Cov}(n_1^s, X_2) = -\sigma_{ns}^2. \tag{65}$$

To find the regression coefficients β_1 and β_2, we use

$$\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} = \begin{pmatrix} \mathrm{Var}(X_1) & \mathrm{Cov}(X_1, X_2) \\ \mathrm{Cov}(X_1, X_2) & \mathrm{Var}(X_2) \end{pmatrix}^{-1} \begin{pmatrix} \mathrm{Cov}(n_1^s, X_1) \\ \mathrm{Cov}(n_1^s, X_2) \end{pmatrix}. \tag{66}$$

Substituting the variances:

$$\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} = \begin{pmatrix} \sigma_{vs}^2 + \sigma_{ns}^2 & \sigma_{ns}^2 \\ \sigma_{ns}^2 & \sigma_{vo}^2 + \sigma_{ns}^2 \end{pmatrix}^{-1} \begin{pmatrix} \sigma_{ns}^2 \\ -\sigma_{ns}^2 \end{pmatrix}. \tag{67}$$

The determinant is:

$$D = \sigma_{vs}^2 \sigma_{vo}^2 + \sigma_{ns}^2(\sigma_{vs}^2 + \sigma_{vo}^2). \tag{68}$$

Thus the inverse matrix is:

$$\frac{1}{D} \begin{pmatrix} \sigma_{vo}^2 + \sigma_{ns}^2 & \sigma_{ns}^2 \\ \sigma_{ns}^2 & \sigma_{vs}^2 + \sigma_{ns}^2 \end{pmatrix}. \tag{69}$$

Multiplying yields:

$$\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} = \frac{1}{D} \begin{pmatrix} \sigma_{ns}^2 \, \sigma_{vo}^2 \\ -\sigma_{ns}^2 \, \sigma_{vs}^2 \end{pmatrix}. \tag{70}$$

Hence:

$$\beta_1 = \frac{\sigma_{ns}^2 \sigma_{vo}^2}{D}, \qquad \beta_2 = -\frac{\sigma_{ns}^2 \sigma_{vs}^2}{D}. \tag{71}$$

Next, compute the variance of the conditional expectation:

$$\mathrm{Var}(E[n_1^s \mid \mathcal{F}_1]) = \beta_1^2 \, \mathrm{Var}(X_1) + 2\beta_1\beta_2 \, \mathrm{Cov}(X_1, X_2) + \beta_2^2 \, \mathrm{Var}(X_2), \tag{72}$$

Finally, substituting yields the closed-form:

$$R^2 = \frac{\sigma_{ns}^2(\sigma_{vs}^2 + \sigma_{vo}^2)}{\sigma_{ns}^2(\sigma_{vs}^2 + \sigma_{vo}^2) + \sigma_{vs}^2\sigma_{vo}^2}. \tag{73}$$