Ownership Links and Return Predictability*

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Abstract

We investigate the return predictability between subsidiaries and their parent firms by using an international sample of parent firms with complex ownership structures from 23 developed markets. We find that portfolio returns of the ownership-weighted subsidiaries can significantly predict the future returns of a parent firm in terms of statistics and economics. Specifically, a simple long/short portfolio strategy for a global sample sorted by lagged monthly returns of subsidiaries yields an FF6 abnormal return of 107 (value-weighted) basis points per month. We further find foreign subsidiaries, different-industry subsidiaries, and minor ownership subsidiaries generate larger predictive power than local subsidiaries, same-industry subsidiaries, and major ownership subsidiaries for future returns of parent firms. We find that subsidiaries' complexity, subsidiaries' importance, limits to arbitrage, and investor limited attention may be mechanisms and reasons for the underreaction of parent firm returns for subsidiaries' returns.

JEL Classification: G11, G14, G15.

Keywords: Return Predictability, Complexity, Importance, Limits-to-Arbitrage, Limited Investor Attention, Parent Firms, Subsidiaries.

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1. **Introduction**

La Porta et al. (1999) illustrated that public parent firms in Europe and Asia present a complex ownership structure, compared with Berle and Means's image of a flat ownership of modern firms. There are plenty of potential benefits associated to this complex ownership structure, including the potential for operating and financing efficiently and a relatively low cost of monitoring. Investing in these complexed structured parent firms may present, however, tremendous challenges to some investors that have limited capacities and resources to deal with complicated value-relevant information. The presence of ownership structural horizontal complexities and vertical complexities, have the latent capacity to bring about market inefficiencies in the form of gradual, rather than immediate, information diffusion into stock prices (Hong and Stein, 2007; Duffie, 2010). It is possible to enable the information which derives from distant or poorly understood subsidiaries to cause the slow information incorporation to parent firms.

A parent firm, which controls its subsidiaries by ownership links, is exposed to unexpected stock price shocks because of stock price fluctuations of its financially linked subsidiaries. Particularly, a positive or negative shock to the main subsidiaries which are owned by their parent firm directly or indirectly is likely to rise or reduce the parent firm's future financial performance. There are at least two conceivable explanations to understand the return effect. Firstly, from an investment perspective, the partial equity ownership of subsidiaries can be regarded as an investment on behalf of their parent firm. If the stock price of subsidiaries increases, the parent firm's stock price should also increase contemporaneously to reflect appreciating assets. In other words, the equity in other firms represents an asset. If this asset increases in value, the market value of the parent firm will reflect it. Secondly, from an accounting perspective, since total or partial earnings of subsidiaries are included in their parent firm's total earnings in its consolidated financial statements[1], changes in earnings of subsidiaries affect the stock prices of subsidiaries and their parent firm. But the speed of information diffusion to subsidiaries and the parent firm is different. This is the main intuition and motivation behind this paper.

[1] Consolidated financial statements are the combined financial statements of a parent company and its subsidiaries.

Cohen and Frazzini (2008) documented return predictability across economically linked firms. They found that lagged one month's return of main customers can predict the monthly returns of their suppliers. But the mechanism behind the economic links is different from that behind the financial links. Economic links refer to the firm's supply chain network, reflecting the firm's sales and operations activities. E.g. the firm has suppliers and/or customers; Financial link refers to the company's ownership network, reflecting the company's investment and financing status. E.g. the firm has parent firms and/or subsidiaries. Their differences are also reflected in the changes in earnings on the financial statements. Customers' earnings are not part of the suppliers' total earnings in financial statements. Changes in earnings of customers influence sales of the suppliers and generate a new change in earnings to the suppliers. However, subsidiaries' total or partial earnings are indeed directly involved in the parent firm's total earnings in financial statements because of ownership links. According to U.S. GAAP (Generally Accepted Accounting Principles) and IFRS (International Financial Reporting Standards)[2], parent firms must prepare annual and quarter consolidated financial statements to report the financial well-being of both the parent firm and all of its subsidiaries.[3]

A large body of evidence confirms interfirm return predictability among firms that have economic links. Many scholars found the economically linked firms exist return predictability. Cohen and Frazzini (2008) assess predictability between customers and suppliers.[4] Cohen and Low (2012) concentrate on the links between standalones and conglomerates.[5] Huang (2015), and Finke and Weigert (2017) showed that US firms and worldwide multinational firms' foreign operation information can predict their

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[2] Since the end of the 1990s, the two predominant accounting standards are U.S. GAAP (Generally Accepted Accounting Principles) and IFRS (International Financial Reporting Standards).

[3] Both U.S. GAAP and IFRS require parent companies to consolidate subsidiaries (in which they own more than 50% of the voting rights). When it comes to associate entities, in which the parent owns between 20% and 50%, IFRS standards require the parent to consolidate the entity if the company is presumably controlled by the parent ('de facto control'), whereas U.S. GAAP require to consolidate these entities only if the parent demonstrates the exercise of a significant influence ('effective control') through voting rights or board control. In either case, consolidated financial statements use the equity method.

[4] Using a data set of firms' principal customers to identify a set of economically related firms, they show that stock prices do not incorporate news involving related firms, generating predictable subsequent price moves.

[5] They find the same piece of information affects two sets of firms: one set of firms requires straightforward processing to update prices, while the other set requires more complicated analyses to incorporate the same piece of information into prices.

returns.[6] Cao et al. (2016) found that strategic alliances[7] lead to return predictability. However, return predictability among firms that are linked financially is less understood. Li et al. (2016) found lagged monthly returns of US local subsidiaries can predict returns of US parent firms in this month. The investor's inattention and limits to arbitrage lead to the return effect. Our study differs to theirs in other important dimensions. This paper firstly provides comprehensive and thorough analysis and evidence to show global, regional, and individual country sample results. In addition, we find a series of new anomalies and predictors by sorting subsidiaries into subsamples based on different categories. More importantly, we explore and propose new alternative mechanisms and drivers to explain and understand this subsidiaries' momentum effect.

In this article, we study the return predictability between subsidiaries and their parent firm in the complex ownership structures and test a global sample including twenty-three developed markets. This broader international sample enables us to investigate whether subsidiaries' predictability effect is a common feature to markets globally or not. More importantly, we find that subsamples of subsidiaries have different predictive power based on different subsidiaries' classifications. For instance, subsidiaries in indirect layer have different return predictability effect with subsidiaries in direct layer. Foreign subsidiaries have different return predictability effect with local subsidiaries. Subsidiaries in different industries with the parent firm have different return predictability effect with subsidiaries in same industry with the parent firm. Minor ownership subsidiaries have different return predictability effect with major ownership subsidiaries.

We show that subsidiaries' information has significant predictive ability for parent firm's future stock returns on a global scale through different geographical subsamples. In the worldwide sample, from January 2005 to December 2016, the return spread is 1.15% in month t between parent firms' stocks with the highest monthly returns of ownership-weighted subsidiaries' portfolio at month t-1 and parent firms' stocks with

[6] They both find value-relevant foreign information only gradually dilutes into stock prices of multinational firms.

[7] Chan, Kensinger, Keown, and Martin (1997) document that alliances are formed for a number of reasons including licensing, marketing or distribution, development or research, technology transfer or systems integration, or some combination of the above.

the lowest monthly returns of ownership-weighted subsidiaries' portfolio at month t-1. After controlling for risk factors, using Fama and French six-factor (Fama and French, 2018), we obtain 1.07% (t-statistic is 6.16) monthly abnormal returns of the value-weighted parent firms' portfolio. In addition, we find monthly abnormal returns of the value-weighted portfolio through the different geographical subsamples such as Asia-Pacific, Europe, and North America which equal to 1.03%, 1.47%, and 1.49%, respectively.

What's more, lagged-one monthly subsidiaries' returns make a statistically and economically significant difference on future monthly returns of parent firm in multivariate Fama-Macbeth stock-level regressions after controlling assorted firm characteristics. The predictive relationship between past monthly returns of subsidiaries and one-month-ahead returns of parent firm remains significant in the statistical and economic sense after controlling the aforementioned characteristics of firms.

We further compare two parent firms' self-financing portfolios' abnormal returns by dividing subsidiaries' sample into two subsamples based on four categories. Firstly, we separate the subsidiaries' sample into two subsamples: local subsidiaries and foreign subsidiaries. The abnormal returns of a self-financing portfolio using foreign subsidiaries' information are larger than the abnormal returns of a self-financing portfolio using local subsidiaries' information. We find that foreign subsidiaries have stronger predictive power than that in local subsidiaries by Fama-Macbeth regressions. That is because the information incorporation of foreign subsidiaries is slower than the information incorporation of local subsidiaries on account of difficult acquisition process of information from long geographical distances, discrepant languages and cultures.

Secondly, we separate the subsidiaries' sample into two subsamples: same industrial subsidiaries and different industrial subsidiaries. The abnormal returns of a self-financing portfolio using different industrial subsidiaries' information are larger than the abnormal returns of a self-financing portfolio using same industrial subsidiaries' information. We find that different industrial subsidiaries have stronger predictive power than that in same industrial subsidiaries by Fama-Macbeth regressions. That is because the partial predictive power of same industrial subsidiaries is absorbed by industry momentum effects.

Thirdly, we separate the subsidiaries' sample into two subsamples: major ownership subsidiaries and minor ownership subsidiaries. The abnormal returns of a self-financing portfolio using minor ownership subsidiaries' information are larger than the abnormal returns of a self-financing portfolio using major ownership subsidiaries' information. We find that minor ownership subsidiaries have stronger predictive power than that in major ownership subsidiaries. That is because the number of minor ownership subsidiaries is much more than the number of major ownership subsidiaries. Investors may lack of methods and abilities to analyse big dataset.

We then shed light on possible mechanisms and drivers that conduct this return effect. There are two traditional market friction mechanisms: limited investors' attention and limits-to-arbitrage. We discover that the return predictability can be weakly explained by limited investors' attention, measured by turnover, analyst coverage, and institutional investor holdings. However, the return effect can be strongly explained by limits-to-arbitrage and is pronounced among parent firm stocks with less market capitalisation, and higher idiosyncratic volatility. We also work out one distinct return predictability mechanism: investor limited information processing capacities. In contrast with the sales' complexity returns predictability mechanism proposed by Cohen and Lou (2012), we propose return predictability mechanism of ownership complexity. Investors are trouble in dealing with complex ownership information and subsidiaries' portfolio returns. We find that the more ownership is dispersed by a parent firm's subsidiaries, the stronger subsidiaries' return predictability is.

What's more, we also examine whether the subsidiaries' momentum effect is more pronounced to the parent firm which has larger sizes of subsidiaries' portfolio. We find that comparing a parent firm which has larger sizes of subsidiaries' portfolio with one which has smaller sizes of subsidiaries' portfolio, the former is more likely to be affected by subsidiaries' shocks.

The most similar research that is relevant to us is Cohen and Lou (2012). They found lagged standalone's information can forecast the future returns of a conglomerate. Sales complexity and limits-to-arbitrage lead to this return effect. However, limited investor attention cannot explain this return effect.

Our study is related to a broader literature on interfirm return predictability due to gradual information diffusion according economic, and financial links. Hou (2007) argued that the slow diffusion of industry information is a principal cause of the lead-lag effect in stock returns. Cohen and Frazzini (2008) as well as Menzly and Ozbas (2010) found that stock prices do not promptly incorporate news about economically related firms which generate return predictability through assets. Rizova (2013) explored the interactions between international trade and stock markets and observed that stock markets' returns of trading partners do a forecast on trade flows and future returns. Cohen and Lou (2012) documented return predictability from single industry firms to peers. Moreover, Cao et al. (2015) showed that how stock returns of strategic alliance partners predict each other. Huang (2015), Finke and Weigert (2017) investigated the hypothesis that value-relevant foreign information slowly diffuses into the stock prices of US and 21 multinational firms in the developed countries. Finally, Li et al. (2016) provided US evidence on subsidiaries-to-parent return predictability and parent-to-subsidiaries return predictability. However, unlike the subsidiaries-to-parent return predictability, the parent-to-subsidiaries return predictability does not seem to be caused by corporate equity ownership, but by industry momentum effects. Bertrand and Mullainathan (2003) indicated that the US firm ownership pattern is not the norm around the world. In fact, they may seem distinct from a U.S. perspective, nevertheless, many firms around the world are organised into so-called pyramids. Our paper emphasizes the existing literature by documenting that worldwide parent firms' return predictability is due to gradual information diffusion across multi-layer, multi-national, multi-industry, multi-shareholding percentage ownership links. These new anomalies of using past subsidiaries' returns to predict future parent firms' returns is not only a thought-provoking empirical fact with implications for algorithmic trading or systematic investment, but it also has fundamental implications for improvements of asset pricing models.

The reminder of the paper proceeds as follows. Section 2 describes our data collection procedures, and summary statistics as well as explains the methodology of the empirical analysis. Section 3 shows that parent firm stocks with high lagged subsidiaries' returns earn higher future (risk-adjusted) returns than stocks with low lagged subsidiaries' returns worldwide and across geographical subsamples. Section 4 provides stock-level Fama-Macbeth's cross-sectional regressions by plenty of specifications. Section 5 conducts robustness checks. In section 6, we analyse the return predictability effect by sorting subsidiaries into subsamples based on different categories. Section 7 sheds light on potential mechanisms for subsidiaries effect. Section 8 examines the impact of transaction costs on the profitability of the subsidiary momentum trading strategy. Section 9 makes a brief but comprehensive conclusion.

2. **Data and Methodology**

2.1 Data

We study the twenty-three developed markets based on the latest MSCI world developed market index as of December 2017. We collect price, volume, and return data for US firms from the Centre for Research in Security Prices (CRSP) and for non-US firms from Thomson Reuter's Eikon. Institutional ownership data and analyst coverage for all firms in the sample are obtained from Thomson Reuters Institutional Holdings (13F) and Thomson Reuters I/B/E/S, respectively. We exclude parent firms' stocks with prices less than $5 to avoid market microstructure problems. We cover all industrial firms except firms in financial sector (with two-digit NAICS code = 52). The sample period is from January 2008 to December 2017 with a total of 120 months. As common in the international asset pricing literature, all stocks returns are denominated in USD.[8] As in Fama and French (2012), we use the one-month US T-bill rate for the USA and the remaining countries to calculate monthly excess returns.[9]

We collect ownership links and shareholdings data from FactSet database. We find a public listed parent firm has average 1.68 public listed main subsidiaries[10] per year in a global sample.

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8 E.g. Griffin (2002), Fama and French (2012).
9 Our results are stable if we use local currency returns and work with raw returns instead of excess returns.
10 Main subsidiaries mean above 10% shares are hold by the parent firm.

Our aim is to investigate the return predictability from subsidiaries to their parent firm. If the ownership percentage of a directly or indirectly owned subsidiary is small, its return effect to the parent firm can be neglected. Thus, we have a reasonable cut-off of the ownership stake to study return effect from main subsidiaries to their parent firm. La Porta et al. (2000) set at least 10% voting rights to define a large ownership stake. Claessens et al. (2000) and Ginlinger et al. (2017) used a 20% cut-off to retain an ownership percentage equal to or more than 20%. We also use 20 percent of ownership as a cutoff following the literature.[11] Since 2005, there has been a strong push for harmonization of accounting standards and principles with the mandatory adoption of International Financial Reporting Standards (IFRS) for publicly traded firms, which largely coincides with U.S. GAAP. Both U.S. GAAP and IFRS require parent companies to consolidate controlled subsidiaries. IFRS standards require the parent to consolidate the entity if there is de facto control, which is interpreted as the parent owning a stake of 20% or more.

In order to test ten years' return predictability, we collect ten yearly time-varying ownership links. We use the ownership links at the end of June of year y-1 to test return predictability from January to December in year y.

2.2 subsidiaries momentum

The regressor of interest in our paper is lagged-one monthly returns of subsidiaries. It refers to as $\mathrm{Subs}_{i,t-1}$. $\mathrm{Subs}_{i,t-1}$ is constructed as the ownership-weighted portfolio returns of subsidiaries:

$$\mathrm{Subs}_{i,t-1} = \sum_j Own_{i,j,t-1} * Ret_{j,t-1},$$

$$Own_{i,j,t-1} = \frac{ShareHold_{\,i,j,t-1} * Size_{j,t-1}}{\sum_j ShareHold_{\,i,j,t-1} * Size_{j,t-1}},$$

[11] We use the 10%, 15%, 25%, and 30% of ownership as a cutoff, but the results are not influenced.

where $\text{Subs}_{i,t-1}$ denotes parent firm i's ownership-weighted portfolio returns of all subsidiaries, $Own_{i,j,t-1}$ is parent firm i's ownership stakes to subsidiary j on month t-1, $Ret_{j,t-1}$ is the subsidiary j's returns on month t-1, $ShareHold_{\ i,j,t-1}$ is parent firm i's shareholding percentages to the subsidiary j on month t-1, $Size_{j,t-1}$ is the market capitalisation of subsidiary j at month t-1. For example, a parent firm (P) has two subsidiaries (S1 and S2) in the first layer and S1 has a subsidiary (S11) in the first layer. S11 is a second-layer subsidiary to the parent firm (P). The market capitalisations of P, S1, S2 and S11 are 200 million, 100 million, 50 million, and 50 million, respectively. A parent firm P has shareholdings 60% and 100% to S1 and S2. S1 has a shareholding 50% to S11. In other words, P has a shareholding 30% to S11. Thus, two kinds of predictors are below:

$$\text{Subs}_{i,t-1} = \frac{60\% \ * 100 * \ Ret_{S1,t-1} + \ 100\% * 50 * \ Ret_{S2,t-1} + 30\% * 50 * \ Ret_{S11,t-1}}{60\% * 100 + \ 100\% * 50 + 30\% * 50}$$

2.3 Summary statistics

The sample is made from January 2008 to December 2017. Parent firms' mean return is 2% per month. Subsidiaries' mean return is 3% per month. There are 1.68 ownership links for each parent firm on average in twenty-three developed markets. Table I provides summary statistics.

(Insert Table 1 about here)

3. Univariate Portfolio Sorts

In this section, we report an empirical analysis of univariate portfolio sorts. The goal of portfolio sorts is to examine cross-sectional variation of expected returns with the response to a common predictor.

In each month t, we rank parent firm returns based on the ranking of their subsidiaries' portfolio returns of month t-1. Then we classify parent stocks into 5 quintiles. Quintile 1 parent firms have lowest subsidiaries' portfolio returns of lagged one month. Quintile 5 parent firms have highest subsidiaries' portfolio returns of lagged one month. Then, we report the value weighted and equal weighted portfolio returns of these quintiles as well as the hedged portfolio returns of Quintile 5 minus Quintile 1with corresponding statistical significance level.[12] Portfolio sorts are conducted for five regions: the worldwide sample (Global), the worldwide sample excluding the USA (Global ex. USA), Asia-Pacific, Europe, and North America. Finally, results are reported in Table II.

(Insert Table 2 about here)

Panel A demonstrates that monthly excess returns of parent firm stocks which have highest lagged one month's returns of subsidiaries' portfolio have obviously higher monthly excess returns than those which have lowest lagged one month's returns of subsidiaries' portfolio. In the global samples, value-weighted parent firms' stocks in the highest quintile earn average monthly excess returns of 0.22%, but value-weighted parent firms' stocks in the lowest quintile earn average monthly excess returns of -0.97%. The return spread is 1.19% with 1% significance level. The value-weighted portfolio return spreads of the other region samples are 1.21% (Global ex USA), 0.87% (Asia-Pacific), 1.54% (Europe), and 1.58% (North America). All these spreads in returns are 1% statistically significant.

Panel B reports the achievement about the five-factor risk-adjusted returns for each quintile portfolios and hedged portfolio (Q5-Q1). We can use a regional version of Fama-French (2015) five-factor model to control five elementary systemic risks. The value-weighted portfolio abnormal returns are 1.07% (Global), 1.10% (Global ex USA), 1.02% (Asia-Pacific), 1.50% (Europe), and 1.50% (North America).

In Panel C, we use the Fama-French (2018) six-factor model to capture abnormal returns. The Fama-French six-factor model adds momentum factor into original five-factor model. The value-weighted portfolio abnormal returns become 1.07% (Global), 1.10% (Global ex USA), 1.03% (Asia-Pacific), 1.47% (Europe), and 1.49% (North America).

[12] In order to adjust for serial correlation in monthly stock returns, we use Newey and West (1987) standard errors with six lags in the statistical tests.

As a brief statement of the main points, the results of Table 2 illustrate that lagged-one monthly returns of subsidiaries portfolio have predictive power to monthly returns of parent firm returns. Moreover, the abnormal returns cannot be explained by implying asset pricing models, including global and regional Fama-French (2015; 2018) five-factor, and six-factor models.

4. **Multivariate Regressions**

In this section, we make use of Fama and MacBeth (1973)'s two step procedure to analyse whether the subsidiaries-to-parent predictability remains robust after regulating a set of risk factors and an array of different firm characteristics. The stock level's Fama-Macbeth regression is made up of two steps. In the first step, we utilize the cross-sectional regression in each month as following:

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,c,t} + \lambda_{2,d,t} + \lambda_{3,t}\, Subs_{i,t-1} + \lambda_{4,t}{}'\, X_{i,t-1} + \varepsilon_{i,t}$$

where $RET_{i,t} - R_{f,t}$ is the excess return on parent stock i in month t; $\lambda_{1,c,t}$ is a country-specific dummy variable which is equal to one if firm i is from country c and zero otherwise; $\lambda_{2,d,t}$ is a industry-specific dummy variable which is equal to one if firm i is from industry d and zero otherwise; $Subs_{i,t-1}$ is lagged subsidiary stock return on month t-1; $\mathrm{X}_{\mathrm{i,t-1}}$ represents a vector of firm characteristics, including natural logarithm of the market capitalization measured in million dollars (Banz. 1981), natural logarithm of book-to-market equity ratio (Basu, 1983), $\mathrm{RET}_{\mathrm{i,t-12:\,t-2}}$ the cumulative return of stock i from month t-12 to t-2 (Jegadeesh and Titman, 1993), $\mathrm{RET}_{\mathrm{i,t-1}}$ short-term reversal (Jegadeesh, 1990 and Lo and MacKinlay, 1990), Turnover (Rouwenhorst, 1999 and Ibbotson et al., 2013), $\mathrm{Ind\_mom\_ret}_{\mathrm{i,t-1}}$ to account for industry momentum (Grinblatt and Moskowitz, 1999; Nijman, Swinkels, and Verbeek, 2004), asset growth (AG) to define as year-over-year growth rate of total asset. Gross profitability (GP) to define as revenue minus cost of goods sold scaled by assets.

The second step is to verify whether the average coefficient estimates are statistically different from zero. We can apply Newey and West (1987)'s correction with six lags to calculate standard errors.

(Insert table 3 about here)

Table 3 present regression results of excess returns of parent firm on $Subs_{i,t-1}$ and a vector of control variables in global sample and lots of different regional samples. The results demonstrate that the coefficient of $Subs_{i,t-1}$ is statistically significant at 1% level for the global sample, the Asia-Pacific sample, and the North America sample. The results demonstrate that the coefficient of $Subs_{i,t-1}$ is statistically significant at 5% level for the Global ex USA sample and the Europe sample. Also, the predictive power of lagged subsidiaries' returns is not subsumed by stock return's reversal, momentum, industry momentum.

To sum up, Fama-MacBeth regression results indicate the predictive effect of lagged subsidiaries returns. Also, the predictive effect cannot be subsumed by several firm characteristics.

5. **Robustness test**

This section supplies additional analyses and stability checks to guarantee robustness for our main empirical results. We perform univariate portfolio sorts in the global samples to reveal the results of different stability and robustness checks. Table 4 reports the results of diverse robustness checks. All abnormal returns are adjusted by Fama and French (2018) six-factor model.

Firstly, we examine the subperiods of portfolio abnormal returns. In the period between January 2008 and December 2012, we find value-weighted portfolio alpha is 1.25 (t = 6.29). In the period between January 2013 and December 2017, we find value-weighted portfolio alpha is 0.97 (t = 3.71).

We also examine the subsamples of subsidiaries based on different classification. Both local subsidiaries and foreign subsidiaries can predict future parent firm returns. The value-weighted portfolio abnormal returns of using local subsidiaries and using foreign subsidiaries are 0.68% (t-statistic 4.35) and 1.01% (t-statistic 5.36). Both same industrial subsidiaries and different industrial subsidiaries can predict future parent firm returns. The value-weighted portfolio abnormal returns of using same industrial subsidiaries and using different industrial subsidiaries are 0.49% (t-statistic 2.91) and 1.01% (t-statistic 4.88). Both major ownership subsidiaries and minor ownership subsidiaries can predict future parent firm returns. The value-weighted portfolio abnormal returns of using major ownership subsidiaries and using minor ownership subsidiaries are 0.75% (t-statistic 4.73) and 0.95% (t-statistic 4.90).

(Insert Table 4 about here)

6. **Predictive information of subsidiaries in subsamples**

6.1 Predictive power of local subsidiaries vs. foreign subsidiaries

In Table 5, we conduct Fama and MacBeth (1973)'s two step procedure to analyse whether the predictive power of local subsidiaries and foreign subsidiaries remains robust after regulating an array of different firm characteristics. In columns of odd numbers, we test whether local subsidiaries can predict future parent firm's returns. The dependent variable is excess returns of parent firm and the explanatory variable of interest is lagged returns of local subsidiaries. In columns of even numbers, we test whether foreign subsidiaries can predict future parent firm's returns. The dependent variable is excess returns of parent firm and the explanatory variable of interest is lagged returns of foreign subsidiaries. We conclude that foreign subsidiaries have larger predictive power than local subsidiaries due to larger coefficient and t-statistic value.

(Insert Table 5 about here)

6.2 Predictive power of same industrial subsidiaries vs. different industrial subsidiaries

In Table 6, we conduct Fama and MacBeth (1973)'s two step procedure to analyse whether the predictive power of same industrial subsidiaries and different industrial subsidiaries[13] remains robust after regulating an array of different firm characteristics. In columns of odd numbers, we test whether same industrial subsidiaries can predict future parent firm's returns. The dependent variable is excess returns of parent firm and

[13] Throughout the paper, we use 2017 North America Industry Classification System (NAICS) first four-digit code as industry classification.

the explanatory variable of interest is lagged returns of same industrial subsidiaries. In columns of even numbers, we test whether different industrial subsidiaries can predict future parent firm's returns. The dependent variable is excess returns of parent firm and the explanatory variable of interest is lagged returns of different industrial subsidiaries. We conclude that different industrial subsidiaries have larger predictive power than same industrial subsidiaries due to larger coefficient and t-statistic value.

(Insert Table 6 about here)

6.3 Predictive power of major ownership subsidiaries vs. minor ownership subsidiaries

In Table 7, we conduct Fama and MacBeth (1973)'s two step procedure to analyse whether the predictive power of major ownership subsidiaries and minor ownership subsidiaries[14] remains robust after regulating an array of different firm characteristics. In columns of odd numbers, we test whether major ownership subsidiaries can predict future parent firm's returns. The dependent variable is excess returns of parent firm and the explanatory variable of interest is lagged returns of major ownership subsidiaries. In columns of even numbers, we test whether minor ownership subsidiaries can predict future parent firm's returns. The dependent variable is excess returns of parent firm and the explanatory variable of interest is lagged returns of minor ownership subsidiaries. We conclude that minor ownership subsidiaries have larger predictive power than major ownership subsidiaries due to larger coefficient and t-statistic value.

(Insert Table 7 about here)

7. **Mechanisms**

The evidence in section 4 and 6 suggests that standard risk factors and changes in risk are unlikely to explain the return predictability. In this section, we shed light on possible mechanisms to explain and understand the predictive power of subsidiaries' returns.

[14] Major ownership subsidiary means that parent firm holds >50% shareholding to that subsidiary. Minor ownership subsidiary means that parent firm holds <= 50% shareholding to that subsidiary.

As for testing mechanisms, we make use of Fama-Macbeth regressions by adding an interaction term between the lagged subsidiaries' returns ($Subs_{i,t-1}$) and the dummy variable ($\mathrm{proxy}_{\mathrm{i,t-1}}$).

$$\mathrm{RET}_{\mathrm{i,\,t}} - \mathrm{R}_{\mathrm{f,t}} = \alpha + \beta_1 Subs_{i,t-1} + \beta_2 \mathrm{proxy}_{\mathrm{i,t-1}} + \beta_3 Subs_{i,t-1} \times \mathrm{proxy}_{\mathrm{i,t-1}} + \mathrm{X}'_{\mathrm{i,t-1}}\gamma + \epsilon_{\mathrm{i,t}}$$

(Insert Table 8 about here)

9.1 Ownership complexity

In this section, we examine the mechanism of complicated ownership analysis which affects the price updating of the parent firm in a certain extent. If one parent firm has many directly owned subsidiaries (located at first layer) and indirectly owned subsidiaries (located at higher layers), investors will have limited resources and capacity to process these complicated ownerships value-relevant information. Next we suppose that the more complicated the parent firm' ownerships are, the more severe the lag in incorporating information into parent prices will be, and thus the stronger the return predictability will be. To verify this predictability, we design an ownership complexity index (OCI) to measure how the ownership complicates a parent firm according to a parent firm's segment ownerships. The OCI of parent firm i is constructed as:

$$\mathbf{OCI}_i = \sum_j \left(\frac{\mathrm{ownership}_{i,j}}{\sum_j \mathrm{ownership}_{i,j}}\right)^2,$$

$$\mathrm{ownership}_{i,j} = \mathrm{shareholding}_{i,j} * market\ capitalization_j,$$

where $\mathrm{shareholding}_{i,j}$ is the parent firm i's shareholding percentage to subsidiary j. $market\ capitalization_j$ is the market capitalization of subsidiary j. For instance, a parent firm P hold three subsidiaries S1, S2, S3 with ownerships 40 million, 30 million, and 30 million, respectively. the ownership complexity index (OCI) for this conglomerate P is conveyed as $(.4)^2 + (.3)^2 + (.3)^2 = 0.34$. The idea behind this measure is that the more dispersed a parent firm's ownerships are, the more complicated information needed to incorporate into its stock price is. Cohen and Lou (2012) tested sales complexity and return predictability. They use Herfindahl index to measure sales complexity of a conglomerate. Our OCI[15] measure has similar format with Herfindahl index but uses ownerships instead of sales. We assume that the smaller OCI value is, the stronger the return predictability is.

The results of the test are reported in Column 1 of Table 8. The regression specification is similar to those in Table 3, i.e., a Fama-MacBeth predictive regression with the dependent variable being parent firm return ($RET_{i,t}$) in the following month. In addition to the interaction term between the dummy variable and $Subs_{i,t-1}$, the dummy variable itself along with all control variables from the full specification (Table 3, Column 1) are also included, which are unreported for brevity. We observe from Column 1 that the coefficient estimate on the interaction term between an indicator of less complicated firms and past subsidiaries' return ($Subs_{i,t-1}$) is negative and statistically significant, -5.93 (t=-3.05). For comparison, the unconditional coefficient on $Subs_{i,t-1}$ is 9.12. Thus, consistent with the ownership complexity of parent firms driving the return predictability pattern, parent firms that are relatively less complicated, and so require simpler processing to incorporate information about any single ownership segment into prices, exhibit less pronounced predictable returns.

9.2 Limits to arbitrage

In a frictionless market, all predictable returns should be completely arbitraged away. However, Shleifer and Vishny (1997) indicate that mispricing may not disappear completely due to limits to arbitrage. A prediction of this argument is that, for stocks with more binding limits to arbitrage, we should see a stronger return effect, as more sophisticated investors are less able (or willing) to fully update these firms' prices. We employ two variables that are commonly used in the literature to capture limits to arbitrage in the stock market: idiosyncratic volatility and firm size. While we are not claiming these are perfect proxies, we do believe, especially in the case of idiosyncratic volatility, that these proxies are likely correlated with classic limits to arbitrage, such as the ability to retain positions (capital) in the face of prices moving (temporarily) further away from fundamental values.

[15] We also test other format measures, e.g. the sum of absolute values, but the results are not influenced.

To test this prediction, we construct two dummy variables that equal one if the parent firm is above the sample median in terms of idiosyncratic volatility and firm size, respectively, and zero otherwise. As shown in Column 4 of Table 8, the coefficient estimate on the interaction term between the idiosyncratic volatility dummy and $Subs_{i,t-1}$ is large and statistically significant, 5.23 (t=3.35), which implies that the magnitude of the documented return effect is over 50% larger for stocks with high idiosyncratic volatility relative to those with low idiosyncratic volatility. This is consistent with our prediction that firms that are more likely to have large temporary price swings, and are thus less attractive to arbitrage capital, should exhibit a stronger return effect. In the same vein, Column 3 shows that, while the complicated-information-processing return effect among large parent firms is strong and significant, the effect in small parent firms is even larger. Both of these findings lend support to our prediction that complications in information processing have an even larger impact on difficult-to-arbitrage stocks.

9.3 Importance of subsidiaries

What's more, we also examine whether the subsidiaries' momentum effect is more pronounced to the parent firm which has larger sizes of subsidiaries' portfolio. We find that comparing a parent firm which has larger sizes of subsidiaries' portfolio with one which has smaller sizes of subsidiaries' portfolio, the former is more likely to be affected by subsidiaries' shocks and in turn acts on their subsidiaries in particular.

As shown in Column 2 of Table 8, while one parent firm has larger sizes of subsidiaries' portfolio, the return effect is stronger. The coefficient estimate on the interaction term between the relative sizes (Size_S / Size_P) dummy and $Subs_{i,t-1}$ is large and statistically significant, 4.38 (t=3.23), which implies that the magnitude of the documented return effect is over 50% larger for stocks with high Size_S / Size_P relative to those with low Size_S / Size_P.

9.4 Investors' limited attention

In the final three columns of Table 8, we test whether our results are entirely driven by an investors' inattention explanation, i.e., that investors are unaware of a piece of information and/or a particular stock. We still employ some common proxies for (in)attention to test this more formally. Specifically, if investors' limited attention plays a significant role here, we would expect stronger return predictability for parent firms that attract less investor attention. We use three common proxies for inattention in the literature: lower institutional investor ownership, lower turnover, and lower analyst coverage. Note that institutional ownership here is the residual institutional ownership after being orthogonalized with respect to firm size.

The results are reported in Columns 5 to 7. All three interaction terms are only weakly significant and small in magnitude. This lends further support that the return effect is not only simply driven by investors ignoring this underlying information or the underlying stocks but is essentially driven by other mechanisms.

11. Transaction Costs

In this section, we examine the impact of transaction costs on the profitability of the subsidiary momentum trading strategy. Cao et al. (2016) show the calculation methods of trading costs. We obtain closing bid and ask prices from CRSP for US stocks and from Eikon for other developed markets' stocks. The proportional trading cost for stock i, $\mathrm{cost_i}$, is half the bid–ask spread divided by the price. Let us denote the number of stocks that enter the long portfolio as L1, the number of stocks that exit the long portfolio as L3, and the number that remain in the portfolio as L2. The trading costs for the long side in month t are then

$$Cost_{long,t} = \frac{\sum_{L1} cost_i + \sum_{L2} cost_i}{\frac{(L1+L2)\, +\, (L3+L2)}{2}}$$

The denominator in the above equation is the average number of stocks in the long portfolio in month t. It accounts for the fact that not all stocks are traded each month and that there could be an increase or decrease in the number of stocks in the portfolio over time. A similar analysis applies to the short portfolio.

The monthly trading costs for the long and the short portfolios are then averaged over time. The average trading cost for the long (short) portfolio is 6 (16) basis points per month. This reduces subsidiary momentum trading-strategy profits by 22 basis points from 107 basis points (FF6 alpha) per month to 85 basis points per month (t-statistic =

4.13), which is still economically significant. Note that our cost estimates could be overstated because institutional traders are often able to time their trades and reduce trading costs by supplying liquidity. However, institutional trades are usually large and incur price impact costs. In any case, this analysis provides an estimate of total average trading costs of 22 basis points per month when trades occur at the prevailing bid–ask spreads and do not exceed the quoted depths.

12. Conclusion

This paper analyses whether value-relevant subsidiaries' information has an impact on stock prices of parent firm by using a sample of firms which are from twenty-three developed countries worldwide. On behalf of a parent firm, we expose its subsidiaries' information by applying the ownership-weighted portfolio returns of subsidiaries and illustrate that subsidiaries' information has the significant predictive power for future parent stock returns on a global scale and various regional samples. The alphas of value-weighted global sample portfolio are 1.07% per month based on Fama-French six-factor model. The abnormal returns cannot be explained felicitously by risk factors, and firm characteristics.

In addition, we find a series of new anomalies and a group of new predictors. We consider six subsamples of subsidiaries based on three categories. We find the six subsamples of subsidiaries can predict future returns of parent firms. Through investigating figures of information diffusion, we find that foreign subsidiaries, different industrial subsidiaries, and minor ownership subsidiaries have larger gradual information diffusion than local subsidiaries, same industrial subsidiaries, and major ownership subsidiaries, respectively. Hence, foreign subsidiaries, different industrial subsidiaries, and minor ownership subsidiaries generate larger predictive power than local subsidiaries, same industrial subsidiaries, and major ownership subsidiaries, respectively, to future monthly returns of parent firms.

We shed light on possible mechanisms to expound this return effect. We realize that the predictive effect of subsidiaries' information is significantly stronger for parent firms which have high levels of limits-to-arbitrage, larger sizes of subsidiaries, and more complex ownership.

Appendix A

Definitions of main variables This table briefly defines the main variables used in the empirical analysis of this paper.

Variable name	Description	Source	Type
$subs_{i,t-1}$	parent i's ownership-weighted portfolio returns of subsidiaries	FactSet, CRSP, Eikon	Time-varying updated monthly
$Sharehold_{i,j,t-1}$	parent firm i's shareholding percentages to the subsidiary j at month t-1	FactSet	Time-varying updated yearly
$size_{j,t-1}$	the market capitalisation of subsidiary j on month t-1	CRSP, Eikon	Time-varying updated monthly
$ret_{j,t-1}$	the subsidiary j's returns on month t-1	CRSP, Eikon	Time-varying updated monthly
$Own_{i,j,t-1}$	parent firm i's ownership stakes to subsidiary j on month t-1	FactSet, CRSP, Eikon	Time-varying updated monthly
$RET_{i,t}$	parent firm i's returns on month t denoted in USD	CRSP, Eikon	Time-varying updated monthly
$R_{f,t}$	one month US T-bill rate	CRSP, Eikon	Time-varying updated monthly

Ln(Size)	Log market capitalization on month t-1	CRSP, Eikon	Time-varying updated monthly
Ln(BM)	Log book value at the end of December over the market value on month t-1	CRSP, Eikon	Time-varying updated monthly
$RET_{i,t-12:t-2}$	parent firm i's cumulative return of firm i from month t-12 to month t-2	CRSP, Eikon	Time-varying updated monthly
$RET_{i,t-1}$	parent firm i's return on month t-1	CRSP, Eikon	Time-varying updated monthly
Turnover	Number of shares traded during a day divided by the number of shares outstanding at the end of the day, averaged over the past 12 months.	CRSP, Eikon	Time-varying updated monthly
$Ind\_mom\_ret_{i,t-1}$	Domestic industry return of parent firm i's on month t-1	CRSP, Eikon	Time-varying updated monthly
AG	Asset growth, defined as year-over-year growth rate of total asset	CRSP, Eikon	Time-varying updated monthly

GP	Gross profitability, defined as revenue minus cost of goods sold scaled by assets	CRSP, Eikon	Time-varying updated monthly
MktCap	market capitalization at the end of December of year y	CRSP, Eikon	Time-varying updated yearly
Res Inst Own	Residual institutional ownership is the residual from a cross-sectional regression of the pecentage of shares held by institutional investors on log market capitalization at the end of month t-1	CRSP, Eikon, Thomson-Reuters Institutional Holdings (13F)	Time-varying updated quarterly
Turnover	Number of shares traded during a day divided by the number of shares outstanding at the end of the day, averaged over the past 12 months.	CRSP, Eikon	Time-varying updated monthly
No. Analyst	Log(1 + Num_analysts) at the end of month t-1	CRSP, Eikon, I/B/E/S	Time-varying updated monthly

Relative size	equals difference between the size of parent firm I and the median size for the domestic single sengment firms operating in the same primary industry	CRSP, Eikon, FactSet, Compustat, Worldscope	Time-varying updated monthly

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Table 1: Descriptive statistics

This table presents summary statistics for key variables used in the cross-sectional regressions. The sample covers listed parent firms and listed subsidiaries from twenty-three developed markets from January 2008 to December 2017. Financial firms (with two-digit NAICS code = 52) and stocks with price less than $5 at portfolio formation are excluded. All variables are winsorized within each cross-section at 1% and 99% level. All variables definitions are in Appendix Table A.

Key variables	Mean	Sd	Min	Q1	Med	Q3	Max
$Pars_t$	0.02	0.12	-0.20	-0.01	0.01	0.04	1.22
$Subs_t$	0.03	0.17	-0.67	-0.04	0.04	0.12	0.57
Ln(size)	21.31	0.22	20.76	21.17	21.26	21.50	21.75
Ln(bm)	-0.15	0.14	-0.47	-0.24	-0.18	-0.09	0.26
RET_{t-1}	0.02	0.12	-0.20	-0.02	0.01	0.04	1.22
Mom	0.06	0.19	-0.44	-0.05	0.04	0.18	0.67
AG	0.14	0.36	-0.60	0.00	0.08	0.18	8.83
GP	0.39	0.24	-0.84	0.25	0.37	0.52	1.29
turnover	0.20	0.03	0.18	0.19	0.20	0.20	0.22
Ind_mom_{t-1}	0.02	0.11	-0.30	-0.02	0.02	0.06	0.30

Table 2: Univariate Portfolio Sorts

This table reports the results of value-weighted univariate portfolio sorts. The results are shown for five regions: Global, Global ex USA, Asia-Pacific, Europe, and North America. Panel A presents average excess returns for each quintile portfolio and the 5-1 difference portfolio. Panel B reports risk-adjusted returns for each quintile portfolio and the 5-1 difference portfolio using a regional version of the Fama and French (2015) five-factor model. Panel C reports risk-adjusted returns for each quintile portfolio and the 5-1 difference portfolio using a regional version of the Fama and French (2018) six-factor model. The risk factors are downloaded from the homepage of Kenneth French. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms from twenty-three developed markets from January 2008 to December 2017.

Panel A: Portfolio excess returns

	(1)	(2)	(3)	(4)	(5)
Value Weights	Global	Global ex USA	Asia-Pacific	Europe	North America
1 (Low)	-0.97	-0.88	-0.56	-1.12	-1.24
2	-0.47	-0.38	-0.10	-0.60	-0.15
3	-0.24	-0.02	-0.06	-0.26	-0.23
4	-0.19	0.12	0.08	0.04	0.23
5 (High)	0.22	0.33	0.31	0.42	0.35
5-1	1.19***	1.21***	0.87***	1.54***	1.58***
	(7.33)	(6.58)	(4.15)	(5.42)	(4.25)

Panel B: Fama and French (2015) five-factor alphas

	(1)	(2)	(3)	(4)	(5)
Value Weights	Global	Global ex USA	Asia-Pacific	Europe	North America
1 (Low)	-0.96	-0.83	-0.60	-1.3	-1.23
2	-0.41	-0.3	0.05	-0.9	-0.23
3	-0.18	0.07	-0.04	-0.63	-0.33

4	-0.15	0.08	0.16	0.01	0.16
5 (High)	0.11	0.27	0.42	0.20	0.27
5-1	1.07***	1.10***	1.02***	1.50***	1.50***
	(5.96)	(4.26)	(4.48)	(4.76)	(4.04)

Panel C: Fama and French (2018) six-factor alphas

	(1)	(2)	(3)	(4)	(5)
Value Weights	Global	Global ex USA	Asia-Pacific	Europe	North America
1 (Low)	-0.96	-0.83	-0.64	-1.28	-1.20
2	-0.41	-0.30	0.03	-0.92	-0.22
3	-0.18	0.06	-0.05	-0.65	-0.35
4	-0.14	0.07	0.12	0.04	0.15
5 (High)	0.12	0.27	0.40	0.19	0.29
5-1	1.07***	1.10***	1.03***	1.47***	1.49***
	(6.16)	(4.24)	(4.31)	(4.53)	(3.95)

Table 3: Fama-MacBeth regressions

This table reports the results of Fama and MacBeth (1973) regressions. Panel A reports the excess return of parent firm i, $RET_{i,t}$ is regressed on $Subs_{i,t-1}$ and a vector of control variables. $Subs_{i,t-1}$ is the ownership-weighted subsidiaries return of parent firm i in month t-1. Ln(Size) is the log market capitalization at the end of December of previous calendar year. Ln(BM) is the log book-to-market ratio at the end of December of previous calendar year. Reversal is the lagged parent firm's return. MOM is the lagged parent firm's return from month t-12 through month t-2. TURNOVER is defined as the number of stocks traded during a given day divided by the number of stocks outstanding at the end of day, averaged over the past twelve months. $Ind\_mom_{i,t-1}$ is the lagged domestic industry return. AG is asset growth, defined as year-over-year growth rate of total asset. GP is gross profitability, defined as revenue minus cost of goods sold scaled by assets. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms from twenty-three developed markets from January 2008 to December 2017.

excess return	(1)	(2)	(3)	(4)	(5)
*100	Global	Global ex USA	Asia-Pacific	Europe	North America
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Subs_{i,t-1}$	6.32***	4.86**	2.06***	4.63**	4.15***
	(3.35)	(2.33)	(5.92)	(2.02)	(3.30)
Ln(Size)	-0.10*	-0.13*	-0.07**	-0.06	0.05
	(-1.75)	(-1.81)	(-2.37)	(-1.21)	(0.86)
Ln(BM)	0.23**	0.50***	0.44**	0.43***	-0.17
	(2.11)	(4.04)	(2.32)	(3.26)	(-0.36)
Reversal	-6.73***	-4.19***	-1.41	-6.38**	-9.96***
	(-3.52)	(-3.13)	(-1.11)	(-2.00)	(-3.53)
Mom	-0.28	0.23	0.31	0.89	0.05
	(-0.52)	(0.66)	(0.41)	(0.95)	(0.05)
AG	-0.41***	-0.23**	0.23	-0.44	0.23
	(-2.61)	(-2.34)	(0.63)	(-1.24)	(0.42)
GP	0.01	0.02	0.01	0.04***	0.02
	(0.72)	(1.10)	(0.75)	(2.91)	(0.66)
Turnover	-0.06**	-0.05	-0.06*	-0.07	-0.19*
	(-2.03)	(0.62)	(-1.84)	(-1.43)	(-1.94)
$Ind\_mom_{i,t-1}$	1.06**	1.05**	1.10**	1.14**	1.03**
	(2.51)	(2.09)	(2.11)	(2.12)	(2.33)
Obs.	113,947	106,330	74,794	29,275	9,782
R^2	0.12	0.12	0.13	0.19	0.28

Table 4: Robustness

This table presents robustness checks. We perform univariate portfolio sorts (as in Table 2) on the global sample and value-weighted returns for lowest quintile portfolio, highest quintile portfolio, and the 5-1 difference portfolio using a global version of the Fama and French (2018) six-factor model (as in Panel C of Table 2). The six risk factors are obtained from the homepage of Kenneth French. Column (1) and (2) report two subperiods' results of univariate portfolio sorts of parent firms. Column (3) reports the results of univariate portfolio sorts of only using local subsidiaries. Column (4) reports the results of univariate portfolio sorts of only using foreign subsidiaries. Column (5) reports the results of univariate portfolio sorts of only using same-industry subsidiaries with parent firms. Column (6) reports the results of univariate portfolio sorts of only using different-industry subsidiaries with parent firms. Column (7) reports the results of univariate portfolio sorts of only using major (>50% shareholding percentage) ownership subsidiaries. Column (8) reports the results of univariate portfolio sorts of only using minor (<= 50% shareholding percentage) ownership subsidiaries. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms from twenty-three developed markets from January 2008 to December 2017.

Global	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Value Weights	20080101-20121231	20130101-20171231	local	foreign	same	different	major	minor
1 (Low)	-1.00	-0.87	-0.46	-0.78	-0.38	-0.82	-0.63	-0.80
2	-0.37	-0.51	-0.24	-0.35	-0.35	-0.37	-0.27	-0.27
3	0.02	-0.37	-0.16	-0.29	-0.15	-0.38	-0.12	-0.31
4	-0.11	-0.10	-0.12	-0.31	-0.13	-0.26	-0.11	-0.38
5 (High)	0.25	0.10	0.22	0.23	0.11	0.19	0.12	0.14
5-1	1.25***	0.97***	0.68***	1.01***	0.49***	1.01***	0.75***	0.95***
	(6.29)	(3.71)	(4.35)	(5.36)	(2.91)	(4.88)	(4.73)	(4.90)

Table 5: Predictive power between local and foreign

This table compares the predictive power between local subsidiaries and foreign subsidiaries by using Fama and MacBeth (1973) regressions. The dependent variable is excess returns of parent firm i on month t in five samples, Global, Global ex USA, Asia-Pacific, Europe, and North America. The two independent variables of interest are local subsidiaries on month t-1 and foreign subsidiaries on month t-1. Control variables are same as in Table 2. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms from twenty-three developed markets from January 2008 to December 2017.

excess return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
*100	Global	Global	Global ex USA	Global ex USA	Asia-Pacific	Asia-Pacific	Europe	Europe	North America	North America
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Local\ Subs_{i,t-1}$	6.62*		5.04*		1.83***		5.52*		2.02***	
	(1.84)		(1.76)		(4.45)		(1.83)		(3.13)	
$Foreign\ Subs_{i,t-1}$		7.78***		5.19**		2.48***		6.39**		5.46***
		(2.85)		(2.19)		(6.32)		(2.44)		(3.63)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	91,158	34,184	85,064	31,899	59,835	22,438	23,420	8,783	7,826	2,935
R^2	0.10	0.12	0.11	0.12	0.13	0.13	0.18	0.19	0.26	0.29

Table 6: Predictive power between same and different

This table compares the predictive power between same industrial subsidiaries and different industrial subsidiaries by using Fama and MacBeth (1973) regressions. The dependent variable is excess returns of parent firm i on month t in five samples, Global, Global ex USA, Asia-Pacific, Europe, and North America. The two independent variables of interest are same industrial subsidiaries on month t-1 and different industrial subsidiaries on month t-1. Control variables are same as in Table 2. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms from twenty-three developed markets from January 2008 to December 2017.

excess return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
*100	Global	Global	Global ex USA	Global ex USA	Asia-Pacific	Asia-Pacific	Europe	Europe	North America	North America
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Same\ Ind\ Subs_{i,t-1}$	4.62**		4.52**		1.62***		4.42*		5.02*	
	(2.01)		(2.00)		(5.32)		(1.79)		(1.79)	
$Diff\ Ind\ Subs_{i,t-1}$		8.64**		8.32**		1.97***		14.62**		5.56***
		(2.16)		(2.19)		(6.18)		(2.12)		(3.28)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	74,749	60,620	69,752	56,567	49,065	39,790	19,205	15,574	6,417	5,204
R^2	0.11	0.11	0.11	0.11	0.13	0.13	0.18	0.19	0.27	0.28

Table 7: Predictive power between major and minor

This table compares the predictive power between major ownership subsidiaries and minor ownership subsidiaries by using Fama and MacBeth (1973) regressions. The dependent variable is excess returns of parent firm i on month t in five samples, Global, Global ex USA, Asia-Pacific, Europe, and North America. The two independent variables of interest are major ownership subsidiaries on month t-1 and minor ownership subsidiaries on month t-1. Control variables are same as in Table 2. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms from twenty-three developed markets from January 2008 to December 2017.

excess return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
*100	Global	Global	Global ex USA	Global ex USA	Asia-Pacific	Asia-Pacific	Europe	Europe	North America	North America
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Maj\ own\ Subs_{i,t-1}$	6.31*		5.03*		1.62***		5.74*		2.61***	
	(1.69)		(1.87)		(4.94)		(1.91)		(4.15)	
$Min\ own\ Subs_{i,t-1}$		6.79***		9.28**		2.08***		10.42**		5.82***
		(2.80)		(2.10)		(5.40)		(2.28)		(4.29)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	86,144	36,805	80,385	34,345	56,544	24,158	22,132	9,456	7,396	3,160
R^2	0.10	0.11	0.11	0.12	0.13	0.13	0.18	0.19	0.28	0.29

Table 8: Mechanisms

This table reports Fama-MacBeth forecasting regressions of individual stock returns. The dependent variable is the monthly excess return of the parent firm. The explanatory variables are the lagged subsidiaries return ($Subs_{i,t-1}$), and a number of interaction terms with this variable. There are seven variables to explain and understand different mechanisms, ownership complexity, limits-to-arbitrage, relative sizes of subsidiaries, and limited investor attention, respectively. OCI is ownership complexity index based on the ownership stakes of the given parent in previous calendar year. Idio Vol is the idiosyncratic volatility in previous calendar year. MktCap is the market capitalization of the parent at the end of December in previous calendar year. Size_S/Size_P is the ratio of market capitalization of the subsidiary over market capitalization of the parent at the end of December in previous calendar year. Res Inst Own is institutional ownership of the parent firm orthogonalized with regard to firm size at the end of December. Turnover is the turnover measured as the average daily turnover in the prior year, and No. Analysts is the number of analysts covering the firm at the end of December in previous calendar year. All interaction terms are based on indicator variables that take the value of one if the underlying variable is above the sample median in each year and zero otherwise. All regressions also include the dummy itself, and lagged control variables. Control variables are same as in Table 3 and are unreported for brevity. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms from twenty-three developed markets from January 2008 to December 2017.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
*100	Global	Global	Global	Global	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Subs_{i,t-1}$	9.12***	3.68***	8.53***	3.22***	8.86***	7.77***	8.26***
	(3.28)	(2.72)	(3.14)	(2.87)	(2.98)	(2.76)	(2.69)
$Subs_{i,t-1}$ * (OCI > Median)	-5.93***						
	(-3.05)						
$Subs_{i,t-1}$ * (Size_S/Size_P > Median)		4.38***					
		(3.23)					
$Subs_{i,t-1}$ * (MktCap > Median)			-4.88***				
			(-3.18)				
$Subs_{i,t-1}$ * (Idio Vol > Median)				5.23***			
				(3.35)			
$Subs_{i,t-1}$ * (Res Inst Own > Median)					-5.23**		
					(-1.97)		
$Subs_{i,t-1}$ * (Turnover > Median)						-3.28*	
						(-1.76)	
$Subs_{i,t-1}$ * (No. Analyst > Median)							-4.44*
							(-1.89)
CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	113,947	113,947	113,947	113,947	113,947	113,947	113,947
R^2	0.13	0.13	0.12	0.12	0.11	0.11	0.11