5-2021

Internal capital markets and return predictability in complex ownership firms

Angelica GONZALEZ
University of Edinburgh

Sergei SARKISSIAN
University of Edinburgh

Jun TU
Singapore Management University, tujun@smu.edu.sg

Ran ZHANG
Shanghai Jiaotong University

Return Predictability in Firms with a Complex Ownership Network

Angelica Gonzalez
University of Edinburgh

Sergei Sarkissian
McGill University and University of Edinburgh

Jun Tu
Singapore Management University

Ran Zhang
Shanghai Jiao Tong University

First draft: November 20, 2017
This draft: November 15, 2020

*Gonzalez is from University of Edinburgh, Business School, EH8 9JS, United Kingdom; email: angelica.gonzalez@ed.ac.uk. Sarkissian is from McGill University, Montreal, H3A 1G5, Canada and University of Edinburgh, Edinburgh, EH8 9JS, United Kingdom; email: sergei.sarkissian@mcgill.ca. Tu is from Singapore Management University, Lee Kong Chian School of Business, 178899, Singapore; email: tujun@smu.edu.sg. Zhang is from Shanghai Jiao Tong University, Antai College of Economics & Management, Shanghai, 200030, China; email: r.zhang@sjtu.edu.cn. We would like to thank Maria Boutchkova, Lauren Cohen (discussant), Amit Goyal, Bing Han, Gbenga Ibikunle, David McMillan, Ni Peng (discussant), Yilmaz Yildiz (discussant), Jianfeng Yu, Lu Zheng (discussant), and Guofu Zhou for their numerous insightful suggestions, as well as acknowledge the insights received from the participants of the 2019 American Finance Association, the 2018 European Financial Management Association, the 2018 Financial Management Association Doctoral Consortium, and the 2018 Multinational Finance Society meetings, as well as from the participants of seminars at Fudan University, Shanghai Jiao Tong University, Shenzhen Audencia Business School, Southern University of Science and Technology, Southwestern University of Finance and Economics, Sun Yat-sen University, University of Edinburgh, University of Science and Technology of China, University of Washington, and Xiamen University. Sarkissian acknowledges financial support from the Social Sciences and Humanities Research Council (SSHRC). Tu acknowledges financial support from the Sim Kee Boon Institute for Financial Economics. Zhang acknowledges financial support from the Shanghai Institute of International Finance and Economics. This paper is sponsored by Shanghai Pujiang Program. An earlier version of this paper was circulated as "Ownership Links and Return Predictability".

Return Predictability in Firms with a Complex Ownership Network

Abstract

Using global cross-ownership data, we find return predictability for four possible cases in ownership-linked firms (OLFs): subsidiary−parent, parent−subsidiary, subsidiary−subsidiary, and parent−parent. A long/short portfolio strategy sorted by the lagged monthly returns of OLFs yields the monthly Fama-French six-factor alpha of 79−113 bps. These results, which are observed only after the establishment of ownership links, are not subsumed by industry or cross-country momentums or by alternative inter-firm relations, including customer−supplier links, strategic alliances, common boards, and shared analyst coverage. The OLF return predictability is best explained by active internal capital markets—a mechanism unique to firms with a complex ownership network.

JEL Classification: G11, G14, G15
Keywords: Decision-making commonality, Earnings surprises, Investors' inattention, Limits to arbitrage

1. Introduction

Stock return predictability is among the most widely studied phenomena that challenge the notion of efficient capital markets. Despite the richness of past research on return predictabilities or cross-sectional return anomalies based on hundreds of firm characteristics,[1] the question whether the ownership network can drive return predictability among ownership-linked firms (thereafter refers to as OLFs) remains open. A major challenge in addressing this question is that OLFs can have other ties among themselves, such as various economic links and common board members that are not necessarily related to their ownership network. In this paper, we address this challenge using a global cross-ownership data panel and exploring the mechanisms that are unique to OLFs.

In contrast to the usual simple ownership of US firms where one parent (subsidiary) firm may have only one subsidiary (parent), globally, publicly listed parent firms tend to have a more complex ownership structure where parent firms frequently have multi-layer and multi-country subsidiaries (La Porta et al., 1999; Bertrand and Sendhil, 2003). In this setting, information transmission delays and associated return predictability can occur across four ownership structures (see Figure 1). The first two structures—namely, subsidiary−parent and parent−subsidiary—are vertical and can be directly or indirectly connected to each other. The second two structures—namely, subsidiary−subsidiary, connected through common parent firms, and parent−parent, connected through common subsidiaries—are horizontal and can be directly or indirectly connected to each other.[2] The two vertical structures with direct links are the only possible ones for a simple one-parent−one-subsidiary ownership case. The two horizontal structures and all indirect configurations are additional possibilities that exist only in a complex multi-parent−multi-subsidiary ownership network and, therefore, are essential for a better understanding of the drivers of predictability. For instance, firms with complex ownership links frequently have significant internal capital market activities, which are not always optimal and

[1] For the long list of such anomalies and their chronology, see Harvey et al. (2016).
[2] Within horizontal ownership structures, a direct link is assumed when two subsidiaries are directly connected to a common parent firm or when two parent firms are directly connected to a common subsidiary.

value-enhancing (Stulz, 1990; Meyer et al., 1992; Lamont, 1997; Shin and Stulz, 1998) and may lead to delayed information diffusion into stock prices (Hong and Stein, 1999; 2007). Therefore, complex ownership structure makes it possible to investigate the mechanisms unique to OLFs, such as active internal capital markets, as an opportunity to directly examine whether ownership links can induce cross-firm return predictability. In addition, a substantially larger cross-section of ownership connection configurations can help to more confidently determine the probable sources of any ownership-linked predictability.

In this paper, we examine return predictability among OLFs using a global sample across 23 developed markets in 2006−2018; after data filtering, the sample contains 2,052 parent firms and 3,664 subsidiaries. We observe return predictability in all four possible cases of ownership network—namely, parent−subsidiary, subsidiary−parent, subsidiary−subsidiary, and parent−parent. Based on this global sample of firms with complex ownership structure, we propose two mechanisms specific to OLFs: (1) ownership complexity (as a type of firm information complexity) and (2) active internal capital markets (ICMs) that may induce return predictability in OLFs. ICMs dominate all other mechanisms, including two commonly used explanations—investors' inattention and limits to arbitrage—in explaining return predictability in OLFs.

We find that subsidiaries' information has a significant predictive ability for parent firm's future stock returns. World-wide, the Fama and French (2018) six-factor alpha is on average 113 bps (t-statistic = 3.66) per month: it is the difference between the value-weighted parent firms' portfolio alpha with the highest past month return of ownership-weighted subsidiaries' portfolio and that with the lowest past month return of ownership-weighted subsidiaries' portfolio. To test parent−subsidiary return predictability, we apply the following strategy. For each subsidiary in a given month, we calculate the control-weighted portfolio return of parent firms that own the subsidiary with at least 20% stakes. Next, we sort subsidiaries into quintile portfolios using the returns earned by a portfolio of their parent firms in the previous month. We find that the lagged parent firms' portfolio return predicts the next month subsidiaries' return. Specifically, a portfolio long in subsidiaries, i.e. whose parent firms showed the best performance in the previous month, and short in subsidiaries, i.e. whose parent firms performed the worst in the previous month, yields the value-weighted monthly six-factor alpha of 77 bps (t-statistic = 2.54). A similar approach yields the same monthly alphas of subsidiary−subsidiary and parent−parent return predictabilities of 76 bps and 79 bps, respectively. Over a period of four to five months, all four types of OLF return predictabilities monotonically decrease to zero.

The results of multivariate Fama-MacBeth cross-sectional regression tests with various firm-, industry-, and country-level control variables show that the predictive relationship between past-month returns of OLFs and next-month returns of the focal firm retains its economic and statistical significance for all four types of ownership links. Furthermore, we show that the new predictability phenomenon is not subsumed by industry or cross-country momentums or by various alternative inter-firm relations, including customer−supplier links, strategic alliance partners, common institutional investors, common board members, and shared analyst coverage. We also observe the largest predictability for the subsidiary−parent link and the lowest predictability for the parent−parent link, which may be due to the relative strength of the ownership connection across the four types of links. Finally, OLFs show predictability not only for firms' returns, but also for their fundamental performance metrics, such as the focal firm's unexpected earnings. This indicates that, due to the complicated information processing across OLFs, the impact of news (unexpected earnings) of OLFs on the earnings of the focal firm may not be fully digested by the financial analysts of the focal firm; therefore, the unexpected earnings of OLFs can predict the earnings surprises of the focal firm.

To address endogeneity concerns, we analyze return predictability of OLFs around the changes in the cross-firm ownership structure. To this end, we use the difference-in-difference method and a four-year time window comprising two years before and two years after the event. Our expectation is that OLFs would exhibit return predictability only after the formation of cross-firm ownership links. We divide the sample into two groups: while the "treatment" group comprises all cases where a firm without an ownership link transitions into a firm with an ownership link, the "control" group of firms includes companies without ownership changes. The two groups are then matched by industry and based on the following four firm characteristics: market capitalization, book-to-market ratio, asset growth, and gross profitability. In line with our expectations, our results reveal the existence of return predictability after changes in ownership only in the treatment group, i.e. for those firms that form ownership links. We do not observe return predictability of OLFs in the control group either before or after the (pseudo) date of change in ownership links.

These empirical results are consistent with the *ex-ante* expected return predictability due to the expectedly complicated information processing across OLFs with ICMs. For instance, Berger and Ofek (1995) showed that several ICM activities, such as overinvestment and cross-subsidization, decrease information processing efficiency. However, we additionally consider four other mechanisms that also could potentially affect the phenomenon of return predictability in OLFs. The first of these four mechanisms is the investors' limited attention (Huang, 2015; Lee et al., 2019; Ali and Hirshleifer, 2020). The second mechanism is limits to arbitrage (Shleifer and Vishny, 1997). The third is the commonality of decision making in OLFs, which may result from common board members (Burt et al., 2020), common institutional investors (Gao et al., 2017), or shared analysts (Ali and Hirshleifer, 2020). Finally, the fourth additional mechanism is ownership complexity of focal firms, which is a type of information complexity associated with firm complexity (Daniel et al. 1998; 2001; Hirshleifer, 2001; Cohen and Lou, 2012). Of the aforementioned five mechanisms, limited attention and limits to arbitrage are two generic mechanisms commonly used in the predictability literature, while ICM and ownership complexity are the mechanisms that are unique to the ownership network context and that are newly proposed in this study. Commonality of decision making is another newly proposed mechanism. In subsequent individual tests and horseraces among the above five potential reasons, we find that, focal firms exhibit a slow price response to their OLF returns mostly due to active ICMs, and, in part, owing to the complexity of ownership structure itself. We further substantiate the predominant role of ICMs in explaining return predictability in OLFs by showing their importance particularly for OLFs located in countries with more opaque capital markets and a weaker rule of law.

Return predictability among firms with economic links is well documented in previous research. For instance, Cohen and Frazzini (2008) evaluated predictability between customers and suppliers. Furthermore, Huang (2015) and Finke and Weigert (2017) established that information from foreign operations gradually dilutes into stock prices of multinational firms. Likewise, Cao et al. (2016) found that strategic alliance firm partners exhibits return predictability. However, economic and ownership links are different in their nature. Specifically, while economic links refer to the firm's supply chain network and reflect the firm's sales and operations activities, ownership links refer to the company's shareholding network, reflecting the company's investment and financing status. Along with potential economic and business activities, firms within the ownership network may also have other complex and opaque relationships. For instance, ICM activities, such as overinvestment or cross-subsidization, can complicate investors' understanding of information from firms linked to each other through complex ownership.

Return predictability in firms with a complex ownership network remains poorly understood. For instance, Li et al. (2016)—to the best of our knowledge, the only concurrent study on a similar subject – documented that the lagged returns of US local subsidiaries (parent firms) can predict returns of US parent firms (subsidiaries). Of note, however, our study differs from Li et al. (2016) in two important dimensions. First, observing return predictability across OLFs does not imply that it is driven by the ownership network itself, since it may result from economic or other links across firms. In this respect, Li et al. (2016) showed that, once the intra-industry lead-lag relation is controlled for, their parent-subsidiary return predictability disappears. While many previous studies adopted such indirect approach of accounting for alternative explanations of cross-firm return predictability, this approach always leaves the possibility that other unaccounted links are driving the results. In contrast, we not only use the usual indirect approach to show that economic links do not drive our findings, but also provide the ownership network-based mechanisms, such as the ICM activities, and show that these mechanisms can directly explain return predictability in OLFs. Together, our results based on using direct and indirect approaches confirm the parent-subsidiary return predictability, implying that Li et al.'s (2016) results may be fragile. The second dimension of difference between our study and Li et al. (2016) is that, unlike Li et al. (2016), we also examine return predictability in OLFs for all four possible cases of ownership network, including subsidiary−subsidiary and parent−parent.

The rest of the paper is organized as follows. Section 2 describes the data and empirical methodology. Section 3 reports the results of the univariate analysis of return predictability in OLFs. Section 4 presents our main tests in a multivariate framework. In this section, we also analyze changes in the OLF return predictability in response to ownership link changes. Section 5 discusses the mechanisms to explain return predictability in OLFs. Section 6 concludes.

2. Data and Predictors

In this section, we describe our global ownership data sample and introduce OLF predictors for the four types of OLFs. We also provide the summary statistics for parent firms and subsidiaries.

2.1. Data

Our sample covers parent firms and subsidiaries from 23 developed markets defined by Fama and French (2012; 2017) and for which risk factors are available in the K. French library. These markets include 2 North American markets (Canada and the United States), 16 European markets (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom), Japan, and 4 Asia-Pacific markets (Australia, Hong Kong (China), New Zealand, and Singapore). We collect price, volume, and return data for US firms and non-US firms from the Centre for Research in Security Prices (CRSP) and Refinitiv Eikon, respectively. Institutional ownership data and analyst coverage for all firms in the sample come from FactSet Ownership and Refinitiv I/B/E/S, respectively. We also collect ownership links and shareholding percentages data from the merged Orbis-FactSet database.[3] Since FactSet provides the data from 1999, while Orbis' data are available only from 2005, the starting year of the merged dataset is set to 2005. The total number of available distinct parent firms and subsidiaries from the Orbis-FactSet database is 3,862 and 8,970, respectively.[4] To avoid market microstructure problems, stocks with prices below $5 are excluded from the analyses. We cover all industrial firms and exclude the financial sector (with two-digit NAICS code = 52). The sample period is from January 2006 to December 2018 and contains a total of 156 monthly observations. All stock returns are denominated in US dollars. To calculate monthly excess returns in all markets, we use the one-month US T-bill rate.

Since our aim is to examine return predictability in ownership networks, there should be a reasonable cut-off for ownership stakes. In previous studies, La Porta et al. (2000) set at least 10% voting rights to define a large ownership stake, while Claessens et al. (2000) used a 20% cut-off. Furthermore, based on recent updates to International Financial Reporting Standards (IFRS) for publicly traded firms, a company is assumed to have a significant influence in another company if its ownership in that company is no less than 20%.[5] Accordingly, we also use 20 percent of ownership as a cut-off.[6] To test the OLF return predictability from January 2006 to December 2018, we collect 13 annual time-varying ownership links from 2005 to 2017. The resulting sample contains a total of 2,052 parent firms and 3,664 subsidiaries.

---

[3] We cross-validate the ownership links and shareholding data in Orbis and FactSet—the two main data sources that provide ownership links and shareholding percentages. Instead of using either one of these datasets separately, we merge them. This is done for the following reasons. Firstm, while Orbis provides detailed parent and subsidiaries information for each focal firm, their shareholding percentages are not always numerical. Second, although FactSet only provides the main owner/parent firm to each focal firm, their shareholding percentages are numerical. Therefore, the merged dataset uses the advantages of both data sources and starts from 2006. Following Kalemli-Ozcan et al. (2015), we decode non-numeric indicators of percentage shares owned by a parent firm.

[4] The US-based sample used by Li et al. (2016) before filtering contains 543 parent firms and 732 subsidiaries. However, after filtering, Li et al. (2016) obtained a stock sample of "28,101 distinct parent-month observations". Since their stock sample period was 26 years (1985-2010), the average number of parent firms each month was 90, which is also the number of observations in Column (1) of Table 6 in Li et al. (2016) and similar to that in our US subsample. Consequently, Li et al. (2016) used only about 18 firms in each quintile portfolio, which raises the possibility of non-systematic risks in such under-diversified portfolios.

[5] See http://www.ifrs.org/issued-standards/list-of-standards/ias-28-investments-in-associates-and-joint-ventures.

[6] We also use the ownership cut-off levels of 10%, 15%, 25%, and 30%; however, our main findings remain intact.

2.2. Four predictors of ownership-linked firms

The first regressor of interest to us is the one month lagged return of subsidiaries, $Sub_{i,t-1}$, which is constructed as the ownership-weighted portfolio returns of all subsidiaries of parent firm i (see Eq. (1)):

$$Sub_{i,t-1} = \sum_j Own_{i,j,t-1} \times R_{j,t-1}, \tag{1}$$

where $Own_{i,j,t-1}$ is parent firm i's ownership stake in subsidiary j in month $t-1$, and $R_{j,t-1}$ is the subsidiary j's return in month $t-1$. $Own_{i,j,t-1}$ is defined as:

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

where $ShareHold_{i,j,t-1}$ is parent firm i's shareholding percentages in subsidiary j in month $t-1$, and $Size_{j,t-1}$ is the market capitalization of subsidiary j in month $t-1$. Let us assume that a parent firm P has two subsidiaries in its first layer, $S1$ and $S2$, while $S1$ also has a subsidiary $S11$ in its first layer. Then, $S11$ is the second-layer subsidiary for parent firm P. Then let us suppose that the market capitalizations of P, $S1$, $S2$, and $S11$ are 200 million, 100 million, 50 million, and 50 million, respectively. In addition, parent firm P has shareholdings of 60% and 100% in $S1$ and $S2$, respectively, while $S1$ has a shareholding of 50% in $S11$. Said differently, P has a shareholding of 30% in $S11$. Then, the subsidiaries predictor, $Sub_{i,t-1}$, is calculated as follows:

$$Sub_{i,t-1} = \frac{60\% \times 100 \times R_{S1,t-1} + 100\% \times 50 \times R_{S2,t-1} + 30\% \times 50 \times R_{S11,t-1}}{60\% \times 100 + 100\% \times 50 + 30\% \times 50}.$$

The second regressor of interest to us is the one month lagged return of parent firms, $Par_{i,t-1}$, constructed here as the control-weighted portfolio returns of all parent firms of subsidiary i (see Eq. (2)):

$$Par_{i,t-1} = \sum_j Control_{i,j,t-1} \times R_{j,t-1}, \tag{2}$$

where $Control_{i,j,t-1}$ is subsidiary i's stake controlled by parent firm j in month $t-1$, and $R_{j,t-1}$ is parent firm j's return in month $t-1$, while $Control_{i,j,t-1}$ is defined as:

$$Control_{i,j,t-1} = \frac{ShareHold_{i,j,t-1}}{\sum_j ShareHold_{i,j,t-1}},$$

where $ShareHold_{i,j,t-1}$ is subsidiary i's shareholding percentages controlled by parent firm j in month $t-1$. Let is suppose some subsidiary S has two parent firms in the first layer, $P1$ and $P2$, while $P1$ also has a parent firm $P11$ in its first layer. Then, $P11$ is the second-layer parent firm for subsidiary S. Let is suppose that $P1$ holds a 30% stake in S, $P2$ holds 20% stakes of S, while $P11$ has a 50% shareholding in $P1$. Said differently, $P11$ has a shareholding of 15% in S. Then, the subsidiaries predictor, $Par_{i,t-1}$, is calculated as:

$$Par_{i,t-1} = \frac{30\% \times R_{P1,t-1} + 20\% \times R_{P2,t-1} + 15\% \times R_{P11,t-1}}{30\% + 20\% + 15\%}.$$

Finally, the third and fourth predictors are the one month lagged returns of sister subsidiaries, $Sis\_Sub_{i,t-1}$, which are subsidiaries with common parent firms, and sister parent firms, $Sis\_Par_{i,t-1}$, which are parent firms with common subsidiaries. These two predictors are straightforwardly constructed based on the value-weighted portfolio returns of sister subsidiaries of subsidiary i and sister parent firms of parent firm i, respectively (see Eqs. (3)-(4)):

$$Sis\_Sub_{i,t-1} = \sum_j w_{i,j,t-1} R_{j,t-1}, \tag{3}$$

and

$$Sis\_Par_{i,t-1} = \sum_j w_{i,j,t-1} R_{j,t-1}, \tag{4}$$

where $w_{i,j,t-1}$ is subsidiary (parent firm) i's sister subsidiary (parent firm) j's weight in month $t-1$, and $R_{j,t-1}$ is sister subsidiary (parent firm) j's return in month $t-1$.[7]

Table 1 reports the summary statistics for listed parent firms and subsidiaries from 23 developed markets. Firm characteristics include firm's market capitalization, book-to-market ratio, asset growth, gross profitability, and momentum. All variables are defined in the Appendix and are winsorized within each cross-section at 1% and 99% levels. Panel A reports the full

[7] Note that any of the four ownership links can be either direct or indirect. A parent firm (subsidiary) is directly linked to a subsidiary (parent firm) if they are connected without an intermediate subsidiary (a parent firm). Similarly, sister subsidiaries (sister parent firms) are directly linked if they are connected through a parent firm (a subsidiary) without any intermediate subsidiary (a parent firm).

sample summary statistics of parent and subsidiary firms and for the four types of OLFs: subsidiary−parent (Sub−Par), parent−subsidiary (Par−Sub), subsidiary−subsidiary (Sub−Sub), and parent−parent (Par−Par). The average numbers of parent firms and subsidiaries in our sample are 1,287 and 2,208, respectively. Each parent (subsidiary) firm has two subsidiaries (one parent firm) in the median. Similarly, the median number of sister subsidiaries (parent firms) is two (one). However, the maximum number of subsidiaries for a given parent firm is nine, while the maximum number of parent firms for a given subsidiary is four.

Panel B of Table 1 reports country-level statistics on the number of parent firms and subsidiaries, as well as the average number of sister subsidiaries and sister parent firms. Columns 1-2 show the yearly average number of parent firms and subsidiaries in each country, while Columns 3-4 show the average number of subsidiary−parent and parent−subsidiary links in each country, respectively. Columns 5-6 show the average number of links between sister subsidiaries and sister parent firms in each country, respectively. The largest number of both parent firms and subsidiaries—476 and 949, respectively—are in Japan, followed by France (132 parent firms and 217 subsidiaries). Japanese firms also have the largest average number of subsidiaries per parent firm and parent firms per subsidiary—3.50 and 1.93, respectively.

Panel C of Table 1 reports the summary statistics of the five firm characteristics for parent firms and subsidiaries. We can see that, on average, parent firms are more than six-fold larger than subsidiaries. The other four firm characteristics for parent firms and subsidiaries are almost identical—except for average and median momentum, which is over 50% larger for subsidiaries than parent firms. This finding is consistent with the understanding that, due to less efficient pricing, smaller firms show a higher momentum as compared to larger firms.

3. Univariate Analysis

This section reports univariate analysis of stock return predictability in a complex ownership network. Our aim is to examine cross-sectional variation in expected returns of OLFs in response to a common predictor. We start with one-period return predictability tests on the full data sample.

We then also perform long-term predictability tests.

3.1. Univariate portfolio sort tests of short-term OLF return predictability

First, we examine the existence of the following four OLF return predictability patterns: subsidiary−parent, parent−subsidiary, subsidiary−subsidiary, and parent−parent. To accomplish this for each month t, we rank parent firm (or subsidiary) returns based on the ranking of their subsidiaries' (or parent firms') portfolio returns in month $t-1$. Similarly, for each month t, we rank subsidiary (or parent firm) returns based on the ranking of their sister subsidiaries' (or sister parent firms') portfolio returns in month $t-1$. In the next step, we classify parent firm (or subsidiary) stocks into five quintiles where Quintile 1 has the lowest lagged subsidiaries' (or parent firms') portfolio returns, while Quintile 5 has the highest lagged subsidiaries' (or parent firms') portfolio returns. Then, we report the value-weighted and equally-weighted portfolio returns of the lowest and highest quintiles, as well as the hedged portfolio returns of Quintile 5 minus Quintile 1 (i.e. Q5–Q1) with the corresponding statistical significance level.

Table 2 reports the test results of value- and equally-weighted univariate portfolio sorts for four types of return predictabilities in OLFs using the excess and risk-adjusted returns. Panel A shows the excess returns for all five quintile portfolios, as well as the results for the Q5-Q1 difference portfolio. Column 1 in Panel A shows that the excess returns of parent firm stocks with the highest lagged one month returns of subsidiaries' portfolio is significantly higher than the corresponding values with the lowest lagged one month returns of subsidiaries' portfolio. The value-weighted parent firms' stocks in the highest quintile earn an average monthly excess return of 99 bps, as compared to that of –19 (i.e. negative 19) bps for the value-weighted parent firms' stocks in the lowest quintile. The return spread is 118 bps, and it is significant at the 1% level. The equally-weighted portfolio return spread is 143 bps and again has 1% significance level. Columns 2-4 show similar evidence for both value-weighted and equally-weighted portfolios of predictor firms' returns across the remaining three OLF return predictability directions. The value-weighted spread is 97 bps in the parent−subsidiary case, 85 bps in subsidiary−subsidiary case, and 103 bps in the parent−parent case.

In Panel B, we use a global version of the Fama and French (2015) five-factor model. Column 1 shows that the five-factor alpha (α_FF5) of parent firm stocks with the highest lagged one month returns of subsidiaries' portfolio is significantly higher than the corresponding values with the lowest lagged one month returns of subsidiaries' portfolio. The value-weighted parent firms' stocks in the highest quintile earn the average monthly α_FF5 of 30 bps, as compared to that of –83 (i.e. negative 83) bps for the value-weighted parent firms' stocks in the lowest quintile. The return spread is 113 bps, and it is significant at the 1% level. The equally-weighted portfolio return spread is 122 bps and has the same 1% significance level. Columns 2-4 provide similar evidence for both value-weighted and equally-weighted portfolios of predictor firms' returns across the remaining three OLF return predictability directions. The value-weighted spread is 82 bps, 73 bps, and 88 bps in the parent−subsidiary, subsidiary−subsidiary, and parent−parent cases, respectively.

Finally, in Panel C of Table 2, we use the Fama and French (2018) six-factor model to capture abnormal returns. The Fama and French (2018) six-factor model adds a momentum factor into the Fama and French (2015) five-factor model. After this change, the value-weighted and equally-weighted portfolio risk-adjusted returns (α_FF6) of the subsidiary−parent predictability become 113 bps and 126 bps, respectively. The value-weighted spreads for parent−subsidiary, subsidiary−subsidiary, and parent−parent OLF return predictability directions are 77 bps, 76 bps, and 79 bps per month, respectively. Taken together, the results in Table 2 demonstrate the economically and statistically significant return predictability among firms with ownership links.[8]

3.2. Univariate portfolio sort tests of long-term OLF return predictability

It is important to understand whether or not the observed predictability lasts several periods after the formation of the corresponding OLF portfolios. To explore this possibility, in Table 3, we

[8] In the Internet Appendix, we report the results of the OLF return predictability tests across time periods and different geographic regions and find highly statistically significant results in all these tests.

show the long-term portfolio alphas of value-weighted univariate portfolio sorts of focal firms for all four types of return predictabilities in OLFs. The table reports monthly risk-adjusted return from two to six months ahead after the portfolio formation. Panel A provides the abnormal returns for the Q5-Q1 difference portfolio using the Fama and French (2015) five-factor model, α_FF5. We observe a monotonic decrease in economic and statistical predictability over time across all four types of ownership links. Some statistical evidence of predictability (at the 10% level) for the subsidiary−parent case remains up until the month $t + 5$, while that for the other three types of ownership links persists up to month $t + 4$.

Panel B reports the abnormal returns for the Q5-Q1 difference portfolio using the Fama and French (2018) six-factor model, α_FF6. Overall, the predictability patterns are similar to those in Panel A of Table 3. Specifically, across all columns of the table we again observe a steady decrease in the OLF return predictability. However, the decrease in predictability is less steep. While we still observe marginal predictability in subsidiary−parent and parent−subsidiary cases in month $t + 6$, that for subsidiary−subsidiary and parent−parent cases lasts until month $t + 5$, rather than until month $t + 4$ as in the previous panel. In summary, the results of univariate tests in Tables 2 and 3 provide a consistent picture of the existence of short-term return predictability in OLF that dissipates over the course of several months.[9]

4. Multivariate Analysis

In this section, we use Fama and MacBeth's (1973) regressions to analyze whether stock return predictability within ownership networks remains robust after controlling for major risk factors and different firm characteristics. We then demonstrate that the OLF predictability is also present for focal firm's fundamental performance metrics. In addition, we address the endogeneity concerns that could influence our results on return predictability in OLFs.

[9] In the Internet Appendix, we report the results of univariate test based on risk-adjusted returns and long-term portfolio alphas as in Tables 2 and 3, respectively, but with Burt and Hrdlicka's (2020) adjustment. This adjustment does not considerably affect our results.

4.1. Multivariate regressions of OLF return predictability

The stock level's Fama-MacBeth regression consists of the following two steps. In the first step, we use cross-sectional regression in each month as following:

$$ret_{i,t} = \lambda_{0,t} + \lambda_{1,c,t} + \lambda_{2,d,t} + \lambda_{3,t}\, OLF_{i,t-1} + \lambda_{4,t}{}'\, \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t}, \tag{5}$$

where $ret_{i,t}$ is the excess return of focal firm's stock i in month t; $\lambda_{1,c,t}$ is a country-specific dummy variable, equal to one if focal firm i is from country c, and zero otherwise; $\lambda_{2,d,t}$ is a industry-specific dummy variable, equal to one if focal firm i is in industry d, and zero otherwise (using two-digit NAICS codes); $OLF_{i,t-1}$ is one of the lagged return predictors—namely, $Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, and $Sis\_Par_{i,t-1}$ in different specifications. The control vector of lagged variables, $\boldsymbol{X}_{i,t-1}$, includes $Ln(Size)$, the log of firm size; $Ln(B/M)$, the log of book-to-market equity ratio; return momentum, Mom, the cumulative return of stock i from month $t-12$ to month $t-2$ (Jegadeesh and Titman, 1993); $R_{i,t-1}$, the stock return of focal firm i in month $t-1$; *Turnover*, the number of shares traded divided by the number of shares outstanding during a day, averaged over the past 12 months (Rouwenhorst, 1999); asset growth, AG, the year-over-year growth rate of total assets (Cooper et al., 2008); gross profitability, GP, the revenue minus cost of goods sold scaled by assets (Novy-Marx, 2013); and industry momentum, Ind_Mom (Moskowitz and Grinblatt, 1999). To compute standard errors, we use the Newey-West adjustment with six lags.[10]

Table 4 summarizes the results of the tests based on the multivariate regressions, including the point estimates, their absolute *t*-statistics, as well as the number of observations and the adjusted R-squared. Panel A shows estimations across the four types of the OLF predictability directions based on focal firms' excess returns as the dependent variable. The results in this panel demonstrate that all four OLF predictors—namely, $Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, and $Sis\_Par_{i,t-1}$—are positive and statistically significant at the 1% level for their respective dependent variables, i.e. the excess returns of parent, subsidiary, sister subsidiary and sister

[10] The choice of the lag length from 1 to 12 does not influence the statistical significance of any of the tests.

parent firms. In line with our expectation, in economic terms, return predictability is stronger among the firms with closer vertical ownership links, such as subsidiary–parent, followed by parent–subsidiary, and weaker for the firms with more distant horizontal ownership links, such as subsidiary–subsidiary and especially parent–parent. While explaining the relative strength of return predictability between the first two vertical ownership connection cases may be difficult, understanding the weakest predictability evidence for the horizontal parent-parent link is more straightforward. In this case, on average two larger firms are ownership-connected only through a much smaller company, their common subsidiary (see Table 1, Panel C). Therefore, for such connection, regardless of the underlying source of information delay between the two constituent ownership links—namely, from one large parent firm to a small subsidiary or from the same subsidiary to the second large parent firm—its strength should ultimately be lower than that over the two separate links. Of note, the predictive power of all four lagged OLF returns is not subsumed by the control variables.

Panels B and C of Table 4 report similar estimations using risk-adjusted returns as dependent variables. The risk-adjusted returns (alphas) for focal firm i in month t are computed as the difference between focal firm i's excess return and its expected factor returns based on the Fama and French (2015) five-factor model (Panel B) and the Fama and French (2018) six-factor model (Panel C) in month t, α_FF5, and α_FF6, respectively. In our estimations, we use regional risk factors, Mkt, Smb, Hml, Rmw, Cma, and Mom from Kenneth French's website.[11] Following Fama and French (1992), Cao et al. (2016), and Finke and Weigert (2017), we calculate factor loadings for each focal firm using a time-series regression over the entire sample period.[12] For the sake of conciseness, we omit reporting the estimates of control variables in these two panels. Overall, the results are similar to those in Panel A of Table 4. Again, all four OLF predictors—$Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, and $Sis\_Par_{i,t-1}$—are positive and significant at the 1% level prediction ability for the risk-adjusted

[11] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[12] We obtain similar results using rolling estimates.

returns (α_FF5, and α_FF6) of parent, subsidiary, sister subsidiary, and sister parent firms. Interestingly, the magnitude of the corresponding point estimates is only marginally smaller than those in Panel A for excess returns. In addition, as can be seen Panel A, the largest predictability is recorded for the subsidiary−parent link, while the lowest – for the parent−parent one (in Panel C, the coefficients on $Sub_{i,t-1}$ and $Sis\_Par_{i,t-1}$ are 3.02 and 1.03, respectively). Therefore, similarly to the results of univariate tests, the multivariate regressions setting also provides evidence of a strong predictive effect of the lagged returns of OLFs for stock returns of focal firms, both excess and risk-adjusted.[13]

A reader might suggest that firm's ownership links pick up alternative links between firms, such as supplier−customer relations, strategic alliance partners, common board members, shared analyst coverage, and so forth. Therefore, it may be assumed that the observed return predictability in OLFs simply reflects the predictability effects reported in earlier studies. Due to the scarcity of international data on inter-firm linkages, we address this concern in the following two ways (see the Internet Appendix).

First, we repeat univariate and multivariate estimations on the sample of financial firms from 23 developed markets. These firms differ from those in all other industries by their lack of any explicit economic linkages. Our test results are similar to those in Panel C of Tables 2 and 4, implying that OLF return predictability in OLFs does not require any direct economic links among firms with ownership links.

Second, we repeat our estimations in Table 4 on the US firm sample only, for which various inter-firm data are available. In this sample, there is no parent−parent case and only 19 subsidiary−subsidiary cases, which limit our estimations to only two ownership links: subsidiary−parent and parent−subsidiary.[14] The independent variables accounting for other

---

[13] We also re-run the tests in Table 4 with an addition of cross-country momentum proxy—namely, the lagged return on the equally-weighted equity market indices from the OLF countries. This alteration has negligible impact on our findings in all estimations. These results are available upon request. In the Internet Appendix, we also report univariate and multivariate test results of OLF return predictability for firms from 26 emerging markets.

[14] For instance, we find that only four out of 109 subsidiaries are customers of their parent firms, and only 10 out of 90 parent firms are customers to their subsidiaries.

inter-firm relations added to the tests are as follows: (1) the lagged supplier industry momentum of the focal firm; (2) the lagged customer industry momentum of the focal firm (Menzly and Ozbas, 2010); (3) the lagged customer momentum of the focal firm (Cohen and Frazzini, 2008); (4) the lagged pseudo-conglomerate portfolio return of the focal firm (Cohen and Lou, 2012); (5) the lagged strategic alliance partners' portfolio return of the focal firm (Cao et al., 2016); (6) the lagged technological partners' portfolio return of the focal firm (Lee et al., 2019); (7) the lagged average return of all other stocks headquartered in the same city of US 20 largest cities (Parsons et al., 2020); (8) the lagged weighted-average return of stocks connected through common board members with the focal firm (Burt et al., 2020); (9) the lagged weighted-average return of stocks connected through the common analyst coverage with the focal firm (Ali and Hirshleifer, 2020); and (10) the lagged weighted-average return of stocks connected through common institutional investors with the focal firm (Gao et al., 2017).

We successively conduct the Fama-MacBeth cross-sectional regressions on the excess returns of focal firms in the presence of each of the aforementioned alternative inter-firm momentum variables. The test results show that the two OLF predictors for the US firm sample—namely, $Sub_{i,t-1}$ and $Par_{i,t-1}$, retain their economic importance and statistical significance at least at the 5% level in all estimations for subsidiary−parent and parent−subsidiary predictability tests, respectively, implying implies that return predictability in OLFs cannot be subsumed by other inter-firm effects.

4.2. Forecasting fundamental performance metrics

In this section, we seek to understand whether predictability exists not only for OLF stock returns, but also for their fundamental performance metrics.[15] Said differently, we aim to find out whether OLFs are fundamentally interrelated. To explore this possibility, we test whether OLFs predict standardized unexpected earnings (SUEs) of focal firms. Of note, since SUEs capture

[15] We also find that OLFs exhibit predictability for focal firms' cash flows, profits, ROA, revenues, and sales (see the Internet Appendix).

unanticipated changes in the focal firm's earnings and are not return-based, these test results are not confounded by measurement error or omitted risk factors.

In Table 5, we examine whether OLF returns can forecast the focal firm's future SUEs using the Fama-MacBeth regression setting. Panel A reports the overall results for one-quarter predictability for the four OLF investment strategies. The dependent variable is $SUE_{i,t}$, i.e. the unexpected earnings of focal firm i at time t, which is winsorized in the cross-section at the 1% and 99% levels. The independent variable of interest is the one-quarter lagged return of OLFs. This variable is computed from the preceding three months. Along with standard firm controls from Table 4 and country- and industry-fixed effects, we also include the focal firm's own lagged SUEs (up to four quarters). All independent variables are distributed to deciles ranging from zero to one. The results demonstrate that returns of OLFs predict focal firms' future unexpected earnings, confirming that the lagged returns of OLFs anticipate the directional changes of focal firm fundamentals and, therefore, can drive earnings announcement returns.

In Panel B of Table 5, we report the results of testing the unexpected earnings predictability over longer periods, i.e. up to four quarters ahead. Accordingly, dependent variable in these panels is $SUE_{i,t+k}$ of the focal firm, where k = 0, 1, 2, 3. The results show that, for all four possible cross-firm ownership links, all coefficients of lagged returns of OLFs are positive; however, from Quarter 1 to Quarter 4, their economic and statistical significance decreases, suggesting a decay of the forecasting power over time. These results also indicate that return predictability in OLFs is consistent with a gradual information diffusion of cash flows, and that it is unlikely to be related to changes in the underlying risk structure of firms. In Section 5, we provide an in-depth discussion of the results of our analysis of the main drivers of predictability in OLFs.

4.3. Ownership link changes

In this section, we address the endogeneity concerns that could impact our findings on predictability in OLFs. For instance, the reason why OLFs exhibit predictability may be due not to a specific ownership structure, but be caused by some omitted firm characteristics, general low level of information transparency in our sample firms, and so forth. To explore this possibility, we examine whether the ability of OLFs to forecast returns of focal firms changes in a particular setting—specifically, the one where we can follow the *same* firms before the formation of their ownership links and after the formation of such links. To this end, we use the difference-in-difference (DiD) methodology and a four-year time window embracing two years before and two years after the ownership link event.

The advantage of this setting is that it makes it possible to evaluate time lags in information updating of the same firms, when they transition from ownership-de-linked to ownership-linked. Our expectation is that, if a focal firm has no ownership links with companies that later become ownership-linked to it, then the lagged portfolio returns on these companies would have a weak or no predictability for the focal firm's future returns. The OLF return predictability arises only when the same companies become interlinked through ownership.

We identify all cases where a firm without any ownership links transforms into a firm with at least one ownership link. These firms form our sample of real-focal firms or the treatment group for each ownership link. Consequently, we define $Treatment$ as a dummy variable, which is set to one if a focal firm has undergone through such transition, and zero otherwise. In addition, we define $Postlink$ as a dummy variable, which equals one after the establishment of ownership links, and zero otherwise. We include observations within two years prior to the change in firm ownership links and those within two years after the change.

For the real-focal firm in the treatment group, we select pseudo-focal firms in the control group prior to the change in ownership links. This procedure consists of the following four steps. First, we choose pseudo-focal firms in the same industry (two-digit NAICS code) as the real-focal firm within two years prior to the change in ownership links. Second, we select ten pseudo-focal firms that are most similar to a given real-focal firm within two years prior to the change in ownership links. We determine this similarity based on the average ranking of the following four firm characteristics: size, book-to-market ratio, asset growth, and gross profitability. Third, we run the Fama-MacBeth regressions and compare the OLF predictive coefficients of the control group with those of the "treatment" group within two years prior to the status change. We use the same OLFs to predict returns of both pseudo-focal and real-focal firms. Finally, for each real-focal firm, we select firms with the most similar OLF predictive coefficients as those of matched pseudo-focal firms.

Panel A of Table 6 reports the differences between real- and pseudo-focal firms for each of their four firm characteristics, along with the corresponding estimate of the OLF predictive coefficient prior to the event date. We report these differences for all four types of OLFs with their respective *t*-statistics. We additionally record the number of real and pseudo-focal firms for each ownership link. The results suggest that all differences in characteristics between the "treatment" and "control" groups are small and insignificant. Therefore, we can confidently conclude that the two groups are similar to each other before ownership link changes in focal firms.

Panel B of Table 6 depicts the results of the DiD test on the OLF return predictability before and after the changes in firm ownership links. The dependent variable is the monthly excess return of real- and pseudo-focal firms. The regressor of interest here is the triple interaction term between the OLF predictor ($Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, or $Sis\_Par_{i,t-1}$) and $Treatment$ and $Postlink$ dummy variables. All four predictors are subsumed under one generic name, $OLF_{i,t-1}$. The controls include the corresponding OLF predictor, the aforementioned two dummy variables, and other variables from Table 4. Consistently with our expectations, the test results for all four types of firm ownership indicate that, when a firm establishes ownership links, its corresponding OLF predictor becomes significant at the 1% level. We observe the largest economic magnitude for the subsidiary−parent predictability. In contrast, we find no predictability evidence among treatment firms prior to the formation of ownership links. In its turn, the return predictability is completely absent in the control group—both before and after the event date.

Figure 2 visualizes the results of Table 6 and depicts OLF predictive coefficients of real-focal firms and pseudo-focal firms before and after the formation of ownership links. The figure has four plots for each of the four types of ownership links. The event window embraces 24 months before and after the event month. We depict the monthly estimates of predictor coefficients for treatment and controls groups, as well as their mean values over the 24-month period before and after the event. The plots show that, before the event date, the coefficients on all four OLF predictors for both treatment and control groups of firms are effectively zero. However, after the formation of ownership links, the treatment firms experience a positive shift in OLF predictability, suggesting that linked firms have predictive power only after they become factually connected through ownership.

5. Explaining Return Predictability in OLFs

This section reports the results of our analysis of five non-mutually exclusive mechanisms that could potentially explain the documented return predictability in firms with ownership links. These five mechanisms are (1) investors' inattention; (2) limits to arbitrage; (3) decision commonality; (4) ownership complexity; and (5) active internal capital markets. Our aim is to identify which of these five mechanisms are the most dominant. To this end, we run our statistical tests for each explanatory mechanism and horse-race them to determine their relative importance.

First, assuming that investors' limited attention plays an important role for return predictability in OLFs, we expect it to be stronger when investors have a lower attention. To test this prediction, we use the following four variables to capture investors' inattention to focal firms commonly used in the literature: analyst coverage, institutional holdings, search index, and advertising cost (e.g., Huang, 2015; Lee et al., 2019; Ali and Hirshleifer, 2020). Analyst coverage is computed by orthogonalizing the analyst coverage of the focal firm with respect to its market capitalization. Institutional holding is evaluated by orthogonalizing the institutional ownership of the focal firm with respect to its market capitalization. Following Da et al. (2011), we define search index as the retail investor attention through the Google search volume index. Advertising cost is the firm advertising and promotional expenses from Refinitiv Eikon. All these measures are taken as reciprocals.[16]

Second, in a frictionless market, predictable stock returns are arbitraged away. However, due to high limits to arbitrage (Shleifer and Vishny, 1997), some mispricing may not completely be ruled out. In this respect, Mitchell et al. (2002) found strong impediments to arbitrage even when a firm's market value is less than the sum of its publicly traded parts. Therefore, when stocks have high arbitrage implementation costs, we expect a stronger return predictability effect, since sophisticated institutional investors may find it unprofitable to trade in mispriced securities. To measure the limits to arbitrage in equity markets, we use the following four commonly used variables: equity volatility, idiosyncratic volatility, illiquidity, and the reciprocal of the trading volume (Ang et al., 2006; 2009; Augustin et al., 2020). Equity volatility is the quarterly volatility of firm's stock returns. We compute idiosyncratic volatility as the residuals' standard deviation based on the regression of daily stock returns on the Fama and French (1993) three-factor model in the previous month (requiring at least 10 daily returns). Our measure of illiquidity is the Amihud (2002) measure based on the price impact, while the trading volume is the log of the dollar value of traded shares.

Third, return predictability in OLFs may be driven by decision commonality in ownership connected companies. For instance, Burt et al. (2020) reported that board members common to two OLFs could implement corporate decisions within one firm and then apply the same policies to another firm, which could lead to an asynchronous market response to these OLFs and, therefore, induce return predictability. Furthermore, Gao et al. (2017) found that common institutional holdings can induce return predictability even in economically non-connected firms. Therefore, if the same institutional investors hold two OLFs, these investors' large portfolio reallocations could again impact decision making in those ownership-linked firms, even with no common board members. In addition, Ali and Hirshleifer (2020) established that firms—particularly, those with complex and indirect linkages covered by the same financial

[16] We do not consider firm size as another proxy for investors' inattention, since it can also be easily related to other mechanisms, e.g. limits to arbitrage.

analysts—show strong cross-firm predictability. Consequently, the management of two ownership connected firms, which are monitored and ranked by the same analysts, could again consider similar corporate policy decisions. Therefore, we use the following three decision commonality proxies: corporate board overlap, common institutional holdings, and the number of shared analysts. The board membership data are from BoardEx.

Fourth, Chan et al. (1996) found that price continuation results from a gradual response to information. In addition, Daniel et al. (1998; 2001) and Hirshleifer (2001) reported that investors' behavioral biases increase in situations of more information uncertainty. Furthermore, Barinov et al. (2016) linked firm complexity to larger post-earnings announcement drifts, while Cohen and Lou (2012) demonstrated the existence of stock return predictability from easy-to-analyze firms to more complicated ones. Similarly, the more complex is the process of information gathering from OLFs, the longer is the response to information, and the stronger should be return predictability in OLFs. Accordingly, in this study, we consider the following three proxies of ownership complexity: the number of OLFs for a given focal firm, the number of foreign OLFs for a given focal firm, and the number of different industry OLFs for a given focal firm.

Finally, the fifth possible mechanism of the OLF return predictability is the existence of internal capital markets. Since cash flows from a parent firm or one of its subsidiaries can be used to fund investment needs in other ownership-linked subsidiaries or parent firms, the speed of investors' response to information of OLFs may depend on the existence of ICM. However, these investments may not necessarily be value-enhancing for the firm. For instance, several previous studies show that a parent firm may subsidize one loss-making subsidiary by transferring funds from more profitable subsidiaries (e.g., Stulz, 1990; Meyer et al., 1992; Lamont, 1997; Shin and Stulz, 1998; Inderst and Mueller, 2003). In addition, Berger and Ofek (1995) established that ICM activities, such as overinvestment and cross-subsidization, can decrease information processing efficiency in a group and lead to firm value discounts. Furthermore, Lamont and Polk (2001) found that firms with larger value discounts have higher subsequent returns. Accordingly, even if the parent firm's investors are conscious of all ownership links of that firm, these investors may still be skeptical about whether, for instance, a positive cash flow announcement for one subsidiary would constitute a positive piece of information for the parent firm. Accordingly, we predict that the more active is the ICM of the parent firm (or subsidiary), the more severe would be the lag in incorporating information into the subsidiary's (or parent firm's) price and, therefore, the stronger would return predictability in OLFs.

To determine whether the ICM is active, we use the Shin and Stulz (1998) methodology. We consider only stocks with complete ownership links over the 36-month period. First, we examine subsidiary−parent and parent−parent return predictabilities. In this case, a parent firm has different subsidiaries.[17] For the smallest subsidiary i of parent firm j, we run the following time-series regression over 36 months (see Eq. (6)):

$$\frac{I_{i,j,t}}{TA_{j,t-1}} = \alpha_{0,j} + \beta_{1,j}\frac{C_{not\ i,j,t}}{TA_{j,t-1}} + \beta_{2,j}\frac{S_{i,j,t-1} - S_{i,j,t-2}}{S_{i,j,t-2}} + \beta_{3,j}\frac{C_{i,j,t}}{TA_{j,t-1}} + \\ + \beta_{4,j}q_{i,j,t-1} + \epsilon_{j,t}, \qquad (6)$$

where $I_{i,j,t}$ is the gross investment of the smallest subsidiary i of focal parent firm j; $TA_{j,t-1}$ is the book value of the total assets of focal parent firm j; $C_{not\ i,j,t}$ is the sum of the cash flow of all subsidiaries of focal parent firm j, except that of the smallest subsidiary i; $S_{i,j,t-1}$ is the sales of the smallest subsidiary i of focal parent firm j; $C_{i,j,t}$ is the cash flow of the smallest subsidiary i of focal parent firm j; $q_{i,j,t-1}$ is Tobin's q for the smallest subsidiary i of focal parent firm j.[18]

Second, we examine parent−subsidiary and subsidiary−subsidiary return predictabilities.

[17] Our tests with the parent firm's largest subsidiary yield similar results. The results are available upon request.

[18] The applicability of ICM calculated from Eq. (10) to both subsidiary−parent and parent−parent ownership links is based on the convention in return predictability studies for inter-firm links. For instance, with this convention, when checking whether firm size affects the predictability of Y from X, only Y is sorted on size, instead of using some weighted-average of sizes of Y and X. In reality, the size of X should also affect the predictability of Y from X; however, the correct relative weights over Y and X are difficult to estimate. Given that the weight on Y should dominate the weight on X, we can have a LASSO (Least Absolute Shrinkage and Selection Operator) type of truncation to set the weight on X to zero. In our scenario, a focal parent firm can have multiple sister parent firms through multiple commonly owned subsidiaries. For ICMs, we have to estimate the weight of each sister parent firm and the weight of the focal parent firm and then take their weighted-average. However, since the weight on ICMs of the focal parent firm should dominate the weights on ICMs of sister parent firms, we set the weights of ICMs of all sister parent firms to zero. Therefore, based on the existing convention, both parent−parent and subsidiary−parent cases computationally have the same ICMs. The same rationale applies to our Eq. (11) for both parent−subsidiary and subsidiary−subsidiary cases.

In this case, one subsidiary may have different parent firms. Therefore, we run the following time-series regression for each focal subsidiary i over 36 months (see Eq. (7)):

$$\frac{I_{i,t}}{TA_{i,t-1}} = \alpha_{0,i} + \beta_{1,i}\frac{C_{not\ i,t}}{TA_{i,t-1}} + \beta_{2,i}\frac{S_{i,t-1} - S_{i,t-2}}{S_{i,t-2}} + \beta_{3,i}\frac{C_{i,t}}{TA_{i,t-1}} + $$
$$+ \beta_{4,i} q_{i,t-1} + \epsilon_{i,t}, \tag{7}$$

where $I_{i,t}$ is the gross investment of focal subsidiary i, $TA_{i,t-1}$ is the book value of the total assets of focal subsidiary i; $C_{not\ i,t}$ is the sum of the cash flow of focal subsidiary i's all parent firms' all subsidiaries, except for focal subsidiary i; $S_{i,t-1}$ is the sales of focal subsidiary i; $C_{i,t}$ is the cash flow of focal subsidiary i; and $q_{i,t-1}$ is Tobin's q for focal subsidiary i. To correct for heteroskedasticity and autocorrelation, the standard errors in the above two regressions are Newey-West adjusted. Following Shin and Stulz (1998), we consider ICM "active" if β_1 in Eq. (6) and (7) is significant at the 10%, 5% or 1% levels.

Table 7 shows the results of our tests on five independent mechanisms of return predictability in OLFs using individual firm characteristics. For each firm characteristic, we split the sample at the median into "High" and "Low" subsamples. In the next step, for each of the four ownership links and each firm characteristic, we run the corresponding specification in Panel A of Table 4 by interacting the appropriate $OLF_{i,t-1}$ with a dummy variable "High," which is equal to unity if the value of the firm characteristic is above the median, and zero otherwise. The estimated coefficient on $OLF_{i,t-1} \times High$ reflects the difference in the strength of return predictability in OLFs between "High" or "Low" values of the specific firm characteristic. All regressions also include the dummy variable itself, and, as in Table 4, the lagged control variables and country- and industry-fixed effects. In line with our expectation, we find evidence on the relevance of all mechanisms to the OLF return predictability. However, the strongest economic and statistical results are recorded for ICM, when the significance level of coefficient β_1 in Eq. (6) and (7) is 5% or 1%. The impact of ownership complexity also turns out to be strong, as its all four individual proxies are significant at the 5% or 1% levels across all four ownership links. The weakest outcome is obtained for the three decision commonality measures—for most part, they lead to only 10% significance in the difference between the "High" and "Low" subsamples in the impact of respective firm characteristics on return predictability. The results of our tests on individual variables proxying investors' inattention and limits to arbitrage demonstrate that the importance of these two mechanisms is likely to be between that of ownership complexity and decision commonality. We also observe that the extent of predictability differs between "High" and Low" subsamples similarly for each firm characteristic across the four types of OLFs, with the largest being observed for the vertical subsidiary−parent pair and the lowest—for the horizontal parent−parent one. This outcome is consistent with the same ranking of OLF return predictability across the four ownership connections in Table 4.

Our next goal is to re-estimate the tests in Table 7 using aggregate measures for our mechanisms of return predictability in OLFs and evaluate their relative importance in joint tests, since these mechanisms are not independent from each other. To this end, we first obtain the composite measures of each of the first four explanatory mechanisms: the composite investors' inattention (CII) metric, the composite limits to arbitrage (CLA) metric, the composite ownership complexity (COC) metric, and the composite decision commonality (CDC) metric. Each of these four metrics is constructed by averaging the rankings of constituent firm characteristics for each mechanism. We then define four dummy variables—namely, $High\_CII$, $High\_CLA$, $High\_COC$, and $High\_CDC$—to be equal to unity if CII, CLA, COC, and CDC, respectively, are above the median, and zero otherwise. We define a dummy variable $High\_ICM$ to be equal to unity if the ICM is active at the 5% level, and zero otherwise.

Table 8 reports our test results for five independent mechanisms of return predictability in OLFs using composite firm characteristics and their joint test. It includes four panels (Panel A-D) for each of the four types of ownership-linked return predictability. Each panel has six columns. Columns 1-5 in each panel reflect the individual testing outcomes of the five possible explanatory mechanisms for predictability in OLFs using our composite metrics. We report only the coefficients on interactive terms between each OLF predictor, $OLF_{i,t-1}$ ($Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, or $Sis\_Par_{i,t-1}$), and our five dummy variables indicating above the median values of our four explanatory mechanisms metrics, i.e. $High\_CII$, $High\_CLA$, $High\_COC$, $High\_CDC$, and $High\_ICM$, as well as the coefficients on the corresponding non-interactive OLF predictors themselves. The results show that the slopes on all interactive $OLF_{i,t-1}$ terms across all panels are significant at least at the 5% level. Moreover, the slopes on the interactive $OLF_{i,t-1}$ terms are significant at the 1% level across several columns and panels. This again indicates that all five mechanisms can underlie the empirical findings on return predictability in OLFs with a complex ownership network.

Next, to understand the relative importance of each of the above five mechanisms that may be responsible for return predictability in OLFs, we horse race all five possible mechanisms against each other in a joint estimation again using the Fama-MacBeth setting (see Columns 6 of Panels A-D, Table 8). Indeed, since the correlation among composite proxies for all five mechanisms is positive, significant results for one explanation of predictability may simply reflect the importance of the other ones. For instance, when the activity of ICM is high within a given ownership connected firm, fewer analysts may be willing to cover it, and fewer institutional investors may want to hold stakes in such firm. This could lead to higher investors' inattention and more limits to arbitrage. The results show that all coefficients on the interactive term $OLF_{i,t-1} \times High\_ICM$ are positive and retain their 1% significance in a joint estimation. The point estimates corresponding to the other mechanisms either become substantially weaker or completely lose their statistical significance. However, our predictability results may partially be related to ownership complexity: the point estimates on $OLF_{i,t-1} \times High\_COC$ are significant at the 10% level in Column 6 for all types of OLFs, except for the weakest parent–parent one. Overall, our tests show that ICMs provide the best explanation of the documented return predictability in OLFs.

Many previous studies explained the activity of ICMs by poor corporate governance and opaque country-level investment culture (Scharfstein and Stein, 2002; Desai et al., 2004; Ozbas and Scharfstein, 2010; Sautner and Villalonga, 2010; Gugler et al., 2013). Therefore, we can further substantiate the predominant role of ICMs in explaining return predictability in OLFs by showing their importance particularly for OLFs located in countries with a weaker rule of law (ROL). To this end, we proxy ROL in each of the 23 developed countries by the anti-self-dealing index (Djankov et al., 2008), which is a number between zero and unity.

Table 9 shows the results of our tests on the impact of ROL on the extent to which active ICMs explain return predictability in OLFs. As in Table 8, we use Fama-MacBeth regressions and control for other four mechanisms for return predictability in OLFs. We define a dummy variable Low_ROL to be equal to unity if OLFs are from countries with the anti-self-dealing index below 0.5, and zero otherwise. All four specific ownership predictors are subsumed under one generic name, $OLF_{i,t-1}$. The variable of interest here is $OLF_{i,t-1} \times High\_ ICM \times Low\_ROL$. We do not report the other terms resulting from this triple interaction term. The table shows that the coefficient of interest is positive and significant at the 10% level for all four types of return predictability in OLFs. However, the coefficient on $OLF_{i,t-1} \times High\_ICM$ remains significant at the 5% level in all estimations. In these tests, we lose the marginal significance of the composite ownership complexity measure.

Overall, our test results show that two out of three specific mechanisms newly proposed in our study—namely, ownership complexity and particularly active internal capital markets—tend to be more powerful than the two generic mechanisms commonly used in the literature—namely, investors' inattention and limits to arbitrage. Specifically, the existence of active internal capital markets among firms with ownership links appears to be the most important explanation of return predictability in OLFs. This finding distinguishes the source of predictability in firms with ownership links from that of other cross-firm return anomalies, which are usually explained by low investor attention or high arbitrage costs.

6. Conclusion

In this study, we used the data from 23 developed markets to explore return predictability in firms with multi-layer ownership structure. Our results demonstrate that the lagged one month returns of ownership-linked firms can predict the next month return of the focal firm. We find that four trading strategies—namely, subsidiary−parent, parent−subsidiary, subsidiary−subsidiary, and parent−parent—generate abnormal returns that are not subsumed by risk factors and firm characteristics. The largest return predictability is generated for the subsidiary−parent ownership link, while the lowest—for the parent-parent one.

To interpret our findings on ownership-link implied return predictability, we consider five possible mechanisms: two generic ones commonly used in the literature (namely, investors' inattention and limits to arbitrage), one new yet applicable to many return predictability studies (namely, commonality in decision making), and two novel and specific to our study (namely, ownership complexity, as a particular type of firm information complexity, and active internal capital markets). The results of our tests reveal the dominant role of active internal capital markets, and, to a certain extent, ownership complexity as the underlying drivers of return predictability among ownership-linked firms.

Overall, using global cross-ownership data, we are able to demonstrate that a complex ownership network may lead to complicated information processing and hence return predictability across OLFs. On the one hand, we provide this evidence indirectly, by showing that the observed predictability cannot be explained by industry- or cross-country momentums, as well as by other known inter-firm effects, including customer−supplier links, strategic alliance partners, common institutional investors, common board members, and shared analyst coverage. On the other hand, we also provide direct evidence, by showing that the novel predictability phenomenon can be explained by the mechanisms that are unique to firms with a complex ownership, such as internal capital market activities.

References

Ali, U., and Hirshleifer, D. (2020). Shared analyst coverage: Unifying momentum spillover effects. *Journal of Financial Economics*, 136, 649-675.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets*, 5, 31-56.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2006). The cross-section of volatility and expected returns, *Journal of Finance*, 61, 259–299.

Ang, A., Hodrick, R., Xing, Y., and Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further U.S. evidence, *Journal of Financial Economics*, 91, 1–23.

Augustin, P., Jiao, F., Sarkissian, S., and Schill, M. (2020). Cross-listings and the dynamics between credit and equity returns, *Review of Financial Studies*, 33, 112-154.

Barinov, A., Park, S., and Yildizhan, C. (2016). Firm complexity and post-earnings-announcement drift. Working Paper, UC Riverside.

Berger, P. and Ofek, E. (1995). Diversification's effect on firm value. *Journal of Financial Economics* 37, 39-65.

Bertrand, M., and Sendhil, M. (2003). Pyramids. *Journal of the European Economic Association*, 1, 478-483.

Burt, A., and Hrdlicka, C. (2020). Where does the predictability from sorting on returns of economically linked come from? *Journal of Financial and Quantitative Analysis*, forthcoming.

Burt, A., Hrdlicka, C., Harford, J. (2020). How much do directors influence firm value? *Review of Financial Studies*, 33, 1818-1847.

Cao, J., Tarun, C., and Chen, L. (2016). Alliances and return predictability. *Journal of Financial and Quantitative Analysis*, 51, 1689-1717.

Chan, L. K., Jegadeesh, N., and Lakonishok, J. (1996). Momentum strategies. *Journal of Finance*, 51, 1681–1713.

Claessens, S., Simeon, D., and Lang, L. (2000). The separation of ownership and control in East Asian corporations. *Journal of Financial Economics*, 58, 81-112.

Cohen, L., and Frazzini, A. (2008). Economic links and predictable returns. *Journal of Finance*, 63, 1977-2011.

Cohen, L., and Lou, D. (2012). Complicated firms. *Journal of Financial Economics*, 104, 383-400.

Cooper, M., Gulen, H., and Schill, M.J. (2008). Asset growth and the cross-section of stock returns. *Journal of Finance*, 63, 1609-1651.

Da, Z., Engelberg, J., and Gao, P. (2011). In search of attention. *Journal of Finance*, 66, 1461-1499.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A. (1998). Investor psychology and security market over- and under-reactions. *Journal of Finance*, 53, 1839–1886.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A. (2001). Overconfidence, arbitrage, and equilibrium asset pricing. *Journal of Finance*, 56, 921–965.

Desai, M., Foley, F., Hines Jr., J. (2004). A multinational perspective on capital structure choice and internal capital markets. *Journal of Finance* 59, 2451–2488.

Djankov, S., LaPorta, R., Lopez-de-Silanes, F., and Shleifer, A. (2008). The law and economics of self-dealing. *Journal of Financial Economics* 88, 430-465.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns, *Journal of Finance*, 47, 472–465.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, 3–56.

Fama, E. F., and French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105(3), 457-472.

Fama, E. F., and French, K. R. (2017). International tests of a five-factor asset pricing model. *Journal of Financial Economics*, 123(3), 441-463.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116, 1–22.

Fama, E. F., and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128, 234-252.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: empirical tests. *Journal of Political Economy*, 81, 607–636.

Finke, C., and Weigert, F. (2017). Does foreign information predict the returns of multinational firms worldwide? *Review of Finance*, 21, 2199–2248.

Gao, G., Moulton, P. and Ng, D. (2017). Institutional ownership and return predictability across economically unrelated stocks. *Journal of Financial Intermediation*, 31, 45-63.

Ginglinger, E., Camille, H., and Luc, R. (2018). Are investors aware of ownership connections? ECGI Working Paper No. 525/2017.

Gugler, K., Peev, E., and Segalla, E. (2013). The internal workings of internal capital markets: cross-country evidence, *Journal of Corporate Finance*, 20, 59-73.

Harvey, C., Liu, Y., and Zhu, H. (2016). …and the cross-section of expected returns. *Review of Financial Studies*, 29, 5-68.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *Journal of Finance*, 56, 1533–1596.

Hong, H. and Stein, J.C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, 54, 2143-2184.

Hong, H. and Stein, J. C. (2007). Disagreement and the stock market. *Journal of Economic Perspectives*, 21, 109–128.

Huang, X. (2015). Thinking outside the borders: investors' underreaction to foreign operations information. *Review of Financial Studies*, 28, 3109-3152.

Inderst, R., Mueller, H. (2003). Internal versus external financing: an optimal contracting approach. *Journal of Finance*, 58, 1033–1062.

Jegadeesh, N., and Titman, S. (1993). Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance*, 48, 65–91.

Kalemli-Ozcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V., and Yesiltas, S. (2015). How to construct nationally representative firm level data from the ORBIS global database. NBER Working Paper No. w21558.

La Porta, R., Lopez-de-Silanes, F., and Shleifer, A. (1999). Corporate ownership around the world. *Journal of Finance*, 54, 471-517.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., and Vishny, R. (2000). Investor protection and corporate governance. *Journal of Financial Economics*, 58, 3-27.

Lamont, O. (1997). Cash flow and investment: Evidence from internal capital markets. *Journal of Finance*, 52, 83-109.

Lamont, O., and Polk, C. (2001). The diversification discount: Cash flows versus returns. *Journal of Finance*, 56, 1693-1721.

Lee, C. M., Sun, S. T., Wang, R., and Zhang, R. (2019). Technological links and predictable returns. *Journal of Financial Economics*, 132, 76-96.

Li, J., Tang, Y., and Yan, A. (2016). Corporate equity ownership and expected stock returns. Working Paper, Fordham University.

Menzly, L., and Ozbas, O. (2010). Market segmentation and cross-predictability of returns. *Journal of Finance*, 65, 1555-1580.

Meyer, M., Milgrom, P., and Roberts, J. (1992). Organizational prospects, influence costs, and ownership changes. *Journal of Economics & Management Strategy*, 1, 9-35.

Mitchell, M., Pulvino, T. and Stafford, E. (2002). Limited arbitrage in equity markets. *Journal of Finance*, 57, 551-584.

Moskowitz, T., and Grinblatt, M. (1999). Do industries explain momentum? *Journal of Finance*, 54, 1249-1290.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108, 1-28.

Ozbas, O., and Scharfstein, D.S. (2010). Evidence on the dark side of internal capital markets. *Review of Financial Studies*, 23, 581–599.

Rouwenhorst, K. G. (1999). Local return factors and turnover in emerging stock markets. *Journal* *of Finance*, 54, 1439–1464.

Sautner, Z., and Villalonga, B. (2010). Corporate governance and internal capital markets. HBS Working Paper No. 1530565.

Shin, H.H., and Stulz, R.M. (1998). Are internal capital markets efficient? *Quarterly Journal of Economics*, 113, 531-552.

Scharfstein, D.S., and Stein, J. (2002). The dark side of internal capital markets: divisional rent-seeking and inefficient investment. *Journal of Finance*, 55, 2537-2564.

Shleifer, A., and Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, 52, 35-55.

Stulz, R. (1990). Managerial discretion and optimal financing policies. *Journal of Financial Economics*, 26, 3-27.

Appendix: Variable Definitions and Data Sources

Variable	Description	Source	Frequency
$Sub_{i,t-1}$	Parent firm i's ownership-weighted portfolio returns of subsidiaries in month $t-1$	CRSP, Eikon, FactSet, Orbis	Monthly
$Par_{i,t-1}$	Subsidiary i's control-weighted portfolio returns of parent firms in month $t-1$	CRSP, Eikon, FactSet, Orbis	Monthly
$Sis\_Sub_{i,t-1}$	Subsidiary i's value-weighted portfolio returns of its sister subsidiaries in month $t-1$	CRSP, Eikon, FactSet, Orbis	Monthly
$Sis\_Par_{i,t-1}$	Parent firm i's value-weighted portfolio returns of its sister parent firms in month $t-1$	CRSP, Eikon, FactSet, Orbis	Monthly
$R_{i,t}$	Focal firm i's return in month t	CRSP, Eikon, FactSet, Orbis	Monthly
$ret_{i,t}$	Focal firm i's excess return in month t over a one-month US T-bill rate	K. French Data	Monthly
Ln(Size)	Log market capitalization	CRSP, Compustat, Eikon	Monthly
Ln(B/M)	Log book value at the end of December over the market capitalization in month *t*-1	CRSP, Eikon, Compustat	Monthly
Mom	Focal firm's cumulative return over *t*-12 to *t*-2 months	CRSP, Eikon	Monthly
Turnover	# of daily shares traded over # of shares outstanding at the day end, averaged over the past 12 months	CRSP, Eikon	Monthly
Ind_Mom	The value-weighted industry return of the focal firm	CRSP, Eikon K. French Data	Monthly
AG	Asset growth – an annual growth rate of total assets	CRSP, Compustat, Eikon	Monthly
GP	Gross profitability – the revenue minus cost of goods sold scaled by assets	CRSP, Eikon, Compustat	Monthly
ResInstOwn	The residual percentage of shares held by institutions, orthogonalized by firm's market capitalization	CRSP, Eikon, FactSet	Monthly
# Analysts	Number of analysts following a firm	CRSP, Compustat, Eikon, I/B/E/S	Monthly
IVol	Standard deviation of the Fama and French (1993) regression residuals of daily stock returns past month	CRSP, Compustat, Eikon, K. French Data	Monthly

Table 1: Descriptive statistics

This table shows the summary statistics for all publicly listed parent and subsidiary firms from 23 developed markets between January 2006 and December 2018. All financial firms (two-digit NAICS code = 52) and stocks priced less than $5 at the portfolio formation date are excluded. Panel A reports the full sample summary statistics of parent and subsidiary firms and for four types of ownership-linked firms (OLFs), subsidiary-parent (Sub-Par), parent-subsidiary (Par-Sub), subsidiary-subsidiary (Sub-Sub), and parent-parent (Par-Par). Panel B presents country-level statistics. Columns 1 and 2 show the yearly average number of parent firms and subsidiaries in each country, respectively. Column 3 and 4 show the average number of subsidiary-parent and parent-subsidiary links in each country, respectively. Column 5 and 6 show the average number of links between sister subsidiaries and between sister parent firms in each country, respectively. Panel C shows the summary statistics of firm characteristics. Firm characteristics include market capitalization (Size), book-to-market ratio (B/M), asset growth (AG), gross profitability (GP), and Momentum (Mom). All variables are defined in the Appendix and winsorized within each cross-section at 1% and 99% levels.

Panel A: Full sample description

	Mean	SD	Min	Med	Max
Number of parent firms	1,287	108	1,021	1,193	1,575
Number of subsidiaries	2,208	201	1,630	2,087	2,818
Number of subsidiaries per parent firm (Sub-Par)	2.58	1.97	1	2	9
Number of parent firms per subsidiary (Par-Sub)	1.42	1.11	1	1	4
Number of sister subsidiaries per subsidiary (Sub-Sub)	2.40	1.81	1	2	6
Number of sister parent firms per parent firm (Par-Par)	1.30	0.97	1	1	4

Table 1 (continued)

Panel B: Country-level statistics

	Yearly average number of		Average number of		Average number of sister	
	Parent firms	Subsidiaries	Sub-Par	Par-Sub	Subsidiaries	Parent firms
Australia	58	95	1.33	1.00	1.00	N/A
Austria	5	8	2.20	1.25	2.00	1.50
Belgium	16	23	2.13	1.17	2.00	1.08
Canada	43	72	2.51	1.39	2.33	1.27
Denmark	5	8	2.20	1.25	2.13	1.50
Finland	4	5	2.00	1.20	2.00	1.00
France	132	217	2.47	1.36	2.30	1.24
Germany	83	144	2.61	1.44	2.43	1.32
Greece	7	9	1.86	1.00	1.00	N/A
Hong Kong (China)	96	169	2.65	1.46	2.47	1.34
Ireland	3	3	1.33	1.00	1.00	N/A
Italy	10	14	2.20	1.21	2.00	1.50
Japan	476	949	3.50	1.93	3.26	1.76
Netherlands	18	28	2.33	1.29	2.20	1.19
New Zealand	3	3	1.33	1.00	1.00	N/A
Norway	29	46	2.41	1.33	2.25	1.22
Portugal	7	10	2.14	1.20	2.00	1.50
Singapore	82	105	1.91	1.06	1.79	N/A
Spain	16	25	2.31	1.28	2.18	1.18
Sweden	40	76	2.85	1.57	2.66	1.44
Switzerland	38	54	2.13	1.19	1.99	1.08
UK	26	36	1.31	1.00	1.00	N/A
USA	90	109	1.26	1.00	1.00	N/A

Panel C: Firm characteristics

Parent firm	Mean	SD	Min	Med	Max
Size ($ bln)	18.56	32.73	2.46	17.85	49.31
B/M	0.75	0.93	0.16	0.56	1.62
Asset Growth (AG)	0.15	0.38	-0.65	0.09	6.30
Gross Profitability (GP)	0.41	0.25	-0.91	0.38	1.22
Momentum (Mom)	0.15	0.55	-0.95	0.07	12.45
Subsidiary	**Mean**	**SD**	**Min**	**Med**	**Max**
Size ($ bln)	2.95	8.45	0.59	3.07	14.50
B/M	0.69	0.64	0.14	0.45	1.53
Asset Growth (AG)	0.22	0.38	0.00	0.15	1.41
Gross Profitability (GP)	0.46	0.37	-0.45	0.43	1.29
Momentum (Mom)	0.23	0.65	-0.98	0.12	15.26

Table 2: Univariate portfolio sorts

This table shows the abnormal returns of value-weighted (VW) and equally-weighted (EW) univariate portfolio sorts of focal firms for four types of return predictabilities in ownership-linked firms (OLFs): parent-subsidiary, subsidiary-parent, subsidiary-subsidiary, and parent-parent. The sample includes firms from 23 developed markets from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. The results are shown for four types of OLFs: subsidiary-parent (Sub-Par), parent-subsidiary (Par-Sub), subsidiary-subsidiary (Sub-Sub), and parent-parent (Par-Par). Panel A reports the excess returns for all quintile portfolios (with Q1 being the lowest, and Q5 being the highest) as well as the returns for the Q5-Q1 difference portfolio. Panel B reports abnormal returns for the lowest and highest quintile portfolios as well as the Q5-Q1 difference portfolio using the Fama and French (2015) five-factor model. Panel C reports abnormal returns for the lowest and highest quintile portfolios as well as the Q5-Q1 difference portfolio using the Fama and French (2018) six-factor model. The risk-adjusted abnormal returns (alphas) are computed based on the developed market factors from the K. French data library. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Excess returns

	(1)	(2)	(3)	(4)
VW	Sub-Par	Par-Sub	Sub-Sub	Par-Par
Q1 (Low)	-0.19	0.03	0.11	0.08
Q2	0.19	0.51*	0.51*	0.42*
Q3	0.60**	0.29	0.40*	0.85**
Q4	0.38	0.75**	0.68**	0.59*
Q5 (High)	0.99**	1.01**	0.96**	1.12**
Q5 – Q1	1.18*** (4.23)	0.97*** (3.41)	0.85*** (3.22)	1.03*** (3.84)
EW				
Q1 (Low)	-0.35	-0.22	-0.12	0.00
Q2	0.03	0.49*	0.46*	0.33
Q3	0.71**	0.14	0.22	0.77**
Q4	0.38	0.68**	0.71**	0.54*
Q5 (High)	1.08**	1.14**	1.08**	1.14**
Q5 – Q1	1.43*** (5.09)	1.37*** (4.83)	1.20*** (4.56)	1.15*** (4.26)

Table 2 (continued)

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

	(1)	(2)	(3)	(4)
VW	Sub-Par	Par-Sub	Sub-Sub	Par-Par
Q1 (Low)	-0.83**	-0.49*	-0.45*	-0.52**
Q5 (High)	0.30*	0.33*	0.28	0.36*
Q5 – Q1	1.13***	0.82***	0.73***	0.88***
	(3.68)	(2.84)	(2.73)	(3.05)
EW				
Q1 (Low)	-0.89**	-0.70**	-0.63**	-0.61**
Q5 (High)	0.33*	0.45*	0.40*	0.43*
Q5 – Q1	1.22***	1.15***	1.03***	1.05***
	(3.97)	(3.99)	(3.85)	(3.63)

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

	(1)	(2)	(3)	(4)
VW	Sub-Par	Par-Sub	Sub-Sub	Par-Par
Q1 (Low)	-0.81**	-0.48*	-0.45*	-0.46*
Q5 (High)	0.32*	0.29	0.30*	0.33*
Q5 – Q1	1.13***	0.77**	0.76***	0.79***
	(3.66)	(2.54)	(2.79)	(2.78)
EW				
Q1 (Low)	-0.91**	-0.64**	-0.66**	-0.54**
Q5 (High)	0.35*	0.37*	0.44*	0.39*
Q5 – Q1	1.26***	1.01***	1.10***	0.93***
	(4.09)	(3.40)	(4.01)	(3.25)

Table 3: Long-term portfolio alphas

This table shows the long-term portfolio alphas of value-weighted univariate portfolio sorts of focal firms for four types of return predictabilities in ownership-linked firms (OLFs): parent-subsidiary, subsidiary-parent, subsidiary-subsidiary, and parent-parent. The sample includes firms from 23 developed markets from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. The results are shown for four types of OLFs: subsidiary-parent (Sub-Par), parent-subsidiary (Par-Sub), subsidiary-subsidiary (Sub-Sub), and parent-parent (Par-Par). The table reports monthly five-factor alphas and six-factor alphas for Q5-Q1 difference portfolio from two to six months ahead after portfolio formation. Panel A reports the abnormal returns for the Q5-Q1 difference portfolio using the Fama and French (2015) five-factor model. Panel B reports the abnormal returns for the Q5-Q1 difference portfolio using the Fama and French (2018) six-factor model. The risk-adjusted abnormal returns (alphas) are computed based on the developed market factors from the K. French data library. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fama and French (2015) five-factor Q5-Q1 difference portfolio alphas

	(1)	(2)	(3)	(4)
	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$t + 2$	0.98***	0.69**	0.61**	0.72**
	(3.05)	(2.49)	(2.24)	(2.51)
$t + 3$	0.84**	0.60**	0.49*	0.61**
	(2.54)	(2.00)	(1.93)	(2.06)
$t + 4$	0.69**	0.52*	0.42*	0.50*
	(2.23)	(1.78)	(1.65)	(1.82)
$t + 5$	0.56*	0.45	0.36	0.41
	(1.83)	(1.48)	(1.40)	(1.48)
$t + 6$	0.46	0.36	0.32	0.37
	(1.50)	(1.33)	(1.20)	(1.27)

Panel B: Fama and French (2018) six-factor Q5-Q1 difference portfolio alphas

	(1)	(2)	(3)	(4)
	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$t + 2$	0.97***	0.66**	0.61**	0.68**
	(2.97)	(2.10)	(2.43)	(2.46)
$t + 3$	0.79**	0.58*	0.50**	0.59**
	(2.45)	(1.87)	(2.03)	(2.16)
$t + 4$	0.68**	0.48*	0.43*	0.52*
	(2.19)	(1.65)	(1.79)	(1.83)
$t + 5$	0.59*	0.42	0.38	0.42
	(1.87)	(1.35)	(1.54)	(1.49)
$t + 6$	0.51	0.37	0.33	0.35
	(1.56)	(1.11)	(1.38)	(1.26)

Table 4: Multivariate regressions of OLF return predictability

This table shows the estimation results from cross-sectional Fama and MacBeth (1973) regressions for four trading strategies of ownership-linked firms (OLFs). The sample includes firms from 23 developed markets from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. The dependent variable in Panel A is the excess return of the focal firm, $ret_{i,t}$, in Panels B – the risk-adjusted return from the Fama and French (2015) five-factor model, α_FF5, and in Panel C – from the Fama and French (2018) six-factor model, α_FF6. The risk-adjusted returns are computed based on the developed market factors from the K. French data library. The explanatory variables include the lagged one-month portfolio returns of OLFs ($Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, or $Sis\_Par_{i,t-1}$), firm size, $Ln(Size)$, book-to-market ratio, $Ln(B/M)$, focal firm's own lagged monthly return, $R_{i,t-1}$, medium-term price momentum, Mom, asset growth, AG, gross profitability, GP, stock turnover, $Turnover$, and industry momentum, Ind_Mom. All variables are defined in the Appendix, are based on the last non-missing observation for each month t and winsorized at 1% and 99% levels. All regressions include country and industry (measured at two-digit NAICS codes) fixed effects, but their estimates are not shown. The absolute *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Excess returns

	(1)	(2)	(3)	(4)
DV: $ret_{i,t}$*100	Parent	Subsidiary	Subsidiary	Parent
$Sub_{i,t-1}$	4.78*** (3.05)			
$Par_{i,t-1}$		3.09*** (3.87)		
$Sis\_Sub_{i,t-1}$			2.32*** (3.03)	
$Sis\_Par_{i,t-1}$				1.29*** (3.58)
Ln(Size)	-0.21* (1.71)	-0.24*** (3.35)	-0.30*** (4.71)	-0.16** (2.10)
Ln(B/M)	0.40** (2.12)	0.22** (2.02)	0.13 (0.29)	0.22*** (2.65)
$R_{i,t-1}$	-4.92*** (3.27)	-1.49 (1.25)	-3.27*** (3.41)	-1.28** (1.99)
Mom	-0.60 (0.58)	1.63* (1.94)	-0.34 (0.72)	1.48* (1.78)
AG	-0.66** (2.45)	-0.05 (0.10)	-0.24 (1.32)	-0.94*** (3.42)
GP	0.04 (0.97)	0.47*** (2.91)	0.19 (1.17)	0.07 (1.27)
Turnover	-0.10** (2.09)	-0.22 (0.75)	-0.17** (2.06)	-0.76*** (2.94)
Ind_Mom	0.83* (1.76)	1.27** (2.14)	1.29** (2.48)	0.79* (1.70)
Country & Industry FEs	Y	Y	Y	Y
Obs.	200,772	344,448	212,869	76,695
R^2	0.12	0.12	0.10	0.08

Table 4 (continued)

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

	(1)	(2)	(3)	(4)
DV: $\alpha\_FF5_{i,t}$*100	Parent	Subsidiary	Subsidiary	Parent
$Sub_{i,t-1}$	3.53** (2.27)			
$Par_{i,t-1}$		2.05*** (2.68)		
$Sis\_Sub_{i,t-1}$			1.52** (2.08)	
$Sis\_Par_{i,t-1}$				0.98** (2.45)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	200,772	344,448	212,869	76,695
R^2	0.08	0.09	0.07	0.06

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

	(1)	(2)	(3)	(4)
DV: $\alpha\_FF6_{i,t}$*100	Parent	Subsidiary	Subsidiary	Parent
$Sub_{i,t-1}$	3.02** (1.98)			
$Par_{i,t-1}$		2.22*** (2.88)		
$Sis\_Sub_{i,t-1}$			1.44* (1.90)	
$Sis\_Par_{i,t-1}$				1.03*** (2.86)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	200,772	344,448	212,869	76,695
R^2	0.07	0.09	0.07	0.06

Table 5: Forecasting earnings surprises

This table shows the results of Fama-MacBeth regressions of the predictability of ownership-linked firms (OLFs) for standardized unexpected earnings (SUEs). The SUEs are calculated as the yearly change in quarterly earnings scaled by the standard deviation of unexpected earnings over the eight past quarters. The explanatory variables include the preceding three months portfolio returns of OLFs, $OLF_{i,t-1}$ (i.e., $Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, or $Sis\_Par_{i,t-1}$). The results are reported for four types of OLF predictability: subsidiary-parent (Sub-Par), parent-subsidiary (Par-Sub), subsidiary-subsidiary (Sub-Sub), and parent-parent (Par-Par). All the independent variables are distributed to deciles and scaled from 0 to 1. The dependent variable is winsorized at 1% and 99% levels in the cross-section. The control variables are from Table 4 as well as one- to four-quarter lags of the firm's own SUEs. All regressions include country and industry fixed effects, but their estimates are not shown. Panel A reports regression results for the next quarter's SUEs. Panel B reports regression results of future SUEs for the next four fiscal quarters. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with four lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: One-quarter ahead forecast

	(1)	(2)	(3)	(4)
DV: $SUE_{i,t}$ *100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$OLF_{i,t-1}$	0.60***	0.67***	0.36***	0.46***
	(2.75)	(5.05)	(2.61)	(2.98)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	35,650	61,162	37,798	13,618
R^2	0.46	0.54	0.39	0.43

Panel B: Extended forecast

DV: $SUE_{i,t+k}$ k = 0, 1, 2, 3	Quarter 1	Quarter 2	Quarter 3	Quarter 4
Subsidiary – Parent predictability				
$Sub_{i,t-1}$	0.60***	0.50**	0.33**	0.22
	(2.75)	(2.42)	(2.23)	(1.57)
Controls, Country & Industry FEs	Y	Y	Y	Y
Parent – Subsidiary predictability				
$Par_{i,t-1}$	0.67***	0.45***	0.25**	0.14
	(5.05)	(3.73)	(2.32)	(1.21)
Controls, Country & Industry FEs	Y	Y	Y	Y
Subsidiary – Subsidiary predictability				
$Sis\_Sub_{i,t-1}$	0.36***	0.25*	0.16	0.04
	(2.61)	(1.83)	(1.52)	(0.45)
Controls, Country & Industry FEs	Y	Y	Y	Y
Parent – Parent predictability				
$Sis\_Par_{i,t-1}$	0.46***	0.28*	0.21	0.08
	(2.98)	(1.70)	(1.60)	(0.77)
Controls, Country & Industry FEs	Y	Y	Y	Y

Table 6: Impact of ownership link changes on the OLF return predictability

This table uses the difference-in-difference (DiD) method to test the return predictability before and after the establishment of ownership links within the same group of firms. The sample includes firms from 23 developed markets from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. We identify all cases in which a firm without any ownership links transforms into a firm with at least one ownership link. We include observations within two years before and within two years after the transition of ownership links. $Treatment$ is a dummy variable, which equals one if a focal firm has undergone through such transition and zero otherwise. $Postlink$ is a dummy variable, which equals one in any month after the formation of ownership links and zero otherwise. For the real-focal firm in the treatment group, we select pseudo-focal firms in the control group prior to the change in ownership links. It is a four-step procedure. First, we choose pseudo-focal firms which are in the same industry (two-digit NAICS code) as the real-focal firm in two years prior to the change in ownership links. Second, we select ten most similar pseudo-focal firms to a given real-focal firm in two years prior to the change in ownership links based on the average ranking of four firm characteristics: size, book-to-market ratio, asset growth, and gross profitability. Third, we run the Fama-MacBeth regressions and compare the OLF predictive coefficients for the control group of firms with those of the "treatment" group within two years prior to the status change. We use the same OLF to predict returns of both pseudo-focal and real-focal firms. Finally, we select most similar OLF predictive coefficient firms as matched pseudo-focal firms for each real-focal firm. This procedure gives us a total of 546 firms in the control sample. Panel A shows the ex-ante differences between the treatment and control groups of firms. Panel B shows DiD test results on the OLF return predictability before and after the changes in firm ownership links. The dependent variable is the monthly excess return of the (real- and pseudo-) focal firm, $ret_{i,t}$. The regressor of interest is the triple interaction term between the lagged monthly return on one of the four OLF predictors, $OLF_{i,t-1}$, i.e., $Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, or $Sis\_Par_{i,t-1}$, and $Treatment$ and $Postlink$ dummy variables. Control variables include the corresponding OLF predictor, $Treatment$ and $Postlink$ dummy variables, their interaction term, $Treatment \times Postlink$, as well as other controls from Table 4. All regressions include country and industry fixed effects, but their estimates are not shown. The absolute t-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6 (continued)

Panel A: Ex-ante differences between treatment and control groups of firms

Subsidiary - Parent (102 Real – 124 Pseudo)	Difference	*t*-statistic
Size ($ bln)	1.62	(0.23)
BM	-0.09	(0.20)
AG	-0.01	(0.48)
GP	0.06	(0.10)
$Sub_{i,t-1}$	-0.24	(0.56)
Parent - Subsidiary (156 Real – 232 Pseudo)		
Size ($ bln)	0.24	(0.22)
BM	0.04	(0.15)
AG	0.02	(0.25)
GP	-0.05	(0.16)
$Par_{i,t-1}$	-0.28	(0.56)
Subsidiary - Subsidiary (97 Real – 143 Pseudo)		
Size ($ bln)	0.43	(0.24)
BM	0.04	(0.20)
AG	0.03	(0.47)
GP	-0.03	(0.36)
$Sis\_Sub_{i,t-1}$	-0.12	(0.27)
Parent - Parent (40 Real – 47 Pseudo)		
Size ($ bln)	1.82	(0.49)
BM	-0.08	(0.49)
AG	-0.02	(0.42)
GP	0.02	(0.31)
$Sis\_Par_{i,t-1}$	-0.11	(0.23)

Panel B: The effect of changes in ownership links on return predictability

	(1)	(2)	(3)	(4)
DV: $ret_{i,t}$*100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$OLF_{i,t-1} \times$ *Treatment* $\times$ *Postlink*	3.72*** (2.59)	2.39*** (3.55)	1.36*** (2.65)	1.01*** (3.59)
$OLF_{i,t-1} \times$ *Treatment*	-0.19 (0.38)	-0.18 (0.75)	-0.10 (0.35)	-0.10 (0.84)
$OLF_{i,t-1} \times$ *Postlink*	0.21 (0.88)	0.15 (0.53)	0.13 (0.57)	0.14 (0.96)
$OLF_{i,t-1}$	1.16 (1.28)	1.22 (1.49)	0.75 (1.53)	0.42 (1.05)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	10,812	18,548	11,462	4,130
R^2	0.08	0.07	0.05	0.04

Table 7: Firm characteristics and mechanisms of the OLF return predictability

This table shows the tests results on five independent mechanisms of the OLF return predictability using Fama-MacBeth regressions and individual firm characteristics. The five competing mechanisms are (1) investors' inattention, (2) limits to arbitrage, (3) ownership complexity, (4) decision commonality, and (5) active internal capital markets (ICM). Investors' inattention consists of four metrics: analyst coverage, institutional holdings, search index, and advertising cost. Analyst coverage is the residual analyst coverage computed by orthogonalizing the analyst coverage of the focal firm with respect to its market capitalization. Institutional holding is the residual institutional ownership computed by orthogonalizing the institutional ownership of the focal firm with respect to its market capitalization. Search index is the retail investor attention through the Google search volume index following Da et al. (2011). Advertising cost is the firm advertising and promotional expenses from Refinitiv Eikon. All these measures are taken as reciprocals (R). Limits to arbitrage consist of four metrics: equity volatility, idiosyncratic volatility, illiquidity, and the reciprocal of trading volume. Equity volatility is the quarterly volatility of firm's stock returns. Idiosyncratic volatility is the residuals' standard deviation based on the regression of daily stock returns on the Fama and French (1993) three-factor model in the previous month (requiring at least 10 daily returns). Illiquidity is the Amihud (2002) illiquidity measure based on the price impact. Trading volume is the log of the dollar value of traded shares. Decision commonality consists of three metrics: corporate board overlap, common institutional holdings, and the number of shared analysts. Board overlap is the overlapping number of corporate board members between OLFs and the focal firm. The corporate board data are from BoardEx. Common institutional holding is the overlapping number of institutional investors between OLFs and the focal firm. Shared analysts is the overlapping number of analysts between OLFs and the focal firm. Ownership complexity consists of four metrics: the number of OLFs, the number of foreign OLFs, the number of indirectly linked OLFs, and the number of different industry OLFs. We follow Shin and Stulz (1998) to determine whether the ICM is active. We consider only stocks with complete ownership links over the 36-month period. For subsidiary-parent and parent-parent return predictabilities we run the following regressions for the smallest subsidiary of a parent firm over 36 months:

$$\frac{I_{i,j,t}}{TA_{j,t-1}} = \alpha_{0,j} + \beta_{1,j}\frac{C_{not\ i,j,t}}{TA_{j,t-1}} + \beta_{2,j}\frac{S_{i,j,t-1} - S_{i,j,t-2}}{S_{i,j,t-2}} + \beta_{3,j}\frac{C_{i,j,t}}{TA_{j,t-1}} + \beta_{4,j}q_{i,j,t-1} + \epsilon_{j,t},$$

where $I_{i,j,t}$ is the gross investment of the smallest subsidiary $i$of focal parent firm j; $TA_{j,t-1}$ is the book value of the total assets of focal parent firm j; $C_{not\ i,j,t}$ is the sum of the cash flow of all subsidiaries of focal parent firm j except that of the smallest subsidiary i; $S_{i,j,t-1}$ is the sales of the smallest subsidiary i of focal parent firm j; $C_{i,j,t}$ is the cash flow of the smallest subsidiary i of focal parent firm j; $q_{i,j,t-1}$ is Tobin's q for the smallest subsidiary i of focal parent firm j. For parent-subsidiary and subsidiary-subsidiary return predictabilities we run the following regression for each focal subsidiary over 36 months:

$$\frac{I_{i,t}}{TA_{i,t-1}} = \alpha_{0,i} + \beta_{1,i}\frac{C_{not\ i,t}}{TA_{i,t-1}} + \beta_{2,i}\frac{S_{i,t-1} - S_{i,t-2}}{S_{i,t-2}} + \beta_{3,i}\frac{C_{i,t}}{TA_{i,t-1}} + \beta_{4,i}q_{i,t-1} + \epsilon_{i,t},$$

where $I_{i,t}$ is the gross investment of focal subsidiary i, $TA_{i,t-1}$ is the book value of the total assets of focal subsidiary i, $C_{not\ i,t}$ is the sum of the cash flow of focal subsidiary i's all parent firms' all subsidiaries except focal subsidiary i, $S_{i,t-1}$ is the sales of focal subsidiary i, $C_{i,t}$ is the cash flow of focal subsidiary i, and $q_{i,t-1}$ is Tobin's q for focal subsidiary i. In both above regressions, the standard errors are Newey-West adjusted for heteroskedasticity and autocorrelation. We define ICM to be "active" if β_1 in the above two equations is significant at the 10%, 5%, or 1% levels. Each firm characteristic is split at the median into High and Low subsamples. Then for each of the four ownership links and each firm characteristic, we run the corresponding specification in Panel A of Table 4 by interacting the appropriate $OLF_{i,t-1}$ with "High" dummy variable. All regressions also include the dummy variable itself, lagged control variables from Table 4, as well as country and industry fixed effects, but their estimates are not shown. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7 (continued)

		High-Low			
		Sub-Par	Par-Sub	Sub-Sub	Par-Par
Investors' inattention	Analyst Coverage (R)	2.57** (1.99)	1.41*** (2.58)	1.47* (1.79)	0.26* (1.93)
	Institutional Holdings (R)	2.07** (1.99)	1.66*** (2.67)	1.51** (2.05)	0.25** (1.96)
	Search Index (R)	2.55* (1.93)	1.43*** (2.60)	1.70** (2.07)	0.32* (1.74)
	Advertising Cost (R)	2.49** (2.02)	1.69*** (2.66)	1.56* (1.65)	0.27** (2.06)
Limits to Arbitrage	Equity Volatility	3.13*** (2.86)	1.41** (1.96)	1.57** (2.09)	0.22** (1.96)
	Idiosyncratic Volatility	3.20*** (2.67)	1.26** (2.01)	1.68** (2.12)	0.23** (2.30)
	Illiquidity	3.36*** (2.89)	1.41* (1.89)	1.50** (2.28)	0.22** (2.16)
	Trading Volume (R)	2.56*** (2.98)	1.41* (1.76)	1.71** (2.22)	0.25** (2.18)
Decision Commonality	Board Overlap	2.12* (1.71)	1.36* (1.88)	1.50* (1.80)	0.23* (1.93)
	Common Inst. Holdings	2.07 (1.60)	1.40** (2.03)	1.36* (1.66)	0.22* (1.83)
	Shared Analysts	2.06* (1.86)	1.26* (1.92)	1.54* (1.74)	0.24** (2.03)
Ownership Complexity	# OLFs	3.25*** (2.75)	1.78*** (2.75)	2.07*** (2.68)	0.48** (2.28)
	# Foreign OLFs	3.00*** (3.47)	1.44*** (2.69)	1.77*** (2.73)	0.41** (2.57)
	# Indirectly Linked OLFs	3.43*** (2.87)	1.81** (2.46)	1.71*** (3.09)	0.47** (2.22)
	# Different Industry OLFs	3.35*** (3.41)	1.83*** (2.58)	1.67** (2.45)	0.44** (2.24)
Internal Capital Markets	ICM 10% significance	3.46*** (4.38)	1.79*** (3.30)	2.00*** (4.60)	0.42*** (3.19)
	ICM 5% significance	4.68*** (6.04)	2.25*** (4.71)	2.77*** (5.84)	0.57*** (4.53)
	ICM 1% significance	5.02*** (6.46)	2.35*** (4.95)	2.81*** (6.25)	0.58*** (4.95)

Table 8: Joint evaluation of mechanisms of the OLF return predictability

This table shows the tests results on five independent mechanisms of the OLF return predictability using Fama-MacBeth regressions and composite firm characteristics. The five competing mechanisms are (1) investors' inattention, (2) limits to arbitrage, (3) ownership complexity, (4) decision commonality, and (5) active internal capital markets (ICM). Investors' inattention consists of four metrics: the reciprocals of the number of analysts covering a firm, residual institutional holdings, the search index, which is the Google search volume index, as well as the advertising cost, which is the cost of advertising media and promotional expenses. Limits to arbitrage consist of four metrics: equity volatility, idiosyncratic volatility, illiquidity, and the reciprocal of trading volume. Decision commonality consists of three metrics: corporate board overlap, common institutional holdings, and the number of shared analysts. Ownership complexity consists of four metrics: number of OLFs, number of foreign OLFs, number of indirectly linked OLFs, and number of different industry OLFs. We construct composite measures of each of the first four mechanisms, namely, composite investors' inattention (CII), composite limits to arbitrage (CLA), composite decision commonality (CDC), and composite ownership complexity (COC). We define dummy variables $High\_CII$, $High\_CLA$, $High\_CDC$, and $High\_COC$ to be equal unity if the corresponding composite measure is above the median and zero otherwise. The ICM measure is described in Table 7. We define ICM to be "active" if β_1 in the above two equations is significant at the 5% level and define a dummy variable $High\_ICM$ to be equal unity if the ICM is active and zero otherwise. All regressions also include the dummy variable itself and lagged control variables from Table 4 as well as country and industry fixed effects, but their estimates are not shown. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Subsidiary - Parent predictability

DV: $ret_{i,t}$*100	(1)	(2)	(3)	(4)	(5)	(6)
$Sub_{i,t-1}$	4.48**	4.56**	4.62**	4.12**	4.14**	3.19*
	(2.43)	(2.50)	(2.46)	(1.96)	(2.16)	(1.82)
$Sub_{i,t-1}$ × *High_CII*	2.63**					1.30
	(2.09)					(1.21)
$Sub_{i,t-1}$ × *High_CLA*		3.28***				1.91
		(3.25)				(1.54)
$Sub_{i,t-1}$ × *High_CDC*			2.22*			1.26
			(1.81)			(1.03)
$Sub_{i,t-1}$ × *High_COC*				3.88***		1.85*
				(3.53)		(1.85)
$Sub_{i,t-1}$ × *High_ICM*					4.68***	3.05***
					(6.04)	(4.14)
Controls, Country & Industry FEs	Y	Y	Y	Y	Y	Y

Table 8 (continued)

Panel B: Parent - Subsidiary predictability

DV: $ret_{i,t}$*100	(1)	(2)	(3)	(4)	(5)	(6)
$Par_{i,t-1}$	2.53***	2.80***	2.89***	2.47***	2.44***	1.89**
	(3.30)	(3.33)	(3.69)	(3.20)	(3.12)	(2.06)
$Par_{i,t-1} \times High\_CII$	1.64***					0.94
	(2.75)					(1.40)
$Par_{i,t-1} \times High\_CLA$		1.64**				1.10
		(2.42)				(1.53)
$Par_{i,t-1} \times High\_CDC$			1.41*			0.83
			(1.91)			(1.07)
$Par_{i,t-1} \times High\_COC$				1.78***		1.09*
				(2.73)		(1.79)
$Par_{i,t-1} \times High\_ICM$					2.25***	1.56***
					(4.71)	(3.28)
Controls, Country & Industry FEs	Y	Y	Y	Y	Y	Y

Panel C: Subsidiary - Subsidiary predictability

DV: $ret_{i,t}$*100	(1)	(2)	(3)	(4)	(5)	(6)
$Sis\_Sub_{i,t-1}$	1.93***	2.06***	2.07***	1.73**	1.66**	1.44*
	(2.58)	(2.69)	(2.72)	(2.35)	(2.32)	(1.89)
$Sis\_Sub_{i,t-1} \times High\_CII$	1.85**					1.02
	(2.21)					(1.12)
$Sis\_Sub_{i,t-1} \times High\_CLA$		1.90***				1.14
		(2.58)				(1.62)
$Sis\_Sub_{i,t-1} \times High\_CDC$			1.60**			0.89
			(1.97)			(1.12)
$Sis\_Sub_{i,t-1} \times High\_COC$				2.00***		1.19*
				(3.33)		(1.75)
$Sis\_Sub_{i,t-1} \times High\_ICM$					2.77***	1.92***
					(5.84)	(3.84)
Controls, Country & Industry FEs	Y	Y	Y	Y	Y	Y

Table 8 (continued)

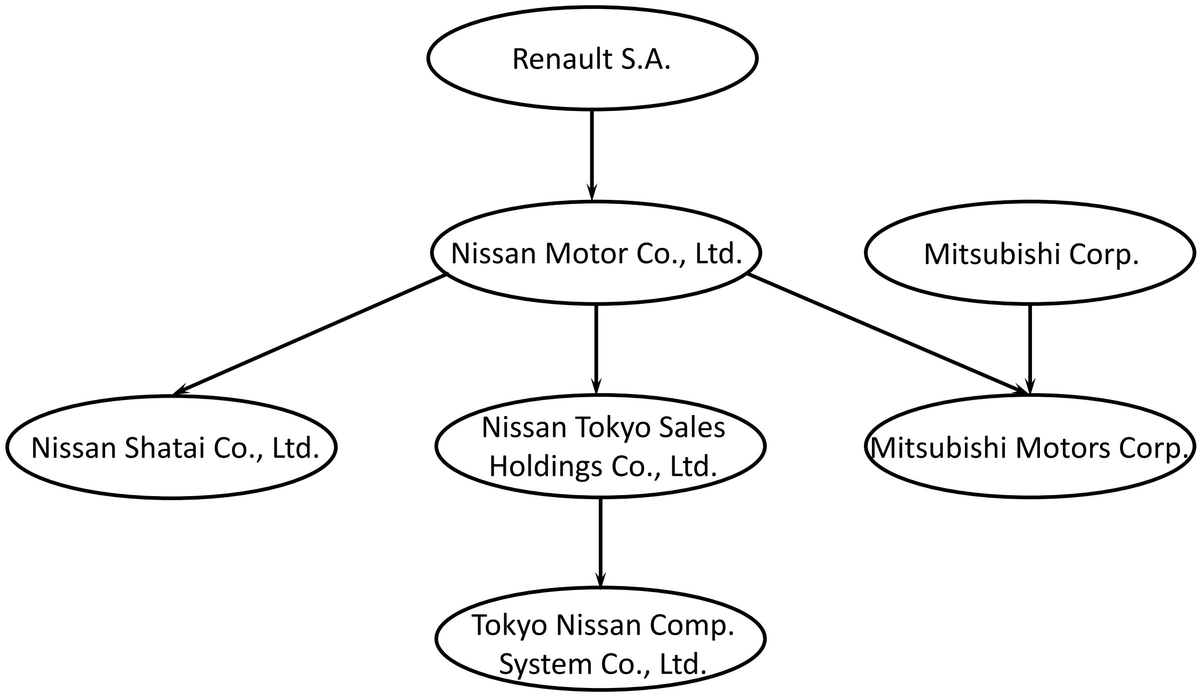
Panel D: Parent - Parent predictability

DV: $ret_{i,t}$*100	(1)	(2)	(3)	(4)	(5)	(6)
$Sis\_Par_{i,t-1}$	1.11***	1.33***	1.29***	1.15**	1.09***	0.75**
	(2.65)	(2.85)	(2.65)	(2.52)	(2.60)	(2.06)
$Sis\_Par_{i,t-1} \times High\_CII$	0.32**					0.20
	(2.22)					(1.24)
$Sis\_Par_{i,t-1} \times High\_CLA$		0.27**				0.16
		(2.28)				(1.24)
$Sis\_Par_{i,t-1} \times High\_CDC$			0.23**			0.13
			(2.06)			(1.14)
$Sis\_Par_{i,t-1} \times High\_COC$				0.50***		0.22
				(2.94)		(1.62)
$Sis\_Par_{i,t-1} \times High\_ICM$					0.57***	0.38***
					(4.53)	(3.49)
Controls, Country & Industry FEs	Y	Y	Y	Y	Y	Y

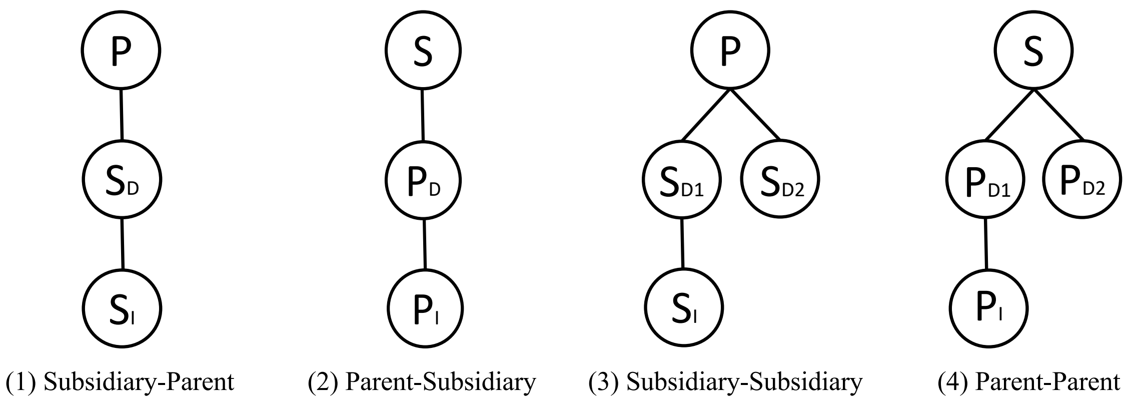
Table 9: The rule of law and the activity of internal capital markets

This table shows the impact of the country's rule of law (ROL) on the activity of internal capital market (ICM) using Fama-MacBeth regressions while controlling for other mechanism for OLF return predictability. ROL in each of the 23 developed countries is proxied by the anti-self-dealing index from Djankov et al. (2008). The OLFs have four types: subsidiary-parent (Sub-Par), parent-subsidiary (Par-Sub), subsidiary-subsidiary (Sub-Sub), and parent-parent (Par-Par). We include the interaction terms between the lagged subsidiaries' returns, $Sub_{i,t-1}$, the lagged parent firms' returns, $Par_{i,t-1}$, the lagged sister subsidiaries' returns, $Sis\_Sub_{i,t-1}$, or the lagged sister parent firms' returns, $Sis\_Par_{i,t-1}$, and four dummy variables reflecting four competing mechanisms: (1) investors' inattention, (2) limits to arbitrage, (3) ownership complexity, (4) decision commonality, and (5) active internal capital markets at a time. All specific ownership predictors are shown with a generic name, $OLF_{i,t-1}$. The composite proxies for each of the first four mechanisms, composite investors' inattention (CII), composite limits to arbitrage (CLA), composite decision commonality (CDC), composite ownership complexity (COC), the activity measure of ICM, as well as the dummy variables, *High_CII*, *High_CLA*, *High_CDC*, and *High_COC* are defined in Table 8. A dummy variable Low_ROL is equal unity if OLFs are from countries with the anti-self-dealing index of below 0.5 and zero otherwise. All regressions also include the dummy variable itself and lagged control variables from Table 4 as well as country and industry fixed effects, but their estimates are not shown. Interactive terms *Low_ ROL*, *High_ ICM* × *Low_ ROL*, and $OLF_{i,t-1}$ × *Low_ ROL* are also not shown. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

DV: $ret_{i,t}$*100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$OLF_{i,t-1}$ × *High_ICM* × *Low_ROL*	1.10*	0.55*	0.62**	0.12*
	(1.92)	(1.68)	(2.01)	(1.66)
$OLF_{i,t-1}$ × *High_ ICM*	2.09***	1.08**	1.36***	0.25**
	(3.13)	(2.33)	(3.06)	(2.29)
$OLF_{i,t-1}$	2.95*	1.74**	1.16*	0.78**
	(1.71)	(2.55)	(1.92)	(2.11)
$OLF_{i,t-1}$ × *High_CII*	0.70	0.51	0.55	0.10
	(0.73)	(0.84)	(0.69)	(0.76)
$OLF_{i,t-1}$ × *High_CLA*	1.00	0.60	0.60	0.08
	(0.89)	(0.90)	(0.88)	(0.70)
$OLF_{i,t-1}$ × *High_CDC*	0.66	0.41	0.45	0.07
	(0.58)	(0.63)	(0.60)	(0.65)
$OLF_{i,t-1}$ × *High_COC*	1.09	0.63	0.70	0.12
	(1.10)	(1.00)	(1.03)	(0.96)
Controls, Country & Industry FEs	Y	Y	Y	Y



Plot A: An example of a multi-layer and multi-country ownership structure – Renault S.A.



Plot B: Four types of ownership links

Figure 1: Illustration of complex ownership links

This figure shows complexity of ownership links. Plot A gives an example of multi-layer and multi-country ownership links based on Renault S.A. (Groupe Renault). Plot B gives four possible types of ownership links between parent firms (P) and subsidiaries (S), namely, two vertical ones: (1) subsidiary-parent, (2) parent- subsidiary; and two horizontal ones: (3) subsidiary-subsidiary (sister subsidiaries), connected through a common parent firm, and (4) parent-parent (sister parent firms), connected through a common subsidiary. Each ownership link can be direct (P_D or S_D) or indirect (P_I or S_I). A parent firm (subsidiary) is directly linked to a subsidiary (parent firm) if they are connected without an intermediate subsidiary (a parent firm). Similarly, sister subsidiaries (sister parent firms) are directly linked if they are connected through a parent firm (a subsidiary) without an intermediate subsidiary (a parent firm). For instance, Renault S.A. and Mitsubishi Corp. are indirect sister parent firms, since they have a common subsidiary (Mitsubishi Motors Corp.), but Renault S.A. holds Mitsubishi Motors through Nissan Motor Co., Ltd. Each parent firm (subsidiary) can be local or foreign and/or be in the same or different industry relative to the linked subsidiary (parent firm).

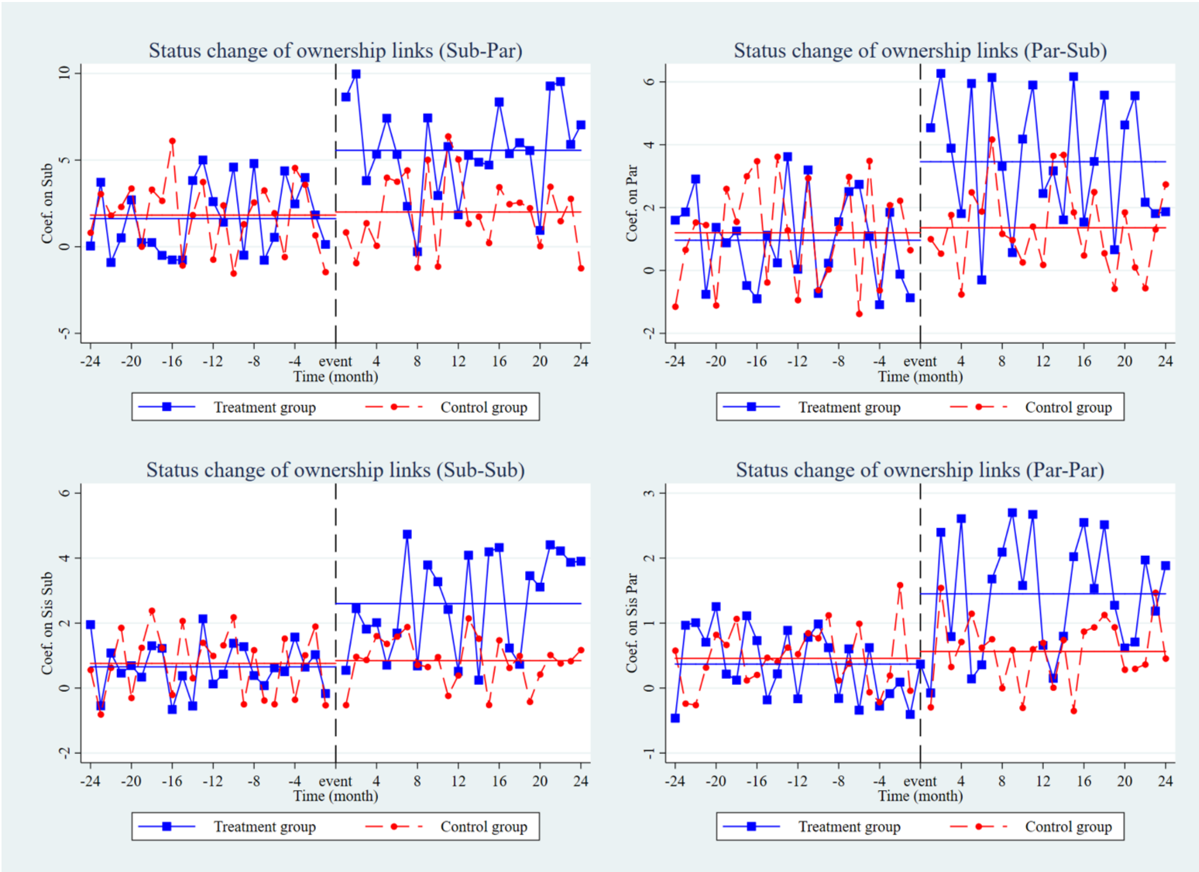


Figure 2: Predictive coefficients of OLF before and after ownership links

This figure shows the predictive OLF coefficients to real- and pseudo-focal firms before and after the change in ownership links based on Table 6 estimations, as well as their mean values before and after the event. The sample includes firms from 23 developed markets from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. We identify all cases in which a firm without any ownership links transforms into a firm with at least one ownership link. This firms form our "Treatment" group for each ownership link (blue solid line with squares). For each real-focal firm, we select one pseudo-focal firm in the control group prior to the change in ownership links. It is a four-step procedure. First, we choose pseudo-focal firms which are in the same industry as the real-focal firm in two years prior to the change in ownership links. Second, we select ten most similar pseudo-focal firms to a given real-focal firm in two years prior to the change in ownership links based on the average ranking of four firm characteristics: size, book-to-market ratio, asset growth, and gross profitability. Third, we run the Fama-MacBeth regressions and compare the OLF predictive coefficients for the control group of firms with those of the "Treatment" group within two years prior to the status change. We use the same OLF to predict returns of both pseudo-focal and real-focal firms. Finally, we select most similar OLF predictive coefficient firms as matched pseudo-focal firms for each real-focal firm. This procedure gives us the "Control group" for each ownership link (red dashed line with circles). The shown coefficients from top left to right bottom plots are the point estimates of $Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, and $Sis\_Par_{i,t-1}$, respectively, from Table 6.

Internet Appendix

Return Predictability in Firms with a Complex Ownership Network

Table A.1 checks the strength of the documented OLF return predictability is stable over time. It shows the six-factor alphas of focal firms, α_FF6, of four OLF return predictability strategies for two time periods of equal duration: January 2006 – June 2012 and July 2012 – December 2018. In the first period, the value-weighted (equally-weighted) portfolio alphas of the four strategies—i.e., the Q5-Q1 spreads for subsidiary-parent, parent-subsidiary, subsidiary-subsidiary, and parent-parent ownership links—are 127 bps (141 bps), 78 bps (109 bps), 80 bps (112 bps), and 84 bps (99 bps) per month, respectively. The alphas of four strategies are all significant at the 1% level. In the second period, the value-weighted (equally-weighted) portfolio alphas of the same four strategies are 101 bps (111 bps), 69 bps (96 bps), 72 bps (101 bps), and 73 bps (89 bps) per month, respectively. Except for one case, the alphas of all four strategies in all cases are again significant at the 1% level. The only occurrence of 5% significance is recorded for the value-weighted parent-subsidiary alpha in the second sub-period. Overall, we find very similar results between the two time periods in both economic and statistical terms, which implies a high consistency of the observed OLF return predictability phenomenon over time.

Table A.2 show the six-factor alphas for four types of ownership links across five geographic regions based on the focal firms' locations. There regions are Global excluding the United States, Japan, Asia-Pacific, Europe, and North America. In Panel B, for the subsidiary-parent return predictability, we observe that, although the α_FF6 values in various regions differ in magnitude, they all are statistically significant. Furthermore, the results show that North America has the highest alphas, 134 bps (value-weighted) and 153 bps (equally-weighted), while Japan has the lowest, 81 bps (value-weighted) and 92 bps (equal-weighed). In Panel C, we look at regional abnormal return patterns of parent-subsidiary return predictability. Again, with one exception, all focal firms' alphas are significant at the 1% or 5% levels. The lowest predictability is again found for Japan based on value-weighted portfolio returns—50 bps with 10% significance. Panels D and E report regional abnormal returns of return predictability between sister subsidiaries and between sister parent firms, respectively. The Q5-Q1 spread for six-factor alphas of subsidiary-subsidiary predictability in different regions ranges from 53 bps to 122 bps, while that for these alphas of parent-parent predictability ranges from 57 bps to 108 bps. Across all estimations, the statistical significance of the Q5-Q1 spread in Panels D and E is high (at least the 5% level).

Tables A.3 and A.4 show the univariate test results based on risk-adjusted returns and long-term portfolio alphas as in Tables 2 and 3, respectively, with the Burt and Hrdlicka (2020) adjustment. To construct these tables, we use portfolio returns computed from idiosyncratic returns of ownership-linked firms (OLFs) rather than their raw returns to sort focal firms into quintile portfolios at time t. In Panel A of Tables A.3 and A.4, we use the abnormal returns from the Fama and French (2015) five-factor model, α_FF5, while in Panel B – from the Fama and French (2018) six-factor model, α_FF6.

In Table A.3 we observe that the magnitudes of both types of alphas across both panels are slightly smaller than the corresponding values reported in Table 2. However, all Q5-Q1 spread portfolio returns are still significant at 5% or 1% levels. In Table A.4 we again observe a monotonic decrease in economic and statistical predictability over time across all four types of ownership links. The point estimates and their statistical significance are only marginally smaller than in Table 3. These results reveal that both at short and long horizons the information derived from the raw returns of firms with OLFs is mostly orthogonal to the firms' common exposure to asset pricing factor returns.

Tables A.5 and A.6 show the results of OLF return predictability tests in emerging markets using univariate portfolio sorts and Fama-MacBeth regressions, respectively. The estimations are conducted using the Fama and French five-factor and six-factor alphas. Emerging markets includes 26 markets from the K. French's data library, namely: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, South Korea, Taiwan, Thailand, Turkey, and United Arab Emirates. As can be seen in Table A.5, OLFs generate significant Q5–Q1 alpha spread in emerging markets. Note that these abnormal returns are larger in magnitude than the corresponding spreads in developed markets in Table 2. This is expected given the lower efficiency of emerging markets. These results reveal that the OLF return predictability is a common phenomenon in global markets.

A reader might still think that firm's ownership links pick up some unobserved economic relations beyond supplier-customer firm links studied in Cohen and Frazzini (2008). We address this concern by repeating our estimations on a sample of financial firms from 23 developed markets. These firms differ from those in all other industries by the lack of explicit economic linkages. Tables A.7 and A.8 show the results of OLF return predictability tests among financial firms using univariate portfolio sorts and Fama-MacBeth regressions, respectively. The estimations are again shown for the Fama-French five-factor and six-factor alphas. Our results in economic and statistical terms are very similar to those in Tables 2 and 4. Therefore, we can conclude that any possible economic links among firms with ownership links do not impact the OLF return predictability evidence.

Table A.9 shows whether the OLF return predictability disappears after controlling for previously reported inter-firm momentum effects. We include the following ten inter-firm momentum variables: (1) supplier industry returns and (2) customer industry returns (Menzly and Ozbas, 2010); (3) customers' returns (Cohen and Frazzini, 2008); (4) "pseudo-conglomerate" portfolio returns (Cohen and Lou, 2012); (5) strategic alliance partners' returns (Cao et al., 2016); (6) technological partners' returns (Lee et al., 2019); (7) geographic peers' returns (Parsons et al., 2020); (8) firm returns with common board members (Burt et al., 2020); (9) shared analyst coverage peers' returns (Ali and Hirshleifer, 2020); and (10) common institutional investors peers' returns (Gao et al., 2017). We limit this analysis to the US firm sample only due to the fact that those above mentioned inter-firm momentum variables are not available for non-US firms. We only estimate subsidiary-parent and parent-subsidiary return predictabilities using the US firm sample, since there are rare cases of sister subsidiaries and sister parent firms in the United States. We also add but do not report control variables from Table 4 in all regressions. Column (1) in reports the basic results without inter-firm link controls. Columns (2-12) show that the OLF return predictability is not subsumed by any of the ten existing inter-firm links when they enter regressions individually. Therefore, we conclude that the OLF return predictability cannot be subsumed by previously reported inter-firm links.

Table A.10 reports panel regression results of the predictive power of OLFs for focal firms' three fundamental performance measures – cash flow growth, profit growth, and growth in return on assets (ROA). All three dependent variables are the market-adjusted. The control variables are the same as those in Table 4. Furthermore, along with country and industry fixed effects, we also include the year fixed effects. The standard errors are clustered by year. Due to space constraints, the coefficients on control variables and fixed effects are not reported. All variables are taken at the end of each calendar year, winsorized at the 1% and 99% levels, and are cross-sectionally standardized to have zero mean and unit variance. Panel A reports the tests for predicting cash flow growth of focal firms, ΔCF. In this case, we regress the annual cash flow growth of focal firms on both the contemporaneous and lagged one year average cash flow growth of their OLF across the four possible categories: $Sub\_\Delta CF_t$, $Par\_\Delta CF_t$, $Sis\_Sub\_\Delta CF_t$, and $Sis\_Par\_\Delta CF_t$. Panel B shows the test results for predicting profit growth of focal firms, ΔP. Here, we regress the annual profit growth of focal firms on both the contemporaneous and lagged one year average profit growth of their OLF—namely, $Sub\_\Delta P_t$, $Par\_\Delta P_t$, $Sis\_Sub\_\Delta P_t$, and $Sis\_Par\_\Delta P_t$. All estimated coefficients, both contemporaneous and predictive, across both panels are significant at least at the 1% or 5% level. Panel C shows the test results for predicting ROA growth, ΔROA. Here, we regress the annual profit growth of focal firms on both the contemporaneous and lagged one year average profit growth of their OLF—namely, $Sub\_\Delta ROA_t$, $Par\_\Delta ROA_t$, $Sis\_Sub\_\Delta ROA_t$, and $Sis\_Par\_\Delta ROA_t$. We observe that again all slope coefficients, both contemporaneous and predictive, are significant at 1% or 5% levels. Therefore, the test results in Table A.10 suggest that OLF are fundamentally related to each other, and there are multidimensional performance links among such firms.

Finally, Tables A.11 and A.12 show that OLF returns can forecast revenue and sales surprises of the focal firm, respectively. The setting of these tables is similar to that of Table 5. Panel A reports the overall results for one-quarter predictability for four OLF investment strategies. The dependent variable in Table A.11 is $SUR_{i,t}$ – the unexpected revenue of focal firm i at time t, while that in Table A.12 is $SUS_{i,t}$ – the unexpected sales of focal firm i at time t. The independent variable of interest is the one-quarter lagged return of OLFs, computed from the preceding three months. Besides standard firm controls form Table 4 and country and industry fixed effects, we also include the focal firm's own corresponding lagged standardized unexpected measure (up to four quarters). All independent variables are distributed to deciles ranging from zero to one. The dependent variable is winsorized in the cross-section at 1% and 99%. We find that the returns of OLFs predict focal firms' future unexpected revenue and sales. In Panels B through E of Table A.11 (Table A.12), we test the unexpected revenue (sales) predictability over longer periods – up to four quarters ahead. The dependent variable in these panels is $SUR_{i,t+k}$ or $SUS_{i,t+k}$ of the focal firm, where k = 0, 1, 2, 3. We find that all coefficients of lagged returns of OLFs, for all four possible ownership links in all panels, are positive, but their economic and statistical significance, as in Table 5-B, decreases from Quarter 1 to Quarter 4, that is, the forecasting power decays over time.

References

Ali, U., and Hirshleifer, D. (2020). Shared analyst coverage: Unifying momentum spillover effects. *Journal of Financial Economics*, 136, 649-675.

Burt, A., and Hrdlicka, C. M. (2020). Where does the predictability from sorting on returns of economically linked come from? *Journal of Financial and Quantitative Analysis*, forthcoming.

Burt, A., Hrdlicka, C., and Harford, J. (2020). How Much Do Directors Influence Firm Value?. *Review of Financial Studies*, 33(4), 1818-1847.

Cao, J., Tarun, C., and Chen, L. (2016). Alliances and return predictability. *Journal of Financial and Quantitative Analysis*, 51, 1689-1717.

Cohen, L., and Frazzini, A. (2008). Economic links and predictable returns. *Journal of Finance*, 63, 1977-2011.

Cohen, L., and Lou, D. (2012). Complicated firms. *Journal of Financial Economics*, 104, 383-400.

Fame, E. F. and French, K. R. (2015). A five-factor asset pricing model, *Journal of Financial*

Economics, 116, 1–22.

Fame, E. F., and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2), 234-252.

Gao, G., Moulton, P. and Ng, D. (2017). Institutional ownership and return predictability across economically unrelated stocks. *Journal of Financial Intermediation*, 31, 45-63.

Lee, C. M., Sun, S. T., Wang, R., and Zhang, R. (2019). Technological links and predictable returns. *Journal of Financial Economics*, 132, 76-96.

Menzly, L., and Ozbas, O. (2010). Market segmentation and cross-predictability of returns. *Journal of Finance*, 65, 1555-1580.

Parsons, C. A., Sabbatucci, R., and Titman, S. (2020). Geographic lead-lag effects. *Review of Financial Studies*, 33, 4721-4770.

Table A.1: Sub-period tests of the OLF return predictability

This table shows the Fama and French (2018) six-factor alphas for value-weighted (VW) and equally-weighted (EW) univariate portfolio sorts of focal firms for ownership-linked firms (OLFs) in sub-periods. The sample includes firms from 23 developed markets from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. The results are shown for four types of OLFs: subsidiary-parent (Sub-Par), parent-subsidiary (Par-Sub), subsidiary-subsidiary (Sub-Sub), and parent-parent (Par-Par). The risk-adjusted returns are computed as in Table 3. The alphas are reported for two equal sub-periods (January 2006 to June 2012 and July 2012 to December 2018) for the lowest and highest quintile portfolios and the Q5-Q1 difference portfolio based on four OLF trading strategies. For each quintile portfolio, the board overlap is split at the median into low and high subsamples. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sub-Par		Par-Sub		Sub-Sub		Par-Par	
VW	1st half	2nd half	1st half	2nd half	1st half	2nd half	1st half	2nd half
Q1 (Low)	-0.91**	-0.72**	-0.48*	-0.43*	-0.48*	-0.43*	-0.49*	-0.42*
Q5 (High)	0.36*	0.28*	0.29*	0.26*	0.32*	0.29*	0.35*	0.31*
Q5 – Q1	1.27***	1.01***	0.78***	0.69**	0.80***	0.72***	0.84***	0.73***
	(4.12)	(3.28)	(2.62)	(2.29)	(2.95)	(2.67)	(2.93)	(2.58)
EW								
Q1 (Low)	-1.01***	-0.79**	-0.68**	-0.60**	-0.67**	-0.61**	-0.57**	-0.52**
Q5 (High)	0.40*	0.31*	0.40*	0.36*	0.45*	0.40*	0.42*	0.37*
Q5 – Q1	1.41***	1.11***	1.09***	0.96***	1.12***	1.01***	0.99***	0.89***
	(4.54)	(3.61)	(3.65)	(3.23)	(4.12)	(3.76)	(3.47)	(3.10)

Table A.2: Sub-regional tests of the OLF return predictability

This table shows the Fama and French (2018) six-factor abnormal returns for value-weighted (VW) and equally-weighted (EW) univariate portfolio sorts of focal firms in different regional samples for ownership-linked firms (OLFs). The sample includes firms from 23 developed markets from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. The risk-adjusted returns are computed based on the developed market factors from the K. French data library. Panels A-D show univariate portfolio sorts for four OLF strategies in different regions: Global ex USA, Japan, Asia-Pacific, Europe, and North America. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Subsidiary – Parent predictability

	(1)	(2)	(3)	(4)	(5)
VW	Global ex USA	Japan	Asia-Pacific	Europe	North America
Q1 (Low)	-0.76**	-0.58**	-0.62**	-0.89**	-0.96**
Q5 (High)	0.29*	0.23	0.24	0.34*	0.38*
Q5 – Q1	1.06***	0.81***	0.87***	1.23***	1.34***
	(3.42)	(2.63)	(2.81)	(4.01)	(4.35)
EW					
Q1 (Low)	-0.87**	-0.66**	-0.69**	-1.02***	-1.10***
Q5 (High)	0.34*	0.26*	0.27*	0.40*	0.43*
Q5 – Q1	1.21***	0.92***	0.96***	1.42***	1.53***
	(3.90)	(2.96)	(3.14)	(4.57)	(4.96)

Panel B: Parent – Subsidiary predictability

	(1)	(2)	(3)	(4)	(5)
VW	Global ex USA	Japan	Asia-Pacific	Europe	North America
Q1 (Low)	-0.49*	-0.31*	-0.51**	-0.47*	-0.38*
Q5 (High)	0.29*	0.19	0.30*	0.28*	0.23
Q5 – Q1	0.78**	0.50*	0.81***	0.75**	0.61**
	(2.57)	(1.68)	(2.73)	(2.52)	(2.05)
EW					
Q1 (Low)	-0.70**	-0.46*	-0.71**	-0.68**	-0.55**
Q5 (High)	0.42*	0.27*	0.42*	0.40*	0.32*
Q5 – Q1	1.12***	0.73**	1.13***	1.08***	0.87***
	(3.67)	(2.45)	(3.76)	(3.63)	(2.92)

Table A.2 (continued)

Panel C: Subsidiary – Subsidiary predictability

	(1)	(2)	(3)	(4)	(5)
VW	Global ex USA	Japan	Asia-Pacific	Europe	North America
Q1 (Low)	-0.48*	-0.32*	-0.53**	-0.47*	-0.35*
Q5 (High)	0.32*	0.21	0.35*	0.32*	0.24
Q5 – Q1	0.81*** (3.00)	0.53** (1.96)	0.88*** (3.26)	0.79*** (2.91)	0.59** (2.16)
EW					
Q1 (Low)	-0.68**	-0.45*	-0.73**	-0.68**	-0.53**
Q5 (High)	0.46*	0.30*	0.49*	0.45*	0.36*
Q5 – Q1	1.14*** (4.21)	0.76*** (2.80)	1.22*** (4.51)	1.14*** (4.21)	0.89*** (3.27)

Panel D: Parent – Parent predictability

	(1)	(2)	(3)	(4)	(5)
VW	Global ex USA	Japan	Asia-Pacific	Europe	North America
Q1 (Low)	-0.45*	-0.33*	-0.37*	-0.50**	-0.54**
Q5 (High)	0.33*	0.24	0.26*	0.37*	0.39*
Q5 – Q1	0.78*** (2.72)	0.57** (2.00)	0.64** (2.21)	0.87*** (3.03)	0.93*** (3.24)
EW					
Q1 (Low)	-0.53**	-0.39*	-0.44*	-0.59**	-0.63**
Q5 (High)	0.38*	0.28*	0.32*	0.42*	0.45*
Q5 – Q1	0.91*** (3.17)	0.67** (2.34)	0.76*** (2.67)	1.01*** (3.51)	1.08*** (3.76)

Table A.3: Univariate portfolio sorts after correcting bias

This table shows the calendar-time portfolio returns using the Burt and Hrdlicka (2020) adjustment for value-weighted (VW) and equally-weighted (EW) univariate portfolio sorts of focal firms for four types of return predictabilities in ownership-linked firms (OLFs): parent-subsidiary, subsidiary-parent, subsidiary- subsidiary, and parent-parent. The sample includes firms from 23 developed markets from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. To construct this table, we use portfolio returns computed using OLF idiosyncratic returns rather than their raw returns to sort focal firms into quintile portfolios. Panel A reports abnormal returns for the lowest (Q1) and highest (Q5) quintile portfolios as well as the Q5-Q1 difference portfolio using the Fama and French (2015) five-factor model. Panel B reports abnormal returns for lowest and highest quintile portfolios as well as the Q5-Q1 difference portfolio using the Fama and French (2018) six-factor model. The risk-adjusted abnormal returns (alphas) are computed based on the developed market factors from the K. French data library. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

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

	(1)	(2)	(3)	(4)
VW	Sub-Par	Par-Sub	Sub-Sub	Par-Par
Q1 (Low)	-0.64**	-0.43*	-0.36*	-0.48*
Q5 (High)	0.23	0.29	0.22	0.33*
Q5 – Q1	0.87***	0.72**	0.58**	0.81***
	(2.81)	(2.47)	(2.20)	(2.82)
EW				
Q1 (Low)	-0.68**	-0.60**	-0.51**	-0.56**
Q5 (High)	0.25	0.40*	0.32*	0.39*
Q5 – Q1	0.94***	1.00***	0.84***	0.95***
	(3.04)	(3.45)	(3.13)	(3.28)

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

	(1)	(2)	(3)	(4)
VW	Sub-Par	Par-Sub	Sub-Sub	Par-Par
Q1 (Low)	-0.62**	-0.40*	-0.38*	-0.43*
Q5 (High)	0.24	0.24	0.25	0.32*
Q5 – Q1	0.86***	0.64**	0.64**	0.75***
	(2.81)	(2.17)	(2.34)	(2.65)
EW				
Q1 (Low)	-0.68**	-0.56**	-0.54**	-0.50**
Q5 (High)	0.27	0.33*	0.36*	0.36*
Q5 – Q1	0.95***	0.89***	0.90***	0.86***
	(3.09)	(2.96)	(3.29)	(3.02)

Table A.4: Long-term portfolio alphas after correcting bias

This table shows the long-term portfolio alphas using the Burt and Hrdlicka (2020) adjustment for value-weighted univariate portfolio sorts of focal firms for four types of return predictabilities in ownership-linked firms (OLFs): parent-subsidiary, subsidiary-parent, subsidiary-subsidiary, and parent-parent. The sample includes firms from 23 developed markets from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. To construct this table, we use portfolio returns computed using OLF idiosyncratic returns rather than their raw returns to sort focal firms into quintile portfolios. The table reports monthly five-factor alphas and six-factor alphas for Q5-Q1 difference portfolio from two to six months ahead after portfolio formation. Panel A reports the abnormal returns for the Q5-Q1 difference portfolio using the Fame and French (2015) five-factor model. Panel B reports the abnormal returns for the Q5-Q1 difference portfolio using the Fame and French (2018) six-factor model. The risk-adjusted abnormal returns (alphas) are computed based on the developed market factors from the K. French data library. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fame and French (2015) five-factor Q5-Q1 difference portfolio alphas

	(1)	(2)	(3)	(4)
	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$t+2$	0.77**	0.65**	0.51**	0.70**
	(2.39)	(2.19)	(1.97)	(2.48)
$t+3$	0.69**	0.55*	0.44*	0.63**
	(2.25)	(1.87)	(1.73)	(2.13)
$t+4$	0.60*	0.49*	0.39	0.53**
	(1.85)	(1.67)	(1.46)	(1.97)
$t+5$	0.49	0.41	0.33	0.46
	(1.58)	(1.43)	(1.28)	(1.58)
$t+6$	0.42	0.35	0.26	0.40
	(1.35)	(1.12)	(1.02)	(1.37)

Panel B: Fame and French (2018) six-factor Q5-Q1 difference portfolio alphas

	(1)	(2)	(3)	(4)
	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$t+2$	0.74**	0.55*	0.55**	0.65**
	(2.41)	(1.91)	(2.03)	(2.38)
$t+3$	0.65**	0.50*	0.51*	0.58**
	(2.16)	(1.67)	(1.78)	(2.10)
$t+4$	0.58*	0.42	0.43	0.50*
	(1.89)	(1.47)	(1.63)	(1.74)
$t+5$	0.50*	0.38	0.38	0.45
	(1.66)	(1.28)	(1.36)	(1.51)
$t+6$	0.42	0.29	0.31	0.35
	(1.39)	(1.06)	(1.06)	(1.31)

Table A.5: Univariate portfolio sorts in emerging markets

This table shows the emerging market results of value-weighted (VW) and equally-weighted (EW) univariate portfolio sorts for four types of return predictabilities in ownership-linked firms (OLFs): parent-subsidiary, subsidiary-parent, subsidiary-subsidiary, and parent-parent. There are 26 emerging markets in K. French' data library: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, South Korea, Taiwan, Thailand, Turkey, United Arab Emirates. The sample period is from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. Panel A reports abnormal returns for the lowest (Q1) and highest (Q5) quintile portfolios as well as the Q5-Q1 difference portfolio using the Fama and French (2015) five-factor model in emerging markets. Panel B reports abnormal returns for lowest and highest quintile portfolios as well as the Q5-Q1 difference portfolio using the Fama and French (2018) six-factor model in emerging markets. The risk-adjusted abnormal returns (alphas) are computed based on the emerging market factors from the K. French data library. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

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

	(1)	(2)	(3)	(4)
VW	Sub-Par	Par-Sub	Sub-Sub	Par-Par
Q1 (Low)	-0.98**	-0.54**	-0.53**	-0.71**
Q5 (High)	0.37*	0.45*	0.34*	0.43*
Q5 – Q1	1.35***	0.99***	0.86***	1.14***
	(4.44)	(3.52)	(3.23)	(3.91)
EW				
Q1 (Low)	-1.12***	-0.96**	-0.92**	-0.77**
Q5 (High)	0.37*	0.61**	0.56**	0.58**
Q5 – Q1	1.49***	1.57***	1.49***	1.34***
	(4.71)	(5.43)	(5.52)	(4.71)

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

	(1)	(2)	(3)	(4)
VW	Sub-Par	Par-Sub	Sub-Sub	Par-Par
Q1 (Low)	-1.02***	-0.72**	-0.61**	-0.65**
Q5 (High)	0.39*	0.36*	0.38*	0.42*
Q5 – Q1	1.41***	1.08***	0.99***	1.08***
	(4.55)	(3.47)	(3.65)	(3.76)
EW				
Q1 (Low)	-1.24***	-0.79**	-0.97**	-0.74**
Q5 (High)	0.43*	0.54**	0.52**	0.46*
Q5 – Q1	1.68***	1.33***	1.49***	1.20***
	(5.34)	(4.56)	(5.33)	(4.13)

Table A.6: Multivariate regressions in emerging markets

This table shows the estimation results from cross-sectional Fama and MacBeth (1973) regressions for four trading strategies of ownership-linked firms (OLFs) in 26 emerging markets from K. French' data library: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, South Korea, Taiwan, Thailand, Turkey, UAE. The sample period is from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. The dependent variable in Panel A the Fama and French (2015) five-factor alpha, α_FF5; in Panel B – the Fama and French (2018) six-factor alpha, α_FF6. The explanatory variables include the lagged one-month portfolio returns of OLFs ($Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, or $Sis\_Par_{i,t-1}$) as well as all other controls from Table 4, i.e., firm size, book-to-market ratio, focal firm's own lagged monthly return, medium-term price momentum, asset growth, gross profitability, stock turnover, and industry momentum. All variables are defined in the Appendix, are based on last non-missing available observation for each month t and are winsorized at 1% and 99% levels. All regressions include country and industry fixed effects, but their estimates are not shown. The absolute *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

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

	(1)	(2)	(3)	(4)
DV: $\alpha\_FF5_{i,t}$*100	Parent	Subsidiary	Subsidiary	Parent
$Sub_{i,t-1}$	6.52*** (3.45)			
$Par_{i,t-1}$		4.22*** (4.13)		
$Sis\_Sub_{i,t-1}$			3.10*** (3.98)	
$Sis\_Par_{i,t-1}$				2.04*** (4.08)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	43,458	72,910	47,600	18,160
R^2	0.15	0.14	0.12	0.09

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

	(1)	(2)	(3)	(4)
DV: $\alpha\_FF6_{i,t}$*100	Parent	Subsidiary	Subsidiary	Parent
$Sub_{i,t-1}$	5.47*** (3.14)			
$Par_{i,t-1}$		4.50*** (4.84)		
$Sis\_Sub_{i,t-1}$			2.95*** (2.77)	
$Sis\_Par_{i,t-1}$				2.09*** (4.33)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	43,458	72,910	47,600	18,160
R^2	0.14	0.13	0.11	0.08

Table A.7: Univariate portfolio sorts for financial sector firms

This table shows the financial sector results of value- and equal-weighted univariate portfolio sorts for four types of return predictabilities in ownership-linked firms (OLFs): parent-subsidiary, subsidiary-parent, subsidiary-subsidiary, and parent-parent. There are 23 developed markets from January 2006 to December 2018. Stocks with prices less than $5 at the portfolio formation date are excluded. Panel A reports abnormal returns for the lowest (Q1) and highest (Q5) quintile portfolios as well as the Q5-Q1 difference portfolio using the Fama and French (2015) five-factor model. Panel B reports abnormal returns for lowest and highest quintile portfolios as well as the Q5-Q1 difference portfolio using the Fama and French (2018) six-factor model. The risk-adjusted abnormal returns (alphas) are computed based on the developed market factors from the K. French data library. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

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

	(1)	(2)	(3)	(4)
VW	Sub-Par	Par-Sub	Sub-Sub	Par-Par
Q1 (Low)	-0.61**	-0.37*	-0.32*	-0.39*
Q5 (High)	0.21	0.25	0.20	0.26
Q5 – Q1	0.82***	0.61**	0.52**	0.65**
	(2.91)	(2.18)	(2.07)	(2.41)
EW				
Q1 (Low)	-0.64**	-0.52**	-0.44*	-0.43*
Q5 (High)	0.24	0.34*	0.28*	0.31*
Q5 – Q1	0.88***	0.85***	0.72***	0.74***
	(3.04)	(3.15)	(2.99)	(2.89)

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

	(1)	(2)	(3)	(4)
VW	Sub-Par	Par-Sub	Sub-Sub	Par-Par
Q1 (Low)	-0.59**	-0.34*	-0.32*	-0.34*
Q5 (High)	0.24	0.21	0.21	0.24
Q5 – Q1	0.83***	0.55*	0.53**	0.58**
	(2.84)	(1.96)	(2.19)	(2.21)
EW				
Q1 (Low)	-0.68**	-0.46*	-0.48*	-0.38*
Q5 (High)	0.25	0.28*	0.31*	0.28*
Q5 – Q1	0.93***	0.73***	0.80***	0.66**
	(3.10)	(2.63)	(3.04)	(2.54)

Table A.8: Multivariate regressions for financial sector firms

This table shows the estimation results from cross-sectional Fama and MacBeth (1973) regressions for four trading strategies of ownership-linked firms (OLFs) in the financial sector. There are 23 developed markets from January 2006 to December 2018. Stocks with prices less than $5 at the portfolio formation date are excluded. The dependent variable in Panel A is the risk-adjusted return from the Fama and French (2015) five-factor model, α_FF5; in Panel B – the risk-adjusted return from the Fama and French (2018) six-factor model, α_FF6. The explanatory variables include the lagged one-month portfolio returns of OLFs ($Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, or $Sis\_Par_{i,t-1}$) as well as all other controls from Table 3, i.e., firm size, book-to-market ratio, focal firm's own lagged monthly return, medium-term price momentum, asset growth, gross profitability, stock turnover, and industry momentum. All variables are defined in the Appendix, are based on last non-missing available observation for each month t, and are winsorized at 1% and 99% levels. All regressions include country and industry fixed effects, but their estimates are not shown. The absolute *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fama and French (2015) five-factor alpha

	(1)	(2)	(3)	(4)
DV: $\alpha\_FF5_{i,t}$*100	Parent	Subsidiary	Subsidiary	Parent
$Sub_{i,t-1}$	2.71* (1.91)			
$Par_{i,t-1}$		1.54** (2.20)		
$Sis\_Sub_{i,t-1}$			1.15* (1.72)	
$Sis\_Par_{i,t-1}$				0.71** (2.21)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	26,421	46,722	23,488	8,120
R^2	0.06	0.06	0.05	0.04

Panel B: Fama and French (2018) six-factor alpha

	(1)	(2)	(3)	(4)
DV: $\alpha\_FF6_{i,t}$*100	Parent	Subsidiary	Subsidiary	Parent
$Sub_{i,t-1}$	2.41* (1.70)			
$Par_{i,t-1}$		1.72** (2.36)		
$Sis\_Sub_{i,t-1}$			1.11 (1.59)	
$Sis\_Par_{i,t-1}$				0.80** (2.37)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	26,421	46,722	23,488	8,120
R^2	0.05	0.07	0.05	0.04

Table A.9: Tests with alternative inter-firm momentum links

This table reports the results of Fama-MacBeth regressions of the OLF predictability in the presence of alternative inter-firm momentum variables for the US sample. The sample period is from January 2006 to December 2018. The dependent variable (multiplied by 100) is the monthly excess return of the focal firm. The independent variable of interest is $Sub_{i,t-1}$ and $Par_{i,t-1}$. $Sup\_Ind_{i,t-1}$ and $Cus\_Ind_{i,t-1}$ are the lagged supplier industry momentum and customer industry momentum of the focal firm (Menzly and Ozbas, 2010); $Cus_{i,t-1}$ is the lagged the customer momentum of the focal firm (Cohen and Frazzini, 2008); $PC_{i,t-1}$ is the lagged pseudo-conglomerate portfolio return of the focal firm (Cohen and Lou, 2012); $SA_{i,t-1}$ is lagged strategic alliance partners' portfolio return of the focal firm (Cao et al., 2016); $Tech_{i,t-1}$ is the lagged technological partners' portfolio return of the focal firm (Lee et al., 2019); $Geo_{i,t-1}$ is the lagged average return of all other stocks headquartered in the same city of US 20 largest cities (Parsons et al., 2020). $CB_{i,t-1}$ is the lagged weighted-average return of stocks connected through common board members with the focal firm (Burt et al., 2020). $CA_{i,t-1}$ is the lagged weighted-average return of stocks connected through common analyst coverage with the focal firm (Ali and Hirshleifer, 2020). $CI_{i,t-1}$ is the lagged weighted-average return of stocks connected through common institutional investors with the focal firm (Gao et al., 2017). Control variables are from Table 4, but their coefficients and those of industry fixed effects are not reported. The standard errors are Newey-West adjusted with six lags. The absolute *t*-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.9 (continued)

Panel A: Subsidiary-Parent predictability

DV: Excess returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Sub_{i,t-1}$	2.77*** (3.25)	2.08*** (2.88)	1.88*** (2.98)	1.52** (2.45)	1.94*** (2.59)	2.06** (2.53)	1.97*** (2.71)	1.83*** (2.99)	1.78** (2.57)	2.13*** (2.86)	2.08*** (2.81)	2.03*** (2.81)
$Sup\_Ind_{i,t-1}$		1.54** (2.35)		1.25* (1.88)								
$Cus\_Ind_{i,t-1}$			1.98** (2.42)	1.65** (2.09)								
$Cus_{i,t-1}$					1.83* (1.94)							
$PC_{i,t-1}$						1.77** (2.01)						
$SA_{i,t-1}$							1.16** (2.21)					
$Tech_{i,t-1}$								1.82** (2.20)				
$Geo_{i,t-1}$									1.20* (1.86)			
$CB_{i,t-1}$										1.51* (1.80)		
$CA_{i,t-1}$											1.04** (2.01)	
$CI_{i,t-1}$												1.68** (2.15)
Controls & Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	14,040	11,985	11,985	11,985	4,045	4,167	3,953	4,667	12,287	5,691	8,673	9,916
R^2	0.07	0.08	0.08	0.08	0.07	0.08	0.08	0.08	0.07	0.07	0.08	0.08

Table A.9 (continued)

Panel B: Parent-Subsidiary predictability

DV: Excess returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Par_{i,t-1}$	2.12***	1.51**	1.35**	1.15**	1.70**	1.35**	1.48**	1.70**	1.39**	1.62**	1.62**	1.50**
	(2.68)	(2.32)	(2.17)	(2.02)	(2.42)	(2.22)	(2.03)	(2.39)	(2.21)	(2.14)	(2.03)	(2.05)
$Sup\_Ind_{i,t-1}$		1.12*		0.90								
		(1.79)		(1.57)								
$Cus\_Ind_{i,t-1}$			1.03*	0.77*								
			(1.84)	(1.70)								
$Cus_{i,t-1}$					0.57**							
					(2.43)							
$PC_{i,t-1}$						0.69**						
						(2.47)						
$SA_{i,t-1}$							1.15**					
							(2.05)					
$Tech_{i,t-1}$								1.42**				
								(2.23)				
$Geo_{i,t-1}$									0.89**			
									(2.21)			
$CB_{i,t-1}$										0.63*		
										(1.92)		
$CA_{i,t-1}$											0.78**	
											(2.27)	
$CI_{i,t-1}$												1.06
												(1.54)
Controls & Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	17,004	14,315	14,315	14,315	4,146	4,240	4,053	4,934	13,377	6,092	10,204	10,810
R^2	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.06	0.05	0.06	0.05

Table A.10: Forecasting growth in cash flow, profit, and ROA growth

This table shows panel regression results of the predictive power of ownership-linked firms (OLFs) for focal firms' two fundamental performance measures (F): cash flow growth (ΔCF) in Panel A, profit growth (ΔP) in Panel B, and ROA growth in Panel C. The sample includes firms from 23 developed markets from January 2006 to December 2018. All financial firms and stocks priced less than $5 at the portfolio formation date are excluded. Variables $Sub\_\Delta F_t$, $Par\_\Delta F_t$, $Sis\_Sub\_\Delta F_t$, and $Sis\_Par\_\Delta F_t$ are the average growth in each of the two performance measures for four types of OLFs. All variables are taken at the end of each calendar year and winsorized at 1% and 99% levels. Independent variables are cross-sectionally standardized to have zero mean and unit variance. Control variables are from Table 4 and are defined in the Appendix. All regressions include country (C), industry (I), and year (Y) fixed effects, but their estimates are not shown. The standard errors are clustered by year. The *t*-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Panel A: Predicting cash flow growth of focal firms

	Parent		Subsidiary		Subsidiary		Parent	
DV: ΔCF	*t*	*t* + 1	*t*	*t* + 1	*t*	*t* + 1	*t*	*t* + 1
$Sub\_\Delta CF_t$	0.494***	0.147***						
	(8.28)	(3.71)						
$Par\_\Delta CF_t$			0.216***	0.049***				
			(6.88)	(3.14)				
$Sis\_Sub\_\Delta CF_t$					0.179***	0.061***		
					(5.39)	(3.65)		
$Sis\_Par\_\Delta CF_t$							0.028***	0.006**
							(4.29)	(2.15)
ΔCF_t		0.306***		0.100***		0.154***		0.012**
		(4.67)		(4.49)		(5.01)		(2.46)
Controls, C, I & Y FEs	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	16,731	15,444	28,704	26,496	17,739	16,374	6,391	5,899
R^2	0.17	0.15	0.14	0.12	0.12	0.11	0.12	0.11

Panel B: Predicting profit growth of focal firms

	Parent		Subsidiary		Subsidiary		Parent	
DV: ΔProfits	*t*	*t* + 1	*t*	*t* + 1	*t*	*t* + 1	*t*	*t* + 1
$Sub\_\Delta P_t$	0.575***	0.167***						
	(8.49)	(5.05)						
$Par\_\Delta P_t$			0.217***	0.072***				
			(6.49)	(2.97)				
$Sis\_Sub\_\Delta P_t$					0.134***	0.050***		
					(5.33)	(3.24)		
$Sis\_Par\_\Delta P_t$							0.084***	0.025**
							(4.17)	(2.54)
ΔP_t		0.421***		0.160***		0.114***		0.057***
		(5.37)		(3.62)		(3.65)		(3.78)
Controls, C, I & Y FEs	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	16,731	15,444	28,704	26,496	17,739	16,374	6,391	5,899
R^2	0.19	0.17	0.18	0.16	0.14	0.13	0.13	0.12

Table A.10 (continued)

Panel C: Predicting ROA growth of focal firms

	Parent		Subsidiary		Subsidiary		Parent	
DV: ΔROA	*t*	*t* + 1	*t*	*t* + 1	*t*	*t* + 1	*t*	*t* + 1
$Sub\_\Delta ROA_t$	0.553*** (7.99)	0.140*** (4.74)						
$Par\_\Delta ROA_t$			0.210*** (6.74)	0.052*** (3.48)				
$Sis\_Sub\_\Delta ROA_t$					0.126*** (4.89)	0.030*** (2.96)		
$Sis\_Par\_\Delta ROA_t$							0.012*** (4.08)	0.005** (2.50)
ΔROA_t		0.281*** (4.92)		0.121*** (4.13)		0.070*** (3.42)		0.010*** (2.76)
Controls, C, I & Y FEs	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	16,731	15,444	28,704	26,496	17,739	16,374	6,391	5,899
R^2	0.16	0.14	0.15	0.13	0.13	0.11	0.12	0.10

Table A.11: Forecasting revenue surprises

This table shows the results of Fama-MacBeth regressions of the predictability of ownership-linked firms (OLFs) for standardized unexpected revenues (SURs). The SURs are calculated as the yearly change in quarterly revenues scaled by the standard deviation of unexpected revenues over the eight past quarters. The explanatory variables include the preceding three months portfolio returns of OLFs, $OLF_{i,t-1}$ (i.e., $Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, or $Sis\_Par_{i,t-1}$). The results are reported for four types of OLF predictability: subsidiary-parent (Sub-Par), parent-subsidiary (Par-Sub), subsidiary-subsidiary (Sub-Sub), and parent-parent (Par-Par). All the independent variables are distributed to deciles and scaled from 0 to 1. The dependent variable is winsorized at 1% and 99% levels in the cross-section. The control variables are from Table 4 as well as one- to four-quarter lags of the firm's own SURs. All regressions include country and industry fixed effects, but their estimates are not shown. Panel A reports regression results for the next quarter's SURs. Panel B reports regression results of future SURs for the next four fiscal quarters. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with four lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: One-quarter ahead forecast

	(1)	(2)	(3)	(4)
DV: $SUR_{i,t}$ *100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$OLF_{i,t-1}$	1.48*** (2.78)	1.33*** (5.59)	0.96*** (3.22)	1.35*** (3.69)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	35,650	61,162	37,798	13,618
R^2	0.41	0.55	0.33	0.41

Panel B: Extended forecast

DV: $SUR_{i,t+k}$ $k = 0, 1, 2, 3$	Quarter 1	Quarter 2	Quarter 3	Quarter 4
Subsidiary – Parent predictability				
$Sub_{i,t-1}$	1.48*** (2.78)	1.15** (2.35)	0.85 (1.46)	0.53 (0.91)
Controls, Country & Industry FEs	Y	Y	Y	Y
Parent – Subsidiary predictability				
$Par_{i,t-1}$	1.33*** (5.59)	1.05*** (4.44)	0.64** (2.43)	0.31 (1.48)
Controls, Country & Industry FEs	Y	Y	Y	Y
Subsidiary – Subsidiary predictability				
$Sis\_Sub_{i,t-1}$	0.96*** (3.22)	0.66** (2.01)	0.37 (1.18)	0.16 (0.47)
Controls, Country & Industry FEs	Y	Y	Y	Y
Parent – Parent predictability				
$Sis\_Par_{i,t-1}$	1.35*** (3.69)	0.82** (2.45)	0.43 (1.32)	0.19 (0.58)
Controls, Country & Industry FEs	Y	Y	Y	Y

Table A.12: Forecasting sales surprises

This table shows the results of Fama-MacBeth regressions of the predictability of ownership-linked firms (OLFs) for standardized unexpected sales (SUSs). The SUSs are calculated as the yearly change in quarterly sales scaled by the standard deviation of unexpected sales over the eight past quarters. The explanatory variables include the preceding three months portfolio returns of OLFs, $OLF_{i,t-1}$ (i.e., $Sub_{i,t-1}$, $Par_{i,t-1}$, $Sis\_Sub_{i,t-1}$, or $Sis\_Par_{i,t-1}$). The results are reported for four types of OLF predictability: subsidiary-parent (Sub-Par), parent-subsidiary (Par-Sub), subsidiary-subsidiary (Sub-Sub), and parent-parent (Par-Par). All the independent variables are distributed to deciles and scaled from 0 to 1. The dependent variable is winsorized at 1% and 99% levels in the cross-section. The control variables are from Table 4 as well as one- to four-quarter lags of the firm's own SUSs. All regressions include country and industry fixed effects, but their estimates are not shown. Panel A reports regression results for the next quarter's SUSs. Panel B reports regression results of future SUSs for the next four fiscal quarters. The *t*-statistics are in parentheses and the standard errors are Newey-West adjusted with four lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: One-quarter ahead forecast

	(1)	(2)	(3)	(4)
DV: $SUS_{i,t}$ *100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$OLF_{i,t-1}$	1.15**	1.18***	0.66**	1.01***
	(2.37)	(5.25)	(2.10)	(3.36)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	35,650	61,162	37,798	13,618
R^2	0.52	0.47	0.33	0.46

Panel B: Extended forecast

DV: $SUS_{i,t+k}$ $k = 0, 1, 2, 3$	Quarter 1	Quarter 2	Quarter 3	Quarter 4
Subsidiary – Parent predictability				
$Sub_{i,t-1}$	1.15**	0.91**	0.66	0.42
	(2.37)	(1.99)	(1.29)	(0.82)
Controls, Country & Industry FEs	Y	Y	Y	Y
Parent – Subsidiary predictability				
$Par_{i,t-1}$	1.18***	0.87***	0.49**	0.29
	(5.25)	(4.09)	(2.17)	(1.49)
Controls, Country & Industry FEs	Y	Y	Y	Y
Subsidiary – Subsidiary predictability				
$Sis\_Sub_{i,t-1}$	0.66**	0.44	0.20	0.12
	(2.10)	(1.37)	(0.82)	(0.27)
Controls, Country & Industry FEs	Y	Y	Y	Y
Parent – Parent predictability				
$Sis\_Par_{i,t-1}$	1.01***	0.63**	0.31	0.19
	(3.36)	(2.26)	(1.12)	(0.35)
Controls, Country & Industry FEs	Y	Y	Y	Y