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Internal capital markets and predictability in complex ownership firms[☆]

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ABSTRACT

Using global cross-firm ownership data, we find that both stock returns and cash-flow news of ownership-linked firms predict focal firm's returns for all types of ownership structures: subsidiary−parent, parent−subsidiary, subsidiary−subsidiary, and parent−parent. This effect, observed only after the establishment of cross-firm ownership, is not subsumed by focal firm or industry momentum, or alternative inter-firm relations, including customer−supplier links and shared analyst coverage. Our findings are explained by mispricing due to internal capital markets – a mechanism unique to complex ownership firms. Higher internal capital market activity among ownership-linked firms also induces larger investments and lower external financing of the focal firm.

1. Introduction

Stock return predictability is among the most widely studied phenomena that challenge the notion of efficient capital markets. Despite the richness of 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 OLFs) remains open. A major challenge in addressing this question is that OLFs can have other ties among themselves, such as various

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[1] For the review of such anomalies see Richardson et al. (2010), Harvey et al. (2016).

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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 that allows us to circumvent some of the limitations of flat ownership structures and explore, for the first time, mechanisms that are unique to OLFs.

In contrast to the usual simple ownership of US firms, where one parent (subsidiary) firm has only one subsidiary (parent); globally, publicly listed parent firms tend to have a more complex ownership structure, where parent firms frequently have multi-country and multi-layer subsidiaries (La Porta et al., 1999; Bertrand and Sendhil, 2003). In this setting, usual for multinational enterprises (MNEs), information transmission delays and associated return predictability can occur across four ownership structures (see Fig. 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 existing primarily in MNEs with a complex multi-parent−multi-subsidiary ownership network and, therefore, are essential for a better understanding of the drivers of predictability.

Firms with complex ownership links often have significant internal capital market (ICM) activities, which are not always optimal and value-enhancing (Stulz, 1990; Lamont, 1997; Shin and Stulz, 1998; Boutin et al., 2013; Gugler et al., 2013; D'Mello et al., 2017) and may lead to delayed information diffusion to stock prices (Hong and Stein, 1999). In the latest decades, many MNE subsidiaries have become independent in their operations and showed substantial within-firm ability to impact capital distribution and cross-subsidization decisions, thus decreasing the efficiency of the firm's ICM (Birkinshaw et al., 1998; Mudambi, 1999; Mudambi and Navarra, 2004). MNEs specifically rely on ICMs to transfer resources obtained via local debt markets of their subsidiaries or other shared ownership entities to other parts of MNEs (Fisch and Schmeisser, 2020). This further aggravates information delays and inefficiencies in the capital use within MNEs. Therefore, complex ownership and a large cross-section of ownership links allows us to investigate the mechanisms unique to OLFs, e.g., an active ICM, as an opportunity to directly examine whether ownership links can induce cross-firm return predictability.

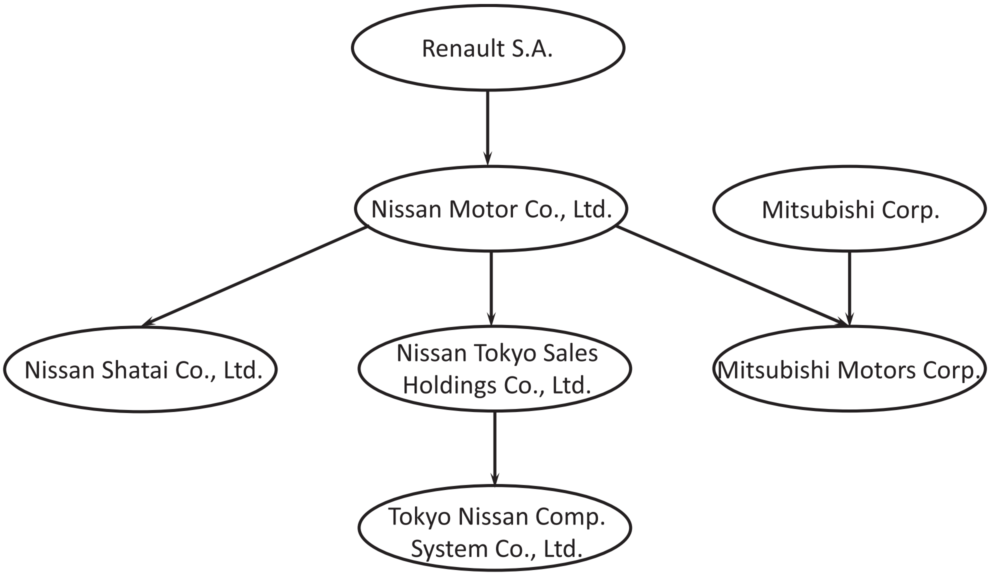
In this paper, we examine return predictability among OLFs using a global sample across 23 developed markets in 2006–2018; after data filtering, the sample contains 2052 parent firms and 3664 subsidiaries. We observe return predictability in all four possible cases of ownership network—namely, subsidiary−parent, parent−subsidiary, subsidiary−subsidiary, and parent− parent. For example, worldwide, the Fama and French (2018) subsidiary−parent 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, worldwide, 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 a value-weighted monthly six-factor alpha of 77 bps (t-statistic = 2.54). A similar approach yields comparable 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 momentum 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.

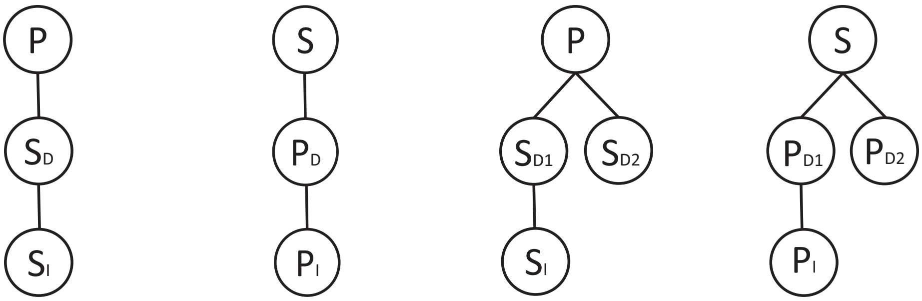
To address the endogeneity concerns, we analyze return predictability of OLFs around the changes in the cross-firm ownership structure. To this end, we use the difference-in-difference method and a four-year time window which comprises of two years before and two years after the event. We expect that 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 includes companies without ownership changes. The two groups are then matched by industry and 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 return predictability exists after changes in ownership only in the treatment group, i.e. for those firms that form ownership links. We do not observe return predictability in OLFs in the control group either before or after the (pseudo) date of change in ownership links.

As pointed out by Lewellen (2010), Richardson et al. (2010), and others, any study that addresses a return anomaly needs to discriminate between risk and mispricing explanations. Our results are consistent with the *ex-ante* expected return predictability due to the complicated information processing across OLFs with ICMs, and therefore support the mispricing view of the observed phenomenon. For instance, Berger and Ofek (1995) show that several ICM activities such as overinvestment and cross-subsidization

[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.



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



(1) Subsidiary-Parent (2) Parent-Subsidiary (3) Subsidiary-Subsidiary (4) Parent-Parent

Plot B: Four types of complex ownership links

Fig. 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).

decrease information processing efficiency. Many studies document predictive power of accrual and cash flows for firm-level and aggregate stock returns (e.g., Ball and Shivakumar, 2006; Hirshleifer et al., 2009). Hence, we use the framework of Campbell and Shiller (1988), Campbell (1991), and Michaely et al. (2021) and decompose returns of OLFs into cash-flow news, discount rate news, and cash flow volatility for each type of ownership relation for a given focal firm. We find that focal firm returns are significantly affected by the changes in cash-flow news of their OLFs. The impact of discount rate news and cash flow volatility is largely insignificant on risk-adjusted returns. This implies that complex ownership firms are fundamentally related to each other through the level of cash flows. Given this evidence, in the follow-up tests, we use the Shin and Stulz (1998) methodology of determining the ICM activity and directly show that focal firms exhibit a slow price response to their OLF returns and cash-flow news due to active within-firm capital reallocations. That is, more active ICMs are associated with more return predictability in OLFs across all four types of cross-ownership links as well as across countries.

Return predictability among firms with economic links, unlike firms with a complex ownership, is well known (Cohen and Frazzini, 2008; Cao et al., 2016; Finke and Weigert, 2017).[3] However, economic and ownership links are different in their nature: 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. As such, even though ICM activities often complicate investors' understanding of firm specific information, they sometimes induce efficiency too. Stein (1997, 2002) shows that ICMs allow fund shifts to profitable projects, thus, reducing the need for credit. Almeida et al. (2015) find that internal capital reallocation allows firms with better growth opportunities to undertake more investments. Building on these insights, we consider a model between changes in capital expenditure and external financing on the one side and the lagged cash-flow news, discount rate news, and cash flow volatility of OLFs on the other side, while controlling for various focal firm characteristics. Consistent with intuition, we find that cash-flow news of OLFs positively predict capital expenditures of the focal firm and negatively predict its debt and equity financing. These results again illustrate a fundamental and delayed linkage among OLFs through cash flows and support the mispricing origin of predictability in OLFs.

We further support the mispricing argument based on the importance of the ICM channel for return predictability by testing for the persistence of focal firm's earnings surprises from cash flow surprises of its OLFs. 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 financial analysts of the focal firm; therefore, the unexpected earnings of OLFs can predict the earnings surprises of the focal firm. Thus, the existence of return predictability among firms with multi-layer ownership structure is a mispricing phenomenon due to ICM activity – a mechanism unique to such firms.

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 the changes in OLF return predictability in response to ownership link changes. Section 5 explains the 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 for which risk factors are available in the K. French library. These markets include two 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 four 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 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.[4] 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 3862 and 8970, respectively. 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. Claessens et al. (2000) used a 20% cut-off to define a large ownership stake. Moreover, 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

[3] Li et al. (2016) show that returns of US local subsidiaries (parent firms) predict returns of US parent firms (subsidiaries). However, once the intra-industry lead-lag relation is controlled for, their parent-subsidiary return predictability disappears. Ginglinger et al. (2018) focus on price delays around earnings announcements in OLFs firms rather than return predictability. They use 2015 static cross-ownership data to trace back 15 years of ownership links, thus causing a survivorship bias in their estimations.

[4] We cross-validate and merge Orbis and FactSet datasets—the two sources that provide ownership links and shareholding percentages—for the following reasons. First, Orbis provides detailed parent and subsidiaries data for each focal firm, but their shareholding percentages are not always numerical. Second, FactSet only provides the main owner/parent firm to each focal firm, yet 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.

company if its ownership in that company is no less than 20%.[5] Accordingly, we also use 20% 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 2052 parent firms and 3664 subsidiaries.

2.2. Four predictors of ownership-linked firms

The first regressor of interest 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:

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

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 the following weighted average:

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

The second regressor of interest 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:

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

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 us 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 us 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 the weighted average:

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

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 constructed based on the value-weighted portfolio returns of sister subsidiaries of subsidiary i and sister parent firms of parent firm i, respectively, i.e.:

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

and

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

[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%, and our main findings remain intact.

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 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 1287 and 2208, 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 five 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 perform both one-period return and 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 presents the excess returns for five quintile portfolios and the Q5-Q1 difference portfolio. Column 1 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 negative 19 bps for the value-weighted parent firms' stocks in the lowest quintile. This return spread of 118 bps is significant at the 1% level. The equally-weighted portfolio return spread is 143 bps and again is highly significant. Columns 2–4 show similar evidence for both value-weighted and equally-weighted portfolios of predictor firms' returns across the remaining three OLF predictability directions. The value-weighted spread is 97 bps in the parent−subsidiary case, 85 bps in the subsidiary−subsidiary case, and 103 bps in the parent−parent case.

In Panel B of Table 2, we use the Fama and French (2018) six-factor model to capture abnormal returns of the focal firm.[8] 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 predictabilities are now 77 bps, 76 bps, and 79 bps per month, respectively. Taken together, the results in Table 2

[7] 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).

[8] The Fama and French (2018) six-factor model adds momentum to the Fama and French (2015) five-factor model.

Table 1
Summary statistics.

Panel A: Full sample description

	Mean	SD	Min	Med	Max
Number of parent firms	1287	108	1021	1193	1575
Number of subsidiaries	2208	201	1630	2087	2818
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

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
Capital Expenditure (CapEx)	0.21	0.08	−0.39	0.19	0.81
Debt ($ bln)	2.02	3.08	0.05	0.78	19.91
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
Capital Expenditure (CapEx)	0.24	0.06	−0.27	0.22	0.79
Debt ($ bln)	1.48	2.29	0.04	0.68	10.47

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), capital expenditure (CapEx), and debt (Debt). All variables are defined in the Appendix and winsorized within each cross-section at 1% and 99% levels.

Table 2
Univariate portfolio sorts.

Panel A: Excess returns.

	Value-weighted portfolio sorts				Equally-weighted portfolio sorts			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sub-Par	Par-Sub	Sub-Sub	Par-Par	Sub-Par	Par-Sub	Sub-Sub	Par-Par
Q1 (Low)	−0.19	0.03	0.11	0.08	−0.35	−0.22	−0.12	0.00
Q2	0.19	0.51*	0.51*	0.42*	0.03	0.49*	0.46*	0.33
Q3	0.60**	0.29	0.40*	0.85**	0.71**	0.14	0.22	0.77**
Q4	0.38	0.75**	0.68**	0.59*	0.38	0.68**	0.71**	0.54*
Q5 (High)	0.99**	1.01**	0.96**	1.12**	1.08**	1.14**	1.08**	1.14**
Q5 – Q1	1.18***	0.97***	0.85***	1.03***	1.43***	1.37***	1.20***	1.15***
	(4.23)	(3.41)	(3.22)	(3.84)	(5.09)	(4.83)	(4.56)	(4.26)

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

	Value-weighted portfolio sorts				Equally-weighted portfolio sorts			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sub-Par	Par-Sub	Sub-Sub	Par-Par	Sub-Par	Par-Sub	Sub-Sub	Par-Par
Q1 (Low)	−0.81**	−0.48*	−0.45*	−0.46*	−0.91**	−0.64**	−0.66**	−0.54**
Q5 (High)	0.32*	0.29	0.30*	0.33*	0.35*	0.37*	0.44*	0.39*
Q5 – Q1	1.13***	0.77**	0.76***	0.79***	1.26***	1.01***	1.10***	0.93***
	(3.66)	(2.54)	(2.79)	(2.78)	(4.09)	(3.40)	(4.01)	(3.25)

This table shows the abnormal returns of value-weighted and equally-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 the K. French data library 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 the excess returns for all quintile portfolios and the Q5-Q1 difference portfolio. Panel B reports abnormal returns for Q1 and Q5 quintile portfolios and the Q5-Q1 difference portfolio using the Fama and French (2018) six-factor model. 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.

demonstrate the economically and statistically significant return predictability among firms with ownership links.[9]

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 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 the monthly abnormal returns from month two to six for the Q5-Q1 difference portfolio using the Fama and French (2018) six-factor model, α_FF6. Across all columns of the table we observe a steady decrease in the OLF return predictability. However, the decrease in predictability is different across the types of ownership links. While we still observe marginal predictability in the subsidiary−parent case in month $t + 5$, that for parent−subsidiary, subsidiary−subsidiary, and parent−parent cases lasts until month $t + 4$. In sum, 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.[10]

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 (Table A.1 and A.2), we report the results of the OLF return predictability tests across time periods and in different geographic regions and obtain statistically highly significant results in these tests.

[10] In the Internet Appendix, we conduct 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 (2021) adjustment. This adjustment does not considerably affect our results (see Table A.3 and A.4 in the Internet Appendix).

Table 3
Long-term portfolio alphas.

Panel A: 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)

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 six-factor alphas using the Fama and French (2018) six-factor model for Q5-Q1 difference portfolio from two to six months ahead after the portfolio formation. 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.

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.[11]

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 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.

Panel B of Table 4 reports 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 (2018) six-factor model in month *t*, *α_FF6*. In our estimations, we use regional risk factors, *Mkt*, *Smb*, *Hml*, *Rmw*,

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

Table 4
Multivariate regressions of OLF return predictability.

Panel A: Excess returns				
	(1)	(2)	(3)	(4)
DV: $ret_{i,\ t}$*100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$Sub_{i,\ t-1}$	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*	−0.24***	−0.30***	−0.16**
	(1.71)	(3.35)	(4.71)	(2.10)
Ln(B/M)	0.40**	0.22**	0.13	0.22***
	(2.12)	(2.02)	(0.29)	(2.65)
$R_{i,\ t-1}$	−4.92***	−1.49	−3.27***	−1.28**
	(3.27)	(1.25)	(3.41)	(1.99)
Mom	−0.60	1.63*	−0.34	1.48*
	(0.58)	(1.94)	(0.72)	(1.78)
AG	−0.66**	−0.05	−0.24	−0.94***
	(2.45)	(0.10)	(1.32)	(3.42)
GP	0.04	0.47***	0.19	0.07
	(0.97)	(2.91)	(1.17)	(1.27)
Turnover	−0.10**	−0.22	−0.17**	−0.76***
	(2.09)	(0.75)	(2.06)	(2.94)
Ind_Mom	0.83*	1.27**	1.29**	0.79*
	(1.76)	(2.14)	(2.48)	(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

Panel B: Fama and French (2018) six-factor alphas				
	(1)	(2)	(3)	(4)
DV: $\alpha\_FF6_{i,\ t}$*100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$Sub_{i,\ t-1}$	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

Cma, and *Mom* from Kenneth French's website.[12] Following 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.[13] 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 for the risk-adjusted returns of parent, subsidiary, sister subsidiary, and sister parent firms. The magnitude of the respective point estimates is only marginally smaller than those for excess returns. In addition, as in 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.

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.

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

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 (see Tables A.5 in the Internet Appendix).

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 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 (see Tables A.6 in the Internet Appendix).

4.2. 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 5 reports the differences between real- and pseudo-focal firms for each of their four firm characteristics, and the corresponding estimates of OLF predictive coefficients prior to the event date. We report these differences for all four types of OLFs with their respective *t*-statistics. We also record the number of real and pseudo-focal firms for each ownership link. The test 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 5 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.

[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.

Table 5
Impact of ownership link changes on the OLF return predictability.

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* × *Postlink*	3.72***	2.39***	1.36***	1.01***
	(2.59)	(3.55)	(2.65)	(3.59)
$OLF_{i,\ t-1}\times$ *Treatment*	−0.19	−0.18	−0.10	−0.10
	(0.38)	(0.75)	(0.35)	(0.84)
$OLF_{i,\ t-1}\times$ *Postlink*	0.21	0.15	0.13	0.14
	(0.88)	(0.53)	(0.57)	(0.96)
$OLF_{i,\ t-1}$	1.16	1.22	0.75	0.42
	(1.28)	(1.49)	(1.53)	(1.05)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	10,812	18,548	11,462	4130
R^2	0.08	0.07	0.05	0.04

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* × *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.

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.

Fig. 2 visualizes the results of Table 5 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

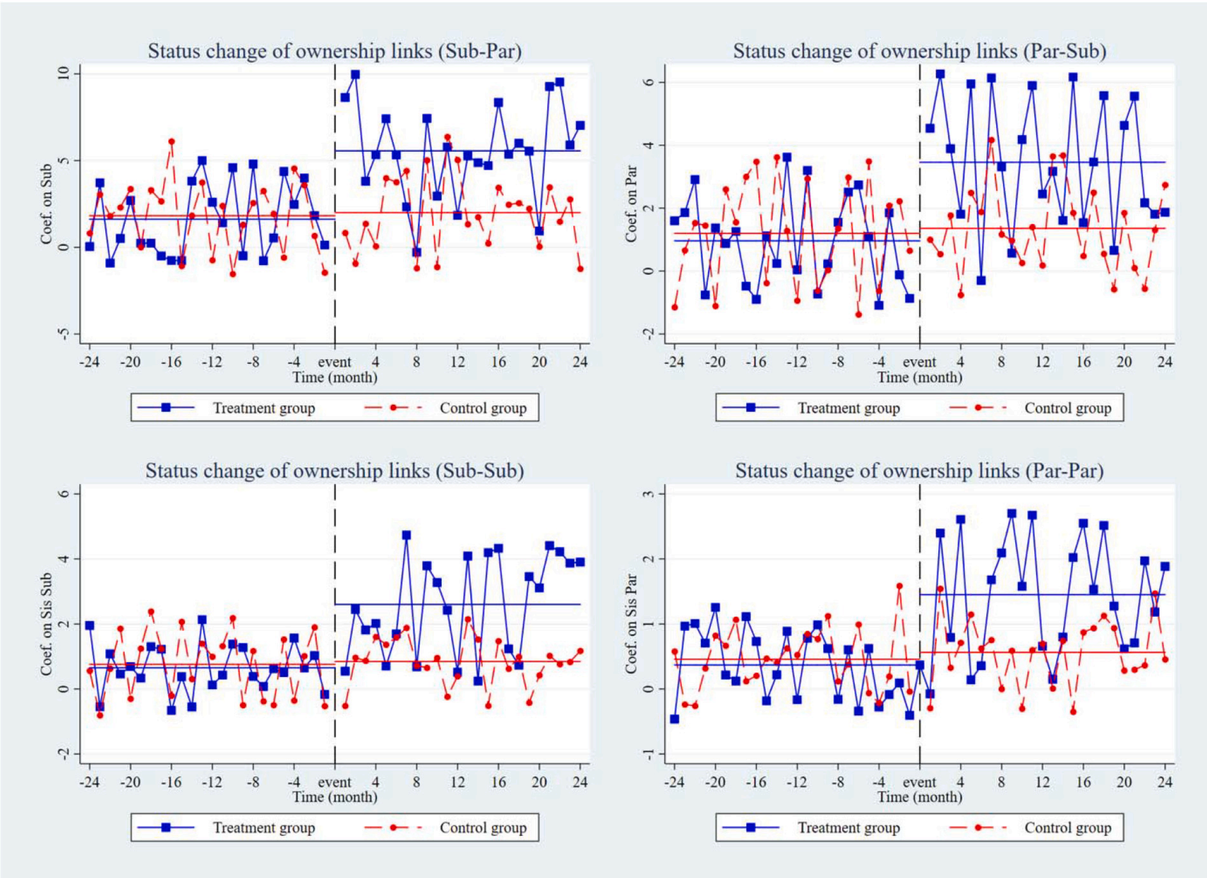


Fig. 2. Predictive coefficients of ownership-linked firms before and after ownership links.
This figure shows the predictive OLF coefficients to real- and pseudo-focal firms before and after the change in ownership links based on Table 6 estimations, as well as their mean values before and after the 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6
Return forecasting with cash flows of OLFs.

Panel A: Excess returns

	(1)	(2)	(3)	(4)
DV: $ret_{i,\ t}$*100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$Sub\_\Delta CFN_{t-1}$	1.18***			
	(3.40)			
$Sub\_\Delta DRN_{t-1}$	−0.50*			
	(1.88)			
$Sub\_\Delta CFV_{t-1}$	0.29*			
	(1.69)			
$Par\_\Delta CFN_{t-1}$		1.09***		
		(3.89)		
$Par\_\Delta DRN_{t-1}$		−0.50**		
		(2.15)		
$Par\_\Delta CFV_{t-1}$		0.26*		
		(1.67)		
$Sis\_Sub\_\Delta CFN_{t-1}$			0.93***	
			(4.29)	
$Sis\_Sub\_\Delta DRN_{t-1}$			−0.37**	
			(2.25)	
$Sis\_Sub\_\Delta CFV_{t-1}$			0.19*	
			(1.78)	
$Sis\_Par\_\Delta CFN_{t-1}$				1.13***
				(4.33)
$Sis\_Par\_\Delta DRN_{t-1}$				−0.53**
				(2.15)
$Sis\_Par\_\Delta CFV_{t-1}$				0.28*
				(1.74)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	31,284	56,153	35,223	12,308
R^2	0.20	0.22	0.14	0.19

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

	(1)	(2)	(3)	(4)
DV: $\alpha\_FF6_{i,\ t}$*100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$Sub\_\Delta CFN_{t-1}$	0.93***			
	(2.80)			
$Sub\_\Delta DRN_{t-1}$	−0.39			
	(1.54)			
$Sub\_\Delta CFV_{t-1}$	0.20			
	(1.35)			
$Par\_\Delta CFN_{t-1}$		0.94***		
		(3.29)		
$Par\_\Delta DRN_{t-1}$		−0.42		
		(1.62)		
$Par\_\Delta CFV_{t-1}$		0.24		
		(1.32)		
$Sis\_Sub\_\Delta CFN_{t-1}$			0.73***	
			(3.83)	
$Sis\_Sub\_\Delta DRN_{t-1}$			−0.33*	
			(1.76)	
$Sis\_Sub\_\Delta CFV_{t-1}$			0.17	
			(1.64)	
$Sis\_Par\_\Delta CFN_{t-1}$				1.00***
				(3.42)
$Sis\_Par\_\Delta DRN_{t-1}$				−0.44*
				(1.78)
$Sis\_Par\_\Delta CFV_{t-1}$				0.26*
				(1.66)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	31,284	56,153	35,223	12,308
R^2	0.15	0.15	0.10	0.14

This table shows the results of Fama-MacBeth regressions of excess and risk-adjusted returns of the focal firm on the lagged changes in cash-flow news (ΔCFN), discount rate news (ΔDRN), and cash flow volatility (ΔCFV) of ownership-linked firms (OLFs). ΔCFN, ΔDRN, and ΔCFV are constructed from quarterly stock return following Michaely et al. (2021). The dependent variable in Panel A is the excess return of the focal firm, $ret_{i,\ t}$, in in Panel B – from the Fama and French (2018) six-factor model, α_FF6. 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 variables are winsorized at 1% and 99% levels in the cross-section. The control variables are 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 eight lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

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

In this section, we provide explanation of the observed predictability in OLFs. Overall, we show that the documented predictability results from mispricing due to internal capital markets rather than omitted risk factors. Our evidence consists of four parts. First, we examine the fundamental linkage among OLFs using cash flow surprises. Second, we show directly the importance of ICM activity for return predictability in complex ownership firms. Third, we illustrate that investment and financing activities of the focal firm are also predictable based on the lagged cash flows of its OLFs. Finally, we support our mispricing arguments by testing for the persistency of earnings surprises of the focal firm from cash flow surprises of its OLFs.

5.1. Predictability in OLFs with cash flows

The return predictability phenomenon in OLFs documented earlier naturally raises the question whether it reflects delayed fundamental links among OLFs. One way to address this issue is to determine if cash flow innovations of OLFs can forecast returns of the focal firm. The particular choice of cash flows is motivated through two angles. First, many studies show significant predictive power of accrual and cash flows for firm-level and aggregate stock returns (e.g., Ball and Shivakumar, 2006; Hirshleifer et al., 2009). Second, and more importantly, as mentioned before, a complex ownership firm often has large and inefficient ICM transactions that are financed by cash flows from operation of its subsidiaries and/or parent firms (Stulz, 1990; Lamont, 1997; Shin and Stulz, 1998). Hence, observing a link between focal firm returns and cash flows of its OLFs would give indirect evidence on the potential importance of the ICM mechanism for the return predictability in complex ownership firms. In addition, Michaely et al. (2021) observe that changes in cash flow volatility rather than the level of cash-flow news are associated with announcement returns from such corporate policies as dividend changes and repurchases. Therefore, to accomplish our goal we use the return decomposition framework based on the log-linear dividend-ratio model of Campbell and Shiller (1988), the vector autoregressive approach of Campbell (1991), as well as Michaely et al. (2021), and construct from quarterly stock returns cash-flow news, discount rate news, and volatility of cash-flow news of OLFs for each type of ownership relation for a given focal firm.

Table 6 shows the results of Fama-MacBeth regressions for predicting focal firms' excess returns (Panel A) and risk-adjusted returns from the Fama and French (2018) six-factor model (Panel B) using the lagged by one quarter changes in cash-flow news (ΔCFN), discount rate news (ΔDRN), and cash flow volatility (ΔCFV) of their OLFs. These tests, like those in Table 4, are based on Eq. (5). The format of both panels is also similar to those in Table 4, and we use the same set of control variables, which, for the sake of convenience, are not shown. The tests in both panels show similar results. We find that changes in cash-flow news of OLFs predict the next period returns of the focal firm. In particular, the CFSs based predictors are positive and highly significant in all estimations. The magnitude of coefficients is only marginally smaller for risk-adjusted returns than for excess returns of focal firms. The importance of changes in discount rate news is distant secondary to those in cash-flow news with 5% statistical significance present only in estimations with excess returns of the focal firm except for the subsidiary-parent link. This implies that cost of capital innovations do not propagate very strongly within the network of complex ownership firms. The sign of this weaker relation is negative and thus consistent with intuition: it implies that focal firm returns decrease with an increasing cost of capital in their OLFs. The impact of changes in cash flow volatility is marginally significant when using excess returns and largely insignificant when using the six-factor model. Thus, Table 6 evidences that focal firm returns are significantly and consistently affected by the lagged changes in cash-flow news of their OLFs implying that complex ownership firms are fundamentally interrelated.

5.2. Internal capital markets and predictability in OLFs

Building on the intuition and implications of our results in Table 6, we consider internal capital market as the main mechanism of the OLF return predictability. 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; Lamont, 1997; Shin and Stulz, 1998; Fisch and Schmeisser, 2020). Also, ICM activities such as overinvestment and cross-subsidization can decrease information processing efficiency in a group and lead to firm value discounts and higher subsequent returns (e.g., Berger and Ofek, 1995). 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 the return predictability in OLFs would be.

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. Initially, we examine subsidiary−parent and parent−parent return predictabilities. In this case, a parent firm has different subsidiaries.[15] For the smallest subsidiary *i* of parent firm *j*, we run the following time-series regression over 36 months:

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

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*; $CF_{not\ i,\ j,\ t}$ 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*; $CF_{i,\ j,\ t}$ 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*.[16]

Then, we examine parent−subsidiary and subsidiary−subsidiary return predictabilities. 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:

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

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*; $CF_{not\ i,\ t}$ 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*; $CF_{i,\ t}$ 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 being "active" if β_1 in Eqs. (6) and (7) are significant at the 10%, 5% or 1% levels.

Table 7 shows the test results of the impact of ICMs on return predictability in OLFs using changes in cash-flow news. The firm's ICM activity is based on 10%, 5%, and 1% significance levels of coefficient β_1. For each ICM activity estimate, we split the sample at the median into "High" and "Low" subsamples. Next, we run the corresponding specification in Panel A of Table 6 by interacting the appropriate $OLF\_\Delta CFN_{i,\ t-1}$ with a dummy variable "High," which is equal to unity if the value of the ICM activity is above the median, and zero otherwise. The estimated coefficient on $OLF\_\Delta CFN_{i,\ t-1} \times High$ reflects the difference in the strength of return predictability in OLFs between "High" or "Low" values for the specific ICM activity measure. All regressions include the dummy variable itself, the lagged control variables and country- and industry-fixed effects. In line with expectation, we find strong evidence on the relevance of ICM to the OLF return predictability: the difference between "High" and "Low" subsamples is significant at 1% irrespective of the ICM activity measure.

We provide cross-country results on the importance of ICM activity for return predictability in OLFs in Fig. 3. It depicts the scatterplots of average OLF return predictability coefficients based on changes in cash-flow news, ΔCFN, for (i) parent firms in each country from ΔCFN of their subsidiaries (Plot A) and (ii) for subsidiaries in each country from ΔCFN of their parent firms (Plot B), depending on the average country-level ICM intensity computed from Eqs. (6–7) using the 5% significance level for coefficient β_1.[17] Both plots also show the corresponding simple regression results including the slope coefficient on the average ICM intensity, its *t*-statistic, and the regression R-squared. In spite of the relatively small sample – 23 data pairs reflecting 23 developed countries – the relation between ICM intensity and OLF return predictability is positive and significant at the 5% level in both plots. Thus, this figure substantiates our result that the ICM activity level in OLFs has a direct and positive effect on the documented level of predictability for their corresponding focal firm returns. All these findings support the mispricing view of the OLF return predictability.

5.3. Internal financing and return predictability

In this subsection, we provide evidence on the relation between OLF return predictability and ICM activity. We show that investments (capital expenditures) and financing policies (debt and equity financing) of a given firm with complex ownership are affected by the intensity of internal fund transfers.

We have observed that stock return predictability in OLFs is best explained by the existence of internal capital markets – an activity,

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

[16] The applicability of ICM calculated from Eq. (6) 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. (7) for both parent−subsidiary and subsidiary−subsidiary cases.

[17] Unfortunately, we cannot produce similar pictures for two horizontal ownership structures (subsidiary-subsidiary and parent-parent) due to the luck of sufficient data per country for both nodes of these types of ownership linkages.

Table 7
Internal capital market activity and return predictability in OLFs.

	High-Low			
Internal Capital Markets	Sub-Par	Par-Sub	Sub-Sub	Par-Par
10% significance of β_1	0.55***	0.38***	0.49***	0.24***
	(5.00)	(3.24)	(6.27)	(3.85)
5% significance of β_1	0.76***	0.50***	0.66***	0.35***
	(6.73)	(5.07)	(8.05)	(5.16)
1% significance of β_1	0.81***	0.53***	0.70***	0.33***
	(7.64)	(5.06)	(8.46)	(5.54)

This table shows the tests results on the impact of internal capital market (ICM) activity on the OLF return predictability using changes in cash-flow news (ΔCFN) and Fama-MacBeth regressions. ΔCFN is computed as in Michaely et al. (2021) and Table 6. 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:

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

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; $CF_{not\ i,\,j,\,t}$ 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:

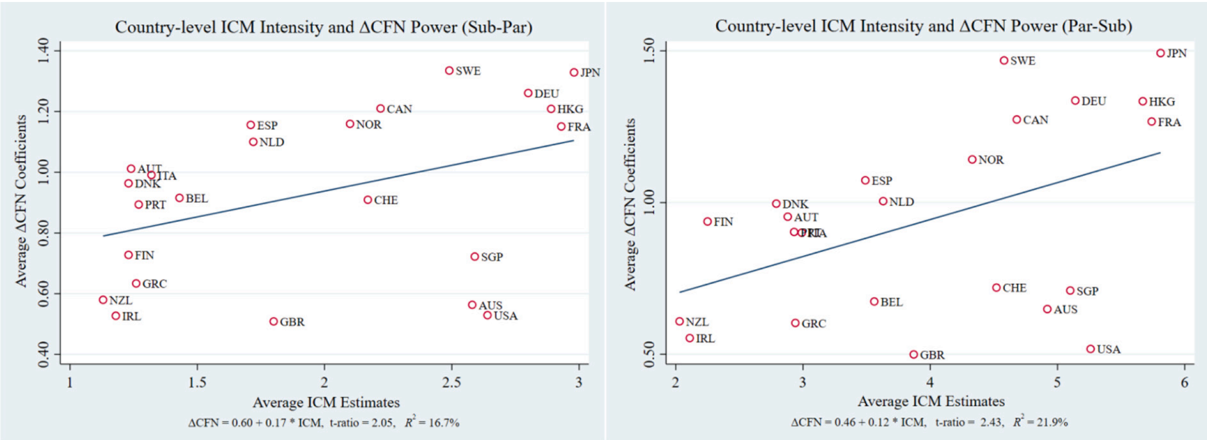
$$\frac{I_{i,t}}{TA_{i,t-1}} = \alpha_{0,i} + \beta_{1,i}\frac{CF_{not\ i,t}}{TA_{i,t-1}} + \beta_{2,i}\frac{S_{i,t-1} - S_{i,t-2}}{S_{i,t-2}} + \beta_{3,i}\frac{CF_{i,t}}{TA_{i,t-1}} + \beta_{4,i}q_{i,t-1} + \epsilon_{i,t},$$

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, $CF_{not\ i,\,t}$ 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, $CF_{i,\,t}$ 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 ICM level is split at the median into "High" and "Low" subsamples. Then for each of the four ownership links and ICM value, we run the corresponding specification in Panel A of Table 6 by interacting the appropriate $OLF\_\Delta CFN_{i,\,t-1}$ with a dummy variable "High," which is equal to unity if the value of the ICM activity is above the median, and zero otherwise. 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. *** denotes statistical significance at the 1% level.

which is often inefficient and opaque to public investors and institutions. However, internal capital markers may also sometimes enable efficiency. For example, Stein (1997, 2002) points out that internal information and capital markets allow shifts in available funds, especially in large organizational hierarchies, towards specific profitable projects, thus reducing their credit constraints. Then, Almeida et al. (2015) show that internal capital reallocation helps firms with greater investment opportunities to invest more and achieve better performance. To substantiate these findings within our setting, we aim to detect a direct influence on capital expenditure and external financing of the focal firm from the lagged returns of its OLFs after controlling for other relevant characteristics of the focal firm. Hence, the predictive regression model for capital expenditures, debt, and equity that we use has the following form:

$$\left\{\begin{array}{l} \Delta CapEx_{i,t} \\ \Delta Debt_{i,t} \\ \Delta Equity_{i,t} \end{array}\right. = \gamma_0 + \gamma_1 \Delta CF_{i,t-1} + \gamma_2 CFN\_OLF_{i,t-1} + \gamma_3 DRN\_OLF_{i,t-1} + \gamma_4 CFV\_OLF_{i,t-1} + Controls_{i,t} + FE_i + e_{i,t} \tag{8}$$

where the dependent variable is the change in capital expenditures, $\Delta CapEx_{i,\,t}$, the change in the sum of short-term and long-term debt issuance, $\Delta Debt_{i,\,t}$, or the change in the sum of common and preferred equity issuance, $\Delta Equity_{i,\,t}$, of focal firm i. $\Delta CF_{i,\,t}$ is the change in cash flows of focal firm i. $CFN\_OLF_{i,\,t-1}$, $DFN\_OLF_{i,\,t-1}$, and $DFN\_OLF_{i,\,t-1}$ are the lagged cash-flow news, discount rate news, and cash flow volatility of all the corresponding OLFs, subsidiaries, parent firms, sister subsidiaries, or sister parent firms of focal firm i, respectively. Cash-flow news, discount rate news, and cash flow volatility are computed as before. The main coefficients of interest are γ_2, γ_3, and γ_4. Given our earlier ICM test results, γ_2 is expected to be positive for capital expenditures and negative for debt. Control variables include the *Size*, *Dividend*, *Working capital*, *Depreciation*, *Interest expense*, *Leverage*, and *Earnings*. *Size* is the natural logarithm of total assets; *Dividend* is an indicator variable equal to unity for dividend payers, and zero for non-dividend payers; *Working capital* is the working capital scaled by total assets; *Depreciation* is the depreciation scaled by total assets; Interest expenses is the interest expenses scaled by total assets; *Leverage* is the total debt scaled by total assets; *Earnings* is the EBIT estimated as earnings before extraordinary items plus interests plus item taxes scaled by sales. Data on capital expenditures, debt, and equity are from the Orbis database. In addition, several studies find that cash flows' impact on investment activities depends on a firm's financing constraints (e.g., Fazzari



Plot A Plot B

Fig. 3. Relation between ICM intensity and OLF predictability across countries.
This figure shows the average OLF return predictability coefficients based on changes in cash-flow news (ΔCFN) for (i) parent firms in each country from ΔCFN of their subsidiaries (Plot A) and (ii) for subsidiaries in each country from ΔCFN of their parent firms (Plot B), depending on the average country-level ICM intensity. The plots also show the corresponding simple regression results including the slope coefficient on the average ICM intensity, its *t*-statistic, and the regression R-squared. ΔCFN are computed as in Michaely et al. (2021) and Table 6. The ICM intensity is computed based on the Shin and Stulz (1998) methodology using the 5% significance level for coefficient β_1 in Eqs. (6–7). 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.

et al., 1988, Kaplan and Zingales, 1997) and that financing activities forecast stock returns (Bradshaw et al., 2006). Therefore, we consider two additional controls, our earlier defined changes in the debt and equity financing, *ΔDebt* and *ΔEquity*, respectively, but include them in the regression model depending on the left-hand-side variable. Eq. (8) also includes country and industry fixed effects for a given focal firm, consistent with earlier estimations.

Panel A of Table 8 shows the test results on the predictability of capital expenditure of the focal firm with the lagged cash-flow news, discount rate news, and cash flow volatility of its OLFs for four types of ownership links after accounting for all control variables. As expected, the estimate of γ_2 is positive in all estimations. It is significant at least at the 5% level for subsidiary-parent and parent-subsidiary links, while for more obscure ownership links such as subsidiary-subsidiary and parent-parent it is significant at the 10% level. This implies that the capital expenditure of the focal firm, among other things, is determined by the lagged cash flows of its OLFs: an increase in internal financing among OLFs increases investing opportunities of the focal firm. Remarkably, the magnitude of the estimate of γ_2 across the four types of ownership links mimics the magnitude of the predictability coefficient in Table 4 for focal firm excess and risk adjusted returns. However, discount rate news and cash flow volatility are insignificant. The focal firm's own lagged cash flow is also positive and significantly affects its capital expenditure next period. Among other controls, the dividend variable is significant and negative in all estimations, indicating that capital expenditures of dividend paying firms is lower than those without dividends. Finally, the two financing variables, especially the changes in the debt issuance, come up positive and significant, implying, not surprisingly, that external financing leads to more investment activities.

Panels B and C of Table 8 show respectively how debt and equity financing of the focal firm is affected by the lagged cash-flow news, discount rate news and cash flow volatility of its OLFs in the presence of control variables. Again, consistent with our expectations, the estimate of γ_2 is negative and very significant in all specifications. This implies that external financing of the focal firm, similar to its investments, is determined by the lagged cash-flow news of its OLFs: an increase in internal financing among OLFs reduces the need for external financing of the focal firm. The behavior of discount rate news, cash flow volatility and all control variables, which are not reported in these two panels, is similar to that of Panel A of this table.

Thus, we can state an important result. The direct link between ICM activity and return predictability in complex ownership firms documented in the preceding subsection is also reflected through the positive relation between general investment and financing activities of the focal firm and the lagged cash flows new of its OLFs implying a fundamental and delayed linkage among OLFs through cash flows.

5.4. Forecasting earnings surprises with cash flow surprises

In this subsection, we provide additional evidence for the mispricing argument based on the importance of ICM channel for return predictability in OLFs. To explore this possibility, we follow previous literature and use a non-price based test (see, among others, Bradshaw et al., 2001). If investors are unable to process information related to transfers of resources across OLFs, then it might be reasonable to assume that financial analysts also share this inability. We test whether cash flow surprises (CFSs) of OLFs predict

Table 8
Predictability of capital expenditures and external financing in OLFs.

Panel A: Capital expenditures

	(1)	(2)	(3)	(4)
DV: $\Delta CapEx_{i,\,t}$*100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$\Delta CF_{i,\,t-1}$	4.21***	2.77***	2.15***	3.08**
	(4.08)	(4.04)	(2.98)	(2.05)
$CFN\_OLF_{i,\,t-1}$	1.50***	1.35**	0.79*	0.50*
	(3.12)	(2.56)	(1.76)	(1.86)
$DRN\_OLF_{i,\,t-1}$	−0.97	−0.86	−0.55	−0.34
	(1.18)	(1.41)	(1.45)	(1.59)
$CFV\_OLF_{i,\,t-1}$	0.69	0.56	0.42	0.24
	(1.25)	(1.41)	(1.45)	(1.48)
Size	0.41	0.23	0.14	0.36
	(1.46)	(0.94)	(1.31)	(1.46)
Dividend	−0.45***	−0.29***	−0.53***	−0.88***
	(2.99)	(2.66)	(4.44)	(2.93)
Working capital	−0.59	−1.39	−0.46	−1.06
	(0.82)	(1.91)	(0.88)	(0.94)
Depreciation	−0.69	−0.40	−0.34*	−0.65
	(1.07)	(1.48)	(1.65)	(1.40)
Interest Expense	−0.10**	−0.31	−0.23	−0.16
	(2.27)	(1.39)	(1.58)	(1.54)
Leverage	0.16	0.21	0.17	0.24
	(1.49)	(1.49)	(1.12)	(1.19)
Earnings	−0.63	−0.30	−0.32	−0.37*
	(1.32)	(1.55)	(1.49)	(1.78)
ΔEquity	0.70**	0.19**	0.28**	0.38**
	(2.48)	(1.99)	(2.18)	(2.04)
ΔDebt	1.31***	0.71**	0.89***	1.02**
	(3.33)	(2.16)	(3.04)	(2.19)
Country & Industry FEs	Y	Y	Y	Y
Obs.	22,170	37,533	21,843	8732
R^2	0.39	0.30	0.31	0.33

Panel B: Debt financing.

	(1)	(2)	(3)	(4)
DV: $\Delta Debt_{i,\,t}$*100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$\Delta CF_{i,\,t-1}$	−8.75***	−6.59***	−4.44***	−7.59***
	(6.43)	(5.50)	(4.38)	(3.52)
$CFN\_OLF_{i,\,t-1}$	−3.56***	−3.36***	−2.31***	−2.14***
	(6.12)	(3.69)	(3.21)	(2.98)
$DRN\_OLF_{i,\,t-1}$	1.27	1.06	1.07	1.16
	(0.63)	(0.75)	(0.74)	(0.83)
$CFV\_OLF_{i,\,t-1}$	−0.90	−0.94	−0.85	−0.96
	(0.71)	(0.90)	(0.74)	(0.66)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	20,383	34,870	19,744	7949
R^2	0.41	0.33	0.34	0.38

Panel C: Equity financing

	(1)	(2)	(3)	(4)
DV: $\Delta Equity_{i,\,t}$*100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$\Delta CF_{i,\,t-1}$	−5.06***	−4.72***	−3.16***	−4.88***
	(5.02)	(4.05)	(3.76)	(2.77)
$CFN\_OLF_{i,\,t-1}$	−2.09***	−2.15***	−1.68***	−1.45**
	(5.45)	(2.94)	(2.74)	(2.29)
$DRN\_OLF_{i,\,t-1}$	0.87	0.77	0.81	0.69
	(0.61)	(0.74)	(0.58)	(0.76)
$CFV\_OLF_{i,\,t-1}$	−0.69	−0.69	−0.61	−0.64
	(0.63)	(0.68)	(0.62)	(0.59)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	20,383	34,870	19,744	7949
R^2	0.45	0.36	0.37	0.42

This table shows the impact on the predictability of capital expenditure and external financing of the focal firm from the return components of its 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. Panels A, B, and C show the results for capital expenditures and debt, respectively. The predictive regression model has the following form:

$$\left\{\begin{array}{l}\Delta CapEx_{i,t} \\ \Delta Debt_{i,t} \\ \Delta Equity_{i,t}\end{array}\right. = \gamma_0 + \gamma_1 \Delta CF_{i,t-1} + \gamma_2 CFN\_OLF_{i,t-1} + \gamma_3 DRN\_OLF_{i,t-1} + \gamma_4 CFV\_OLF_{i,t-1} + Controls_{i,t} + FE_i + e_{i,t},$$

where $\Delta CapEx_{i,\ t}$, $\Delta Debt_{i,\ t}$, $\Delta Equity_{i,\ t}$, and $\Delta CF_{i,\ t}$, are the changes in capital expenditure, debt issuance (both short-term and long-term), equity issuance (both common and preferred stock), and cash flow of focal firm *i*, respectively. $CFN\_OLF_{i,\ t-1}$, $DFN\_OLF_{i,\ t-1}$, and $DFN\_OLF_{i,\ t-1}$ are the lagged cash-flow news, discount rate news, and cash flow volatility of all the corresponding OLFs ($Sub_{i,\ t-1}$, $Par_{i,\ t-1}$, $Sis\_Sub_{i,\ t-1}$, or $Sis\_Par_{i,\ t-1}$) of focal firm *i*, respectively. Cash-flow news, discount rate news and cash flow volatility are computed as in Michaely et al. (2021). Control variables include the size, dividend, working capital, depreciation, interest expense, leverage, and earnings of focal firm ***i***. ***Size*** is the natural logarithm of total assets; ***Dividend*** is an indicator variable equal to unity for dividend payers, and zero otherwise; *Working capital*, *Depreciation*, and *Interest Expense* are working capital, depreciation, and interest expense, respectively, each scaled by total assets; ***Leverage*** is the total debt scaled by total assets; ***Earnings*** is the EBIT estimated as earnings before extraordinary items plus interests plus item taxes scaled by sales. $\Delta Debt$ and $\Delta Equity$, are also used as control variables when appropriate. FE_i are the country and industry fixed effects of focal firm ***i***. In Panels B and C the estimates of control variables are not reported. 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.

standardized unexpected earnings (SUEs) of focal firms.[18] Since SUEs capture 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 9, using the Fama-MacBeth regressions, we show that CFSs of OLFs forecast the focal firm's future SUEs. 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 CFS of OLFs. 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 into deciles ranging from zero to one. The results demonstrate that CFSs of OLFs predict focal firms' future unexpected earnings, confirming that the lagged CFSs of OLFs anticipate the directional changes of focal firm fundamentals and, therefore, can drive earnings announcement returns.

In Panel B of Table 9, we report the results of testing the unexpected earnings predictability over longer periods, i.e. up to four quarters ahead. Accordingly, the 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 the lagged cash flow surprises 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, therefore, is unlikely to be related to changes in the underlying risk structure of firms.

6. Conclusion

In this study, we use the data from 23 developed markets to explore return predictability in firms with multi-country and multi-layer ownership structure that is common to MNEs. Our results show that the lagged one month returns of OLFs can predict the next month returns of the focal firm both worldwide and across various regions. 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. We show that the observed return predictability is driven by a fundamental interrelation among complex ownership firms: focal firm returns are also predicted by the lagged changes in cash-flow news of their subsidiaries or parent firms.

Overall, using global cross-ownership data, we show that a complex ownership network (e.g., of MNEs) may lead to mispricing due to internal capital markets, which is accompanied with complicated information processing, and hence return predictability across OLFs. Moreover, we show that a larger availability of "in-house" money due to increases in internal capital market activity among OLFs also affects their investment and financing policies leading to more capital expenditures and lower need for external debt and equity financing of the focal firm.

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 Panel B – 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-

[18] Cash flow surprises are calculated as the yearly changes in quarterly cash flows scaled by the standard deviation of cash flows over the eight past quarters.

Table 9
Earnings predictability and persistence in cash flow surprises of OLFs.

Panel A: One-quarter ahead forecast

	(1)	(2)	(3)	(4)
DV: $SUE_{i,\ t}$ *100	Sub-Par	Par-Sub	Sub-Sub	Par-Par
$OLF\_CFS_{i,\ t-1}$	0.48**	0.55***	0.32**	0.41***
	(2.35)	(4.33)	(2.27)	(2.72)
Controls, Country & Industry FEs	Y	Y	Y	Y
Obs.	32,424	55,476	33,487	11,866
R^2	0.40	0.51	0.36	0.40

Panel B: Extended forecast

DV: $SUE_{i,\ t+k}$ $k = 0, \ldots, 3$	Quart 1	Quart 2	Quart 3	Quart 4
$Sub\_CFS_{i,\ t-1}$ (Sub – Par)	0.48**	0.41**	0.27*	0.19
	(2.35)	(2.20)	(1.93)	(1.34)
Controls, Country & Industry FEs	Y	Y	Y	Y
$Par\_CFS_{i,\ t-1}$ (Par – Sub)	0.55***	0.39***	0.21**	0.11
	(4.33)	(3.26)	(2.10)	(1.10)
Controls, Country & Industry FEs	Y	Y	Y	Y
$Sis\_Sub\_CFS_{i,\ t-1}$ (Sub – Sub)	0.32**	0.20*	0.13	0.03
	(2.27)	(1.72)	(1.42)	(0.40)
Controls, Country & Industry FEs	Y	Y	Y	Y
$Sis\_Par\_CFS_{i,\ t-1}$ (Par – Par)	0.41***	0.24	0.18	0.07
	(2.72)	(1.51)	(1.52)	(0.68)
Controls, Country & Industry FEs	Y	Y	Y	Y

This table shows the results of Fama-MacBeth regressions of the predictability of ownership-linked firms (OLFs) for the 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 cash flow surprises of OLFs, $OLF\_CFS_{i,\ t-1}$ ($Sub\_CFS_{i,\ t-1}$, $Par\_CFS_{i,\ t-1}$, $Sis\_Sub\_CFS_{i,\ t-1}$, or $Sis\_Par\_CFS_{i,\ t-1}$). 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.

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.

Appendix A. 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
CFS	Cash flow surprise – yearly change in quarterly CFs scaled by the StDev of CFs over the eight past quarters	Eikon, Compustat	Quarterly
CapEx	Capital expenditures	CRSP, Eikon, FactSet, Orbis	Quarterly

(*continued on next page*)

(*continued*)

Variable	Description	Source	Frequency
Debt	Issuance of short-term and long-term debt	CRSP, Eikon, FactSet, Orbis	Quarterly
Equity	Issuance of common and preferred equity	CRSP, Eikon, FactSet, Orbis	Quarterly

Appendix B. Internet appendix

Internet appendix to this article can be found online at https://doi.org/10.1016/j.jcorpfin.2022.102219.

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