Private Subsidiaries' Information Disclosure and the Cross-Sectional Equity Returns of Public Parent Firms*

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September 2020

Abstract

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JEL Classification: G11, G14.

Keywords: Private information; limited attention; limits to arbitrage; return predictability.

*Turan Bali acknowledges financial support from the McDonough School of Business of Georgetown University. Jun Tu acknowledges that the study was funded through a research grant from Sim Kee Boon Institute for Financial Economics. Ran Zhang acknowledges financial support from the Shanghai Institute of International Finance and Economics. This paper is sponsored by Shanghai Pujiang Program. All errors remain our responsibility.

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Abstract

We investigate the impact of potential information hiding or disclosure delay originated from private subsidiaries on the future returns of their public parent firms. We find a significantly positive link between private subsidiaries' information disclosure (PSID) and the cross-section of future equity returns of public parent firms. The economically and statistically significant PSID premium of 0.60% per month is not explained by established factor models and is stronger for stocks that receive less investor attention and that are costlier to arbitrage. Consistent with investor underreaction hypothesis, PSID premium reflects slow diffusion of private information into stock prices rather than compensation for risk.

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1 Introduction

Corporate information disclosure is one of the most efficient ways of communicating with the general public and financial regulators. Accurate, complete, and timely financial reporting and information disclosure are essential to convey firm performance to individual and institutional investors. However, regulatory rules on mandatory information release (e.g., the 2000 fair disclosure rule) are only applicable to public firms but not to private firms. When a public parent firm wants to hide information (e.g., Verrecchia (2001) and Kothari, Shu, and Wysocki (2009)), private subsidiaries can be a natural choice.[1] Indeed, in 2018, there are over 2500 U.S. public firms with private subsidiaries and these public parent firms account for more than 70% of total stock market capitalization of the NYSE, Amex, and Nasdaq. Over the period 2005-2018, the average number of private subsidiaries is 60 per public parent firm. Given such large scale of usage of private subsidiaries by publicly listed firms, it is crucial to examine the impact of potential information hiding or disclosure delay originated from private subsidiaries on the performance of their public parent firms.[2]

In this study, we examine whether the cross-sectional variation in private subsidiaries' information disclosure (PSID) predicts the cross-sectional dispersion in future equity returns of public parent firms. A high (low) PSID is observed when the parent firm is (not) willing to disclose information about its private subsidiaries. The underlying reason could be that its private subsidiaries have positive (negative) information to disclose so that the magnitude of PSID is positively correlated with private subsidiaries' and their parent firm's fundamentals. Also, given that private subsidiaries are often to be opaque, poorly understood, and attract less investor attention, investors may underreact to the PSID, which can be viewed as a leading cross-sectional indicator for the future fundamentals of parent firms. Therefore, we

[1]Earlier studies find that companies have motivations to delay information disclosure, especially bad news. Patell and Wolfson (1982) examine firms' strategic disclosure behaviors when they announce intraday earnings and dividends. They find that good news appears more frequently during trading but bad news is more likely to be released when the stock markets are close. Verrecchia (2001) finds that there are large costs for firms' information disclosures since competitors may copycat proprietary information. Kothari et al. (2009) find that firm managers delay in releasing bad news relative to good news due to a range of incentives, such as career concerns and compensations.

[2]For all public firms and private firms in the market, Asker, Farre-Mensa, and Ljungqvist (2014) estimate that private firms accounted for 86.4 percent of U.S. firms with 500 or more employees, nearly 59 percent of aggregate sales, and nearly 49 percent of aggregate pre-tax profits in 2010. Based on the report of Forbes in 2013, less than 1 percent of the companies in the U.S. are publicly traded on the major exchanges. Meanwhile, private firms are not always lumped into a small business.

hypothesize that the PSID positively predicts the cross-section of future stock returns of parent firms. Our empirical results provide strong support for this hypothesis.[3]

We obtain financial information about private firms from Orbis – the most comprehensive database which contains standardized and comparable data on private firms and corporate ownership, covering over 310 million companies worldwide. Orbis provides seven items of financial information for each private subsidiary under a parent firm, which are operating revenue, total assets, number of employees, income before tax, net income, cash flow, and shareholders' funds.[4] For each public parent firm, we calculate its PSID. For example, one public parent firm has 100 private subsidiaries, 90 of which disclose operating revenue information to the public, 40 disclose total assets information to the public, and 20 disclose number of employee information to the public. If we consider only the three aforementioned financial variables, the private subsidiaries' average information disclosure is (0.9+0.4+0.2)/3 = 0.5. In our tests, we use a total of seven financial variables (out of 10 mentioned above) to calculate the PSID ratio as our key predictor. This measure is consistent with the level of disaggregation of accounting data proposed by Chen, Miao, and Shevlin (2015), which represents the information disclosure quality of firms.

We show that the PSID ratio has significant cross-sectional predictive power for public parent firms' future stock returns. At the end of June of each year, we sort public parent firms into five quintile portfolios based on the previous year's PSID ratios, and find that public parent firms with a higher (lower) PSID ratio earn higher average (lower) returns in subsequent months. Furthermore, the value-weighted arbitrage portfolio that takes a long position in 20% of the stocks with the highest PSID (quintile 5) and takes a short position in 20% of the stocks with the lowest PSID (quintile 1) yields the risk-adjusted returns (alphas) of 0.60%, 0.44%, 0.52%, and 0.55% per month, estimated, respectively, with the six-factor model of Fama and French (2018), the mispricing factor model of Stambaugh and Yuan (2016), the Q-factor model of Hou, Xue, and Zhang (2015), and the behavioral

[3]In the same spirit, the literature finds that the annual report readability and transparency are positively related to the company's performance (e.g., Subramanian, Insley, and Blackwell (1993), Li (2008), and Dempsey, Harrison, Luchtenberg, and Seiler (2012)).

[4]Due to data limitation, the PSID proposed in this study may miss other information disclosed by private subsidiaries. For instance, a parent firm may be afraid of the copycat issue of information disclosure. Releasing the results of the progress in certain R&D programs may indicate that its private subsidiaries have made significant progress since then the release of the R&D progress will not damage the lead position of the parent firm over its competitors.

factor model of Daniel, Hirshleifer, and Sun (2020). All alphas are significant at the 1% level, except for the mispricing factor model with the 5% level of significance. Moreover, the PSID ratio shows a robust, positive and statistically significant predictive power on future excess, industry-adjusted, and DGTW-adjusted (Daniel, Grinblatt, Titman, and Wermers (1997)) returns of their public parent firms in multivariate Fama–MacBeth regressions when we control for a number of firm characteristics and risk factors, including public parent firm's size (SIZE), book-to-market ratio (BM), gross profitability (GP), asset growth (AG), one-month lagged return (STR), medium-term price momentum (MOM), earnings surprise (SUE), Amihud (2002) illiquidity measure (ILLIQ), idiosyncratic volatility (IVOL), turnover ratio (TURNOVER), and the number of private subsidiaries under the parent firm.

If the PSID ratio provides valuable fundamental information, it is supposed to predict high future fundamental performance of the public parent firm. We find that the PSID ratio does indeed significantly predict the public parent firm's fundamental performance, such as return-on-asset (ROA), cash flows, and gross margin in the following years. The fundamental performance results confirm our hypothesis that high PSID ratio indicates favorable fundamentals of their public parent firm, and investors are not able to promptly process and recognize this positive relation.

To provide a better understanding of the economic mechanisms behind the return predictability, we test whether the predictive power of the PSID is driven by investors' limited attention (Hirshleifer, Lim, and Teoh (2009)) and/or limits to arbitrage (Shleifer and Vishny (1997)). We find that the abnormal returns on stocks with low attention-grabbing characteristics are larger than the abnormal returns on stocks with high attention-grabbing features, where the proxies of investor attention are residual media coverage, transient institutional ownership, and absolute SUE.[5] We also find the abnormal returns on stocks with high arbitrage costs are larger than the abnormal returns on stocks with low arbitrage costs, where the proxies for limits to arbitrage include the size-orthogonalized institutional ownership, idiosyncratic volatility, and Amihud (2002) illiquidity measure. Our results indicate that the

[5]See, e.g., Bushee (2001), Hou and Moskowitz (2005), Peng (2005), Peng and Xiong (2006), Hong, Torous, and Valkanov (2007), Cohen and Frazzini (2008), DellaVigna and Pollet (2009), Fang and Peress (2009), Hirshleifer et al. (2009), Da, Engelberg, and Gao (2011), Hirshleifer, Hsu, and Li (2013), Da, Gurun, and Warachka (2014), Bali, Peng, Shen, and Tang (2014), Hirshleifer, Hsu, and Li (2018), and Bali, Hirshleifer, Peng, and Tang (2018).

PSID-based return predictability is likely due to investors' inattention and limits to arbitrage.

However, the return predictability may still be related to systematic or macroeconomic risk, even if the source of risk has not been clearly identifiable, as argued by Lee and So (2015). To investigate this possibility, we use an alternative method to test whether the predictive power of the PSID is consistent with a gradual diffusion of information or news relevant for a firm's future cash flows instead of with a change in the discount rate or risk. We use the PSID ratio to forecast public parent firm's standardized unexpected earnings (SUEs). This test is not confounded by the possible existence of non-measurable risks. The results show that the PSID does indeed predict one-quarter-ahead SUEs of public parent firms, but the predictability disappears in the subsequent quarters. This finding provides further support that the PSID-based return predictability is not likely to be attributed to risk.

To further test whether the risk- or mispricing-based factors can explain the predictive power of the PSID, we follow Engelberg, McLean, and Pontiff (2018) and use the PSID ratio to predict the three-day cumulative abnormal returns around the earnings announcement days. If the ratio predicts the cumulative abnormal returns around the earnings announcement days, then investors' misconceptions about a firm's future performance and cash flows become an important driver of the return predictability phenomenon. Alternatively, without predictable cumulative abnormal returns around the earnings announcement days, the more likely explanation would be based on systematic risk factors driving the predictive power of the PSID. Our results indicate that a higher PSID ratio is associated with significantly higher abnormal returns than a lower PSID ratio is. We also find that around 10% of the abnormal returns of the long-short portfolio strategy are realized in three days around earnings announcements, indicating that our results are more consistent with the mispricing explanation.

In addition, we conduct a more direct test of a potential risk-based explanation by reporting the average market beta, average total volatility, average idiosyncratic volatility, and ex-ante portfolio exposures to the risk factors used in this paper. If stocks in the highest PSID quintile do not have higher average beta, total or idiosyncratic volatility, or if their exposures to the risk factors are not significantly higher than those in the lowest PSID quintile, it would be harder to argue for the risk-based explanation. We also calculate the beta of ex-post quintile portfolio returns with respect to the monthly and quarterly growth rate of consumption. Our results show that the stocks in the highest PSID quintile portfolio have smaller average beta, total and idiosyncratic volatility, and their exposures to most risk factors are smaller than those in the lowest PSID quintile portfolio. The stocks in the highest PSID quintile portfolio have lower exposures to the monthly and quarterly consumption growth rate (i.e., lower consumption beta) than those in the lowest PSID quintile portfolio. Overall, our results provide no evidence of a risk-based explanation for the predictive power of the PSID.

This study is related to the growing research on investors' limited attention to partial information disclosure. Patell and Wolfson (1982) find that investors have lower attention to news released during the market closing time than to news released during the market trading time. DellaVigna and Pollet (2009) find that investors' inattention to earnings announcements on Friday, compared with earnings announcements on other weekdays. Hirshleifer et al. (2009) find that investors underreact to earning surprises and post-earnings-announcement drift is stronger for firms that announce earnings on days that many other firms announce earnings due to investors' limited attention. Cohen and Frazzini (2008) find that suppliers' have delayed responses to the information disclosure of their customers. Cohen and Lou (2012) find that single-segment firm returns predict returns of multi-segment firms operating in the same industry, consistent with the limited attention argument. Lee, Sun, Wang, and Zhang (2019) use patent technology class to define technology-linked firms and find return predictability across these firms. In this paper, we find that investors have limited attention to public parent firms' private subsidiaries' information disclosure so that firms with high information disclosure outperform those with low information disclosure in terms of both raw and risk-adjusted returns.

The rest of the paper is organized as follows. Section 2 describes the data and variables. Section 3 presents the main empirical results on the cross-sectional return predictability. Section 4 tests whether the PSID is a significant indicator of the future fundamentals of public parent firms. Section 5 investigates the sources of predictability. Section 6 distinguishes risk versus mispricing based explanations. Section 7 performs additional analyses. Section 8 concludes the paper.

2 Data, Variables, and Summary Statistics

Our main empirical analyses are based on the Orbis database compiled by Bureau van Dijk (BvD). Orbis covers comprehensive ownership information about 30 million ownership/subsidiaries relationships over time.[6] We collect data from Orbis to identify the ownership links between private subsidiaries and public parent firms listed in the U.S. from 2005 to 2018. At the end of each year for the public firms that own private subsidiaries, we collect company name, ISIN code, ticker symbol, SIC classification, all ownership information including direct and indirect total ownership percentage, as well as all identifying and fundamental information for the subsidiaries. Since we are only interested in the pricing effect of private subsidiaries' information on parent firms, we exclude any public subsidiaries' links based on the listed or unlisted indicator.

We aim to identify the pricing effect of private subsidiaries' information disclosure on public parent firm. Claessens, Djankov, and Lang (2000) use a 20% cutoff to determine if a public firm is fully controlled by a unique ultimate owner. We instead follow the ultimate owner classification of Orbis and define the global ultimate owner as of the parent firm which holds more than 50% of the private firm's shares. The public parent firm ultimately controls its private subsidiary if the ownership percentage is larger than 50%. Thus, the information about major ownership of private subsidiaries is essential to the stock returns of the public parent firms. For each parent firm, we then retrieve information about the subsidiaries that are directly or indirectly held by the parent firm. Following Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych, and Yesiltas (2015), we decode the indicators of percentage owned by parent firm into a specific value since they are not given in a numerical format.[7]

Once we identify the links between public parent firms and private subsidiaries, we use financial information from private subsidiaries' unconsolidated financial accounts to construct the average information disclosure ratio of private subsidiaries. In particular, we extract operating revenue, total assets, number of employees, income before tax (P/L before tax), net

[6] BvD collects the ownership data from a variety of sources including firms' annual reports, the SEC Edgar files, and local data providers.

[7] In particular, we replace percentage with a leading "<", ">", or "±" with the percentage after the symbol; we eliminate possible signs that preceded percentages: "_", "?", or "Â"; we replace special codes "WO" (wholly owned) with 100%, "MO" (majority-owned) with 50.01%, "CQP1" (50% plus 1 share) with 50.01%, "NG" (negligible) with 0.01%, "BR" (branch) with 100%; "JO" (jointly owned) with 50%, and "-" (not significant) or "n.a." (not available) with missing.

income, cash flow, and shareholders funds; seven variables in total for each private subsidiary.[8] As long as a firm updates its financial information, Orbis will promptly record the updated information from a list of reliable information sources. Since Orbis will keep the record for up to five years (Kalemli-Ozcan et al. (2015)), it is possible that one private subsidiary didn't update its financial information promptly and we mistakenly use this stale information. Thus, we convert those stale information into missing value based on the most recent release date of the private subsidiary provided by Orbis. Next, we compute a single ratio for each financial variable defined as the number of private subsidiaries disclosing that financial variable divided by the total number of private subsidiaries under the control of a public firm. As such, we define our main variable of interest, the private information disclosure ratio (PSID), for each public parent firm as the simple average of the ratios of these seven financial variables. We scale the raw number by the number of total private subsidiaries to control for the potential size effect since larger firms tend to have more subsidiaries. For the firms listed in the U.S., we extract the CUSIP information from ISIN code and ticker symbol to match with the CRSP monthly stock data using the CRSP names file.

Table 1 reports the cross-sectional characteristics for firms that own at least one private subsidiary across the years. Across the sample period, the number of firms that own private subsidiaries are around 2500 except for the years of 2010 and 2011, implying that the number of firms owning private subsidiaries is stable over time. In terms of the market capitalization, our sample firms comprise 63% to 72% of the market capitalization of the firms listed at the NYSE, AMEX, and NASDAQ. Finally, the averaged PSID ratios are higher before 2013 given that the number of private subsidiaries is also lower in these years. Regarding the distributions of the ratios of seven key financial variables, operating revenue and the number of employees are the two items that most of the private firms choose to disclose to the investors. Specifically, approximately 36% and 33% of private subsidiaries under a public company disclose information about their operating revenue and number of employees to the public. This is not surprising since these two financial statements are the most common items that private firms choose to disclose especially if they need to raise capital from external investors even though they are not forced to disclose by the law. In contrast, it is less likely

[8]Orbis provides only these seven financial variables for all private and public firms in the old version disks.

for public firms to disclose some of the accounting information about their private subsidiaries including cash flow, total assets, income before tax, net income, and shareholders funds.

We obtain monthly stock returns from the Center for Research in Security Prices (CRSP) and accounting information from Compustat. Our sample starts with all firms listed at the NYSE, AMEX, and NASDAQ. We keep common stocks and exclude financial firms and utilities firms. To reduce the effect of micro-cap firms, we exclude firms that are below the 20th percentile of NYSE market capitalization. We follow Shumway (1997) to adjust stock returns for delisting. Specifically, if a delisting return is missing and the delisting event is performance-related, we set the delisting return as -30%. Since some small firms with a few private subsidiaries may naturally have high PSID compared to firms with at least two private subsidiaries, we further restrict our sample to firms with at least five private subsidiaries in our main analysis to ensure that the return predictability is not driven by small and illiquid stocks.[9] To ensure that the ownership information and other accounting information are fully available to investors, we skip six months until the end of June of next year to form our portfolios. In particular, we match the ownership information and accounting information in year t-1 to the monthly returns from July of year t to June of year t+1.

In the subsequent regression analysis, we also control for other firm characteristics that have been shown to predict future returns. Specifically, SIZE is the firm's market capitalization computed as the logarithm of the market value of the firm's outstanding equity at the end of month t-1. BM is the logarithm of the firm's book value of equity divided by its market capitalization, where the BM ratio is computed following Fama and French (2008). Firms with negative book values are excluded from the analysis. Short-term reversal (STR) is the stock's lagged monthly return. MOM is the stock's cumulative return from the start of month t-12 to the end of month t-2 (skipping the STR month), following Jegadeesh and Titman (1993). Gross Profitability (GP) is the firm's gross profitability, defined as revenue minus cost of goods sold scaled by total assets, following Novy-Marx (2013). Asset Growth (AG) is a percentage of total asset growth between two consecutive fiscal years, following Cooper, Gulen, and Schill (2008). TO is the monthly turnover computed as the number of shares traded divided by the total number of shares outstanding in month t-1. ILLIQ is the

[9] Our results remain quantitatively and qualitatively similar if we include firms with less than five private subsidiaries in our analysis.

monthly illiquidity measure computed as the absolute daily return divided by daily dollar trading volume, averaged in month t-1, following Amihud (2002). IVOL is the idiosyncratic volatility defined as the standard deviation of daily residuals estimated from the regression of daily excess stock returns on the daily market, size, and value factors of Fama and French (1993) in month t-1, following Ang, Hodrick, Xing, and Zhang (2006) over month t-1. SUE is the standardized unexpected earnings defined as actual earnings in the current quarter minus earnings 4 quarters ago, scaled by stock price in the current quarter following Livnat and Mendenhall (2006).

[Insert Table 2 here.]

Our final sample covers 155,591 firm-month observations spanning the period from July 2006 to December 2019. Panel A of Table 2 presents descriptive statistics for the main variables. The average number of private subsidiaries owned by public firms is around 66. Concerning our main variable of interest in this paper, the PSID, we note that the mean value of this ratio is 0.2, which means that around 20% of private subsidiaries will release their key financial information in our sample. In Panel B of Table 2, we report the time-series averages of the monthly cross-sectional correlations between the PSID and other key characteristics. The Pearson correlations between the PSID and most of the other firm characteristics are quite low with absolute values all below 0.1, suggesting that this ratio is distinct from other well-known return predictors. The corresponding Spearman rank correlations are also very low with most of these firm characteristics. Besides, the PSID is positively correlated with future return and current return. Therefore, our proposed PSID may potentially contain valuable, independent information in predicting the cross-sectional variation in future equity returns.

3 Empirical Results

In this section, we conduct the cross-sectional asset pricing tests of the PSID. In particular, we examine whether the PSID can predict the cross-section of future stock returns using portfolio-level and firm-level regression analyses.

3.1 Portfolio-level analysis

To construct the long-short portfolio, at the end of June of each year t from 2006 to 2018, individual stocks of public parent firms are sorted into quintile portfolios based on non-zero PSID at the end of year t-1 from 2005 to 2017 and are held for the next twelve months. We also assign parent firms with zero PSID into a zero group. We skip six months to form the portfolio to make sure that our results are in line with the methodology used by earlier studies. We then compute the value-weighted average excess return of each quintile portfolio and the zero-PSID portfolio over the next twelve months. To examine the cross-sectional relation between the PSID and the future stock returns of public parent firms, we form a long-short portfolios that takes a long position in the highest quintile of PSID and a short position in the lowest quintile of PSID.

[Insert Table 3 here.]

In Panel A of Table 3, we report the average monthly returns of the zero-PSID portfolio, each quintile portfolio, and the long-short portfolio over the one-month Treasury bill rate. We also report the abnormal returns (alphas) estimated with various factor models, including the capital asset pricing model (CAPM) with the market (MKT) factor, the four-factor model (FFC) of Fama and French (1993) and Carhart (1997) with the MKT, size (SMB), book-to-market (HML), and momentum (MOM) factors, the five-factor model (FFCPS) of Fama and French (1993), Carhart (1997), and Pástor and Stambaugh (2003) with the MKT, SMB, HML, MOM, and the liquidity risk (LIQ) factors, the five-factor model (FF5) of Fama and French (2015) with the MKT, SMB, HML, investment (CMA), and profitability (RMW) factors, the six-factor model (FF6) of Fama and French (2018) the MKT, SMB, HML, CMA, RMW, and MOM factors, the q-factor model (HXZ) of Hou et al. (2015) with the MKT, size (SMB_Q), investment ($R_{I/A}$), and profitability (R_{ROE}) factors, the mispricing factor model (SY) of Stambaugh and Yuan (2016) with the MKT, SMB, management (MGMT), and performance (PERF) factors, and the behavioral factor model (DHS) of Daniel et al. (2020) with the MKT, post-earnings-announcement drift (PEAD), and financing (FIN) factors. Controlling for these factors helps to ensure that the PSID ratio indeed contains incremental predictive power beyond these well-known factor models.

Consistent with our assumption that firms with zero PSID are the most opaque firms, the alphas of this group are negative and larger in absolute magnitude than those in the lowest-PSID quintile, without exception. In general, the excess returns and alphas of five quintile portfolios increase monotonically from quintile 1 to quintile 5. The long-short portfolio that buys 20% of the stocks with the highest PSID (quintile 5) and short-sells 20% of the stocks with the lowest PSID (quintile 1) earns a value-weighted average return of 0.55% per month with a t-statistic of 3.16, translating into an annual return of 6.6%.[10] Controlling for the robust risk and mispricing factors does not change the magnitude and statistical significance of the return spreads on the PSID-sorted portfolios for most of the factor models. The only exception is the alpha of the long-short portfolio under the mispricing factor model, where the alpha decreases from 0.63% (CAPM) to 0.44% (SY model) per month and the corresponding t-statistic decreases from 3.62 to 2.54 for the value-weighted portfolio. Finally, the significant relation between PSID and future returns is mainly coming from the long leg of the arbitrage portfolio as the economic magnitude and statistical significance are larger among the stocks in the long leg than those in the short leg. This implies that high PSID firms are undervalued relative to firms with lower PSID, perhaps due to investors' limited attention.[11]

Next, we examine the persistence of the rank of PSID and the persistence of the return predictability of PSID. If the rank of PSID is persistent, investors would be able to learn from the past and we would not be able to detect mispricing over a long sample period. Panel B of Table 3 presents the probability of staying in the same PSID group or moving to any of the other five PSID groups including the zero-PSID group in the next year. Specifically, we present the average probability that a stock in quintile i (defined by the rows) in year t will be in quintile j (defined by the columns) in the year $t+1$. All the probabilities in the matrix should be approximately 17% (six portfolios including the zero-PSID portfolio) - 20% (five quintile PSID portfolios) if the evolution for PSID for each stock is random and the relative magnitude of PSID in one period has no implication about the relative PSID values in the next year. However, Panel B of Table 3 shows that 71.51% of stocks in the lowest PSID

[10]The t-statistics reported in our portfolio and regression analyses are Newey and West (1987) adjusted with six lags to control for heteroskedasticity and autocorrelation.

[11]We report the performance of the equal-weighted portfolios in the online appendix. As shown in Table A1 of the online appendix, the magnitudes of the return and alpha spreads on the equal-weighted portfolio are similar to those on the value-weighted portfolio in Panel A of Table 3. Another notable point in Table A1 is that the economic and statistical significance of the short leg is much lower than the long leg.

quintile (P1) in year t continue to be in the same quintile in year $t+1$. Similarly, 87.25% of the stocks in the highest PSID quintile (P5) in year t continue to be in the same quintile in year $t+1$. More than half of the stocks (54.17%) in the zero-PSID portfolio in year t continue to be in the same zero-PSID portfolio in year $t+1$. These results overall suggest that PSID is a highly persistent equity characteristic.

The previous analyses show that investors underprice (overprice) securities with the highest (lowest) PSID in the past with the expectation that this behavior will persist in the future. If the expectation of PSID was a characteristic that evolved randomly through years, we would expect no relation between PSID and future stock returns. The fact that PSID is persistent and it has an anomalous relation with the cross-section of expected equity returns suggests the possibility that investors underestimate the magnitude of the cross-sectional persistence uncovered in Panel B of Table 3. We delve further into this possibility in the test of long term portfolio returns.

We investigate the long-term predictive power of PSID by calculating the six-factor alphas of the PSID quintiles from two to twelve months after portfolio formation. The results are presented in Table 4. During the second month after portfolio formation, the quintile that contains the stocks with the highest (lowest) PSID has a value-weighted return of 23 (-31) basis points. The difference is equal to 55 basis points and significant with a t-statistic of 2.72. Similarly, the zero-cost strategy has a return of 46 basis points with a t-statistic of 2.39 during the third month after portfolio formation. The predictive power of PSID on future returns diminishes as one moves further away from the portfolio formation month and becomes insignificant after the eight month. These results show that the positive cross-sectional relation between PSID and future returns is not just a one-month affair and the underreaction to PSID persists several months into the future, which is consistent with the theoretical evidence of continuation by Hong and Stein (1999) as a consequence of the gradual diffusion of private firm information.

Furthermore, we examine the performance of each single ratio constructed based on each of the seven financial items. Again, at the end of June of each year, we sort stocks into quintiles based on the non-zero single ratio at the end of previous year. We then form a value-weighted long-short portfolio that takes a long position in the highest PSID ratio quintile portfolio and a short position in the lowest PSID ratio quintile portfolio. The factor models used to test the performance are the same as in Table 3.

Table A2 presents the results. On average, stocks in the highest quintile outperform stocks in the lowest quintile under various factor models for each of the seven ratios. The magnitudes of these excess returns vary from 0.27% to 0.46%. Moreover, the long-short alphas are generally significant after controlling for the robust factor models, while losing significance for some of the single ratios with respect to the four-factor FFC and the five-factor FFCPS models. Remarkably, the economic magnitudes of the long-short profits are much smaller than that of the long-short portfolio constructed using the PSID. This implies that the comprehensive measure of PSID indeed captures more information about firms' future returns compared to just one single ratio.

We further examine the profits from the long-short PSID portfolio by presenting the value-weighted return spreads on a per annum basis from 2006 to 2019. Figure 1 plots the time-series pattern of the annual long-short portfolios. Remarkably, the long-short portfolio returns are negative only in 3 out of the 14 years, and the magnitudes are smaller than 2% in absolute magnitude, while the portfolio returns are above 5% in 8 out of the 14 years, and the value-weighted returns in 2007, 2008, 2014, 2017, and 2018 are above 10%, implying that the PSID-based trading strategy is robust and earns stable positive annual profits. For comparison, the value-weighted long-short strategy earns a monthly return of 0.55% throughout our sample period, which is substantially higher than that of the SMB (-0.002%), the HML (-0.22%), RMW (0.27%), CMA (0.03%), and MOM (0.02%), which are not significant during the same period, except the profitability factor (RMW).

[Insert Figure 1 here.]

We also compare the cumulative performance of the PSID factor to other individual factors used in Table 3. To construct the PSID factor, we follow Fama and French (1993) and sort all stocks into two groups at the June of each year based on their market capitalization with the breakpoint determined by the median market capitalization of stocks traded on the NYSE. We also independently sort all stocks in our sample into three groups using PSID based on the NYSE breakpoints. The intersection of the two size and three PSID groups constitute six portfolios. The PSID factor is the difference in the average return of the two value-weighted high-PSID portfolios and the average return of the two value-weighted low-PSID portfolios. Figure 2 plots the cumulative excess returns of the PSID factor and other factors from July of 2006 to December of 2019. The cumulative returns of the PSID factor are upward trending even through the financial crisis in 2007 and 2008. As of December 2019, only PSID factor and PERF factor can earn more than 100% profits, while most of the established factors earn much lower and even negative profits during the same sample period.

[Insert Figure 2 here.]

3.2 Average portfolio characteristics

We investigate which firm-specific attributes can potentially explain the anomalous significantly positive relation between PSID and expected stock returns. To do so, we sort stocks based on their PSID into quintiles each month and report the time-series averages of the cross-sectional average of various firm-specific characteristics for each quintile. The results are reported in Table 5.

[Insert Table 5 here.]

We report average stock characteristics of each PSID quintile portfolio and long-short portfolio. The characteristics include private subsidiaries' information disclosure (PSID), number of private subsidiaries (NumofPriSub), log value of book-to-market value (BM), log value of market capitalization (SIZE), gross profitability (GP), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), medium-term stock momentum (MOM), short-term reversal (STR), asset growth (AG), standardized unexpected earnings (SUE), turnover (TO), institutional ownership (IO), media coverage (MediaCov), the three-year moving sum of the absolute value of discretionary accruals (Opacity), and a proxy of readability of 10-K fillings (FOG Index).

By construction, the average PSID increases gradually from portfolio 1 to portfolio 5. The average PSID for stocks in portfolio 1 is 0.06 and the average PSID for stocks in portfolio 5 is 0.40. The difference of average PSID for stocks between portfolio 1 and portfolio 5 (P5-P1) is

0.35 and highly significant (t-statistic = 36.84), indicating significant cross-sectional variation in the PSID ratios of public parent firms. As PSID increases across the quintiles, some characteristics increase too. Such characteristics include market capitalization (SIZE), gross profitability (GP), medium-term stock momentum (MOM), short-term reversal (STR), asset growth (AG), standardized unexpected earnings (SUE), institutional ownership (IO), media coverage (MediaCov), and a proxy of readability of 10-K fillings (FOG Index). The increase of average characteristics across the quintiles is economically and statistically significant for almost all of the aforementioned variables. However, the statistical significance is low or absent for asset growth, SUE, and media coverage.

As PSID increases across the quintiles, some characteristics decrease. Such characteristics include the number of private subsidiaries (NumofPriSub), log value of book-to-market ratio (BM), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), turnover (TO), and the three-year moving sum of the absolute value of discretionary accruals (Opacity). The decrease of average characteristics across the quintiles is economically and statistically significant, except the three-year moving sum of the absolute value of discretionary accruals (Opacity).

Prior literature suggests that the firm-specific attributes considered in Table 5 are instrumental in analyzing the cross-section of expected stock returns. Stocks with higher PSID, higher stock momentum returns, higher profitability, and lower idiosyncratic volatility tend to have higher expected returns. Considering the prior findings in the literature and the patterns that the firm-specific attributes exhibit across the PSID quintiles, one may think that momentum, profitability, and/or idiosyncratic volatility drive the significantly positive relation between the PSID and expected stock returns. The fact that stocks with higher PSID have higher stock momentum and lower idiosyncratic volatility suggests that the positive relation between the PSID and future stock returns tends to be in line with the mispricing-based explanation. Furthermore, the stocks with higher PSID have lower book-to-market ratios, larger market capitalization, and higher liquidity, suggesting that the positive relation between the PSID and expected stock returns contradicts with the risk-based explanation. We further analyze these potential driving forces of the return predictability in Section 6.

3.3 Fama-MacBeth cross-sectional regressions

In this section, we conduct firm-level Fama-MacBeth regressions to test if the PSID predicts the cross-section of future monthly returns. This test allows us to examine the predictive power of the key variable of interest (PSID) more precisely while controlling for other known return predictors. Each month, we run a cross-sectional regression of stock returns in that month on the past PSID as well as a number of control variables, including lagged size, book-to-market, gross profitability, asset growth, and earnings surprise. We control for the short-term return reversal, medium-term price momentum, idiosyncratic volatility, illiquidity, and turnover ratio. We also control for the number of private subsidiaries under the parent firm as the predictive power of PSID may be correlated with the number of private firms that public firms own. Following Fama and French (1992), we skip six months between the accounting-related control variables and stock returns to ensure that the accounting information is publicly available to investors. To minimize the effect of outliers, we winsorize all independent variables each month at the 1% level. In Table A3, we report the summary statistics of the PSID ratios across Fama-French 48 industries. Even though the PSID are distributed evenly across all industries, we cannot rule out the possibility that the return predictability is attributed to the industry momentum since some good news contained in the same industry that private subsidiaries belong to may affect private subsidiaries' financial reporting as well as the parent firms' future returns. Therefore, we also control for the industry fixed effects following the 48-industry classification scheme of Fama and French (1997). The stock-level cross-sectional regressions are run each month and the time-series standard errors are adjusted for heteroskedasticity and autocorrelation following Newey and West (1987).

[Insert Table 6 here.]

Table 6 reports the results for firms with at least five private subsidiaries. In column 1, we include the PSID as well as other well-known return predictors in the cross-sectional regressions. Consistent with the portfolio results, we find a positive and significant relation between the PSID and one-month-ahead returns controlling for a large number of predictors. The average slope coefficient on the PSID ratio is 0.75 with a t-statistic of 2.65. The spread in the average standardized PSID between quintiles 5 and 1 is approximately 0.55, and multiplying this spread by the average slope of 0.75 yields an economically significant return difference of 0.41% per month, controlling for all else. In most cases, the slope coefficients on the control variables are consistent with prior literature: Short term reversal (STR) and asset growth (AG) are negatively correlated with the future return, and gross profitability and earnings surprise (SUE) are positively related to the next month's return. However, the sign of momentum (MOM) is negative and insignificant, which is due to the momentum crash in 2009 (Daniel and Moskowitz (2016)) and it becomes positive when we exclude the year 2009 from our sample. In addition, the coefficient on the number of private subsidiaries is positive but insignificant, indicating that the PSID predictability is not driven by this number. In column 2, we further control the industry fixed effect using Fama-French 48 industry classifications. However, the PSID retains significant predictive power, although the magnitude of the coefficient decreases slightly to 0.57.

In column 3, we include $INDRET_{t+1}$, which is computed as the value-weighted Fama-French 48 industry portfolio returns, as a control variable in our main regression to further control for the industry effect. Specifically, we adjust the dependent variable, by subtracting the firm's value-weighted Fama-French 48 industry return $INDRET_{t+1}$ from the firm's current month return. Doing so allows us to tease out the return predictive power from the PSID rather than the one-month industry momentum effect (Moskowitz and Grinblatt (1999)). The coefficient of the PSID remains similar controlling for the industry return directly. In column 4, we further control for the common characteristics that are shown to affect stock returns systematically. Specifically, we follow Daniel et al. (1997) to compute the characteristics-adjusted returns, which is the difference between the firm's return and the corresponding DGTW benchmark portfolio returns. We replace the firm's raw return with this characteristics-adjusted return as the dependent variable and run the same monthly cross-sectional regressions. Again, the magnitude of the slope coefficient on PSID becomes slightly weaker, but it remains highly significant.

Overall, these results indicate that the PSID provides incrementally value-relevant information. The predictive power of the PSID is distinct and robust to the inclusion of other well-known return predictors and asset pricing specifications.

3.4 Bivariate portfolio-level analysis

An alternative explanation of the PSID effect is that the return predictability is related to the information environment of the firms proxied by firm's earnings management (Collins and Hribar (2000); Teoh, Welch, and Wong (1998); Teoh, Welch, and Wong (1998)). By no means we should expect a more transparent environment predicts higher returns, but still we examine the interaction with opacity and test if the PSID effect is independent of the information transparency. Following Hutton, Marcus, and Tehranian (2009), the opacity is measured as the three-year moving sum of the absolute value of discretionary accruals, which is a proxy for the opacity of financial statement information. In addition, even if public firms have to disclose their private subsidiaries' information in their annual reports, to some extent these firms may increase the complexity of the vocabularies or syntax in the reports such that investors cannot easily and accurately interpret the information contained in the reports. Hence, the return predictive power of PSID may be correlated with the readability of financial reports. We measure the readability of the financial report with a fog index, which is a well-known measure of readability in the literature. We focus on the readability of the 10-K annual report as public firms disclose all relevant information in this report.

We perform independent bivariate sort analysis to examine these two alternative explanations. At the end of June of year t from 2006 to 2019, we independently sort firms into quintiles based on the non-zero PSID and into two groups based on these two characteristics using the information at the end of year t-1. This intersection produces ten portfolios for each characteristic. We then form a long-short PSID portfolio in each subgroup. The portfolios are held for the next twelve months. We compute the value-weighted average monthly excess returns and alphas estimated from alternative factor models.

[Insert Table 7 here.]

Panel A of Table 7 presents results from the bivariate portfolios of PSID and the measure of opacity. Across the two opacity groups, the differences in the number of firms and the PSID of each quintile portfolio are quite small, while the size of each PSID-sorted portfolio is generally smaller in those high opacity firms, consistent with the literature that smaller firms are less transparent compared to large firms. The monthly average excess returns and alphas of the long-short portfolio are much larger and significant in the high opacity groups. Specifically, the long-short excess return is 0.69% and the alphas range from 0.53% to 0.69% in the high opacity groups. In contrast, the excess return is 0.46% per month and the alphas are in the range of 0.42% and 0.60% per month in the low opacity groups. However, these returns and alphas are all statistically significant at the 5% significance level or better, suggesting that our main finding is not driven by the opacity effect.

Panel B of Table 7 presents results from double sorting on PSID and the fog index. In general, the high fog index group consists of firms with similar size compared to the low fog index group across the five PSID-sorted portfolios. The abnormal returns on the long-short PSID portfolio in the high fog index group range from 0.32% to 0.51% and statistically significant at the 10% level, except for the mispricing factor model (SY). For the low fog index group, the magnitude of the abnormal returns on the long-short PSID portfolio is much larger and they are all statistically significant at the 1% level. This suggests that the return predictability of the PSID measure is stronger for firms with low readability of their 10-K reports.

In short, the independent double sorts provide strong evidence that the PSID does contain robust, valuable information about future equity returns.

4 Subsequent operating performance

In this section, we examine whether the PSID ratio actually contains valuable information about fundamental performance of the company. If the disclosing patterns of the private subsidiaries are indeed positively related to the firm's real operating activities, we should expect public firms that are disclosing more accounting information on their private subsidiaries continue to perform well in the future. Thus, we conduct yearly Fama-MacBeth regressions of the measures of operating performance on the PSID as well as the control variables used in Table 6. Specifically, we run the following cross-sectional regressions for each year:

$$OP_{i,t+1} = \alpha + \beta_1 * PSID_{i,t} + \beta_2 * OP_{i,t} + \beta_3 * \Delta OP_{i,t} + controls_{i,t} + industry_{i,t} + e_{i,t+1} \quad (1)$$

where $OP_{i,t+1}$ is the firm i's operating performance in year t+1, $\Delta OP_{i,t}$ is the change in operating performance between year t and year t-1, and $industry_i$ is the dummy variable that equals one for the industry that firm i belongs to and zero otherwise based on the Fama-French 48 industry classifications. We include the past operating performance in the model to account for persistence in operating performance. We also include the change in operating performance to control for the mean reversion of operating performance (Fama and French (2000)). We further control for size, book-to-market, momentum, earnings surprise, idiosyncratic volatility, illiquidity, and asset growth in the regressions. To reduce the influence of outliers, we winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and standard deviation of one.

[Insert Table 8 here.]

To measure the operating performance, we use three proxies that are prevalent in the literature, namely return-on-asset (ROA), cash flow (CF), and gross margin (GM). We measure the ROA as income before extraordinary items plus interest expenses divided by lagged total assets. Cash flow is measured as income before extraordinary items minus total accruals divided by average total assets. Gross margin is computed as sales minus cost of goods sold divided by current sales. To reduce the noise in gross margin, we follow Kothari, Laguerre, and Leone (2002) to truncate gross margin at 1 or -1. These three measures all reflect the real operating performance of a company (Hirshleifer et al. (2018), Hirshleifer et al. (2018)).

Table 8 presents the average slope coefficients and intercepts and the corresponding Newey-West t-statistics from the yearly Fama-MacBeth cross-sectional regressions. The results show a significantly positive relationship between the PSID and the proxies of operating performance in the next year. Specifically, in the first two columns, we regress ROA in year t+1 on the PSID as well as the ROA and change in ROA in year t. The coefficient of the PSID is 0.20 and significant at the 5% level after accounting for the control variables and the industry effects, meaning that a one standard deviation increase in the PSID leads to 0.20% increase in the ROA in the next year. Similarly, the coefficients between the PSID and other measures of operating performance are 0.37 for cash flow and 0.30 for gross margin, and are all statistically significant. Furthermore, the significantly positive coefficients on the proxies of operating performance in the current year and the significantly negative coefficients on the change of proxies of operating performance are consistent with the literature on the persistence and mean reversion in the operating performance. Overall, the results indicate that the PSID indeed contains valuable information about the firm's future operating performance.

5 Sources of return predictability

Having established that the predictive power of the PSID may be driven by slow dissemination of disclosure-related information due to investors' underreaction, we seek to understand the cross-sectional sensitivity of our main result to proxies of investors' limited attention and limits to arbitrage. To this end, we perform the multivariate regression analysis on the proxies and the PSID. Specifically, we split the sample into two groups based on the median value of each proxy and run regressions separately for each group to examine whether the PSID effect varies in these two groups.

5.1 Investors' limited attention

One possible explanation is that investors pay limited attention to public firms' disclosure to private subsidiaries' financial information. Barber and Odean (2007) argue that individual investors can only process limited investment choices due to limited time and resources they have. If investors were fully aware of this information, the stock price of a public firm would quickly adjust to the information reflected in disclosing patterns of private subsidiaries. Following the literature, we use three proxies of investor attention: media coverage (Fang and Peress (2009)), transient institutional ownership (Bushee (2001)), and absolute SUE (Bali et al. (2018)). As argued by Bushee (2001) and Hirshleifer et al. (2018), transient institutional investors trade stocks based on strong-term strategies and are thus less likely to pay as much attention to firms' fundamentals as long-term-orientated dedicated institutional investors. Bali et al. (2018) shows that firms with greater absolute earnings surprises are more likely to attract investor attention, increasing investor awareness of firms' specific characteristics. Therefore, firms with lower media coverage, higher transient institutional ownership, or lower absolute SUE receive less attention from investors and should exhibit more sluggish stock price reactions to the information contained in private subsidiaries' information disclosure and greater predictability of stock returns.

[Insert Table 9 here.]

The media coverage is defined as the number of news articles covering the stock in one month, using news from Thomson Reuters News Analytics. If the number of media news is missing, we set it to zero. To purge out the size effect, we regress logarithm of the number of media news on logarithm of firm's market capitalization and use the residual as our proxy of investor attention. The transient institutional investors are classified following Bushee (2001). For absolute SUE, we use the last non-missing SUE value that is released prior to the June of each year during the past 12 months. Panel A of Table 9 reports the regression results accounting for the same set of control variables used in Table 6 and the industry effects. For brevity, we just report the coefficients of our main variable PSID. Consistent with our hypothesis, the results show that the return predictability of the PSID is stronger among stocks with lower investor attention. The magnitudes of coefficients of PSID in the low attention are much larger and statistically significant, while the magnitudes of coefficients are smaller and insignificant in high attention groups. For example, the average slope of PSID in low residual media coverage subsample is 0.88 with a t-statistics of 2.40, while the one in high residual media coverage subsample is only 0.3 with a t-statistics of 1.01. Overall, the results support our hypothesis that the return predictability is driven by investors' limited attention to the information contained in the PSID.

5.2 Limits to arbitrage

Results in the previous section suggest that investors' inattention is a source of the return predictability, but we do not fully understand what sustains this return predictability. In this section, we further explore the role of limits to arbitrage. If the predictive power of the PSID is driven by mispricing to some extent, then we should expect the return predictability to be more pronounced for stocks with high arbitrage costs. In our next test, we use three proxies of limits-to-arbitrage that are prevalent in the literature.

Following Nagel (2005), we use the residual institutional ownership (i.e., size-orthogonalized institutional ownership) at the end of June of each year as an alternative proxy for limits to arbitrage. The second proxy is the idiosyncratic volatility. We follow Ang et al. (2006) and measure the monthly IVOL as the standard deviation of the daily residuals from the regression of daily excess stock returns on the three factors of Fama and French (1993) over the past one month. Finally, following Amihud (2002), we construct the illiquidity measure in the current month as our final proxy. Panel B of Table 9 reports the regression results controlling for the usual suspects in Table 6 and the industry effects. Consistent with argument of limits to arbitrage, the coefficients are higher and significant in high idiosyncratic volatility group and high illiquidity group, and lower in the high institutional ownership group, while the coefficients are smaller and only marginally significant in high institutional ownership group and low illiquidity group. Thus, limits to arbitrage may provide a partial explanation to the return predictability of the PSID-based trading strategy.

5.3 Anomaly-based mispricing and PSID

The results so far suggest that stocks with high PSID tend to be undervalued relative to stocks with low PSID, but we have not yet provided any formal empirical evidence that high-PSID stocks are indeed undervalued. Thus, we investigate this conjecture by assessing the mispricing score of the stocks directly.

Specifically, we employ the composite mispricing measure originally constructed by Stambaugh, Yu, and Yuan (2015) to identify if high-PSID stocks are indeed undervalued. The composite mispricing measure is the average of percentiles of 11 prominent anomalies, including net stock issues, composite equity issues, accruals, net operating assets, asset growth, investment-to-assets, distress, O-score, momentum, gross profitability, and return on assets. At the end of June of each year, we conduct independent double sorts based on a stock's composite mispricing measure and its PSID. We then compute the average composite mispricing measure for stocks in each of 25 portfolios.

[Insert Table 10 here.]

Table 10 shows that high-PSID stocks indeed tend to have a lower average mispricing score compared to low-PSID stocks. Furthermore, the difference in the composite mispricing measures between the low- and high-PSID stocks within each composite mispricing score quintile is statistically significant. This evidence supports our mispricing argument that stocks with high-PSID value are truly undervalued.

6 Risk versus mispricing explanation

The results so far suggest that the standard asset pricing models of risk do not explain the cross-sectional variation in returns associated with the private information disclosure. However, there is still the possibility of a risk-based mechanism that leads to the return predictability. For example, the PSID can predict the future change in risk, which would lead to a change in the firm's expected return. In this case, the high abnormal return of high-PSID stocks is justified as a means of investors' compensation for high risk, instead of an underreaction to the PSID-related information. In this section, we conduct tests to explore whether alternative measures of risk could plausibly explain our results.

6.1 Earnings prediction

If investors could not fully capture the implication of the private information disclosure on the firm's profitability, they would be surprised by the earnings realizations in the future. Thus, we examine whether the PSID can predict the future earnings controlling for the past earnings. We use standardized unexpected earnings (SUE), defined as actual earnings in the current quarter minus earnings 4 quarters ago, scaled by stock price in the current quarter, following Livnat and Mendenhall (2006), to proxy for earnings surprise. We conduct Fama-MacBeth regressions of the SUE from quarter q+3 in year t+1 to quarter q+2 in year t+2 on the PSID and other accounting variables at the end of year t as well as other priced-based controls in last month prior to each quarter. We also control for the industry effects following the 48-industry classification of Fama and French (1997). We winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and standard deviation of one to reduce the effect of outliers. Finally, we also examine the future SUEs over longer time periods, while keeping all independent variables the same. If the PSID contains information about future earnings, we should expect the slope coefficient to be positive and significant.

[Insert Table 11 here.]

Consistent with our expectation, the first column of Table 11 shows that the coefficient on the PSID is 0.10 with a t-statistic of 2.37 accounting for past SUE, control variables, and the industry effects. Moreover, consistent with Bernard and Thomas (1989), the lagged SUE at quarter q is strongly positively correlated with the future SUE. In columns 2 to 4, we repeat the Fama-MacBeth regressions with the same independent variables but replace the dependent variable (SUEs) in subsequent quarters. The coefficients on the PSID decrease monotonically from column 2 to column 4, and they all become statistically insignificant, indicating that the earnings predictability of the PSID decays quickly after one quarter. This is consistent with the underreaction hypothesis that the PSID reflects slow diffusion of cash flow news into stock prices rather than a change in the future discount rate or compensation for risk.

6.2 Return patterns around earnings announcements

To further differentiate the underreaction-to-information mechanism from a risk-based explanation, we examine stock price reactions around earnings announcements. If the return predictability were explained by underlying risk, we would expect the returns to be evenly affected in the subsequent periods. In contrast, if the effect is consistent with mispricing, then the returns must be disproportionately affected around earnings announcements, meaning that the return prediction around earnings announcement should be stronger than that around non-earnings announcement period if investors are surprised by the good or bad news during that period.

We test these two distinct hypotheses by examining stock price reactions around subsequent earnings announcements. This approach is widely used in the literature (see, for example, Bernard and Thomas (1989); La Porta, Lakonishok, Shleifer, and Vishny (1997); Engelberg et al. (2018); Lee et al. (2019)). Following Engelberg et al. (2018), we conduct a panel regression analysis of daily stock returns (DLYRET) on the last available PSID, an earnings announcement window dummy (EDAY), and the interaction term between the two variables. We also include a set of control variables, consisting of the lagged values for each of the past ten days for stock returns, stock returns squared, and trading volume. We also control for day fixed effects and cluster the standard errors by day.

The earnings announcement date is defined as in Engelberg et al. (2018). Specifically, we examine the firm's trading volume scaled by market trading volume for the day before, the day of, and the day after the reported earnings announcement date, which is obtained from Compustat quarterly database. We then define the day with the highest scaled trading volume as the earnings announcement day. We select one-day or three-day earnings announcement window centered on the earnings announcement date in our analysis.

[Insert Table 12 here.]

Columns 1 and 2 in Table 12 report the regression results for one-day window, and columns 3 and 4 present the results for three-day window. In all cases, the coefficients are all positive and significant. Consistent with the mispricing explanation, returns to the high PSID stocks are much larger during earnings news releasing dates. In column 2, the coefficient on PSID is 0.059, while the coefficient of PSID*EDAY interaction term is 0.341, meaning that the return spread in a hedged PSID strategy is 5.78 times higher during an earnings announcement window than on non-announcement days. Analogously, based on column 4, the return spread of PSID strategy is 4.23 times higher during a three-day earnings announcement window than on non-announcement days. This is comparable to the findings of Engelberg, McLean, and Pontiff (2018) that the anomaly returns on average are six times higher on the earning announcement day and three times higher in the three-day earning announcement window. Thus, the evidence supports our mispricing argument that investors do not fully incorporate the PSID-driven return predictability information into their earnings forecasts and are therefore surprised when earnings are realized.

6.3 Testing potential risk-based explanations

The results have so far shown that the standard factor models or traditional measures of risk do not explain the cross-sectional variation in stock returns associated with the PSID effect. In this section, we provide comprehensive evidence from testing alternative risk-based explanations. Specifically, we rely on the established rational asset pricing models and investigate whether these models' implied measures of risk can be the driving force of the PSID-return relation.

We first test whether the CAPM explains the PSID premium. Specifically, we report total volatility, idiosyncratic volatility, and market beta for each PSID-sorted quintile portfolio as well as the zero-PSID portfolio. The CAPM implied measures of market beta, total volatility, and idiosyncratic volatility are estimated for each month using the past 60-month individual stock returns. Table 13 shows that the CAPM does not explain the PSID premium as the high-PSID stocks have lower total volatility, lower idiosyncratic volatility, and lower market beta than the low-PSID stocks.

[Insert Table 13 here.]

Next, we investigate if the PSID effect can be explained by the intertemporal CAPM (ICAPM) of Merton (1973) and/or the consumption CAPM (CCAPM) of Breeden (1979). Following Ang et al. (2006) and Campbell, Giglio, Polk, and Turley (2018), we use the change in VIX – S&P500 index option implied volatility – as the second factor of the two-factor ICAPM model.[12] Specifically, we estimate the VIX beta for each stock and each month by running the time-series regressions of excess stock returns on the excess market returns and the change in VIX in the past 60 months. To test for the CCAPM explanation, we compute the consumption beta for each stock and each month by regressing the excess stock returns on the consumption growth rate in the past 60 months.[13] We convert the quarterly consumption data to monthly frequency using linear and cubic spline interpolation methods and the consumption beta estimates turn out to be similar from both methods.[14] Results in Table 13 show that neither the ICAPM nor the CCAPM explains the PSID effect. Specifically, the high-PSID stocks tend to have a higher VIX beta than the low-PSID stocks,

[12] Campbell et al. (2018) extend Merton's original model by proposing a two-factor ICAPM with stochastic volatility in which an unexpected increase in future market volatility represents deterioration in the investment opportunity set.

[13] The central implication of the CCAPM is that the expected return on an asset is related to "consumption risk," that is, how much uncertainty in consumption would come from holding the asset. Assets that lead to a large amount of uncertainty offer large expected returns, as investors want to be compensated for bearing consumption risk. Thus, the expected excess return on a risky asset is proportional to the covariance of its return and consumption in the period of the return.

[14] The quarterly consumption data (CAY) are obtained from Martin Lettau's online data library: https://sites.google.com/view/martinlettau/data?authuser=0.

implying lower future return for the high-PSID stocks in the ICAPM framework. Also, as presented in Table 13, the VIX beta difference between the low-PSID and high-PSID groups is statistically insignificant. In addition, the high-PSID stocks have a lower consumption beta than the low-PSID stocks, rejecting the CCAPM explanation for the PSID premium.

Finally, we investigate the magnitude of the factor exposures to see if the PSID-driven return spread is positively loaded on these factors. Specifically, we estimate stock exposure to each factor (ex-ante factor beta) for each month by regressing the excess stock returns on each of these well-established factors in the past 60 months. Generally, the stocks in the highest PSID quintile have lower factor exposures than those in the lowest PSID quintile. The exceptions are the MOM beta, PERF beta, ROE beta, and PEAD beta, and only the differences on two behavioral factors, PERF beta and PEAD beta, between the low-PSID and high-PSID stocks are significant. Overall, these results indicate that the predictive power of the PSID is not explained by alternative measures of risk.

6.4 PSID vs. low-risk anomalies

Table 13 shows that the average total volatility (TVOL), idiosyncratic volatility (IVOL), and market beta (BETA) of the high-PSID stocks is somewhat lower than the average TVOL, IVOL, and BETA of the low-PSID stocks, rejecting the standard risk-based explanation. However, these results suggest that the PSID premium may potentially be explained by the betting-against-beta, idiosyncratic volatility, or lottery demand effects. Contrary to the fundamental principle that higher risk is compensated with higher expected return, Ang et al. (2006) and Frazzini and Pedersen (2014) show that high-volatility (high-beta) stocks underperform low-volatility (low-beta) stocks. Bali, Cakici, and Whitelaw (2011) and Bali, Brown, Murray, and Tang (2017) show that market beta, idiosyncratic volatility, and demand for lottery-like stocks are highly correlated and retail investors' preference for lottery stocks is a driving factor in these well-established low-risk anomalies. To test whether the cross-sectional relation between PSID and the future equity returns of public parent firms is explained by the low-risk anomalies, we control for the betting-against-beta (BAB), idiosyncratic volatility (IVOL), and the lottery demand (MAX) factors of Ang et al. (2006), Frazzini and Pedersen

(2014), and Bali et al. (2011, 2017).[15] Specifically, we estimate the abnormal returns of the PSID-sorted portfolios reported in Table 3, Panel A, by extending the well-established factor models with the BAB, IVOL, and MAX factors. Table A4 of the online appendix shows that the alpha spreads on the long-short portfolios of PSID remain economically and statistically significant after controlling for the BAB, IVOL, and MAX factors, indicating that the low-risk anomalies do not explain the PSID premium.

7 Additional analyses

7.1 PSID and analyst forecast errors

Given that the private subsidiaries' information disclosure (PSID) contains value-relevant information about firm's future performance, we next examine if professionals, such as financial analysts, can fully understand the value relevance of PSID. If these financial analysts indeed underreact to such information, it is also likely for investors who rely on financial analysts to suffer from the same bias.

Specifically, we conduct Fama-MacBeth regressions of analyst forecast errors (AFE) in year t+1 on PSID and control variables in year t. The analyst forecast error is measured as the difference between actual earnings per share (EPS) and the latest analyst consensus forecast before the fiscal year end of the year being forecasted, scaled by lagged total assets. Control variables include lagged analyst forecast errors (AFE), size, book-to-market, gross profitability, asset growth, earnings surprise, short-term reversal (STR), momentum (MOM), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), turnover ratio (TURNOVER), and the number of private subsidiaries. We also control for the industry effects. All independent variables are based on the last non-missing observation for each year t and are standardized to zero mean and standard deviation of one. We conduct the cross-sectional analysis for each year. To reduce the effect of outliers, we winsorize all variables at the 1% and 99% levels

[15] The BAB and MAX factors are borrowed respectively from Frazzini and Pedersen (2014) and Bali et al. (2017): http://www.lhpedersen.com/data and https://sites.google.com/a/georgetown.edu/turan-bali. For the idiosyncratic volatility (IVOL) factor, we follow Fama and French (1993) and sort all stocks into two groups at the end of each month based on their market capitalization with the breakpoint determined by the median market capitalization of stocks traded on the NYSE. We also independently sort all stocks in our sample into three groups using IVOL based on the NYSE breakpoints. The intersection of the two size and three IVOL groups constitute six portfolios. The IVOL factor is the difference in the average return of the two value-weighted high-IVOL portfolios and the average return of the two value-weighted low-IVOL portfolios.

each year.

[Insert Table 14 here.]

Model 1A and Model 1B in Table 14 report the time-series averages of the slope coefficients and the corresponding t-statistics without and with the industry effects, respectively. The results show that analysts indeed underreact to the PSID as the PSID can positively predict the future analyst forecast errors. More specifically, in Model 1B, one standard deviation increase in PSID can induce a 0.03% increase in the next year's analyst forecast errors, with a t-statistic of 2.01. This is also economically significant as the sample mean (median) of the forecast errors is 0.09% (0.00%).

In short, these results suggest that even professionals such as financial analysts cannot fully incorporate the valuable information contained in the PSID. As many investors make investment decisions based on the analyst earnings forecasts, we would expect that these investors will also underreact to such information, which is again consistent with the limited attention explanation for the predictive power of the PSID.

7.2 PSID and institutional trading

Next we examine if sophisticated investors, such as institutional investors, exploit such value-relevant information from PSID in their investment decisions, i.e., if institutional investors incorporate the information contained in PSID, they should trade in the direction indicated by PSID. Similar to the regressions with analyst forecast errors, we conduct annual Fama-MacBeth regressions of net purchases by institutional investors on lagged PSID, controlling for the same set of firm characteristics. The net purchases by institutional investors are computed as yearly change in the fraction of the a firm's shares outstanding held by institutional investors. Model 2A and Model 2B in Table 14 present the results. Consistent with our hypothesis, the insignificant coefficients on the PSID ratio suggest that more informed institutional investors do not respond to the information contained in the private subsidiaries' information disclosure, providing further support for retail investors' limited attention and underreaction to such information.

8 Conclusions

This paper examines the asset pricing implications of private information disclosure about public parent firm. We find that the information contained in the disclosing behaviors of public firms' private subsidiaries is slowly incorporated into stock prices. A proxy for such private information disclosure does predict the cross-sectional variation in future equity returns of public parent firms significantly, and the established factor models do not explain the predictive power of this measure. Further analyses show that the proxies for investors' inattention and limits-to-arbitrage are associated with stronger return predictability, suggesting that the PSID-return relation is consistent with the mispricing explanation.

We conduct comprehensive analyses to differentiate the risk vs. mispricing explanations. First, we examine the market reactions around earnings announcements and find that the predictive power of the PSID is stronger around earnings announcements than that around non-earnings announcement periods. Second, we find that market professionals such as financial analysts cannot fully process the information contained in PSID. Third, the stocks in the highest PSID quintile portfolio have lower average beta, total and idiosyncratic volatility, and their exposures to the established risk factors are lower than those in the lowest PSID quintile portfolio. These results suggest that the return predictability is driven by mispricing rather than underlying risk.

Our findings may have implications on the valuation of corporate disclosure on its private subsidiaries' information. If the markets are slow in responding to firms' value-relevant disclosing patterns, there will be a potential misallocation of resources across these firms. Thus, a better understanding of the mechanism of the investors' underreaction to the PSID related information may shed lights on facilitating information incorporation and achieving higher market efficiency.

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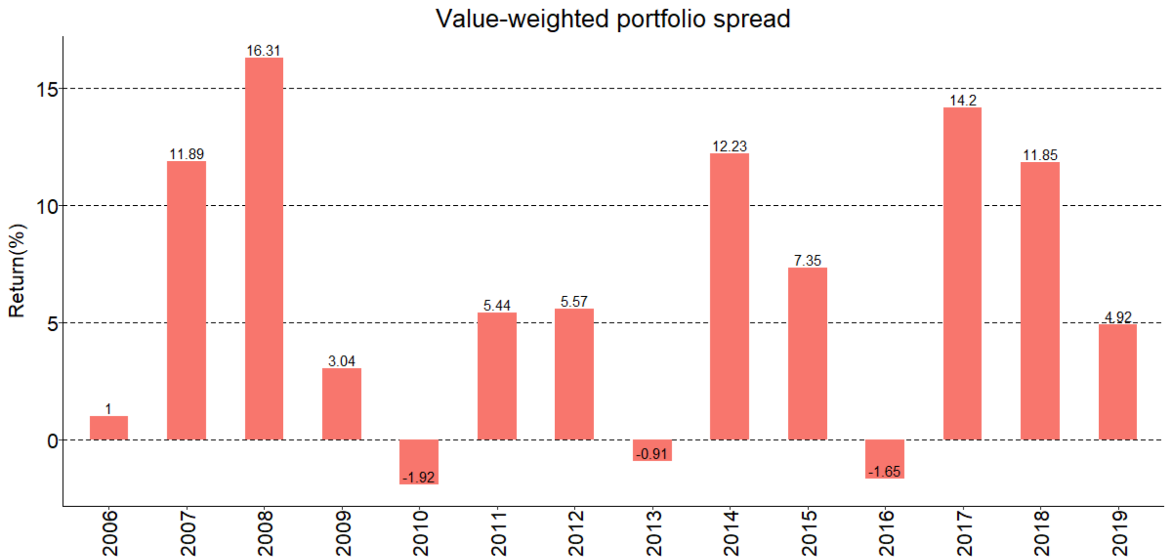

Figure 1: Annual value-weighted returns of the long-short portfolio

This figure shows the annual value-weighted returns of the long-short portfolio sorted on non-zero PSID. At the end of June of each year t from 2006 to 2019, the portfolios are sorted into quintiles based on non-zero PSID at the end of year t-1 from 2005 to 2018, and are held for the next twelve months (July of year t to June of year t+1). The long-short portfolio buys the top quintile of the PSID and sells the bottom quintile of the PSID. There are six months in 2006 and twelve months in other years.

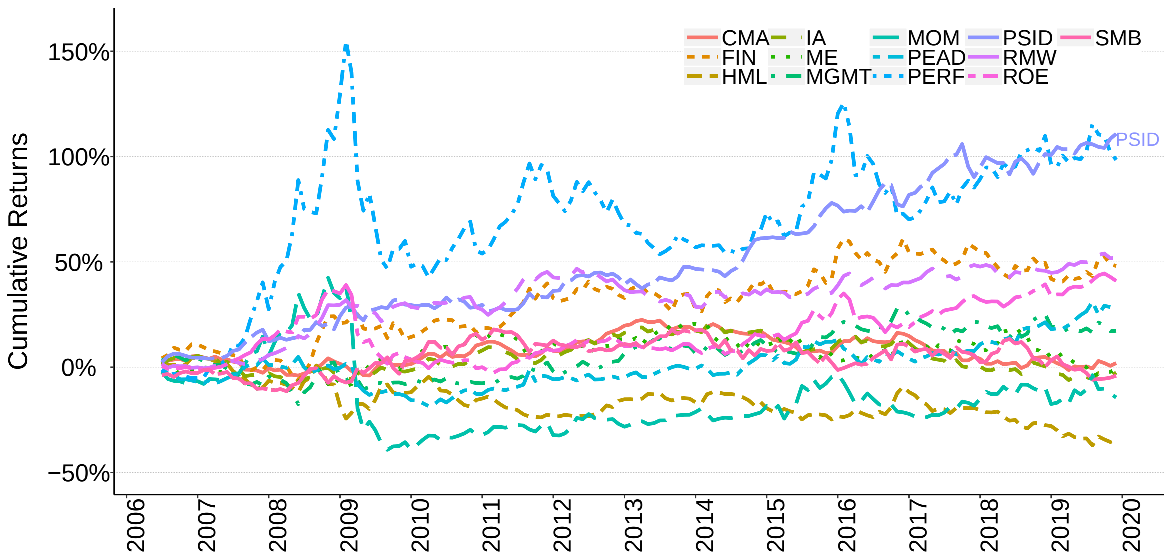

Figure 2: Cumulative returns of the PSID factor and other factors

This figure plots the cumulative value-weighted returns of the PSID factor and other individual factors used in Table 3 from July of 2006 to December of 2019. Following the Fama and French (1993), the PSID factor is constructed by the 2×3 structure, controlling the firm size. There are six months in 2006 and twelve months in other years.

Table 1: Summary statistics across years

This table reports the time series average or sum for firms that own at least one private subsidiary across years. We report average value on number of firms, firm size, PSID ratio, number of private subsidiaries, and ratio for each of seven financial variables as well as the sum of portion (in percentage) of the market capitalization of firms that own at least one private subsidiary relative to the NYSE/NASDAQ/AMEX total market capitalization. The overall sample period is from 2005 to 2018.

Year	# of firms	Portion(%)	PSID	NumofPriSub	Revenue	Assets	Number of employees	Income before tax	Net income	Cash flow	Shareholder funds
2005	2506	63.11	0.29	21	0.43	0.14	0.42	0.12	0.12	0.11	0.14
2006	2860	69.28	0.18	39	0.34	0.11	0.35	0.09	0.09	0.08	0.11
2007	2617	66.09	0.18	29	0.36	0.14	0.33	0.11	0.11	0.08	0.12
2008	2519	67.49	0.23	30	0.35	0.14	0.35	0.11	0.11	0.07	0.14
2009	2457	66.94	0.21	31	0.26	0.15	0.34	0.12	0.12	0.08	0.15
2010	2315	65.72	0.22	32	0.28	0.17	0.33	0.13	0.13	0.08	0.16
2011	2361	66.25	0.24	34	0.35	0.16	0.36	0.13	0.14	0.08	0.16
2012	2480	67.78	0.20	37	0.32	0.15	0.31	0.12	0.13	0.07	0.15
2013	2481	64.40	0.19	39	0.28	0.14	0.29	0.11	0.12	0.07	0.14
2014	2745	67.87	0.14	51	0.24	0.11	0.27	0.08	0.08	0.05	0.10
2015	2593	71.39	0.10	53	0.13	0.12	0.13	0.10	0.10	0.06	0.12
2016	2522	69.87	0.11	53	0.13	0.13	0.14	0.10	0.11	0.07	0.13
2017	2559	71.29	0.11	57	0.14	0.13	0.15	0.11	0.11	0.07	0.13
2018	2579	71.33	0.13	60	0.16	0.15	0.17	0.11	0.11	0.07	0.14

Table 2: Summary statistics

This table reports summary statistics for the key variables in the sample. The sample consists of all common stocks (share codes equal to 10 or 11) that are listed on NYSE, Nasdaq, and Amex. Financial firms (with one-digit SIC = 6), utility firms (with two-digit SIC = 49), and stocks that are below the 20th percentile of NYSE market capitalization are excluded from the analysis. The sample is further restricted to firms with at least five private subsidiaries. PSID is computed as simple average of the ratios of seven financial variables (Operating revenue, Total assets, Number of employees, Income before tax, net income, cash flow, and shareholders funds) disclosed by the private subsidiaries of public firms scaled by total number of private subsidiaries. NumofPriSub is the total number of private subsidiaries under each public firm. RET_{t+1} is the future monthly return. SIZE is the firm's market capitalization computed as the logarithm of the market value of the firm's outstanding equity at the end of month t-1. BM is the logarithm of the firm's book value of equity divided by its market capitalization, where the BM ratio is computed following Fama and French (2008). Firms with negative book values are excluded from the analysis. Short-term reversal (STR) is the stock's lagged monthly return. MOM is the stock's cumulative return from the start of month t-12 to the end of month t-2 following Jegadeesh and Titman (1993). Gross Profitability (GP) is the firm's gross profitability following Novy-Marx (2013), which is equal to revenue minus cost of goods sold scaled by total assets. Asset Growth (AG) is a percentage of total asset growth between two consecutive fiscal years following Cooper et al. (2008). TO is the monthly turnover computed as the number of trading shares divided by the total number of shares outstanding in month t-1. ILLIQ is the monthly illiquidity measure following Amihud (2002), which is computed using daily data in month t-1. IVOL is the idiosyncratic volatility following Ang et al. (2006) over month t-1. SUE is the standardized unexpected earnings defined as actual earnings in the current quarter minus earnings 4 quarters ago, scaled by stock price in the current quarter following Livnat and Mendenhall (2006). IO is the total shares held by institutions from 13F filings in each quarter scaled by total shares outstanding. MediaCov is the number of media news covering the firm. Opacity is defined as the three-year moving sum of the absolute value of discretionary accruals following Hutton et al. (2009). Fog index is a proxy of readability of 10-K fillings. All variables except PSID and NumofPrisub in the sample are winsorized at the 1% level for both tails to mitigate the effect of outliers. The mean, standard deviation (SD), minimum, median and maximum of each variable are presented in panel A, and their pairwise correlations with the PSID are presented in panel B. The overall sample period is from July 2006 to December 2019.

Panel A: Descriptive statistics

	Mean	Sd	Min	Med	Max
PSID	0.20	0.14	0.00	0.19	0.91
NumofPriSub	66.45	122.68	5.00	28.00	4115.00
SIZE	8.25	1.35	4.13	8.03	12.48
BM	-0.94	0.78	-4.09	-0.88	1.28
GP	0.34	0.21	-0.34	0.30	1.13
ILLIQ	0.14	0.42	0.00	0.04	22.87
IVOL	0.02	0.01	0.00	0.01	0.13
MOM	0.24	0.48	-0.94	0.15	4.42
STR	0.01	0.10	-0.63	0.01	1.46
AG	1.11	0.26	0.60	1.06	3.20
SUE	0.12	2.07	-51.67	0.11	29.25
TO	0.47	0.85	0.02	0.21	10.99
IO	77.63	21.71	0.00	82.92	100.00
MediaCov	32.36	48.41	0.00	17.00	458.83
Opacity	0.16	0.15	0.01	0.11	1.27
FOG Index	20.11	1.06	17.41	20.03	25.37
RET_{t+1}	0.01	0.10	-0.63	0.01	1.46

Panel B: Pearson (Spearman) correlations below (above) the diagonal

	PSID	NumofPriSub	SIZE	BM	GP	ILLIQ	IVOL	MOM	STR	AG	SUE	TO	IO	MediaCov	Opacity	FOG Index	RET_{t+1}
PSID		-0.040	0.122	-0.121	0.144	-0.092	-0.146	0.059	0.035	0.020	0.052	-0.133	0.026	0.014	-0.034	0.035	0.033
NumofPriSub	-0.100		0.382	0.009	-0.033	-0.339	-0.159	0.012	-0.002	-0.109	-0.006	-0.087	-0.077	0.271	-0.115	0.075	-0.003
SIZE	0.121	0.303		-0.248	-0.046	-0.931	-0.339	0.167	0.061	0.035	0.112	-0.039	-0.191	0.552	-0.143	0.092	-0.013
BM	-0.124	0.015	-0.231		-0.466	0.222	0.024	0.022	0.021	-0.192	-0.125	-0.009	-0.030	-0.050	-0.105	0.009	0.018
GP	0.097	-0.048	-0.033	-0.430		0.033	0.035	0.001	0.002	0.036	0.022	0.016	0.110	-0.049	0.110	-0.115	0.003
ILLIQ	-0.044	-0.064	-0.374	0.086	0.000		0.311	-0.165	-0.037	-0.022	-0.082	-0.168	0.107	-0.586	0.099	-0.086	0.008
IVOL	-0.121	-0.075	-0.321	0.028	0.017	0.346		-0.237	-0.042	0.066	-0.078	0.581	0.128	0.142	0.200	-0.062	-0.032
MOM	0.043	-0.016	0.121	0.044	-0.003	-0.167	-0.227		-0.019	-0.065	0.293	-0.137	0.003	-0.036	0.021	0.029	-0.009
STR	0.029	-0.006	0.051	0.021	0.005	-0.005	-0.046	-0.028		-0.018	0.031	-0.063	-0.004	0.010	0.010	0.008	-0.007
AG	-0.009	-0.062	0.003	-0.088	-0.075	-0.003	0.090	-0.060	-0.017		0.044	0.049	0.069	-0.037	0.093	-0.006	-0.017
SUE	0.048	-0.010	0.103	-0.093	0.023	-0.146	-0.127	0.245	-0.000	0.008		-0.072	-0.004	-0.042	-0.034	-0.004	-0.017
TO	-0.115	-0.055	-0.107	0.006	0.007	-0.098	0.534	-0.051	-0.051	0.075	-0.062		0.270	0.270	0.182	-0.046	-0.035
IO	0.057	-0.038	-0.127	-0.040	0.081	-0.068	0.042	-0.015	-0.009	0.024	0.008	0.132		-0.132	0.125	0.019	-0.011
MediaCov	0.041	0.241	0.612	-0.058	-0.020	-0.136	0.053	-0.035	-0.002	-0.024	-0.021	0.122	-0.143		-0.017	0.064	-0.008
Opacity	-0.057	-0.083	-0.052	-0.066	0.005	0.003	0.123	0.028	0.003	0.096	-0.019	0.144	0.019	0.019		0.028	0.010
FOG Index	0.028	0.023	0.094	0.026	-0.131	-0.040	-0.062	0.023	0.008	-0.004	0.001	-0.041	-0.013	0.044	0.001		0.007
RET_{t+1}	0.028	-0.007	-0.025	0.017	0.005	0.094	-0.011	-0.018	0.037	-0.017	-0.071	-0.037	-0.013	-0.007	0.003	0.007	

Table 3: Univariate portfolio analysis

Panel A of this table reports average monthly excess returns and alphas on value-weighted portfolios sorted on the PSID. At the end of June of each year t from 2006 to 2019, the portfolios are sorted into quintiles based on non-zero PSID at the end of year t-1 from 2005 to 2018, and are held for the next twelve months (July of year t to June of year t+1). Zero is the portfolio formed by firms with the PSID equal to 0. P1 is the portfolio of stocks with the lowest PSID and P5 is the portfolio of stocks with the highest PSID. L/S is a zero-cost portfolio that buys stocks in the quintile 5 of the PSID and sells stocks in quintile 1 of the PSID. All returns and alphas are expressed in percentage. Excess return is the raw return of the portfolio over the risk-free rate. Alpha is the intercept from a regression of monthly excess return on factor models. Factor models include: CAPM model, a four-factor model including Fama-French three-factor and Carhart (1997) momentum factor (FFC), a five-factor model including FFC and the liquidity factor of Pástor and Stambaugh (2003) (FFCPS), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q-factor model (HXZ), Stambaugh and Yuan (2016) mispricing-factor model (SY), and Daniel et al. (2020) behavior factor model (DHS). Newey and West (1987) adjusted t-statistics are shown below the coefficient estimates. The sample periods of all factor models are from July 2006 to December 2019. Panel B reports transition probabilities for PSID at a lag of one year between 2005 and 2018. For each PSID quintile in year t, the percentage of stocks that fall into each of the year t + 1 PSID quintile is calculated, and the time-series averages of these transition probabilities are presented.

Panel A: Returns and alphas of PSID quintile portfolios

Rank	Excess Return	CAPM	FFC	FFCPS	FF5	FF6	HXZ	SY	DHS
Zero	0.28	-0.67	-0.52	-0.49	-0.50	-0.49	-0.42	-0.37	-0.46
	(0.51)	(-1.88)	(-1.51)	(-1.43)	(-1.38)	(-1.38)	(-1.19)	(-1.07)	(-1.24)
P1	0.51	-0.27	-0.28	-0.25	-0.38	-0.38	-0.21	-0.19	-0.20
	(1.42)	(-2.23)	(-2.34)	(-2.20)	(-3.11)	(-3.13)	(-1.73)	(-1.73)	(-1.60)
P2	0.87	0.19	0.18	0.19	0.03	0.03	0.06	0.18	0.15
	(2.81)	(2.08)	(1.96)	(2.05)	(0.41)	(0.39)	(0.69)	(1.93)	(1.56)
P3	0.80	0.02	-0.05	-0.04	-0.05	-0.05	0.01	0.10	0.00
	(2.24)	(0.14)	(-0.47)	(-0.39)	(-0.53)	(-0.52)	(0.08)	(0.96)	(0.02)
P4	0.88	0.14	0.08	0.10	0.08	0.04	0.04	0.14	0.12
	(2.65)	(1.68)	(1.04)	(0.94)	(0.49)	(0.48)	(0.43)	(1.56)	(1.32)
P5	1.06	0.36	0.27	0.26	0.22	0.22	0.23	0.32	0.34
	(3.33)	(3.73)	(3.21)	(3.12)	(2.59)	(2.59)	(2.66)	(3.41)	(3.44)
L/S	0.55	0.63	0.55	0.51	0.60	0.60	0.44	0.52	0.54
	(3.16)	(3.62)	(3.26)	(3.14)	(3.42)	(3.46)	(2.54)	(3.03)	(3.03)

Panel B: Transition matrix of PSID portfolios

	PSID rank in year t+1					
PSID rank in year t	Zero	P1	P2	P3	P4	P5
Zero	54.17%	33.00%	4.17%	8.00%	0.00%	0.00%
P1	0.05%	71.51%	17.72%	5.78%	3.66%	1.28%
P2	0.05%	13.74%	63.74%	15.25%	5.21%	2.01%
P3	0.03%	2.06%	15.57%	67.80%	11.55%	2.99%
P4	0.03%	0.98%	1.73%	15.50%	72.21%	9.55%
P5	0.00%	0.44%	0.53%	1.05%	10.73%	87.25%

Table 4: Long-term portfolio performance

This table presents longer-term return comparisons between equity quintiles formed monthly based on PSID between 2005 and 2018. Zero is the portfolio of stocks with the zero PSID. P1 is the portfolio of stocks with the lowest PSID and P5 is the portfolio of stocks with the highest PSID. L/S is a zero-cost portfolio that buys stocks in the quintile 5 of the PSID and sells stocks in quintile 1 of the PSID. The table reports Fama and French (2018) six-factor alphas for zero portfolio and each of quintile portfolios from two to twelve months ahead after portfolio formation. The last column in each panel shows the differences of monthly Fama and French (2018) six-factor alphas between quintiles 5 and 1. Newey and West (1987) adjusted t-statistics are presented in parentheses.

Post-sorting months	Zero	P1(Low)	P2	P3	P4	P5(High)	L/S
m+2	-0.49	-0.31	0.05	-0.08	0.08	0.23	0.55
	(-0.43)	(-2.35)	(0.57)	(-0.82)	(0.87)	(2.39)	(2.72)
m+3	-0.38	-0.25	0.07	-0.01	0.08	0.21	0.46
	(-0.35)	(-2.06)	(0.75)	(-0.12)	(0.95)	(2.22)	(2.39)
m+4	-0.28	-0.15	0.09	0.02	0.12	0.20	0.35
	(-0.26)	(-1.46)	(0.98)	(0.22)	(1.30)	(2.01)	(2.02)
m+5	0.18	-0.09	0.09	0.01	0.15	0.19	0.29
	(0.18)	(-0.96)	(1.00)	(0.11)	(1.67)	(1.87)	(1.73)
m+6	-0.23	-0.12	0.08	0.04	0.12	0.19	0.31
	(-0.23)	(-1.20)	(0.92)	(0.50)	(1.32)	(1.84)	(1.87)
m+7	-0.94	-0.1	0.04	0.04	0.17	0.17	0.27
	(-1.05)	(-0.94)	(0.39)	(0.43)	(1.89)	(1.64)	(1.68)
m+8	-0.69	-0.12	0.03	-0.01	0.22	0.16	0.28
	(-0.70)	(-1.14)	(0.36)	(-0.13)	(2.08)	(1.60)	(1.73)
m+9	-1.05	-0.11	0.03	-0.04	0.22	0.14	0.25
	(-1.07)	(-0.95)	(0.28)	(-0.33)	(2.29)	(1.39)	(1.51)
m+10	-1.44	-0.09	0.01	-0.03	0.21	0.13	0.22
	(-1.59)	(-0.83)	(0.11)	(-0.21)	(2.00)	(1.33)	(1.46)
m+11	-1.62	-0.10	-0.05	-0.02	0.28	0.10	0.20
	(-1.90)	(-1.02)	(-0.58)	(-0.17)	(2.76)	(0.99)	(1.41)
m+12	-1.24	-0.14	-0.05	-0.02	0.27	0.11	0.25
	(-1.52)	(-1.33)	(-0.58)	(-0.17)	(2.90)	(1.12)	(1.48)

Table 5: Average portfolio characteristics

This table presents average portfolio characteristics for portfolios formed based on the PSID. Zero is the portfolio formed by firms with the PSID equal to 0. P1 is the portfolio of stocks with the lowest PSID and P5 is the portfolio of stocks with the highest PSID. L/S is a zero-cost portfolio that buys stocks in the quintile 5 of the PSID and sells stocks in quintile 1 of the PSID. The table reports the time-series averages of the monthly averages for PSID and various firm-specific characteristics for each decile. The last two columns show the differences for the firm-specific characteristics between P1 and P5 and the associated Newey and West (1987) adjusted t-statistics. PSID and other firm-specific characteristics are defined in Table 2. The overall sample period is from July 2006 to December 2019.

Variables	Zero	P1	P2	P3	P4	P5	P5-P1	t-stat
PSID	0.00	0.06	0.13	0.20	0.28	0.40	0.35	(36.84)
NumofPriSub	16.89	91.89	55.53	63.10	72.69	53.08	-38.81	(-11.16)
SIZE	7.48	8.08	8.17	8.21	8.38	8.47	0.39	(7.89)
BM	-1.17	-0.83	-0.88	-0.88	-0.98	-1.12	-0.30	(-9.64)
GP	0.38	0.32	0.33	0.32	0.35	0.38	0.06	(17.55)
ILLIQ	0.20	0.15	0.15	0.14	0.13	0.11	-0.04	(-2.36)
IVOL	0.02	0.02	0.02	0.02	0.01	0.01	-0.00	(-7.18)
MOM	0.24	0.21	0.23	0.23	0.24	0.25	0.04	(3.75)
STR	0.00	0.01	0.01	0.01	0.01	0.01	0.00	(4.98)
AG	1.17	1.12	1.11	1.11	1.12	1.12	0.00	(0.22)
SUE	0.17	0.11	0.11	0.06	0.17	0.18	0.07	(1.65)
TO	0.56	0.51	0.47	0.44	0.42	0.41	-0.10	(-4.66)
IO	74.76	75.70	76.27	77.87	78.52	80.08	4.38	(8.78)
MediaCov	17.73	30.44	31.08	32.59	34.33	34.23	3.79	(1.77)
Opacity	0.19	0.17	0.16	0.15	0.15	0.15	-0.02	(-1.20)
FOG Index	20.01	20.05	20.05	20.10	20.09	20.19	0.14	(5.41)

Table 6: Fama-MacBeth regressions

This table reports the results from the Fama and MacBeth (1973) regressions. The sample period is from July 2006 to December 2019. The PSID and other accounting variables at year t is matched to monthly stock returns from July of year t+1 to June of year t+2. The monthly price-based variables are based on last non-missing observations prior to each month. The dependent variable is the firm's future raw return in the first two columns, the firm's future excess return over its value-weighted industry peers' return (Column 3), or the firm's DGTW adjusted return (Column 4). We include industry dummies and classify each firm's industry peers based on Fama-French 48 industry classifications. All returns are expressed in percentage. PSID and other firm-specific characteristics are defined in Table 2. All explanatory variables are based on the last non-missing available observation for each month t-1. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey and West (1987) adjusted for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at the 10%, the 5%, and the 1% level, respectively.

Independent Variables	RET	RET	RET -$INDRET$	DGTW-adj. RET
PSID	0.75***	0.57**	0.79***	0.57***
	(2.65)	(2.22)	(2.71)	(2.83)
STR	-1.77**	-1.98***	-1.54*	-1.92**
	(-2.16)	(-2.80)	(-1.79)	(-2.56)
MOM	-0.54	-0.68	-0.51	-0.64
	(-0.94)	(-1.21)	(-0.82)	(-1.07)
AG	-0.06	-0.05	-0.11	-0.09
	(-0.43)	(-0.42)	(-0.75)	(-0.82)
BM	-0.14*	-0.09	-0.11	-0.07
	(-1.83)	(-1.36)	(-1.45)	(-0.98)
GP	0.21	0.24	0.31	0.37
	(0.62)	(0.87)	(0.87)	(1.29)
SIZE	-0.05	-0.05	-0.05	-0.05
	(-1.07)	(-1.08)	(-0.96)	(-1.05)
SUE	0.09***	0.10***	0.06**	0.07***
	(2.63)	(3.31)	(2.04)	(2.76)
TO	-0.51	-0.07	-0.55	-0.11
	(-1.24)	(-0.23)	(-1.24)	(-0.32)
ILLIQ	2.36	8.73	11.40	25.31
	(0.07)	(0.25)	(0.36)	(0.77)
IVOL	-13.04*	-13.71**	-9.67	-11.91*
	(-1.78)	(-2.19)	(-1.29)	(-1.79)
NumofPriSub	0.00	0.00	0.00	0.00
	(0.63)	(0.77)	(0.56)	(0.71)
Intercept	1.19*	0.99*	1.03	0.82
	(1.83)	(1.80)	(1.44)	(1.37)
Industry FEs	No	Yes	No	Yes
N	155591	155591	155591	154833
Adj.R^2	0.081	0.153	0.078	0.152

Table 7: Double-sorted portfolio analysis

This table reports the double-sorted results on how the portfolio result varies with firm's characteristics. At the end of June of year t from 2006 to 2018, the portfolios are independently sorted into quintiles based on non-zero PSID of year t-1 from 2005 to 2017 and two groups based on each of following characteristics: opacity and fog index. Opacity is constructed as the three-year moving sum of the absolute value of discretionary accruals following Hutton et al. (2009), and it is a proxy of the opacity of the financial reports. Fog index is a proxy of readability of 10-K fillings. We constructed a long-short PSID portfolio within each group and hold for next twelve months (July of year t to June of year t+1). Value-weighted portfolio excess returns and alpha are reported and are expressed in percentage. Excess return is the raw return of the portfolio over the risk-free rate. Alpha is the intercept from a regression of monthly excess return on factor models. Factor models include: Fama and French (2015) five-factor model, Fama and French (2018) six-factor model, Hou et al. (2015) q-factor model, Stambaugh and Yuan (2016) mispricing-factor model, and Daniel et al. (2020) behavioral factor model. Number of firms, average PSID and mean market capitalization in each portfolio are also reported. Newey and West (1987) adjusted t-statistics are shown below the coefficient estimates. The sample periods is from July 2006 to December 2019.

Panel A: Double sort on opacity

Low opacity

PSID Rank	# of firms	PSID	Size	Excess Return	FF5	FF6	HXZ	SY	DHS
P1	89.00	0.06	10362.32	0.48	-0.40	-0.40	-0.26	-0.21	-0.24
				(1.37)	(-2.92)	(-2.90)	(-2.08)	(-1.90)	(-1.97)
P2	91.00	0.13	13180.09	0.84	0.10	0.10	0.09	0.18	0.17
				(2.82)	(1.13)	(1.15)	(0.94)	(2.11)	(1.79)
P3	89.00	0.20	12144.76	0.78	-0.03	-0.03	-0.00	0.10	-0.00
				(2.22)	(-0.28)	(-0.26)	(-0.03)	(0.91)	(-0.02)
P4	93.00	0.28	17415.93	0.84	-0.01	-0.01	0.02	0.11	0.10
				(2.28)	(-0.12)	(-0.12)	(0.17)	(1.10)	(0.88)
P5	89.00	0.40	16388.17	0.94	0.20	0.20	0.17	0.26	0.23
				(2.88)	(1.75)	(1.75)	(1.51)	(2.25)	(2.15)
L/S				**0.46**	**0.60**	**0.60**	**0.47**	**0.47**	**0.49**
				(2.96)	(2.95)	(2.94)	(2.30)	(2.72)	(2.86)

High opacity

PSID Rank	# of firms	PSID	Size	Excess Return	FF5	FF6	HXZ	SY	DHS
P1	91.00	0.06	6846.57	0.56	-0.34	-0.34	-0.14	-0.13	-0.12
				(1.28)	(-1.91)	(-1.91)	(-0.99)	(-0.91)	(-0.83)
P2	89.00	0.13	9880.30	0.71	-0.20	-0.20	-0.11	0.01	-0.09
				(1.74)	(-1.27)	(-1.27)	(-0.67)	(0.03)	(-0.54)
P3	90.00	0.20	13863.65	0.94	0.07	0.07	0.09	0.20	0.14
				(2.05)	(0.41)	(0.41)	(0.65)	(1.35)	(0.91)
P4	86.00	0.28	14549.62	0.72	-0.14	-0.14	-0.12	-0.03	0.11
				(2.04)	(-1.02)	(-1.05)	(-0.91)	(-0.17)	(0.71)
P5	90.00	0.41	20338.75	1.25	0.35	0.35	0.39	0.47	0.52
				(3.64)	(2.31)	(2.26)	(2.46)	(2.77)	(3.11)
L/S				**0.69**	**0.69**	**0.68**	**0.54**	**0.60**	**0.64**
				(2.71)	(2.61)	(2.57)	(2.37)	(2.66)	(2.85)

Panel B: Double sort on fog index									
Low fog index									
PSID Rank	# of firms	PSID	Size	Excess Return	FF5	FF6	HXZ	SY	DHS
P1	103.00	0.06	7783.57	0.36	-0.52	-0.51	-0.36	-0.36	-0.33
				(0.88)	(-3.14)	(-3.12)	(-2.51)	(-2.45)	(-2.33)
P2	105.00	0.13	11410.73	0.90	0.05	0.05	0.06	0.17	0.16
				(2.83)	(0.41)	(0.40)	(0.44)	(1.28)	(1.10)
P3	99.00	0.20	10638.81	0.79	-0.05	-0.05	0.02	0.12	0.08
				(2.02)	(-0.33)	(-0.31)	(0.16)	(0.98)	(0.58)
P4	99.00	0.28	14775.79	0.77	-0.09	-0.09	-0.09	0.01	0.03
				(2.23)	(-0.71)	(-0.74)	(-0.77)	(0.12)	(0.22)
P5	90.00	0.40	18048.61	1.02	0.22	0.22	0.21	0.29	0.30
				(3.13)	(2.14)	(2.10)	(2.03)	(2.43)	(2.58)
L/S				**0.66**	**0.74**	**0.73**	**0.58**	**0.65**	**0.64**
				(3.26)	(3.62)	(3.56)	(3.08)	(3.29)	(3.45)
High fog index									
PSID Rank	# of firms	PSID	Size	Excess Return	FF5	FF6	HXZ	SY	DHS
P1	95.00	0.06	8991.02	0.66	-0.27	-0.27	-0.08	-0.05	-0.08
				(1.67)	(-1.80)	(-1.81)	(-0.61)	(-0.35)	(-0.54)
P2	92.00	0.13	10430.33	0.80	0.01	0.01	0.05	0.18	0.11
				(2.16)	(0.09)	(0.09)	(0.38)	(1.45)	(0.95)
P3	99.00	0.20	14334.54	0.89	0.03	0.03	0.07	0.16	0.02
				(2.12)	(0.23)	(0.24)	(0.51)	(1.12)	(0.13)
P4	98.00	0.28	15735.90	0.97	0.17	0.17	0.15	0.25	0.21
				(2.62)	(1.77)	(1.83)	(1.50)	(2.67)	(2.18)
P5	107.00	0.40	17996.14	1.09	0.22	0.22	0.24	0.34	0.38
				(3.29)	(1.45)	(1.43)	(1.51)	(2.06)	(2.42)
L/S				**0.42**	**0.50**	**0.50**	0.32	**0.38**	**0.46**
				(1.97)	(1.83)	(1.82)	(1.34)	(1.68)	(2.05)

Table 8: Subsequent fundamental performance

This table reports the results from the Fama and MacBeth (1973) regressions of individual firm's fundamental performance measured in year t+1 on the PSID and other control variables in year t. ROA is income before extraordinary items plus interest expenses divided by lagged total assets. Cash flows (CF) is income before extraordinary items minus total accruals (i.e., changes in current assets plus changes in short-term debt and minus changes in cash, changes in current liabilities, and depreciation expenses) divided by average total assets. GM (gross margin) is measured by sales minus cost of goods sold divided by current sales. If GM exceeds 1, it is set to 1. If GM is lower than – 1, it is set to – 1. ΔROA_t ($\Delta Cash_t$ and ΔGM_t) is change in ROA (Cash and GM) from year t-1 to year t. We classify each firm's industry peers based on Fama-French 48 industry classifications. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and one standard deviation. The control variables include size, book-to-market, momentum, asset growth (AG), idiosyncratic volatility (IVOL), and Amihud's illiquidity ratio (ILLIQ). Cross-sectional regressions are run every calendar year, and the time-series standard errors are Newey and West (1987) adjusted for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at the 10%, the 5%, and the 1% level, respectively.

Independent Variables	ROA_{t+1}	ROA_{t+1}	CF_{t+1}	CF_{t+1}	GM_{t+1}	GM_{t+1}
PSID	0.38***	0.20**	0.69***	0.37**	0.40***	0.30***
	(3.56)	(2.35)	(3.64)	(2.42)	(4.36)	(4.03)
ROA_t	4.82***	4.37***				
	(17.10)	(14.10)				
ΔROA_t	-0.98***	-0.91***				
	(-6.94)	(-5.97)				
$Cash_t$			5.01***	4.35***		
			(7.88)	(6.86)		
$\Delta Cash_t$			-2.71***	-2.15***		
			(-9.72)	(-7.94)		
GM_t					19.46***	19.34***
					(95.25)	(91.22)
ΔGM_t					-0.42	-0.49*
					(-1.68)	(-2.12)
SIZE		0.21***		0.66***		0.18**
		(4.01)		(3.52)		(2.81)
BM		-1.30***		-1.16***		-0.63***
		(-7.40)		(-3.73)		(-4.12)
MOM		0.98***		0.63***		0.60***
		(10.81)		(4.14)		(7.32)
AG		-0.82***		-0.63***		-0.17
		(-11.26)		(-5.86)		(-1.64)
SUE		1.34***		1.10***		0.44***
		(17.17)		(8.94)		(4.03)
IVOL		-0.41***		-1.10***		-0.04
		(-4.86)		(-8.85)		(-0.25)
ILLIQ		0.15***		0.07		-0.03
		(3.58)		(0.68)		(-0.52)
Intercept	6.86***	6.54***	4.34***	4.12***	41.90***	41.81***
	(15.67)	(17.54)	(6.17)	(7.58)	(45.38)	(46.21)
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	12136	12136	12674	12674	13021	13021
Adj. R^2	0.447	0.571	0.179	0.250	0.896	0.900

Table 9: Limited attention and limits to arbitrage

This table reports the results of subsamples analysis from the Fama and MacBeth (1973) regressions. The sample period is July 2006 to December 2019. The PSID and other accounting variables in year t is matched to monthly stock returns from July of year t+1 to June of year t+2. Panel A split the samples into two subsamples based on whether the proxies of investor attention are below or above median value. Panel B split the samples into two subsamples based on whether the proxies of limits to arbitrage are below or above median value. Proxies of investor attention include residual media coverage, transient institutional ownership, and absolute SUE following Bali et al. (2018). Proxies of limits to arbitrage include residual institutional ownership, idiosyncratic volatility, and Amihud's illiquidity measure. Media coverage is the number of media news covering the firm in a month, using data from Thomson Reuters News Archive. Transient institutional investors are classified following Bushee (2001). Absolute SUE is defined as the absolute value of SUE based on the last non-missing SUE during the 12 months preceding June. Residual institutional ownership is the residual of institutional ownership orthogonalized with respect to the firm market capitalization following Nagel (2005). Idiosyncratic volatility is constructed following Ang et al. (2006). Amihud illiquidity measure is calculated following Amihud (2002). Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey and West (1987) adjusted for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at the 10%, the 5%, and the 1% level, respectively.

Panel A: Subsamples split by proxies of investor attention

	Residual Media Coverage		Transient Institutions		Absolute SUE	
	Low	High	Low	High	Low	High
PSID	0.88**	0.30	0.53*	1.03***	0.81**	0.45
	(2.40)	(1.01)	(1.70)	(2.77)	(2.41)	(1.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	47604	47651	72189	72107	75949	76030
Adj. R^2	0.077	0.086	0.094	0.069	0.086	0.086

Panel B: Subsamples split by proxies of limits to arbitrage

	Residual IO		IVOL		ILLIQ	
	Low	High	Low	High	Low	High
PSID	0.88***	0.61*	0.35	0.99***	0.57*	0.71**
	(2.61)	(1.91)	(1.01)	(2.88)	(1.67)	(2.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	77839	77785	77810	77781	75949	76030
Adj. R^2	0.102	0.070	0.084	0.075	0.086	0.086

Table 10: Anomaly-based mispricing measure and PSID

This table reports the average composite mispricing measure from the bivariate portfolios based on independent double sorts on the composite mispricing measure and PSID. At the end of June of year t from 2006 to 2018, the portfolios are independently sorted into quintiles based on composite mispricing measure and quintiles by non-zero PSID of year t-1 from 2005 to 2017. The composite mispricing measure is the average of the ranking percentiles produced by 11 anomaly variables following following Stambaugh et al. (2015). The last two columns show the differences of monthly composite mispricing measure and t-statistics between PSID quintiles within each mispricing quintile. Newey and West (1987) adjusted t-statistics are shown below the coefficient estimates.

	P1 (Low PSID)	P2	P3	P4	P5 (High PSID)	H-L	t-stat
Low Misp	30.50	30.55	30.53	30.49	30.16	-0.34	(-3.43)
2	39.33	39.37	39.30	39.40	39.27	-0.05	(-1.75)
3	45.88	45.76	45.70	45.79	45.78	-0.10	(-3.05)
4	52.75	52.55	52.79	52.63	52.38	-0.36	(-3.44)
High Misp	65.20	64.42	63.70	64.02	64.61	-0.60	(-4.36)

Table 11: Earnings prediction

This table reports the results from the Fama and MacBeth (1973) regressions of individual firm's SUE measured in next four quarters on the past PSID and other control variables. All independent variables are based on last non-missing observations prior to each quarter. We classify each firm's industry peers based on Fama-French 48 industry classifications. PSID and other firm-specific characteristics are defined in Table 2. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and standard deviation of one. Cross-sectional regressions are run every calendar quarter, and the time-series standard errors are Newey and West (1987) adjusted for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Independent Variables	SUE_{q+1}	SUE_{q+2}	SUE_{q+3}	SUE_{q+4}
PSID	0.10**	0.07	0.06	0.00
	(2.37)	(1.32)	(1.02)	(0.13)
SUE_q	0.78***	0.57***	0.67***	0.86***
	(3.91)	(5.47)	(5.64)	(3.85)
Dividend	-0.11***	-0.05**	-0.02	0.06
	(-3.88)	(-2.30)	(-1.27)	(1.52)
NGE	-0.02	-0.33	-0.53	-0.62*
	(-0.17)	(-1.27)	(-1.44)	(-1.82)
MOM	0.62***	0.39***	0.18**	0.22
	(3.57)	(2.75)	(2.65)	(1.43)
STR	0.28**	0.18**	0.21*	0.11***
	(2.12)	(2.36)	(1.89)	(3.10)
BM	-0.28*	-0.22	-0.22	-0.16
	(-1.91)	(-1.05)	(-1.05)	(-0.76)
SIZE	-0.15*	-0.04	-0.01	-0.00
	(-1.97)	(-1.32)	(-0.52)	(-0.12)
AG	-0.16**	-0.12**	-0.11*	-0.04
	(-2.41)	(-2.02)	(-1.94)	(-1.27)
ILLIQ	-0.57	-0.13	-0.06*	-0.08
	(-1.48)	(-1.47)	(-1.73)	(-0.85)
IVOL	-0.40	-0.10*	-0.16	-0.06
	(-1.67)	(-1.68)	(-1.24)	(-0.37)
TO	-0.31**	-0.15*	-0.06	-0.10
	(-2.60)	(-1.92)	(-1.34)	(-1.10)
Intercept	-0.54	-0.32	-0.22	-0.22
	(-1.23)	(-1.10)	(-1.09)	(-0.75)
Industry FEs	Yes	Yes	Yes	Yes
N	52013	50474	48941	47497
Adj. R^2	0.099	0.145	0.144	0.147

Table 12: Earnings announcement returns prediction

This table reports regressions of announcement window daily returns (DLYRET) on day-fixed effects, the PSID variable, earnings day dummy variables, and other lagged control variables (coefficients unreported). An earnings announcement is defined as the one-day or three-day window centered on an earnings release, i.e., days t - 1, t , and t + 1. EDAY is a dummy variable and equals one if the daily observation is during an announcement window, and zero otherwise. Following Engelberg et al. (2018) , we obtain earnings announcement dates from the Compustat quarterly database, examine the firm's trading volume scaled by market trading volume for the day before, the day of, and the day after the reported earnings announcement date, and define the day with the highest volume as the earnings announcement day. Control variables include lagged values for each of the past ten days for stock returns, stock returns squared, and trading volume. Standard errors are clustered on time. T -statistics are in parentheses, coefficients marked with * , ** , and *** are significant at 10%, 5%, and 1%, respectively. The sample period is from July 2006 to December 2019.

	Panel A: one-day window		Panel B: three-day window	
Dep.variable (%)	DLYRET	DLYRET	DLYRET	DLYRET
PSID	0.046**	0.059***	0.047**	0.060***
	(2.35)	(3.05)	(2.42)	(3.11)
PSID * EDAY	0.343***	0.341***	0.254***	0.254***
	(3.39)	(3.13)	(2.63)	(2.63)
EDAY	0.060	0.058	0.010	0.010
	(0.93)	(0.89)	(0.13)	(0.33)
Lagged controls	No	Yes	No	Yes
Day fixed effects	Yes	Yes	Yes	Yes
N	3473445	3451066	3473445	3451066
Adj. R^2	0.286	0.286	0.286	0.287

Table 13: Risk-based explanations

This table presents results of risk-based explanations by presenting average portfolio risk attributes for zero-PSID portfolio, each quantile portfolio sorted on PSID, and differences for the firm-specific risk attributes between quintiles 5 and 1 and the associated Newey and West (1987) adjusted t-statistics. Zero is the portfolio formed by firms with the PSID equal to 0. P1 is the portfolio of stocks with the lowest PSID and P5 is the portfolio of stocks with the highest PSID. TVOL is the monthly return volatility over the past 60 months for each stock. VIX is the monthly change in VIX index following Ang et al. (2006). Beta for each stock on TVOL, VIX, consumption growth rate, and each risk factor is computed using past 60 months observations. The sample periods of all factor models are from July 2006 to December 2019.

Risk	Zero	P1	P2	P3	P4	P5	P5-P1	t-stat
CAPM								
TVOL	0.12	0.11	0.10	0.10	0.10	0.10	-0.01	(-3.60)
IVOL	0.02	0.02	0.02	0.02	0.01	0.01	-0.00	(-7.18)
MKT Beta	1.12	1.07	1.01	1.07	1.08	1.07	-0.00	(-0.16)
ICAPM								
VIX beta	-0.08	-0.06	-0.03	-0.04	-0.05	-0.04	0.02	(0.44)
CCAPM								
Consumption Growth Beta	0.64	0.69	0.64	0.73	0.67	0.53	-0.14	(-1.33)
Factor exposures								
SMB Beta	1.00	0.68	0.64	0.65	0.56	0.54	-0.14	(-3.99)
HML Beta	-0.15	0.04	-0.03	-0.03	-0.08	-0.18	-0.22	(-5.76)
RMW Beta	0.04	0.23	0.11	0.10	-0.01	-0.11	-0.33	(-6.54)
CMA Beta	-0.38	0.07	0.10	-0.01	-0.02	0.02	-0.04	(-0.59)
MOM Beta	-0.06	-0.14	-0.13	-0.12	-0.11	-0.09	0.05	(1.56)
LIQ Beta	-0.01	0.10	0.07	0.07	0.05	0.04	-0.06	(-2.90)
MGMT Beta	-0.73	-0.75	-0.70	-0.79	-0.73	-0.78	-0.03	(-0.53)
PERF Beta	-0.70	-0.74	-0.69	-0.71	-0.70	-0.68	0.06	(2.30)
IA Beta	-0.43	-0.15	-0.17	-0.31	-0.30	-0.32	-0.17	(-2.16)
ROE Beta	-1.32	-1.39	-1.30	-1.37	-1.31	-1.31	0.09	(1.28)
FIN Beta	-1.01	-0.91	-0.87	-0.94	-0.96	-1.00	-0.09	(-1.86)
PEAD Beta	-0.88	-0.95	-0.79	-0.86	-0.83	-0.82	0.14	(2.94)

Table 14: PSID, analyst forecast errors, and institutional trading

This table reports the results from the Fama and MacBeth (1973) regressions of analyst forecast errors and institutional trading in year t+1 on PSID and controls in year t. In model 1A and 1B, the dependent variable is analyst forecast errors (AFE). In model 2A and 2B, the dependent variable is institutional net buys (INB). Analyst forecast errors (AFE) is defined as the difference between actual earnings per share (EPS) and the latest analyst consensus forecast before the fiscal year end of the year being forecasted, scaled by lagged total assets. Institutional net buys (INB) is defined as the yearly change in institutional investors holding on a stock, with holding is a fraction of a firm's ownership. We classify each firm's industry peers based on Fama-French 48 industry classifications. PSID and other firm-specific characteristics are defined in Table 2. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and standard deviation of one. Cross-sectional regressions are run every calendar year, and the time-series standard errors are Newey and West (1987) adjusted for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at the 10%, the 5%, and the 1% level, respectively.

	Analyst Forecast Errors		Institutional Net Buys	
Independent Variables	Model 1A	Model 1B	Model 2A	Model 2B
PSID	0.0002*	0.0003**	0.1322	0.0739
	(1.97)	(2.01)	(0.91)	(0.61)
AFE_t	0.0140***	0.0140***		
	(4.01)	(4.15)		
INB_t			-0.7260***	-0.7102***
			(-3.38)	(-3.34)
SIZE	0.0010***	0.0009***	-0.0963**	-0.1418*
	(2.62)	(3.82)	(-2.06)	(-1.73)
BM	0.0000	-0.0001	-0.2670**	-0.2659*
	(0.10)	(-0.62)	(-2.14)	(-1.84)
MOM	-0.0011**	-0.0011**	0.3779***	0.4192***
	(-2.32)	(-2.22)	(4.81)	(5.49)
AG	-0.0006***	-0.0006***	0.0614	0.0770
	(-3.16)	(-3.31)	(0.69)	(0.86)
SUE	-0.0003	-0.0003	-0.1890**	-0.1852***
	(-1.59)	(-1.54)	(-2.31)	(-4.22)
GP	-0.0010***	-0.0011***	-0.1812*	-0.0764
	(-3.15)	(-3.17)	(-1.70)	(-0.81)
TO	-0.0005	0.0001	-0.1166	-0.0486
	(-1.57)	(0.33)	(-0.87)	(-0.37)
IVOL	0.0003***	0.0004***	0.2867***	0.2661***
	(2.96)	(2.81)	(5.39)	(5.48)
ILLIQ	0.0004**	0.0004**	0.1598	0.2241
	(2.03)	(2.01)	(1.12)	(1.50)
STR	-0.0002***	-0.0003**	0.3908***	0.3520***
	(-1.51)	(-2.50)	(6.10)	(7.09)
NumofPriSub	0.0001**	0.0001*	-0.0311	0.0166
	(2.05)	(1.88)	(-0.42)	(0.18)
Intercept	0.0039	-0.0012***	-0.2914	0.3284
	(1.78)	(-3.31)	(-0.50)	(0.42)
Industry FEs	No	Yes	No	Yes
N	12897	12897	12319	12319
Adj. R^2	0.065	0.067	0.040	0.054

Appendix for Online Publication

“Private Subsidiaries’ Information Disclosure and the Cross-Sectional Equity Returns of Public Parent Firms”

This Online Appendix includes tables referred to but not included in the main body of the paper, which provide robustness checks and additional findings.

Table A1: Equal-weighted portfolio results sorted on PSID

This table reports average monthly excess returns and alphas on equal-weighted portfolios sorted on the PSID. At the end of June of each year t from 2006 to 2019, the portfolios are sorted into quintiles based on non-zero PSID at the end of year t-1 from 2005 to 2018, and are held for the next twelve months (July of year t to June of year t+1). Zero is the portfolio formed by firms with the PSID equal to 0. P1 is the portfolio of stocks with the lowest PSID and P5 is the portfolio of stocks with the highest PSID. L/S is a zero-cost portfolio that buys stocks in the quintile 5 of the PSID and sells stocks in quintile 1 of the PSID. All returns and alphas are expressed in percentage. Excess return is the raw return of the portfolio over the risk-free rate. Alpha is the intercept from a regression of monthly excess return on factor models. All factor models are based on factors used in Table 3. Newey and West (1987) adjusted t-statistics are shown below the coefficient estimates. The sample periods of all factor models are from July 2006 to December 2019.

Rank	Excess Return	CAPM	FFC	FFCPS	FF5	FF6	HXZ	SY	DHS
Zero	0.41	-0.58	-0.36	-0.35	-0.40	-0.39	-0.30	-0.23	-0.26
	(0.76)	(-1.78)	(-1.29)	(-1.23)	(-1.33)	(-1.35)	(-0.99)	(-0.66)	(-0.79)
P1	0.59	-0.36	-0.20	-0.18	-0.29	-0.28	-0.11	-0.06	-0.19
	(1.33)	(-2.14)	(-1.84)	(-1.63)	(-2.14)	(-2.54)	(-0.85)	(-1.23)	(-1.11)
P2	0.91	0.00	0.12	0.15	0.04	0.05	0.14	0.24	0.13
	(2.18)	(0.01)	(1.53)	(1.88)	(0.45)	(0.56)	(1.38)	(2.93)	(1.01)
P3	0.96	-0.02	0.10	0.12	0.07	0.08	0.15	0.25	0.15
	(2.13)	(-0.15)	(1.14)	(1.40)	(0.68)	(0.87)	(1.41)	(2.78)	(1.03)
P4	1.07	0.12	0.20	0.22	0.18	0.19	0.23	0.35	0.26
	(2.46)	(0.90)	(2.46)	(2.62)	(1.90)	(2.21)	(2.32)	(3.81)	(2.02)
P5	1.10	0.17	0.23	0.25	0.23	0.24	0.30	0.39	0.33
	(2.60)	(1.36)	(2.89)	(3.24)	(2.40)	(2.91)	(3.24)	(4.36)	(2.77)
L/S	0.51	0.53	0.43	0.42	0.52	0.52	0.42	0.45	0.53
	(3.76)	(3.84)	(3.35)	(3.32)	(3.98)	(4.03)	(3.13)	(3.43)	(3.85)

Table A2: Portfolio returns for each single ratio

This table reports average monthly excess returns and alphas on value-weighted long-short portfolios sorted based on each single ratio of private information disclosure. At the end of June of each year t from 2006 to 2019, the portfolios are sorted into quintiles based on the ratio at the end of year t-1 from 2005 to 2018, and are held for the next twelve months (July of year t to June of year t+1). All returns and alphas are expressed in percentage. Excess return is the raw return of the portfolio over the risk-free rate. Alpha is the intercept from a regression of monthly excess return on factor models. All factor models are based on factors used in Table 3. Newey and West (1987) adjusted t-statistics are shown below the coefficient estimates. The sample periods of all factor models are from July 2006 to December 2019.

Single ratio	Excess Return	CAPM	FFC	FFCPS	FF5	FF6	HXZ	SY	DHS
Revenue	0.46	0.48	0.43	0.44	0.49	0.49	0.38	0.43	0.44
	(2.97)	(3.13)	(2.55)	(2.45)	(2.89)	(2.81)	(2.33)	(2.67)	(2.81)
Total assets	0.42	0.39	0.32	0.35	0.44	0.44	0.36	0.38	0.46
	(3.11)	(2.66)	(2.07)	(2.47)	(2.49)	(2.47)	(2.22)	(2.55)	(2.77)
NumofEmployee	0.40	0.42	0.29	0.27	0.36	0.36	0.32	0.35	0.45
	(2.46)	(2.60)	(1.90)	(1.73)	(2.34)	(2.32)	(2.09)	(2.40)	(2.41)
Income before tax	0.27	0.23	0.15	0.17	0.28	0.28	0.24	0.23	0.22
	(2.09)	(1.73)	(1.18)	(1.27)	(1.90)	(1.95)	(1.73)	(1.84)	(1.51)
Net income	0.42	0.34	0.28	0.29	0.43	0.43	0.35	0.40	0.41
	(1.75)	(1.50)	(0.99)	(1.08)	(1.74)	(1.78)	(1.40)	(1.58)	(1.73)
Cash flow	0.31	0.30	0.22	0.22	0.37	0.37	0.33	0.31	0.39
	(1.97)	(1.83)	(1.27)	(1.30)	(1.96)	(1.97)	(1.88)	(1.88)	(1.97)
Shareholders funds	0.31	0.27	0.19	0.22	0.34	0.34	0.27	0.28	0.31
	(2.43)	(1.96)	(1.64)	(1.66)	(2.07)	(2.07)	(1.79)	(2.02)	(1.99)

Table A3: PSID within industries

This table reports the pooled mean, standard deviation (Sd), minimum (Min), median (Med), and Maximum (Max) of the private information disclosure ratio (PSID) for firms with at least one private subsidiary in industries according to Fama-French 48 industry classifications. A firm's PSID is the averaged ratio of the seven financial variables' ratios, defined as the number of private subsidiaries disclosing the particular financial variable divided by the total number of private subsidiaries under the control of a public parent firm. The overall sample period is from 2005 to 2018.

FF48	Industry	Mean	Sd	Min	Med	Max
1	Agriculture	0.09	0.10	0.00	0.05	0.43
2	Food Products	0.15	0.13	0.00	0.13	1.00
3	Candy & Soda	0.16	0.12	0.00	0.14	0.64
4	Beer & Liquor	0.12	0.10	0.00	0.10	0.40
5	Tobacco Products	0.19	0.16	0.00	0.14	0.60
6	Recreation	0.21	0.14	0.00	0.20	0.64
7	Entertainment	0.12	0.12	0.00	0.09	0.86
8	Printing and Publishing	0.15	0.11	0.00	0.13	0.76
9	Consumer Goods	0.21	0.16	0.00	0.18	1.00
10	Apparel	0.19	0.13	0.00	0.17	0.64
11	Healthcare	0.13	0.12	0.00	0.10	0.71
12	Medical Equipment	0.26	0.17	0.00	0.26	1.00
13	Pharmaceutical Products	0.22	0.19	0.00	0.17	1.00
14	Chemicals	0.23	0.15	0.00	0.22	1.00
15	Rubber and Plastic Products	0.24	0.17	0.00	0.22	0.86
16	Textiles	0.19	0.15	0.00	0.17	0.67
17	Construction Materials	0.21	0.15	0.00	0.20	0.86
18	Construction	0.13	0.14	0.00	0.07	0.71
19	Steel Works Etc	0.18	0.13	0.00	0.17	0.69
20	Fabricated Products	0.22	0.13	0.00	0.21	0.57
21	Machinery	0.26	0.14	0.00	0.25	1.00
22	Electrical Equipment	0.22	0.17	0.00	0.19	1.00
23	Automobiles and Trucks	0.22	0.14	0.00	0.21	1.00
24	Aircraft	0.22	0.12	0.00	0.21	0.64
25	Shipbuilding, Railroad Equipment	0.20	0.14	0.00	0.19	0.52
26	Defense	0.17	0.13	0.00	0.14	0.57
27	Precious Metals	0.11	0.10	0.00	0.09	0.43
28	Non-Metallic and Industrial Metal Mining	0.13	0.14	0.00	0.08	0.71
29	Coal	0.10	0.08	0.00	0.08	0.50
30	Petroleum and Natural Gas	0.12	0.13	0.00	0.08	0.86
31	Utilities	0.16	0.14	0.00	0.12	0.86
32	Communication	0.16	0.15	0.00	0.13	1.00
33	Personal Services	0.17	0.15	0.00	0.14	1.00
34	Business Services	0.22	0.16	0.00	0.20	1.00
35	Computers	0.25	0.16	0.00	0.24	1.00
36	Electronic Equipment	0.24	0.17	0.00	0.21	1.00
37	Measuring and Control Equipment	0.28	0.17	0.00	0.27	1.00
38	Business Supplies	0.21	0.15	0.00	0.18	0.88
39	Shipping Containers	0.21	0.12	0.00	0.20	0.57
40	Transportation	0.15	0.14	0.00	0.12	0.86
41	Wholesale	0.19	0.15	0.00	0.16	1.00
42	Retail	0.13	0.13	0.00	0.09	0.76
43	Restaurants, Hotels, Motels	0.10	0.11	0.00	0.07	0.64
44	Banking	0.08	0.10	0.00	0.05	0.62
45	Insurance	0.10	0.11	0.00	0.07	0.86
46	Real Estate	0.08	0.13	0.00	0.03	0.86
47	Trading	0.07	0.11	0.00	0.01	0.86
48	Almost Nothing	0.15	0.16	0.00	0.11	1.00

Table A4: Alternative factor models

This table reports average monthly alphas on value-weighted portfolios sorted on the PSID. At the end of June of each year t from 2006 to 2019, the portfolios are sorted into quintiles based on non-zero PSID at the end of year t-1 from 2005 to 2018, and are held for the next twelve months (July of year t to June of year t+1). Zero is the portfolio formed by firms with the PSID equal to 0. P1 is the portfolio of stocks with the lowest PSID and P5 is the portfolio of stocks with the highest PSID. L/S is a zero-cost portfolio that buys stocks in the quintile 5 of the PSID and sells stocks in quintile 1 of the PSID. All returns and alphas are expressed in percentage. All returns and alphas are expressed in percentage. Excess return is the raw return of the portfolio over the risk-free rate. Alpha is the intercept from a regression of monthly excess return on factor models. All factor models are based on factors used in Table 3 augmented with the FMAX factor, the BAB factor, or the IVOL factor. Panel A reports results of factors augmented with the BAB factor. Panel B reports result of factors augmented with the IVOL factor. Panel C reports result of factors augmented with the MAX factor.Newey and West (1987) adjusted t-statistics are shown below the coefficient estimates. The sample periods of all factor models are from July 2006 to December 2019.

Panel A: Factors augmented with the BAB factor

Rank	CAPM	FFC	FFCPS	FF5	FF6	HXZ	SY	DHS
L/S	0.63	0.58	0.57	0.64	0.65	0.46	0.54	0.55
	(3.56)	(3.48)	(3.31)	(3.58)	(3.72)	(2.64)	(3.13)	(3.05)

Panel B: Factors augmented with the IVOL factor

Rank	CAPM	FFC	FFCPS	FF5	FF6	HXZ	SY	DHS
L/S	0.67	0.53	0.50	0.67	0.63	0.41	0.51	0.52
	(3.84)	(2.61)	(2.62)	(2.89)	(2.88)	(2.27)	(2.72)	(3.01)

Panel C: Factors augmented with the MAX factor

Rank	CAPM	FFC	FFCPS	FF5	FF6	HXZ	SY	DHS
L/S	0.43	0.41	0.43	0.45	0.47	0.38	0.43	0.40
	(2.45)	(2.36)	(2.41)	(2.58)	(2.69)	(2.14)	(2.49)	(2.26)