Limits-to-arbitrage, Investment Frictions, and the Investment Effect: New Evidence☆

F.Y. Eric C. Lam*
Hong Kong Institute for Monetary Research
Hong Kong Monetary Authority
55/F, Two International Finance Centre
8 Finance Street, Central, Hong Kong
E-mail: cfylam@hkma.gov.hk
Tel: (852)-2597-0802

Ya Li
LSK School of Business and Administration
The Open University of Hong Kong
Ho Man Tin, Hong Kong
E-mail: yali@ouhk.edu.hk
Tel: (852)-2768-6942

Wikrom Prombutr
Department of Finance
College of Business Administration
California State University, Long Beach
California, United States of America
E-mail: wikrom.prombutr@csulb.edu
Tel: (562)-985-4567

K.C. John Wei
School of Accounting and Finance
Hong Kong Polytechnic University
Hong Hum, Kowloon, Hong Kong
E-mail: johnwei@ust.hk
Tel: (852)-2766-4953

This version: Jan 2019

☆ We thank Wei-Peng Chen, Chia-Wei Huang, Roger Loh, and conference participants at the 2017 China International Conference in Finance (CICF) in Hangzhou, China, the 2016 European Financial Management Association (EFMA) annual meeting in Basel, and the 2016 International Symposium on Business and Management in Tokyo. We are particularly grateful for the constructive and insightful comments and suggestions from anonymous referees and John A Doukas (the editor). Eric Lam acknowledges partial financial support received from the Research Grants Council of the Hong Kong Special Administrative Region, China (project no. 299913-ECS and project no. 12501414) during his faculty appointment at the Hong Kong Baptist University. The views expressed in this paper are those of the authors, and do not necessarily reflect those of the Hong Kong Institute for Monetary Research or the Hong Kong Monetary Authority. All errors are ours.

Limits-to-arbitrage, Investment Frictions, and the Investment Effect:
New Evidence

Abstract

This study comprehensively reexamines the debate over behavioral and rational explanations for the investment effect in an updated sample. We closely follow the previous literature and provide several differences. Our tests include five prominent measures of corporate investment and corporate profitability in q-theory and recent investment-based asset pricing models. Both classical and Bayesian inferences show that limits-to-arbitrage tend to be supported by more evidence than investment frictions for all investment measures. When idiosyncratic volatility and cash flow volatility are used in measuring investment frictions, the inference is more favorable for the rational explanation.

JEL Classification: G14, G31, G32, M41, M42

Keywords: Limits-to-arbitrage; Investment frictions; q-theory; Investment; Stock returns

1. Introduction

Titman, Wei, and Xie (2004) and Cooper, Gulen, and Schill (2008), among others, find that stocks of firms with high capital investment or high total asset growth underperform those of firms with low capital investment or low total asset growth, which is generally referred to as the investment or asset growth effect. Lam and Wei (2011) compare the predictions of the mispricing hypothesis on the asset growth effect with the limits-to-arbitrage suggested by Shleifer and Vishny (1997) and q-theory with investment frictions, as proposed by Li and Zhang (2010). While Li and Zhang (2010) show that limits-to-arbitrage tend to be more important, the extensive direct comparisons by Lam and Wei (2011) show that there is evidence supporting all the hypotheses. Whether one explanation is empirically more important for the investment effect thus remains unclear. We address this unresolved issue in our study, which differs from Lam and Wei (2011) in several ways.

First, we extend the sample period, examining data from July 1963 to December 2017, to increase the power of the tests. Second, in addition to total asset growth (Cooper, Gulen, and Schill (2008)), which is the only investment measure used by Lam and Wei (2011), we examine four other common measures: investment-to-assets (Titman, Wei, and Xie (2004); Lyandres, Sun, and Zhang (2008)), net operating assets (Hirshleifer, Hou, Teoh, and Zhang (2004)), net share issuance (Pontiff and Woodgate (2008)), and composite share issuance (Daniel and Titman (2006)). Third, we use the same 10 proxies of limits-to-arbitrage and four proxies of investment frictions as Lam and Wei, but construct a composite index for each friction category, instead of individual measures, to make a fair and precise comparison. Fourth, unlike Lam and Wei, we control for corporate profitability to analyze investment frictions, thus aligning the tests more closely with the prediction of q-theory. Fifth, Lam and Wei (2011) perform individual or joint tests from subsamples split by arbitrage frictions and/or investment frictions. We instead estimate the Fama and MacBeth (1973) regressions with the interaction term between investment and limits-to-arbitrage or investment frictions. Finally, in addition to classical inferences, we take the Bayesian approach to hypothesis testing, using the minimum Bayes factors suggested by Harvey (2017).

Overall, our individual and joint tests using classical and Bayesian inferences yield similar results, but differ from those of Lam and Wei (2011). In general, we find greater evidence for mispricing with limits-to-arbitrage than for q-theory with investment frictions on the investment effect. First, in our individual tests, without controlling for the competing hypothesis, we find that 80% of the cases support arbitrage frictions while 44% support investment frictions (80% versus 44%). Second, the joint tests show that 80% of the Fama-MacBeth regression slopes on the interaction term between investment and arbitrage frictions are negative and statistically significant at the 5% level. The two insignificant slopes come from weighted least-squares (WLS) regressions using net or composite share issuance as the measure of investment. In contrast, only a small number of cases show that the investment effect is significantly related to investment frictions as predicted by q-theory. Only 14% of the Fama-MacBeth regression slopes of the interaction term between investment and investment frictions are negative and statistically significant at the 5% level. All significant cases come from OLS regressions, with investment-to-assets generating the most evidence, followed by total asset growth. Other investment measures provide no evidence for the investment frictions hypothesis.

The Bayesian inferences provide similar findings. We start with a prior odds ratio of 4 to 1; that is, the prior probability that the null (investment frictions or arbitrage frictions are not important) is true is 80% and the prior likelihood that the alternative (investment frictions or arbitrage frictions are important) is true is 20%. We find that in about 51% of the regression coefficient estimates, the posterior probability of the arbitrage frictions null being true is less than 5%. The results with OLS and WLS regressions are significant when the measure of investment is total asset growth or investment-to-assets. In contrast, the posterior probability of the investment frictions null being true is less than 5% in only about 7% of the regression coefficient estimates. All of the significant results are exclusively derived from using investment-to-assets as the measure of investment with OLS regressions. Interestingly, the overall results show that investment-to-assets appears to be the most important measure of investment in terms of supporting either hypothesis, followed by total asset growth, net operating assets, and then net share issuance, with composite share issuance being the least important.

Our findings suggest that the mispricing hypothesis with limits-to-arbitrage empirically outperforms q-theory with investment frictions in explaining the investment effect. This is consistent with Li and Zhang (2010). However, we cannot rule out the q-theory explanation. The q-theory is unsurprisingly a viable economic mechanism for understanding the return predictability of investment-to-assets, as it focuses on corporate capital investment. The limits-to-arbitrage hypothesis, however, is more important because it can explain return predictability for a broadly defined measure of investment, even with WLS regressions in some cases. The findings suggest that compared with small-cap stocks, arbitrage frictions are less important, and investment frictions are not important at all for large-cap stocks. Yet, the relative importance of the two frictions depends on the set of variables used in the construction of the indices. For example, when idiosyncratic and cash flow volatilities are used as investment frictions measures instead of arbitrage frictions measures, there are more evidence for q-theory but less evidence for limits-to-arbitrage.

The investment effect continues to receive attention from academics and practitioners alike.[1] Lam and Wei (2011) point out that the limits-to-arbitrage hypothesis should make similar predictions as the investment-frictions hypothesis, as proxies for both are highly correlated. As the evidence drawn from individual tests may support both hypotheses, it is important to conduct joint tests to distinguish between the two explanations. Although Lipson, Mortal, and Schill (2011) and Li and Sullivan (2011; 2015) provide evidence that limits-to-arbitrage play a significant role in the return predictability of total asset growth, their tests do not control for investment frictions or profitability. Extending the joint test framework of Lam and Wei is thus crucial to testing the limits-to-arbitrage hypothesis. Our findings confirm the conclusion of Lipson, Mortal, and Schill (2011) and Li and Sullivan (2011; 2015) that limits-to-arbitrage are important.

We make several contributions to the literature. First, we confirm that the mispricing hypothesis with limits-to-arbitrage can better explain the investment effect than can q-theory with investment frictions. Our sample contains a longer time series than that used by Lam and Wei (2011), and our cross-sectional regressions are estimated with all stocks rather than a subset. Instead of a horse race based on different numbers of significant arbitrage friction measures versus significant investment friction measures, we test a composite index of arbitrage frictions against a composite index of investment frictions. The construction of these composite indices follows Stambaugh, Yu, and Yuan (2015), who construct a composite proxy for stock mispricing. As each individual measure contains noise, our approach of constructing a composite index by averaging rankings within each category of frictions should be able to diversify the noise in the

[1] Recent papers touching upon the asset growth effect include Cooper, Gulen, and Schill (2010), Cooper and Priestley (2011), Gray and Johnson (2011), Lipson, Mortal, and Schill (2011), Titman, Wei, and Xie (2013), Watanabe, Xu, Yao, and Yu (2013), Li and Sullivan (2011, 2015), Mao and Wei (2016), and Papanastasopoulos (2017), among others.

cross-section, and can provide a fairer and more precise comparison between the two hypotheses. Our conclusion is robust to both classical and Bayesian inferences.

Second, we provide more and cleaner evidence supporting the limits-to-arbitrage hypothesis. As investment frictions are controlled for (as a control in regression or used to orthogonalize arbitrage frictions), the results of our joint tests of arbitrage versus investment frictions, which support the limits-to-arbitrage hypothesis, can be unambiguously interpreted. Thus, our results complement other evidence on the mispricing explanation for the investment or total asset growth effect (e.g., Cooper, Gulen, and Schill (2008, 2010); Gray and Johnson (2011); Mao and Wei (2016); Papanastasopoulos (2017); Cao, Gray, and Zhong (2018)). Third, we show that limits-to-arbitrage play an important role in not only the return predictability of total asset growth, but also other prominent measures of investment, such as investment-to-assets, net operating assets, net share issuance, and composite share issuance.

Fourth, we explore Bayesian inferences as promoted by Harvey （2017）in performing the asset pricing tests. This approach has not previously been used in the relevant literature. It starts the prior that either limits-to-arbitrage or investment frictions are irrelevant, then investigate how much the data update this prior. The Bayesian findings largely resemble results obtained from classical inferences.

The work is positioned to be a companion to Lam and Wei (2011), who separately test various limits-to-arbitrage and investment frictions hypothesis. Our paper differs from Lam and Wei (2011) in several important dimensions. First, we construct composite indices for two proxies instead of using them individually. Second, Lam and Wei (2011) compare the competing hypotheses by contrasting the investment-return regression slopes across tercile sorted by either arbitrage frictions or investment frictions. This paper examines the same issue using the regression slope when investment in interacted with one (or both) of the composite indices. We also analyze the effect of the residual frictions indices by orthogonalizing the indices against each other. In addition, comparing with Li and Zhang (2010), this paper emphasizes the importance of controlling for corporate profitability in examining the effect of investment frictions predicted by q-theory.

The remainder of this paper is presented as follows. In Section 2, the predictions of the mispricing hypothesis with limits-to-arbitrage and q-theory with investment frictions on the investment effect are reviewed. In Section 3, our sample construction is discussed and the variables defined. Section 4 reports the empirical findings, and Section 5 concludes the paper.

2. Hypothesis Development

This section reviews how arbitrage and investment frictions affect the investment effect.

2.1. Mispricing and limits-to-arbitrage

In terms of behavioral finance, the investment effect is the consequence of transient mispricing. Titman, Wei, and Xie (2004) attribute the capital investment effect to agency problems. They suggest that managers tend to overinvest due to their empire-building tendency, combined with the possibility that analysts and investors underreact to this overinvestment. As investors are too slow or even fail to correctly incorporate information on firm investment into share prices, stocks tend to be mispriced. Cooper, Gulen, and Schill (2008) propose an extrapolation bias explanation. They argue that if investors are overly optimistic about the future benefits associated with asset expansion, then stocks with high growths in assets may be temporarily overvalued and subsequently generate low abnormal returns. The reverse is true for firms with asset contraction. Such over-extrapolation or overreaction to past performance generates a negative relation between growth in assets and future stock returns.

If a stock is mispriced, profit opportunities attract rational investors, and their arbitrage activities should correct the mispricing. In an ideal setting where arbitrage opportunities are riskless, obvious, and costless to exploit, prices should reflect all available information accurately, and any mispricing should be corrected immediately. However, in a realistic market where arbitrage is risky and costly, implementable arbitrage opportunities are limited. Although arbitrageurs may trade against the mispricing, its correction will take longer when limits-to-arbitrage are more severe.

Informed arbitrageurs should quickly correct and profit from price-value deviations, while the limits-to-arbitrage hypothesis (Shleifer and Vishny (1997); Gromb and Vayanos (2010)) suggests the opposite when arbitrage is risky and costly. Arbitrage may become risky and costly for two reasons. First, it may be unfavorable when risk-averse traders cannot satisfactorily diversify or hedge the risk of an intended position. As arbitrageurs are typically under-diversified and it is difficult to locate the perfect substitutes required for hedging, idiosyncratic stock return volatility is a serious concern (e.g., Pontiff (1996); Wurgler and Zhuravskaya (2002)). Pontiff (2006) shows that arbitrageurs prefer not to hold stocks that have high idiosyncratic volatility. Weaker shareholder sophistication, such as noise traders, should also make arbitrage riskier (Bartov, Radhakrishnan, and Krinsky (2000); Chen, Hong, and Stein (2002)).

Second, assessments of a firm’s intrinsic value can be uncertain. When a stock’s cash flow is volatile, its fundamental value is ambiguous, which reduces the precision of mispricing identification, and when market opinions about a stock’s future earnings diverge, arbitrageurs are less confident in their valuations. Zhang (2006) shows that the price drifts following analyst forecast revisions and price momentum are stronger when cash flow volatility is higher or analyst forecasts are more dispersed. Arbitrageurs are also more reluctant to trade a stock when information is less transparent. Gleason and Lee (2003) show that the price drifts following earnings forecast revisions are stronger when analyst coverage is lower.

Third, costs and technical barriers to trading deter arbitrage because they make trading against mispricing unprofitable and difficult to implement. An obvious cost is brokerage commission, which Bhardwaj and Brooks (1992) illustrate is inversely related to share price. Another cost is the bid-ask spread charged by dealers for making markets and providing liquidity. A stock is difficult to trade when the dollar trading volume is low, as it requires more time to fill an order or to trade a large block of shares (Bhushan (1994)). A desired position is difficult to establish when the impact of order flow on stock price is high, restricting the amount of capital that can be invested in and liquidated from the stock at a specific price. Furthermore, arbitrage typically requires short selling, which is problematic when low passive institutional ownership leads to a low stock loan supply (D'Avolio (2002); Nagel (2005)) and a high likelihood of short squeeze (Dechow, Hutton, Meulbroek, and Sloan (2001)).

If the return predictability of investment is due to mispricing, then the investment effect is stronger when arbitrage is riskier and costlier. Accordingly, the prediction of the mispricing hypothesis with limits-to-arbitrage on the investment effect is stated as follows.

H1: The investment effect is stronger when arbitrage frictions are more severe.

2.2. q-theory and investment frictions

In the two-period investment-based asset pricing model, Li and Zhang (2010) and Hou, Xue, and Zhang (2015) postulate that firm *i* possesses the asset base $A_{i,0}$ at time 0 and produces the output $\pi_i(A_{i,0})$, where π_i is an increasing production function. If the firm chooses to invest capital $I_{i,0}$, then the asset base at time 1 is $A_{i,1} = A_{i,0} + I_{i,0}$. The firm has an adjustment cost $C(I_{i,0}, A_{i,0}, \lambda_i) > 0$, where λ_i is the investment frictions parameter. C and $\partial C/\partial I_{i,0}$ are increasing and convex in $I_{i,0}$ and λ_i, which means that the firm experiences a higher adjustment cost when the investment amount or investment frictions are higher. The firm then liquidates with a zero-residual value of capital assets after producing output $\pi_i(A_{i,1})$ at time 1. When such a firm faces an expected return of R_i, it will choose $I_{i,0}$ to maximize its present value at time 0:

$$Max_{I_{i,0}}\, PV_i = \pi_i\big(A_{i,0}\big) - I_{i,0} - C\big(I_{i,0}, A_{i,0}, \lambda_i\big) + \pi_i\big(A_{i,1}\big)/(1 + R_i). \tag{1}$$

The first-order condition of the optimization problem is

$$R_i = \frac{d\pi_i\big(A_{i,1}\big)/dA_{i,1}}{1 + \partial C\big(I_{i,0}, A_{i,0}, \lambda_i\big)/\partial I_{i,0}} - 1. \tag{2}$$

Equation (2) states that the firm sets investment to a level at which the discounted marginal benefit of investment $[d\pi_i(A_{i,1})/dA_{i,1}]/(1+R_i)$ equals the marginal cost of investment $1+\partial C(I_{i,0},A_{i,0},\lambda_i)/\partial I_{i,0}$.[2] Holding corporate profitability $d\pi_i(A_{i,1})/dA_{i,1}$ constant, the firm invests more when expected return is lower, and vice versa. Such a corporate policy generates a negative relation between investment and expected return. Equation (2) further implies that a given reduction in expected return is associated with a smaller increase in investment when investment frictions are higher.[3] When investment entails no friction, investment is fully responsive to changes in the expected return. On the other hand, when investment has frictions, investment becomes less responsive to changes in the expected return. The idea is that even though the discount rate is lower, and the net present value of new investment is higher, firms have

[2] Several studies have used this mechanism to explain other stock return effects, such as the book-to-market equity effect (Xing (2008)), the new issuance effect (Lyandres, Sun, and Zhang (2008)), the external financing effect (Li, Livdan, and Zhang (2009); Huang, Lam, and Wei (2014)), and the accruals effect (Wu, Zhang, and Zhang (2010)).
[3] See Li and Zhang (2010) for formal proofs.

difficulty to invest, since making new investment also involve deadweight loss that offset the value added. Thus, the responsiveness of investment to changes in the required return decreases with the severity of frictions. This means that the negative relation between investment and expected return is stronger when investment is costlier to make. Accordingly, the prediction of q-theory with investment frictions on the investment effect is stated as follows.

H2: Holding corporate profitability constant, the investment effect is stronger when investment frictions are more severe.

3. Data Description

We analyze NYSE/Amex/Nasdaq non-financial common stocks with positive book values of equity (Fama and French (1992; 1993)). Annual financial statements are taken from Compustat. Monthly and daily stock market data are obtained from the Center for Research in Security Prices (CRSP). Financial analyst data are taken from I/B/E/S. Institutional shareholding records are taken from Thomson Reuters Institutional (13f) Holdings. Monthly stock returns from July of year t to June of year t+1 are merged with financial statements for the fiscal year ending in year t–1 and stock attributes measurable at the end of June of year t. Delisting returns following Shumway and Warther (1999) are used to alleviate survivorship bias. The firms in our sample appear in Compustat for at least two consecutive fiscal years, and hence selection and backfill biases are minimal. Our sample contains annual firm characteristics from 1962 to 2016 and monthly stock returns from July 1963 to December 2017.

3.1. Measures of investment

We include five measures of investment commonly used in the literature: (1) total asset growth (*TAG*); (2) investment-to-assets (*I*/*A*); (3) net operating assets (*NOA*); (4) net share issuance (*NSI*); and (5) composite share issuance (*CSI*). *TAG* measures the overall annual corporate expansion or contraction. Fama and French (2015, 2016) use the return predictability of *TAG* to construct an investment factor. *I*/*A* measures the yearly change in inventory, plant, property, and equipment. *NOA* measures the annual change in operating assets relative to operating liabilities. *NSI* measures the yearly change in the number of equity shares outstanding. *CSI* measures the five-year change in market capitalization net of cumulative stock returns.[4] Hou, Xue, and Zhang (2015) show that *I*/*A*, *NOA*, *NSI*, and *CSI* robustly predict stock returns.

3.2. The composite measures of arbitrage frictions and investment frictions

Our empirical measure of relative cross-sectional arbitrage frictions is based on a simple composite ranking that combines 10 stock characteristics associated with arbitrage frictions. The characteristics, taken from Lam and Wei (2011), are (1) idiosyncratic stock return volatility (*IVOL*), (2) cash flow volatility (*CVOL*), (3) dispersion in analyst earnings forecasts (*DISP*), (4) the Amihud (2002) illiquidity measure (*ILLIQ*), and (5) the bid-ask spread (*BIDASK*), (6) analyst coverage (*COV*), (7) shareholder sophistication ($INST_N$), (8) share price (*PRICE*), (9) dollar trading volume (*DVOL*), and (10) institutional ownership ($INST_H$).[5] These stock characteristics are updated annually at the end of June each year.[6]

[4] Detailed definitions of the variables are relegated to the Appendix.
[5] These proxies are widely used in studies testing the limits-to-arbitrage hypothesis on other stock return effects. See, for example, Ali, Hwang, and Trombley (2003), Mashruwala, Rajgopal, and Shevlin (2006), Duan, Hu, and McLean (2010), McLean (2010), Lipson, Mortal, and Schill (2011), and Yan and Zheng (2017).
[6] Even these arbitrage-frictions variables can be updated more frequently, some of the investment-frictions variables can only be update annually. To be fair, both sets of variables are updated annually.

We combine the above stock characteristics to generate a univariate measure that correlates with the severity of relative arbitrage frictions in the cross section of stocks. While each characteristic is itself an arbitrage frictions proxy, our purpose in combining them is to generate a single variable that diversifies away some noise in each individual characteristic and hence increase accuracy in testing our hypotheses. After independently sorting all stocks into percentiles by each characteristic, we assign per characteristic a rank to each stock to reflects the sorting on that given characteristic. The highest rank is assigned to the value of the characteristic associated with the highest arbitrage frictions. At the end of June each year, we rank stocks by *IVOL*, and those with the highest *IVOL* receive the highest rank. The same procedure is independently applied for *CVOL*, *DISP*, *ILLIQ*, and *BIDASK*. We also independently rank stocks by *COV*, but here those with the lowest *COV* receive the highest rank. Such assignment is independently repeated for $INST_N$, *PRICE*, *DVOL*, and $INST_H$. A stock's composite arbitrage frictions rank (*AF*) is then the arithmetic mean of its rankings for these 10 characteristics. The construction of this composite index draws heavily on Stambaugh, Yu, and Yuan (2015), who construct a composite proxy for stock mispricing. The composite measure is cross sectional and it only represents relative arbitrage frictions. The stocks with the highest *AF* are referred to as the stocks with the most severe arbitrage frictions within the cross section and the stocks with the lowest ranking are referred to as the stocks with the least severe arbitrage frictions within the cross section.

Our empirical measure of relative cross-sectional investment frictions is also a simple composite ranking, based on a stock's four stock characteristics associated with investment frictions. The characteristics, taken from Lam and Wei (2011), are (1) asset size (*ASSET*), (2) firm age (*AGE*), (3) payout ratio (*PAYOUT*), and (4) the credit rating dummy (*RATING*). These stock characteristics are updated annually at the end of June each year.

We combine the above investment frictions characteristics to generate a univariate measure that correlates with the severity of relative investment frictions in the cross section of stocks in the same way that we construct *AF*. The construction of this composite index also follows Stambaugh, Yu, and Yuan (2015). Again, our purpose in combining the characteristics is to generate a single variable that diversifies away some noise in each individual characteristic and hence increase accuracy in testing our hypotheses. After independently sorting all stocks into percentiles by each characteristic, we assign per characteristic a rank to each stock to reflects the sorting on that given characteristic. The highest rank is assigned to the value of the characteristic associated with the highest investment frictions. At the end of June each year, we rank stocks by *ASSET*, and those with the lowest *ASSET* receive the highest rank. The same procedure is independently applied for *AGE* and *PAYOUT*. To align with the other assignments, stocks whose *RATING* are zero receive the highest rank and those whose *RATING* are one receive the lowest rank. A stock's composite investment frictions rank (*IF*) is then the arithmetic mean of its rankings for these four characteristics. The composite measure is cross sectional and it merely represents relative investment frictions. The stocks with the highest *IF* are referred to as the stocks with the most severe investment frictions within the cross section and the stocks with the lowest ranking are referred to as the stocks with the least severe investment frictions within the cross section.

3.3 Measures of corporate profitability and other controls

Our tests of the investment frictions hypothesis control for corporate profitability, and we use five measures of profitability common in the literature: (1) return on equity (*ROE*), (2) return on assets (*ROA*), (3) operating profitability (from Fama and French (2015, 2016)) (*OP_FF*), (4) gross profitability-to-assets (*GP*/*A*), and (5) operating profitability (from Ball, Gerakos, Linnainmaa, and Nikolaev (2015)) (*OP_BGLN*). *ROE* and *ROA* are standard profitability measures. Fama and French (2015, 2016) use the return predictability of *OP_FF* to construct a profitability factor. The recent literature shows that *GP*/*A* and *OP_BGLN* are profitability attributes important for average stock returns (Novy-Marx (2013); Ball, Gerakos, Linnainmaa, and Nikolaev (2015)). All of our tests use standard controls for average return determinants, including the CAPM beta (β), natural logarithm of market equity (Ln(*ME*)), natural logarithm of book-to-market (Ln(*B*/*M*)), and prior one-year stock return skipping June (*PRet*).

Table 1 presents the summary statistics and a correlation matrix for the main firm characteristics used in our analysis. The statistics and correlations are computed annually and are then averaged over time. Most of the statistics and correlations are comparable to those in earlier studies such as Lam and Wei (2011). The correlations between *TAG*, *I/A*, *NOA*, and *NSI* are relatively high, ranging from 0.35 (between *NOA* and *NSI*) to 0.66 (between *TAG* and *I/A*), while the correlations between *CSI* and the other four measures of investment are relatively low, ranging from 0.09 to 0.20. *AF* and *IF* are highly correlated at 0.57, suggesting that care needs to taken to clearly distinguish the two hypotheses.

4. Empirical Results

Our tests are nested in the following Fama-MacBeth cross-sectional regression:

$$\begin{aligned} R_{i,t} = a &+ \gamma_1 Inv_{i,t\text{-}1} + \gamma_2 AF_{i,t\text{-}1} + \gamma_3 Inv_{i,t\text{-}1} \times AF_{i,t\text{-}1} + \gamma_4 IF_{i,t\text{-}1} + \gamma_5 Inv_{i,t\text{-}1} \times IF_{i,t\text{-}1} \\ &+ c_1 Profit_{i,t\text{-}1} + c_2 Profit_{i,t\text{-}1} \times AF_{i,t\text{-}1} + c_3 Profit_{i,t\text{-}1} \times IF_{i,t\text{-}1} \\ &+ c_4' Controls_{i,t\text{-}1} + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where $R_{i,t}$ is the return on stock i in month t, Inv is one of the five investment measures, *AF* is the arbitrage frictions composite index, *IF* is the investment frictions composite index, *Profit* is one of five corporate profitability measures, and *Controls* represents the standard controls. $R_{i,t}$ is updated every month while Inv, *AF*, *IF*, *Profit*, and *Controls* are updated annually. The right-hand-side variables are winsorized at the 0.5^{th} and 99.5^{th} percentiles to avoid outliers. The cross-sectional regressions are estimated month by month using ordinary least squares (OLS) or weighted least squares (WLS) using market capitalization as the weight. The OLS estimation gives equal weight to each stock, while the WLS estimation gives larger weight to large-cap stocks.

We report the time-series averages and perform statistical inferences on the estimated slopes of interest. The key variables of interest are Inv and the interaction terms *Inv*×*AF* and *Inv*×*IF*. A negative *Inv* slope refers to the negative relation between investment and future stock returns (i.e., the investment effect). The arbitrage frictions hypothesis (**H1**) predicts the slope coefficient on *Inv*×*AF* to be negative, suggesting that the investment effect is more profound for stocks with more severe arbitrage frictions. The investment frictions hypothesis (**H2**) predicts that the slope coefficient on *Inv*×*IF* is negative, indicating that the investment effect is stronger for stocks with more investment frictions. Other slope coefficients associated with *Inv* and *Profit* are also tabulated for reference. The *t*-statistics (*t-stat*) are based on the Newey and West (1987) robust standard errors with autocorrelations up to 12 lags. The negative slopes of interest that are statistically significant at the 5% level are presented in boldface.

4.1. The investment effect

Table 2 reports the estimation results when a measure of investment and standard controls are included in equation (3) with or without a corporate profitability control. q-theory requires corporate profitability to be controlled for in examining the negative relation between investment and future stocks returns. The mispricing hypothesis, in contrast, does not have this requirement. Here, the slope on *Inv* (γ_1) is of interest. When the cross-sectional regressions are estimated by OLS, all of the *Inv* slopes are negative and significant at the 5% level. There is a negative relation between investment and future stock returns. The investment effect is robust across all five measures of investment.

[Table 2 here]

Even when the regressions are estimated by WLS, all of the *Inv* slopes are negative and the majority is significant at the 5% level. About 83% (= 50/60) of the coefficients are significant. The coefficients are not significant when investment is measured by *I*/*A* without corporate profitability, or with corporate profitability of *ROE*, *GP*/*A*, or *OP_BGLN* as a control in the regressions. The coefficients are not significant at all when investment is measured by *CSI* with or without controlling for corporate profitability. The negative slopes are significant in the other specifications.[7]

4.2. Individual tests for arbitrage frictions

To test the arbitrage-frictions hypothesis (**H1**) using individual tests (i.e., without controlling for investment frictions), we retain a measure of investment, the arbitrage frictions composite index, and the interaction between investment and arbitrage frictions, together with standard controls in equation (3). Table 3 reports the estimation results. For this test, the slope

[7] The slopes are negative and significant in the subperiod before 1990, the subperiod after 1990, and during 2007 to 2008. The WLS slopes are weaker during 2007-2008.

coefficient on $Inv \times AF$ (γ_3) is of interest. When the cross-sectional regressions are estimated by OLS, 100% (= 25/25) of the $Inv \times AF$ slope coefficients are negative and significant at the 5% level. Across all five measures of investment, the investment effect is thus stronger when arbitrage frictions are more severe. All of the results are consistent with the arbitrage frictions hypothesis.

[Table 3 here]

For the regressions with WLS estimations, 60% (= 15/25) of the $Inv \times AF$ slope coefficients are negative and significant at the 5% level. The negative and significant slopes appear when investment is measured by *TAG*, *I/A*, or *NOA*. The coefficients are not significant when *NSI* or *CSI* is the investment measure. Fewer results are consistent with the arbitrage frictions hypothesis when returns on large-cap stocks are given more weight. It appears that limits-to-arbitrage are less important for large-cap stocks.[8]

Note that the arbitrage frictions composite index and the investment frictions composite index are positively and highly correlated, with a correlation of 0.57 (Panel B of Table 1). These consistent results from individual tests should not be interpreted as solely as evidence supporting the arbitrage frictions hypothesis. We cannot rule out the interpretation that these results are also consistent with the investment frictions hypothesis (**H2**).

4.3. Individual tests for investment frictions

To test the investment frictions hypothesis (**H2**) using individual tests (i.e., without controlling for arbitrage frictions), we retain a measure of investment, the investment frictions composite index, and the interaction between investment and investment frictions, together with

[8] The results for excluding market cap as the control are the same (OLS:100%, WLS:60%)

corporate profitability and the standard controls in equation (3). To complete the specification, we include the interaction term between corporate profitability and investment frictions, as q-theory predicts that there is a role for investment frictions in the relation between corporate profitability and stock returns (see, e.g., Jiang, Qi, and Tang, 2018).[9] Table 4 reports the estimation results. The slope coefficient on *Inv*×*IF* (γ_3) is of interest for this test specification.

[Table 4 here]

When the regressions are estimated by OLS, 68% (= 17/25) of the *Inv*×*IF* slope coefficients (γ_3) are negative and significant at the 5% level. These results come from the cases when *TAG*, *I*/*A*, or *NOA* is the measure of investment, regardless of which measure of corporate profitability is the control, or when investment is measured by *NSI* with GP/A and *OP_BGLN* being the control for corporate profitability. These results indicate that the investment effect is significantly more pronounced among stocks with higher investment frictions, which is consistent with the investment frictions hypothesis. The slope coefficients on *Inv*×*IF* are not significant when investment is measured by *CSI* or *NSI* (except when the control of profitability is *OP_BGLN*).

For the regressions with WLS estimations, 20% (= 5/25) of the *Inv*×*AF* slope coefficients are negative and significant at the 5% level. The negative and significant slopes appear only when *I*/*A* is the measure of investment, irrespective of which measure of corporate profitability is the control. The coefficients on *Inv*×*AF* are not significant at all for other cases. The results of

[9] Under several regularity conditions, q-theory with investment frictions predicts that corporate profitability is positively associated with future stock returns, holding capital investment constant. The association between investment frictions and the profitability effect can be positive or negative, depending on the specification of the adjustment cost function, among others (Zhang (2017)).

few cases are consistent with the investment frictions hypothesis. It appears that investment frictions are less important for large-cap stocks.[10]

The specification that generates results that are consistent versus inconsistent with the investment frictions hypothesis does not depend on which specific measure of corporate profitability is the control. However, it does depend on the measure of investment. Like the individual tests for arbitrage frictions, the consistent results from the individual tests here should not be interpreted as evidence exclusively supporting the investment frictions hypothesis. The possibility that these results are also consistent with the arbitrage frictions hypothesis (**H1**) cannot be ruled out.

Although it is not the focus of this study, we also observe that the slope coefficients on profitability (γ4) are all positive, ranging from 0.157 (*t*-stat = 0.88) to 4.558 (*t*-stat = 7.38), suggesting a positive profitability effect even after controlling for other return predictors. We also observe that the majority 76% (= 38/50) of the slope coefficients on $Profit \times IF$ (γ5) are negative and that 38% (=19/50) are significant at the 10% level or better, suggesting that the positive profitability effect is weaker among stocks with more severe investment frictions.[11]

4.4. Joint tests for arbitrage and investment frictions

From the individual tests, 80% (= 40/50) of the results are consistent with the arbitrage frictions hypothesis and 44% (= 22/50) with the investment frictions hypothesis. Given the high correlation between the measures of arbitrage and investment frictions, these results do not yet

[10] The results for excluding market cap as the control are the same (OLS: 68%, WLS: 20%).
[11] The results for excluding market cap as the control are similar. The slope coefficients on profitability (γ_4) are all positive, ranging from 0.165 (t-stat=0.94) to 4.007 (t-stat=6.47). 74% (=37/50) of γ_5 are negative and 38% (19/50) are significant at the 10% level.

provide a clear view of which hypothesis is empirically more important for the investment effect. To address this problem, we turn to the joint-test framework of Lam and Wei (2011).

To test the arbitrage frictions hypothesis (**H1**) using joint tests (i.e., with investment frictions controlled for), we retain a measure of investment, the arbitrage frictions composite index, the interaction between investment and arbitrage frictions, the investment frictions composite index, and the interaction between investment and investment frictions, together with the standard controls in equation (3). The interaction between investment and investment frictions serves as the control for the impact of investment frictions on the investment effect. Table 5 reports the estimation results. For this test, the slope coefficient on $Inv{\times}AF$ (γ_3) is of interest.

[Table 5 here]

The results highly resemble those from the individual tests. Adding a control for the impact of investment frictions on the investment effect does not alter the evidence consistent with the arbitrage frictions hypothesis. When the cross-sectional regressions are estimated by OLS, 100% (=25/25) of the $Inv{\times}AF$ slope coefficients are negative and significant at the 5% level. This again means that across all five measures of investment, the negative return-investment relation is more profound among stocks with more sever arbitrage frictions. All of the results are consistent with the arbitrage frictions hypothesis.

For the regressions estimated by WLS, 60% (= 15/25) of the $Inv{\times}AF$ slope coefficients are negative and significant at the 5% level. The negative and significant slopes appear again when *TAG*, *I*/*A*, or *NOA* is the measure of investment. The coefficients are not significant when investment is measured by *NSI* or *CSI*. Again, the results of fewer cases are consistent with the arbitrage frictions hypothesis, suggesting that limits-to-arbitrage are less important for large-cap stocks.[12]

Given the joint tests control for the impact of investment frictions on the investment effect, the consistent results could be interpreted as supporting the arbitrage frictions hypothesis, as 80% (= 40/50) of the results support this hypothesis. Ample evidence supports the role of arbitrage frictions across measures of investment, although exceptions appear when regressions are estimated by WLS.

To test the investment frictions hypothesis (**H2**) using joint tests (i.e., with arbitrage frictions controlled for), we estimate the full equation (3). The interaction between investment and arbitrage frictions serves as the control for the impact of arbitrage frictions on the investment effect. The interaction between corporate profitability and arbitrage frictions is also included to complete the model, as studies show that the relation between corporate profitability and future stock returns may be due to mispricing (e.g., Wang and Yu (2013)).[13] Table 6 reports the estimation results. The slope coefficient on $Inv \times IF$ (γ_3) is of interest in this test.

[Table 6 here]

The results are different from those of the individual tests. Adding the control for the impact of arbitrage frictions on the investment effect substantially reduces the evidence consistent with the investment frictions hypothesis. When the cross-sectional regressions are estimated by OLS, 28% (= 7/25) of the $Inv \times IF$ slope coefficients are negative and significant at the 5% level. These results are significant when investment is measured by *TAG* and the control for corporate profitability is *GP/A* and *OP_BGLN*, or when *I/A* is the measure of investment,

[12] For the slope coefficient on $Inv \times AF$ (γ_3), the results for excluding market cap as control are similar (OLS: 100%, WLS: 64%). In total, 82% of the results support this hypothesis for robustness check.

[13] If the relation is due to mispricing, then it should be stronger when arbitrage frictions are more severe.

irrespective of which measure of corporate profitability is the control. In other cases, the slope coefficients on *Inv*×*IF* are not significant.

For the regressions with WLS estimations, 0% (= 0/25) of the *Inv*×*IF* slope coefficients is negative and significant at the 5% level. For any of the five measures of investment, we cannot find any case consistent with the investment frictions hypothesis. It appears that investment frictions are not important for large-cap stocks.

Under the joint tests, which control for the impact of arbitrage frictions on the investment effect, the consistent results could be interpreted as supporting the investment frictions hypothesis. However, there is only limited evidence for this, as only 14% (= 7/50) of the results support this hypothesis. Interestingly, investment-to-asset provides most of the evidence for the investment frictions hypothesis.

Comparing the profitability effects in Tables 4 and 6, we also observe that the slope coefficients on profitability (γ4) are all positive with slightly larger magnitudes, ranging from 0.061 (*t*-stat = 0.28) to 4.651 (*t*-stat = 6.51), suggesting a strongly positive profitability effect even with more controls. Most interestingly, 100% (50/50) of the slope coefficients on $Profit \times IF$ (γ5) are negative and 60% (30/50) are significant at the 10% level or better, suggesting that the positive profitability effect is weaker among stocks with more severe investment frictions. Compared with those in Table 4, the results in Table 6 suggest that the profitability effect is stronger, and the role of investment frictions on the profitability effect is also stronger when arbitrage frictions are also controlled for.[14]

The joint tests for arbitrage and investment frictions provide a clear view on which hypothesis is empirically more important for the investment effect. Comparatively, the evidence

[14] For the slope coefficient on *Inv*×*IF* (γ_3), the results for excluding market cap as control are similar (OLS: 28%, WLS: 0%). In total, 14% of the results support this hypothesis for robustness check.

supporting the arbitrage frictions hypothesis (from Table 5) is much greater than that supporting the investment frictions hypothesis (from Table 6). For the investment effect, the mispricing hypothesis with limits-to-arbitrage thus appears to be more important than q-theory with investment frictions. However, our results do not reject q-theory in general, as this is important and useful in explaining the return predictability of investment-to-assets, particularly for equal-weighted returns.

4.5. Residual arbitrage and investment frictions and the investment effect

The correlation between arbitrage frictions and investment frictions is considerably high. To further distinguish between the two competing explanations, we orthogonalize the two indices by regressing arbitrage frictions on investment frictions and study the effect of the residual arbitrage frictions (*ResAF*) on the investment anomaly. For the regressions estimated by OLS, 100% (=25/25) of the *Inv*×*ResAF* slope coefficients are negative and significant at the 5% level. This further supports that the negative return-investment relation being more profound among stocks with more severe arbitrage frictions. All of the results are consistent with the arbitrage-frictions hypothesis.

[Table 7 here]

For the regressions estimated by WLS, 56% (=14/25) of the *Inv*×*ResAF* slope coefficients are negative and significant at the 5% level. The significant negative slopes appear when *TAG*, *I*/*A*, or *NOA* is the investment measure. The coefficients are not significant when investment is measured by *NSI* or *CSI*. This again suggests that arbitrage frictions are less important for large-cap stocks. Overall, 78% (=39/50) of the results support the arbitrage-frictions hypothesis. The majority of the results support the role of arbitrage frictions across various measure of the investment effect, although some exceptions appear when regressions are estimated by WLS.[15]

[Table 8 here]

We also orthogonalize the two indices by regressing investment frictions on arbitrage frictions and study the effect of the residual investment frictions (*ResIF*) on the investment anomaly. For the regressions estimated by OLS, 20% (=5/25) of the *Inv*×*ResIF* slope coefficients are negative and significant at 5% level. The results are significant only when investment is measured by *I*/*A*. For the regressions estimated with WLS, 0% (=0/25) of the interaction slope coefficients is significant at the 5% level. We cannot find any case being consistent with the investment-frictions hypothesis. Overall, there is limited evidence for the role of investment frictions as only 10% (=5/50) of the results are significant. Interestingly, invest-to-asset generates all the evidence for the investment-frictions hypothesis.[16]

4.6. Results from Bayesian inferences

In addition to the classical inferences in the previous subsections, we perform tests with Bayesian inferences using the minimum Bayes factor (MBF) recommended by Harvey (2017). The MBF is the lower bound among all Bayes factors, and given the data used, it provides the strongest evidence *against* the null hypothesis. The MBF is more practical than the full Bayesian approach, as it does not depend on prior specifications of alternative hypotheses, and it is easy to compute in our context. Here, the MBF is $\exp(-t^2/2)$, where t is the observed time-series t-statistic of the Fama-MacBeth regression slope coefficient of interest.

[15] For the slope coefficient on *Inv*×*ResAF* (γ_3), the results for excluding market cap as control are similar (OLS: 100%, WLS: 60%). In total, 80% of the results support this hypothesis for robustness check.
[16] For the slope coefficient on *Inv*×*ResIF* (γ_3), the results for excluding market cap as control are similar (OLS: 20%, WLS: 0%). In total, 10% of the results support this hypothesis for robustness check.

To start the inference, we set the prior odds ratio of the null being true versus the null being false to 4-to-1. The null thus has an 80% (= 4/(4+1)) prior probability of being true and the alternative 20% (= 1/(4+1)). In our context, there is an 80% chance that a slope coefficient of interest is zero and a 20% chance it is not. This prior corresponds to the "perhaps" category in Harvey (2017), for effects that are economically reasonable, and some evidence has been provided for this in the literature. After observing our data and estimation results, the Bayesianized *p*-value or posterior probability of the null being true is then MBF×prior/(1+MBF×prior).

For robustness checks, we replace the MBF with the Symmetric and Descending-Minimum Bayes Factor (SD-MBF). The SD-MBF restricts the prior probability density for alternatives to be symmetric and descending around the null. Here, the SD-MBF is –exp(1)×*p*×Ln(*p*), where *p* is the observed *p*-value corresponding to the *t*-statistic of the Fama-MacBeth regression slope coefficient of interest. It is always larger and provides weaker evidence against the null than the MBF. The Bayesianized *p*-value here is SD-MBF×prior/(1+SD-MBF×prior).

We examine three null hypotheses. First, investment does not predict future stock returns (Null_1). This relates to testing the investment effect itself and the *Inv*-slope (γ_1) estimates reported in Table 2. Second, when controlling for investment frictions, arbitrage frictions have no impact on the investment effect (Null_2). This relates to testing the arbitrage frictions hypothesis (**H1**) using joint tests and the *Inv*×*AF*-slope (γ_3) estimates reported in Table 5. Third, when controlling for arbitrage frictions, investment frictions have no impact on the investment effect (Null_3). This relates to testing the investment frictions hypothesis (**H2**) using joint tests and the *Inv*×*IF*-slope (γ_3) estimates reported in Table 6.

Table 9 reports the Bayesianized *p*-values of the three nulls, iterating over the various specifications. Panel A reports the results based on MBF and Panel B on SD-MBF. When the cross-sectional regressions are estimated by OLS, the results from both panels show that the posterior probabilities of Hypothesis 1 being true are all much less than 5%, except when *CSI* is the measure of investment, irrespective of whether profitability is controlled, or which measure of corporate profitability is used and except for *NOA* is the measurement of investment and profitability is controlled by operating profitability. These correspond to 77% (= 46/60) of the results. There is strong evidence that future stock returns are associated with *TAG*, *I/A*, *NOA*, or *NSI*. However, the results from the regressions estimated by WLS indicate that the evidence supporting the investment effect is much weaker. For the WLS regression, the Bayesianized *p*-value of Null_1 is less than 5% only when investment is measured by *TAG* and corporate profitability is measured by *ROE*, *ROA*, or *OP_FF* for MBF (only *OP_FF* for SD-MBF), or when *NSI* is the measure of investment, irrespective of whether profitability is controlled or which measure of corporate profitability is used. These correspond to 32% (= 19/60) of the cases. While the classical inference widely supports the investment effect, the Bayesian inference indicates that the effect is much less important for large-cap stocks. The investment effect is also in doubt when the measure of investment is *CSI*.

[Table 9 here]

Regarding the arbitrage frictions versus investment frictions hypotheses, the Bayesian and classical inferences do yield similar findings. From the OLS regressions, 92% (= 46/50) of the MBF-based posterior probabilities and 72% (= 36/50) of the SD-MBF-based posterior probabilities find Null_2 is true at less than 5%. The posterior probability is not lower than 5% when investment is measured by *I/A* in all residual model or normal mode but controlled by

OP_FF and *GPA* or when investment is measured by *NSI* in all residual model and one for *TAG* residual model when controlled by *ROA*. There is ample evidence for the arbitrage frictions hypothesis. From the WLS regressions, 19% (= 19/100) of the posterior probabilities find Null_2 is true at less than 5%. The probabilities are lower than 5% only when the measure of investment is *TAG* and part of *I/A* is, but not for *NOA*, *NSI*, or *CSI*. As less evidence supports arbitrage frictions (i.e., against Null_2) with WLS regressions, this again indicates that limits-to-arbitrage are less important for large-cap stocks.

Far fewer cases support the investment frictions hypothesis. From the OLS regressions, 20% (= 10/50) of the MBF-based posterior probabilities and 8% (= 4/50) of the SD-MBF-based posterior probabilities find Null_3 is true at less than 5%. These significant probabilities result exclusively from using *I/A* as the measure of investment. From the WLS regressions, 0% (= 0/100) of the posterior probabilities find Null_3 is true at less than 5%. The lack of evidence suggests that investment frictions are not important for large-cap stocks.

In total, 51% (= 101/200) of the Bayesianized *p*-values (i.e., 82% (= 82/100) from OLS and 19% (= 19/100) from WLS) support the arbitrage frictions hypothesis. The material Bayesian updates come from almost all measures of investment, but are less so for *CSI* with OLS regressions. However, for WLS regressions, the significant results are only from *TAG* and *I/A*. In contrast, only 7% (= 14/200) in total of the Bayesianized *p*-values (i.e., 14% (= 14/100) from OLS and 0% (= 0/100) from WLS) support the investment frictions hypothesis. All of the material Bayesian updates are from OLS regressions using *I/A* as the measure of investment[17].

The findings remain similar if we focus on *TAG* as the investment measure, as this is the most common measure of investment in the literature for testing how the mispricing with limits-

[17] For the Bayesianized *p*-values, the results for excluding market cap as control are similar (total: 49.5%, OLS: 81%, WLS: 18% support the arbitrage-frictions hypothesis.; total: 6.5%, OLS: 13%, WLS: 0% support the investment-frictions hypothesis.

to-arbitrage versus q-theory with investment frictions can explain the investment effect. We find that 85% (=34/40) of the Bayesianized *p*-values (95% (= 19/20) from OLS and 75% (= 15/20) from WLS regressions) support the arbitrage frictions hypothesis. In contrast, 0% (= 0/40) of the Bayesianized *p*-values (0% (= 0/20) from OLS and 0% (= 0/20) from WLS regressions) support the investment frictions hypothesis. The results favor the investment frictions hypothesis when *I/A* is used as the measure of investment. We show that 35% (= 14/40) of the Bayesianized *p*-values (70% (= 14/20) from OLS and 0% (= 0/20) from WLS regressions) support the investment friction hypothesis[18].

The joint tests using Bayesian inferences also clearly demonstrate which hypothesis is empirically more important for the investment effect. Comparatively, more evidence supports the arbitrage frictions hypothesis than the investment frictions hypothesis. The mispricing hypothesis with limits-to-arbitrage thus appears more important in explaining the investment effect than does q-theory with investment frictions. Again, our results do not reject q-theory in general. q-theory focuses more on new capital investment, so it is unsurprising that investment-to-assets is the most successful case for explaining the investment effect by q-theory with investment frictions.

4.7. The impact of using *IVOL* and *CFVOL* as investment frictions proxies

Following Lam and Wei (2011), idiosyncratic stock return volatility (*IVOL*) and cash flow volatility (*CVOL*) are used as arbitrage frictions proxies. However, the two measures might as

[18] Taking *TAG* as the example, (1) the results for excluding market cap as control are similar (85% support the arbitrage-frictions hypothesis, 0% support the investment-frictions hypothesis). (2) The results for shifting *IVOL* and *CFVOL* from the arbitrage-frictions index to the investment-frictions index are different (42.5% support the arbitrage-frictions hypothesis, 37.5% support the investment-frictions hypothesis). (3) The results for both excluding *ME* and shifting *IVOL* and *CFVOL* are also different (50% support the arbitrage-frictions hypothesis, 30% support the investment-frictions hypothesis).

well be proxies for investment frictions. More volatile firms are more likely to hit default boundary, causing financing constraints to be more binding. Besides, the volatilities tend to affect firms' access to the equity market. Therefore, we reproduce the results in Table 5 to Table 8 with *IVOL* and *CFVOL* shifted from the arbitrage-frictions index to the investment-frictions index. The alternative results are presented in Table 10. In testing the marginal impact of arbitrage frictions on the investment effect, the slope coefficient on *Inv*×*AF* ((*A*) γ_3) is of interest. 40% (=10/25) of the *Inv*×*AF* slope coefficients are negative and significant at 5% level for OLS estimation whereas the corresponding proportion is 36% (=9/25) for WLS. For the marginal impact of investment frictions on the investment effect, the slope coefficient on *Inv*×*IF* ((*B*) γ_3) is of interest. 80% (=20/25) of the *Inv*×*IF* slope coefficients are negative and significant at the 5% level for OLS estimation whereas the corresponding percentage is 16% (=4/25) for WLS.

[Table 10 here]

The slope coefficient on the *Inv*×*ResAF* ((*C*) γ_3) is of interest in testing the impact of residual arbitrage frictions on the investment effect. For the regressions estimated by OLS, 48% (=12/25) of the *Inv*×*ResAF* slope coefficients are negative and significant at the 5% level whereas 0% (=0/25) of the coefficients are significant for WLS. For the impact of residual investment frictions on the investment effect, the slope coefficient on the *Inv*×*ResIF* ((*D*) γ_3) is of interest. For the regressions estimated by OLS, 80% (=20/25) of the *Inv*×*ResIF* slope coefficients are negative and significant at the 5% level whereas the corresponding percentage is 20% (=5/25) for WLS. Based on the Bayesianized *p*-values, 8.5% of the estimates support the arbitrage-frictions hypothesis while 27.5% of the estimates support the investment-frictions hypothesis. Using *IVOL* and *CFVOL* as investment frictions proxies instead of arbitrage frictions proxies makes q-theory with investment frictions more powerful than the mispricing hypothesis with limits-to-arbitrage in explaining the investment effect.

5. Conclusions

The mispricing hypothesis with limits-to-arbitrage and q-theory with investment frictions are two common explanations for the negative relation between investment and average stock returns. Motivated by the positive correlations between proxies of arbitrage and investment frictions, Lam and Wei (2011) use joint tests to compare the predictions of the two hypotheses, and find similar support for each. Our study closely follows that of Lam and Wei (2011), and extends it to re-examine the unresolved issue of which explanation is empirically more important for the investment effect.

Our results indicate that the mispricing hypothesis with limits-to-arbitrage tends to be more important in explaining the investment effect. Both classical and Bayesian inferences provide ample evidence for the arbitrage frictions hypothesis across common measures of investment, including total asset growth, investment-to-assets, net operating assets, net share issuance, and composite share issuance. We find much less evidence to support the investment frictions hypothesis. However, we do find stronger support for q-theory with investment frictions when investment-to-assets is the measure of investment, which is not surprising, as q-theory focuses more on corporate capital investment than do other measures of investment. There is also more support for the investment frictions hypothesis when idiosyncratic and cash flow volatilities are used as investment frictions measures rather than arbitrage frictions measures.

The supporting evidence for the both hypotheses is weaker when large-cap stocks are given more weight in WLS regressions. Our findings should not be interpreted as evidence against the q-theory, particularly when investment-to-assets is the measure of investment. Interestingly, of the five measures of investment supporting either investment or arbitrage frictions, investment-to-assets appears to be the most important, followed by total asset growth, net operating assets, and then net share issuance. Composite share issuance is the least important.

References

Ali, Ashiq, Lee-Seok Hwang, and Mark A. Trombley, 2003. Arbitrage risk and the book-to-market anomaly. Journal of Financial Economics 69, 355–373.

Amihud, Yakov, 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Ball, Ray, Joseph Gerakos, Juhani T. Linnainmaa, and Valeri V. Nikolaev, 2015. Deflating profitability. Journal of Financial Economics 117, 225–248.

Bartov, Eli, Suresh Radhakrishnan, and Itzhak Krinsky, 2000. Investor sophistication and patterns in stock returns after earnings announcements. Accounting Review, 75, 43–63.

Bhardwaj, Ravinder K., and Leroy D. Brooks, 1992. The January anomaly: effects of low share price, transaction costs, and bid-ask bias. Journal of Finance 47, 553–575.

Bhushan, Ravi, 1994. An informational efficiency perspective on the post-earnings announcement drift. Journal of Accounting and Economics 18, 45–66.

Cao, Viet N., Philip Gray, Angel Zhong, 2018. Investment-related anomalies in Australia: evidence and explanations. International Review of Financial Analysis, forthcoming.

Chen, Joseph, Harrison Hong, and Jeremy C. Stein, 2002. Breadth of ownership and stock returns. Journal of Financial Economics 66, 171–205.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008. Asset growth and the cross-section of stock returns. Journal of Finance 63, 1609–1651.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2010. The investment effect in stock returns, Journal of Investment Management 8, 1–15.

Cooper, Ilan, and Richard Priestley, 2011. Real investment and risk dynamics. Journal of Financial Economics 101, 182–205.

D'Avolio, Gene, 2002. The market for borrowing stock. Journal of Financial Economics 66, 271–306.

Daniel, Kent, and Sheridan Titman, 2006. Market reaction to tangible and intangible information. Journal of Finance 52, 1–33.

Dechow, Patricia M., Amy P. Hutton, Lisa K. Meulbroek, and Richard G. Sloan, 2001. Short-sellers, fundamental analysis, and stock returns. Journal of Financial Economics 61, 77–106.

Duan, Ying, Gang Hu, and R. David McLean, 2010. Costly arbitrage and idiosyncratic risk: evidence from short sellers. Journal of Financial Intermediation 19, 564–579.

Fama, Eugene F., and Kenneth R. French, 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fama, Eugene F., and Kenneth R. French, 2016. Dissecting anomalies with a five-factor model. Review of Financial Studies 29, 69–103.

Fama, Eugene F., and James D. MacBeth, 1973. Risk, return and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.

Gleason, Cristi A., and Charles M.C. Lee, 2003. Analyst forecast revisions and market price discovery. Accounting Review 78, 193–225.

Gray, Philip, and Jessica Johnson, 2011. The relationship between asset growth and the cross-section of stock returns. Journal of Banking and Finance 35, 670–680.

Gromb, Denis, and Dimitri Vayanos, 2010. Limits of arbitrage. Annual Review of Financial Economics 2, 251–275.

Harvey, Campbell R., 2017. Presidential address: the scientific outlook in financial economics. Journal of Finance 72, 1399–1440.

Hirshleifer, David, Kewei Hou, Siew H. Teoh, and Yinglei Zhang, 2004. Do investors overvalue firms with bloated balance sheets? Journal of Accounting and Economics 38, 297–331.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015. Digesting anomalies: an investment approach. Review of Financial Studies 28, 650–705.

Huang, Yuan, F.Y. Eric C. Lam, and K.C. John Wei, 2014. The *q*-theory explanation for the external financing effect: new evidence. Journal of Banking and Finance 49, 69–81.

Jiang, Fuwei, Xinlin Qi, and Guohao Tang, 2018. Q-theory, mispricing, and profitability premium: evidence from China. Journal of Banking and Finance 87, 135–149.

Lam, F.Y. Eric, and K.C. John Wei, 2011. Limits-to-arbitrage, investment frictions, and the asset growth anomaly. Journal of Financial Economics 102, 127–149.

Li, Dongmei, and Lu Zhang, 2010. Does *q*-theory with investment frictions explain anomalies in the cross-section of returns? Journal of Financial Economics 98, 297–314.

Li, Xi, and Rodney N. Sullivan, 2011. The limits to arbitrage revisited: the accrual and asset growth anomalies. Financial Analysts Journal 67, 50–66.

Li, Xi, and Rodney N. Sullivan, 2015. Investing in the asset growth anomaly across the globe. Journal of Investment Management 13, 87–107.

Lipson, Marc L., Sandra Mortal, and Michael J. Schill, 2011. On the scope and drivers of the asset growth effect. Journal of Financial and Quantitative Analysis 46, 1651–1682.

Li, Erica X., Dmitry Livdan, and Lu Zhang, 2009, Anomalies, Review of Financial Studies 22, 2973-3004.

Lyandres, Evgeny, Le Sun, and Lu Zhang 2008. The new issues puzzle: testing the investment-based explanation. Review of Financial Studies 21, 2825–2855.

Mao, Mike Qinghao, and K.C. John Wei, 2016. Cash flow news and the investment effect in the cross-section of stock returns. Management Science 62, 2504–2519.

Mashruwala, Christina, Shivaram Rajgopal, and Terry Shevlin, 2006. Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs. Journal of Accounting and Economics 42, 3–33.

McLean, R. David 2010. Idiosyncratic risk, long-term reversal, and momentum. Journal of Financial and Quantitative Analysis 45, 883–906.

Nagel, Stefan, 2005. Short sales, institutional investors, and the cross-section of stock returns. Journal of Financial Economics 78, 277–309.

Newey, Whitney K., and Kenneth D. West, 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Novy-Marx, Robert, 2013. The other side of value: the gross profitability premium. Journal of Financial Economics 108, 1–28.

Papanastasopoulos, Georgios A., 2017. Asset growth anomaly in Europe: do profits and losses matter? Economics Letters 156, 106–109.

Pontiff, Jeffrey, 1996. Costly arbitrage: evidence from closed-end funds. Quarterly Journal of Economics 111, 1135–1151.

Pontiff, Jeffrey, 2006. Costly arbitrage and the myth of idiosyncratic risk. Journal of Accounting and Economics 42, 35–52.

Pontiff, Jeffrey, and Artemiza Woodgate, 2008. Share issuance and cross-sectional returns. Journal of Finance 63, 921–945.

Shleifer, Andrei, and Robert W. Vishny, 1997. The limits of arbitrage. Journal of Finance 52, 35–55.

Shumway, Tyler, and Vincent A. Warther, 1999. The delisting bias in CRSP's Nasdaq data and its implications for the size effect. Journal of Finance 54, 2361–2379.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. Journal of Finance 70, 1903–1948.

Titman, Sheridan, K.C. John Wei, and Feixue Xie, 2004. Capital investments and stock returns. Journal of Financial and Quantitative Analysis 39, 677-700.

Titman, Sheridan, K.C. John Wei, and Feixue Xie, 2013. Market development and the asset growth effect: international evidence. Journal of Financial and Quantitative Analysis 48, 1405–1432.

Wang, Huijun, and Jianfeng Yu, 2013. Dissecting the profitability premium. Working paper.

Watanabe, Akiko, Yan Xu, Tong Yao, and Tong Yu, 2013. The asset growth effect: insights from international equity markets. Journal of Financial Economics 108, 529–563.

Wu, Jin Ginger, Lu Zhang, and X. Frank Zhang, 2010. The *q*-theory approach to understanding the accrual anomaly. Journal of Accounting Research 48, 177–223.

Wurgler, Jeffrey A., and Ekaterina Zhuravskaya, 2002. Does arbitrage flatten demand curves for stocks? Journal of Business 75, 583–607.

Xing, Yuhang, 2008. Interpreting the value effect through the q-theory: an empirical investigation. Review of Financial Studies 21, 1767–1795.

Yan, Xuemin (Sterling), and Lingling Zheng, 2017. Fundamental analysis and the cross-section of stock returns: a data-mining approach. Review of Financial Studies 30, 1382–1423.

Zhang, X. Frank, 2006. Information uncertainty and stock returns. Journal of Finance 61, 105–136.

Zhang, Lu, 2017. The investment CAPM. European Financial Management 23, 545–603.

Appendix. Definitions of variables

AGE: Firm age, measured as the number of years a stock has appeared in CRSP at the end of June of calendar year *t*. Data source: CRSP.

ASSET: Asset size, measured as the book value of total assets (item AT) at the end of fiscal year *t*–1. Data source: Compustat.

β: Capital Asset Pricing Model (CAPM) beta, estimated as the slope coefficient of the time-series regression of monthly stock returns in excess of the risk-free rate on the market return minus the risk-free rate with a full history of 36 months of observations ending in June of calendar year *t*. Data source: CRSP and Kenneth French Data Library.

BIDASK: Average daily bid-ask spread, which is calculated as 2×|(Price–(Ask+Bid)/2)|/Price at the end of a trading day, over the year ending in June of calendar year *t*. Price is the closing share price and Ask (Bid) is the ask (bid) quote. Data source: CRSP.

BM: Book-to-market equity ratio, calculated as the book value of equity at the end of fiscal year *t*–1 divided by market capitalization at the end of year *t*–1. Book equity is total assets (item AT) minus liabilities (item LT), plus balance sheet deferred taxes (item TXDB) and investment tax credits (item ITCI), minus preferred stock liquidation value (item PSTKL) if available, or redemption value (item PSTKRV) if available, or carrying value (item PSTK) if available. Market capitalization is closing stock price multiplied by number of shares outstanding. Data source: Compustat and CRSP.

CVOL: Cash flow volatility, measured as the standard deviation of cash flow from operations over the past five fiscal years ending in year *t*–1. A minimum of three years of observations is required. Cash flow from operations is earnings before extraordinary items (item IB) minus accruals, scaled by the average of total assets (item AT) over fiscal year *t*–1. Accruals is the change in current assets (item ACT) less the change in cash and short-term investments (item CHE) less the change in current liabilities (item LCT) less depreciations (item DP) plus the change in debt included in current liabilities (item DLC) plus the change in income taxes payable (item TXP) over fiscal year *t*–1. Data source: Compustat.

COV: Analyst coverage, measured as the latest number of analysts following the stock available from the beginning of January of calendar year *t* to the end of June of calendar year *t*. Data source: I/B/E/S.

CSI: Composite share issuance, calculated as the difference between the continuously compounded growth in market capitalization over the five years between the end of June of calendar year *t*–5 and the end of June of calendar year *t* and the continuously compounded growth in stock price over the five years between the end of June of calendar year *t*–5 and the end of June of calendar year *t*. Data source: CRSP.

DISP: Dispersion in analyst forecasts, calculated as the latest standard deviation of one year ahead earnings per share forecasts on the stock (item STDEV) available from the beginning of January of calendar year *t* to the end of June of calendar year *t* scaled by the closing stock price at the end of June of calendar year *t*. Data source: I/B/E/S and CRSP.

DVOL: Average daily dollar trading volume, which is closing price times the trading day's share trading volume, over the year ending in June of calendar year *t*. Data source: CRSP.

GP/*A*: Gross profit-to-assets, measured as gross profit (item GP) over fiscal year *t*–1 scaled by total assets (item AT) at the end of fiscal year *t*–1. Data source: Compustat.

I/*A*: Investment-to-asset ratio, calculated as the change in the sum of inventories (item INVT) and gross property, plant, and equipment (item PPEGT) over fiscal year *t*–1, scaled by total assets (item AT) at the end of fiscal year *t*–2. Data source: Compustat.

ILLIQ: The Amihud (2002) illiquidity measure, computed as the time-series average of absolute value of daily returns scaled by the trading day's dollar trading volume over the year ending in June of calendar year *t*. Data source: CRSP.

$INST_H$: Institutional ownership, measured as the latest percentage of outstanding shares held by institutional investors available from the beginning of January of calendar year *t* to the end of June of calendar year *t*. Data source: Thompson Reuters (13F) Institutional Holdings and CRSP.

$INST_N$: Shareholder sophistication, which is the latest number of institutional investors holding a firm's shares available from the beginning of January of calendar year *t* to the end of June of calendar year *t*. Data source: Thompson Reuters (13F) Institutional Holdings.

IVOL: Idiosyncratic stock return volatility, estimated as the standard deviation of residuals from a market model with monthly stock returns as the dependent variable and the S&P 500 return as the independent variable with 36 months of observations ending in June of calendar year *t*. A full three-year history is required. Data source: CRSP.

ME: Market value of equity, calculated as closing stock price multiplied by the number of shares outstanding at the end of June of year *t*. Data source: CRSP.

NOA: Net operating assets, calculated as the difference between operating assets and operating liabilities at the end of fiscal year *t*–1 scaled by total assets (item AT) at the end of fiscal year *t*–2. Operating assets is total assets (item AT) minus cash and short-term investments (item CHE). Operating liabilities is total assets (item AT) less current liabilities (item DLC), long-term debt (item DLTT), minority interests (item MIB), preferred stocks (item PSTK), and common equity (item CEQ). Data source: Compustat.

NSI: Net share issuance, calculated as the natural logarithm of the ratio of split-adjusted shares outstanding (item CSHO multiplied by item ADJEX_C) at the end of fiscal year *t*–1 to that at end of fiscal year *t*–2. Data source: Compustat.

OP_BGLN: Operating profitability from Ball, Gerakos, Linnainmaa, and Nikolaev (2015), measured as gross profit (item GP) minus selling and general administrative expenditures (item XSGA), plus research and development expenditures (item XRD) over fiscal year *t*–1, scaled by total assets (item AT) at the end of fiscal year *t*–1. Data source: Compustat.

OP_FF: Operating profitability from Fama and French (2015, 2016, 2017), measured as gross profit (item GP) minus selling and general administrative expenditures (item XSGA), minus interest expense (item XINTD) for fiscal year *t*–1, scaled by book equity at the end of fiscal year *t*–1. Book equity is total assets (item AT) minus liabilities (item LT), plus balance sheet deferred taxes (item TXDB) and investment tax credits (item ITCI), minus preferred stock liquidation value (item PSTKL) if available, or redemption value (item PSTKRV) if available, or carrying value (item PSTK) if available. Data source: Compustat.

PAYOUT: Payout ratio terciles ranking, ranked in descending order according to all distributions to equity holders including share repurchases (item PRSTKC), dividends to preferred stocks (item DVP), and dividends to common stock, scaled by operating income before depreciation (item OIBDP) for fiscal year *t*–1. Stocks with zero or negative earnings but positive distributions belong to the low payout tercile while stocks with zero or negative earnings and zero distributions belong to the high payout tercile. Data source: Compustat.

PRET: Prior return, calculated as the compounded monthly stock return from June of calendar year *t*–1 to May of calendar year *t*. Data source: CRSP.

PRICE: Closing share price, or the average of bid and ask prices if closing price is unavailable, at the end of June of calendar year *t*. Data source: CRSP.

RATING: Credit rating dummy, which is equal to one if either S&P domestic long term issuer credit rating (item SPLTICRM), S&P subordinated debt rating (item SPSDRM), or S&P domestic short term issuer credit rating (item SPSTICRM) is available between the beginning of January of calendar year *t* and the end of June of calendar year t. Otherwise, the dummy is equal to zero. Data source: Compustat.

ROA: Return on assets, measured as income before extraordinary item (item IB) over fiscal year t–1 scaled by total assets (item AT) at the end of fiscal year t–2. Data source: Compustat.

ROE: Return on equity, measured as income before extraordinary item (item IB) over fiscal year t–1 scaled by book equity at the end of fiscal year t–2. Book equity is total assets (item AT) minus liabilities (item LT), plus balance sheet deferred taxes (item TXDB) and investment tax credits (item ITCI), minus preferred stock liquidation value (item PSTKL) if available, or redemption value (item PSTKRV) if available, or carrying value (item PSTK) if available. Data source: Compustat.

TAG: Total asset growth, calculated as total assets (item AT) at the end of fiscal year t–1 minus total assets (item AT) at the end of fiscal year t–2, scaled by total assets (item AT) at the end of fiscal year t–2. Data source: Compustat.

Table 1. Summary statistics

Panel A reports time-series averages of the cross-sectional mean (Mean), standard deviation (Stddev), minimum (Min), 25th percentile (25P), 50th percentile (50P), 75th percentile (75P), and maximum (Max) of the main firm characteristics in our analysis. *TAG* is total asset growth, *I/A* is investment-to-assets, *NOA* is net operating assets, and *NSI* is net share issuance for a fiscal year. *CSI* is composite share issuance for the five years ending June of a calendar year. *AF* is the arbitrage-frictions composite index and *IF* is the investment-frictions composite index computed at the end of June of each year. Detailed definitions of variables are provided in the Appendix. All variables are winsorized at the 0.5th percentile and the 99.5th percentile. Panel B reports the time-series averages of the cross-sectional Pearson correlations between the variables. The sample period is from 1962 through 2017.

Panel A. Descriptive statistics

	Mean	*Stddev*	*Min*	*25P*	*50P*	*75P*	*Max*
TAG	0.12	0.38	–0.47	–0.03	0.07	0.19	2.64
IA	0.05	0.22	–0.44	–0.01	0.05	0.12	1.16
NOA	0.57	0.39	–0.08	0.36	0.60	0.80	2.23
NSI	0.01	0.18	–0.50	0.00	0.00	0.03	0.94
CSI	–0.15	0.90	–1.43	–0.93	0.00	0.46	2.24
ROE	–0.10	0.68	–2.56	–0.10	0.09	0.16	1.71
OP_FF	0.21	0.45	–2.39	0.11	0.24	0.35	2.99
ROA	–0.03	0.24	–0.85	–0.02	0.04	0.08	0.36
GPA	0.37	0.27	–0.43	0.19	0.34	0.51	1.40
OP	0.13	0.14	–0.46	0.08	0.14	0.20	0.51
AF	2.01	0.82	1.00	1.00	2.00	3.00	3.00
IF	2.04	0.79	1.00	1.02	2.00	3.00	3.00
IVOL	0.12	0.07	0.02	0.08	0.11	0.15	1.16
CVOL	0.09	0.25	0.00	0.03	0.06	0.10	10.28
DISP	0.01	0.03	0.00	0.00	0.00	0.01	1.09
BIDASK	0.02	0.03	0.00	0.01	0.02	0.03	0.15
$INST_H$	0.44	0.27	0.00	0.21	0.43	0.64	0.88
PAYOUT	1.26	2.79	1.00	1.02	1.09	1.24	2.94
RATING	0.20	0.35	0.00	0.00	0.00	0.35	0.95
β	0.78	0.18	0.51	1.06	1.43	1.80	1.98
BM	0.93	1.30	0.01	0.42	0.72	1.14	41.29
PRET	0.14	1.05	–0.88	–0.20	0.02	0.28	36.22
COV	4	6	0	0	1	5	40
AGE	16	15	1	5	11	22	64
PRICE	20.95	27.54	0.37	6.83	14.98	28.16	782.62
$INST_N$	103	138	1	23	58	121	1197
DVOL	1.05E+9	4.52E+9	5.61E+4	1.44E+7	1.05E+8	5.86E+8	1.50E+11
ILLIQ	5.66E-8	3.02E–7	3.60E–12	6.08E–10	4.05E–9	2.44E–8	1.08E–5
ASSET	1.59E+9	8.12E+9	1.26E+6	4.46E+7	1.72E+8	7.38E+8	2.83E+11
ME	1.57E+9	7.29E+9	7.92E+5	4.37E+7	1.75E+8	7.17E+8	1.84E+11

Panel B. Pearson correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) *TAG*															
(2) *I/A*	0.66														
(3) *NOA*	0.53	0.58													
(4) *NSI*	0.50	0.44	0.35												
(5) *CSI*	0.09	0.12	0.12	0.20											
(6) *ROE*	0.35	0.44	0.37	0.43	0.27										
(7) *OP_FF*	0.10	0.10	0.13	–0.06	0.09	0.28									
(8) *ROA*	0.36	0.44	0.39	0.37	0.29	0.88	0.38								
(9) *GPA*	–0.02	0.07	0.01	–0.07	0.01	0.17	0.32	0.25							
(10) *OP*	0.11	0.14	0.11	–0.07	0.12	0.31	0.66	0.46	0.51						
(11) *AF*	–0.08	–0.05	–0.03	0.03	–0.22	–0.20	–0.23	–0.26	–0.01	–0.32					
(12) *IF*	0.00	–0.02	–0.04	–0.04	–0.43	–0.25	–0.19	–0.29	0.06	–0.15	0.57				
(13) β	0.06	0.04	0.01	0.08	0.06	0.09	0.10	0.01	0.05	0.00	0.04	0.08			
(14) *ME*	0.02	0.03	–0.01	0. -00	0.12	0.07	0.07	0.09	0.01	0.12	–0.23	–0.22	0.23		
(15) *BM*	–0.11	–0.06	0.04	-0.01	–0.02	0.02	–0.07	0.01	–0.11	–0.17	0.15	–0.04	0.12	–0.06	
(16) *PRET*	0.01	–0.01	–0.01	0.03	–0.05	0.01	0.02	0.00	0.01	0.02	0.00	0.05	0.08	0.00	–0.03

Table 2. Cross-sectional regressions of future returns on capital investment

This table reports the estimated slope coefficients γ_1 and c_1 of the Fama-MacBeth regression

$$R_{i,t} = a + \gamma_1 Invest_{i,t-1} + \gamma_2 Profit_{i,t-1} + c_2' Controls_{i,t-1} + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly stock return between the end of June of year *t* to the end of June of year *t*+1. *Invest* is an investment measure, including total asset growth (*TAG*), investment-to-assets (*I*/*A*), net operating assets (*NOA*) or net share issuance (*NSI*) for the fiscal year ending year *t*–1, or composite share issuance (*CSI*) for the five years ending at June of year *t*. The monthly cross-sectional regressions are estimated with OLS or WLS. *Profit* is a corporate profitability measure, including return on equity (*ROE*), return on assets (*ROA*), operating profitability from Fama and French (2015) (*OP_FF*), gross-profitability-to-assets from Novy-Marx (2013) (*GP*/*A*), or operating profitability from Ball et al. (2015) (*OP_BGLN*) for the fiscal year ending in year *t*–1. *Controls* are the CAPM beta (β), natural logarithm of market equity (Ln(*ME*)), natural logarithm of book-to-market (Ln(*B*/*M*)), and prior one-year compounded stock return skipping June of year *t* (*PRet*). *Controls* are measured at the end of June of year *t*. Detailed definitions of variables are provided in the Appendix. All right-hand-side variables are winsorized at the 0.5th percentile and the 99.5th percentile. The *t*-statistics (*t-stat*) are based on the Newey-West robust standard errors with autocorrelations up to 12 lags and reported in parentheses. The sample period of monthly returns is from the end of June of 1963 through the end of December of 2017.

Invest	Estimation method	γ_1	*t-stat*	*Profit*	γ_2	*t-stat*
TAG	OLS	–0.671	(–7.95)			
	WLS	–0.315	(–2.97)			
	OLS	–0.744	(–8.92)	*ROE*	0.326	(3.79)
	WLS	–0.344	(–3.16)	*ROE*	0.272	(2.49)
	OLS	–0.759	(–8.70)	*ROA*	1.214	(3.85)
	WLS	–0.373	(–3.36)	*ROA*	1.472	(4.47)
	OLS	–0.766	(–9.44)	*OP_FF*	0.268	(3.83)
	WLS	–0.384	(–3.55)	*OP_FF*	0.213	(2.52)
	OLS	–0.635	(–7.59)	*GP*/*A*	0.584	(3.89)
	WLS	–0.256	(–2.53)	*GP*/*A*	0.627	(3.54)
	OLS	–0.708	(–8.46)	*OP_BGLN*	2.196	(6.83)
	WLS	–0.283	(–2.76)	*OP_BGLN*	1.670	(4.77)
I/*A*	OLS	–0.775	(–5.05)			
	WLS	–0.288	(–1.66)			
	OLS	–0.855	(–5.57)	*ROE*	0.288	(3.20)
	WLS	–0.340	(–1.91)	*ROE*	0.241	(2.08)
	OLS	–0.893	(–5.80)	*ROA*	1.051	(3.22)
	WLS	–0.369	(–2.06)	*ROA*	1.304	(3.63)
	OLS	–0.889	(–5.97)	*OP_FF*	0.239	(3.30)
	WLS	–0.357	(–2.00)	*OP_FF*	0.172	(1.91)
	OLS	–0.776	(–5.03)	*GP*/*A*	0.622	(4.03)
	WLS	–0.248	(–1.43)	*GP*/*A*	0.615	(3.30)
	OLS	–0.919	(–6.05)	*OP_BGLN*	2.206	(6.54)
	WLS	–0.305	(–1.76)	*OP_BGLN*	1.678	(4.51)

Table 2 (continued)

Invest	Estimation method	γ_1	*t-stat*	*Profit*	γ_2	*t-stat*
NOA	OLS	–0.438	(–5.06)			
	WLS	–0.162	(–2.20)			
	OLS	–0.490	(–5.83)	*ROE*	0.294	(3.38)
	WLS	–0.167	(–2.28)	*ROE*	0.241	(2.25)
	OLS	–0.527	(–6.56)	*ROA*	1.064	(3.43)
	WLS	–0.170	(–2.32)	*ROA*	1.322	(4.05)
	OLS	–0.508	(–6.24)	*OP_FF*	0.248	(3.60)
	WLS	–0.173	(–2.32)	*OP_FF*	0.160	(1.88)
	OLS	–0.439	(–5.19)	*GP/A*	0.610	(3.99)
	WLS	–0.160	(–2.28)	*GP/A*	0.647	(3.52)
	OLS	–0.522	(–6.13)	*OP_BGLN*	2.227	(6.71)
	WLS	–0.151	(–2.17)	*OP_BGLN*	1.741	(4.80)
NSI	OLS	–1.193	(–7.04)			
	WLS	–0.675	(–4.22)			
	OLS	–1.181	(–7.97)	*ROE*	0.213	(2.47)
	WLS	–0.725	(–4.53)	*ROE*	0.225	(2.07)
	OLS	–1.105	(–7.69)	*ROA*	0.790	(2.48)
	WLS	–0.711	(–4.25)	*ROA*	1.291	(3.87)
	OLS	–1.245	(–8.07)	*OP_FF*	0.193	(2.70)
	WLS	–0.764	(–4.87)	*OP_FF*	0.185	(2.22)
	OLS	–1.069	(–7.17)	*GP/A*	0.552	(3.74)
	WLS	–0.616	(–3.95)	*GP/A*	0.658	(3.65)
	OLS	–0.969	(–6.85)	*OP_BGLN*	1.913	(6.00)
	WLS	–0.589	(–3.71)	*OP_BGLN*	1.697	(4.65)
CSI	OLS	–0.049	(–2.18)			
	WLS	–0.013	(–0.34)			
	OLS	–0.053	(–2.44)	*ROE*	0.230	(2.62)
	WLS	–0.019	(–0.49)	*ROE*	0.215	(1.98)
	OLS	–0.059	(–2.79)	*ROA*	0.838	(2.70)
	WLS	–0.027	(–0.72)	*ROA*	1.264	(4.02)
	OLS	–0.053	(–2.44)	*OP_FF*	0.183	(2.56)
	WLS	–0.020	(–0.52)	*OP_FF*	0.154	(1.89)
	OLS	–0.053	(–2.48)	*GP/A*	0.631	(4.15)
	WLS	–0.013	(–0.33)	*GP/A*	0.692	(3.84)
	OLS	–0.061	(–2.91)	*OP_BGLN*	2.082	(6.35)
	WLS	–0.018	(–0.46)	*OP_BGLN*	1.761	(4.88)

Table 3. The impact of arbitrage frictions on the investment effect

This table reports the estimated slope coefficients γ_1 and γ_3 of the Fama-MacBeth regression

$$R_{i,t} = a + \gamma_1 Invest_{i,t-1} + \gamma_2 AF_{i,t-1} + \gamma_3 Invest_{i,t-1} \times AF_{i,t-1} + c_1 Profit_{i,t-1} + c_2' Controls_{i,t-1} + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly stock return between the end of June of year t to the end of June of year t+1. *Invest* is an investment measure, including total asset growth (*TAG*), investment-to-assets (*I*/*A*), net operating assets (*NOA*) or net share issuance (*NSI*) for the fiscal year ending year t–1, or composite share issuance (*CSI*) for the five years ending at June of year t. *AF* is the composite arbitrage-frictions rank constructed at the end of June of year t. *Profit* is a corporate profitability measure, including return on equity (*ROE*), return on assets (*ROA*), operating profitability from Fama and French (2015, 2016, 2017) (*OP_FF*), gross-profitability-to-assets from Novy-Marx (2013) (*GP*/*A*), or operating profitability from Ball et al. (2015) (*OP_BGLN*) for the fiscal year ending in year t–1. *Controls* are the CAPM beta (β), natural logarithm of market equity (Ln(*ME*)), natural logarithm of book-to-market (Ln(*B*/*M*)), and prior one-year compounded stock return skipping June of year t (*PRet*). *Controls* are measured at the end of June of year t. Detailed definitions of variables are provided in the Appendix. All right-hand-side variables, except *AF*, are winsorized at the 0.5$^{\text{th}}$ percentile and the 99.5$^{\text{th}}$ percentile. The t-statistics (t-*stat*) are based on the Newey-West robust standard errors with autocorrelations up to 12 lags and reported in parentheses. The sample period of monthly returns is from the end of June of 1963 to the end of December of 2017.

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	c_1	*t-stat*
TAG	OLS	0.259	(1.45)	–0.417	(–5.80)	*ROE*	0.308	(3.86)
	WLS	0.064	(0.35)	–0.291	(–3.19)	*ROE*	0.275	(2.50)
	OLS	0.161	(0.87)	–0.384	(–5.10)	*ROA*	1.152	(3.87)
	WLS	0.022	(0.12)	–0.282	(–3.12)	*ROA*	1.450	(4.44)
	OLS	0.250	(1.40)	–0.423	(–5.80)	*OP_FF*	0.255	(3.80)
	WLS	0.024	(0.13)	–0.289	(–3.12)	*OP_FF*	0.209	(2.50)
	OLS	0.359	(2.12)	–0.413	(–5.87)	*GP*/*A*	0.554	(3.77)
	WLS	0.131	(0.74)	–0.277	(–3.12)	*GP*/*A*	0.608	(3.45)
	OLS	0.384	(2.24)	–0.456	(–6.51)	*OP_BGLN*	2.188	(7.26)
	WLS	0.108	(0.61)	–0.278	(–3.14)	*OP_BGLN*	1.656	(4.74)
I/*A*	OLS	0.534	(2.22)	–0.654	(–5.92)	*ROE*	0.291	(3.55)
	WLS	0.560	(1.70)	–0.708	(–3.55)	*ROE*	0.255	(2.23)
	OLS	0.457	(1.82)	–0.636	(–5.64)	*ROA*	1.066	(3.52)
	WLS	0.535	(1.61)	–0.712	(–3.56)	*ROA*	1.326	(3.78)
	OLS	0.523	(2.14)	–0.663	(–5.84)	*OP_FF*	0.240	(3.51)
	WLS	0.586	(1.76)	–0.738	(–3.58)	*OP_FF*	0.173	(1.95)
	OLS	0.514	(2.07)	–0.600	(–5.15)	*GP*/*A*	0.566	(3.69)
	WLS	0.589	(1.75)	–0.664	(–3.20)	*GP*/*A*	0.590	(3.21)
	OLS	0.462	(1.94)	–0.641	(–5.81)	*OP_BGLN*	2.148	(6.77)
	WLS	0.527	(1.55)	–0.660	(–3.14)	*OP_BGLN*	1.646	(4.45)

Table 3 (continued)

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	c_1	*t-stat*
NOA	OLS	0.229	(1.72)	–0.366	(–4.92)	*ROE*	0.298	(3.77)
	WLS	0.173	(1.11)	–0.291	(–2.89)	*ROE*	0.225	(2.10)
	OLS	0.258	(2.00)	–0.396	(–5.77)	*ROA*	1.090	(3.84)
	WLS	0.203	(1.29)	–0.317	(–3.11)	*ROA*	1.304	(3.98)
	OLS	0.238	(1.77)	–0.380	(–5.14)	*OP_FF*	0.255	(4.01)
	WLS	0.204	(1.29)	–0.323	(–3.13)	*OP_FF*	0.161	(1.91)
	OLS	0.244	(1.81)	–0.349	(–4.47)	*GP/A*	0.577	(3.84)
	WLS	0.164	(1.04)	–0.277	(–2.64)	*GP/A*	0.635	(3.48)
	OLS	0.266	(2.05)	–0.398	(–5.34)	*OP_BGLN*	2.237	(7.27)
	WLS	0.206	(1.32)	–0.305	(–2.92)	*OP_BGLN*	1.741	(4.77)
NSI	OLS	0.115	(0.45)	–0.526	(–4.04)	*ROE*	0.186	(2.28)
	WLS	–1.006	(–2.67)	0.200	(0.84)	*ROE*	0.199	(1.83)
	OLS	0.030	(0.12)	–0.469	(–3.70)	*ROA*	0.703	(2.32)
	WLS	–0.958	(–2.62)	0.174	(0.74)	*ROA*	1.252	(3.80)
	OLS	0.130	(0.50)	–0.559	(–4.25)	*OP_FF*	0.174	(2.54)
	WLS	–0.982	(–2.64)	0.154	(0.67)	*OP_FF*	0.181	(2.25)
	OLS	0.262	(1.00)	–0.541	(–4.05)	*GP/A*	0.524	(3.60)
	WLS	–0.889	(–2.31)	0.197	(0.80)	*GP/A*	0.646	(3.59)
	OLS	0.200	(0.78)	–0.480	(–3.86)	*OP_BGLN*	1.856	(6.15)
	WLS	–0.841	(–2.21)	0.178	(0.75)	*OP_BGLN*	1.689	(4.66)
CSI	OLS	0.108	(1.94)	–0.076	(–2.75)	*ROE*	0.209	(2.55)
	WLS	0.079	(0.96)	–0.080	(–1.70)	*ROE*	0.222	(2.01)
	OLS	0.101	(1.81)	–0.075	(–2.73)	*ROA*	0.776	(2.66)
	WLS	0.071	(0.90)	–0.080	(–1.75)	*ROA*	1.260	(4.04)
	OLS	0.113	(2.05)	–0.078	(–2.86)	*OP_FF*	0.170	(2.52)
	WLS	0.064	(0.82)	–0.068	(–1.56)	*OP_FF*	0.153	(1.90)
	OLS	0.099	(1.78)	–0.072	(–2.63)	*GP/A*	0.597	(4.01)
	WLS	0.077	(0.99)	–0.074	(–1.67)	*GP/A*	0.674	(3.78)
	OLS	0.110	(1.97)	–0.080	(–2.95)	*OP_BGLN*	2.043	(6.63)
	WLS	0.067	(0.88)	–0.070	(–1.61)	*OP_BGLN*	1.723	(4.78)

Table 4. The impact of investment frictions on the investment effect

This table reports the estimated slope coefficients γ_1, γ_3, γ_4 and γ_5 of the Fama-MacBeth regression

$$R_{i,t} = a + \gamma_1 Invest_{i,t-1} + \gamma_2 IF_{i,t-1} + \gamma_3 Invest_{i,t-1} \times IF_{i,t-1} + \gamma_4 Profit_{i,t-1} + \gamma_5 Profit_{i,t-1} \times IF_{i,t-1} + c_1' Controls_{i,t-1} + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly stock return between the end of June of year *t* to the end of June of year *t*+1. *Invest* is an investment measure, including total asset growth (*TAG*), investment-to-assets (*I*/*A*), net operating assets (*NOA*) or net share issuance (*NSI*) for the fiscal year ending year *t*–1, or composite share issuance (*CSI*) for the five years ending at June of year *t*. *IF* is the composite investment-frictions rank constructed at the end of June of year *t*. *Profit* is a corporate profitability measure, including return on equity (*ROE*), return on assets (*ROA*), operating profitability from Fama and French (2015, 2016, 2017) (*OP_FF*), gross-profitability-to-assets from Novy-Marx (2013) (*GP*/*A*), or operating profitability from Ball et al. (2015) (*OP_BGLN*) for the fiscal year ending in year *t*–1. *Controls* are the CAPM beta (β), natural logarithm of market equity (Ln(*ME*)), natural logarithm of book-to-market (Ln(*B*/*M*)), and prior one-year compounded stock return skipping June of year *t* (*PRet*). *Controls* are measured at the end of June of year *t*. Detailed definitions of variables are provided in the Appendix. All right-hand-side variables, except *IF*, are winsorized at the 0.5^{th} percentile and the 99.5^{th} percentile. The *t*-statistics (*t-stat*) are based on the Newey-West robust standard errors with autocorrelations up to 12 lags and reported in parentheses. The sample period of monthly returns is from the end of June of 1963 to the end of December of 2017.

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	γ_4	*t-stat*	γ_5	*t-stat*
TAG	OLS	–0.023	(–0.14)	–0.302	(–4.38)	*ROE*	0.652	(4.03)	–0.133	(–2.11)
	WLS	–0.356	(–1.87)	–0.008	(–0.09)	*ROE*	0.401	(1.70)	–0.047	(–0.48)
	OLS	–0.179	(–1.09)	–0.237	(–3.49)	*ROA*	3.142	(5.12)	–0.769	(–3.35)
	WLS	–0.436	(–2.33)	0.029	(0.33)	*ROA*	2.115	(2.62)	–0.365	(–1.06)
	OLS	–0.077	(–0.45)	–0.290	(–4.21)	*OP_FF*	0.471	(4.55)	–0.084	(–1.64)
	WLS	–0.407	(–2.14)	0.003	(0.03)	*OP_FF*	0.248	(1.36)	0.000	(0.00)
	OLS	0.108	(0.68)	–0.308	(–4.59)	*GP*/*A*	0.811	(3.84)	–0.116	(–1.31)
	WLS	–0.252	(–1.48)	–0.018	(–0.21)	*GP*/*A*	0.557	(2.12)	0.053	(0.44)
	OLS	0.078	(0.51)	–0.319	(–5.26)	*OP_BGLN*	3.807	(6.68)	–0.664	(–2.79)
	WLS	–0.250	(–1.41)	–0.031	(–0.36)	*OP_BGLN*	1.183	(1.82)	0.344	(1.11)
I/*A*	OLS	0.391	(1.62)	–0.611	(–5.16)	*ROE*	0.632	(3.78)	–0.129	(–1.98)
	WLS	0.211	(0.67)	–0.426	(–2.52)	*ROE*	0.350	(1.41)	–0.041	(–0.39)
	OLS	0.246	(0.99)	–0.561	(–4.69)	*ROA*	2.887	(4.35)	–0.696	(–2.82)
	WLS	0.156	(0.49)	–0.410	(–2.37)	*ROA*	1.838	(2.15)	–0.307	(–0.85)
	OLS	0.376	(1.55)	–0.620	(–5.38)	*OP_FF*	0.429	(4.07)	–0.071	(–1.38)
	WLS	0.209	(0.67)	–0.436	(–2.56)	*OP_FF*	0.158	(0.84)	0.030	(0.35)
	OLS	0.472	(1.97)	–0.597	(–4.92)	*GP*/*A*	0.786	(3.61)	–0.092	(–1.09)
	WLS	0.268	(0.83)	–0.405	(–2.38)	*GP*/*A*	0.503	(1.82)	0.072	(0.60)
	OLS	0.317	(1.35)	–0.580	(–5.08)	*OP_BGLN*	4.002	(6.49)	–0.737	(–3.01)
	WLS	0.196	(0.62)	–0.399	(–2.38)	*OP_BGLN*	1.217	(1.84)	0.333	(1.09)

Table 4 (continued)

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	γ_4	*t-stat*	γ_5	*t-stat*
NOA	OLS	0.039	(0.27)	–0.266	(–3.26)	*ROE*	0.659	(4.09)	–0.142	(–2.31)
	WLS	0.019	(0.12)	–0.159	(–1.64)	*ROE*	0.377	(1.70)	–0.063	(–0.66)
	OLS	0.053	(0.38)	–0.287	(–3.71)	*ROA*	3.070	(4.92)	–0.773	(–3.35)
	WLS	0.033	(0.20)	–0.170	(–1.76)	*ROA*	1.969	(2.45)	–0.376	(–1.11)
	OLS	0.041	(0.29)	–0.277	(–3.52)	*OP_FF*	0.442	(4.42)	–0.074	(–1.54)
	WLS	0.023	(0.14)	–0.168	(–1.73)	*OP_FF*	0.157	(0.88)	0.026	(0.32)
	OLS	0.077	(0.54)	–0.262	(–3.03)	*GP/A*	0.829	(3.83)	–0.111	(–1.28)
	WLS	–0.009	(–0.05)	–0.135	(–1.34)	*GP/A*	0.573	(2.15)	0.055	(0.47)
	OLS	0.053	(0.38)	–0.280	(–3.43)	*OP_BGLN*	4.235	(7.03)	–0.810	(–3.32)
	WLS	0.031	(0.19)	–0.153	(–1.57)	*OP_BGLN*	1.337	(2.06)	0.310	(1.03)
NSI	OLS	–0.521	(–1.80)	–0.292	(–1.95)	*ROE*	0.787	(4.90)	–0.237	(–3.68)
	WLS	–0.923	(–2.75)	0.084	(0.44)	*ROE*	0.441	(1.91)	–0.112	(–1.12)
	OLS	–0.566	(–1.91)	–0.227	(–1.51)	*ROA*	3.478	(5.74)	–1.082	(–4.66)
	WLS	–0.925	(–2.62)	0.085	(0.41)	*ROA*	2.104	(2.55)	–0.509	(–1.43)
	OLS	–0.636	(–2.20)	–0.268	(–1.84)	*OP_FF*	0.575	(5.70)	–0.162	(–3.11)
	WLS	–0.986	(–2.87)	0.106	(0.54)	*OP_FF*	0.288	(1.59)	–0.047	(–0.55)
	OLS	–0.331	(–1.11)	–0.317	(–2.10)	*GP/A*	0.895	(4.23)	–0.170	(–1.90)
	WLS	–0.778	(–2.48)	0.064	(0.37)	*GP/A*	0.598	(2.27)	0.035	(0.30)
	OLS	–0.244	(–0.85)	–0.307	(–2.20)	*OP_BGLN*	4.371	(7.35)	–1.018	(–4.06)
	WLS	–0.809	(–2.51)	0.121	(0.67)	*OP_BGLN*	1.274	(1.90)	0.287	(0.92)
CSI	OLS	–0.039	(–0.54)	–0.009	(–0.28)	*ROE*	0.748	(4.44)	–0.211	(–3.13)
	WLS	–0.046	(–0.53)	0.024	(0.61)	*ROE*	0.394	(1.73)	–0.086	(–0.90)
	OLS	–0.058	(–0.81)	–0.004	(–0.11)	*ROA*	3.456	(5.54)	–1.041	(–4.36)
	WLS	–0.057	(–0.68)	0.027	(0.70)	*ROA*	2.091	(2.66)	–0.479	(–1.42)
	OLS	–0.037	(–0.52)	–0.010	(–0.32)	*OP_FF*	0.527	(5.00)	–0.144	(–2.64)
	WLS	–0.048	(–0.56)	0.024	(0.59)	*OP_FF*	0.232	(1.35)	–0.025	(–0.32)
	OLS	–0.031	(–0.46)	–0.012	(–0.40)	*GP/A*	0.952	(4.45)	–0.160	(–1.76)
	WLS	–0.028	(–0.33)	0.014	(0.36)	*GP/A*	0.642	(2.46)	0.034	(0.30)
	OLS	–0.060	(–0.86)	–0.006	(–0.18)	*OP_BGLN*	4.558	(7.38)	–1.013	(–3.91)
	WLS	–0.026	(–0.29)	0.009	(0.23)	*OP_BGLN*	1.409	(2.13)	0.276	(0.91)

Table 5. The marginal impact of arbitrage frictions on the investment effect

This table reports the estimated slope coefficients γ_1 and γ_3 of the Fama-MacBeth regression

$$R_{i,t} = a + \gamma_1 Invest_{i,t-1} + \gamma_2 AF_{i,t-1} + \gamma_3 Invest_{i,t-1} \times AF_{i,t-1}$$
$$+ c_1 IF_{i,t-1} + c_2 Invest_{i,t-1} \times IF_{i,t-1} + c_3 Profit_{i,t-1} + c_4' Controls_{i,t-1} + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly stock return between the end of June of year *t* to the end of June of year *t*+1. *Invest* is an investment measure, including total asset growth (*TAG*), investment-to-assets (*I*/*A*), net operating assets (*NOA*) or net share issuance (*NSI*) for the fiscal year ending year *t*–1, or composite share issuance (*CSI*) for the five years ending at June of year *t*. *AF* is the composite arbitrage-frictions rank constructed at the end of June of year *t*. *IF* is the investment-frictions rank constructed at the end of June of year *t*. *Profit* is a corporate profitability measure, including return on equity (*ROE*), return on assets (*ROA*), operating profitability from Fama and French (2015, 2016, 2017) (*OP_FF*), gross-profitability-to-assets from Novy-Marx (2013) (*GP*/*A*), or operating profitability from Ball et al. (2015) (*OP_BGLN*) for the fiscal year ending in year *t*–1. *Controls* are the CAPM (β), natural logarithm of market equity (Ln(*ME*)), natural logarithm of book-to-market (Ln(*B*/*M*)), and prior one-year compounded stock return skipping June of year *t* (*PRet*). *Controls* are measured at the end of June of year *t*. Detailed definitions of variables are provided in the Appendix. All right-hand-side variables, except *AF* and *IF*, are winsorized at the 0.5$^{\text{th}}$ percentile and the 99.5$^{\text{th}}$ percentile. The *t*-statistics (*t-stat*) are based on the Newey-West robust standard errors with autocorrelations up to 12 lags and reported in parentheses. The sample period of monthly returns is from the end of June of 1963 to the end of December of 2017.

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	c_3	*t-stat*
TAG	OLS	0.480	(2.57)	–0.337	(–4.33)	*ROE*	0.304	(3.75)
	WLS	–0.025	(–0.13)	–0.409	(–3.71)	*ROE*	0.279	(2.56)
	OLS	0.468	(2.51)	–0.338	(–4.30)	*ROA*	0.255	(3.86)
	WLS	–0.046	(–0.24)	–0.397	(–3.62)	*ROA*	0.210	(2.70)
	OLS	0.388	(2.01)	–0.304	(–3.74)	*OP_FF*	1.135	(3.75)
	WLS	–0.063	(–0.33)	–0.395	(–3.65)	*OP_FF*	1.433	(4.45)
	OLS	0.574	(3.27)	–0.338	(–4.37)	*GP*/*A*	0.544	(3.67)
	WLS	0.051	(0.28)	–0.389	(–3.59)	*GP*/*A*	0.601	(3.39)
	OLS	0.630	(3.56)	–0.381	(–4.96)	*OP_BGLN*	2.160	(6.99)
	WLS	0.044	(0.23)	–0.392	(–3.71)	*OP_BGLN*	1.621	(4.72)
I/*A*	OLS	0.876	(3.37)	–0.393	(–3.61)	*ROE*	0.297	(3.59)
	WLS	0.676	(1.85)	–0.614	(–3.17)	*ROE*	0.256	(2.29)
	OLS	0.876	(3.34)	–0.392	(–3.48)	*ROA*	0.246	(3.66)
	WLS	0.697	(1.90)	–0.618	(–3.15)	*ROA*	0.176	(2.11)
	OLS	0.818	(3.05)	–0.367	(–3.25)	*OP_FF*	1.084	(3.55)
	WLS	0.645	(1.73)	–0.616	(–3.20)	*OP_FF*	1.284	(3.71)
	OLS	0.859	(3.17)	–0.344	(–3.05)	*GP*/*A*	0.558	(3.59)
	WLS	0.660	(1.76)	–0.575	(–3.01)	*GP*/*A*	0.579	(3.12)
	OLS	0.842	(3.24)	–0.382	(–3.51)	*OP_BGLN*	2.132	(6.53)
	WLS	0.602	(1.62)	–0.574	(–2.92)	*OP_BGLN*	1.626	(4.44)

Table 5 (continued)

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	c_3	*t-stat*
	OLS	0.298	(1.83)	–0.300	(–5.53)	*ROE*	0.297	(3.73)
	WLS	0.178	(1.00)	–0.251	(–2.18)	*ROE*	0.219	(2.10)
	OLS	0.316	(1.94)	–0.306	(–5.58)	*ROA*	0.258	(4.16)
	WLS	0.209	(1.16)	–0.276	(–2.36)	*ROA*	0.164	(2.09)
NOA	OLS	0.349	(2.24)	–0.315	(–6.07)	*OP_FF*	1.092	(3.82)
	WLS	0.210	(1.14)	–0.276	(–2.42)	*OP_FF*	1.255	(3.93)
	OLS	0.311	(1.86)	–0.287	(–5.15)	*GP/A*	0.573	(3.76)
	WLS	0.147	(0.79)	–0.254	(–2.22)	*GP/A*	0.632	(3.44)
	OLS	0.346	(2.16)	–0.332	(–6.08)	*OP_BGLN*	2.227	(7.08)
	WLS	0.201	(1.12)	–0.271	(–2.34)	*OP_BGLN*	1.731	(4.82)
	OLS	0.079	(0.24)	–0.465	(–3.72)	*ROE*	0.185	(2.21)
	WLS	–0.944	(–2.52)	0.004	(0.02)	*ROE*	0.205	(1.88)
	OLS	0.110	(0.33)	–0.477	(–3.79)	*ROA*	0.176	(2.58)
	WLS	–0.924	(–2.52)	–0.047	(–0.20)	*ROA*	0.182	(2.38)
	OLS	–0.031	(–0.10)	–0.435	(–3.42)	*OP_FF*	0.683	(2.21)
NSI	WLS	–0.889	(–2.43)	–0.028	(–0.12)	*OP_FF*	1.223	(3.72)
	OLS	0.236	(0.70)	–0.480	(–3.77)	*GP/A*	0.515	(3.50)
	WLS	–0.850	(–2.28)	–0.028	(–0.11)	*GP/A*	0.635	(3.52)
	OLS	0.175	(0.53)	–0.444	(–3.61)	*OP_BGLN*	1.837	(5.94)
	WLS	–0.804	(–2.19)	–0.052	(–0.22)	*OP_BGLN*	1.660	(4.62)
	OLS	0.062	(0.79)	–0.093	(–3.55)	*ROE*	0.212	(2.54)
	WLS	0.024	(0.25)	–0.081	(–1.88)	*ROE*	0.218	(2.02)
	OLS	0.071	(0.90)	–0.094	(–3.63)	*ROA*	0.173	(2.57)
	WLS	0.014	(0.14)	–0.073	(–1.79)	*ROA*	0.156	(2.05)
	OLS	0.057	(0.73)	–0.091	(–3.48)	*OP_FF*	0.777	(2.62)
CSI	WLS	0.021	(0.22)	–0.084	(–1.97)	*OP_FF*	1.243	(4.11)
	OLS	0.056	(0.73)	–0.087	(–3.35)	*GP/A*	0.594	(3.96)
	WLS	0.027	(0.28)	–0.074	(–1.86)	*GP/A*	0.669	(3.75)
	OLS	0.060	(0.78)	–0.096	(–3.74)	*OP_BGLN*	2.046	(6.50)
	WLS	0.025	(0.27)	–0.075	(–1.89)	*OP_BGLN*	1.741	(4.89)

Table 6. The marginal impact of investment frictions on the investment effect

This table reports the estimated slope coefficients γ_1, γ_3, γ_4, γ_5, c_2 of the Fama-MacBeth regression

$$R_{i,t} = a + \gamma_1 Invest_{i,t-1} + \gamma_2 IF_{i,t-1} + \gamma_3 Invest_{i,t-1} \times IF_{i,t-1} + \gamma_4 Profit_{i,t-1} + \gamma_5 Profit_{i,t-1} \times IF_{i,t-1}$$
$$+ c_1 AF_{i,t-1} + c_2 Invest_{i,t-1} \times AF_{i,t-1} + c_3 Profit_{i,t-1} \times AF_{i,t-1} + c_4{}' Controls_{i,t-1} + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly stock return between the end of June of year *t* to the end of June of year *t*+1. *Invest* is an investment measure, including total asset growth (*TAG*), investment-to-assets (*I*/*A*), net operating assets (*NOA*) or net share issuance (*NSI*) for the fiscal year ending year *t*–1, or composite share issuance (*CSI*) for the five years ending at June of year *t*. *IF* is the composite investment-frictions rank constructed at the end of June of year *t*. *AF* is the composite arbitrage-frictions rank constructed at the end of June of year *t*. *Profit* is a corporate profitability measure, including return on equity (*ROE*), return on assets (*ROA*), operating profitability from Fama and French (2015, 2016, 2017) (*OP_FF*), gross-profitability-to-assets from Novy-Marx (2013) (*GP*/*A*), or operating profitability from Ball et al. (2015) (*OP_BGLN*) for the fiscal year ending in year *t*–1. *Controls* are the CAPM beta (β), natural logarithm of market equity (Ln(*ME*)), natural logarithm of book-to-market (Ln(*B*/*M*)), and prior one-year compounded stock return skipping June of year *t* (*PRet*). *Controls* are measured at the end of June of year *t*. Detailed definitions of variables are provided in the Appendix. All right-hand-side variables, except *AF* and *IF*, are winsorized at the 0.5th percentile and the 99.5th percentile. The *t*-statistics (*t-stat*) are based on the Newey-West robust standard errors with autocorrelations up to 12 lags and reported in parentheses. The sample period of monthly returns is from the end of June of 1963 to the end of December of 2017.

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	γ_4	*t-stat*	γ_5	*t-stat*	*c2*	*t-stat*
	OLS	0.432	(2.27)	–0.139	(–1.88)	*ROE*	0.692	(3.31)	–0.174	(–2.70)	–0.347	(–4.31)
	WLS	–0.022	(–0.11)	0.229	(2.15)	*ROE*	0.247	(0.89)	–0.171	(–1.64)	–0.480	(–4.35)
	OLS	0.243	(1.27)	–0.094	(–1.26)	*ROA*	3.213	(4.47)	–0.748	(–3.25)	–0.313	(–3.60)
	WLS	–0.139	(–0.68)	0.280	(2.72)	*ROA*	2.207	(2.32)	–0.630	(–1.87)	–0.473	(–4.15)
TAG	OLS	0.347	(1.78)	–0.139	(–1.92)	*OP_FF*	0.530	(3.87)	–0.110	(–2.12)	–0.323	(–4.00)
	WLS	–0.062	(–0.32)	0.245	(2.20)	*OP_FF*	0.165	(0.78)	–0.120	(–1.25)	–0.493	(–4.40)
	OLS	0.551	(3.10)	–0.169	(–2.33)	*GP*/*A*	0.724	(3.15)	–0.168	(–1.82)	–0.319	(–4.12)
	WLS	0.000	(0.00)	0.159	(1.59)	*GP*/*A*	0.517	(1.74)	–0.061	(–0.50)	–0.364	(–3.34)
	OLS	0.585	(3.42)	–0.142	(–2.09)	*OP_BGLN*	3.815	(5.61)	–0.666	(–2.75)	–0.387	(–5.10)
	WLS	0.015	(0.08)	0.192	(1.88)	*OP_BGLN*	1.003	(1.33)	–0.158	(–0.51)	–0.432	(–3.95)
	OLS	0.789	(2.98)	–0.390	(–3.36)	*ROE*	0.688	(3.25)	–0.160	(–2.51)	–0.398	(––3.63)
	WLS	0.681	(1.83)	–0.111	(–0.64)	*ROE*	0.163	(0.57)	–0.181	(–1.54)	–0.679	(–3.53)
	OLS	0.628	(2.31)	–0.357	(–3.04)	*ROA*	2.979	(3.99)	–0.704	(–3.02)	–0.373	(––3.40)
	WLS	0.625	(1.65)	–0.101	(–0.57)	*ROA*	1.837	(1.87)	–0.575	(–1.66)	–0.674	(–3.45)
I/*A*	OLS	0.769	(2.87)	–0.400	(–3.63)	*OP_FF*	0.495	(3.50)	–0.098	(–1.94)	–0.392	(–3.54)
	WLS	0.730	(1.95)	–0.109	(–0.62)	*OP_FF*	0.061	(0.28)	–0.096	(–0.98)	–0.728	(–3.69)
	OLS	0.833	(3.15)	–0.421	(–3.56)	*GP*/*A*	0.662	(2.83)	–0.157	(–1.73)	–0.332	(–2.98)
	WLS	0.629	(1.70)	–0.147	(–0.85)	*GP*/*A*	0.446	(1.54)	–0.082	(–0.66)	–0.537	(–2.92)
	OLS	0.737	(2.89)	–0.362	(–3.25)	*OP_BGLN*	3.961	(5.43)	–0.685	(–2.82)	–0.400	(–3.74)
	WLS	0.595	(1.64)	–0.106	(–0.62)	*OP_BGLN*	1.014	(1.37)	–0.196	(–0.64)	–0.608	(–3.27)

Table 6 (continued)

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	γ_4	*t-stat*	γ_5	*t-stat*	*c2*	*t-stat*
NOA	OLS	0.270	(1.65)	–0.076	(–1.06)	*ROE*	0.744	(3.56)	–0.173	(–2.78)	–0.308	(–5.77)
	WLS	0.191	(1.07)	–0.054	(–0.50)	*ROE*	0.220	(0.85)	–0.157	(–1.39)	–0.255	(–2.18)
	OLS	0.300	(1.92)	–0.082	(–1.15)	*ROA*	3.278	(4.56)	–0.763	(–3.40)	–0.329	(–6.47)
	WLS	0.222	(1.23)	–0.042	(–0.39)	*ROA*	2.083	(2.18)	–0.530	(–1.57)	–0.292	(–2.58)
	OLS	0.281	(1.72)	–0.085	(–1.24)	*OP_FF*	0.527	(3.84)	–0.102	(–2.08)	–0.315	(–5.64)
	WLS	0.230	(1.26)	–0.040	(–0.38)	*OP_FF*	0.103	(0.50)	–0.064	(–0.66)	–0.307	(–2.58)
	OLS	0.289	(1.79)	–0.098	(–1.30)	*GP/A*	0.746	(3.17)	–0.165	(–1.84)	–0.274	(–4.98)
	WLS	0.145	(0.80)	–0.044	(–0.40)	*GP/A*	0.549	(1.87)	–0.093	(–0.76)	–0.226	(–1.98)
	OLS	0.301	(1.96)	–0.071	(–0.97)	*OP_BGLN*	4.303	(5.99)	–0.745	(–3.04)	–0.336	(–6.26)
	WLS	0.208	(1.17)	–0.049	(–0.46)	*OP_BGLN*	1.266	(1.68)	–0.156	(–0.52)	–0.259	(–2.25)
NSI	OLS	–0.023	(–0.07)	–0.076	(–0.47)	*ROE*	0.935	(4.46)	–0.237	(–3.57)	–0.407	(–2.92)
	WLS	–1.086	(–2.77)	0.154	(0.64)	*ROE*	0.323	(1.19)	–0.193	(–1.73)	0.023	(0.09)
	OLS	–0.145	(–0.42)	–0.053	(–0.33)	*ROA*	3.898	(5.41)	–0.961	(–4.30)	–0.064	(–0.26)
	WLS	–1.077	(–2.70)	0.181	(0.76)	*ROA*	2.247	(2.37)	–0.614	(–1.81)	–0.333	(–2.13)
	OLS	–0.136	(–0.42)	–0.035	(–0.21)	*OP_FF*	0.693	(5.21)	–0.160	(–2.90)	–0.423	(–3.00)
	WLS	–1.111	(–2.82)	0.231	(0.93)	*OP_FF*	0.283	(1.34)	–0.110	(–1.11)	–0.064	(–0.26)
	OLS	0.232	(0.68)	–0.094	(–0.59)	*GP/A*	0.837	(3.61)	–0.207	(–2.26)	–0.436	(–3.46)
	WLS	–0.916	(–2.50)	0.121	(0.53)	*GP/A*	0.527	(1.79)	–0.102	(–0.85)	0.035	(0.13)
	OLS	0.290	(0.92)	–0.088	(–0.57)	*OP_BGLN*	4.651	(6.51)	–0.826	(–3.35)	–0.428	(–3.48)
	WLS	–0.888	(–2.38)	0.172	(0.76)	*OP_BGLN*	1.179	(1.52)	–0.113	(–0.37)	0.000	(0.00)
CSI	OLS	0.038	(0.47)	0.036	(1.21)	*ROE*	0.842	(3.83)	–0.216	(–3.29)	–0.085	(–3.26)
	WLS	0.024	(0.25)	0.050	(1.22)	*ROE*	0.261	(0.95)	–0.168	(–1.61)	–0.090	(–2.10)
	OLS	0.014	(0.17)	0.036	(1.21)	*ROA*	3.667	(4.99)	–0.897	(–3.99)	–0.076	(–2.92)
	WLS	0.015	(0.16)	0.058	(1.47)	*ROA*	2.211	(2.34)	–0.565	(–1.71)	–0.097	(–2.30)
	OLS	0.044	(0.55)	0.033	(1.09)	*OP_FF*	0.614	(4.37)	–0.145	(–2.73)	–0.085	(–3.28)
	WLS	0.007	(0.07)	0.048	(1.15)	*OP_FF*	0.195	(0.97)	–0.093	(–1.00)	–0.078	(–1.85)
	OLS	0.052	(0.68)	0.033	(1.16)	*GP/A*	0.846	(3.64)	–0.195	(–2.09)	–0.086	(–3.33)
	WLS	0.021	(0.23)	0.041	(1.01)	*GP/A*	0.551	(1.90)	–0.101	(–0.85)	–0.074	(–1.87)
	OLS	0.016	(0.21)	0.035	(1.22)	*OP_BGLN*	4.620	(6.29)	–0.770	(–3.05)	–0.079	(–3.09)
	WLS	0.032	(0.33)	0.048	(1.19)	*OP_BGLN*	1.156	(1.51)	–0.184	(–0.62)	–0.096	(–2.34)

Table 7. The impact of residual arbitrage frictions on the investment effect

This table reports the estimated slope coefficients γ_1 and γ_3 of the Fama-MacBeth regression

$$R_{i,t} = a + \gamma_1 Invest_{i,t-1} + \gamma_2 ResAF_{i,t-1} + \gamma_3 Invest_{i,t-1} \times ResAF_{i,t-1} + c_1 Profit_{i,t-1} + c_2{}' Controls_{i,t-1} + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly stock return between the end of June of year *t* to the end of June of year *t*+1. *Invest* is an investment measure, including total asset growth (*TAG*), investment-to-assets (*I*/*A*), net operating assets (*NOA*) or net share issuance (*NSI*) for the fiscal year ending year *t*–1, or composite share issuance (*CSI*) for the five years ending at June of year *t*. *ResAF* is the residual arbitrage-frictions rank. It is constructed from orthogonalizing *AF* with respect to *IF* in the cross section at the end of June of year *t*. *Profit* is a corporate profitability measure, including return on equity (*ROE*), return on assets (*ROA*), operating profitability from Fama and French (2015, 2016, 2017) (*OP_FF*), gross-profitability-to-assets from Novy-Marx (2013) (*GP*/*A*), or operating profitability from Ball et al. (2015) (*OP_BGLN*) for the fiscal year ending in year *t*–1. *Controls* are the CAPM beta (β), natural logarithm of market equity (Ln(*ME*)), natural logarithm of book-to-market (Ln(*B*/*M*)), and prior one-year compounded stock return skipping June of year *t* (*PRet*). *Controls* are measured at the end of June of year *t*. Detailed definitions of variables are provided in the Appendix. All right-hand-side variables, except *ResAF*, are winsorized at the 0.5th percentile and the 99.5th percentile. The *t*-statistics (*t-stat*) are based on the Newey-West robust standard errors with autocorrelations up to 12 lags and reported in parentheses. The sample period of monthly returns is from the end of June of 1963 to the end of December of 2017.

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	c_1	*t-stat*
	OLS	–0.702	(–8.58)	–0.274	(–3.48)	*ROE*	0.305	(3.64)
	WLS	–0.473	(–4.15)	–0.400	(–3.16)	*ROE*	0.285	(2.61)
	OLS	–0.722	(–8.42)	–0.244	(–2.97)	*ROA*	1.138	(3.64)
	WLS	–0.493	(–4.29)	–0.386	(–3.11)	*ROA*	1.446	(4.43)
TAG	OLS	–0.725	(–9.15)	–0.276	(–3.45)	*OP_FF*	0.256	(3.67)
	WLS	–0.504	(–4.51)	–0.379	(–3.10)	*OP_FF*	0.219	(2.64)
	OLS	–0.599	(–7.42)	–0.276	(–3.50)	*GP*/*A*	0.556	(3.74)
	WLS	–0.373	(–3.53)	–0.376	(–2.98)	*GP*/*A*	0.602	(3.38)
	OLS	–0.662	(–8.17)	–0.311	(–3.98)	*OP_BGLN*	2.164	(6.98)
	WLS	–0.397	(–3.74)	–0.366	(–3.02)	*OP_BGLN*	1.633	(4.71)
	OLS	–0.849	(–5.64)	–0.343	(–3.10)	*ROE*	0.275	(3.15)
	WLS	–0.458	(–2.43)	–0.385	(–2.10)	*ROE*	0.245	(2.11)
	OLS	–0.885	(–5.86)	–0.316	(–2.75)	*ROA*	1.007	(3.15)
	WLS	–0.479	(–2.53)	–0.390	(–2.14)	*ROA*	1.274	(3.56)
I/*A*	OLS	–0.884	(–6.08)	–0.343	(–2.98)	*OP_FF*	0.231	(3.23)
	WLS	–0.469	(–2.51)	–0.385	(–2.08)	*OP_FF*	0.171	(1.89)
	OLS	–0.774	(–5.13)	–0.298	(–2.59)	*GP*/*A*	0.589	(3.84)
	WLS	–0.351	(–1.92)	–0.358	(–1.97)	*GP*/*A*	0.599	(3.23)
	OLS	–0.904	(–6.06)	–0.330	(–2.96)	*OP_BGLN*	2.151	(6.59)
	WLS	–0.405	(–2.23)	–0.344	(–1.88)	*OP_BGLN*	1.645	(4.44)

Table 7 (continued)

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	c_1	*t-stat*
NOA	OLS	–0.503	(–6.10)	-0.304	(–5.59)	*ROE*	0.285	(3.38)
	WLS	–0.229	(–2.56)	-0.156	(–1.27)	*ROE*	0.229	(2.14)
	OLS	–0.535	(–6.75)	-0.317	(–6.11)	*ROA*	1.032	(3.40)
	WLS	–0.235	(–2.63)	-0.180	(–1.49)	*ROA*	1.271	(3.90)
	OLS	–0.524	(–6.56)	-0.311	(–5.66)	*OP_FF*	0.246	(3.61)
	WLS	–0.240	(–2.66)	-0.175	(–1.42)	*OP_FF*	0.162	(1.90)
	OLS	–0.454	(–5.50)	-0.292	(–5.25)	*GP/A*	0.584	(3.86)
	WLS	–0.224	(–2.68)	-0.171	(–1.41)	*GP/A*	0.638	(3.48)
	OLS	–0.529	(–6.32)	-0.334	(–6.14)	*OP_BGLN*	2.206	(6.90)
	WLS	–0.216	(–2.58)	-0.178	(–1.47)	*OP_BGLN*	1.725	(4.77)
NSI	OLS	–1.100	(–7.66)	-0.377	(–3.02)	*ROE*	0.197	(2.34)
	WLS	–0.764	(–4.48)	-0.035	(–0.14)	*ROE*	0.226	(2.09)
	OLS	–1.045	(–7.47)	-0.356	(–2.74)	*ROA*	0.733	(2.34)
	WLS	–0.755	(–4.20)	-0.059	(–0.24)	*ROA*	1.279	(3.86)
	OLS	–1.161	(–7.89)	-0.389	(–3.07)	*OP_FF*	0.183	(2.59)
	WLS	–0.811	(–4.87)	-0.084	(–0.35)	*OP_FF*	0.188	(2.30)
	OLS	–0.991	(–7.05)	-0.386	(–3.05)	*GP/A*	0.532	(3.64)
	WLS	–0.652	(–3.91)	-0.051	(–0.20)	*GP/A*	0.643	(3.56)
	OLS	–0.906	(–6.64)	-0.355	(–2.88)	*OP_BGLN*	1.880	(6.13)
	WLS	–0.635	(–3.82)	-0.084	(–0.34)	*OP_BGLN*	1.680	(4.63)
CSI	OLS	–0.050	(–2.22)	-0.091	(–3.64)	*ROE*	0.218	(2.57)
	WLS	–0.054	(–1.17)	-0.084	(–2.15)	*ROE*	0.218	(2.00)
	OLS	–0.056	(–2.57)	-0.088	(–3.55)	*ROA*	0.795	(2.63)
	WLS	–0.063	(–1.43)	-0.088	(–2.26)	*ROA*	1.246	(4.02)
	OLS	–0.050	(–2.20)	-0.091	(–3.71)	*OP_FF*	0.178	(2.52)
	WLS	–0.053	(–1.15)	-0.079	(–2.04)	*OP_FF*	0.153	(1.89)
	OLS	–0.051	(–2.28)	-0.086	(–3.45)	*GP/A*	0.610	(4.07)
	WLS	–0.044	(–0.99)	-0.079	(–2.05)	*GP/A*	0.676	(3.76)
	OLS	–0.061	(–2.84)	-0.094	(–3.83)	*OP_BGLN*	2.068	(6.60)
	WLS	–0.050	(–1.09)	-0.078	(–2.04)	*OP_BGLN*	1.739	(4.84)

Table 8. The impact of residual investment frictions on the investment effect

This table reports the estimated slope coefficients γ_1, γ_3, γ_4 and γ_5 of the Fama-MacBeth regression

$$R_{i,t} = a + \gamma_1 Invest_{i,t-1} + \gamma_2 ResIF_{i,t-1} + \gamma_3 Invest_{i,t-1} \times ResIF_{i,t-1} + \gamma_4 Profit_{i,t-1} + \gamma_5 Profit_{i,t-1} \times ResIF_{i,t-1} + c_1' Controls_{i,t-1} + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly stock return between the end of June of year *t* to the end of June of year *t*+1. *Invest* is an investment measure, including total asset growth (*TAG*), investment-to-assets (*I*/*A*), net operating assets (*NOA*) or net share issuance (*NSI*) for the fiscal year ending year *t*–1, or composite share issuance (*CSI*) for the five years ending at June of year *t*. *ResIF* is the residual investment-frictions rank. It is constructed from orthogonalizing *IF* with respect to *AF* in the cross section at the end of June of year *t*. *Profit* is a corporate profitability measure, including return on equity (*ROE*), return on assets (*ROA*), operating profitability from Fama and French (2015, 2016, 2017) (*OP_FF*), gross-profitability-to-assets from Novy-Marx (2013) (*GP*/*A*), or operating profitability from Ball et al. (2015) (*OP_BGLN*) for the fiscal year ending in year *t*–1. *Controls* are the CAPM beta (β), natural logarithm of market equity (Ln(*ME*)), natural logarithm of book-to-market (Ln(*B*/*M*)), and prior one-year compounded stock return skipping June of year *t* (*PRet*). *Controls* are measured at the end of June of year *t*. Detailed definitions of variables are provided in the Appendix. All right-hand-side variables, except *ResIF*, are winsorized at the 0.5th percentile and the 99.5th percentile. The *t*-statistics (*t-stat*) are based on the Newey-West robust standard errors with autocorrelations up to 12 lags and reported in parentheses. The sample period of monthly returns is from the end of June of 1963 to the end of December of 2017.

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	γ_4	*t-stat*	γ_5	*t-stat*
TAG	OLS	–0.741	(–9.39)	–0.070	(–1.01)	*ROE*	0.336	(3.85)	–0.152	(–2.43)
	WLS	–0.305	(–2.92)	0.238	(2.12)	*ROE*	0.281	(2.54)	–0.175	(–1.66)
	OLS	–0.751	(–8.82)	–0.047	(–0.67)	*ROA*	1.301	(4.01)	–0.578	(–2.64)
	WLS	–0.325	(–2.96)	0.265	(2.34)	*ROA*	1.426	(4.44)	–0.551	(–1.62)
	OLS	–0.762	(–9.92)	–0.070	(–1.03)	*OP_FF*	0.271	(3.85)	–0.094	(–1.81)
	WLS	–0.344	(–3.29)	0.258	(2.22)	*OP_FF*	0.222	(2.88)	–0.128	(–1.36)
	OLS	–0.628	(–7.98)	–0.103	(–1.51)	*GP*/*A*	0.578	(3.85)	–0.153	(–1.64)
	WLS	–0.233	(–2.40)	0.153	(1.43)	*GP*/*A*	0.615	(3.52)	–0.022	(–0.18)
	OLS	–0.693	(–8.79)	–0.078	(–1.24)	*OP_BGLN*	2.248	(7.07)	–0.540	(–2.27)
	WLS	–0.252	(–2.57)	0.168	(1.52)	*OP_BGLN*	1.667	(4.94)	0.036	(0.12)
I/*A*	OLS	–0.888	(–5.87)	–0.378	(–3.20)	*ROE*	0.308	(3.40)	–0.139	(–2.25)
	WLS	–0.368	(–2.14)	–0.097	(–0.54)	*ROE*	0.241	(2.080	–0.186	(–1.59)
	OLS	–0.923	(–6.04)	–0.363	(–2.99)	*ROA*	1.161	(3.44)	–0.513	(–2.24)
	WLS	–0.402	(–2.34)	–0.098	(–0.54)	*ROA*	1.234	(3.56)	–0.544	(–1.54)
	OLS	–0.917	(–6.29)	–0.394	(–3.51)	*OP_FF*	0.248	(3.45)	–0.080	(–1.59)
	WLS	–0.381	(–2.21)	–0.068	(–0.39)	*OP_FF*	0.180	(2.21)	–0.107	(–1.13)
	OLS	–0.803	(–5.25)	–0.415	(–3.42)	*GP*/*A*	0.615	(3.95)	–0.149	(–1.62)
	WLS	–0.293	(–1.79)	–0.153	(–0.85)	*GP*/*A*	0.588	(3.19)	–0.038	(–0.30)
	OLS	–0.931	(–6.13)	–0.370	(–3.20)	*OP_BGLN*	2.279	(6.78)	–0.559	(–2.34)
	WLS	–0.348	(–2.15)	–0.126	(–0.71)	*OP_BGLN*	1.681	(4.73)	0.004	(0.01)

Table 8 (continued)

Invest	Estimation method	γ_1	*t-stat*	γ_3	*t-stat*	*Profit*	γ_4	*t-stat*	γ_5	*t-stat*
NOA	OLS	–0.492	(–5.79)	–0.090	(–1.23)	*ROE*	0.306	(3.51)	–0.150	(–2.45)
	WLS	–0.169	(–2.42)	–0.028	(–0.24)	*ROE*	0.229	(2.13)	–0.183	(–1.64)
	OLS	–0.528	(–6.43)	–0.101	(–1.39)	*ROA*	1.162	(3.65)	–0.568	(–2.68)
	WLS	–0.168	(–2.43)	–0.025	(–0.22)	*ROA*	1.240	(3.95)	–0.536	(–1.59)
	OLS	–0.513	(–6.25)	–0.100	(–1.45)	*OP_FF*	0.253	(3.74)	–0.081	(–1.63)
	WLS	–0.163	(–2.32)	–0.003	(–0.02)	*OP_FF*	0.174	(2.28)	–0.080	(–0.89)
	OLS	–0.447	(–5.23)	–0.108	(–1.38)	*GP/A*	0.608	(3.96)	–0.149	(–1.62)
	WLS	–0.160	(–2.38)	–0.013	(–0.11)	*GP/A*	0.625	(3.45)	–0.062	(–0.50)
	OLS	–0.518	(–6.00)	–0.091	(–1.20)	*OP_BGLN*	2.312	(7.04)	–0.607	(–2.56)
	WLS	–0.146	(–2.18)	–0.019	(–0.18)	*OP_BGLN*	1.756	(5.05)	0.001	(0.00)
NSI	OLS	–1.200	(–8.00)	–0.069	(–0.43)	*ROE*	0.232	(2.66)	–0.210	(–3.23)
	WLS	–0.776	(–4.77)	0.123	(0.51)	*ROE*	0.232	(2.07)	–0.197	(–1.73)
	OLS	–1.108	(–7.58)	–0.064	(–0.41)	*ROA*	0.904	(2.770	–0.755	(–3.64)
	WLS	–0.766	(–4.44)	0.145	(0.59)	*ROA*	1.216	(3.74)	–0.592	(–1.73)
	OLS	–1.256	(–8.11)	–0.033	(–0.21)	*OP_FF*	0.200	(2.80)	–0.139	(–2.55)
	WLS	–0.795	(–4.99)	0.210	(0.84)	*OP_FF*	0.198	(2.61)	–0.108	(–1.09)
	OLS	–1.082	(–7.19)	–0.100	(–0.63)	*GP/A*	0.549	(3.72)	–0.189	(–2.03)
	WLS	–0.678	(–4.23)	0.093	(0.41)	*GP/A*	0.629	(3.56)	–0.040	(–0.33)
	OLS	–0.970	(–6.83)	–0.085	(–0.56)	*OP_BGLN*	2.013	(6.43)	–0.697	(–2.90)
	WLS	–0.611	(–3.79)	0.191	(0.83)	*OP_BGLN*	1.693	(4.84)	0.070	(0.23)
CSI	OLS	–0.062	(–2.74)	0.055	(1.89)	*ROE*	0.254	(2.86)	–0.205	(–3.18)
	WLS	–0.011	(–0.28)	0.040	(0.97)	*ROE*	0.223	(2.05)	–0.152	(–1.44)
	OLS	–0.067	(–2.99)	0.054	(1.87)	*ROA*	0.985	(3.09)	–0.754	(–3.63)
	WLS	–0.015	(–0.39)	0.051	(1.25)	*ROA*	1.220	(4.05)	–0.508	(–1.55)
	OLS	–0.062	(–2.72)	0.053	(1.82)	*OP_FF*	0.195	(2.71)	–0.131	(–2.45)
	WLS	–0.014	(–0.38)	0.036	(0.85)	*OP_FF*	0.176	(2.38)	–0.085	(–0.92)
	OLS	–0.063	(–2.80)	0.050	(1.81)	*GP/A*	0.635	(4.19)	–0.186	(–1.96)
	WLS	–0.007	(–0.17)	0.028	(0.69)	*GP/A*	0.666	(3.80)	–0.061	(–0.50)
	OLS	–0.076	(–3.51)	0.053	(1.86)	*OP_BGLN*	2.219	(6.90)	–0.705	(–2.85)
	WLS	–0.012	(–0.33)	0.027	(0.64)	*OP_BGLN*	1.800	(5.26)	0.011	(0.04)

Table 9. Probability of the null hypothesis being true using minimum Bayes factors

This table reports Bayesianized *p*-values, given our data, calculated as MBF×prior/(1+MBF×prior) or SD-MBF×prior/(1+SD-MBF×prior). MBF (minimum Bayes factor) and SD-MBF (symmetric and descending-minimum Bayes Factor) are based on the observed time-series *t*-statistic (*t*) and *p*-value (*p*) of the Fama and MacBeth (1973) regression coefficient estimate of interest, where MBF = $\exp(-t^2/2)$ and SD-M*BF* = $-\exp(1)\times p\times \mathrm{Ln}(p)$. The prior odds ratio of the null being true versus the null being false is set at 4-to-1. The null hypotheses are H1: investment does not predict returns, H2: arbitrage frictions do not matter for the investment-return relation ((i) controlling for investment frictions or (ii) using residual arbitrage-frictions rank), and H3: investment frictions do not matter for the investment-return relation ((i) controlling for arbitrage frictions or (ii) using residual investment-frictions rank).

Panel A. MBF-based Bayesianized *p*-values

	Profitability					
	Nil	*ROE*	*ROA*	*OP_FF*	*GP/A*	*OP_BGLN*
Investment	H1: investment does not predict returns					
Estimated by OLS						
TAG	0.000	0.000	0.000	0.000	0.000	0.000
I/A	0.000	0.000	0.000	0.000	0.000	0.000
NOA	0.000	0.000	0.000	0.000	0.000	0.275
NSI	0.000	0.000	0.000	0.000	0.000	0.000
CSI	0.271	0.169	0.169	0.075	0.156	0.055
Estimated by WLS						
TAG	0.046	0.026	0.014	0.007	0.140	0.081
I/A	0.502	0.392	0.392	0.351	0.590	0.000
NOA	0.313	0.262	0.213	0.229	0.229	0.326
NSI	0.001	0.000	0.000	0.000	0.002	0.004
CSI	0.791	0.780	0.755	0.777	0.791	0.783

Table 9 (continued)

	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
	H2: arbitrage frictions do not matter for the investment-return relation									
Estimated by OLS										
TAG	0.000	0.009	0.000	0.046	0.004	0.010	0.000	0.009	0.000	0.001
I/A	0.006	0.032	0.009	0.084	0.020	0.045	0.037	0.123	0.008	0.048
NOA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NSI	0.004	0.040	0.003	0.086	0.003	0.035	0.003	0.037	0.006	0.059
CSI	0.007	0.005	0.005	0.007	0.009	0.004	0.014	0.010	0.004	0.003
Estimated by WLS										
TAG	0.004	0.026	0.006	0.031	0.005	0.032	0.006	0.045	0.004	0.040
I/A	0.026	0.306	0.027	0.288	0.023	0.315	0.041	0.365	0.053	0.406
NOA	0.271	0.641	0.198	0.569	0.176	0.593	0.254	0.597	0.206	0.576
NSI	0.800	0.798	0.797	0.795	0.797	0.790	0.799	0.797	0.796	0.791
CSI	0.406	0.284	0.446	0.237	0.365	0.333	0.415	0.329	0.401	0.333
	H3: investment frictions do not matter for the investment-return relation									
Estimated by OLS										
TAG	0.406	0.706	0.644	0.762	0.388	0.702	0.209	0.561	0.311	0.650
I/A	0.014	0.023	0.038	0.044	0.005	0.008	0.007	0.011	0.020	0.023
NOA	0.695	0.652	0.674	0.604	0.650	0.583	0.632	0.607	0.714	0.661
NSI	0.782	0.785	0.791	0.786	0.796	0.796	0.771	0.766	0.773	0.774
CSI	0.658	0.401	0.658	0.410	0.688	0.433	0.671	0.437	0.655	0.415
Estimated by WLS										
TAG	0.284	0.297	0.090	0.206	0.262	0.254	0.531	0.590	0.406	0.558
I/A	0.765	0.776	0.773	0.776	0.767	0.788	0.736	0.736	0.767	0.757
NOA	0.779	0.795	0.788	0.796	0.788	0.800	0.787	0.799	0.783	0.797
NSI	0.765	0.778	0.750	0.771	0.722	0.738	0.777	0.786	0.750	0.739
CSI	0.655	0.714	0.576	0.647	0.674	0.736	0.706	0.759	0.663	0.765

Table 9 (continued)

Panel B. SD-MBF-based Bayesianized *p*-value

	Profitability					
	Nil	*ROE*	*ROA*	*OP_FF*	*GP*/*A*	*OP_BGLN*
Investment	H1: investment does not predict returns					
Estimated by OLS						
TAG	0.000	0.000	0.000	0.000	0.000	0.000
I/*A*	0.000	0.000	0.000	0.000	0.000	0.000
NOA	0.000	0.000	0.000	0.000	0.000	0.534
NSI	0.000	0.000	0.000	0.000	0.000	0.000
CSI	0.529	0.403	0.231	0.403	0.383	0.181
Estimated by WLS						
TAG	0.159	0.100	0.057	0.032	0.357	0.245
I/*A*	0.711	0.637	0.637	0.605	0.757	0.000
NOA	0.571	0.520	0.463	0.482	0.482	0.583
NSI	0.003	0.001	0.003	0.000	0.008	0.019
CSI	0.712	0.762	0.794	0.768	0.707	0.754

Table 9 (continued)

	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
	H2: arbitrage frictions do not matter for the investment-return relation									
Estimated by OLS										
TAG	0.002	0.040	0.002	0.159	0.017	0.044	0.002	0.038	0.000	0.007
I/A	0.026	0.116	0.040	0.249	0.078	0.155	0.132	0.327	0.036	0.162
NOA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NSI	0.018	0.141	0.014	0.254	0.048	0.125	0.015	0.132	0.026	0.193
CSI	0.032	0.024	0.025	0.032	0.040	0.019	0.059	0.044	0.017	0.012
Estimated by WLS										
TAG	0.019	0.100	0.025	0.114	0.023	0.116	0.028	0.155	0.019	0.141
I/A	0.097	0.564	0.103	0.547	0.090	0.573	0.145	0.616	0.177	0.648
NOA	0.529	0.779	0.443	0.747	0.413	0.759	0.511	0.760	0.453	0.751
NSI	0.147	0.533	0.612	0.649	0.497	0.716	0.476	0.612	0.632	0.712
CSI	0.648	0.543	0.676	0.492	0.616	0.589	0.654	0.585	0.644	0.589
	H3: investment frictions do not matter for the investment-return relation									
Estimated by OLS										
TAG	0.648	0.798	0.780	0.790	0.634	0.797	0.458	0.743	0.568	0.782
I/A	0.057	0.090	0.135	0.152	0.025	0.036	0.031	0.048	0.078	0.090
NOA	0.796	0.783	0.790	0.764	0.782	0.754	0.776	0.765	0.799	0.786
NSI	0.757	0.746	0.707	0.740	0.622	0.622	0.780	0.786	0.777	0.776
CSI	0.785	0.644	0.785	0.651	0.794	0.667	0.790	0.670	0.784	0.654
Estimated by WLS										
TAG	0.543	0.556	0.263	0.453	0.520	0.511	0.727	0.757	0.648	0.741
I/A	0.787	0.772	0.777	0.772	0.784	0.733	0.800	0.800	0.784	0.793
NOA	0.764	0.649	0.733	0.632	0.729	0.147	0.736	0.476	0.754	0.590
NSI	0.787	0.766	0.796	0.780	0.800	0.799	0.770	0.740	0.796	0.799
CSI	0.784	0.799	0.751	0.781	0.790	0.800	0.798	0.792	0.787	0.787

Table 10. The impact of using IVOL and CFVOL as investment frictions proxies

This table reports the estimated slope coefficients γ_3 of the following Fama-MacBeth regressions with *IVOL* and *CFVOL* shifted from the arbitrage-frictions index to the investment-frictions index.

$$(A)\ R_{i,t} = a + \gamma_1 Invest_{i,t-1} + \gamma_2 AF_{i,t-1} + \gamma_3 Invest_{i,t-1} \times AF_{i,t-1} + c_1 IF_{i,t-1} + c_2 Invest_{i,t-1} \times IF_{i,t-1} + c_3 Profit_{i,t-1} + c_4' Controls_{i,t-1} + \epsilon_{i,t}$$

$$(B)\ R_{i,t} = a + \gamma_1 Invest_{i,t-1} + \gamma_2 IF_{i,t-1} + \gamma_3 Invest_{i,t-1} \times IF_{i,t-1} + \gamma_4 Profit_{i,t-1} + \gamma_5 Profit_{i,t-1} \times IF_{i,t-1} + c_1 AF_{i,t-1} + c_2 Invest_{i,t-1} \times AF_{i,t-1} + c_3 Profit_{i,t-1} \times AF_{i,t-1} + c_4' Controls_{i,t-1} + \epsilon_{i,t}$$

$$(C)\ R_{i,t} = a + \gamma_1 Invest_{i,t-1} + \gamma_2 ResAF_{i,t-1} + \gamma_3 Invest_{i,t-1} \times ResAF_{i,t-1} + c_1 Profit_{i,t-1} + c_2' Controls_{i,t-1} + \epsilon_{i,t}$$

$$(D)\ R_{i,t} = a + \gamma_1 Invest_{i,t-1} + \gamma_2 ResIF_{i,t-1} + \gamma_3 Invest_{i,t-1} \times ResIF_{i,t-1} + \gamma_4 Profit_{i,t-1} + \gamma_5 Profit_{i,t-1} \times ResIF_{i,t-1} + c_1' Controls_{i,t-1} + \epsilon_{i,t}$$

All right-hand-side variables, except *AF*, *IF*, *ResAF* and *ResIF* are winsorized at the 0.5^{th} percentile and the 99.5^{th} percentile. The *t*-statistics (*t-stat*) are based on the Newey-West robust standard errors with autocorrelations up to 12 lags and reported in parentheses. The sample period of monthly returns is from the end of June of 1963 to the end of December of 2017.

Invest	Estimation method	*(A)* $\gamma3$	*t-stat*	*(B)* γ_3	*t-stat*	*Profit*	*(C)* γ_3	*t-stat*	*(D)* γ_3	*t-stat*
TAG	OLS	–0.225	(–4.31)	–0.304	(–4.53)	*ROE*	–0.184	(–3.46)	–0.194	(–3.15)
	WLS	–0.263	(–2.34)	–0.058	(–0.52)	*ROE*	–0.165	(–1.36)	–0.105	(–0.99)
	OLS	–0.200	(–3.71)	–0.237	(–3.71)	*ROA*	–0.160	(–2.91)	–0.162	(–2.69)
	WLS	–0.254	(–2.29)	–0.009	(–0.08)	*ROA*	–0.163	(–1.34)	–0.054	(–0.48)
	OLS	–0.230	(–4.42)	–0.300	(–4.36)	*OP_FF*	–0.191	(–3.58)	–0.187	(–2.95)
	WLS	–0.243	(–2.29)	–0.067	(–0.59)	*OP_FF*	–0.142	(–1.21)	–0.108	(–0.99)
	OLS	–0.211	(–4.73)	–0.292	(–4.57)	*GP/A*	–0.173	(–3.23)	–0.189	(–3.36)
	WLS	–0.229	(–2.10)	–0.097	(–0.88)	*GP/A*	–0.134	(–1.11)	–0.120	(–1.11)
	OLS	–0.242	(–4.73)	–0.305	(–4.93)	*OP_BGLN*	–0.198	(–3.81)	–0.197	(–3.55)
	WLS	–0.232	(–2.16)	–0.101	(–0.89)	*OP_BGLN*	–0.131	(–1.10)	–0.131	(–1.20)
I/A	OLS	–0.168	(–1.74)	–0.691	(–5.61)	*ROE*	–0.144	(–1.45)	–0.692	(–5.23)
	WLS	–0.340	(–1.71)	–0.457	(–2.06)	*ROE*	–0.037	(–0.17)	–0.495	(–2.20)
	OLS	–0.140	(–1.42)	–0.647	(–5.30)	*ROA*	–0.114	(–1.11)	–0.664	(–5.06)
	WLS	–0.342	(–1.77)	–0.419	(–1.86)	*ROA*	–0.050	(–0.23)	–0.451	(–2.00)
	OLS	–0.158	(–1.63)	–0.693	(–5.79)	*OP_FF*	–0.137	(–1.36)	–0.696	(–5.42)
	WLS	–0.337	(–1.70)	–0.462	(–2.10)	*OP_FF*	–0.014	(–0.07)	–0.489	(–2.19)
	OLS	–0.129	(–1.33)	–0.663	(–5.47)	*GP/A*	–0.117	(–1.17)	–0.664	(–5.15)
	WLS	–0.295	(–1.59)	–0.491	(–2.15)	*GP/A*	–0.006	(–0.03)	–0.526	(–2.28)
	OLS	–0.156	(–1.63)	–0.646	(–5.47)	*OP_BGLN*	–0.142	(–1.45)	–0.653	(–5.13)
	WLS	–0.285	(–1.50)	–0.510	(–2.22)	*OP_BGLN*	0.011	(0.05)	–0.542	(–2.34)

Table 10 (continued)

Invest	Estimation method	(*A*) $\gamma 3$	*t-stat*	(*B*) γ_3	*t-stat*	*Profit*	(*C*) γ_3	*t-stat*	(*D*) γ_3	*t-stat*
NOA	OLS	–0.122	(–2.33)	–0.267	(–3.16)	*ROE*	–0.124	(–2.36)	–0.285	(–3.29)
	WLS	–0.233	(–2.00)	–0.100	(–0.99)	*ROE*	–0.100	(–0.84)	–0.116	(–1.12)
	OLS	–0.124	(–2.35)	–0.282	(–3.49)	*ROA*	–0.124	(–2.33)	–0.302	(–3.66)
	WLS	–0.251	(–2.26)	–0.110	(–1.06)	*ROA*	–0.107	(–0.93)	–0.117	(–1.12)
	OLS	–0.122	(–2.28)	–0.283	(–3.48)	*OP_FF*	–0.125	(–2.33)	–0.298	(–3.59)
	WLS	–0.230	(–1.93)	–0.119	(–1.16)	*OP_FF*	–0.085	(–0.69)	–0.128	(–1.23)
	OLS	–0.106	(–1.97)	–0.276	(–3.22)	*GP/A*	–0.110	(–2.04)	–0.284	(–3.19)
	WLS	–0.234	(–2.09)	–0.101	(–0.96)	*GP/A*	–0.104	(–0.91)	–0.102	(–0.97)
	OLS	–0.155	(–2.90)	–0.263	(–3.14)	*OP_BGLN*	–0.158	(–2.91)	–0.281	(–3.22)
	WLS	–0.254	(–2.26)	–0.137	(–1.33)	*OP_BGLN*	–0.111	(–0.97)	–0.137	(–1.34)
NSI	OLS	–0.135	(–0.83)	–0.549	(–3.20)	*ROE*	–0.075	(–0.48)	–0.534	(–3.26)
	WLS	0.109	(0.35)	0.109	(0.45)	*ROE*	0.040	(0.13)	0.133	(0.54)
	OLS	–0.104	(–0.66)	–0.515	(–2.87)	*ROA*	–0.050	(–0.33)	–0.493	(–2.91)
	WLS	0.099	(0.33)	–0.017	(–0.07)	*ROA*	0.018	(0.06)	0.045	(0.18)
	OLS	–0.155	(–0.96)	–0.495	(–2.95)	*OP_FF*	–0.096	(–0.61)	–0.463	(–2.85)
	WLS	0.083	(0.28)	0.125	(0.51)	*OP_FF*	0.014	(0.05)	0.124	(0.53)
	OLS	–0.136	(–0.82)	–0.485	(–3.00)	*GP/A*	–0.072	(–0.45)	–0.475	(–2.94)
	WLS	0.151	(0.48)	0.153	(0.61)	*GP/A*	0.085	(0.28)	0.176	(0.72)
	OLS	–0.101	(–0.62)	–0.498	(–3.01)	*OP_BGLN*	–0.033	(–0.21)	–0.485	(–2.98)
	WLS	0.111	(0.36)	0.056	(0.22)	*OP_BGLN*	0.043	(0.15)	0.106	(0.44)
CSI	OLS	–0.051	(–1.95)	–0.017	(–0.53)	*ROE*	–0.051	(–2.00)	–0.001	(–0.04)
	WLS	0.014	(0.33)	–0.048	(–1.23)	*ROE*	0.039	(0.95)	–0.048	(–1.23)
	OLS	–0.050	(–1.93)	–0.016	(–0.52)	*ROA*	–0.050	(–1.92)	–0.003	(–0.08)
	WLS	0.013	(0.31)	–0.036	(–0.95)	*ROA*	0.034	(0.84)	–0.036	(–0.96)
	OLS	–0.051	(–1.96)	–0.021	(–0.69)	*OP_FF*	–0.051	(–1.96)	–0.004	(–0.14)
	WLS	0.022	(0.53)	–0.045	(–1.20)	*OP_FF*	0.042	(1.03)	–0.044	(–1.15)
	OLS	–0.045	(–1.77)	–0.025	(–0.86)	*GP/A*	–0.046	(–1.82)	–0.010	(–0.37)
	WLS	0.026	(0.65)	–0.057	(–1.54)	*GP/A*	0.046	(1.17)	–0.057	(–1.50)
	OLS	–0.052	(–2.07)	–0.021	(–0.70)	*OP_BGLN*	–0.053	(–2.11)	–0.007	(–0.24)
	WLS	0.022	(0.55)	–0.055	(–1.48)	*OP_BGLN*	0.040	(1.01)	–0.061	(–1.57)