Profitability Anomalies and Mispricing: A Cautionary Tale[☆]

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Abstract

We show that limits to arbitrage (especially arbitrage risk) are associated with returns of the gross and cash-based operating profitability anomalies, suggesting mispricing plays a role in their returns and, thus, eliminating them as priced risk factors. In contrast, returns generated from the traditional operating profitability strategy have no relation with barriers to arbitrage and exhibit no evidence of mispricing. Given the differences between the profitability measures are purely definitional, researchers should proceed with caution when searching for risk-related profitability measures. Additionally, SG&A expenses and accruals explain some differential effects of arbitrage risk on the returns to various profitability anomalies.

Keywords: gross profitability, operating profitability, cash-based operating profitability, arbitrage, idiosyncratic volatility, transaction costs, short-sale constraints, investor sophistication, mispricing, SG&A expenses, accruals

JEL Classification: G11; G12

I. Introduction

Previous profitability anomaly studies rely on alternative profitability measures in efforts to find a stronger predictor of future returns. For example, recently examined measures of profitability include gross profitability (Novy-Marx, 2013), operating profitability (Ball et al., 2015), and cash-based operating profitability (Ball et al., 2016). Interestingly, however, redefining profitability may introduce mispricing effects into the definition via certain accounting variables being subject to mispricing; this mispricing would appear as a stronger link between future returns and redefined profitability. Given the proliferation of different profitability measures, it is in the interest of researchers and investors alike to determine if the anomalous returns based on various profitability measures are related to mispricing effects or risk pricing.[1] In this study, we examine the role of limits to arbitrage as an agent of mispricing in various profitability anomalies in order to both rule out prospective candidates from the pool of potential risk factors and to caution those interested in profitability measures against creating new definitions of profitability without considering mispricing effects.

The profitability anomaly has important implications in the asset pricing literature, particularly if profitability is viewed as a priced risk factor.[2] Systematic risk is a key principal of asset pricing because investors expect compensation for bearing such risk. Mispricing, on the other hand, is generated through market imperfections and is beneficial to investors only if the profits available to arbitrageurs outweigh the related costs. Priced risk should be unrelated to mispricing effects; as such, the absence of a relation between return predictability and mispricing is a necessary (but not sufficient) condition in establishing the existence of a priced risk factor. One example of market frictions that could result in

[1] Anecdotal evidence also suggests some professional investment managers pay considerable attention to profitability anomalies. For example, Dimensional Fund Advisors, AQR, and Efficient Frontier Advisors have incorporated measures similar to gross profitability in their trading strategies. Further, a recent article in The Wall Street Journal quotes a money manager as saying "There's something there, I don't think it [gross profitability] can be ignored." http://www.wsj.com/articles/SB10001424127887323293704578334491900368844. For further discussions of gross profitability by industry practitioners, see Forbes (2013) and CFA Institute Magazine (2014).

[2] For example, Fama and French (2015, 2016) argue that the cross-sectional return predictability of firms' operating profitability is consistent with the dividend discount model and, as such, include profitability as an additional risk factor in their asset pricing models. They find that the addition of a profitability factor substantially improves their model's ability to explain stock returns.

seemingly abnormal returns is a systematic mispricing effect due to limits to arbitrage. Since risk-averse rational traders avoid, or are otherwise impeded from, trading stocks with high limits to arbitrage, arbitrage opportunities presented by mispricing are not quickly and completely exploited (Pontiff, 1996; Shleifer and Vishny, 1997; Pontiff, 2006). Accordingly, if limits to arbitrage act as a deterrent for profitability being fully priced, we expect the return predictability associated with profitability measures to be stronger (weaker) for stocks with larger (smaller) limits to arbitrage.[3]

We start by examining stock returns based on three profitability measures with both Fama-MacBeth (1973) cross-sectional regressions and hedge portfolio analyses. We focus our analyses on gross profitability (Novy-Marx, 2013), operating profitability (Ball et al., 2015), and cash-based operating profitability (Ball et al., 2016) ratios because these three measures are shown to have stock return predictability, are incrementally different from each other by just a few accounting variables, and only differ in the numerator of the ratio.[4] The cross-sectional regressions show a strong statistical and economic relation between future returns and all three profitability measures. In addition, consistent with Novy-Marx (2013) and Ball, et al. (2015, 2016), we find that long-short hedge strategies based on gross, operating, and cash-based operating profitability measures earn, respectively, an average (Fama-French (1993)-Carhart (1997) alpha) 58.5, 45.5, and 74.8 (64.1, 47.5, and 73.6) basis points per month. On the surface, it appears that both the gross and cash-based operating profitability strategies outperform the operating profitability strategy. However, the (additional) return predictability of these profitability measures could be due to mispricing effects, not compensation for risk unaccounted for in a factor model.

[3] Previous studies show that limits to arbitrage contribute to a wide variety of asset-pricing anomalies including book-to-market, accruals, momentum, S&P 500 inclusion, post-earnings-announcement drift, insider trading, and ROE (Wurgler and Zhuravskaya, 2002; Ali, Hwang, and Trombley, 2003; Mendenhall, 2004; Mashruwala, Rajgopal, and Shevlin, 2006; Arena, Haggard, and Yan, 2008; Wang and Yu, 2013).

[4] We wish to examine how small, seemingly innocuous changes to the profitability definition may induce mispricing effects. Thus, we concentrate on measures that change the definition of profitability only in the numerator and avoid measures that differ in both the numerator and the denominator, such as the measure in Fama and French (2015) who scale operating profitability less interest expense by book equity. However, in unreported results, an operating probability measure analogous to the Fama and French definition but more consistent with the Ball et al. (2015) measure, operating profitability less interest expense scaled by total assets, we find very similar results to the operating probability measure defined in equation (2).

Next, we examine the effect of limited arbitrage on stock returns based on each profitability measure (i.e. the impact of limited arbitrage on profitability-associated returns). Our proxies for limits to arbitrage include arbitrage risk (idiosyncratic volatility), arbitrage costs (share price, bid-ask spread, and trading volume), short sale constraints (short interest ratio and institutional ownership), and investor sophistication (analyst coverage). Fama-MacBeth (1973) cross-sectional regressions confirm the differential effect of limits to arbitrage on the return predictability in two of profitability measures. The coefficients on the interaction terms between idiosyncratic volatility and profitability measures are significantly positive for gross and cash-based operating profitability measures. Additionally, the coefficients on the interaction terms between the short interest ratio and gross and cash-based operating profitability measures indicate that short sale constraints affect stock returns associated with these profitability measures. Returns associated with gross profitability are also affected by institutional ownership and analyst coverage. However, the results are strongest with respect to arbitrage risk, which supports the notion that idiosyncratic volatility is a sizeable barrier to arbitrage activity (Ali, Hwang, and Trombley, 2003; Pontiff, 2006; Mashruwala, Rajgopal, Shevlin, 2006; Au, Doukas, and Onayev, 2009). In contrast to the results associated with gross and cash-based operating profitability, we find no relation between any of our proxies for limits to arbitrage and the operating profitability measure. In the rest of our analysis, we focus on idiosyncratic volatility as a prominent proxy for limit to arbitrage (Pontiff, 1996; Wurgler and Zhuravskaya, 2002; Stambaugh, Yu, and Yuan, 2015).

Portfolio analyses demonstrate that, for stocks with high idiosyncratic volatility, a long-short strategy based on gross, operating, and cash-based operating profitability measures earns monthly returns of 77.7, 48.9, and 87.9 basis points, respectively. In contrast, for stocks with low idiosyncratic volatility, the same hedge strategy corresponds to monthly returns of 30.8, 35.2, and 22.5 basis points, respectively. Our results show surprising differences in the effect of arbitrage risk on the returns to hedge strategies across profitability anomalies. Specifically, we find that for gross and cash-based operating profitability anomalies, the difference in returns to long-short strategies between stocks with extreme idiosyncratic volatility is statistically and economically significant even after controlling for size, book-to-market, and prior twelve-month stock returns. In sharp contrast, for the operating profitability measure, we find no significant difference in returns to a hedge strategy between stocks with high and low idiosyncratic volatilities.

These results suggest that specific limits to arbitrage play an important role in the returns to long-short strategies based on gross and cash-based operating profitability, suggesting that limited arbitrage imposes a significant barrier for exploiting these anomalies. Thus, the evidence supports a conclusion that the return predictability of these anomalies are driven, at least partially, by systematic mispricing. On the other hand, inconsistent with systematic mispricing, we find no relation between limits to arbitrage and the return to a hedge strategy based on operating profitability. Based on the notion that investors should expect compensation based on the amount of systematic risk they bear and not mispricing, the overall results suggest that gross and cash-based operating profitability (as defined) not be considered as priced risk factors. However, we cannot dismiss a relation between operating profitability and systematic risk based on a mispricing argument.

We further examine the roles of underlying accounting treatments as causes of the differential effects of arbitrage risk on the hedge strategies across profitability anomalies. In contrast to gross profit, that is based on revenue and cost of goods sold (Novy-Marx, 2013), operating profit is obtained by subtracting cost of goods sold and selling, general, and administrative expenses (SG&A), excluding expenditures on research and development, from revenue (Ball et al., 2015). Recent studies document that SG&A expenses represent investments in organizational capital that affect stock returns and value of the firm (Lev and Radhakrishnan, 2005; Eisfeldt and Papanikolaou, 2013; Ball et al., 2015). Cash-based operating profitability excludes accounting accruals (a non-cash component of earnings) (Sloan, 1996) from operating profit (Ball et al., 2016). Mashruwala, Rajgopal, and Shevlin (2006) show that stocks with extreme accruals are associated with high arbitrage risk, making an accruals-based hedge strategy unattractive to arbitrageurs and to professional money managers (Lev and Nissim, 2006; Ali et al., 2008). We find a significantly positive relation between SG&A expenses scaled by total assets and gross profitability, and a significantly negative relation between accruals scaled by total assets and cash-based operating profitability. More importantly, our analysis shows that the respective accounting treatments in profitability measures explain the differential effects of arbitrage risk on the returns of hedge strategies across profitability anomalies. The significantly positive relation between gross (cash-based operating) profitability and arbitrage risk is subsumed by the interaction between SG&A (accruals) and idiosyncratic volatility.

Our study contributes to a large and growing literature that examines the role of limits-to-arbitrage in asset pricing anomalies and provides a cautionary tale about redefining profitability in order to achieve a "better profitability factor." First, we document that gross and cash-based operating profitability anomalies occur due to systematic mispricing, particularly in association with limits to arbitrage. This finding suggests that although arbitrageurs understand the opportunities presented by profitability anomalies, exposure to excessive limits to arbitrage (especially idiosyncratic volatility) discourages them from fully arbitraging the anomalies away. This rationale is consistent with Shleifer and Vishny's (1996) argument that arbitrageurs with limited capital and short investment horizons may be reluctant to heavily trade on anomalies because mispricing could widen unexpectedly in the short run. Hence, since mispricing (via limited arbitrage) serves as an explanation for gross and cash-based operating profitability anomalies, these two measures of profitability should be ruled out as potential priced risk factors. Second, inconsistent with systematic mispricing, we find no relation between limits to arbitrage and the return to a hedge strategy based on operating profitability anomaly. The finding that operating profitability appears to be immune to mispricing due to limits to arbitrage supports the notion that operating profitability remains a potential risk factor that helps to explain the cross section of stock returns (Wahal, 2017). Our study implies that the relation between systematic risk and operating profitability merits further investigation in empirical and theoretical research. Creating new profitability measures should be approached with great thoughtfulness and caution, as our findings suggest that it is rather easy to introduce mispricing effects into the profitability definition. Finally, we provide an accounting based explanation for the differential role of arbitrage risk across profitability anomalies.

The rest of paper is organized as follows. Section II provides background, describes the data and replicates the profitability anomalies for our sample. Section III presents our empirical results. Section IV examines the effects of accounting treatments on the relation between arbitrage risk and the returns to profitability anomalies. Section V presents our conclusion.

II. Background, Data, and Replication of Profitability Anomalies

II.A. Profitability Anomalies

An increasing body of literature documents that profitability anomalies have significant power in cross section of stock returns (Novy-Marx, 2013; Fama and French, 2015; Hou, Xue, and Zhang, 2015; Ball et al., 2015; 2016). These studies show that hedge strategies that are long in high profitability stocks and short in low profitability stocks (hereafter long-short or hedge strategy) yield significant risk-adjusted abnormal returns. Moreover, profitability anomalies subsume most of the earnings-related anomalies (e.g., earnings-to-price), numerous seemingly unrelated anomalies (e.g., failure probability, the distress risk, net stock issuance, and free cash flow) and the accrual anomaly (Chen, Novy-Marx and Zhang, 2011; Novy-Marx, 2013; Ball et al., 2016; Linnainmaa and Roberts, 2018, and Wahal, 2017).

Novy-Marx (2013) argues that gross profitability, as measured in terms of gross profit scaled by total assets, is a cleaner measure of economic profit than alternative measures of profitability because it is unaffected by non-operating items, such as leverage and taxes. Consequently, he shows that a gross profitability measure predicts cross section of stock returns. Ball et al. (2015) argue that selling, general, and administrative (SG&A) expenses represent a significant proportion of business operations costs. To better match current expenses and revenues, they adjust gross profit by deducting SG&A expenses (excluding research and development expenditures), called as operating profit, and find that operating profitability (operating profit scaled by total assets) have a better explanatory power in cross section of stock returns than gross profitability.[5] Finally, Ball, et al. (2016) find that an increase in operating profitability due to a non-cash earnings component (accruals) by Sloan (1996) has no relation with the cross section of stock returns. Thus, they exclude accruals from operating profit and find that the obtained cash-based operating profitability is a significant predictor of future stock performance that effectively subsumes the accrual anomaly (Dechow, 1994; Sloan, 1996).

II.B. Data and Variable Construction

We obtain monthly stock returns from the Center for Research in Security Prices (CRSP) and accounting data from Compustat. Our sample includes all firms traded on the NYSE, Amex, and Nasdaq, and exclude financial firms (i.e., those with the one-digit standard industrial classification (SIC) code of six) and focus only on ordinary common shares. Whenever possible, we adjust stock returns for delisting by using the CRSP file with delisting returns according to the following procedure. If a delisting return is missing, and the delisting is performance-related, we impute a return of -30% (Shumway, 1997; Shumway and Warther, 1999; Beaver, McNichols, and Price, 2007). Then we merge monthly stock returns from CRSP with fiscal year-end accounting information from Compustat lagged by the standard six months. Our sample period spans from July 1963 to December 2016. We also require firms to have no missing values for the market value of equity, book-to-market, current month returns, and returns for the prior one-year period. Similar to Novy-Marx (2013) and Ball et al. (2015, 2016), we compute the gross profitability (GP/TA), operating profitability (OP/TA), and cash-based operating profitability (COP/TA) as follows:

$$\mathrm{GP/TA} = \frac{\mathrm{Revenue\ (REVT)} - \mathrm{COGS}}{\mathrm{Total\ Assets\ (AT)}}, \qquad (1)$$

[5] Linnainmaa and Roberts (2018) and Wahal (2017) document that predictability associated with firm profitability measured as gross and operating profitability anomaly remains significant in out-of-sample forecasts and post-discovery sample periods.

$$\mathrm{OP/TA} = \frac{\text{Revenue (REVT)} - \text{COGS} - \text{SG\&A(XSGA} - \text{XRD)}}{\text{Total Assets (AT)}}, \tag{2}$$

$$\mathrm{COP/TA} = \frac{\text{Revenue (REVT)} - \text{COGS} - \text{SG\&A(XSGA} - \text{XRD)} - \text{Accruals}}{\text{Total Assets (AT)}}, \tag{3}$$

where accruals are calculated by using the balance sheet approach in accordance with Sloan (1996) as follows: [6]

$$\begin{aligned} \text{Accruals} = {} & \Delta\text{Current Assets (ACT)} - \Delta\text{Cash(CH)} - [\Delta\text{Current Liabilities (LCT)} \\ & -\Delta\text{Debt in Current Liabilities (DLC)} - \Delta\text{Income Taxes Payable (TXP)}] \\ & -\text{Depreciation (DP)}, \end{aligned} \tag{4}$$

Following Ball et al. (2015), we compute selling, general, and administrative (SG&A) expenses as Compustat item XSGA minus expenditures on research and development (Compustat item XRD). Because Compustat item XSGA includes XRD, by subtracting XRD we isolate SG&A expenses from the research and development expenditures. For the remainder of this paper, we refer to SG&A expenses as net of research and development expenditure.

Panel A of Table I reports the time-series averages of the cross-sectional means, medians, and standard deviations of the profitability measures as well as the size ($\log(\mathrm{ME})$), book-to-market ($\log(\mathrm{B/M})$), and measures of past performance for one month ($r_{1,0}$), and twelve to two months ($r_{12,2}$). $\mathrm{Log(ME)}$ is the natural logarithm of the market value of equity. $\mathrm{Log(B/M)}$ is the natural logarithm of the book-to-market ratio and defined as the book equity at the end of every June divided by market value of equity from December of the previous year. $r_{1,0}$ is the last one-month return. $r_{12,2}$ is the cumulative return over the second through twelve months with one month lagged. Following Novy-

[6] For a robustness check, following Ball et al. (2016), we also use cash flow statement accruals to convert operating profitability to a cash basis as operating profitability plus the decrease in accounts receivable (RECCH) minus the decrease in inventory (INVCH) minus the increase in accounts payable and accrued liabilities (APALCH) minus the net change in other assets and liabilities minus the increase in accrued income taxes, scaled by total assets (AT). Although not reported for purposes of brevity, we find similar results.

Marx (2013) and Ball et al. (2015, 2016), we winsorize all independent variables at the 1% and 99% levels.

As reported in Table I, the average annual gross, operating, and cash-based operating profitability measures are, respectively, 0.41%, 0.14%, and 0.12% of total assets. The estimates in Table I are comparable those of Novy-Marx (2013) and Ball, et al. (2015, 2016). Panel A reveals significant variation among firms with different profitability measures. The average standard deviations are 0.23%, 0.11%, and 0.14% for gross, operating, and cash-based operating profitability measures, respectively. Table I also reports time-series averages of cross-sectional correlation coefficients among profitability measures. As expected, Panel B shows that operating and cash-based operating profitability measures have the highest average cross-sectional correlation.

II.C. Profitability Anomalies and Cross Section of Stock Returns

In this section, we replicate the findings of Novy-Marx (2013) and Ball et al. (2015, 2016). Panel A of Table II presents the results of Fama and MacBeth (1973) regressions of monthly returns on profitability measures and control variables that include size ($\log(\mathrm{ME})$), book-to-market ($\log(\mathrm{B/M})$), and past performance measures over previous one month ($\mathrm{r}_{1,0}$), and twelve to two months ($\mathrm{r}_{12,2}$). Time-series averages of coefficient estimates are obtained from monthly cross-sectional regressions with *t*–statistics computed from standard errors that are adjusted for heteroskedasticity and serial correlation following Newey and West (1987).

Column (1) of Panel A shows that, for the sample period between 1963 and 2010, the estimated coefficient for gross profitability (GP/TA) (0.846 with *t*–statistic of 5.16) is close to the estimate reported by Novy-Marx (2013). Similarly, for the sample period between 1963 and 2013, columns (2) and (3) confirm the findings of Ball et al. (2015, 2016). The estimated coefficients for OP/TA and COP/TA are 2.203 (*t*–statistic = 5.46) and 2.220 (*t*–statistic = 9.60), respectively. Columns (4) through (6) show corresponding estimates by using an extended sample period up to at the end of December

2016. The coefficients and statistical significance of profitability measures remain similar to the estimates in Novy-Marx (2013) and Ball et al. (2015, 2016). Finally, in column (7) (column (8)) we include both gross and operating (cash-based operating) profitability measures as explanatory variables. Although GP/TA is still positive and significant, after controlling for OP/TA (COP/TA), the coefficient on GP/TA drops from 0.889 with a *t*–statistic of 5.73 to 0.586 with *t*–statistic of 3.11 (0.577 with a *t*–statistic of 3.28). These results are consistent with Ball et al. (2015, 2016) and suggest that operating and cash-based operating profitability measures have greater explanatory powers as predictors of future stock performance than gross profitability measure.

Panel B of Table II reports the estimates of average monthly returns across equally-weighted portfolios sorted by profitability measures using for the sample period of 1963-2016. For each year at the end of June, we form quintile portfolios based on GP/TA, OP/TA, and COP/TA and measure average monthly returns over the next year (from July at year t to June at year t + 1). This procedure generates on average 486 stocks per quintile portfolio. We also compute the differences in returns, as well as the Fama and French (1993) three-factor (α^{3F}) and the Carhart (1997) four-factor alphas (α^{4F}), between extreme profitability quintile portfolios, Q5 – Q1. The average returns increase across the quintiles of profitability measures. For example, firms with the highest gross profitability earn 1.441% per month and those with the lowest gross profitability earn 0.856% per month on average. A similar pattern is observed across different quintiles for operating and cash-based operating profitability measures. The long in high and the short in low profitability stock portfolio strategies earn significant returns. For example, the difference in returns between portfolios of stocks in the highest and lowest gross profitability quintiles is 0.585% with a *t*–statistic of 4.74. A similar pattern is observed across highest and lowest profitability quintiles for operating and cash-based operating profitability measures. Fama and French (1993) three-factor model generates, respectively, 0.709%, 0.643%, and 0.896% using gross, operating, and cash-based operating profitability measures. Even after controlling for the previous twelve month stock returns (momentum), we find that the difference in returns between portfolios in the highest and lowest profitability categories remains statistically significant. Overall, our analysis confirms the presence of profitability anomalies (Novy-Marx, 2013; Ball, et al.; 2015; 2016).

III. Empirical Results

The predictability associated with profitability anomalies has generated a debate over whether these anomalies represent compensation for risk or systematic mispricing (Stambaugh, Yu, and Yuan, 2012; Ball et al., 2015; Akbas et al., 2015; Fama and French, 2015, 2016; Bouchaud et al., 2017). If the profitability anomalies reflect systematic mispricing then professional arbitrageurs would exploit this opportunity and quickly eliminate the mispricing. In this section we examine the role of limits to arbitrage in profitability anomalies. In doing so, we shed light on the extent to which gross, operating, and cash-based operating profitability anomalies are related to mispricing effects.

III.C. Profitability Anomalies: Mispricing and the Effects of Limits to Arbitrage

Arbitrageurs may shy away from fully exploiting profitability anomalies due to arbitrage risk, costs (i.e., transaction costs, short-sale constraints), and investor sophistication. In this section we consider the effect of these barriers to arbitrage on returns to the profitability anomalies. More importantly, we examine the incremental effect of idiosyncratic volatility while taking into account arbitrage costs and investor sophistication measures. Other studies examine a specific barrier to arbitrage and profitability-related returns. For instance, Stambaugh, Yu, and Yuan (2012) find support for an explanation of irrational market mispricing by demonstrating that a strategy of long-short gross profitability is stronger following periods of high investor sentiment. Additionally, Akbas et al. (2015) detect positive future returns to long-short gross profitability strategy following periods of high aggregate mutual fund flows, suggesting that flow-related trades by mutual fund managers contribute to return predictability of gross profitability anomaly. Finally, Bouchaud et al. (2017) present a sticky expectations model and empirically show that profitability anomalies can be explained by market participants' under-reaction to news. We differ from these studies on two important dimensions: we examine several definitions of profitability and investigate many limits to arbitrage simultaneously.

Shleifer and Vishny (1997) argue that when arbitrage is risky, systematic mispricing will not necessarily be quickly and completely traded away. This is because arbitrageurs who face with limited capital and short horizons are unable to foresee shift in noise traders' preferences. In addition, Pontiff (1996; 2006) and Wurgler and Zhuravskaya (2002) argue that the idiosyncratic portion of portfolio volatility cannot be avoided by holding offsetting positions in stocks and indexes as a proxy for the absence of close substitutes or arbitrage risk. Consistent with this notion of idiosyncratic volatility as a barrier to arbitrage, Au, Doukas, and Onayev (2009) demonstrate short sellers concentrate their trades in stocks with low idiosyncratic volatility. Following Ali, Hwang, and Trombley (2003), Ang et al. (2006), Mashruwala, Rajgopal, and Shevlin (2006) and Stambaugh, Yu, and Yuan, (2015), we use the historical volatility of the monthly residuals from the Fama and French (1993) and Carhart (1997) four-factor model ($\mathrm{IVOL_{4F}}$) as a proxy for arbitrage risk. We obtain variances of the residuals from the regressions of monthly stock returns on the returns of the CRSP value-weighted market index or on the Carhart (1997) four factors over the previous 36 months (minimum of 30 months) ending June 30.[7]

We also consider several measures of transaction costs and their effects on profitability anomalies. High stock liquidity enables investors to "buy or sell significant quantities of a security quickly, anonymously, and with minimal or no price impact" (Campbell, Lo, and MacKinlay, 1997), and therefore to freely trade against anomalies. On the other hand, entry barriers in the form of transaction costs can prevent investors from arbitraging away profitability anomalies. To examine the effects of liquidity and transaction costs on the return to a long-short strategy based on profitability anomalies, we follow the previous literature and use several measures that capture different aspects of liquidity and

[7] In the alternative specification for expected arbitrage risk proxy, we use daily instead of monthly stock returns to regress it on the returns of the CRSP value-weighted market index or the Carhart (1997) four factors over the previous 250 days ending June 30 and we then compute the variance of the residuals. Although not reported for purposes of brevity, the main results remain intact. This procedure is similar to Ang et al., 2006.

transaction costs. Specifically, we use share price (Price) and dollar trading volume (Volume) in the same way as Ali, Hwang, and Trombley (2003) and Mashruwala, Rajgopal, and Shevlin (2006). Additionally, bid-ask spread (BidAsk) also contributes to the cost associated with arbitraging mispriced stocks (e.g. Bhardwaj and Brooks, 1992; Lam and Wei, 2011).

Share price is used as a proxy for transaction costs (Ball, Kothari, and Shanken, 1995) because it is inversely related to direct transaction costs such as quoted bid-ask spreads and trading commissions. Share price is the closing price per share at the end of June. We exclude stocks with the share prices of less than five dollars. Volume is the proxy for transaction costs and liquidity (Bhushan, 1994; Chordia, Roll, and Subrahmanyam, 2001). It is computed as the daily closing price multiplied by the daily shares traded, averaged over the preceding twelve-month period at the end of June. We adjust the turnover of Nasdaq stocks by a factor of a half to account for double counting on Nasdaq (Atkins and Dyl, 1997; Nagel 2005). Firm size is a potential proxy for arbitrage costs, investor sophistication, and firm liquidity, and is the market value of equity. It is measured as stock price times the number of shares outstanding for each firm at the end of June. Share prices, number of shares outstanding, and trading volumes are obtained from CRSP stock data file over the full sample period of July 1963 to December 2016. If the profitability anomalies are due to transaction costs, then we should expect the anomalies to be stronger among stocks with higher transactions costs and lower liquidity. That is, we expect a negative coefficient on the interaction term between share price (or volume) and profitability anomalies.

Arbitrage costs may be also affected by stock availability. Ali, Hwang, and Trombley (2003) argue that short sellers face less risk of a "short squeeze" if more stocks are available for institutional investors which, consequently, makes it easier to arbitrage and reduces arbitrage costs. Moreover, institutional investors are considered to be active and sophisticated market participants who can identify mispriced stocks and trade against anomalies (Chichernea, Ferguson, and Kassa, 2015). Additionally, extant literature also documents that analysts following stocks facilitate information exchange and improve investors' sophistication (Walther, 1997; Hong, Lim, and Stein, 2000). Hence, short sellers, analysts following, and institutional investors may influence barriers to arbitrage. If the profitability anomalies are due to limits to arbitrage, then we should expect the anomalies to be stronger among stocks with higher arbitrage costs and lower investor sophistication. That is, we expect a negative coefficient on the interaction term between short-sale constraints (or investor sophistication) measures and profitability anomalies.

As a proxy for short-sale constraints, we use the short interest ratio and percentage of institutional investors, as suggested by previous studies (Ali, Hwang, and Trombley, 2003; D'Avorio, 2002; Nagel, 2005; Asquith, Pathak, Ritter, 2005). Short interest ratio (Short) is the number of shares sold short divided by the number of shares outstanding. Compustat provides the monthly short interest data. We define percentage of institutional investors (IOWN) at the end of a year as the total number of shares held by institutions divided by the total number of shares outstanding. As the measures of investor sophistication, we use the average number of analysts following a stock over the preceding twelve months at the end of June (#Analyst). Institutional ownership (IOWN) is obtained from the 13-F Thomson Financial database and the number of analysts following is obtained from the I/B/E/S database. We assign zero analysts to a firm if such firm is not present in the I/B/E/S database, following Ali, Hwang, and Trombley (2003) and Bhushan (1994). Since the 13-F Thomson Financial database is from 1980, our analysis using IOWN is limited to the period between 1980 and 2016.

We now turn to examining the role of limited arbitrage in profitability anomalies in a multivariate framework. Consistent with Mashruwala, Rajgopal, and Shevlin (2006) and the procedure described in the previous section, at the end of each June stocks are ranked into five profitability quintiles (Q1 (Low) to Q5 (High)) based on gross, operating, or cash-based operating profitability measures. Independent of the profitability rankings, we further rank stocks into five groups based on the magnitudes of each limit to arbitrage or profitability (highest quintile is assigned rank of 5 and lowest is assigned rank of 1). We then transform the each of the rank measures so that they take the values ranging between -0.5 and 0.5, denoted as $\mathrm{Variable}^{\mathrm{Rank}}$ (e.g. $\mathrm{Prof}^{\mathrm{Rank}}$ of -0.5 represents the lowest quintile of profitability). As noted in Bernard and Thomas (1990) and Mashruwala, Rajgopal, and Shevlin (2006), this procedure has the advantage that the coefficient on $\mathrm{Prof}^{\mathrm{Rank}}$ can be interpreted as returns to zero-investment profitability portfolio.[8]

Next, we estimate the following cross-sectional regression for every month:

$$\begin{aligned} r_{it} = \alpha_t + \beta_{1t}(\mathrm{Profitability}_{it-1}^{\mathrm{Rank}} \times \text{Limit to Arbitrage}_{ijt-1}^{\mathrm{Rank}}) + \beta_{2t}\mathrm{Profitability}_{it-1}^{\mathrm{Rank}} \\ +\beta_{3t}\text{Limit to Arbitrage}_{it-1}^{\mathrm{Rank}} + \beta_{4t}\mathrm{Controls}_{it-1} + \varepsilon_{it}\,, \end{aligned} \tag{5}$$

where r_{it} is monthly return for stock *i* at month *t*. $\mathrm{Profitability}_{it-1}^{\mathrm{Rank}}$ is the scaled profitability quintile rank of stock *i* at the end of each June, and $\text{Limit to Arbitrage}_{ijt-1}^{\mathrm{Rank}}$ is the scaled limit to arbitrage quintile rank of limit to arbitrage *j* of stock *i* in year *t-1*. Although not reported for purposes of brevity, our results are similar if we do not scale profitability ranks and limit to arbitrage ranks. Control variables include size ($\log(\mathrm{ME})$), book-to-market ($\log(\mathrm{B/M})$), and past performance measured at horizons of one month ($r_{1,0}$), and twelve to two months ($r_{12,2}$). The regressions in Eq. (5) are estimated for each month using cross-sectional stock returns following the Fama and MacBeth (1973) procedure.

Table III reports the results of cross-sectional regressions, with time-series averages of monthly coefficient estimates with *t*–statistics computed from standard errors adjusted for heteroskedasticity and serial correlations following Newey and West (1987). Transaction costs appear in Panel A and short-sale constraints and investor sophistication variables in Panel B. Using the procedures already described, we rank measures of short-sale constraints, investor sophistication, and transaction costs into their respective quintiles. The results in Panel A show that the interaction between share price and gross profitability measure is significantly negative (columns 1 and 4). A similar effect is observed for the cash-based operating profitability measure (column 12) but not for the operating profitability measure. Similarly, columns (1) and (4) of Panel B show that the interaction variable between short-sale constraints ($\mathrm{Short}^{\mathrm{Rank}}$ and $\mathrm{IOWN}^{\mathrm{Rank}}$) and gross profitability is significantly negative, which supports

[8] The ranking process is executed as follows: Every year, we assign a quintile-based rank from one to five to each profitability and limit to arbitrage variable. We then transform this rank by subtracting one and dividing by 4. Finally, we subtract 0.5 from each of these transformed ranks so that the quintile ranks range from -0.5 to 0.5.

the notion that returns to gross profitability-based hedging are greater for firms with lower short-sale constraints. Also, as shown in Column (15), the interaction between short-sale constraints and cash-based operating profitability is negative and significant. On the other hand, the interaction between short-sale constraints and the operating profitability measures are statistically insignificant. In addition, we find no significant relation between investor sophistication ($\text{\#Analyst}^{\text{Rank}}$) and the gross and cash-based operating profitability measures. The lack of relation between investor sophistication and these profitability measures is consistent with the recent study by Edelen, Ince, and Kadlec (2016) who document the limited interest of institutional investors in these anomalies. More importantly, in both panels the interaction term between $\text{Prof}^{\text{Rank}}$ and $\text{IVOL}_{\text{4F}}^{\text{Rank}}$ remains positive and significant for gross and cash-based operating profitability measures, suggesting that the incremental explanatory power of arbitrage risk is robust to arbitrage costs and barriers.

These findings are consistent with the previous literature. For example, Ali, Hwang, and Trombley (2003) and Mashruwala, Rajgopal, and Shevlin (2006) also find no significant effects of short-sale constraints, investor sophistication, and transaction costs on book-to-market and accrual anomalies. We also perform portfolio analyses similar to Table IV but with measure of transaction costs, short-sale constraints, and investor sophistication. Although the results are not reported for purposes of brevity, we find that the returns to a long-short strategy based on gross and cash-based operating profitability are stronger for stocks with higher (lower) short-sale constraints (stock prices). On the other hand, we again find no significant relation between these variables and operating profitability. The results also support the notion that idiosyncratic volatility is a major deterrent for arbitrage activity (Ali, Hwang, and Trombley, 2003; Mashruwala, Rajgopal, and Shevlin, 2006; Pontiff, 2006). Since IVOL is shown to be a powerful barrier to arbitrage, we focus on it specifically in the rest of our analyses.

III.D. Profitability Anomalies and Arbitrage Risk

Consistent with the procedure described in the previous section, at the end of each June stocks are ranked into five profitability quintiles (Q1 (Low) to Q5 (High)) based on gross, operating, or cash-based operating profitability measures. For robustness purposes, we use two proxies for idiosyncratic volatility by obtaining variances of the residuals from both the regressions of monthly stock returns on the returns of the CRSP value-weighted market index and on the Carhart (1997) four factors over the previous 36 months (minimum of 30 months) ending June 30, denoted $\mathrm{IVOL}_{\mathrm{1F}}$ and $\mathrm{IVOL}_{\mathrm{4F}}$, respectively. Independent of the profitability rankings, we further rank stocks into five groups based on the magnitudes of arbitrage risk proxies, $\mathrm{IVOL}_{\mathrm{1F}}$ or $\mathrm{IVOL}_{\mathrm{4F}}$. For example, stocks in the highest (lowest) idiosyncratic volatility are assigned to $\mathrm{IVOL}^{\mathrm{Group}}$=5 ($\mathrm{IVOL}^{\mathrm{Group}}$=1). Table IV reports the time series means of cross-sectional averages of idiosyncratic volatility groups ($\mathrm{IVOL}_{\mathrm{1F}}^{\mathrm{Group}}$ and $\mathrm{IVOL}_{\mathrm{4F}}^{\mathrm{Group}}$) across five profitability quintiles corresponding, respectively, to gross, operating, and cash-based operating profitability measures in Panels A, B, and C. The table also shows differences in average idiosyncratic volatility groups between high and low, high and medium, and medium and low profitability portfolios. The medium portfolio is an equal-weighted portfolio created using the second, third, and fourth quintile portfolios.

Table IV shows that, across the different profitability measures in Panels A, B, and C, stocks in the extreme low profitability quintiles have higher IVOL rankings. In other words, idiosyncratic volatility is higher for stocks in the low profitability quintiles than in those of high or medium profitability quintiles. Consistent with Stambaugh, Yu, and Yuan (2012), this finding suggests that mispricing is more likely to be prevalent among stocks in the short-leg of the profitability strategies. Panel A shows that stocks in extreme high gross profitability quintile exhibit significantly higher idiosyncratic volatility than stocks in the medium gross profitability quintile. In contrast, for the operating profitability in Panel B and the cash-based operating profitability in Panel C, the difference in $\mathrm{IVOL}_{\mathrm{1F}}^{\mathrm{Group}}$ (and $\mathrm{IVOL}_{\mathrm{4F}}^{\mathrm{Group}}$) between the high and medium profitability quintiles is not significant at any conventional level. Overall, this analysis indicates that arbitrage risk may play an important role in explaining the profitability anomalies associated with gross, operating, and cash-based operating profitability measures.

We now turn to examining the role of arbitrage risk in profitability anomalies in a multivariate framework, using two measures of idiosyncratic volatility. We estimate the following cross-sectional regression for every month:

$$\begin{aligned} \mathrm{r_{it}} = \alpha_t + \beta_{1t}(\mathrm{Profitability}^{\mathrm{Rank}}_{\mathrm{it-1}} \times \mathrm{IVOL}^{\mathrm{Rank}}_{\mathrm{it-1}}) + \beta_{2t}\mathrm{Profitability}^{\mathrm{Rank}}_{\mathrm{it-1}} \\ +\beta_{3t}\mathrm{IVOL}^{\mathrm{Rank}}_{\mathrm{it-1}} + \beta_{4t}\mathrm{Controls}_{\mathrm{it-1}} + \varepsilon_{\mathrm{it}}\,, \end{aligned} \tag{6}$$

where $\mathrm{r_{it}}$ is monthly return for stock *i* at month *t*. $\mathrm{Profitability}^{\mathrm{Rank}}_{\mathrm{it-1}}$ is the scaled profitability quintile rank of stock *i* at the end of each June, and $\mathrm{IVOL}^{\mathrm{Rank}}_{\mathrm{it-1}}$ is the scaled idiosyncratic volatility quintile rank of stock *i* in year *t-1*. Similar to the previous analysis, we rank the values of profitability measures (separately for gross, operating, and cash-based operating profitability) and idiosyncratic volatility measures for every firm into quintiles for each year and transform the profitability rank measures so that profitability and IVOL measures take the values ranging between -0.5 and 0.5, denoted as profitability rank ($\mathrm{Prof}^{\mathrm{Rank}}$). Similarly, $\mathrm{IVOL}^{\mathrm{Rank}}$ is the scaled annual quintile rank for idiosyncratic volatility measures: $\mathrm{IVOL_{1F}}$ or $\mathrm{IVOL_{4F}}$. Control variables are again size ($\log(\mathrm{ME})$), book-to-market ($\log(\mathrm{B/M})$), and past performance measured at horizons of one month ($\mathrm{r_{1,0}}$), and twelve to two months ($\mathrm{r_{12,2}}$). The regressions in Eq. (6) are estimated for each month using cross-sectional stock returns following the Fama and MacBeth (1973) procedure.

Table V reports the results of the regression using Eq. (6) in terms of average coefficients, including the interaction term between scaled firm profitability and idiosyncratic volatility quintile ranks ($\mathrm{Prof}^{\mathrm{Rank}} \times \mathrm{IVOL}^{\mathrm{Rank}}$). Consistent with our earlier findings in Section II.B., the coefficients on $\mathrm{Prof}^{\mathrm{Rank}}$ are significantly positive across all panels, highlighting the significant predictability associated with profitability measures. The results in Table V demonstrates significant differences in the incremental role of arbitrage risk on the returns to long-short strategies. For example, for the gross profitability anomaly in Panel A, the coefficients of the interaction between gross profitability and idiosyncratic volatility measures are significantly positive in columns (1) and (2). To put the incremental effect of idiosyncratic volatility into perspective, the stocks in the highest gross profitability portfolio quintile ($\mathrm{Prof}^{\mathrm{Rank}}$ = 0.5) and highest idiosyncratic quintile ($\mathrm{IVOL}_{\mathrm{4F}}^{\mathrm{Rank}}$ = 0.5) in column (1), have average monthly returns of 0.400% (0.006 × 0.5 + 0.004 × (0.5 × 0.5)). In contrast, average monthly returns for firms in the highest gross profitability quintile ($\mathrm{Prof}_{\mathrm{GP}}^{\mathrm{Rank}}$ = 0.5) and lowest idiosyncratic volatility quintile ($\mathrm{IVOL}_{\mathrm{4F}}$ = -0.5) are 0.200% (0.006 × 0.5 + 0.004 × (0.5 × -0.5)). These results suggest that arbitrage risk significantly contributes to the gross profitability anomaly. In contrast, columns (3) and (4) of Panel B show no incremental role of arbitrage risk on the returns to a hedge strategy based on an operating profitability anomaly. This is because the coefficients of the interaction term between operating profitability and idiosyncratic volatility measures are not significant at any conventional level. Finally, similar to the gross profitability anomaly in Panel A, cash-based operating profitability in Panel C shows positive and significant coefficients for the interaction terms. This suggests that the returns to a cash-based operating profitability strategy are also increasing in idiosyncratic volatility.

The results in Table V show that the coefficients of $\mathrm{Prof}^{\mathrm{Rank}}$ are positive and significant even when interaction with idiosyncratic volatility is included. Hence, arbitrage risk only partially subsumes the predictive power of gross and cash-based operating profitability measures. We interpret these results as evidence that the cross-sectional return predictability associated with these measures is not completely attributable to mispricing. It is also noteworthy that the coefficients of idiosyncratic risk are not statistically significant at any conventional level. This result is consistent with Huang et al. (2010) who find that idiosyncratic volatility is merely a manifestation of a short-term stock reversal. Specifically, they show that idiosyncratic volatility no longer predicts cross section of future stock returns when past returns ($\mathrm{r}_{1,0}$) are taken into account.[9]

[9] Although whether idiosyncratic risk is priced in asset returns has been subject to considerable attention in the literature, the empirical results so far are mixed. For literature on the relation between idiosyncratic volatility and the cross section of stock returns, see, among others, Malkiel and Xu (2002), Bali et al. (2005), Bali and Cakici (2008),

Turning now to the effect of arbitrage risk on the returns to hedge strategies based on profitability anomalies, Table VI reports the returns to a long-short hedge strategy based on profitability anomalies for stocks in the high ($\mathrm{IVOL}^{\mathrm{Group}}$=5) and low ($\mathrm{IVOL}^{\mathrm{Group}}$=1) idiosyncratic volatility groups. Panels A, B, and C present results for gross, operating, and cash-based operating profitability, respectively. In each panel, we also report the differences in returns to the long-short (Q5 – Q1) strategy between the high ($\mathrm{IVOL}^{\mathrm{Group}}$=5) and low ($\mathrm{IVOL}^{\mathrm{Group}}$=1) idiosyncratic volatility groups. These panels also show the corresponding return differences adjusted based on the Fama-French (1993) three-factor ($\alpha^{3\mathrm{F}}$) and the Carhart (1997) four-factor models ($\alpha^{4\mathrm{F}}$).

Based on the gross profitability ranking in Panel A, the return to portfolio of stocks with the highest idiosyncratic volatility is more than twice the return to portfolio of stocks with the lowest idiosyncratic volatility. Specifically, the difference in the returns to long-short (Q5 – Q1) hedge strategy is 0.777% (*t*–statistic = 4.25) for the stocks with the highest idiosyncratic volatility ($\mathrm{IVOL}_{1\mathrm{F}}^{\mathrm{Group}} = 5$) and 0.308% (*t*–statistic = 3.02) for the stocks with the lowest idiosyncratic volatility ($\mathrm{IVOL}_{1\mathrm{F}}^{\mathrm{Group}} = 1$). The difference in Q5 – Q1 between the extreme $\mathrm{IVOL}_{1\mathrm{F}}$ groups is economically significant, 0.469% per month with a *t*-statistic = 2.79. It remains significant even after controlling for size, book-to-market, and momentum factors. In sharp contrast, Panel B shows no difference in the returns to long-short hedge strategies based on operating profitability between the high and low idiosyncratic volatility groups. Finally, the results for cash-based operating profitability in Panel C show that the returns to a long-short hedge strategy are almost four times higher for the high idiosyncratic volatility group than for the low idiosyncratic volatility group. Similar to the results in Panel A, in Panel C the difference in returns between the extreme $\mathrm{IVOL}_{1\mathrm{F}}$ groups is statistically significant, 0.654% per month with *t*–

Chua, Goh, and Zhang (2010), Ang et al. (2006), Boehme et al. (2009), Jiang, Xu, and Yao (2009), Chen, Chollete, and Ray (2010), Fink, Fink, and He (2012), and Guo, Kassa, and Ferguson (2014).

statistic = 3.93. It remains significant after accounting for size, book-to-market, and momentum factors. Similar results are found when idiosyncratic risk is calculated based on $\mathrm{IVOL_{4F}}$ (right hand side of Table IV).

These findings reveal the differential effects of arbitrage risk on the returns to long-short strategies of different profitability anomalies. Specifically, the profitability associated with the hedge strategy based on gross profitability by Novy-Marx (2013) and cash-based operating profitability by Ball et al. (2016) is concentrated in firms with high idiosyncratic return volatility. In sharp contrast, we find no significant relation between arbitrage risk and the returns to a hedge strategy based on operating profitability by Ball et al. (2015). As shown in Table IV, our results are not driven by a small number of observations. Table IV also reports, for each idiosyncratic volatility group, $\mathrm{IVOL^{Group}}$=5 and $\mathrm{IVOL^{Group}}$=1, the average number of stocks that fall in the high (Q5) and low (Q1) profitability quintiles. For example, for $\mathrm{IVOL_{1F}^{Group}}$=5 ($\mathrm{IVOL_{1F}^{Group}}$=1), the average numbers of firms in the highest and lowest gross profitability quintiles are 81 and 66 (80 and 90) out of the average number of 486 stocks in each quintile as sorted according to profitability measures.

Overall, our results show surprising differences in the effect of arbitrage risk on the returns to hedge strategies across profitability anomalies. Specifically, arbitrage risk plays an important role in the cross section return predictability of gross and cash-based operating profitability anomalies. Although arbitrageurs are aware of the well-documented stock return predictability associated with gross and cash-based operating profitability anomalies, excessive exposure to idiosyncratic volatility prevents them from eliminating the mispricing. In sharp contrast, inconsistent with systematic mispricing, we find that arbitrage risk has no incremental effect on the return to a hedge strategy based on operating profitability by Ball et al. (2015). The lack of relation between arbitrage risk and the operating profitability anomaly further supports the notion that the operating profitability anomaly could be related to systematic risk as argued by Ball et al. (2015), Fama and French (2015, 2016), and Wahal

(2017). In Section IV, we further explore a potential explanation for the differential effects of arbitrage risk on hedge strategies across profitability anomalies.[10]

IV. Further Analysis

We so far have established two key findings. First, the effect of arbitrage risk on the predictability of profitability anomalies varies across profitability measures. Gross profitability (Novy-Marx, 2013) and cash-based operating profitability (Ball et al., 2016) are greater for firms with high idiosyncratic volatility, making these anomalies risky for arbitrageurs to exploit. In sharp contrast, no significant association exists between operating profitability (Ball et al., 2015) and idiosyncratic volatility. Second, the differential effect of arbitrage risk remains significant even after accounting for transaction costs, short-sale constraints, and investor sophistication. In the next section, we further investigate the differential role of arbitrage risk on return predictability across profitability anomalies.

IV.A. Univariate Analysis of Profitability Measures, Arbitrage Risk, SG&A Expenses, and Accruals

Although profitability measures pertain to profit margins, as discussed in Section II.A., these measures differ how they assess firm profitability. In contrast to gross profitability measure that takes into account only revenues and cost of goods sold (Novy-Marx, 2013), operating profitability excludes SG&A expenses (net of research and development expenditures) from gross profit (Ball et al., 2015). Lev and Radhakrishnan (2005) argue that SG&A expenses represent organizational capital and significantly affect firm performance and value.[11] Recent studies find a significant relation between SG&A expenses and the cross section of stock returns (Eisfeldt and Papanikolaou, 2013; Ball et al., 2015). Cash-based operating profitability removes accounting accruals from operating profitability (Ball

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[10] This also has the additional benefit of examining a longer sample period than that used for the analysis reported in Table III.

[11] Lev, Radhakrishnan, and Evans (2016) provide an excellent literature review on organizational capital.

et al., 2016). Mashruwala, Rajgopal, and Shevlin (2006) show that return to a hedge strategy based on accruals is especially pronounced in firms with high idiosyncratic volatility, suggesting that excessive arbitrage risk associated with extreme accruals makes the strategy unattractive to arbitrageurs and professional money managers (Lev and Nissim, 2006; Ali et al. 2008).

To explore the relation between SG&A expenses, accruals, profitability anomalies, and idiosyncratic volatility, we rank stocks into quintiles (Q1 (Low) to Q5 (High)) according to the magnitude of SG&A expenses (SG&A/TA) and according to accruals (Accruals/TA), both scaled by total assets. Similar to the procedure described in Section III, independent of SG&A expenses and accruals rankings, stocks are further assigned into their corresponding quintile groups based on profitability measures and idiosyncratic risk (i.e., $\mathrm{GP/TA^{Group}}$, $\mathrm{OP/TA^{Group}}$, $\mathrm{COP/TA^{Group}}$, and $\mathrm{IVOL^{Group}}$). Table VII reports the time series means of a cross-sectional average ranking groups of profitability and idiosyncratic risk measures across five quintiles of SG&A/TA in Panel A and Accruals/TA in Panel B. The table also presents differences between high and low, high and medium, and medium and low SG&A/TA (Accruals/TA) portfolios.

Table VII reveals the differences in SG&A expenses and accruals across profitability measures. In Panel A we find a strong monotonic relation between SG&A expenses and gross profitability. The difference in the $\mathrm{GP/TA^{Group}}$ between the extreme SG&A/TA quintiles is 3.208 (significant at the 1% level). In contrast to gross profitability, the difference between the extreme portfolios across SG&A quintiles is smaller for operating and cash-based operating profitability measures. In addition, neither operating nor cash-based operating profitability measures exhibit a monotonic association with SG&A expenses. Panel A also shows that idiosyncratic volatility in the top SG&A/TA quintile is significantly higher than in the medium and bottom SG&A/TA quintiles, suggesting a significant relation between SG&A expenses and idiosyncratic volatility. Furthermore, Panel B shows a stronger monotonic relation of accruals with cash-based operating profitability measure than with gross and operating profitability measures. Idiosyncratic volatility in the extreme accruals groups is significantly higher than in the intermediate accruals quintiles. That is, consistent with the findings of Mashruwala, Rajgopal, and

Shevlin (2006), Accruals/TA has a U-shaped relation with idiosyncratic return volatility. In summary, these results illustrate that profitability measures and idiosyncratic risk differ, depending on the values of SG&A expenses and accruals.

IV.B. Profitability Anomalies and Idiosyncratic Volatility: The Effects of SG&A Expenses and Accruals

To the extent that stocks in the extreme SG&A expenses and accrual quantiles are associated with mispricing, differences in these accounting treatments in profitability anomalies may explain the differential effect of arbitrage risk on long-short hedge strategies based on profitability measures. To examine the effects of SG&A expenses and accruals, we augment Eq. (6) to include $(\mathrm{SG\&A/TA})^{\mathrm{Rank}}$ and $(\mathrm{Accruals/TA})^{\mathrm{Rank}}$. As described in Section III.B., $(\mathrm{SG\&A/TA})^{\mathrm{Rank}}$ and $(\mathrm{Accruals/TA})^{\mathrm{Rank}}$ are the scaled annual quintile ranks for SG&A expenses and accruals scaled by total assets, correspondingly. Table VIII reports time-series averages of coefficient estimates obtained from monthly cross-sectional regressions with *t*–statistics computed from standard errors adjusted for heteroskedasticity and serial correlations following Newey and West (1987).

Consistent with the previous literature (Sloan, 1996; Eisfeldt and Papanikolaou, 2013; Ball et al., 2015), we find a significantly positive (negative) relation between SG&A expenses (accruals) and the cross section of stock returns. Moreover, the coefficients of the interaction terms between SG&A expenses and idiosyncratic volatility measures are significantly positive in columns (1) and (2). This suggests that the effects of SG&A expenses on returns are amplified for stocks with higher arbitrage risk. Consistent with Mashruwala, Rajgopal, and Shevlin (2006), the coefficients of the interaction terms between accruals and idiosyncratic volatility measures, $(\mathrm{Accruals/TA})^{\mathrm{Rank}} \times \mathrm{IVOL}^{\mathrm{Rank}}$, in columns (3) and (4) are significantly negative. The results in columns (1) to (4) suggest that a hedge strategy that is long in high SG&A (low accruals) stocks and short in low SG&A (high accruals) stocks generates additional returns when stocks in the extreme SG&A (accruals) portfolios have high idiosyncratic volatility. Next, we include both gross profitability and SG&A expenses with the interaction terms between these variables and arbitrage risk. The results in columns (5) and (6) show that although the coefficients on $(\mathrm{SG\&A/TA})^{\mathrm{Rank}} \times \mathrm{IVOL}^{\mathrm{Rank}}$ remain significant and positive, the interaction term between gross profitability and idiosyncratic volatility becomes statistically insignificant. Similarly, columns (7) and (8) show that after accounting for $(\mathrm{Accruals/TA})^{\mathrm{Rank}} \times \mathrm{IVOL}^{\mathrm{Rank}}$, there is no significant relation between stock returns and the interaction terms between measures of cash-based operating profitability and arbitrage risk. Overall, these results, relative to the results in Table V, suggest that the differences in the effects of arbitrage risk on the returns to gross and cash-based operating profitability measures can be attributed to the exposure of these anomalies to SG&A expenses and accruals.

V. Conclusion

Recent studies document that gross, operating, and cash-based operating profitability measures have a significant predictive power in cross section of stock returns (Novy-Marx, 2013; Ball et al., 2015; 2016). These anomalies have attracted significant attention in the literature and have motivated inclusion of additional factors in the traditional asset pricing models (Fama and French, 2015, Chen, Novy-Marx, and Zhang, 2011, Barinov, 2015). Nevertheless, whether these anomalies represent compensation for risk or systematic mispricing continues to be debated in the literature (Stambaugh, Yu, and Yuan, 2012; Ball et al., 2015; Akbas et al., 2015; Fama and French, 2015, 2016; Bouchaud et al., 2016).

In this study, we investigate the effect of limits to arbitrage on profitability anomalies in search of evidence of mispricing effects. If limited arbitrage prevents profitability measures from being fully priced, causing mispricing (Shleifer and Vishny, 1997), we expect profitability anomalies to be stronger for stocks with higher barriers to arbitrage. Our results show that the return predictability of gross and cash-based operating profitability measures is related to limits to arbitrage (particularly arbitrage risk), which supports a systematic mispricing relation, not a risk one. On the other hand, inconsistent with systematic mispricing, we find no evidence that arbitrage risk is related to the predictive power of operating profitability. This finding provides an additional support that operating profitability anomaly could represent compensation for risk (Ball et al., 2015; Fama and French, 2015, 2016). Thus, gross and cash-based operating profitability anomalies should not be considered as potential priced risk factors since mispricing (via limited arbitrage) serves as an explanation for these anomalies. Additionally, we cannot rule out operating profitability as a priced risk factor as it appears to be immune to mispricing associated with limited arbitrage. Finally, we show that the differential effects of idiosyncratic volatility on returns to a long-short strategy across gross, operating, and cash-based operating profitability anomalies are attributable to their respective accounting treatments. Overall, the evidence suggests those interested in either using a particular profitability strategy or considering refining a profitability measure use caution and recognize mispricing rather than risk may be imbedded in profitability strategies depending on the definition of profitability. While we cannot eliminate operating profitability as a type of systematic risk, more research is required to confirm it is a priced risk factor.

References

Akbas, F., W. J. Armstrong, S. Sorescu, and A. Subrahmanyam, 2015, "Smart Money, Dumb Money, and Capital Market Anomalies," *Journal of Financial Economics* 118, 355-382.

Ali, A., L. S. Hwang, and M. A. Trombley, 2003, "Arbitrage Risk and the Book-to-Market Anomaly," *Journal of Financial Economics* 69, 355-373.

Ali, A., X. Chen, T. Yao, and T. Yu, 2008, "Do Mutual Funds Profit from the Accruals Anomaly?" *Journal of Accounting Research* 46, 1-26.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang, 2006, "The Cross-Section of Volatility and Expected Returns," *Journal of Finance* 51, 259–299.

Arena, M. P., K.S. Haggard, and X. Yan, 2008, "Price Momentum and Idiosyncratic Volatility," *Financial Review* 43, 159-190.

Asquith, P., P.A. Pathak, and J.R. Ritter, 2005, "Short Interest, Institutional Ownership, and Stock Returns," *Journal of Financial Economics* 78, 243-276.

Atkins, A. B., and E. A. Dyl, 1997, "Market Structure and Reported Trading Volume: NASDAQ versus the NYSE," *Journal of Financial Research 20*, 291-304.

Au, A.S., J.A. Doukas, and Z. Onayev, 2009, "Daily short interest, idiosyncratic risk, and stock returns," *Journal of Financial Markets* 12, 290-316.

Bali, T. G., and N. Cakici, 2008, "Idiosyncratic Volatility and the Cross Section of Expected Returns," *Journal of Financial and Quantitative Analysis* 43, 29-58.

Bali, T. G., Cakici, N., Yan, X. S., & Zhang, Z., 2005, "Does Idiosyncratic Risk Really Matter?" *Journal of Finance 60*, 905-929.

Ball, R., J. Gerakos, J. T. Linnainmaa, and V. Nikolaev, 2015, "Deflating Profitability," *Journal of Financial Economics* 117, 225-248.

Ball, R., J. Gerakos, J. T. Linnainmaa, and V. Nikolaev, 2016, "Accruals, Cash Flows, and Operating Profitability in the Cross Section of Stock Returns," *Journal of Financial Economics* 121, 28-45.

Ball, R., S.P. Kothari, and J. Shanken, 1995, "Problems in Measuring Portfolio Performance: An Application to Contrarian Investment Strategies," *Journal of Financial Economics* 38, 79-107.

Barinov, A., 2015, "Profitability Anomaly and Aggregate Volatility Risk," University of California Riverside Working Paper.

Beaver, W., M. McNichols, and R. Price, 2007, "Delisting Returns and Their Effect on Accounting-Based Market Anomalies," *Journal of Accounting and Economics* 43, 341-368.

Bernard, V. L., and J. K. Thomas, 1990, "Evidence that Stock Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings," *Journal of Accounting and Economics* 13, 305-340.

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

Bhushan, R., 1994, "An Informational Efficiency Perspective on the Post-Earnings Announcement Drift," *Journal of Accounting and Economics* 18, 45-65.

Boehme R.D., B.R. Danielsen, P. Kumar, and S.M. Sorescu, 2009, "Idiosyncratic risk and the cross-section of stock returns: Merton (1987) meets Miller (1977)," *Journal of Financial Markets* 12, 438-468.

Bouchaud, J.P., P. Krueger, A. Landier, and D. Thesmar, 2017, "Sticky Expectations and the Profitability Anomaly," *Journal of Finance*, Forthcoming.

Campbell, J.Y., A. W. Lo, and A. C. MacKinlay, 1997, "The Econometrics of Financial Markets," Princeton University Press, Princeton, NJ.

Carhart, M. M., 1997, "On Persistence in Mutual Fund Performance," *Journal of Finance* 52, 57-82.

Chen, J., L. Chollete, and R. Ray, 2010, "Financial distress and idiosyncratic volatility: An empirical investigation," *Journal of Financial Markets* 13, 249-267.

Chen, L., R. Novy-Marx, and L. Zhang, 2011, "An Alternative Three-Factor Model," Working paper, CKGSB, University of Rochester, and Ohio State University.

Chichernea, D.C., M.F. Ferguson, and H. Kassa, 2015, "Idiosyncratic Risk, Investor Base, and Returns," *Financial Management* 44, 267-293.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001, "Market Liquidity and Trading Activity," *Journal of Finance* 56, 501-530.

Chua, T. C., J. Goh, and Z. Zhang, 2010, "Expected Volatility, and the Cross-Section of Stock Returns," *Journal of Financial Research* 33, 103-123.

D'Avolio, G., 2002, "The Market for Borrowing Stock," *Journal of Financial Economics* 66, 271-306.

Dechow, P. M., 1994, "Accounting Earnings and Cash Flows as Measures of Firm Performance: The Role of Accounting Accruals," *Journal of Accounting and Economics* 18, 3-42.

Edelen, R.M., O.S. Ince, and G.B. Kadlec, 2016, "Institutional Investors and Stock Return Anomalies," *Journal of Financial Economics* 119, 472-488.

Eisfeldt, A. L. and D. Papanikolaou, 2013, "Organization Capital and the Cross-section of Expected Returns," *Journal of Finance* 68, 1365-1406.

Fama, E. F. and J. D. MacBeth, 1973, "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy* 81, 607-636.

Fama, E. F. and K. R. French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* 33, 3-56.

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

Fama, E. F. and K. R. French, 2016, "Dissecting Anomalies with a Five-factor Model," *Review of Financial Studies* 29, 69-103.

Fink, J.D., K.E. Fink, and H. He, 2012, "Expected Idiosyncratic Volatility Measures and Expected Returns," *Financial Management* 41, 519-553.

Guo, H., H. Kassa, and M.F. Ferguson, 2014, "On the Relation between EGARCH Idiosyncratic Volatility and Expected Stock Returns," *Journal of Financial and Quantitative Analysis* 49(1), 271-296.

Hong, H., T. Lim, and J. C. Stein, 2000, "Bad News Travels slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies," *Journal of Finance* 55, 265–295.

Hou, K., C. Xue, and L. Zhang, 2015, "Digesting Anomalies: An Investment Approach," *Review of Financial Studies* 28(3), 650-705.

Huang, W., Q. Liu, S.G. Rhee, and L. Zhang, 2010, "Return Reversals, Idiosyncratic Risk, and Expected Returns," *Review of Financial Studies* 23, 147-168.

Jiang, G. J., D. Xu, and T. Yao, 2009, "The Information Content of Idiosyncratic Volatility," *Journal of Financial and Quantitative Analysis* 44, 1-28.

Lam, F.Y.E.C. and K.C.J. Wei, 2011, "Limits-to-arbitrage, investment frictions, and the asset growth anomaly," *Journal of Financial Economics* 102(1), 127-149.

Lev, B., and D. Nissim, 2006, "The Persistence of the Accruals Anomaly," *Contemporary Accounting Research* 23, 193-226.

Lev, B., Radhakrishnan, S. and Evans, P.C., 2016, "Organizational capital: A CEO's guide to measuring and managing enterprise intangibles," New York: The Center for Global Enterprise.

Lev, Baruch, and Suresh Radhakrishnan, 2005, "The valuation of organization capital," in Carol Corrado, John Haltiwanger, and Dan Sichel, eds.: *Measuring Capital in the New Economy*, (National Bureau of Economic Research, Inc., Cambridge, MA).

Linnainmaa, J. T. and M. R. Roberts, 2018, "The History of the Cross Section of Stock Returns," *Review of Financial Studies*, Forthcoming.

Malkiel, B. G., and Y. Xu, 2002, "Idiosyncratic Risk and Security Returns," Working Paper, University of Texas at Dallas.

Mashruwala, C., S. Rajgopal, and T. 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.

Mendenhall, R.R., 2004, "Arbitrage Risk and Post-earnings-announcement Drift," *Journal of Business* 77, 875-894.

Nagel, S., 2005, "Short Sales, Institutional Investors and the Cross-Section of Stock Returns," *Journal of Financial Economics* 78, 277-309.

Newey, W. K., and K. D. West, 1987, "Hypothesis Testing with Efficient Method of Moments Estimation," *International Economic Review* 28, 777-787.

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

Pontiff, J., 1996, "Costly Arbitrage: Evidence from Closed-End Funds," *Quarterly Journal of Economics* 111, 1135-1151.

Pontiff, J., 2006, "Costly Arbitrage and the Myth of Idiosyncratic Risk," *Journal of Accounting and Economics* 42, 35-52.

Shleifer, A., and R. W. Vishny, 1997, "The Limits of Arbitrage," *Journal of Finance* 52(1), 35-55.

Shumway, T., and V. A. Warther, 1999, "The Delisting Bias in CRSP's Nasdaq Data and Its Implications for the Size Effect," *Journal of Finance* 54, 2361-2379.

Shumway, T., 1997, "The Delisting Bias in CRSP Data," *Journal of Finance* 52, 327-340.

Sloan, R. G., 1996, "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?" *Accounting Review* 71, 289-315.

Stambaugh, R. F., J. Yu, and Y. Yuan, 2012, "The Short of It: Investor Sentiment and Anomalies." *Journal of Financial Economics* 104, 288-302.

Stambaugh, R. F., J. Yu, and Y. Yuan, 2015, "Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle." *Journal of Finance* 70, 1903-1948.

Wahal, S., 2017, "The Profitability and Investment Premium: Pre-1963 Evidence," Arizona State University Working Paper.

Walther, B. R., 1997, "Investor Sophistication and Market Earnings Expectations," *Journal of Accounting Research* 35, 157-179.

Wang, H., and J. Yu, 2013, "Dissecting the Profitability Premium," University of Delaware and Tsinghua University Working Paper.

Wurgler, J. and E. Zhuravskaya, 2002, "Does Arbitrage Flatten Demand Curves for Stocks?" *Journal of Business* 75, 583-608.

Table I. Summary Statistics

This table reports summary statistics of firms' characteristics (Panel A) and Pearson correlation coefficients for operating profitability measures (Panel B). Firms' characteristics include gross, operating, and cash-based operating profitability measures, book-to-market, market value of equity, and past returns. Following Novy-Marx (2013) and Ball et al. (2015, 2016) profitability measures are computed at the end of each June. Gross profitability (GP/TA) is defined as revenues minus cost of goods sold (gross profit) scaled by total assets. Operating profitability (OP/TA) is defined as gross profit minus selling, general, and administrative expenses (net of research and development expenditures), scaled by total assets. Cash-based operating profitability (COP/TA) is defined as operating profit minus the change in accounts receivable minus the change in inventory minus the change in prepaid expenses plus the change in deferred revenue, the change in trade accounts payable plus the change in accrued expenses, scaled by total assets. Each profitability measure is scaled by the previous year's book value of total assets. $\log(B/M)$ is the natural logarithm of the book-to-market ratio defined as the book equity at the end of each June divided by market value of equity from December of the prior year. $\log(ME)$ is the natural logarithm of the market value of equity. $r_{1,0}$ is the prior one month return. $r_{12,2}$ is the prior year's return excluding the last month. The table reports the time series averages of the cross-sectional mean and median of each variable. All variables are winsorized at the 1 and 99% level. The sample consists of common stocks listed on the NYSE, Amex, and Nasdaq. We exclude financial firms and missing observations of market value of equity, book-to-market ratio, book value of total assets, current month returns, and last year returns. The sample period is from July 1963 to December 2016.

Panel A. Firms Characteristics

	Mean	Median	St. Dev
Gross Profitability (GP/TA)	0.411	0.374	0.227
Operating Profitability (OP/TA)	0.144	0.147	0.112
Cash-based Operating Profitability (COP/TA)	0.124	0.130	0.137
$\log(B/M)$	4.690	4.580	1.820
$\log(ME)$	-0.478	-0.416	0.731
$r_{1,0}$	0.010	0.002	0.010
$r_{12,2}$	0.125	0.059	0.434

Panel B. Correlation Coefficients among Profitability Measures

	GP/TA	OP/TA	COP/TA
GP/TA	1		
OP/TA	0.465	1	
COP/TA	0.334	0.713	1

Table II. Profitability Anomalies and Cross Section of Stock Returns

Panel A reports the results from Fama and MacBeth (1973) regressions of monthly stock returns on gross (GP/TA), operating (OP/TA), and cash-based operating profitability (COP/TA) measures, size ($\log(\mathrm{ME})$), book-to-market ($\log(\mathrm{B/M})$), and past performance measures over prior one month ($r_{1,0}$), and twelve to two months ($r_{12,2}$) as described in Table I. Column (1) of Panel A reports replication results of Table 1 in Novy-Marx (2013) by using a sample period of 1963-2010. Columns (2) and (3) of Panel A report replication results of Table 2 in Ball et al. (2016) by using a sample period of 1963-2013. Columns (4)–(8) of Panel A report results over 1963-2016. Panel B reports monthly equal-weighted average returns to quintile portfolios sorted on each profitability measure. Panel B also reports the difference in returns between the extreme quintiles of profitability measures (Q5-Q1), as well as risk-adjusted performance based on the Fama-French (1993) three-factor (α^{3F}) and the Carhart (1997) four-factor models (α^{4F}). The *t*–statistics are computed from standard errors that are adjusted for heteroskedasticity and serial correlation following Newey and West (1987). ***, **, * denote statistical significance at the 1%, 5%, or 10% levels, respectively.

Panel A. Fama and MacBeth Regressions

	Novy-Marx (2013) 1963-2010	Ball et. al. (2016) 1963-2013		Extended Sample Period 1963-2016				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GP/AT	0.846***			0.889***			0.586***	0.577***
	(5.16)			(5.73)			(3.11)	(3.28)
OP/AT		2.203***			2.292***		1.735***	
		(5.46)			(5.85)		(4.20)	
COP/AT			2.220***			2.230***		1.855***
			(9.60)			(9.79)		(7.94)
log(ME)	-0.001**	-0.001***	-0.001**	-0.001**	-0.001***	-0.001**	-0.001**	-0.001**
	(-2.03)	(-2.66)	(-2.52)	(-2.19)	(-2.74)	(-2.57)	(-2.22)	(-2.16)
log(B/M)	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(5.40)	(5.40)	(5.34)	(5.60)	(5.31)	(5.22)	(5.66)	(5.50)
$r_{1,0}$	-0.060***	-0.057***	-0.057***	-0.055***	-0.055***	-0.054***	-0.056***	-0.055***
	(-12.83)	(-12.60)	(-12.51)	(-12.15)	(-12.15)	(-12.06)	(-12.45)	(-12.37)
$r_{12,2}$	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.006***	0.006***
	(3.07)	(3.41)	(3.40)	(3.41)	(3.50)	(3.51)	(3.28)	(3.29)
Avg. N	2,487	2,468	2,468	2,428	2,428	2,428	2,428	2,428
Adj. R^2	0.041	0.040	0.039	0.039	0.040	0.038	0.042	0.041

Panel B. Portfolio Sorts of Profitability Measures

Q5 (High)	Q4	Q3	Q2	Q1 (Low)	Difference: H – L Ret	α^{3F}	α^{4F}
Gross Profitability (GP/TA)							
1.441	1.369	1.241	1.141	0.856	0.585***	0.709***	0.641***
					(4.74)	(5.88)	(5.61)
Operating Profitability (OP/TA)							
1.374	1.277	1.284	1.192	0.919	0.455***	0.643***	0.475***
					(2.74)	(4.55)	(2.96)
Cash-based Profitability (COP/TA)							
1.500	1.392	1.269	1.123	0.752	0.748***	0.896***	0.736***
					(5.59)	(8.14)	(5.87)

Table III. Profitability Anomalies: The Effects of Arbitrage Costs and Investor Sophistication

This table reports the results from Fama and MacBeth (1973) regressions of monthly stock returns on profitability measures, idiosyncratic volatility, proxy measures for transaction costs, short-sale constraints, investor sophistication, and control variables as defined in Tables I and III. At the end of each June, all stocks in the sample are sorted into five quintiles based on gross (GP/TA), operating (OP/TA), cash-based operating profitability (COP/TA) measures. Independent of the profitability measure rankings, stocks are also ranked into corresponding quintiles based on idiosyncratic volatility measure ($\mathbf{IVOL_{4F}}$), transaction cost measures, short-sale constraints, and investor sophistication. Transaction cost measures (Panel A) include share price (Price), bid-ask spread (BidAsk), and trading volume (Volume). Short-sale constraints and investor sophistication measures (Panel B) include Short interest ratio (Short), institutional ownership (IOWN), and number of analysts estimates (#Analyst) available in I/B/E/S. All variables are the scaled annual quintile rank variables described in Section III.C. The *t*–statistics are in parentheses and adjusted for heteroskedasticity and serial correlations following Newey and West (1987). ***, **, * denotes statistical significance at the 1%, 5%, or 10% levels, respectively. The sample period is from July 1963 to December 2016 in Panel A, and from July 1981 to December 2016 in Panel B.

Panel A. Transaction Costs

	Gross Profitability GP/TA					Operating Profitability OP/TA					Cash-based Operating Profitability COP/TA				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$\text{Prof}^{\text{Rank}} \times \text{Price}^{\text{Rank}}$	-0.006***				-0.003	0.001				-0.004	-0.003*				-0.002
	(-3.17)				(-0.85)	(0.27)				(-1.23)	(-1.69)				(-1.20)
$\text{Prof}^{\text{Rank}} \times \text{BidAsk}^{\text{Rank}}$		0.002			0.001		-0.002			-0.003		0.002			-0.001
		(0.99)			(0.27)		(-0.72)			(-0.90)		(1.13)			(-0.32)
$\text{Prof}^{\text{Rank}} \times \text{Volume}^{\text{Rank}}$			-0.004***		0.001			0.002		0.002			-0.006***		-0.002
			(-2.62)		(0.67)			(0.98)		(0.96)			(-3.03)		(-1.11)
$\text{Prof}^{\text{Rank}} \times \text{IVOL}_{4F}^{\text{Rank}}$				0.004**	0.004**				-0.002	-0.002				0.004**	0.003**
				(2.22)	(2.08)				(-0.85)	(-1.01)				(2.17)	(2.13)
$\text{Price}^{\text{Rank}}$	-0.001				-0.002	-0.003				-0.002	-0.002				-0.002
	(-0.51)				(-1.08)	(-1.27)				(-1.28)	(-0.87)				(-0.94)
$\text{BidAsk}^{\text{Rank}}$		-0.000			0.001		0.002			0.002		0.001			0.001
		(-0.02)			(0.34)		(0.58)			(0.95)		(0.37)			(0.68)
$\text{Volume}^{\text{Rank}}$			-0.001		-0.001			0.000		-0.001			-0.000		-0.001
			(-0.32)		(-0.52)			(0.00)		(-0.39)			(-0.12)		(-0.50)
$\text{IVOL}_{4F}^{\text{Rank}}$				-0.002	-0.002*				-0.002	-0.003**				-0.002	-0.002
				(-1.12)	(-1.81)				(-0.90)	(-2.06)				(-0.84)	(-1.61)
$\text{Prof}^{\text{Rank}}$	0.006***	0.006***	0.006***	0.006***	0.006***	0.008***	0.008***	0.008***	0.008***	0.008***	0.009***	0.009***	0.009***	0.009***	0.009***
	(5.09)	(4.95)	(5.16)	(4.87)	(4.95)	(7.87)	(8.27)	(7.32)	(7.82)	(8.47)	(11.09)	(11.86)	(11.17)	(11.63)	(11.68)
Controls								$\log(\text{ME})$, $\log(\text{B/M})$, $r_{1,0}$, $r_{12,2}$							
Avg. N.	1,912	1,912	1,912	1,912	1,912	1,912	1,912	1,912	1,912	1,912	1,912	1,912	1,912	1,912	1,912
Adj. R^2	0.048	0.05	0.051	0.05	0.058	0.047	0.05	0.05	0.05	0.057	0.046	0.049	0.049	0.049	0.056

Panel B. Short-Sale Constraints and Investor Sophistication

	Gross Profitability GP/TA					Operating Profitability OP/TA					Cash-based Operating Profitability COP/TA				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$\text{Prof}^{\text{Rank}} \times \text{Short}^{\text{Rank}}$	-0.004***				-0.003**	-0.001				-0.002	-0.002				-0.002*
	(-2.67)				(-2.20)	(-0.89)				(-1.40)	(-1.31)				(-1.87)
$\text{Prof}^{\text{Rank}} \times \text{IOWN}^{\text{Rank}}$		-0.002*			-0.004***		0.001			-0.002		0.000			-0.001
		(-1.89)			(-2.85)		(0.78)			(-0.99)		(0.23)			(-0.73)
$\text{Prof}^{\text{Rank}} \times \#\text{Analyst}^{\text{Rank}}$			-0.001		0.004**			0.000		0.001			0.001		0.002
			(-0.49)		(2.30)			(0.08)		(0.46)			(0.71)		(1.64)
$\text{Prof}^{\text{Rank}} \times \text{IVOL}_{4\text{F}}^{\text{Rank}}$				0.004**	0.002*				-0.002	0.001				0.003**	0.002*
				(2.23)	(1.88)				(-0.98)	(0.88)				(2.13)	(1.93)
$\text{Short}^{\text{Rank}}$	0.001				-0.001	0.001				-0.001	0.001				-0.001
	(0.87)				(-0.85)	(0.98)				(-0.80)	(1.05)				(-0.79)
$\text{IOWN}^{\text{Rank}}$		0.001			0.002**		0.001			0.002**		0.001			0.002**
		(1.03)			(2.14)		(0.87)			(2.04)		(1.00)			(2.02)
$\#\text{Anst}^{\text{Rank}}$			0.002*		0.001			0.002*		-0.003			0.003*		0.002
			(1.89)		(0.50)			(1.82)		(-1.52)			(1.94)		(1.27)
$\text{IVOL}_{4\text{F}}^{\text{Rank}}$				-0.002	-0.002				-0.002	-0.002				-0.001	-0.002
				(-0.92)	(-1.03)				(-0.72)	(-0.88)				(-0.68)	(-0.79)
$\text{Prof}^{\text{Rank}}$	0.006***	0.006***	0.006***	0.006***	0.006***	0.008***	0.008***	0.008***	0.008***	0.008***	0.009***	0.009***	0.009***	0.009***	0.009***
.	(5.27)	(5.29)	(5.20)	(5.16)	(5.11)	(7.03)	(7.06)	(6.76)	(8.21)	(8.16)	(10.49)	(10.44)	(10.09)	(11.82)	(11.47)
Controls	$\log(\text{ME}), \log(\text{B/M}), r_{1,0}, r_{12,2}$														
Avg. N.	2,397	2,397	2,397	2,397	2,397	2,397	2,397	2,397	2,397	2,397	2,397	2,397	2,397	2,397	2,397
Adj. R^2	0.044	0.044	0.043	0.049	0.052	0.043	0.043	0.043	0.049	0.052	0.042	0.042	0.042	0.048	0.051

Table IV. Profitability Anomalies and Arbitrage Risk: Mean Quintile Rankings of IVOL in Profitability Quintiles

At the end of each June, all stocks in the sample are ranked into five quintiles separately based on gross (GP/TA), operating (OP/TA), and cash-based operating profitability (COP/TA) measures described in Table I. Independent of the profitability measures rankings, stocks are also ranked into five groups based on idiosyncratic volatility measures and assigned corresponding rank values into their corresponding groups ($\mathrm{IVOL}_{1F}^{\mathrm{Group}}$ and $\mathrm{IVOL}_{4F}^{\mathrm{Group}}$). This table reports the time-series averages of the cross-sectional mean of idiosyncratic volatility groups ($\mathrm{IVOL}_{1F}^{\mathrm{Group}}$ and $\mathrm{IVOL}_{4F}^{\mathrm{Group}}$) across five profitability quantiles as well as the differences in the average idiosyncratic volatility groups between high and low (H-L), high and medium (H-M), and medium and low (M-L) profitability portfolio quintiles. The medium portfolio is the equal-weighted combination of the second, third, and fourth quintiles. Panels A, B, and C report results for gross (GP/TA), operating (OP/TA), and cash-based operating (COP/TA) profitability measures, respectively. Idiosyncratic volatility of a stock, IVOL_{1F} (IVOL_{4F}) is the variance of the residuals obtained by regressing monthly stock returns on the returns of the CRSP value-weighted market index (the Carhart (1997) four factors) over the previous 36 months (minimum of 30 months) of monthly returns observations ending June 30. ***, **, * denote statistical significance at the 1%, 5%, or 10% levels, respectively. The sample period is from July 1963 to December 2016.

	Q5 (High)	Q4	Q3	Q2	Q1 (Low)	Differences H-L	Differences H-M	Differences M-L
	Panel A. Gross Profitability (GP/TA)							
$\mathrm{IVOL}_{1F}^{\mathrm{Group}}$	3.026	2.945	2.910	2.913	3.215	-0.188***	0.103**	0.291***
$\mathrm{IVOL}_{4F}^{\mathrm{Group}}$	3.040	2.943	2.909	2.904	3.214	-0.174***	0.121***	0.295***
	Panel B. Operating Profitability (OP/TA)							
$\mathrm{IVOL}_{1F}^{\mathrm{Group}}$	2.775	2.621	2.746	3.086	3.867	-1.092***	-0.042	1.050***
$\mathrm{IVOL}_{4F}^{\mathrm{Group}}$	2.792	2.629	2.747	3.077	3.852	-1.060***	-0.025	1.035***
	Panel C. Cash-based Operating Profitability (COP/TA)							
$\mathrm{IVOL}_{1F}^{\mathrm{Group}}$	2.826	2.609	2.788	3.121	3.816	-0.990***	-0.009	0.981***
$\mathrm{IVOL}_{4F}^{\mathrm{Group}}$	2.835	2.615	2.784	3.117	3.808	-0.973***	0.001	0.973***

Table V. Profitability Anomalies and Arbitrage Risk: Cross-sectional Regressions of Monthly Returns

This table reports the results from Fama and MacBeth (1973) regressions of monthly stock returns on profitability measures, idiosyncratic volatility, and control variables as described in Table I and Table III. At the end of each June, all stocks in the sample are ranked into five quintile portfolios based on gross profitability (GP/TA) in Panel A, operating profitability (OP/TA) in Panel B, and cash-based operating profitability measure (COP/TA) in Panel C. Independent of the profitability measure rankings, stocks are also ranked into five groups based on idiosyncratic volatility measures ($\mathrm{IVOL_{1F}}$, $\mathrm{IVOL_{4F}}$). $\mathrm{Prof^{Rank}}$ is the scaled annual quintile rank for GP/TA, OP/TA, and COP/TA. $\mathrm{IVOL^{Rank}}$ is the scaled annual quintile rank for the idiosyncratic volatility measure ($\mathrm{IVOL_{1F}}$ and $\mathrm{IVOL_{4F}}$) described in Section III.C. The *t*-statistics are in parentheses and computed from standard errors adjusted for heteroskedasticity and serial correlations following Newey and West (1987). ***, **, * denotes statistical significance at the 1%, 5%, or 10% levels, respectively. The sample period is from July 1963 to December 2016.

	Panel A. Gross Profit GP/AT		Panel B. Operating Profit OP/AT		Panel C. Cash-based Operating Profitability COP/AT	
	(1)	(2)	(1)	(2)	(1)	(2)
$\mathrm{Prof^{Rank}} \times \mathrm{IVOL_{1F}^{Rank}}$	0.003**		-0.002		0.003**	
	(2.02)		(-0.91)		(2.16)	
$\mathrm{Prof^{Rank}} \times \mathrm{IVOL_{4F}^{Rank}}$		0.004**		-0.002		0.004**
		(2.15)		(-0.84)		(2.39)
$\mathrm{Prof^{Rank}}$	0.006***	0.006***	0.008***	0.008***	0.008***	0.008***
	(5.15)	(5.14)	(8.29)	(8.22)	(11.59)	(11.48)
$\mathrm{IVOL_{1F}^{Rank}}$	-0.002		-0.001		-0.001	
	(-0.89)		(-0.64)		(-0.60)	
$\mathrm{IVOL_{4F}^{Rank}}$		-0.002		-0.002		-0.001
		(-0.83)		(-0.72)		(-0.65)
Control			$\log(\mathrm{ME})$, $\log(\mathrm{B/M})$, $r_{1,0}$, $r_{12,2}$			
Avg. N	2029	2029	2029	2029	2029	2029
Adj. R^2	0.049	0.049	0.049	0.048	0.048	0.047

Table VI. Profitability Anomalies and Arbitrage Risk: Portfolio Returns and Factor Model Alphas

This table reports the performance of a long-short hedge strategy based on profitability measures for high and low idiosyncratic volatility stocks. At the end of each June, all stocks in the sample are ranked into five quintile portfolios based on gross (GP/TA), operating (OP/TA), and cash-based operating (COP/TA) profitability measure in Panels A, B, and C, respectively. Independent of profitability measure ranking, stocks are also ranked into five groups based on idiosyncratic volatility measures, and assigned corresponding rank values into their corresponding groups ($\mathrm{IVOL}_{1F}^{Group}$ and $\mathrm{IVOL}_{4F}^{Group}$). For each extreme idiosyncratic volatility group ($\mathrm{IVOL}^{Group} = 5$ and $\mathrm{IVOL}^{Group} = 1$) the table reports the average monthly returns between the highest and the lowest profitability quintiles (Q5-Q1). The table also reports the differences in returns of Q5-Q1 between the extreme idiosyncratic volatility groups as well as risk-adjusted performance based on the Fama-French (1993) three-factor (α^{3F}) and the Carhart (1997) four-factor models (α^{4F}). Profitability and idiosyncratic volatility measures are described in Table I and Table III. N stands for the average number of stocks that fall in the high (Q5) and low (Q1) profitability quintiles. The *t*–statistics are reported in the parentheses. ***, **, * denotes statistical significance at the 1%, 5%, or 10% levels, respectively. The sample period is from July 1963 to December 2016.

	$\mathrm{IVOL}_{1F}^{Group}$=5	$\mathrm{IVOL}_{1F}^{Group}$=1	Difference in $\mathrm{IVOL}_{1F}^{Group}$ 5 – 1			$\mathrm{IVOL}_{4F}^{Group}$= 5	$\mathrm{IVOL}_{4F}^{Group}$= 1	Difference in $\mathrm{IVOL}_{4F}^{Group}$ 5 – 1		
			Return	α^{3F}	α^{4F}			Return	α^{3F}	α^{4F}
	IVOL_{1F}					IVOL_{4F}				
Panel A: Gross Profitability (GP/TA)										
High(Q5)-Low(Q1)	0.777***	0.308***	0.469***	0.411**	0.366**	0.731***	0.300***	0.430***	0.329**	0.310*
t – statistic	(4.28)	(3.02)	(2.79)	(2.44)	(2.10)	(4.03)	(2.92)	(2.59)	(1.99)	(1.80)
N	[81,66]	[80,90]				[80,90]	[79,66]			
Panel B: Operating Profitability (OP/TA)										
High(Q5)-Low(Q1)	0.489**	0.352***	0.137	0.128	0.068	0.479**	0.318**	0.162	0.100	0.061
t – statistic	(2.43)	(2.74)	(0.73)	(0.70)	(0.36)	(2.37)	(2.32)	(0.88)	(0.56)	(0.33)
N	[56,136]	[98,24]				[56,136]	[96,24]			
Panel C: Cash-based Operating Profitability (COP/TA)										
High(Q5)-Low(Q1)	0.879***	0.225**	0.654***	0.596***	0.543***	0.868***	0.252**	0.615***	0.547***	0.554***
t – statistic	(6.25)	(2.05)	(3.93)	(3.61)	(3.22)	(6.04)	(2.24)	(3.72)	(3.37)	(3.29)
N	[63,124]	[100,23]				[62,124]	[99,24]			

Table VII. Mean Profitability and IVOL Quintile Rankings in SG&A and Accrual Quintiles

At the end of each June, all stocks in the sample are ranked into quintiles separately based on SG&A/TA (Panel A) and accruals (Panel B). SG&A expenses exclude R&D expenses and are scaled by total assets (SG&A/TA). Accruals/TA is measured as a change in accounts receivables minus change in inventory minus change in prepaid expenses plus change in deferred revenue plus change in trade accounts payable scaled by total assets. Independent of SG&A/TA and Accruals/TA rankings, stocks are ranked into quintiles and assigned to corresponding groups based on gross ($\mathrm{GP/TA^{Group}}$), operating ($\mathrm{OP/TA^{Group}}$), cash-based operating profitability ($\mathrm{COP/TA^{Group}}$), and idiosyncratic volatility ($\mathrm{IVOL_{1F}^{Group}}$and $\mathrm{IVOL_{4F}^{Group}}$). For each quintile based on SG&A/TA or Accruals/TA, this table reports the time-series averages of cross-sectional means for $\mathrm{GPAT^{Group}}$, $\mathrm{OPAT^{Group}}$, $\mathrm{COPAT^{Group}}$, $\mathrm{IVOL_{1F}^{Group}}$ and $\mathrm{IVOL_{4F}^{Group}}$, as well as the differences between high and low (H-L), high and medium (H-M), and medium and low (M-L) SG&A/TA (Accruals/TA) portfolios in Panel A (Panel B). The medium portfolio is the equal-weighted combination of the second, third, and fourth quintiles. ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. ***, **, * denotes statistical significance at the 1%, 5%, or 10% levels, respectively. The sample period is from July 1963 to December 2016.

	Q5 (High)	Q4	Q3	Q2	Q1 (Low)	Differences H-L	H-M	M-L
				Panel A. SG&A/TA				
$\mathrm{GP/TA^{Group}}$	4.660	3.742	2.959	2.187	1.453	3.208***	1.698***	-1.510***
$\mathrm{OP/TA^{Group}}$	3.011	3.115	3.132	3.012	2.730	0.281***	-0.075*	-0.356***
$\mathrm{COP/TA^{Group}}$	3.005	3.024	3.066	3.012	2.894	0.111***	-0.029	-0.140***
$\mathrm{IVOL_{1F}^{Group}}$	3.221	3.134	2.996	2.888	2.763	0.458***	0.215***	-0.242***
$\mathrm{IVOL_{4F}^{Group}}$	3.231	3.131	2.989	2.880	2.772	0.458***	0.232***	-0.227***
				Panel B. Accruals/TA				
$\mathrm{GP/TA^{Group}}$	3.278	3.171	2.901	2.769	2.881	0.397***	0.331***	-0.066
$\mathrm{OP/TA^{Group}}$	3.139	3.249	3.139	2.959	2.515	0.624***	0.024	-0.601***
$\mathrm{COP/TA^{Group}}$	1.945	2.830	3.159	3.353	3.713	-1.768***	-1.169***	0.599***
$\mathrm{IVOL_{1F}^{Group}}$	3.445	2.884	2.619	2.755	3.376	0.069*	0.694***	0.625***
$\mathrm{IVOL_{4F}^{Group}}$	3.446	2.885	2.624	2.753	3.371	0.075*	0.695***	0.620***

Table VIII. Profitability Anomalies and Idiosyncratic Volatility: The Effects of SG&A Expenses and Accruals

This table reports the results from Fama and MacBeth (1973) regressions of monthly returns on SG&A expenses, accruals, profitability measures, idiosyncratic volatility, and control variables as defined in Table I and Table III. At the end of each June, all stocks in our sample are separately sorted into quintiles based on SG&A expenses (SG&A/TA), accruals (Accruals/TA), gross profitability (GP/TA), operating profitability (OP/TA), cash-based operating profitability (COP/TA), and idiosyncratic volatility measures ($\mathbf{IVOL_{1F}}$ and $\mathbf{IVOL_{4F}}$). All variables are the scaled annual quintile ranks described in Section III.C. The *t*–statistics are in parentheses and adjusted for heteroskedasticity and serial correlations following Newey and West (1987). ***, **, * denotes statistical significance at the 1%, 5%, or 10% levels, respectively. The sample period is from July 1981 to December 2016.

	SG&A/TA		Accruals/TA		GP/TA		COP/TA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathrm{Prof}^{\mathrm{Rank}} \times \mathrm{IVOL}_{1F}^{\mathrm{Rank}}$					0.000		0.001	
					(0.13)		(0.45)	
$\mathrm{Prof}^{\mathrm{Rank}} \times \mathrm{IVOL}_{4F}^{\mathrm{Rank}}$						-0.001		0.001
						(-0.38)		(0.29)
$(\mathrm{SG\&A/TA})^{\mathrm{Rank}} \times \mathrm{IVOL}_{1F}^{\mathrm{Rank}}$	0.004*				0.007*			
	(1.76)				(1.92)			
$(\mathrm{SG\&A/TA})^{\mathrm{Rank}} \times \mathrm{IVOL}_{4F}^{\mathrm{Rank}}$		0.007**				0.008**		
		(2.01)				(2.26)		
$(\mathrm{Accruals/TA})^{\mathrm{Rank}} \times \mathrm{IVOL}_{1F}^{\mathrm{Rank}}$			-0.002*				-0.002*	
			(-1.83)				(-1.76)	
$(\mathrm{Accruals/TA})^{\mathrm{Rank}} \times \mathrm{IVOL}_{1F}^{\mathrm{Rank}}$				-0.003**				-0.004**
				(-2.35)				(-2.07)
$(\mathrm{SG\&A/TA})^{\mathrm{Rank}}$	0.003***	0.003***			-0.005***	-0.005***		
	(2.97)	(2.87)			(-3.80)	(-3.81)		
$(\mathrm{Accruals/TA})^{\mathrm{Rank}}$			-0.003***	-0.003***			0.001	0.001
			(-5.08)	(-4.96)			(1.36)	(1.36)
$\mathrm{Prof}^{\mathrm{Rank}}$					0.010***	0.010***	0.009***	0.009***
					(8.00)	(7.97)	(9.54)	(9.39)
Controls	$\log(\mathrm{ME})$, $\log(\mathrm{B/M})$, $r_{1,0}$, $r_{12,2}$, $\mathrm{IVOL}_{1F}^{\mathrm{Rank}}$ ($\mathrm{IVOL}_{4F}^{\mathrm{Rank}}$)							
Avg. N	2,029	2,029	2,029	2,029	2,029	2,029	2,029	2,029
Adj. R^2	0.050	0.048	0.047	0.046	0.052	0.050	0.050	0.049