WHAT'S IN A NAME? A CAUTIONARY TALE OF PROFITABILITY ANOMALIES AND LIMITS TO ARBITRAGE

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Abstract

The recent literature investigating profitability anomalies defines profitability in various ways (i.e., gross, operating, and cash based). We show that limits to arbitrage are associated with returns of gross and cash-based operating profitability anomalies, suggesting mispricing. In contrast, returns

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from the operating profitability strategy have no relation with barriers to arbitrage and exhibit no evidence of mispricing. Additionally, we show that the differential effects of limited arbitrage-related mispricing of gross and cash-based operating profitability anomalies are attributable to their respective correlations with selling, general, and administrative (SG&A) expense and accruals anomalies. We find that SG&A return predictability, like that of accruals, is related to limits to arbitrage. These findings suggest that investors and researchers should proceed with caution when searching for return predictability by redefining profitability measures.

JEL Classification: G11, G12, M41

I. Introduction

Since the advent of the efficient market theory, researchers have been documenting cross-sectional anomalies where selected firm or security characteristics appear to have stock return predictability (for a copious list of anomalies, see Harvey, Liu, and Zhu 2016). Although rational asset pricing theory suggests that return predictability is related to systematic risk premia, it is also possible that predictability occurs because of market mispricing. Mispricing in a completely efficient market should be quickly corrected by rational arbitrageurs who wish to profit from less sophisticated or uninformed investors who price assets in a manner that does not reflect fundamental value. However, as Shleifer and Vishny (1997) explain, if there are barriers or limits to arbitrage, mispricing will persist and the flow of wealth to sophisticated arbitrageurs will be delayed. This delay then gives the appearance of return predictability. Conversely, limits to arbitrage should be unrelated to an anomaly's return predictability if the future returns are due to systematic risk premia.

One of the asset pricing anomalies that has recently gained attention is the profitability anomaly. An interesting characteristic of this accounting-based anomaly is that profitability can be defined in many ways, depending on the economic or accounting rationale. For example, Novy-Marx (2013) formally documents the gross profitability anomaly, Ball et al. (2015) demonstrate an operating profitability anomaly, and Ball et al. (2016) show a cash-based operating profitability anomaly. Given the proliferation of profitability measures in the search for improved anomalous return prediction, it is in the interest of researchers and investors alike to determine whether the anomalous returns based on various profitability measures are related to limits to arbitrage and, hence, market mispricing. Although the literature contains many empirical studies linking anomaly predictability and limits to arbitrage, the profitability anomaly is largely overlooked.[1] Furthermore, to the best of our knowledge, no studies examine the effects of limits to arbitrage among various definitions of profitability. Thus, we focus on three profitability anomalies—gross, operating, and cash-based operating—and investigate the relation between their return predictability and limits to arbitrage.[2] These measures are incrementally different from each other by small, but crucial, accounting adjustments, particularly selling, general, and administrative (SG&A) expenses and accruals. Consequently, limits to arbitrage may have different effects across the return predictability

[1]For example, return predictability related to firm characteristics such as earnings (Mendenhall 2004), book-to-market equity ratio (Ali, Hwang, and Trombley 2003), accruals (Mashruwala, Rajgopal, and Shevlin 2006), asset growth (Lam and Wei 2011), cash holdings (Li and Luo 2016), momentum (Arena, Haggard, and Yan 2008), and S&P 500 index membership (Wurgler and Zhuravskaya 2002) has been linked to limits to arbitrage.

[2]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), which is operating profitability less interest expense scaled by book equity. However, in unreported results, an operating probability measure analogous to the Fama and French (2015) definition (operating profitability less interest expense scaled by total assets) yields similar results to that of the Ball et al. (2015) measure.

of the three anomalies. In fact, our empirical results support this differential effect. Specifically, we find that limits to arbitrage contribute to the return predictability of both the gross and cash-based operating profitability anomalies, but not the operating profitability anomaly.

We begin our study by verifying that the three profitability anomalies exist in our sample period using both Fama–MacBeth (1973) cross-sectional regressions and hedge portfolio analyses, thus confirming the findings of previous studies (Novy-Marx 2013; Ball et al. 2015, 2016).[3] Next, we examine the effect of limits to arbitrage on stock return predictability based on each profitability measure (i.e., the impact of limits to arbitrage on profitability-associated hedge portfolio returns). If limits to arbitrage deter profitability from being fully priced, we expect the return predictability associated with profitability measures to be stronger (weaker) for stocks with larger (smaller) limits to arbitrage. Our proxies for limits to arbitrage include arbitrage risk (idiosyncratic volatility) and a composite index of various arbitrage costs, including bid–ask spread, Amihud (2002) illiquidity measure, firm size, trading volume, institutional ownership (both number of institutions and total percentage of outstanding shares owned), and analyst coverage.[4]

When examining the individual effects of arbitrage risk and arbitrage costs, portfolio analyses reveal surprising differences in the effect of limits to arbitrage on the return predictability across different profitability measures. Specifically, we find that both arbitrage risk and arbitrage costs play an important explanatory role in the risk-adjusted returns to long–short strategies based on gross and cash-based operating profitability, which suggests that limits to arbitrage impose

[3]Hedge portfolio refers to a portfolio that executes a strategy long in a firm characteristic deemed high and short in a firm characteristic deemed low.

[4]We follow Ali, Hwang, and Trombley (2003), Mashruwala, Rajgopal, and Shevlin (2006), Lam et al. (2011), and Lam, Wei, and Wei (2017) in defining arbitrage costs and arbitrage risk.

significant barriers to exploiting the mispricing associated with these two firm characteristics. In sharp contrast, we find no relation between any of our proxies for limits to arbitrage and the return predictability of operating profitability. The results from Fama–MacBeth (1973) cross-sectional regressions support all the findings of the portfolio analyses. Taking all the evidence together supports the hypothesis that limits to arbitrage contribute to the return predictability of gross and cash-based profitability, but not that of operating profitability.

We further examine the roles of underlying accounting treatments (i.e., differing definitions of profitability) as potential causes of the differential effects of limits to arbitrage on the return predictability of the profitability anomalies. In contrast to simple gross profit, operating profit is obtained by subtracting the cost of goods sold and SG&A expenses, excluding research and development (R&D) expenditures, from revenue (Ball et al. 2015). Recent studies document that SG&A expenses represent investments in organizational capital that affect stock returns and firm value (Lev and Radhakrishnan 2005; Anderson et al. 2007; Eisfeldt and Papanikolaou 2013; Ball et al. 2015). Banker et al. (2019) find that SG&A expenses are mispriced and have return predictability in the cross-section of stock returns. Furthermore, cash-based operating profitability excludes accounting accruals from operating profit (Ball et al. 2016). Studies such as Sloan (1996) show that accruals have return predictability. However, 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 (Lev and Nissim 2006; Ali et al. 2008). Thus, mispricing due to each accounting component of the profitability ratios could be contributing to their overall return predictability. To explore this possibility, we further examine the relation between limits to arbitrage, SG&A expenses, accruals, and the profitability measures. For brevity, however, we focus on arbitrage risk as a predominant proxy for limits to arbitrage in the rest of our analysis.

We find a large and significant positive (negative) correlation between SG&A expenses (accruals) scaled by total assets and gross (cash-based operating) profitability. Thus, sorting stocks by gross (cash-based operating) profitability is similar to sorting stocks by SG&A expenses (accruals). In contrast, the relation between operating profitability, SG&A expenses, and accruals is economically small. Thus, SG&A expense and accrual effects do not confound sorting stocks by operating profitability. In further analyses, we provide novel evidence that limits to arbitrage contribute to the return predictability of SG&A expenses. Consistent with previous studies, we also confirm that limits to arbitrage affect the return predictability from accruals. The positive and significant relation between gross profitability and arbitrage risk is subsumed by the interaction between SG&A expenses and arbitrage risk, leading to no mispricing effects in the gross profitability strategy. Additionally, there are no limits to arbitrage mispricing effects associated with cash-based operating profitability when accruals are accounted for. Taken together, this evidence suggests that the respective accounting treatments in profitability measures explain the differential effects of arbitrage risk on the return predictability across different profitability anomalies. In other words, these results reconcile the differential effect of limits to arbitrage across the profitability measures and suggest that the accounting adjustments induce or resolve mispricing effects.

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 to achieve a "better profitability measure." First, we document that limits to arbitrage help explain the return predictability associated with gross and cash-based operating profitability. These findings related to gross and operating profitability suggest that although arbitrageurs may understand the opportunities presented by these profitability anomalies, exposure to excessive limits to arbitrage (especially arbitrage risk) discourages them from fully and rapidly correcting mispricing. This rationale is consistent with Shleifer and Vishny's (1997) argument that arbitrageurs with limited capital and short investment horizons may be reluctant to trade heavily on anomalies because mispricing could widen unexpectedly in the short run. However, inconsistent with a mispricing argument, we find that operating profitability has no relation with limits to arbitrage.

Second, we show that limits to arbitrage helps explain the return predictability of SG&A expenses. This result is novel, as previous studies (e.g., Eisfeldt and Papanikolaou 2013; Ball et al. 2015; Banker et al. 2019) document the return predictability of SG&A expenses, but no study focuses on limits to arbitrage as the source of SG&A mispricing. Last, we find that the apparent mispricing of gross (cash-based operating) profitability is actually an artifact of a high positive (negative) correlation with SG&A expenses (accruals). Considering all our evidence, creating new profitability measures should be approached with great thoughtfulness and caution, as our findings suggest that it is easy to unintentionally introduce mispricing effects into the profitability definition when ignoring limits to arbitrage.

II. Literature Review

Profitability Anomalies

Novy-Marx (2013) documents the gross profitability anomaly, a hedge strategy long in high-gross-profitability stocks and short in low-gross-profitability stocks, which yields significant abnormal returns. He argues that gross profitability is the purest accounting-based measure of economic profitability because it is unaffected by nonoperating items such as leverage and taxes. Gross profitability has also attracted considerable attention from professional investment managers for several reasons. First, the return predictability of gross profitability is robust. For example, gross profitability is unrelated to Sloan's (1996) accrual anomaly and subsumes most of the earnings-related anomalies (e.g., earnings to price) and numerous seemingly unrelated anomalies (e.g., failure probability, distress risk, net stock issuance, and free cash flow) (Novy-Marx 2013). Second, although gross profitability is considered a growth investment strategy, value-oriented fund managers could also benefit from implementing profitability-related investment strategies, as it provides an excellent hedge for value-style investment strategies (Novy-Marx 2013). Finally, strategies based on gross profitability anomaly are profitable when trading solely on the long leg

(Stambaugh, Yu, and Yuan 2012; Edelen, Ince, and Kadlec 2016). Thus, a gross profitability strategy is implementable even for investors facing short-sale restrictions (such as mutual funds). An article in the *Wall Street Journal* quotes a money manager as saying, "There's something there, I don't think [gross profitability] can be ignored."[5] In addition, Kenchington, Wan, and Yüksel (2019) document that a sizable subset of mutual fund managers successfully employs strategies based on profitability anomalies.

Following Novy-Marx's (2013) pioneering work, a growing literature attempts to redefine profitability to achieve a better (or more accurate) profitability measure. For example, Ball et al. (2015) argue that SG&A expenses represent a significant proportion of business operation costs. As a result, to better match current expenses and revenues, they adjust gross profit by deducting SG&A expenses, define it as operating profitability, and show that it has better explanatory power in the cross-section of stock returns than gross profitability. Furthermore, Ball et al. (2016) demonstrate that an increase in operating profitability resulting from Sloan's (1996) noncash earnings component (accruals) has no relation with the cross-section of stock returns. Thus, they exclude accruals from operating profitability and find that the resulting cash-based operating profitability is a significant predictor of future stock performance that effectively subsumes the accrual anomaly (Dechow 1994; Sloan 1996).

[5] Jason Zweig, "Have Investors Finally Cracked the Stock-Picking Code?" *Wall Street Journal* (March 1, 2013), http://www.wsj.com/articles/SB10001424127887323293704578334491900368844. See also Phil DeMuth, "The Mysterious Factor 'P': Charlie Munger, Robert Novy-Marx and the Profitability Factor," *Forbes* (June 27, 2013), https://www.forbes.com/sites/phildemuth/2013/06/27/the-mysterious-factor-p-charlie-munger-robert-novy-marx-and-the-profitability-factor/#360751b7683f; and S. Trammel, "Quality Control: Can New Research Help Investors Define a 'Quality' Stock?" *CFA Institute Magazine* (March/April 2014), 29–33.

In sum, although a growing literature measures firm profitability differently depending on the accounting or economic rationale, they are different from each other only by incremental accounting adjustments.

Mispricing, Limits to Arbitrage, and Stock Returns

Given the proliferation of profitability measures and their robust return predictability, it is in the interest of researchers and investors alike to determine whether the anomalous returns based on various profitability measures are related to mispricing effects. Recent studies show that the profitability anomaly is driven by market participants' underreaction to news about firm profitability or to a trajectory of firm profitability, which causes the mispricing (Bouchaud et al. 2019; Akbas, Jiang, and Koch 2017). Moreover, consistent with the mispricing argument, Stambaugh, Yu, and Yuan (2012) and Akbas et al. (2015) find that a strategy of long–short gross profitability is stronger following periods of high investor sentiment and during periods of unsophisticated investor flows into mutual funds.

Mispricing is generated through market imperfections and is beneficial to investors only if the profits available to arbitrageurs outweigh the related costs. One example of market frictions that could result in seemingly abnormal risk-adjusted returns is limits to arbitrage. The limits to arbitrage literature contends that because risk-averse traders either avoid or are otherwise impeded from trading on stocks with large barriers to arbitrage, implementable arbitrage opportunities are limited. Thus, mispricing opportunities are often not fully exploited in a timely manner.

The literature documents that several anomalies seem to predict returns because the stocks associated with the anomalies have high limits to arbitrage. For example, Ali, Hwang, and Trombley (2003) show that the book-to-market anomaly is the strongest among stocks with higher transaction costs, a lower percentage of institutional ownership, and higher idiosyncratic return volatility. Zhang (2006) discovers that price continuation anomalies are intensified in environments with high information uncertainty. Mashruwala, Rajgopal, and Shevlin (2006) find that high transaction costs and idiosyncratic volatility contribute to mispricing of the accrual anomaly documented by Sloan (1996). Similar, and consistent with the notion that idiosyncratic volatility is a barrier to arbitrage, Au, Doukas, and Onayev (2009) demonstrate that short sellers concentrate their trades in stocks with low idiosyncratic volatility. Lam and Wei (2011) find that limits to arbitrage, such as transaction costs, contribute to the asset growth anomaly. Interestingly, what is common for all these studies on anomalies is that a larger anomaly return is observed when limits to arbitrage are more pronounced.

The alternative to the mispricing hypothesis is that profitability is related to systematic risk. Motivated by Novy-Marx's (2013) findings, Fama and French (2015, 2016) find that conventional factor models do not capture the variation in average returns related to firm profitability. They reason that profitability is a priced risk based on the argument that the cross-sectional return predictability of firms' operating profitability scaled by book equity is consistent with the dividend discount model.[6] Consistent with a systematic risk pricing argument, Ball et al. (2015) find that the operating profitability strategy generates persistent long-run risk-adjusted returns without any

[6]Hou, Xue, and Zhang (2015, forthcoming), motivated by *q*-theory (e.g., high-profitability stocks have higher discounts rate relative to low-profitability stocks), also suggest that profitability is a systematic risk factor. However, they measure profitability as return on equity (income before extraordinary items divided by shareholders' book equity). Regardless of the theory behind a priced profitability factor, both Fama and French (2015, 2016) and Hou, Xue, and Zhang (2015, forthcoming) determine that profitability in some form should be included as an additional risk factor in asset pricing models.

reversal. The lack of reversal is an important feature, as it is inconsistent with over/underreaction driving the returns (De Bondt and Thaler 1985; Hong and Stein 1999; Ottaviani and Sørensen 2015). Additionally, Wahal (2019) finds that profitability anomalies earn statistically significant returns in out-of-sample periods, suggesting that predictability associated with the profitability anomaly is not spurious or due to data-snooping bias.

In this article we examine the role of limits to arbitrage in profitability anomalies to shed further light on whether the anomalous returns based on various profitability measures are related to mispricing effects. Thus, we propose the following hypothesis: profitability anomalies are stronger (i.e., their hedge strategies earn higher risk-adjusted returns) when limits to arbitrage are higher. If empirical evidence does not support the hypothesis for specific profitability measures, then limits to arbitrage do not explain the returns and these measures may be related to rational risk premia. Although our tests may rule out profitability measures as systematic factors (i.e., they are related to mispricing via limits to arbitrage), they cannot confirm that the measures are related to priced risk.

III. Variable Construction, Sample Selection, and Summary Statistics

Measures of Profitability

Similar to Novy-Marx (2013), we compute the gross profitability (GP/AT) as follows:

$$\mathrm{GP/AT} = \frac{\text{Revenue (REVT)} - \text{COGS}}{\text{Total Assets (AT)}}. \tag{1}$$

In equation (1), gross profit takes into account revenue and cost of goods sold (COGS). Ball et al. (2015) argue that because SG&A expenses represent a significant proportion of business operations costs, gross profit needs to be adjusted for SG&A expenses.[7] They show that operating profit, gross profit minus SG&A expenses, better matches current expenses and revenues and has better explanatory power in a cross-section of stock returns than gross profitability. Following Ball et al. (2015), we define operating profitability as follows:

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

where we compute SG&A expenses as Compustat item XSGA minus expenditures on R&D (XRD). Because Compustat item XSGA includes XRD, by subtracting XRD we isolate SG&A expenses from the R&D expenditures. For the remainder of this article, we refer to SG&A expenses as net of R&D expenditure. Finally, Ball et al. (2016) find that an increase in operating profitability due to Sloan's (1996) noncash earnings component (accruals) has no relation with the cross-section of stock returns. Thus, their measure, cash-based operating profitability, excludes accruals from operating profitability and is defined as follows:

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

where accruals are computed by using the balance sheet approach in accordance with Sloan (1996) as follows:[8]

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[7]SG&A expenses consist of a wide spectrum of nonproduction expenses, including selling expenses (e.g., advertising, marketing, delivery charges, sales commissions) and general and administrative expenses (e.g., mortgage on buildings, utilities, insurance, salaries of all non-sales personnel). Banker et al. (2019) provide a detailed discussion of SG&A expenses.

[8]For a robustness check, following Ball et al. (2016), we use cash-flow statement accruals to convert operating profitability to a cash basis as operating profitability plus the decrease in

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

Ball et al. (2016) show that cash-based operating profitability not only is a significant predictor of future stock performance but also effectively subsumes the accrual anomaly (Dechow 1994; Sloan 1996). As shown in equations (1)–(3), Novy-Marx (2013) and Ball et al. (2015, 2016) compute firm profitability differently depending on the accounting or economic rationale behind the measure. Specifically, these measures are incrementally different from each other by crucial accounting adjustments, particularly SG&A expenses and accruals. This allows us to further explore the sources of potential mispricing and determine whether it is related to mispricing associated with SG&A expenses and accruals.

Measures of Limits to Arbitrage

We consider two broad aspects of limits to arbitrage: arbitrage risk and arbitrage costs. As argued by Wurgler and Zhuravskaya (2002) and Pontiff (2006), arbitrageurs are typically poorly diversified; thus, the idiosyncratic portion of their portfolio volatility cannot be avoided by holding offsetting positions. As a result, idiosyncratic stock return volatility adds substantial risk to arbitrageurs' portfolio without offering a proportional amount of expected return; hence,

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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.

idiosyncratic volatility is often referred to as arbitrage risk and considered a barrier to arbitrage.[9] In our main analysis, we use idiosyncratic stock return volatility (ArbRisk) as a proxy for arbitrage risk, which is obtained based on the Fama–French (1993) three-factor model estimated over the previous 36 months (minimum of 30 months) ending at the end of June *t* (see, e.g., Ali, Hwang, and Trombley 2003; Ang et al. 2006; Mashruwala, Rajgopal, and Shevlin 2006; Stambaugh, Yu, and Yuan 2015). We also confirm that our results are robust to alternative specifications of idiosyncratic volatility that are based on either standard market model (the Center for Research in Security Prices [CRSP] value-weighted market index) or the Carhart (1997) four-factor model using daily (obtained over the previous 250 days with a minimum 200 days at the end of June *t*) or monthly stock returns (obtained over the previous 36 months with a minimum of 30 months).[10]

Arbitrage costs, however, can arise as a result of information uncertainty, low institutional ownership, or transaction costs (Lam, Wei, and Wei 2017). For example, arbitrageurs need sufficient information to identify arbitrage opportunities. Thus, the higher the uncertainty about firm

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[9]Although the pricing of nonsystematic component of volatility in asset returns has received considerable attention in the literature, the empirical results are mixed. This, in turn, suggests that arbitrageurs should be concerned about the nonsystematic component of volatility when they arbitrage mispriced stocks. For the 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), Chua, Goh, and Zhang (2010), Ang et al. (2006), Jiang, Xu, and Yao (2009), Fink, Fink, and He (2012), Guo, Kassa, and Ferguson (2014), Malagon, Moreno, and Rodriguez (2015), and Aabo, Pantzalis, and Park (2017).

[10]Table A1 in the Appendix provides correlation coefficients among various arbitrage risk measures.

underlying fundamentals, the less likely it is that arbitrageurs will reasonably estimate the true value, making arbitrage more difficult (Zhang 2006; Lam and Wei 2011). Previous studies show that institutional ownership, both in percentage of share ownership and number of institutional owners, is related to arbitrage costs in a variety of ways. For example, the literature demonstrates that institutional ownership is associated with higher investor awareness, liquidity, and/or short-sale supply (Ali, Hwang, and Trombley 2003; Lam and Wei 2011; Gompers and Metrick 2001; D'Avolio 2002; Asquith, Pathak, and Ritter 2005; Nagel 2005). Finally, transaction costs associated with trading, illiquidity, and short-sell constraint make arbitrage opportunities difficult to exploit and reduce the profitability of arbitrage trades (Ali, Hwang, and Trombley 2003; Mashruwala, Rajgopal, and Shevlin 2006; Lam and Wei 2011).

In our analysis, to proxy for arbitrage costs (ArbCost), we construct a composite rank measure by combining information uncertainty, institutional ownership, and transaction costs measures. Details on each variable definition and construction are provided in Table A2 in the Appendix. To construct the composite measure, first, at the end of June *t*, we independently rank all stocks into quintiles based on each type of arbitrage costs such that a higher quintile rank indicates a greater relative degree of limits to arbitrage associated with specific type of arbitrage cost.[11] Second, we compute the arithmetic average of quintile ranks across all arbitrage costs measures. ArbCost is constructed similarly to the mispricing measure by Stambaugh, Yu, and Yuan (2015) and the composite index of arbitrage and investment friction measures by Lam and

[11]We sort Size, Volume, IOWN, NOINST, and Analysts in descending order (e.g., high trading volume represents low arbitrage costs and, accordingly, receives a low arbitrage costs rank), and BidAsk and Illiquidity in ascending order (e.g., a high bid–ask spread represents large arbitrage costs and, thus, receives a high arbitrage costs rank).

Wei (2011) and Lam, Wei, and Wei (2017). Each variable in the index captures a different aspect of arbitrage costs associated with information uncertainty, low institutional ownership, low analyst coverage, and transaction costs.[12] By combining various measures into a composite index, we provide a singular, more precise measure of overall arbitrage costs because the noise in each particular type of arbitrage cost is reduced.[13]

Sample Selection and Summary Statistics

We obtain monthly stock returns and number of shares outstanding from CRSP and accounting data from Compustat. Our sample includes the ordinary common shares for all firms traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ. We exclude financial and utility firms (i.e., those with a one-digit Standard Industrial Classification [SIC] code of 6 and those with a four-digit SIC code between 4900 and 4942). Whenever possible, we adjust stock returns for delisting by using the CRSP file with delisting returns following the methodology of Shumway (1997) and Shumway and Warther (1999). We merge monthly stock returns from CRSP with fiscal year-end accounting information from Compustat lagged by the standard six months. We require firms to have no missing values for the market value of equity, book-to-market ratio, book value of total assets, current month returns, and returns for the prior one-year period. For the construction of arbitrage costs measure, we require data from the Thomson Reuters Institutional Managers (13F) holdings database to construct institutional ownership measures (IOWN, NOINST) and the Institutional Brokers' Estimate System (IBES) database to obtain the number of analysts

[12]As shown in Table A3 in the Appendix, the variables are highly correlated with each other and arbitrage risk (ArbRisk). Note that because of data availability, institutional ownership and analysts following appear in the arbitrage costs index starting in 1983.

[13]We thank an anonymous referee for this insightful suggestion.

following.[14] We assign zero analysts to a firm if the firm is not in the IBES database, following Ali, Hwang, and Trombley (2003) and Bhushan (1994). Our sample period spans from July 1963 to December 2018.

Table 1 reports the time-series averages of the cross-sectional means, medians, and standard deviations of the profitability and control measures in Panel A as well as correlation coefficients among profitability measures in Panel B. Our control variables include: book-to-market (B/M), size (ME), and measures of past performance for 1 month ($r_{1,0}$), and 12 to 2 months ($r_{12,2}$). ME is the market value of equity. B/M is 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 1-month return. $r_{12,2}$ is the cumulative return over months 2 through 12 with 1 month lagged. Following Novy-Marx (2013) and Ball et al. (2015, 2016), we winsorize all variables at the 1% and 99% levels.

The average annual gross, operating, and cash-based operating profitability measures are, respectively, 40.5%, 13.8%, and 11.9% of total assets. Panel A of Table 1 reveals significant variation among firms with different profitability measures. The average standard deviations are 22.8%, 11.8%, and 14.2% for gross, operating, and cash-based operating profitability measures, respectively. Panel B shows that profitability measures are highly correlated with each other, particularly between the operating and cash-based operating profitability measures.

IV. Empirical Results: Relation between Profitability Anomalies and Limits to Arbitrage

Profitability Anomalies and the Cross-Section of Expected Stock Returns

In this section, we assess whether the profitability anomalies are pervasive in our sample period by replicating the findings of Novy-Marx (2013) and Ball et al. (2015, 2016). Panel A of Table 2

[14]We use the June 2018 update for the Thomson Reuters Institutional Managers (13F) holdings data set. In the latest update, some the known data quality issues with 13F have been addressed. We thank the anonymous reviewer for pointing this out.

presents the results of Fama–MacBeth (1973) regressions of monthly returns on profitability measures and our control variables. 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), using six lags.[15]

Column 1 in Panel A of Table 2 shows that for the sample period between 1963 and 2010, the estimated coefficient for gross profitability (GP/AT) 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). For our extended sample period between 1963 and 2018, columns 4–8 show that the coefficients and statistical significance of the profitability measures remain similar to the estimates in Novy-Marx (2013) and Ball et al. (2015, 2016). Note that when the different measures are included simultaneously, as in columns 7 and 8, neither profitability measure subsumes the other. Thus, each measure is capturing a unique aspect of stock return predictability.

Panel B of Table 2 reports the estimates of average monthly excess returns for equally weighted profitability portfolios for our sample period. For each year at the end of June, we form quintile portfolios based on each profitability measure and report the average monthly returns in excess of the risk-free rate (R_e) and risk-adjusted returns based on the Fama–French (1993) three-factor ($\alpha^{3\mathrm{F}}$), and Carhart (1997) four-factor ($\alpha^{4\mathrm{F}}$) models. Panel B shows that high-profitability stocks outperform low-profitability stocks in all return measures, as the returns decrease monotonically from high- to low-profitability stocks. For example, in Panel B, stocks in the extreme high gross profitability quintile significantly outperform those in extreme low quintile by 0.589% per month (t = 3.91) in excess returns, R_e, and 0.720% per month (t = 4.80) in risk-adjusted

[15]All results are quantitatively and quantitatively similar using 12 lags.

returns, α^{3F}. Moreover, Panel B shows that both the long leg (high vs. middle) and short leg (middle vs. low) of profitability measures contribute to anomalous return spreads; however, the short leg contributes the most.[16] Additionally, among the risk-adjusted returns, the short leg (where limits to arbitrage should be the highest) of operating profitability exhibits less negative returns with lower statistical significance than those of the other two profitability measures.

In Panel C of Table 2, we further construct value-weighted profitability portfolios based on NYSE quintile breakpoints using firms' profitability as the sort variable. A comparison between Panels B and C reveals interesting differences between anomalous return spreads. Specifically, the risk-adjusted return spread (α^{3F}) is reduced by 10.55% (from 0.720% in Panel B to 0.644% in Panel C) for gross profitability, and by 9.73% (from 0.874% in Panel B to 0.789% in Panel C) for cash-based operating profitability. In contrast, hedge returns on operating profitability, α^{3F}, are increased by 14.20 % (from 0.599% in Panel B to 0.684% in Panel C). These findings indicate that small firms contribute more to hedge returns on gross and cash-based operating profitability than those on operating profitability. These findings also indicate that, to the extent that limits to arbitrage are more concentrated among small firms, the role of limits to arbitrage could be different across different profitability anomalies because the size characteristics differ across the definitions of profitability. Unlike in Panel B, the short legs of the profitability measures in Panel C all exhibit similar returns. Taken together, our results support the findings of Novy-Marx (2013) and Ball et al. (2015, 2016).

Overall, our results confirm the presence of profitability anomalies in our sample period that are documented by Novy-Marx (2013) and Ball et al. (2015, 2016). Moreover, the portfolio results

[16]For the rest of the article, the middle-quintile portfolio is defined as an equally weighted portfolio created using the second-, third-, and fourth-quintile portfolios of the corresponding profitability measure.

(both equally and value weighted) show that the return spreads are driven by both the short and long legs of the profitability anomalies. In the following sections, we examine the role of limits to arbitrage in profitability anomalies.[17] In doing so, we shed light on the extent to which gross, operating, and cash-based operating profitability anomalies are related to mispricing effects.

Profitability Anomalies and Limits to Arbitrage: Mean Quintile Rankings

We begin our empirical analysis by examining the relation between various profitability measures and two measures of limits to arbitrage: arbitrage risk ($\mathrm{ArbRisk}$) and arbitrage costs ($\mathrm{ArbCost}$). At the end of each June, all stocks in our sample are ranked separately 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 all stocks into quintiles based on the magnitudes of either $\mathrm{ArbRisk}$ or $\mathrm{ArbCost}$. Finally, for stocks in each profitability quintile, we calculate the average of assigned quintile rank values across their corresponding limits to arbitrage quintiles ($\mathrm{ArbRisk}^{\mathrm{Quintile}}$ or $\mathrm{ArbCost}^{\mathrm{Quintile}}$). By averaging quintile rank values instead of the magnitudes of underlying measures, it allows us to standardize the range of arbitrage risk and costs measures and remove any potential outliers. Panels A and B of Table 3 report the time-series means of cross-sectional averages, respectively, of $\mathrm{ArbRisk}^{\mathrm{Quintile}}$ and $\mathrm{ArbCost}^{\mathrm{Quintile}}$ rankings in each of the five profitability quintile portfolios. Table 3 also reports the differences in the average quintile rank values for limits to arbitrage measures across various profitability quintile ranks.

Panel A of Table 3 shows that stocks in the extreme low profitability quintiles have higher $\mathrm{ArbRisk}^{\mathrm{Quintile}}$ rankings than those in the extreme high quintiles. For example, stocks in the lowest (highest) gross profitability quintile have a mean $\mathrm{ArbRisk}^{\mathrm{Quintile}}$ of 3.245 (3.053). The

[17]For brevity, we report equally weighted portfolio results for further analyses. The results from value-weighted portfolios are qualitatively and quantitatively similar.

difference in $\text{ArbRisk}^{\text{Quintile}}$ rankings between the extreme gross profitability quintiles (high − Low) is −0.191 (significant at the 1% level) and it is greater in magnitude in a short leg (middle-low) than in a long leg (high-middle). Consistent with Jiang and Zhang (2013) and Stambaugh, Yu, and Yuan (2015), this finding suggests that mispricing is more likely to be prevalent among stocks in the short leg of the profitability strategies. Notably, for gross profitability, arbitrage risk is higher in the extreme quintiles (from which the hedge portfolio is constructed) than in the middle quintile. This finding suggests that any potential mispricing due to arbitrage risk could be more severe for the gross profitability anomaly than for other profitability anomalies. Finally, the results based on $\text{ArbCost}^{\text{Quintile}}$ in Panel B exhibit similar patterns. Overall, this analysis indicates that arbitrage risk and arbitrage costs may play an important role in explaining the return predictability of the profitability anomalies.[18]

Profitability Anomalies and Limits to Arbitrage: Portfolio Analysis

The limits to arbitrage hypothesis suggests that the return spreads on long–short hedge strategies on profitability anomalies should prevail among firms that are difficult to arbitrage. To test this hypothesis, we examine the return spreads on profitability anomalies for stocks in the extreme high ($\text{ArbRisk}^{\text{Quintile}} = 5$ or $\text{ArbCost}^{\text{Quintile}} = 5$) and low ($\text{ArbRisk}^{\text{Quintile}} = 1$ or $\text{ArbCost}^{\text{Quintile}} = 1$) limits to arbitrage quintiles, and report the equally weighted results in Table 4. In addition, Table 4 reports the differences (spreads) in portfolio returns on profitability anomalies between the extreme limits to arbitrage quintiles.

[18]Table A4 in the Appendix shows that our results are robust to alternative specifications for arbitrage risk measures.

Table 4 reveals the differential effects of limits to arbitrage on the return spreads of different profitability anomalies. Specifically, in the case of gross (cash-based operating) profitability anomalies in Panel A, the return spreads for stocks with the highest arbitrage risk are more than two (three) times the return spreads for stocks with the lowest arbitrage risk. Moreover, the differences in the return spreads between the extreme arbitrage risk quintiles are 0.446% (t = 2.75) and 0.638% per month (t = 4.06) for gross and cash-based operating profitability, respectively. These differences remain significant even after controlling for size, book-to-market, and momentum factors. In sharp contrast, there are no significant differences in the return spreads based on operating profitability between the extreme high and low arbitrage risk quintiles. Thus, unlike gross and cash-based operating profitability anomalies, arbitrage risk has no reliable effect on the operating profitability anomaly.

One aspect of these results deserves further discussion. As shown in Panel A of Table 4 for gross (cash-based operating) profitability, the return spread for stocks with the lowest arbitrage risk remains statistically significant even after controlling for size, book-to-market, and momentum factors. We interpret these findings as evidence that the limits to arbitrage, though playing an important role, do not entirely explain the profitability of a hedge strategy on gross and cash-based operating measures. That is, the return predictability of these anomalies is not completely attributable to limits to arbitrage.[19]

We replicate the analysis in Panel A of Table 4 using the composite measure of arbitrage costs and display the results in Panel B. As before, we find that arbitrage costs explain a large portion

[19]Table A4 in the Appendix confirms our results using different specifications for idiosyncratic risk.

of returns to hedge strategies based on gross and cash-based operating profitability but not based on operating profitability.

Overall, our results show surprising differences in the effect of arbitrage risk and arbitrage costs on the returns to hedge strategies across profitability anomalies. Consistent with the mispricing argument, the return predictability of both gross profitability and cash-based operating profitability is stronger for stocks when limits to arbitrage are more severe. In sharp contrast and inconsistent with the mispricing argument, the lack of a relation between the operating profitability anomaly and limits to arbitrage further supports the argument that the return predictability of operating profitability is not the result of mispricing. Notably, the comparison between Panels A and B demonstrates that the effect of limits to arbitrage on the return spread is more pronounced for arbitrage risk than for arbitrage costs, which is consistent with the literature (Ali, Hwang, and Trombley 2003; Pontiff 2006; Mashruwala, Rajgopal, and Shevlin 2006; Au, Doukas, and Onayev 2009; Lam and Wei 2011; Cao and Han 2016; Turtle and Wang 2017; Lam, Wei, and Wei 2017).

Profitability Anomalies and Limits to Arbitrage: Multivariate Analysis

In this section, we extend our portfolio analysis and examine the relation between limits to arbitrage and profitability anomalies in a multivariate setting. Specifically, similar to Li and Zhang (2010) and Lam and Wei (2011), we first compare the magnitude of the slope coefficients estimated using Fama–MacBeth (1973) cross-sectional regressions of stock monthly returns on each profitability anomaly across the quintile subsamples based on limits to arbitrage measures (either $\mathrm{ArbRisk}^{\mathrm{Quintile}}$ or $\mathrm{ArbCost}^{\mathrm{Quintile}}$). Under the limits to arbitrage hypothesis, the positive slope of the profitability measures should be greater in magnitude in the high-limits-to-arbitrage subsample than in the low-limits-to-arbitrage subsample. To test this, for each quintile subsample, we run the following regression:

$$r_{i,t+1} = \alpha_t + \beta_{1,t+1}\text{Prof}_{i,t}^{\text{Rank}} + \beta_{2,t+1}\text{Controls}_{i,t} + \varepsilon_{i,t+1}\ , \tag{5}$$

where r_{it+1} is monthly return for stock *i* at month *t*+1 and $\text{Prof}^{\text{Rank}}$ is the scaled profitability quintile rank of stock *i* at the end of each June *t*.[20] Control variables include size (Log(ME)), book-to-market (Log(B/M)), and past performance measured at horizons of 1 month ($r_{1,0}$), and 12 to 2 months ($r_{12,2}$). Table 5 presents the average slope coefficients of profitability anomalies across the $\text{ArbRisk}^{\text{Quintile}}$ and $\text{ArbCost}^{\text{Quintile}}$ subsamples, as well as the differences in the slope coefficients between the extreme limits to arbitrage subsamples.

As an overview of these results, the slope coefficients of the profitability anomalies for each quintile subsample of limits to arbitrage are plotted in Figure I. From low- to high-limits-to-arbitrage subsamples, we observe a perceptible pattern of increasing coefficient estimates for gross and cash-based operating profitability in Panels A and C, respectively. The slopes in Panel B are not drastically different for operating profitability. Moreover, consistent with the limits to arbitrage hypothesis, both panels of Table 5 show that the slope spreads for gross and cash-based operating profitability measures between the subsamples with extreme high and low limits to arbitrage are positive and significant. These patterns complement our earlier finding that the return spreads on

[20] Specifically, at the end of each June, we assign a quintile-based rank from 1 to 5 to each profitability measure. We then transform each of the rank measures by subtracting 1 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. This procedure has the advantage that the coefficient on $\text{Prof}^{\text{Rank}}$ can be interpreted as returns to a zero-investment profitability portfolio (Bernard and Thomas 1990; Mashruwala, Rajgopal, and Shevlin 2006). Although not reported for brevity, our results are similar if we do not scale profitability ranks.

profitability anomalies are significantly higher when limits to arbitrage are more severe. In contrast, for the operating profitability in Panels A and B of Table 5, the coefficient estimates exhibit an inverse-U pattern. The lack of a positive monotonic increase in the slope coefficients across the limits to arbitrage quintiles casts doubt on the effect of limits to arbitrage on operating profitability. In addition, we find no evidence supporting that the slope coefficient of operating profitability is significantly more positive in the subsample with more severe arbitrage risk or arbitrage costs. Consistent with our earlier analysis in Table 4, Table 5 demonstrates that the effects of arbitrage risk (Panel A) as a limit to arbitrage appear to be more pronounced than those of arbitrage costs (Panel B), particularly for gross and cash-based operating profitability anomalies.

We further investigate the role of limits to arbitrage on profitability anomalies using our two composite measures of limits to arbitrage (ArbRisk and ArbCost) in a multivariate framework as follows:

$$r_{it+1} = \alpha_t + \beta_{1,t+1}(\text{Prof}_{it}^{\text{Rank}} \times \text{Limits to Arbitrage}_{it}^{\text{Rank}}) + \beta_{2,t+1}\text{Prof}_{it}^{\text{Rank}} + \beta_{3,t+1}\text{Limits to Arbitrage}_{it}^{\text{Rank}} + \beta_{4,t+1}\text{Controls}_{it} + \varepsilon_{it+1}\,, \quad (6)$$

where r_{it}, $\text{Prof}^{\text{Rank}}$, $\text{Limits to Arbitrage}_{it-1}^{\text{Rank}}$, and control variables are described earlier. $\text{Limits to Arbitrage}^{\text{Rank}}$ is the scaled limits to arbitrage quintile rank (constructed separately for ArbRisk and ArbCost) of stock *i* at the end of each June *t*. The explanatory variable of interest in equation (6) is the interaction term between scaled firm profitability and limits to arbitrage quintile ranks ($\text{Prof}^{\text{Rank}} \times$ $\text{Limits to Arbitrage}^{\text{Rank}}$). The interaction term directly assesses the difference in the incremental role of limits to arbitrage on the returns to hedge strategies based on profitability anomalies. The regressions in equation (6) are estimated for each month following the Fama–MacBeth (1973) procedure with *t*-statistics computed from standard errors adjusted for heteroskedasticity and serial correlations following Newey and West (1987), with 12 lags. The results are displayed in Table 6.[21]

Table 6 once again reveals the stark difference in the incremental role of limits to arbitrage on the profitability anomalies. For example, for the gross profitability anomaly, the coefficient of the interaction between gross profitability and ArbRisk (ArbCost) is positive and significant in column 1 (column 2). To put the incremental effect of ArbRisk in column 1 into perspective, when the arbitrage risk is most severe ($\mathrm{ArbRisk}^{\mathrm{Rank}}$ = 0.5), the average monthly returns are 0.165% (0.402 × (0.5 × 0.5) + 0.585 × 0.5 − 0.458 × 0.5) for the stocks in the highest gross profitability quintile ($\mathrm{Prof}^{\mathrm{Rank}}$ = 0.5) as opposed to −0.623% (0.402 × (0.5 × −0.5) + 0.585 × −0.5 − 0.458 × 0.5) for the stocks in the lowest gross profitability quintile ($\mathrm{Prof}^{\mathrm{Rank}}$ = −0.5). To compare the incremental role of the two measures of limits to arbitrage, we include both measures as well as their interaction terms in column 3. Although the interaction between $\mathrm{Prof}^{\mathrm{Rank}}$ and $\mathrm{ArbRisk}^{\mathrm{Rank}}$ remains positive and significant (0.348, t = 2.02), the interaction between $\mathrm{Prof}^{\mathrm{Rank}}$ and $\mathrm{ArbCost}^{\mathrm{Rank}}$ becomes insignificant. Consistent with our earlier findings and the literature, this finding suggests that arbitrage risk appears to be a more prominent deterrent than arbitrage costs for arbitrage activity (Ali, Hwang, and Trombley 2003; Mashruwala, Rajgopal, and Shevlin 2006; Lam and Wei 2011). Similarly, the results for cash-based operating profitability exhibit positive and significant coefficients for the interaction terms, providing evidence that the returns to a cash-based operating profitability strategy also increase with limits to arbitrage, particularly in $\mathrm{ArbRisk}^{\mathrm{Rank}}$. In

[21]There are 34 more observations in specifications 1, 4, and 7 because of the unavailability of arbitrage costs measures in the remaining specifications.

contrast, there is no incremental role of either type of limits to arbitrage on returns associated with the operating profitability anomaly.

To summarize, the results in Tables 4–6 show surprising discrepancies in the effects of limits to arbitrage on various profitability anomalies. Specifically, consistent with the limits to arbitrage hypothesis, both arbitrage risk and arbitrage costs significantly contribute to the stock return predictability associated with gross and cash-based operating profitability anomalies. Again, the coefficients of $\text{Prof}^{\text{Rank}}$ remain positive and significant even when the interaction terms with both measures of limits to arbitrage are included. This finding suggests that the mispricing due to limits to arbitrage does not entirely explain the cross-sectional return predictability associated with profitability measures. In sharp contrast, inconsistent with the limits to arbitrage hypothesis, we find that neither arbitrage risk nor arbitrage costs have incremental effects on the returns to a hedge strategy based on operating profitability by Ball et al. (2015). The lack of a relation between measures of limits to arbitrage and the operating profitability anomaly further supports the notion that the operating profitability anomaly is not driven by mispricing.

V. Empirical Results: Accounting-Based Explanations of Differential Effects of Limits to Arbitrage

Our results so far reveal the differential effect of limits to arbitrage on various profitability anomalies. This raises the follow-up question: why do the limits to arbitrage play an imperative role in explaining the return predictability of gross and cash-based operating profitability anomalies but not of operating profitability? The underlying components of profitability measures may provide answers to this question. In this section, we further explore the sources of mispricing for gross and cash-based operating profitability anomalies.

SG&A Expenses, Accruals, Profitability Anomalies, and Limits to Arbitrage: Mean Quintile Rankings

Although all profitability measures explored here pertain to profit margins, as discussed in Section II, they are incrementally different from each other by crucial accounting adjustments such as SG&A expenses and accruals. Specifically, in contrast to the gross profitability measure that considers only revenues and cost of goods sold (Novy-Marx 2013), operating profitability excludes SG&A expenses (net of R&D) 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.[22] Eisfeldt and Papanikolaou (2013) find a positive and significant relation between SG&A expenses and the cross-section of stock returns, and Banker et al. (2019) attribute this return predictability to mispricing of SG&A expenses. Cash-based operating profitability removes accounting accruals from operating profitability (Ball et al. 2016). Mashruwala, Rajgopal, and Shevlin (2006) show that the 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). These incremental, yet critical, differences might be linked to the differential effects of limits to arbitrage on profitability anomalies. Thus, mispricing arising from each particular accounting component of the profitability ratios could be contributing to their overall return predictability.

To explore this possibility, we first examine the relation between limits to arbitrage, SG&A expenses, accruals, and profitability measures. We follow the procedure described in Section IV and Table 3. Specifically, we first rank stocks into quintiles (Q1 [low] to Q5 [high]) according to the magnitude of SG&A expenses (SG&A/AT) and accruals (Accruals/AT), both scaled by total assets. Independent of SG&A and accruals rankings, stocks are further assigned to their corresponding

[22]Lev, Radhakrishnan, and Evans (2016) provide a thorough literature review on organizational capital.

quintile groups based on profitability and arbitrage risk measures ($\mathrm{GP/AT}^{\mathrm{Quintile}}$, $\mathrm{OP/AT}^{\mathrm{Quintile}}$, $\mathrm{COP/AT}^{\mathrm{Quintile}}$, and $\mathrm{ArbRisk}^{\mathrm{Quintile}}$).[23] Panel A (Panel B) of Table 7 reports the average quintile rankings of profitability and arbitrage risk measures in each of the five quintiles of the SG&A/AT (Accruals/AT) quintile portfolios and the differences between those quintile ranks.

Table 7 reveals the significant differences in SG&A expenses and accruals across profitability measures. As shown in Panel A, we find a strong monotonic relation between SG&A expenses and gross profitability. The difference in $\mathrm{GP/AT}^{\mathrm{Quintile}}$ between the extreme SG&A/AT quintiles is 3.189 (significant at the 1% level). This finding suggests that high-gross-profit firms tend to have greater expenses related to promotion, selling, and delivering the firm's products and services, which is reflected in higher SG&A expenses for such firms. The positive correlation between gross profitability and SG&A expenses suggests that forming portfolios based on gross profitability would result in portfolios that appear to be sorted by SG&A expenses; both gross profitability (Novy-Marx 2013) and SG&A expenses (Eisfeldt and Papanikolaou 2013; Banker et al. 2019) are positively related to future stock returns. In contrast to gross profitability, neither the operating nor cash-based operating profitability measure exhibits a monotonic association with SG&A expenses. Moreover, Panel A shows that arbitrage risk in the top SG&A/AT quintile is significantly higher than in the medium and bottom SG&A/AT quintiles, suggesting a significant relation between SG&A expenses and arbitrage risk, and indicating possible mispricing effects. This begs the question: with regard to gross profitability hedge portfolio returns, is gross profitability being mispriced or is SG&A?

[23]For brevity, given the results in the previous section, all further analyses focus on the arbitrage risk measure. Results based on arbitrage costs measure are consistent and available upon request.

Furthermore, Panel B of Table 7 shows a strong, negative, monotonic relation between accruals and the cash-based operating profitability measure. Gross and operating profitability measures do not exhibit the same relation. The negative correlation between cash-based operating profitability and accruals suggests that forming portfolios based on cash-based operating profitability would result in portfolios that are similar to sorting by accruals. The arbitrage risk measure 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 (scaled by total assets) have a U-shaped relation with idiosyncratic return volatility. Thus, what appears to be a mispricing of cash-based operating profitability could be a mispricing of accruals.

In summary, these results illustrate that (1) profitability measures and arbitrage risk differ, depending on the values of SG&A expenses and accruals, and (2) 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 limits to arbitrage, particularly arbitrage risk, on hedge strategies based on profitability measures.

Profitability Anomalies and Limits to Arbitrage: Effects of SG&A Expenses and Accruals

Having documented a significant relation between SG&A expenses (accruals) and gross (cash-based operating) profitability, we next examine how the differences in SG&A expenses and accruals between the probability measures play a role in the predictability associated with mispricing due to limits to arbitrage. Specifically, we augment equation (6) to include $(\mathrm{SG\&A/AT})^{\mathrm{Rank}}$ and $(\mathrm{Accruals/AT})^{\mathrm{Rank}}$. As described in Section V, $(\mathrm{SG\&A/AT})^{\mathrm{Rank}}$ and $(\mathrm{Accruals/AT})^{\mathrm{Rank}}$ are the scaled annual quintile ranks for SG&A expenses and accruals scaled by total assets, respectively. Table 8 reports Fama–MacBeth (1973) coefficient estimates with *t*-statistics computed from standard errors adjusted for heteroskedasticity and serial correlations following Newey and West (1987), with 12 lags.

Columns 1 and 2 of Table 8 show a positive (negative) and significant relation between the cross-section of stock returns and SG&A expenses (accruals), which is consistent with the literature (e.g., Sloan 1996; Eisfeldt and Papanikolaou 2013; Mashruwala, Rajgopal, and Shevlin 2006; Novy-Marx 2013; Ball et al. 2015; Banker et al. 2019).[24] The results also suggest that a hedge strategy that is long in high-SG&A-expenses (low-accruals) stocks and short in low-SG&A-expenses (high-accruals) stocks generates additional returns when the limits to arbitrage are more severe. Specifically, in column 1 (column 2), the coefficient of the interaction term between SG&A expenses (accruals) and arbitrage risk is positive (negative) and significant. Although the effect of limits to arbitrage on the accruals anomaly has been documented (Mashruwala, Rajgopal, and Shevlin 2006), we are unaware of any study that examines the effect of limits to arbitrage on the return predictability of SG&A expenses.

The results from Section IV suggest a positive (negative) correlation between gross (cash-based operating) profitability and SG&A expenses (accruals) that could confound the interpretation of the previous limited arbitrage mispricing analyses. Including SG&A expenses (accruals) in the mispricing analysis resolves this issue. If the significant relation between arbitrage risk and gross (cash-based operating) profitability is driven by SG&A expenses (accruals) being subject to mispricing, we expect the positive coefficient of the interaction term between arbitrage risk and gross (cash-based operating) profitability to be subsumed after we include SG&A expenses (accruals) in the interaction term with arbitrage risk. To test these predictions, in column 3 (column

[24]Banker et al. (2019) relate the positive relation between SG&A expenses and future stock performance to mispricing arising from investors' inability to recognize a long-term impact on a firm's future performance. The authors argue that such mispricing is due to the accounting treatment for SG&A expenses. Our findings complement their study and further offer limits to arbitrage as an alternative explanation of why SG&A expenditures are mispriced.

4) of Table 8, we include both SG&A expenses (accruals) and gross (cash-based operating) profitability measures as well as their interactions with limits to arbitrage.

As shown in column 3 of Table 8, although the interaction term between gross profitability and arbitrage risk becomes statistically insignificant, the coefficient on $(SG\&A/\mathrm{AT})^{\mathrm{Rank}} \times \mathrm{ArbRisk}^{\mathrm{Rank}}$ remains significant and positive. Thus, the positive and significant relation between gross profitability and arbitrage risk is mitigated by the interaction between SG&A expenses and idiosyncratic volatility, leading to no mispricing effects in the gross profitability strategy. The evidence suggests gross profitability itself is not mispriced, but rather it appears mispriced because of its high correlation with SG&A. The operating profitability measure subtracts SG&A expenses from gross profitability and, in doing so, negates the correlation between gross profitability and SG&A expenses. Because operating profitability is not correlated with SG&A expenses, it does not exhibit the mispricing effects that occur with gross profitability.

Column 4 of Table 8 shows that after accounting for $(\mathrm{Accruals}/\mathrm{AT})^{\mathrm{Rank}} \times \mathrm{ArbRisk}^{\mathrm{Rank}}$, there is no significant relation between stock returns and the interaction terms between measures of cash-based operating profitability and arbitrage risk. This finding suggests that introducing accruals to the profitability definition (cash-based operating profitability) reintroduces mispricing effects by making the profitability measure highly correlated with accruals. Similar to the results from examining gross profitability and SG&A expenses, it is not the cash-based profitability measure that is mispriced. Because accruals, which are mispriced, are highly negatively correlated with cash-based operating profitability, the profitability measure merely appears to be mispriced.

Overall, these results help reconcile the differential effect of limits to arbitrage across the profitability measures and suggest that the accounting adjustments across the profitability measures induce (in the case of accruals and cash-based profitability) or resolve (in the case of SG&A expenses and operating profitability) mispricing effects.

VI. Conclusion

Recent studies document that gross, operating, and cash-based operating profitability measures have significant predictive power in the 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 the inclusion of profitability-related factors in traditional asset pricing models (Fama and French 2015; Chen, Novy-Marx, and Zhang 2011). However, systematic risk premia should be unrelated to limits to arbitrage, which create return predictability through mispricing.

In this study, we investigate the effect of limits to arbitrage on the gross, operating, and cash-based operating profitability anomalies in search of evidence of mispricing effects. If limited arbitrage prevents profitability measures from being fully priced, resulting in 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, which supports, at least in part, a mispricing explanation. In contrast, we find no evidence that the predictive power of operating profitability is related to arbitrage risk or arbitrage costs.

Finally, we show that the differential effects of arbitrage risk on the return predictability across gross and cash-based operating profitability anomalies are attributable to their respective correlations with the return predictability of SG&A expenses and accruals, which are also related to limits to arbitrage. In other words, the gross and cash-based operating profitability measures are not necessarily mispriced, but rather appear to be because they are highly related to the accounting elements: SG&A expenses and accruals. Thus, the return predictability associated with profitability measures is not completely attributable to mispricing due to limited arbitrage. Overall, the evidence suggests that those interested in either using a particular profitability strategy or refining a profitability measure should use caution and recognize that mispricing rather than risk may be imbedded in profitability strategies depending on the definition of profitability.

References

Aabo, T., C. Pantzalis, and J. C. Park, 2017, Idiosyncratic volatility: An indicator of noise trading? *Journal of Banking & Finance* 75, 136–51.

Akbas, F., W. J. Armstrong, S. Sorescu, and A. Subrahmanyam, 2015, Smart money, dumb money, and capital market anomalies, *Journal of Financial Economics* 118, 355–82.

Akbas, F., C. Jiang, and P. D. Koch, 2017, The trend in firm profitability and the cross-section of stock returns, *The Accounting Review* 92, 1–32.

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.

Ali, A., L. S. Hwang, and M. A. Trombley, 2003, Arbitrage risk and the book-to-market anomaly, *Journal of Financial Economics* 69, 355–73.

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

Anderson, M., R. Banker, R. Huang, and S. Janakiraman, 2007, Cost behavior and fundamental analysis of SG&A costs, *Journal of Accounting, Auditing, and Finance* 22, 1–28.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 51, 259–99.

Arena, M. P., K. S. Haggard, and X. Yan, 2008, Price momentum and idiosyncratic volatility, *Financial Review* 43, 159–90.

Asquith, P., P. A. Pathak, and J. R. Ritter, 2005, Short interest, institutional ownership, and stock returns, *Journal of Financial Economics* 78, 243–76.

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., N. Cakici, X. S. Yan, and Z. Zhang, 2005, Does idiosyncratic risk really matter? *Journal of Finance* 60, 905–29.

Ball, R., J. Gerakos, J. T. Linnainmaa, and V. Nikolaev, 2015, Deflating profitability, *Journal of Financial Economics* 117, 225–48.

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.

Banker, R. D., R. Huang, N. Ramachandra (Ram), and S. Zhao, 2019, Market valuation of intangible asset: Evidence on SG&A expenditure, *The Accounting Review* 94, 61–90.

Bartov, E., S. Radhakrishnan, and I. Krinsky, 2000, Investor sophistication and patterns in stock returns after earnings announcements, *The Accounting Review* 75, 43–63.

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, 305–40.

Bhushan, R., 1994, An informational efficiency perspective on the post-earnings announcement drift, *Journal of Accounting and Economics* 18, 45–65.

Bouchaud, J. P., P. Krueger, A. Landier, and D. Thesmar, 2019, Sticky expectations and the profitability anomaly, *Journal of Finance* 74, 639–73.

Cao, J., and B. Han, 2016, Idiosyncratic risk, costly arbitrage, and the cross-section of stock returns, *Journal of Banking & Finance* 73, 1–15.

Carhart, M. M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chen, L., R. Novy-Marx, and L. Zhang, 2011, An alternative three-factor model, Working Paper, CKGSB, University of Rochester, and Ohio State University.

Chua, T. C., J. Goh, and Z. Zhang, 2010, Expected volatility, and the cross-section of stock returns, *Journal of Financial Research* 33, 103–23.

Datar, V. T., N. Y. Naik, and R. Radcliffe, 1998, Liquidity and stock returns: An alternative test, *Journal of Financial Markets* 1, 203–19.

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

De Bondt, W. F., and R. Thaler, 1985, Does the stock market overreact? *Journal of Finance* 40, 793–805.

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, 472–88.

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 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.

Fama, E. F., and J. D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–36.

Fink, J. D., K. E. Fink, and H. He, 2012, Expected idiosyncratic volatility measures and expected returns, *Financial Management* 41, 519–53.

Gompers, P. A., and A. Metrick, 2001, Institutional investors and equity prices, *Quarterly Journal of Economics* 116, 229–59.

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, 271–96.

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

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, 265–95.

Hong, H., and J. C. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance* 54, 2143–84.

Hou, K., C. Xue, and L. Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650–705.

Hou, K., C. Xue, and L. Zhang, forthcoming, Replicating anomalies, *Review of Financial Studies*.

Jiang, G. J., D. Xu, and T. Yao, 2009, The information content of idiosyncratic volatility, *Journal of Financial and Quantitative Analysis* 44, 1–28.

Jiang, G. J., and A. J. Zhang, 2013, The shrinking space for anomalies, *Journal of Financial Research* 36, 299–324.

Kenchington, D., C. Wan, and H. Z. Yüksel, 2019, Gross profitability and mutual fund performance, *Journal of Banking & Finance* 104, 31–49.

Lam, F. Y., C. Wei, and K. C. Wei, 2017, Dissecting arbitrage costs, Hong Kong Monetary Authority - Hong Kong Institute for Monetary Research (HKIMR) Working Paper.

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, 127–49.

Lev, B., and D. Nissim, 2006, The persistence of the accruals anomaly, *Contemporary Accounting Research* 23, 193–226.

Lev, B., and S. Radhakrishnan, 2005, The valuation of organization capital, in C. Corrado, J. Haltiwanger, and D. Sichel, eds.: *Measuring Capital in the New Economy* (National Bureau of Economic Research, Cambridge, MA), 73-110.

Lev, B., S. Radhakrishnan, and P. C. Evans, 2016, *Organizational Capital: A CEO's Guide to Measuring and Managing Enterprise Intangibles* (Center for Global Enterprise, New York).

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

Li, X., and D. Luo, 2016, Investor sentiment, limited arbitrage, and the cash holding effect, *Review of Finance* 21, 2141–68.

Malagon, J., D. Moreno, and R. Rodriguez, 2015, The idiosyncratic volatility anomaly: Corporate investment or investor mispricing, *Journal of Banking & Finance* 60, 224–38.

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, 875–94.

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, 777–87.

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

Ottaviani, M., and P. N. Sørensen, 2015, Price reaction to information with heterogeneous beliefs and wealth effects: Underreaction, momentum, and reversal, *American Economic Review* 105, 1–34.

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, 35–55.

Shumway, T., 1997, The delisting bias in CRSP data, *Journal of Finance* 52, 327–40.

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, 2361–79.

Sloan, R. G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings? *The 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, 1903–48.

Stoll, H. R., 2000, Presidential address: Friction, *Journal of Finance* 55, 1479–1514.

Turtle, H., and K. Wang, 2017, The value in fundamental accounting information, *Journal of Financial Research* 40, 113–40.

Wahal, S., 2019, The profitability and investment premium: Pre-1963 evidence, *Journal of Financial Economics* 131, 362–77.

Wurgler, J., and E. Zhuravskaya, 2002, Does arbitrage flatten demand curves for stocks? *Journal of Business* 75, 583–608.

Zhang, X. F., 2006, Information uncertainty and stock returns, *Journal of Finance* 61, 105–36.

Appendix

TABLE A1. Correlation Coefficients among Various Arbitrage Risk Measures.

	1	2	3	4	5
1. $\mathrm{ArbRisk}^{3F-Monthly}$	0.963				
2. $\mathrm{ArbRisk}^{4F-Monthly}$	0.957	0.983			
3. $\mathrm{ArbRisk}^{1F-Daily}$	0.838	0.828	0.826		
4. $\mathrm{ArbRisk}^{3F-Daily}$	0.836	0.827	0.826	0.991	
5. $\mathrm{ArbRisk}^{4F-Daily}$	0.836	0.827	0.826	0.989	0.996

Note: This table reports the time series averages of the cross-sectional Pearson correlation coefficients for various arbitrage risk measures. $\mathrm{ArbRisk}^{1F-Monthly}$, $\mathrm{ArbRisk}^{3F-Monthly}$, and $\mathrm{ArbRisk}^{4F-Monthly}$ are the monthly idiosyncratic volatilities of firms based, respectively, on the Center for Research in Security Prices (CRSP) value-weighted market index, Fama–French (1993) three factors, and Carhart (1997) four factors over the previous 36 months (minimum of 30 months) ending June 30. $\mathrm{ArbRisk}^{1F-Daily}$, $\mathrm{ArbRisk}^{3F-Daily}$, and $\mathrm{ArbRisk}^{4F-Daily}$ are the daily idiosyncratic volatilities of firms based, respectively, on the CRSP value-weighted market index, Fama–French (1993) three factors, and Carhart (1997) four factors over the previous 250 days (minimum of 200 days) ending June 30. The sample period is July 1963 to December 2018.

TABLE A2. Description of Institutional Ownership, Analyst Coverage, and Transaction Costs Variables.

Name	Acronym	Ranking Order	Data Source	Definition	Sample Period	Related Studies
Number of institutions	NOINST	Descending	2018 Thomson Reuters Institutional (13F) holdings	Number of institutions at the end of June. Zero number of institutions is assigned if a firm is not in the 13F database	July 1983–Dec. 2018	Bartov, Radhakrishan, and Krinsky (2000); Ali, Hwang, and Trombley (2003); Mashruwala, Rajgopal, and Shevlin (2006)
Analysts following	Analysts	Descending	IBES	Number of analysts following at the end of June. Zero number of institutions is assigned if a firm is not in IBES	July 1983–Dec. 2018	Hong, Lim, and Stein (2000); Ali, Hwang, and Trombley (2003); Lam and Wei (2011)
Bid-ask spread	BidAsk	Ascending	CRSP	Average daily bid–ask spread divided by the average of daily spread over three most recent months before the end of June	July 1963–Dec. 2018	Stoll (2000); Mashruwala, Rajgopal, and Shevlin (2006)
Firm size	Size	Descending	CRSP	Market capitalization at the end of June	July 1963–Dec. 2018	Ali, Hwang, and Trombley (2003); Mashruwala, Rajgopal, and Shevlin (2006)
Amihud illiquidity	Illiquidity	Ascending	CRSP	Average Amihud illiquidity measure over three most recent months before the end of June	July 1963–Dec. 2018	Amihud (2002)
Trading volume	Volume	Descending	CRSP	Average of daily dollar trading volume over three most recent months at the end of June	July 1963–Dec. 2018	Bhushan (1994); Datar, Naik, and Radcliffe (1998)
Institutional ownership	IOWN	Descending	2018 Thomson Reuters Institutional (13F) holdings	Percentage of shares outstanding held by institutional investors at the end of June	July 1983–Dec. 2018	Ali, Hwang, and Trombley (2003); Lam and Wei (2011)

Note: This table describes definitions and related studies for the main explanatory variables used in this study. CRSP = Center for Research in Security Prices; IBES = Institutional Brokers' Estimate System.

TABLE A3. Correlation between Arbitrage Risk, Arbitrage Costs, Information Costs, and Transaction Costs Measures.

	1	2	3	4	5	6	7	8
1. $\text{ArbCost}^{\text{Quintile}}$	0.578							
2. $\text{Size}^{\text{Quintile}}$	0.505	0.830						
3. $\text{Illiquidity}^{\text{Quintile}}$	0.427	0.880	0.820					
4. $\text{BidAsk}^{\text{Quintile}}$	0.643	0.578	0.435	0.358				
5. $\text{Volume}^{\text{Quintile}}$	0.349	0.833	0.798	0.936	0.266			
6. $\text{IOWN}^{\text{Quintile}}$	0.441	0.804	0.524	0.670	0.447	0.677		
7. $\text{NOINST}^{\text{Quintile}}$	0.506	0.913	0.792	0.873	0.527	0.876	0.779	
8. $\text{Analysts}^{\text{Quintile}}$	0.324	0.754	0.614	0.685	0.325	0.699	0.563	0.690

Note: At the end of each June, all stocks in the sample are ranked into five quintiles based on arbitrage risk, arbitrage costs, information costs, and transaction costs variables and assigned into their corresponding quintiles. This table reports the time-series averages of the cross-sectional Pearson correlation coefficients for the quintile rankings of arbitrage risk ($\text{ArbRisk}^{\text{Quintile}}$), arbitrage costs ($\text{ArbCost}^{\text{Quintile}}$), information costs ($\text{NOINST}^{\text{Quintile}}$ and $\text{Analysts}^{\text{Quintile}}$), and transaction costs ($\text{BidAsk}^{\text{Quintile}}$, $\text{Illiquidity}^{\text{Quintile}}$, $\text{Size}^{\text{Quintile}}$, $\text{Volume}^{\text{Quintile}}$, and $\text{IOWN}^{\text{Quintile}}$) measures. Quintile sorting of the number of institutions ($\text{NOINST}^{\text{Quintile}}$), analysts following ($\text{Analysts}^{\text{Quintile}}$), size ($\text{Size}^{\text{Quintile}}$), trading volume ($\text{Volume}^{\text{Quintile}}$), and institutional ownership ($\text{IOWN}^{\text{Quintile}}$) are in descending order, and the rest are in ascending order. The construction and definitions of all variables are described in Section III and Table A2 in the Appendix. The sample period is July 1963 to December 2018.

TABLE A4. Robustness Results: Alternative Specifications of Arbitrage Risk Measure.

	Arbitrage Risk Quintile Rank				
	$\text{ArbRisk}^{1F-\text{Monthly}}$	$\text{ArbRisk}^{4F-\text{Monthly}}$	$\text{ArbRisk}^{1F-\text{Daily}}$	$\text{ArbRisk}^{3F-\text{Daily}}$	$\text{ArbRisk}^{4F-\text{Daily}}$
GP/AT					
Q5 (High)	3.038	3.053	3.013	3.017	3.020
Q4	2.938	2.937	2.916	2.917	2.918
Q3	2.894	2.891	2.904	2.901	2.902
Q2	2.896	2.891	2.902	2.902	2.900
Q1 (Low)	3.251	3.245	3.268	3.267	3.264
Differences					
High – Low	–0.213***	–0.191***	–0.255***	–0.235***	–0.243***
High – Middle	0.127***	0.146***	0.105***	0.110***	0.114***
Middle – Low	–0.341***	–0.338***	–0.360***	–0.346***	–0.357***
OP/AT					
Q5 (High)	2.755	2.772	2.654	2.654	2.652
Q4	2.613	2.621	2.571	2.570	2.569
Q3	2.748	2.749	2.714	2.714	2.715
Q2	3.092	3.084	3.105	3.105	3.106
Q1 (Low)	3.877	3.860	3.964	3.966	3.967
Differences					
High – Low	–1.122***	–1.087***	–1.309***	–1.207***	–1.314***
High – Middle	–0.062**	–0.045*	–0.142***	–0.163***	–0.145***
Middle – Low	–1.059***	–1.042***	–1.166***	–1.065***	–1.169***
COP/AT					
Q5 (High)	2.822	2.832	2.734	2.733	2.732
Q4	2.605	2.608	2.578	2.578	2.578
Q3	2.779	2.779	2.756	2.757	2.757
Q2	3.121	3.115	3.115	3.112	3.113
Q1 (Low)	3.808	3.800	3.829	3.832	3.833
Differences					
High – Low	–0.985***	–0.968***	–1.094***	–1.065***	–1.101***
High – Middle	–0.009	0.001	–0.082***	–0.098***	–0.083***

Middle – Low	–0.975***	–0.968***	–1.012***	–0.983***	–1.017***

Note: This table reports robustness results for the alternative specifications of arbitrage risk measures. Gross profitability (GP/AT), operating profitability (OP/AT), and cash-based operating profitability (COP/AT) measures are defined in Section III and computed at the end of every June. This table replicates the methodology in Table 3 using alternative arbitrage risk measures. Specifically, it reports the average quintile ranks of arbitrage risk measures for each profitability quintile portfolio (Q5 – Q1), as well as the differences in the average quintile ranks for limits to arbitrage measures between various profitability portfolio quintiles. $\text{ArbRisk}^{\text{1F−Monthly}}$ and $\text{ArbRisk}^{\text{4F−Monthly}}$ are the standard deviation of the residuals obtained from the regressions of monthly stock returns on, respectively, the Center for Research in Security Prices (CRSP) value-weighted market index and Carhart (1997) four factors over the previous 36 months (minimum of 30 months) ending June 30. $\text{ArbRisk}^{\text{1F−Daily}}$, $\text{ArbRisk}^{\text{3F−Daily}}$, and $\text{ArbRisk}^{\text{4F−Daily}}$ are the standard deviation of the residuals obtained from the regressions of daily stock returns on, respectively, the CRSP value-weighted market index, Fama–French (1993) three factors, and Carhart (1997) four factors over the previous 250 days (minimum of 200 days) ending June 30. The sample period is July 1963 to December 2018.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

TABLE A5. Robustness Results: Profitability Anomalies and Alternative Specifications of Arbitrage Risk—Portfolio Analysis.

	High Arbitrage Risk $\text{ArbRisk}^{\text{Quintile}} = 5$	Low Arbitrage Risk $\text{ArbRisk}^{\text{Quintile}} = 1$	Difference in High – Low Arbitrage Risk			
			R_e	α^{CAPM}	α^{3F}	α^{4F}
Panel A. GP/AT						
$\text{ArbRisk}^{\text{1F−Monthly}}$						
High (Q5) – low (Q1) profitability	0.805***	0.335***	0.470***	0.437***	0.417**	0.398**
t-statistic	(4.45)	(3.36)	(2.90)	(2.73)	(2.55)	(2.30)
N	83,95	83,68				
$\text{ArbRisk}^{\text{4F−Monthly}}$						
High (Q5) – low (Q1) profitability	0.762***	0.331***	0.431***	0.404**	0.357**	0.298*
t-statistic	(4.27)	(3.29)	(2.66)	(2.53)	(2.20)	(1.77)
N	85,95	82,67				
$\text{ArbRisk}^{\text{1F−Dailly}}$						
High (Q5) – low (Q1) profitability	0.710***	0.378***	0.333**	0.313**	0.282**	0.258*
t-statistic	(4.21)	(3.68)	(2.09)	(2.08)	(1.98)	(1.78)
N	87,118	94,83				
$\text{ArbRisk}^{\text{3F−Dailly}}$						
High (Q5) – low (Q1) profitability	0.729***	0.384***	0.344**	0.324**	0.291**	0.279*
t-statistic	(4.34)	(3.80)	(2.17)	(2.11)	(2.04)	(1.87)
N	87,117	94,83				
$\text{ArbRisk}^{\text{4F−Dailly}}$						
High (Q5) – low (Q1) profitability	0.724***	0.369***	0.355**	0.335**	0.300**	0.289*
t-statistic	(4.31)	(3.59)	(2.23)	(2.13)	(2.09)	(1.73)
N	88,117	94,84				
Panel B. OP/AT						
$\text{ArbRisk}^{\text{1F−Monthly}}$						
High (Q5) – low (Q1) profitability	0.291	0.265**	0.026	0.061	0.065	0.006
t- statistic	(1.54)	(2.10)	(0.15)	(0.36)	(0.38)	(0.03)
N	56,146	105,26				
$\text{ArbRisk}^{\text{4F−Monthly}}$						
High (Q5) – low (Q1) profitability	0.283	0.358***	-0.074	-0.049	-0.059	-0.139
t-statistic	(1.51)	(2.78)	(-0.44)	(-0.29)	(-0.35)	(-0.80)
N	58,145	103,27				

$\text{ArbRisk}^{1F-Dailly}$						
High (Q5) – low (Q1) profitability	0.262	0.484***	-0.222	-0.182	-0.158	-0.278
t-statistic	(1.53)	(3.88)	(-1.24)	(-1.05)	(-0.89)	(-1.53)
N	45,196	121,31				
$\text{ArbRisk}^{3F-Dailly}$						
High (Q5) – low (Q1) profitability	0.321*	0.500***	-0.179	-0.145	-0.137	-0.260
t-statistic	(1.89)	(4.03)	(-0.99)	(-0.81)	(-0.76)	(-1.41)
N	45,195	121,31				
$\text{ArbRisk}^{4F-Dailly}$						
High (Q5) – low (Q1) profitability	0.313*	0.489***	-0.176	-0.140	-0.120	-0.243
t-statistic	(1.85)	(3.93)	(-0.97)	(-0.79)	(-0.66)	(-1.33)
N	45,196	122,31				
Panel C. COP/AT						
$\text{ArbRisk}^{1F-Monthly}$						
High (Q5) – low (Q1) profitability	0.872***	0.217**	0.655***	0.671***	0.594***	0.582***
t-statistic	(6.10)	(2.06)	(4.25)	(4.44)	(3.90)	(3.78)
N	64,133	104,26				
$\text{ArbRisk}^{4F-Monthly}$						
High (Q5) – low (Q1) profitability	0.924***	0.274***	0.650***	0.675***	0.594***	0.561***
t-statistic	(6.55)	(2.69)	(4.16)	(4.41)	(3.87)	(3.62)
N	64,132	102,27				
$\text{ArbRisk}^{1F-Dailly}$						
High (Q5) – low (Q1) profitability	0.890***	0.411***	0.480***	0.528***	0.445***	0.357**
t-statistic	(6.18)	(3.96)	(3.08)	(3.45)	(2.96)	(2.39)
N	60,170	121,33				
$\text{ArbRisk}^{3F-Dailly}$						
High (Q5) – low (Q1) profitability	0.884***	0.404***	0.480***	0.524***	0.427***	0.341**
t-statistic	(6.27)	(3.91)	(3.08)	(3.42)	(2.83)	(2.25)

N	60,170	121,33				
$\text{ArbRisk}^{\text{4F-Dailly}}$						
High (Q5) – low (Q1) profitability	0.882***	0.395***	0.487***	0.536***	0.450***	0.357**
t-statistic	(6.21)	(3.82)	(3.12)	(3.51)	(2.97)	(2.37)
N	60,170	121,33				

Note: This table reports the performance of a long–short hedge strategy based on the profitability measures for stocks with alternative high and low arbitrage risk measures ($\text{ArbRisk}^{\text{1F-Monthly}}$, $\text{ArbRisk}^{\text{4F-Monthly}}$, $\text{ArbRisk}^{\text{1F-Daily}}$, $\text{ArbRisk}^{\text{3F-Daily}}$, and $\text{ArbRisk}^{\text{4F-Daily}}$). At the end of each June, all stocks in the sample are ranked into five quintiles based on gross (GP/AT), operating (OP/AT), and cash-based operating profitability (COP/AT) measures as described in Section III. Independent of the profitability measures rankings, stocks are also ranked into five groups based on arbitrage risk measures and assigned to their corresponding quintiles ($\text{ArbRisk}^{\text{Quintile}}$). For each extreme quintile of arbitrage risk measure, each panel reports the average monthly excess returns between the highest and lowest profitability quintiles (Q5 – Q1). Each panel also reports the differences in excess returns, R_e, of Q5 – Q1 between the extreme limits to arbitrage quintiles as well as risk-adjusted performance based on the capital asset pricing model (α^{CAPM}), Fama–French (1993) three-factor (α^{3F}) model, and Carhart (1997) four-factor (α^{4F}) model. The construction of arbitrage risk measures is described in Table A4 in the Appendix. Measures of profitability and idiosyncratic volatility are described in Section III. *N* stands for the average number of stocks that fall into the high (Q5) and low (Q1) profitability quintiles. The *t*-statistics are reported in parentheses. The sample period is July 1963 to December 2018.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

TABLE 1. Summary Statistics.

Panel A. Firms Characteristics

Variable	Mean	Median	St. Dev.
GP/AT	0.405	0.369	0.228
OP/AT	0.138	0.143	0.118
COP/AT	0.119	0.127	0.142
B/M	0.833	0.692	0.592
ME ($million)	1,201	211	3,231
$r_{1,0}$ (%)	0.949	0.200	0.949
$r_{12,2}$ (%)	12.667	6.184	43.279

Panel B. Correlation Coefficients among Profitability Measures

	1	2
1. OP/AT	0.467	
2. COP/AT	0.351	0.739

Note: This table reports the time series averages of the cross-sectional means, medians, and standard deviations of firm characteristics (Panel A) and Pearson correlation coefficients for profitability measures (Panel B). Firm characteristics include gross, operating, and cash-based operating profitability measures; book-to-market ratio; market value of equity; and past returns. Gross profitability (GP/AT), operating profitability (OP/AT), and cash-based operating profitability (COP/AT) measures are defined in Section III and computed at the end of every June. B/M is 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. ME is the market value of equity. $r_{1,0}$ is the prior 1-month return. $r_{12,2}$ is the cumulative return over months 2 through 12 with 1 month lagged. 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 and utility 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 July 1963 to December 2018.

TABLE 2. Profitability Anomalies and the Cross-Section of Expected Stock Returns.

Panel A. Fama–MacBeth (1973) Regressions

	Novy-Marx (2013) 1963–2010	Ball et. al. (2016) 1963–2013		Extended Sample Period 1963–2018				
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GP/AT	0.821***			0.873***			0.577***	0.570***
	(5.02)			(5.78)			(3.24)	(3.40)
OP/AT		2.042***			2.165***		1.610***	
		(5.06)			(5.71)		(4.07)	
COP/AT			2.112***			2.201***		1.831***
			(9.30)			(9.92)		(8.36)
Log(B/M)	0.441***	0.420***	0.396***	0.391***	0.369***	0.348***	0.394***	0.374***
	(5.31)	(5.28)	(5.27)	(5.31)	(4.92)	(4.90)	(5.27)	(5.17)
Log(ME)	–0.075**	–0.117***	–0.115***	–0.053*	–0.108***	–0.106***	–0.088**	–0.092**
	(–2.02)	(–2.88)	(–2.75)	(–1.78)	(–2.89)	(–2.73)	(–2.36)	(–2.33)
$r_{1,0}$	–6.082***	–5.817***	–5.778***	–5.300***	–5.312***	–5.274***	–5.419***	–5.393***
	(–12.98)	(–12.78)	(–12.69)	(–11.98)	(–12.03)	(–11.94)	(–12.30)	(–12.21)
$r_{12,2}$	0.620***	0.648***	0.648***	0.632***	0.647***	0.648***	0.601***	0.601***
	(2.82)	(3.13)	(3.13)	(3.28)	(3.37)	(3.37)	(3.15)	(3.14)
Avg. N	2,472	2,453	2,453	2,415	2,415	2,415	2,415	2,415
Adj. R^2	0.041	0.040	0.039	0.039	0.039	0.038	0.041	0.040

Panel B. Excess Returns to Portfolios Sorted on Profitability Measures: Equally Weighted Results

	GP/AT			OP/AT			COP/AT		
	R_e	α^{3F}	α^{4F}	R_e	α^{3F}	α^{4F}	R_e	α^{3F}	α^{4F}
Q5 (high)	1.044***	0.322***	0.476***	0.967***	0.288***	0.399***	1.096***	0.395***	0.513***
	(4.09)	(4.27)	(5.44)	(4.16)	(4.42)	(5.22)	(4.76)	(6.63)	(7.09)
Q4	0.955***	0.205***	0.353***	0.860***	0.104*	0.225***	0.969***	0.215***	0.333***
	(3.89)	(3.39)	(4.96)	(3.86)	(1.88)	(4.07)	(4.39)	(3.87)	(5.65)
Q3	0.828***	0.036	0.199***	0.869***	0.068	0.229***	0.877***	0.072	0.216***
	(3.36)	(0.61)	(2.76)	(3.70)	(1.03)	(3.67)	(3.78)	(1.23)	(3.56)

Q2	0.735***	–0.088	0.079	0.775***	–0.074	0.129	0.710***	–0.138*	0.073
	(2.96)	(–1.28)	(1.09)	(2.95)	(–0.87)	(1.49)	(2.68)	(–1.74)	(0.89)
Q1 (low)	0.455	–0.398***	–0.171	0.549	–0.311**	–0.035	0.354	–0.479***	–0.204
	(1.62)	(–3.17)	(–1.44)	(1.61)	(–2.18)	(–0.22)	(1.08)	(–4.11)	(–1.53)
Differences									
High – low	0.589***	0.720***	0.647***	0.418**	0.599***	0.433***	0.743***	0.874***	0.718***
	(3.91)	(4.80)	(4.94)	(2.33)	(4.02)	(2.95)	(5.19)	(7.71)	(6.52)
High – middle	0.205***	0.271***	0.265***	0.132	0.255***	0.204***	0.244***	0.344***	0.305***
	(3.11)	(4.03)	(4.21)	(1.54)	(3.47)	(3.20)	(3.47)	(5.47)	(5.22)
Middle – low	0.384***	0.450***	0.381***	0.286*	0.345**	0.229*	0.499***	0.530***	0.413***
	(3.51)	(4.14)	(3.98)	(1.72)	(2.46)	(1.65)	(3.95)	(5.64)	(4.20)

Panel C. Excess Returns to Portfolios Sorted on Profitability Measures: Value-Weighted Results

	GP/AT			OP/AT			COP/AT		
	R_e	α^{3F}	α^{4F}	R_e	α^{3F}	α^{4F}	R_e	α^{3F}	α^{4F}
Q5 (high)	0.765***	0.267***	0.348***	0.710***	0.214***	0.287***	0.772***	0.264***	0.349***
	(4.26)	(3.73)	(5.06)	(3.89)	(3.80)	(4.69)	(4.34)	(4.63)	(5.60)
Q4	0.663***	0.102*	0.218***	0.632***	0.043	0.158***	0.667***	0.074	0.163***
	(3.36)	(1.75)	(3.48)	(3.41)	(0.65)	(2.62)	(3.67)	(1.18)	(2.74)
Q3	0.562***	–0.058	0.093	0.578***	–0.064	0.062	0.606***	–0.029	0.096*
	(2.89)	(–0.80)	(1.23)	(3.02)	(–0.79)	(0.85)	(3.16)	(–0.45)	(1.74)
Q2	0.571***	–0.091	0.044	0.574***	–0.135*	–0.008	0.501**	–0.187**	–0.042
	(2.89)	(–1.04)	(0.59)	(2.86)	(–1.75)	(–0.12)	(2.58)	(–2.48)	(–0.61)
Q1 (low)	0.335	–0.377***	–0.211**	0.319	–0.470***	–0.241***	0.219	–0.526***	–0.316***
	(1.41)	(–3.33)	(–2.33)	(1.23)	(–4.45)	(–2.89)	(0.82)	(–5.25)	(–3.85)
Differences									
High – low	0.430***	0.644***	0.559***	0.391***	0.684***	0.528***	0.553***	0.789***	0.665***
	(2.65)	(4.22)	(4.41)	(2.63)	(5.60)	(5.21)	(3.92)	(6.90)	(6.64)
High – middle	0.161**	0.274***	0.226***	0.111	0.250***	0.201***	0.172**	0.292***	0.262***

	(1.98)	(3.44)	(3.04)	(1.36)	(3.61)	(3.35)	(2.49)	(4.91)	(4.72)
Middle – low	0.270**	0.370***	0.333***	0.280**	0.434***	0.327***	0.381***	0.497***	0.403***
	(2.44)	(3.42)	(3.54)	(2.12)	(3.92)	(3.62)	(2.94)	(4.91)	(4.78)

Note: Panel A reports the results from Fama–MacBeth (1973) regressions of monthly stock returns on gross (GP/AT), operating (OP/AT), and cash-based operating profitability (COP/AT) measures; size (Log(ME)); book-to-market (Log(B/M)); and past performance measures over prior 1 month ($r_{1,0}$) and 12 to 2 months ($r_{12,2}$) as described in Section III and Table 1. In Panel A, column 1 reports replication results of Table 1 in Novy-Marx (2013) by using a sample period of 1963–2010. Columns 2 and 3 report replication results of Table 2 in Ball et al. (2016) by using a sample period of 1963–2013. Columns 4–8 report results over 1963–2018. Panel B (Panel C) reports monthly equally weighted (value-weighted) average excess returns (R_e), Fama–French (1993) three-factor alpha (α^{3F}), and Carhart (1997) four-factor alpha (α^{4F}) to quintile portfolios sorted on each profitability measure for the sample period of 1963–2018. Value-weighted results in Panel B are based on the NYSE breakpoints of the corresponding profitability measure and described in more details in Section IV. Panels B and C also report the differences in excess and risk-adjusted returns between various quintiles of profitability measures. The middle quintile portfolio in Panel B (Panel C) is calculated as the equally weighted (value-weighted) portfolio created using the second, third, and fourth quintile portfolios. All coefficients are multiplied by 100. The *t*-statistics, reported in parentheses, are computed from standard errors that are adjusted for heteroskedasticity and serial correlation following Newey and West (1987), with a lag of 12.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

TABLE 3. Profitability Anomalies and Limits to Arbitrage: Mean Quintile Ranks of Arbitrage Risk and Arbitrage Costs in Profitability Quintiles.

	Q5 (High)	Q4	Q3	Q2	Q1 (Low)	Differences		
						High – Low	High – Middle	Middle – Low
Panel A. Profitability Anomalies and Arbitrage Risk ($\mathrm{ArbRisk}^{\mathrm{Quintile}}$)								
GP/AT	3.053	2.937	2.891	2.891	3.245	–0.191***	0.146***	–0.338***
OP/AT	2.772	2.621	2.749	3.084	3.860	–1.087***	–0.045*	–1.042***
COP/AT	2.832	2.608	2.779	3.115	3.800	–0.968***	0.001	–0.968***
Panel B. Profitability Anomalies and Arbitrage Costs ($\mathrm{ArbCost}^{\mathrm{Quintile}}$)								
GP/AT	3.067	2.967	2.945	2.880	3.148	–0.081*	0.136***	–0.218***
OP/AT	2.499	2.595	2.802	3.214	4.085	–1.586***	–0.367***	–1.219***
COP/AT	2.636	2.607	2.832	3.228	3.926	–1.290***	–0.245***	–1.045***

Note: At the end of each June, all stocks in the sample are ranked into five quintiles separately based on gross (GP/AT), operating (OP/AT), and cash-based operating profitability (COP/AT) measures described in Section III. Independent of the profitability measures rankings, stocks are also ranked into five groups based on either an arbitrage risk ($\mathrm{ArbRisk}^{\mathrm{Quintile}}$) or a composite arbitrage costs ($\mathrm{ArbCost}^{\mathrm{Quintile}}$) measure. The constructions of arbitrage risk and arbitrage costs are described in Section III. Panel A (Panel B) reports the time-series averages of the cross-sectional mean of $\mathrm{ArbRisk}^{\mathrm{Quintile}}$ ($\mathrm{ArbCost}^{\mathrm{Quintile}}$) across five profitability quantiles, as well as the differences in the average quintile ranks for the measures of limits to arbitrage between various profitability portfolio quintiles. The medium portfolio is an equally weighted portfolio created using the second, third, and fourth quintile portfolios. The sample period is July 1963 to December 2018.

***Significant at the 1% level.

*Significant at the 10% level.

TABLE 4. Profitability Anomalies and Limits to Arbitrage: Portfolio Analysis.

	High Arbitrage Risk $\text{ArbRisk}^{\text{Quintile}} = 5$	Low Arbitrage Risk $\text{ArbRisk}^{\text{Quintile}} = 1$	Difference in High – Low Arbitrage Risk			
			R_e	α^{CAPM}	$\alpha^{3\text{F}}$	$\alpha^{4\text{F}}$
Panel A. Arbitrage Risk						
GP/AT						
High (Q5) – low (Q1) profitability	0.789***	0.342***	0.446***	0.416***	0.379**	0.335**
t-statistic	(4.40)	(3.41)	(2.75)	(2.61)	(2.33)	(1.99)
N	83,96	82,68				
OP/AT						
High (Q5) – low (Q1) profitability	0.290	0.347***	–0.057	–0.032	–0.053	–0.134
t-statistic	(1.56)	(2.69)	(–0.33)	(–0.19)	(–0.31)	(–0.76)
N	57,145	103,27				
COP/AT						
High (Q5) – low (Q1) profitability	0.902***	0.264**	0.638***	0.659***	0.566***	0.540***
t-statistic	(6.29)	(2.55)	(4.06)	(4.28)	(3.66)	(3.46)
N	64,132	102,27				
Panel B. Arbitrage Costs						
GP/AT						
High (Q5) – low (Q1) profitability	0.658***	0.285**	0.373**	0.315**	0.272*	0.261
t-statistic	(3.86)	(2.03)	(2.25)	(2.11)	(1.84)	(1.52)
N	80,70	74,61				
OP/AT						
High (Q5) – low (Q1) profitability	0.411**	0.240	0.118	0.099	0.094	0.121
t-statistic	(2.43)	(1.11)	(0.45)	(0.38)	(0.36)	(0.77)
N	22,118	118,19				
COP/AT						
High (Q5) – low (Q1) profitability	0.955***	0.439***	0.516***	0.449**	0.332*	0.310*

t-statistic	(7.09)	(2.69)	(2.89)	(2.54)	(1.94)	(1.65)
N	49,112	113,22				

Note: Panel A (Panel B) reports the performance of an equally weighted long–short hedge strategy based on profitability measures for stocks with high and low arbitrage risk (arbitrage costs). At the end of each June, all stocks in the sample are ranked into five quintile portfolios based on gross (GP/AT), operating (OP/AT), and cash-based operating (COP/AT) profitability measures. Independent of profitability measure rankings, stocks are also ranked into five groups based on either an arbitrage risk or arbitrage costs measure, and assigned into their corresponding quintiles ($\mathrm{ArbRisk}^{\mathrm{Quintile}}$ or $\mathrm{ArbCost}^{\mathrm{Quintile}}$). For each extreme quintile of limits to arbitrage (arbitrage risk or arbitrage costs), each panel reports the average monthly excess returns between the highest and lowest profitability quintiles (Q5 – Q1). Each panel also reports the differences in excess returns of Q5 – Q1, R_e, between the extreme limits to arbitrage quintiles as well as risk-adjusted performance based on the capital asset pricing model (α^{CAPM}), Fama–French (1993) three-factor model ($\alpha^{3\mathrm{F}}$), and Carhart (1997) four-factor model ($\alpha^{4\mathrm{F}}$). The construction of the profitability measures and the arbitrage risk and arbitrage costs measures is described in Section III. *N* stands for the average number of stocks that fall into the high (Q5) and low (Q1) profitability quintiles. The *t*-statistics are reported in parentheses. The sample period is July 1963 to December 2018.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

TABLE 5. Regression Slopes on Profitability Measures across Various Limits to Arbitrage Quintiles.

	$\text{ArbRisk}^{\text{Quintile}}$					Difference
Variable	5 (High)	4	3	2	1 (Low)	High – Low
Panel A. Regression Slopes for Each Arbitrage Risk Quintile						
GP/AT	0.828***	0.499***	0.586***	0.417***	0.297***	0.531***
	(5.08)	(3.30)	(4.21)	(3.86)	(3.16)	(3.43)
OP/AT	0.712***	0.652***	0.760***	0.545***	0.505***	0.207
	(4.44)	(4.88)	(6.60)	(4.95)	(5.65)	(1.25)
COP/AT	1.086***	0.897***	0.881***	0.577***	0.538***	0.549***
	(8.59)	(7.68)	(9.17)	(6.23)	(7.26)	(4.09)
Panel B. Regression Slopes for Each Arbitrage Costs Quintile						
GP/AT	0.652***	0.623***	0.597***	0.472***	0.283**	0.369*
	(3.51)	(5.31)	(4.26)	(3.59)	(2.25)	(1.79)
OP/AT	0.664***	0.836***	0.678***	0.553***	0.397***	0.267
	(4.08)	(6.20)	(5.11)	(4.14)	(3.58)	(1.39)
COP/AT	0.926***	0.829***	0.932***	0.728***	0.490***	0.436**
	(7.92)	(7.54)	(7.82)	(6.25)	(5.20)	(2.12)

Note: Panels A and B report the estimated slopes for each quintile portfolio of arbitrage risk and arbitrage costs, respectively. At the end of each June, all stocks in the sample are ranked into five quintile portfolios based on gross (GP/AT), operating (OP/AT), and cash-based operating (COP/AT) profitability. The slopes are estimated using the following Fama–MacBeth (1973) regressions performed separately for each quintile of limits to arbitrage measure:

$$r_{i,t} = \alpha_t + \beta_{1,t}\text{Prof}^{\text{Rank}}_{i,t-1} + \beta_{2,t}\text{Log(ME)}_{i,t-1} + \beta_{3,t}\text{Log(B/M)}_{i,t-1} + \beta_{4,t}r_{i,t-1} + \beta_{5,t}r_{i,t-12:t-1} + \varepsilon_{i,t},$$

where $r_{i,t}$ is monthly stock returns. All coefficients are multiplied by 100. The construction of the profitability measures and the construction of arbitrage risk and arbitrage costs measures are described in Section III. All other variables are defined in Table 1. $\text{Prof}^{\text{Rank}}$ is the scaled annual quintile rank for profitability measure (separately for GP/AT, OP/AT, and COP/AT) as described in Section IV. The quintile rank is transformed by subtracting 1 and dividing by 4; then 0.5 is subtracted from each of these transformed ranks so that the quintile ranks range from −0.5 to 0.5. The *t*-statistics, reported in parentheses, are computed from standard errors that are adjusted for heteroskedasticity and serial correlation following Newey and West (1987), with lag of 12. The sample period is July 1963 to December 2018.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

TABLE 6. Profitability Anomalies and Arbitrage Risk: Cross-Sectional Regressions of Monthly Returns.

	GP/AT			OP/AT			COP/AT		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{Prof}^{\text{Rank}} \times \text{ArbRisk}^{\text{Rank}}$	0.402***		0.348**	–0.229		–0.301	0.424***		0.367**
	(2.80)		(2.02)	(–1.25)		(–1.57)	(2.90)		(2.46)
$\text{Prof}^{\text{Rank}} \times \text{ArbCost}^{\text{Rank}}$		0.246*	0.101		–0.255	0.149		0.306*	0.158
		(1.68)	(0.50)		(–1.26)	(0.65)		(1.93)	(0.86)
$\text{Prof}^{\text{Rank}}$	0.585***	0.581***	0.570***	0.719***	0.692***	0.678***	0.867***	0.852***	0.846***
	(5.43)	(5.22)	(5.00)	(7.81)	(7.11)	(7.41)	(12.10)	(10.92)	(11.52)
$\text{ArbRisk}^{\text{Rank}}$	–0.458***		–0.311*	–0.411**		–0.286*	–0.414**		–0.281*
	(–2.61)		(–1.80)	(–2.40)		(–1.70)	(–2.38)		(–1.67)
$\text{ArbCost}^{\text{Rank}}$		–0.299	–0.173		–0.112	–0.106		–0.305	–0.240
		(–1.33)	(–1.07)		(–0.48)	(–0.66)		(–1.35)	(–1.49)
Log(ME)	–0.087***	–0.105***	–0.107***	–0.130***	–0.136***	–0.142***	–0.128***	–0.137***	–0.141***
	(–2.74)	(–3.28)	(–3.60)	(–4.25)	(–4.26)	(–4.76)	(–4.16)	(–4.29)	(–4.76)
Log(B/M)	0.313***	0.318***	0.305***	0.345***	0.346***	0.341***	0.308***	0.315***	0.307***
	(5.22)	(4.56)	(4.68)	(5.47)	(4.67)	(4.95)	(5.05)	(4.49)	(4.63)
$r_{1,0}$	–5.677***	–5.785***	–5.947***	–5.630***	–5.730***	–5.871***	–5.626***	–5.739***	–5.886***
	(–13.16)	(–12.83)	(–13.31)	(–13.02)	(–12.68)	(–13.09)	(–12.98)	(–12.67)	(–13.08)
$r_{12,2}$	0.569***	0.598***	0.600***	0.579***	0.616***	0.614***	0.569***	0.603***	0.601***
	(3.06)	(2.97)	(3.08)	(3.11)	(3.07)	(3.15)	(3.05)	(2.99)	(3.07)
Avg. N	2,113	2,079	2,079	2,113	2,079	2,079	2,113	2,079	2,079
Adj. R^2	0.046	0.046	0.051	0.046	0.046	0.051	0.046	0.045	0.050

Note: This table reports the results from Fama–MacBeth (1973) regressions of monthly stock returns on profitability measures, limits to arbitrage measures (ArbRisk and ArbCost), and control variables as described in Table 1 and Section III. At the end of each June, all stocks in the sample are ranked into five quintile portfolios based on gross profitability (GP/AT), operating profitability (OP/AT), and cash-based operating profitability (COP/AT). Independent of the profitability measure rankings, stocks are also ranked into five groups based on limits to arbitrage measures (ArbRisk and ArbCost). $\text{Prof}^{\text{Rank}}$ is the scaled annual quintile rank for GP/AT, OP/AT, and COP/AT. $\text{ArbRisk}^{\text{Rank}}$ ($\text{ArbCost}^{\text{Rank}}$) is the scaled annual quintile rank for the ArbRisk (ArbCost) measure described in Section IV. The quintile rank is transformed by subtracting 1 and dividing by 4; then 0.5 is subtracted from each of these transformed ranks so that the quintile ranks range from −0.5 to 0.5. All coefficients are multiplied by 100. The *t*-statistics, reported in parentheses, are computed from standard errors adjusted for heteroskedasticity and serial correlations following Newey and West (1987), with lag of 12. The sample period is July 1963 to December 2018.
***Significant at the 1% level.

**Significant at the 5% level.
*Significant at the 10% level.

TABLE 7. Mean Profitability and Arbitrage Risk Quintile Rankings across SG&A Expenses and Accruals.

	Q5 (High)	Q4	Q3	Q2	Q1 (Low)	Differences		
						High – Low	High – Middle	Middle – Low
Panel A. SG&A/AT								
$\mathrm{GP/AT}^{\mathrm{Quintile}}$	4.643	3.745	2.959	2.200	1.453	3.189***	1.675***	1.514***
$\mathrm{OP/AT}^{\mathrm{Quintile}}$	2.990	3.126	3.135	3.026	2.723	0.267***	–0.105***	0.372***
$\mathrm{COP/AT}^{\mathrm{Quintile}}$	2.988	3.040	3.070	3.024	2.879	0.109***	–0.056**	0.165***
$\mathrm{ArbRisk}^{\mathrm{Quintile}}$	3.261	3.124	2.969	2.861	2.786	0.474***	0.275***	0.198***
Panel B. Accruals/AT								
$\mathrm{GP/AT}^{\mathrm{Quintile}}$	3.271	3.172	2.897	2.778	2.883	0.387***	0.321***	0.065*
$\mathrm{OP/AT}^{\mathrm{Quintile}}$	3.139	3.250	3.141	2.960	2.512	0.626***	0.022	0.604***
$\mathrm{COP/AT}^{\mathrm{Quintile}}$	1.966	2.839	3.155	3.344	3.697	–1.731***	–1.146***	–0.584***
$\mathrm{ArbRisk}^{\mathrm{Quintile}}$	3.404	2.872	2.623	2.772	3.387	0.017	0.648***	–0.631***

Note: At the end of each June, all stocks in the sample are ranked into quintiles separately based on SG&A/AT (Panel A) and accruals (Panel B). Selling, general, and administrative (SG&A) expenses exclude research and development (R&D) expenses and are scaled by total assets (SG&A/AT). Accruals/AT 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/AT and Accruals/AT rankings, stocks are also ranked into quintiles based on gross ($\mathrm{GP/AT}^{\mathrm{Quintile}}$), operating ($\mathrm{OP/AT}^{\mathrm{Quintile}}$), cash-based operating profitability ($\mathrm{COP/AT}^{\mathrm{Quintile}}$), and arbitrage risk ($\mathrm{ArbRisk}^{\mathrm{Quintile}}$) measures. For each quintile based on SG&A/AT or Accruals/AT, this table reports the time-series averages of cross-sectional means for $\mathrm{GP/AT}^{\mathrm{Quintile}}$, $\mathrm{OP/AT}^{\mathrm{Quintile}}$, $\mathrm{COP/AT}^{\mathrm{Quintile}}$, and $\mathrm{ArbRisk}^{\mathrm{Quintile}}$ as well as the differences between various quintiles based on SG&A/AT (Accruals/AT) portfolios in Panel A (Panel B). The middle portfolio is the equally weighted combination of the second, third, and fourth quintiles. The sample period is July 1963 to December 2018.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

TABLE 8. Profitability Anomalies and Arbitrage Risk: Effects of SG&A Expenses and Accruals.

	SG&A/AT	Accruals/AT	GP/AT	COP/AT
	(1)	(2)	(3)	(4)
$\text{Prof}^{\text{Rank}} \times \text{ArbRisk}^{\text{Rank}}$			–0.123	0.199
			(–0.44)	(1.10)
$\text{SG\&A/AT}^{\text{Rank}} \times \text{ArbRisk}^{\text{Rank}}$	0.338**		0.534*	
	(2.06)		(1.76)	
$\text{Accruals/AT}^{\text{Rank}} \times \text{ArbRisk}^{\text{Rank}}$		–0.407***		–0.400**
		(–3.39)		(–2.51)
$\text{SG\&A/AT}^{\text{Rank}}$	0.368***		–0.402***	
	(3.31)		(–3.02)	
$\text{Accruals/AT}^{\text{Rank}}$		–0.317***		0.062
		(–5.71)		(0.84)
$\text{Prof}^{\text{Rank}}$			0.934***	0.890***
			(7.48)	(9.63)
$\text{ArbRisk}^{\text{Rank}}$	–0.515***	–0.533***	–0.437**	–0.414**
	(–2.90)	(–2.99)	(–2.51)	(–2.41)
Log(ME)	–0.083***	–0.108***	–0.101***	–0.131***
	(–2.62)	(–3.48)	(–3.27)	(–4.28)
Log(B/M)	0.283***	0.222***	0.324***	0.311***
	(4.88)	(3.77)	(5.45)	(5.07)
$r_{1,0}$	–5.655***	–5.540***	–5.736***	–5.664***
	(–13.11)	(–12.80)	(–13.29)	(–13.08)
$r_{12,2}$	0.581***	0.617***	0.550***	0.559***
	(3.12)	(3.29)	(2.98)	(3.01)
Avg. N	2,113	2,113	2,113	2,113
Adj. R^2	0.046	0.044	0.048	0.047

Note: This table reports results from Fama–MacBeth (1973) regressions of monthly returns on selling, general, and administrative (SG&A) expenses; accruals; profitability measures; arbitrage risk measure; and control variables as defined in Table 1 and Section III. At the end of each June, all stocks in our sample are separately sorted into quintiles based on SG&A expenses (SG&A/AT), accruals (Accruals/AT), gross profitability (GP/AT), operating profitability (OP/AT), cash-based operating profitability (COP/AT), and arbitrage risk measure (ArbRisk). Profitability (GP/AT, OP/AT, and COP/AT), SG&A expenses (SG&A/AT), accruals (Accruals/AT), and arbitrage risk (ArbRisk) measures are the scaled annual quintile ranks described in Section IV. The quintile rank is transformed by subtracting 1 and dividing by 4; then 0.5 is subtracted from each of these transformed ranks so that the quintile ranks range from −0.5 to 0.5. All coefficients are multiplied by 100. The *t*-statistics, reported in parentheses, are adjusted for heteroskedasticity and serial correlations following Newey and West (1987), with lag of 12. The sample period is July 1981 to December 2018.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

Panel A. Gross Profitability (GP/AT)

Panel B. Operating Profitability (OP/AT)

Panel C. Cash-Based Operating Profitability (COP/AT)

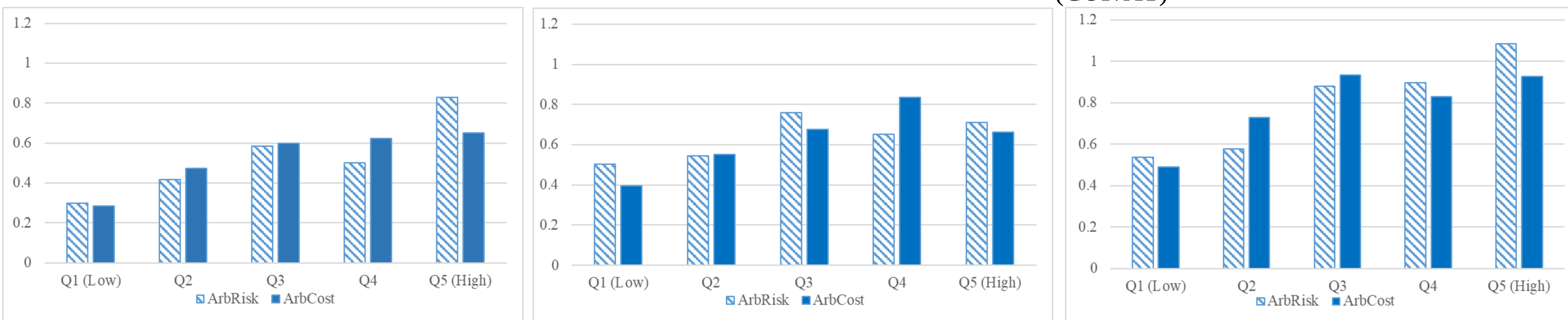

Figure I. Regression Slopes on Profitability Measures across Various Limits to Arbitrage Quintiles. This figure illustrates the estimated slopes on profitability measures from the following Fama–MacBeth (1973) regressions performed separately for each quintile of limits to arbitrage measure:

$$r_{i,t} = \alpha_t + \beta_{1,t}\text{Prof}_{i,t-1}^{\text{Rank}} + \beta_{2,t}\text{Log(ME)}_{i,t-1} + \beta_{3,t}\text{Log(B/M)}_{i,t-1} + \beta_{4,t}r_{i,t-1} + \beta_{5,t}r_{i,t-12:t-1} + \varepsilon_{i,t}.$$

Each panel shows slopes for two measures of limits to arbitrage: arbitrage risk (pattern bar) and arbitrage costs (solid bar), as described in Section III. All coefficients are multiplied by 100. The construction of the profitability measures is described in Section III. All other variables are defined in Table 1. Prof $^{\text{Rank}}$ is the scaled annual quintile rank for profitability measure (separately for GP/AT in Panel A, OP/AT in Panel B, and COP/AT in Panel C) as described in Section IV. The sample period is July 1963 to December 2018.