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Three Essays on Asset Pricing

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THREE ESSAYS ON ASSET PRICING

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by

Xiaomeng Lu

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To: Dean William Hardin
College of Business

This dissertation, written by Xiaomeng Lu, and entitled Three Essays on Asset Pricing, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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Florida International University, 2022

DEDICATION

I dedicate this dissertation to all members of my family, especially my husband, Li. Without their unconditional love and encouragement, the completion of this work would not be possible.

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ABSTRACT OF THE DISSERTATION

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This dissertation consists of three essays that focus on the topics related to Asset Pricing. The first essay proposes a regression-based approach to identify the quality-cheapness (*QC*) investing strategy with quality as a priority and the cheapness-quality (*CQ*) investing strategy with cheapness as a priority. Empirical results show that *QC* strategy outperforms traditional quality investing strategy, and *CQ* strategy outperforms value investing strategy based on the market-to-book ratio. *QC* strategy and *CQ* strategy perform almost equally well in terms of return spreads, but they have different risk exposures, suggesting different sources of return spreads and potential synergy. Further analysis shows that the future investment growth opportunity, time-varying risk, uncertainty, and sentiment all play a partial role in explaining the return spreads in *QC* strategy and *CQ* strategy.

The second essay examines how cultural traits and institutional quality affects quality and value investing return premiums in an international environment. We use Hofstede's individualism index and International Country Risk Guide’s political risk index to measure the extent of a country's overconfidence level and environmental stability. Our empirical analysis suggests that countries with higher individualism scores generally have

a higher quality premium and lower value premium than countries with lower individualism scores. Besides, countries with higher political risk would have higher value premiums, while the difference in quality premium is insignificant between high and low political risk countries. However, the effect of institutional quality is weakened when we take both individualism and political risk into consideration.

The third essay studies the relationship between quality premium and volatility risk. Our empirical analysis suggests that firms' qualities are positively related to the volatility risk, and the quality premium has different performance across different levels of volatility risk. The effect of volatility risk would be different on high-quality and low-quality firms. The results highlight the importance of volatility risk in explaining the source of quality premium.

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CHAPTER 1 PRIORITY OF INVESTING STRATEGY, VALUE OR QUALITY?

JOEL GREENBLATT: *We buy — at all times — the cheapest stocks we can find.*

— Wall Street Journal, October 6, 2019

WARREN BUFFETT: *It is far better to buy a wonderful company at a fair price than a fair company at a wonderful price.*

— The Chairman's Letter, Berkshire Hathaway, Inc., Annual Report, 1989.

1.1 Introduction

Value investing strategy refers to the trading of stocks based on a perceived deviation between their current market price and fundamental value. Traditional value investing strategy shows the tendency that value stocks (such as high book-to-market ratio, earnings yields, etc.) have outperformed growth stocks (e.g., Fama and French, 1992b, 1998; Lakonishok, Shleifer, and Vishny, 1994; Porta *et al.*, 1997; among others). Quality investing strategy emphasizes firms' fundamentals (financial strength, growth, and profitability, etc.), and researchers document that quality investing strategy yields positive risk-adjusted returns (e.g., Piotroski, 2000; Piotroski and So, 2012; Novy-Marx, 2013, 2014; Asness, Frazzini, and Pedersen, 2014, 2019; Jagannathan and Zhang, 2020). Valuation theory suggests a positive relationship between value and quality, i.e., high quality firms tend to have high valuations. Yet value strategy is short quality while quality strategy is short value (cheapness). Although academics and practitioners recognize the merits of value and quality, there is no consensus on which one is of first-order importance. There is little study on how to measure high quality with relatively low price and cheapness with relatively high quality.

We propose two novel investing strategies taking both value and quality into account yet with different priorities, Quality-Cheapness (hereafter *QC*) strategy and Cheapness-Quality (hereafter *CQ*). Taking quality as the first-order priority, *QC* strategy goes long high quality stocks without paying premium price and short low quality stocks with relative high price. Taking cheapness as the first-order priority, *CQ* strategy, on the other hand, goes long cheap stocks with relatively high quality and short expensive stocks with relatively low quality. Our investing strategies are first motivated by valuation theory which suggests that both cheapness (low valuation ratio) and quality (growth, dividend payout, profitability, etc.) are positively related to expected returns (e.g., Fama and French, 2006). Second, empirical study shows that quality and cheapness are negatively correlated, suggesting quality provides a reasonable hedge for cheapness, and vice versa (e.g., Piotroski and So, 2012; Novy-Marx, 2013). Third, Graham and Dodd (1934) original stock screens include both quality and cheapness measures. Graham and Dodd (1934) propose the following ten stock screens:

1. Earnings to price ratio that is double the AAA bond yield
2. PE of the stock has less than 40% of the average PE for all stocks over the last 5 years
3. Dividend Yield > Two-thirds of the AAA Corporate Bond Yield
4. Price < Two-thirds of Tangible Book Value
5. Price < Two-thirds of Net Current Asset Value (NCAV), where net current asset value is defined as liquid current assets including cash minus current liabilities

6. Debt-Equity Ratio (Book Value) has to be less than one
7. Current Assets > Twice Current Liabilities
8. Debt < Twice Net Current Assets
9. Historical growth in EPS (over last 10 years) > 7
10. No more than two years of declining earnings over the previous 10 years

Consistent with valuation theory, the first five factors above are price multiples related measures while the others are firm quality related measures. They emphasize that "investment must always consider the price as well as the quality of the security." These screens reflect their key insight: considering both quality and value. However, valuation theory, empirical study, and the stock screens all keep silence on which one (quality or value) is of first-order priority.

Investment gurus seem to have discrepancy on the priority of value and quality. Warren Buffett obviously favors quality. In a letter to his shareholders, Warren Buffett once said "It is far better to buy a wonderful company at a fair price than a fair company at a wonderful price."[1] Frazzini, Kabiller, and Pedersen (2018) reveal that the performance of the publicly traded companies held by Berkshire Hathaway, Buffett's primary investment vehicle, can largely be attributed to his commitment to buying high quality stocks. Joel Greenblatt, on the other hand, emphasizes the importance of cheapness, saying that "We buy — at all times — the cheapest stocks we can find." in a recent interview with the Wall Street Journal. Evidently, there is no consensus on which one (quality or value) is of first-order priority.

[1] From the Chairman's Letter, Berkshire Hathaway, Inc., Annual Report, 1989.

We present a regression-based approach to identify the two investing strategies. Our approach is in a similar spirit to Bhojraj and Lee (2002), Rhodes-Kropf, Robinson, and Viswanathan (2005), and Bartram and Grinblatt (2018). We run a monthly cross-sectional regression of an individual stock return on its quality. The dependent variable of our regression is stock return instead of valuation ratio as in previous studies. We connect the slope coefficient with book-to-market in this specification based on valuation theory that expected return is a function of both valuation ratio and quality. Please see the detailed discussion in subsection 1.3.2. We take the regression fitted value as a measure of *QC* and the residual as a measure of *CQ*. Conceptually, *QC* (*CQ*) measure is similar to "fundamental" return or "tangible" component ("residual" return or "intangible" component) in Daniel and Titman (2006) and Da, Liu, and Schaumburg (2014). The regression fitted value is a product of the price of quality (estimated slope coefficient) and firm quality.[2] A high value of *QC* indicates high firms' quality with relatively low price, since the estimated slope coefficient is associated with book-to-market ratio. A high value of *CQ* designates expansive price with relatively low firms' quality.

We conduct portfolio analyses using both single-sorting and double-sorting. We find that high *QC* portfolios generate higher excess and risk-adjusted returns than low *QC* portfolios, while low *CQ* portfolios produce higher excess and risk-adjusted returns than high *CQ* portfolios. Our *QC* and *CQ* markedly outperform quality strategy and value strategy, respectively. For example, when quality is based on ordinal measure, the return spread in our *QC* strategy (66 basis point per month) is more than twice as high as that in quality investing strategy (31 basis point per month). The return spread in our *CQ*

[2] We also control industry effects.

strategy (63 basis point per month) is also more than twice as high as that in value strategy based on the market-to-book ratio (30 basis point per month). The Sharpe ratio in *QC* strategy (0.61) and *CQ* strategy (0.70) are also much higher than that in quality strategy (0.37) and value strategy (0.22). We argue that the superior performance of *QC* strategy is due to that it avoids long expensive high quality firms and short cheap low quality firms. Similarly, the superior performance of *CQ* strategy is due to that it avoids long inferior cheap firms and short superior expensive firms.

We show that *QC* strategy subsumes return spread in quality strategy while *CQ* strategy subsumes spread return in value strategy. In contrast, quality (value) strategy does not subsume the return spread in *QC* (*CQ*) strategy, further supporting the superior of *QC* strategy and *CQ* strategy. *QCCQ* strategy, based on independent double-sorted portfolios of *QC* and *CQ*, generates an average return spread of 142 basis point per month (compared to the return spread of 85 basis point per month for quality-value strategy based on independent double-sorted quality and value portfolios). This evidence suggests that *QC* and *CQ* strategies have not only different sources of returns but also potential high synergies.

QC strategy and *CQ* strategy exhibit different risk exposures although they have similar return spreads. *QC* strategy has a negative market beta while *CQ* has a convex (nonlinear right-side smile) market beta. The negative market beta of *QC* strategy indicates its superior performance mainly comes from market downturns, quality shining in challenging times. The nonlinear right-side smile pattern of *CQ* strategy suggests that *CQ* strategy enjoys high returns when market is high as well as has limited loss when market is low.

To further understand the proposed investing strategies, we construct two factors, strong-minus-weak (hereafter, SMW) and cheap-minus-expensive (hereafter, CME), following Fama and French (1993); Asness and Frazzini (2013); Asness, Frazzini, and Pedersen (2019). SMW factor is formed on the intersection of six value-weighted size and *QC* portfolios, while CME factor takes the intersection of six value-weighted size and *CQ* portfolios.[3] As expected, these factors are highly correlated with *QC* and *CQ* arbitrage portfolios and yield significantly positive excess returns and risk-adjusted returns. We find that the reversal factor largely explains SMW (adjusted R^2 of 61%) and CME (adjusted R^2 of 85%) factors although traditional asset pricing factors have limited explanatory power. Asset pricing theory suggests that expected returns are determined by expected future cash flows, time-varying risk, and/or investor sentiment. We explore whether SMW and CME factors are associated with the above three aspects. Our empirical results suggest that it is a challenge to completely understand the return spreads in SMW and CME, although investment growth opportunity, time-varying risk, and behavioral variables are all partially associated with return spreads in SMW and CME.

The rest of the essay is organized as follows. Section 1.2 reviews the prior literature on both value investing and quality investing strategies. Section 1.3 presents fundamental and cheapness measures formation and portfolio strategies. Section 1.4 discusses the data used in this study and shows the performance of our portfolio strategies, and Section 1.5 provides the factor analysis and some understanding of our two-dimension value investing strategy. Section 1.6 concludes.

[3] Please refer to Section 1.5 for details of the factor constructions.

1.2 Related Literature

The history of value investing strategy is traced back to Graham, Dodd, and Cottle's (1934) Security Analysis. This strategy's core concept is to buy undervalued securities (relative to their intrinsic value) by fundamental analyses. Both academics and practitioners show great interest in examining the value investing strategy and align value investing with a valuation ratio-based analysis. Extensive literature documents that those "value" stocks could be identified by valuation indicators such as price-to-earnings ratio (P/E), price-to-book ratio (P/B), cash flow-to-price ratio (CF/P), and dividend yields (D/P) (e.g., Basu, 1977; Rosenberg, Reid, and Lanstein, 1985; Chan, Hamao, and Lakonishok, 1991b; Fama and French, 1992a) and value stocks (high book-to-market) outperform growth stocks (e.g., Fama and French, 1992b, 1998; Lakonishok, Shleifer, and Vishny, 1994; Porta *et al.*, 1997).

Despite the numeral studies on value premium, there is no consensus on the source of value premium. On one side, Fama and French (1992a, 1993, 2005) posit that value premium is associated with financial distress risk. On the other side, Lakonishok, Shleifer, and Vishny (1994) and Porta *et al.* (1997) argue that value premium arises due to market inefficiencies for various behavioral and institutional reasons.

Quality investing strategy seeks to identify firms with outstanding quality characteristics. Quality strategy is highly different from value strategy although quality strategy can be viewed as an alternative value strategy.

Piotroski (2000) chooses nine fundamental indicators to evaluate firms' profitability, financial leverage/liquidity, and operating efficiency. Combining those nine criteria, he defines the F-score and differentiates high book-to-market stocks into high-quality and low-quality. His empirical finding suggests that high BM firms with strong financial performance would significantly out perfume firms with high B/M ratios alone. Piotroski and So (2012) utilize the F-score and argue that the accounting-based value strategy remarkably outperforms the traditional value strategies. Further, Novy-Marx (2013) uses gross profitability as the quality measure and finds that controlling profitability could dramatically improve the value strategy performance. He finds that value and profitability strategies are negatively correlated. Therefore, the combination of two strategies reduces overall volatility but avoids doubling the risk. Besides, considering quality characteristics help traditional value investors find quality stocks at a reasonable price. Asness, Frazzini, and Pedersen (2019) propose a comprehensive quality measure (which captures the profitability, growth, safety, and payout characteristics of a firm) and distinguish between quality stocks from junk stocks. They find that stocks with high quality substantially outperform stocks with low quality. In contrast to the above-mentioned studies (quality measure is based on information available in accounting statements), Jagannathan and Zhang (2020) propose a return-based method to identify high quality stocks and find that high quality firms perform better than other firms during stressful times. Our regression-based method relies on both stock returns and firms' fundamentals.

The determinants of the quality premium seem inconsistent to time-varying risk explanation. Piotroski (2000) suggests an inefficient market story: a firm's past financial performance is not timely and fully reflected in its market price. Besides, Asness, Frazzini, and Pedersen (2019) propose three potential hypotheses for quality premium and provide evidence that is consistent with behavioral explanation, as investors would underprice quality stocks and overprice junk stocks.

1.3 Data and Methodology

In this section, we first describe the data sources and then discuss the construction of *QC*, *CQ*, and *QCCQ* strategies. We conduct portfolio analysis (single-sorts and double-sorts) to test the performance of our *QC*, *CQ*, and *QCCQ* strategies.

1.3.1 Data

Stock returns are collected from the Center for Research in Security Prices (CRSP) daily and monthly stock files. Accounting information is from COMPUSTAT North America Fundamentals Annual and Quarterly databases. Our sample includes all available common stocks which have a CRSP share code of 10 or 11 or have a COMPUSTAT issue code of 0. We exclude stocks listed and traded on OTC exchanges. Following Shumway (1997), delisted stocks are assumed to have a -30% delisting return if their delisting return is missing. We match the accounting data for which the fiscal year ends anywhere in the calendar year t-1with the market information for June of the calendar year t to avoid look-ahead bias. Detailed variable construction and timeline are shown in Table A1 and Figure A1 of the Appendix. The original panel covers from July 1957 to December 2020.

1.3.2 QC Strategy, CQ Strategy, and QCCQ Strategy

Inspired by valuation theory (e.g., Fama and French, 2006) and the methodologies of Bhojraj and Lee (2002), Rhodes-Kropf, Robinson, and Viswanathan (2005), and

Bartram and Grinblatt (2018), we propose a similar cross-sectional regression framework:

$$Return_{i,t} = \alpha_{i,t} + \beta \times Quality_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $Return_{i,t}$ is the current month's stock return, $Quality_{i,t}$ is the measure that captures the current month's overall firm quality.[4] It is noteworthy that our dependent variable is stock return instead of market-to-book ratio. In this specification, we show that the high regression slope coefficient indicates high book-to-market or low price. We then can claim that the high fitted value is associated with high quality with low relative price, *QC* strategy. *CQ* strategy is long firms with low residuals and short firms with high residuals, taking cheapness as priority yet considering quality. To see how it works, we can start with the Gordon growth model,

$$P = \frac{D}{R - G} \tag{2}$$

where *P*, *D*, *R*, *G* denote a stock price, dividend, expected return and growth, respectively. A simple step of algebra delivers

$$R = \left(1 - \lambda + \lambda \frac{B}{P}\right) ROE \tag{3}$$

where λ denotes dividend payout ratio, and *ROE* denotes return on equity.[5] Equation (3) states that expected stock returns are related to book-to-market ratio, expected profitability, and expected investment (e.g., Fama and French, 2006).

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[4] We add the interaction terms between firm quality and industries to alter the slope for each industry. Industry dummies are generated using the Fama-French ten industry classification. The industry classification is obtained from Kenneth French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[5] Here G is estimated as $(1 - \lambda)$*ROE.

Comparing equation (1) with (3), we argue that the coefficient β is positively related to book-to-market ratio, and the high value of *beta* indicates low price. Therefore, the high fitted value indicates high quality with relative low price. This regression framework enables us to identify *QC* strategy and *CQ* strategy, both consider quality and value yet with different priority.

We present two measures of quality. First, we select variables each month to construct the quality z-score based on firms' profitability, growth, and safety as in Asness, Frazzini, and Pedersen (2019).[6] We construct the ordinal measures for each quality variable as the percentile rank, the rank divided by the total number of firms. We average the available ordinal measures for each firm and then re-rank the average across firms. There are several advantages of using ordinal measure. First, it reduces the impact of outliers since the ordinal measure itself will not generate extreme values. Second, averaging the ordinal measures on available quality variables conveniently handle the potential missing data for quality variables. Third, ordinal measure circumvents the hardwired link among the magnitude of quality variables. Specifically, our ordinal measure can be expressed as:

$$o(x) = o_x = \frac{Rank_x}{Count} \tag{4}$$

where $Rank_x$ is the rank of variable x, and Count is the total number of firms with valid data during that month.

[6] Please refer to the Appendix and Asness, Frazzini, and Pedersen (2019) for the choice of quality variables.

We measure a firm's quality from profitability, growth, safety, and payout four aspects. Then, we average the profitability, growth, safety, and payout ordinal measures into a single overall ordinal measure.[7]

Second, we use the gross-profits-over-asset (GPOA) utilized in Novy-Marx (2013) to measure firms' quality. After obtaining firms' quality ordinal-measure (QOM hereafter) and gross profits-over-asset (GPOA hereafter), we run the cross-sectional regression based on equation (1). The regression fitted value is the *QC* measure and the residual value is the *CQ* measure. Finally, we construct *QCCQ* portfolios combining both *QC* and *CQ* measures.

1.3.3 Portfolio Strategies

In this subsection, we construct portfolio analysis to test the performance of our *QC*, *CQ*, and *QCCQ* strategies. We demonstrate *QC* (*CQ*) performs much better than quality (value) strategy and *QCCQ* strategy also performs much better than the strategy combining quality and value.

1.3.3.1 Single-Sorts

We expect that high *QC* (low *CQ*) portfolio yields higher returns than low *QC* (high *CQ*) portfolio. At the end of each month, stocks are ranked in ascending order based on their *QC* or *CQ* measure and then we assign stocks into one of five portfolios based on NYSE breakpoints. We calculate the monthly portfolio return as the value-weighted average returns of all stocks in the portfolio and rebalance portfolios at the end of each month. Next, we regress monthly portfolio returns of each *QC*/*CQ*-sorted

[7] Detailed quality ordinal measures construction is provided in Table A1 of the Appendix.

portfolio as well as the long-short arbitrage portfolio on widely used risk-factors in asset pricing models, which include the CAPM of Sharpe (1964), Lintner (1965), and Mossin (1966) with the market factor (MKT); the Fama-French three-factor model (Fama and French, 1993) with market (MKT), size (SMB), and value (HML) factors; the Fama-French five-factor model (Fama and French, 2015) with Fama and French three-factors plus the profitability (RMW) and investment (CMA) factors in addition to Fama and French three-factors; and the q-factor model (Hou, Xue, and Zhang, 2015) with market (MKT), size (ME), investment (IA), and profitability (ROE) factors.

1.3.3.2 Dependent Double-Sorts

Our *QC* and *CQ* strategies are built upon quality and value strategies (e.g., Fama and French, 1992a; Novy-Marx, 2013; Piotroski and So, 2012; and Asness, Frazzini, and Pedersen, 2019). It is interesting to examine whether *QC* strategy is subsumed by quality and *CQ* strategy is subsumed by value strategy and vice versa.

We conduct conditional double-sorts. Each month we first sort stocks into five quintiles on quality measure, and then within each quintile, we sort the stocks into five quintiles on *QC* measure. In this conditional double-sort, we examine whether *QC* strategy subsumes the return spread in quality strategy. Changing the order of the conditional double-sort, we examine whether quality strategy subsumes return spread in *QC* strategy. Similarly, we conduct conditional double-sorts between *CQ* measure and value measure to examine whether *CQ* strategy and value strategy are subsumed by each other.

1.3.3.3 Independent Double-Sort on QC and CQ

Piotroski and So (2012) and Novy-Marx (2013) argue that the sorting strategy combined on value and quality performs better than a simple 50/50 value and quality portfolio. We examine *QCCQ* strategy based on independent double-sorts on *QC* and *CQ* and compare it with quality-value strategy.

Twenty-five portfolios are formed by independent quintile sorting on *QC* and *CQ*. The new independent sorted portfolios have the characteristics of both quality and cheapness, but with different focuses. *QCCQ* strategy is long portfolio *QC*5/*CQ*1 comprising high quality stocks with relative low price and cheap stocks with relative high quality and short portfolio *QC*1/*CQ*5 comprising low quality firms with relative high price and expensive stocks with relative low quality. Portfolio returns are the value-weighted average monthly returns of all stocks in the portfolio and are recalculated at the end of each month.

		Low Cheapness-Quality Measure	**Middle Firms**	**High Cheapness-Quality Measure**
		CQ1	CQ2 CQ3 CQ4	CQ5
Low Quality-Cheapness Measure	QC1	*Low* quality with relative high price & *Cheap* with relative high quality		*Low* quality with relative high price & *Expensive* with relative low quality (Short)
Middle Firms	QC2 QC3 QC4			
High Quality-Cheapness Measure	QC5	*High* quality with relative low price & *Cheap* with relative high quality (Long)		*High* quality with relative low price & *Expensive* with relative low quality

1.4 Performance of QC, CQ, and QCCQ Strategies

This section presents the performance of *QC*, *CQ*, *QCCQ* strategies. We compare *QC*, *CQ*, *QCCQ* strategies to quality, value, and quality-value strategies respectively.

1.4.1 Performance of QC and CQ strategies

Table 1.1 reports the monthly value-weighted average *QC* measure, log (M/B) ratio, monthly average raw and excess returns, alphas of time series regressions of the portfolio returns on various asset pricing models, return spread and alpha spread between *QC*5 and *QC*1, Newey-West heteroskedasticity and autocorrelation corrected t-statistics and adjusted R-squares, and other characteristics of five *QC*-sorted portfolios. The excess return is calculated as the difference between the portfolio raw return and the one-month Treasury bill rate.

Panels A and B of Table 1.1 (quality based on ordinal measure) show that *QC* portfolios' average raw returns, excess returns, and abnormal returns (alphas) are generally increasing with *QC* measure. The high quality with relative low price portfolio (*QC*5) earns an average monthly raw return of 130 basis point (*t-statistic*=7.88) and excess return of 94 basis point (*t-statistic*=5.71) in the subsequent month, and it generates positive and significant alphas (ranging from 35 to 42 basis point) with respect to different asset pricing models. On the other hand, the low quality with relative high price portfolio (*QC*1) has an average monthly raw return of 64 basis point (*t-statistic* =3.70) and excess return of 29 basis point (*t-statistic* =1.61) and significantly negative alphas, ranging from -21 to -31 basis point.

Consequently, the *QC* strategy, the long-short portfolio ($QC5 - QC1$), yields significantly positive excess returns and alphas in various asset pricing models, excess return of 66 basis point (*t-statistic* =5.47) in the following month. Similarly, the alphas for the long-short portfolio are positive and highly significant as well: 71 basis point (*t-statistic* =5.53) for the CAPM, 73 basis point (*t-statistic* =5.83) for Fama-French three-factor model, 65 basis point (*t-statistic* =4.04) for Fama-French five-factor model, and 56 basis point (*t-statistic* =2.86) for Hou-Xue-Zhang's q-factor model. Comparing the performance of *QC* strategy with quality strategy (Asness, Frazzini, and Pedersen, 2019),[8] we show in Figure 1.1 that *QC* strategy impressively outperforms quality strategy, the monthly average return spread in *QC* strategy (66 basis point) being more than twice as high as the return spread of quality strategy (31 basis point). The superior performance of *QC* strategy is attributed to holding high quality firms without paying premium price and shorting low quality firms selling at premium (quality as priority).

In Panel B, we show that high *QC* portfolios tend to have high quality although not monotonically. Interestingly high *QC* portfolios tend to have low market Beta and volatility. The long-short portfolio on *QC* has a negative Beta (-0.09), indicating *QC*5 portfolio exposes low market risk than *QC*1 portfolio. Not surprisingly, *QC* strategy's Sharp ratio is 0.61, exceptional high.

For robustness, we construct our *QC* portfolios measuring quality based on GPOA as in Novy-Marx (2013) and report the results in Panels C and D of Table 1.1. The performance and characteristics of the *QC* portfolios in Panels C and D are consistent with that in the *QC* portfolios based on quality ordinal measure. Therefore, the superior performance of *QC* measure is robust to different quality aspects.

[8] The results for quality strategy are reported in Table A2 in Appendix.

Focusing on cheapness as priority, Table 1.2 reports the performance and characteristics of our *CQ* sorted portfolios in a similar format as in Table 1.1. There is a strong negative relationship between our *CQ* measure and average returns, as well as the asset pricing model alphas. Panels A and B of Table 1.2 (quality based on ordinal measure) reveal that *CQ* portfolios' average raw returns and excess returns are monotonically decreasing with *CQ* measure, and abnormal returns are generally decreasing with *CQ* measure. The cheap price with relative high quality portfolio (*CQ*1) earns an average monthly raw return of 128 basis point (*t-statistic* =6.12) and excess return of 92 basis point (*t-statistic* =4.37) in the subsequent month, and it generates positive and significant alphas (ranging from 19 to 26 basis point) with respect to different asset pricing models. On the other hand, the expansive price with relative low quality portfolio (*CQ*5) has an average monthly raw return of 65 basis point (t *t-statistic* =3.68) and excess return of 29 basis point (*t-statistic* =1.63) and significantly negative alphas, ranging from -27 to -29 basis point.

The *CQ* strategy, the long-short portfolio ($CQ1 - CQ5$), yields significantly positive excess returns and alphas in various asset pricing models, excess return of 63 basis point (*t-statistic* =5.67) in following month. Similarly, the alphas for the long-short portfolio are positive and highly significant as well: 51 basis point (*t-statistic* =4.58) for the CAPM, 48 basis point (*t-statistic* =4.24) for Fama-French three-factor model, 50 basis point (t statistic=4.07) for Fama-French five-factor model, and 53 basis point (*t-statistic* =3.49) for Hou-Xue-Zhang's q-factor model. Comparing the performance of *CQ* strategy with value strategy,[9] we show in Figure 1.1 that *CQ* strategy impressively outperforms

[9] The results for value strategy are reported in Table A3 in Appendix.

value strategy, the monthly average return spread in *CQ* strategy (63 basis point) being more than twice as high as the return spread of quality strategy (30 basis point). The superior performance of *CQ* strategy is attributed to holding discount price firms without suffering inferior quality (cheapness as priority).

In Panel B, we show that *CQ* increases monotonically with market-to-book ratio, and the quality in *CQ*1 is a little higher than the quality in *CQ*5, reflecting cheapness as priority. The low *CQ* portfolios have high market Beta and volatility. The long-short portfolio on *CQ* has a Beta of 0.21, indicating *CQ*1 portfolio exposes high market risk than *CQ*5 portfolio. *QC* strategy's Sharp ratio is 0.70, remarkable high.

For robustness, we construct our *CQ* portfolios measuring quality based on GPOA as in Novy-Marx (2013) and report the results in Panels C and D of Table 1.2. The performance and characteristics of the *CQ* portfolios in Panels C and D are consistent with that in the *CQ* portfolios based on quality ordinal measure. Therefore, the superior performance of *CQ* measure is robust to different quality aspects.

Notably, the average excess return in *CQ* arbitrage portfolio is comparable to the average excess return in *QC* arbitrage portfolio, showing that *CQ* strategy (cheapness as priority) performs equivalently well as *QC* strategy (quality as priority) in terms of excess return. However, *QC* strategy and *CQ* strategy show different risk exposures. The former has a negative market beta while the later has a positive and convex right-sided smile market beta. The higher return with negative market beta of *QC* strategy indicates that its superior performance mainly comes from market downturns, consistent with quality shining in challenge times. The convex right-sided smile market beta of *CQ* strategy suggests that *CQ* strategy enjoys high returns when market is high as well as has limited loss when market is low. These results suggest that the relative importance of *QC* strategy and *CQ* strategy varies across business cycle although they have similar average excess return.

1.4.2 Performance Comparison between QC (CQ) strategy and Quality (Value) Strategy

To further examine whether *QC* (*CQ*) strategy and quality (value) strategy are subsumed by each other, we present the performance comparison analysis based on dependent double sorting portfolios.

We first compare *QC* strategy with quality strategy. We sort stocks into quintile portfolios in ascending order based on quality measure. Within each quality quintile, we then sort stocks on their *QC* measure, forming 25 portfolios. Panels A and B of Table 1.3 report the results when quality is based on ordinal measure as in Asness, Frazzini, and Pedersen (2019). Panel A-1 shows that *QC* strategy in each quality quintile still generates significantly positive excess returns and abnormal returns in various asset pricing models. The *QC* return spread decreases with quality measure, 106 basis point in Q1 and 45 basis point in Q5. Panel B presents the performance of quality strategy in each *QC* quintile portfolio. In contrast, Quality return spreads tend to be small and insignificant in each *QC* quintile except for *QC*1. Quality Alpha spreads are significant only in *QC*1 and *QC*2, and insignificant and relatively small in all other quintiles. These results show that *QC* return spread subsumes quality return spread and confirm *QC* strategy is far superior to quality strategy. For robustness check, we conduct dependent double-sorts (quality is based on GPOA as in Novy-Marx (2013)) and report the results in Panels C and D of Table 1.3. We find the results are qualitatively similar to the results in Panels A and B. We confirm that *QC* return spread subsumes quality return spread and confirm *QC* strategy is far superior to quality strategy.

We now turn to examine whether *CQ* strategy and value strategy are subsumed by each other. We first sort stocks into quintile portfolios in ascending order based on value measure (market-to-book). Within each value quintile, we then sort stocks on their *CQ* measure, forming 25 portfolios. Panels A and B of Table 1.4 report the results when quality is based on ordinal measure as in Asness, Frazzini, and Pedersen (2019). Panel A-1 suggests that *CQ* strategy in each value quintile still generates significantly positive excess returns and abnormal returns in various asset pricing models. The *CQ* return spread decreases with market-to-book ratio, 119 basis point in MB1 and 32 basis point in MB5. Panel B-1 presents the performance of the value strategy in each *CQ* quintile portfolio. In contrast, Value return spreads tend to be small and insignificant in each *CQ* quintile except for *CQ*1. These results show that *CQ* return spread subsumes value return spread and confirm *CQ* strategy is far superior to value strategy. For robustness check, we conduct dependent double-sorts (quality is based on GPOA as in Novy-Marx (2013)) and report the results in Panels C and D of Table 1.4. We find the results are qualitatively similar to the results in Panels A and B. We confirm that *CQ* return spread subsume quality return spread and confirm *CQ* strategy is far superior to quality strategy.

1.4.3 Performance of QCCQ strategy

We now examine the performance of *QCCQ* strategy combining both *QC* and *CQ* and compare it with the strategy combining quality and value based on independent double sorts. Portfolios are formed by independent quintile sorting on *QC* and *CQ*. The independent double-sorting results are provided in Panel A (quality based on ordinal measure) and Panel B (quality based on GPOA) of Table 1.5. The right-most column (*CQ*1-*CQ*5) of each panel reports the average monthly return spreads or alpha spreads of the portfolio that longs the lowest *CQ* portfolio (*CQ*1) and shorts the highest *CQ* portfolio (*CQ*5). Each panel's bottom row (*QC*5-*QC*1) reports the average monthly return spreads or alpha spreads of the portfolio that longs the highest *QC* portfolio (*QC*5) and shorts the lowest *QC* portfolio (*QC*1). The *QCCQ* strategy is also a self-financing portfolio that longs *QC*5 and *CQ*1 stocks and shorts *QC*1 and *CQ*5 stocks. The lower right cell of each panel reports the corresponding average monthly return spreads and alpha spreads. *QCCQ* strategy yields significantly positive return spread, 142 basis point with *t-statistic* of 10.08, and alpha spreads, 137 basis point with *t-statistic* of 9.52, 137 basis point with *t-statistic* of 9.12, 132 basis point with *t-statistic* of 8.74, and 125 basis point with *t-statistic* of 7.12 corresponding to CAPM, Fama-French three-factor model, Fama-French five-factor model, and Hou-Xue-Zhang q-factor model, respectively. *QCCQ* strategy remarkably outperforms quality-value combining strategy, which also yields significantly positive return spread (85 basis point) and alpha spreads (ranging from 108 to 132 basis point). The detailed results of quality-value combining strategy performance is reported in Table A4 in Appendix.

In a robustness check when quality is based on GPOA as in Novy-Marx (2013), Panel B reports the results. We confirm that *QCCQ* strategy generates significantly positive return spread and is superior to quality-value strategy. The right-most two columns of Figure 1.1 confirm *QCCQ* superior performance. We argue the superior performance of *QCCQ* strategy is not only simply taking both quality and value effect into account but also combining them wisely.

1.4.4 Time-series Performance and Business Cycle

In the above analysis, we show that *QC*, *CQ*, and *QCCQ* strategies have superior performance. Particularly, *QC* and *CQ* strategies generate similar average return spreads but with discrepant risk exposures (negative market beta for *QC* and convex market beta for *CQ*. A natural question that arises is whether *QC* and *CQ* strategies perform equally well across business cycles? To answer this question, we conduct two additional exercises. We plot monthly average return spreads of *QC* (*CQ*) strategy and market excess return over the period from 1957:07 to 2020:12 in Figure 1.2 (1.3). The most striking feature in Figure 1.2 is that the return spreads of *QC* are remarkably higher than market excess return in recessions, consistent with the negative market beta of *QC*. *CQ* strategy return spreads are highly correlated with market excess returns in expansions. *CQ* strategy return spreads tend to be higher than market excess returns in recessions as well, consistent with convex right-sided smile market beta of *CQ*.

We examine return spreads of *QC* and *CQ* strategies and market excess returns in good market (market excess return is above its mean) and bad market (market excess return is below its mean) and report the results in Table A5 in Appendix. Indeed, we find that when quality is based on ordinal measure, *CQ* (*CQ*) average monthly return spreads in bad market is 90 (-3) basis point compared with the related market excess return of negative 312 basis point, confirming tremendous hedging effect of *QC* strategy and limited loss of *CQ* strategy. On the other hand, in good market, the average monthly return spread of *QC* (*CQ*) is 46 (116) basis point compared with the related market excess return of 363 basis point, supporting *CQ* strategy enjoys a higher return in good market. We find qualitative similar results when quality is based on GPOA.

1.5 Factor Analysis of QC and CQ Strategies

1.5.1 Factor Construction and Performance

The results in Section 1.4 suggest that *QC*, *CQ*, and *QCCQ* strategies could generate significant excess returns and abnormal returns with respect to various risk models. To better understand the premiums of *QC*, *CQ*, and *QCCQ* strategies, we design the factor analysis and construct two types of factors: (1) *QC* factor (SMW), which longs strong *QC* stocks and shorts weak *QC* stocks; and (2) *CQ* factor (CME), which longs low *CQ* stocks and shorts high *CQ* stocks.

Following specification (1), we run cross-sectional regressions at the end of each month and obtain the *QC* measure (fitted value) and *CQ* measure (residual). Then, we sort two size portfolios using NYSE median breakpoints and constructed three *QC*/*CQ* portfolios within each size portfolio. The quality-Cheapness factor's (SMW) return is the difference between the average return on two strong *QC* portfolios and the average return on two weak *QC* portfolios:

$$SMW = \frac{1}{2}\left(Small\ QC_{Strong} + Big\ QC_{Strong}\right) - \frac{1}{2}\left(Small\ QC_{Weak} + Big\ QC_{Weak}\right) \quad (5)$$

The Cheapness-Quality factor's (CME) return is the difference between the average returns on two low *CQ* portfolios and the average returns on two high *CQ* portfolios:

$$CME = \frac{1}{2}\left(Small\ CQ_{Low} + Big\ CQ_{Low}\right) - \frac{1}{2}\left(Small\ CQ_{High} + Big\ CQ_{High}\right) \quad (6)$$

Next, we investigate whether the quality and cheapness factors above have comparative explanatory power over our arbitrage assets as the traditional risk factors. We regress our arbitrage portfolios' returns on risk factors used in traditional asset pricing models and our *QC* and *CQ* factors. Panel A of Table 1.6 presents the explanatory power of SMW and CME factors on *QC* arbitrage portfolio $QC5 - QC1$ (quality based on ordinal measure). Both factors could explain the returns of portfolio $QC5 - QC1$ significantly across various models. Nevertheless, SMW factor's coefficients are much more significant than CME factor's coefficients, suggesting that *QC* strategy is more sensitive to the *QC* factor. In Panel B, we show that SMW and CME factors have positively significant coefficients on the returns of portfolio $CQ1{-}CQ5$ (quality based on ordinal measure). It is not surprising that CME factor's coefficients are much more significant than SMW factor's coefficients. Our *CQ* strategy is more driven by the *CQ* factor. Panels C and D of Table 1.6 show the results of *QC* and *CQ* strategies based on GPOA, and the patterns are qualitatively similar. Therefore, we conclude that the *QC* and *CQ* factors could explain our *QC* and *CQ* strategies to a large extent in addition to the commonly used risk factors, and we will use SMW and CME factors to explore the asset performance drivers.

Then, we investigate SMW and CME factors' excess return and alphas for various asset pricing models. Table 1.7 reports the performance of each factor. Panel A of Table 1.7 reports the performance of factors based on quality ordinal measure. Columns (1) to (4) show the factor coefficients and asset pricing model alphas for *QC* factor SMW. Asset pricing model alphas for SMW range from 0.65% to 0.77%. Columns (4) and (8) provide the factor coefficients and alphas for *CQ* factor CME. The alphas are highly significant across all the asset pricing models (range from 0.63% to 0.73%). These patterns are similar to the pattern of single-sorting portfolios on *QC* or *CQ* measure. Similarly, Panel B of Table 1.7 reports the performance of factors based on GPOA. *QC* factor SMW has alphas range from 0.53% to 0.65%, while Cheapness factor CMECP ’s alphas range from 0.53% to 0.66%.

Since our *QC* and *CQ* strategies have similar spirits of momentum and reversal, respectively. We want to know whether our factors are also related to those famous phenomena. Therefore, we regress our factor returns on the momentum factor or the reversal factor conditional on the market excess returns to see the potential relationship.[10] Table 1.8 shows the results. Not surprisingly, we find that the reversal factor is negatively related to the SMW factor, while it is positively related to the CME factor. On the other hand, the momentum factor is negatively related to the CME. Therefore, our *QC* and *CQ* strategies are indeed related to the momentum and reversal phenomena. However, we are still not able to determine whether this pattern is driven by rational or behavioral explanations.

To find the determinants and explain the factors’ abnormal returns, we design tests examining factor performance drivers from five dimensions: investment growth opportunity, risk-related drivers, uncertainties, behavioral, and downside risk. The dependent variables are SMW and CME factors based on quality ordinal measure. We also take the AR(1) residual for our potential return drivers. Besides, Table 1.7 already shows that the market excess return is the most influential risk factor in explaining the returns of SMW and CME factors. Therefore, we control the market excess returns to examine the additional explanatory power of those potential return drivers.

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[10] We include market excess returns as a control variable because it is the only risk factor that has significant coefficients across models in Table 1.7.

1.5.2 Investment Growth Opportunity

We first test if the investment growth opportunity could explain the abnormal returns of SMW and CME factors after controlling the market excess return. Investment growth opportunities are proxied by production growth, consumption growth, and GDP growth. All growth measures are adjusted for inflation. Table 1.9 shows the test results. Panels A and B report the results for SMW and CME factors, respectively. We find that production growth (1 month and 12 months), consumption growth (1 month and 12 months future), and GDP growth (1 month) have positively significant exposures for *QC* factor SMW. We argue that strong *QC* firms would have more future growth opportunities than weak *QC* firms, resulting in a positive coefficient for the SMW factor. On the other hand, production growth (1 month and 12 months), consumption growth (1 month), and GDP growth (1 month) have negatively significant exposures for *CQ* factor CME. This result is because low *CQ* firms have relatively higher risk and lower growth, while high *CQ* firms have a lower risk but higher growth, leading the negative relationship between future growth opportunity and factor CME. Therefore, we conclude that investment growth opportunity variables have different effects on SMW and CME factors.

1.5.3 Risk-Related Drivers

We then consider a group of risk-related variables, which include liquidity risk (Pastor & Stambaugh's liquidity Innovations and modified Amihud illiquidity), volatility risk (VIX Index and aggregate idiosyncratic volatility), ted spread, credit spread, and term spread. We report the regression results in Table 1.10. Panels A and B report the results for SMW and CME factors, respectively. We find that SMW factor is sensitive to

VIX index and IVOL, and both coefficients are positive. Meanwhile, CME factor is only sensitive to IVOL, and the coefficient is negative. Based on this test, we conclude that those risk-related variables have limited additional explanatory power on SMW and CME factors.

1.5.4 Uncertainty Drivers

Next, we focus on the uncertainty variables, which include the Financial, Macro, and Real uncertainties from Jurado, Ludvigson, and Ng (2015) . We report the regression results in Table 1.11. Panels A and B report the results for SMW and CME factors, respectively. In general, SMW factor is not sensitive to any uncertainty variables. On the other hand, CME factor has significant coefficients on financial uncertainty (1-, 3-, and 12-months). We argue that SMW factor may not relate to uncertainty risk, however, financial uncertainty risk would partially explain the returns of CME factor.

1.5.5 Behavioral Drivers

We continue with the behavioral or mispricing explanation of our factor performance. We considered various behavioral proxies. We include the consumer sentiment index from the University of Michigan and the orthogonal/non-orthogonal sentiment index of Baker and Wurgler (2006) and its two components - equity share in new issues (S) and number of IPOs (NIPO). We also include the lottery demand proxied by casino profits in the U.S. It is measured as the quarterly casino industry profits (revenue minus cost of goods sold) scaled by the nominal GDP.[11] Panels A and B of Table 1.12 show that Consumer Sentiment is positively associated with SMW factor. The

[11] The casino industry is defined as firms with the NAICS code of 713210.

equity share in the new issues component of the Sentiment Index has negative exposures on CME factor. Again, we suggest that the behavioral explanation is related to our factor returns but only has limited explanatory power.

1.5.6 Downside Risk

Our previous results suggest that the investment growth opportunity, time-varying risk and uncertainty, and behavioral variables are only able to explain partial of abnormal return in value investing strategy. We then retrospect the time-series performance analysis of our arbitrage portfolios against the market index in Section 1.4.3, which shows that our portfolios have some advantages over the market index, especially during economic recessions. Inspired by these results, we consider the possibility that downside risk plays a role in explaining factor performance.

Existing literature has already discovered that downside risk is highly relevant to various kinds of assets (e.g., Ang, Chen, and Xing, 2006; Lettau, Maggiori, and Weber, 2014; Schneider, Wagner, and Zechner, 2020). To formally examine if the downside risk exposure could explain the factor abnormal returns, we adopt the alternative downside model proposed by Henriksson and Merton (1981):

$$r^{e}_{Factor,t} = \alpha + \beta_{Downside}\, Min\{0, r^{e}_{mkt,t}\} + \beta_{Upside} Max\{0, r^{e}_{mkt,t}\} + \varepsilon_t \qquad (11)$$

where $r^{e}_{Factor,t}$ is the realized factor excess return and $r^{e}_{mkt,t}$ is the realized market excess return. Table 1.13 reports the results of the downside time-series regressions. Columns (1) and (2) of Panel A provide the benchmark results for SMW and CME factors.[12] SMW factor has negative downside beta (marginally significant) and upside beta

[12] QC, CQ, and QCCQ arbitrage portfolio results are reported in Columns (3) to (5) as robustness.

(insignificant), which implies that the Fundamental factors potentially move against or are insensitive to the market during both market downturn and upturn. CME factor has exactly the opposite characteristics. The downside beta and upside beta are both positive, which is also consistent with our finding in Figure 1.4b that *CQ*-based assets take the market risk and require higher returns. The CME factor co-moves with the market in the good times and moves slightly against the market in the bad times. Furthermore, we find that the intercept or the monthly alphas for CME factor is smaller than their CAPM model alphas reported in Table 1.7. CAPM Alphas are 0.39% vs. 0.66% (41% decrease). We further test the explanatory power of downside risk by controlling the effect of additional risk factors from the Fama-French five-factor model and Hou-Xue-Zhang's q-factor model. Panels B and C of Table 1.7 provide the results. The patterns are consistent with our benchmark results, in spite of a shorter sample period. The above empirical evidence suggests that the downside risk model could partially explain the factor abnormal returns that could not be captured by the commonly used risk models we tested in Table 1.7. Therefore, we conclude that downside risk may serve as an alternative explanation for the source of factors' abnormal returns.

1.6 Conclusion

In this study, we propose a regression-based approach to identify two investing strategies: the quality-cheapness (*QC*) strategy with quality as priority and the cheapness-quality (*CQ*) strategy with cheapness as priority. Both *QC* and *CQ* consider quality and cheapness but with different priorities.

We find that the return spreads in our *QC* and *CQ* strategies are sizably higher than those in traditional quality investing strategy and value investing strategy. We show that *QC* strategy and *CQ* strategy perform almost equally well in return spread but with different market risk exposures, suggesting different sources of returns and potential synergy in *QC* and *CQ*, which is confirmed in our *QCCQ* strategy.

We further conduct tests to examine the determinants of return spreads in *QC* and *CQ* and find that investment growth opportunity, time-varying risk, and behavioral variables have some limited explanatory power. Meanwhile, the downside risk also plays a role in explaining the strategy performance. We recognize that we provide a limited understanding although this study takes steps to examine the determinants of the return spreads from different perspectives. We leave this topic for the future research.

Figure 1.1 Average Monthly Return Comparison of Investment Strategies

This figure shows monthly excess returns comparison between *QC* strategy and traditional quality investing strategy based on the quality ordinal measure (left two bars), *CQ* strategy and traditional value investing strategy based on the market-to-book ratio (middle two bars), and *QCCQ* strategy and two-way value investing strategy based on quality ordinal measure and market-to-book ratio (right two bars).

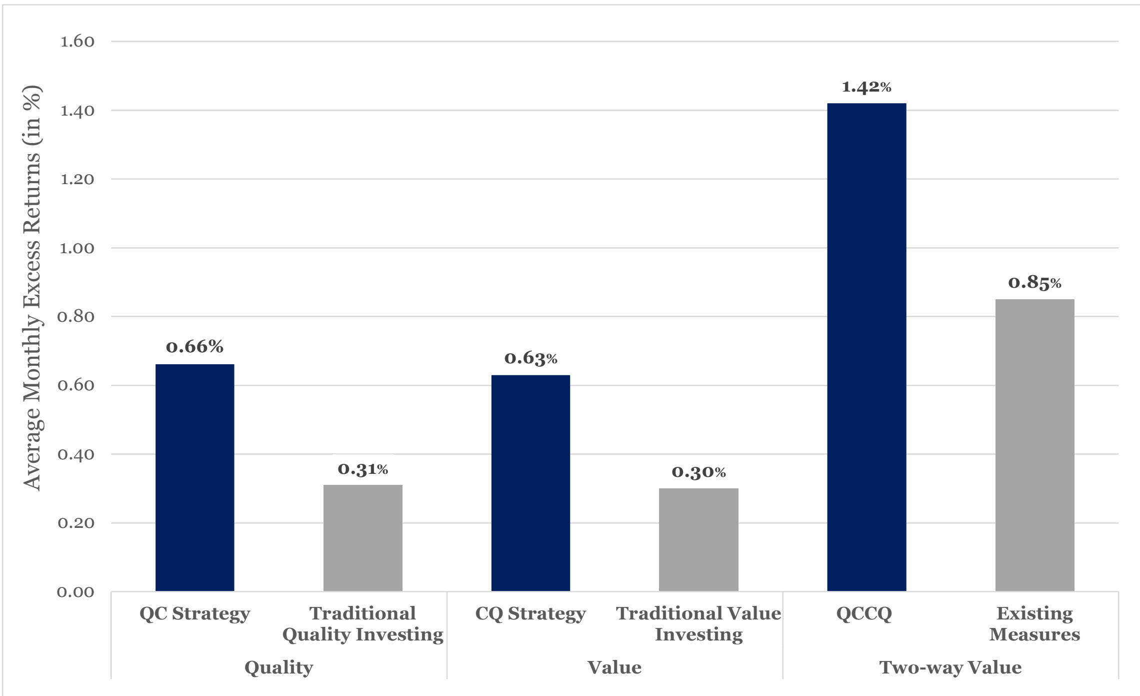


Figure 1.2 QC Measure-sorted Arbitrage Portfolio and Market Index

This figure shows monthly excess returns of Quality-Cheapness Measure-sorted arbitrage portfolios *QC*5 - *QC*1 (Quality based on Ordinal Measure) versus market excess returns. The red line represents the returns of Quality-Cheapness arbitrage portfolio, and the gray line stands for the excess returns of CRSP value-weighted market index. The shaded area indicates the NBER recession period.

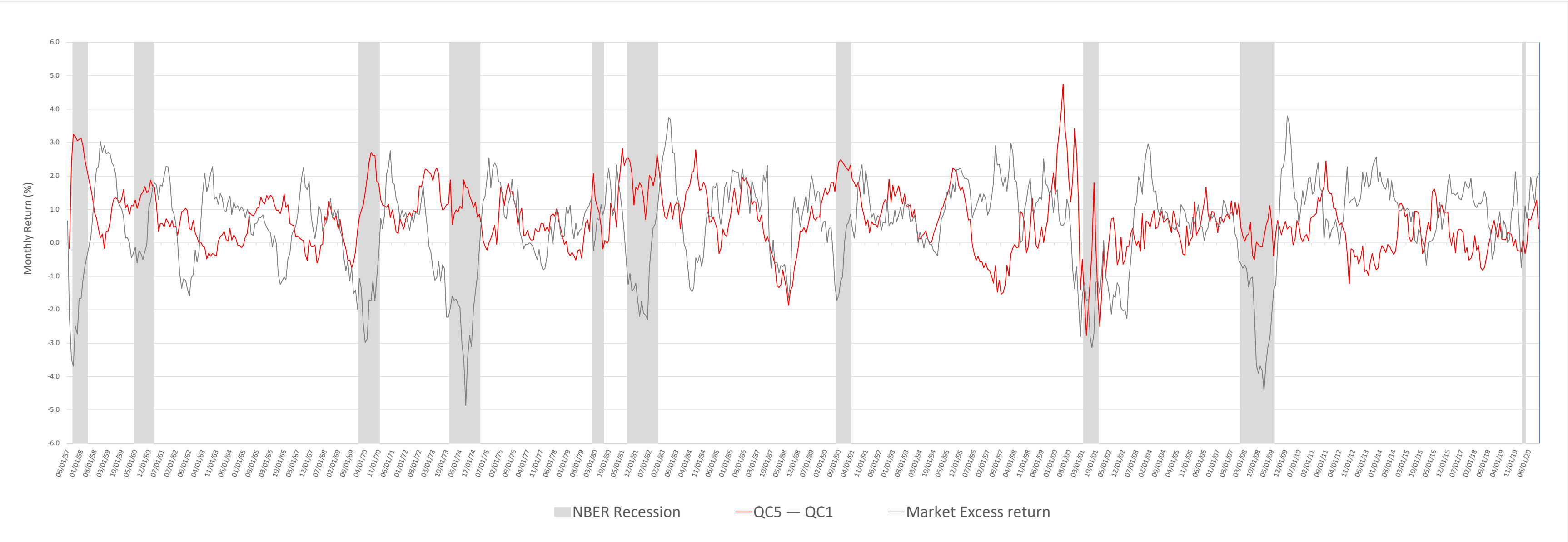


Figure 1.3 CQ Measure-sorted Arbitrage Portfolio and Market Index

This figure shows monthly excess returns of Cheapness-Quality Measure-sorted arbitrage portfolios *CQ*1 - *CQ*5 (Quality based on ordinal measure) versus market excess returns. The red line represents the returns of Cheapness-Quality arbitrage portfolio, and the gray line stands for the excess returns of CRSP value-weighted market index. The shaded area indicates the NBER recession period.

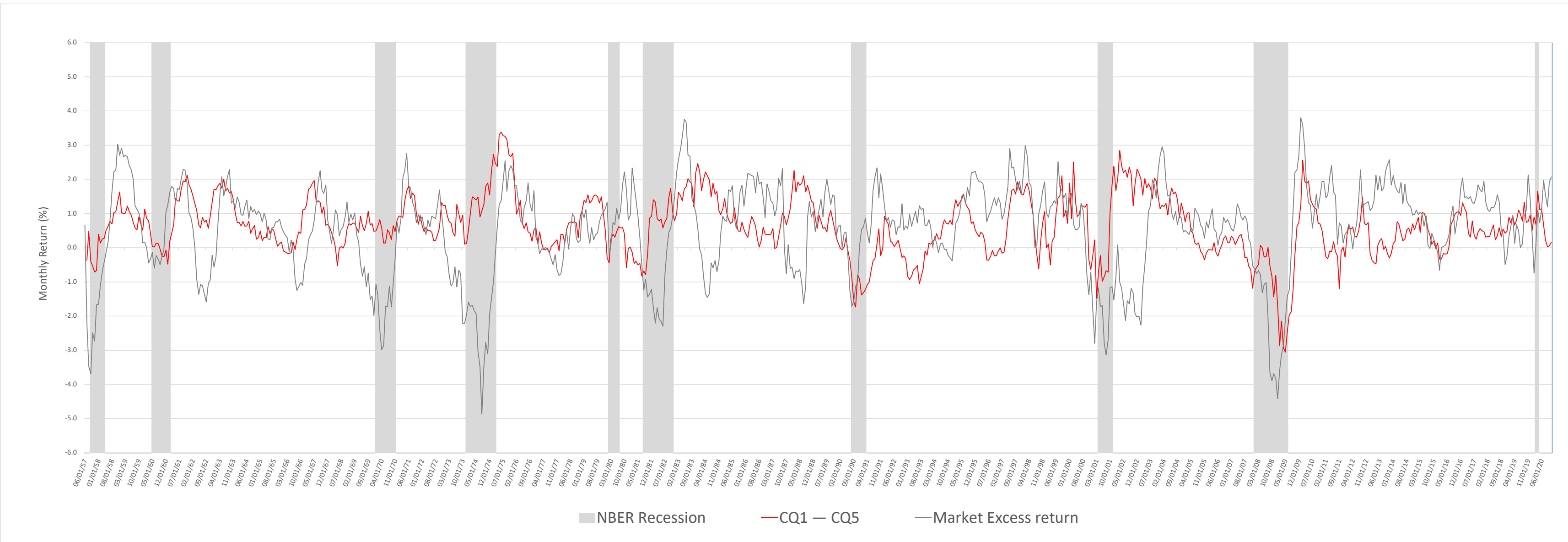
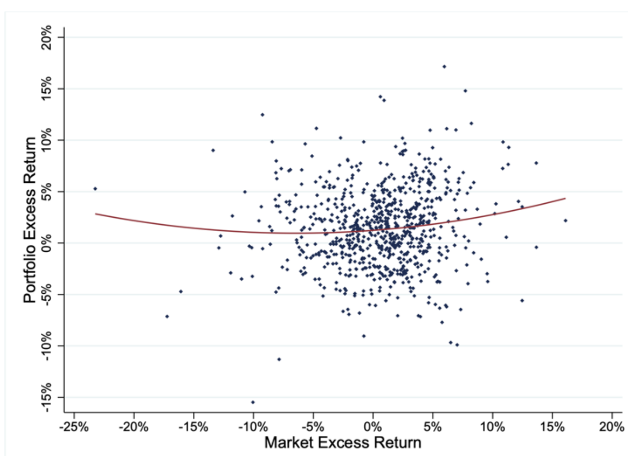


Figure 1.4 Time Series Asset Return Series Against Market Returns

This figure shows monthly excess returns of *QC*, *CQ*, and *QCCQ*-based arbitrage portfolios versus market excess returns with the quadratic fitted trend lines.

(a) *QC*5-*QC*1

(b) *CQ*1-*CQ*5



(c) *QC*5/*CQ*1 – *QC*1/*CQ*5

Table 1.1 Quality-Cheapness Sorted Portfolios Performance

This table shows the portfolio returns based on our Quality-Cheapness Measure (*QC*, regression *fitted value*). The sample period covers from July 1957 to December 2020. At the end of each month, stocks are ranked in ascending order on the basis of their **Quality-Cheapness Measure** and are assigned to five portfolios based on the NYSE breakpoint. Portfolios are value-weighted and rebalanced at the end of each month. The risk factors include the market excess return (MKT), size (SMB), book-to-market (HML), profitability (RMW/ROE), and investment (CMA/INV). Panels A and C show the returns and alphas of portfolios sorted based on *QC* Quality Ordinal Measure (QC_{QOM}) and *QC* Gross-profit-over-asset (QC_{GPOA}), respectively. The bottom row reports returns/alphas of an arbitrage portfolio that longs the high-quality-low-relative-price portfolio (QC5) and shorts the low-quality-high-relative-price portfolio (QC1). Returns and alphas are in monthly percentage, Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. Panels B and D report the characteristics of portfolios sorted based on QC_{QOM} and QC_{GPOA}, respectively. We report portfolios' raw quality measure (QOM or GPOA), MB (defined as log (M/B) ratio), Size, Age, Market Beta, Volatility, Skewness, Kurtosis, and Sharpe ratio. Beta is the loading of the market excess return in CAPM. Volatility is the standard deviation of excess returns in percentage. Sharpe ratios are annualized. The adjusted R^2 is the R^2 of the Fama-French five-factor model.

Panel A: Portfolio Excess return and Alphas - (Quality based on Ordinal Measure)

	QC	**Raw Return**	**Excess Return**	**CAPM Alpha**	**3-factor Alpha**	**5-factor Alpha**	**q-factor Alpha**	**Adjusted** *R*2
QC1	**-0.02**	**0.64**	0.29	**-0.30**	**-0.31**	**-0.30**	-0.21	80.59%
	(-8.10)	(3.70)	(1.61)	(-4.18)	(-4.05)	(-2.97)	(-1.82)	
QC2	0.00	**0.86**	**0.50**	-0.12	**-0.20**	**-0.19**	**-0.21**	89.13%
	(1.00)	(4.40)	(2.54)	(-1.76)	(-2.97)	(-2.70)	(-2.22)	
QC3	**0.01**	**0.99**	**0.63**	0.03	-0.03	-0.07	-0.08	91.00%
	(5.13)	(5.43)	(3.42)	(0.45)	(-0.63)	(-1.12)	(-1.17)	
QC4	**0.02**	**0.99**	**0.63**	0.06	0.02	-0.05	-0.08	87.71%
	(9.36)	(5.53)	(3.48)	(0.91)	(0.27)	(-0.71)	(-0.86)	
QC5	**0.05**	**1.30**	**0.94**	**0.40**	**0.42**	**0.36**	**0.35**	81.19%
	(18.01)	(7.88)	(5.71)	(6.12)	(6.29)	(4.49)	(3.58)	
QC5 - QC1	**0.07**	**0.66**	**0.66**	**0.71**	**0.73**	**0.65**	**0.56**	1.20%
	(24.61)	(5.47)	(5.47)	(5.83)	(5.83)	(4.04)	(2.86)	

Panel B: Portfolio Characteristics - (Quality based on Ordinal Measure)

	Quality	**MB**	**Size**	**Age (Year)**	**Beta**	**Volatility**	**Skewness**	**Kurtosis**	**Sharpe Ratio**
QC1	0.66	1.03	2222.33	13.23	1.02	4.99	-0.22	5.13	0.20
QC2	0.56	0.90	1678.49	13.24	1.08	5.09	-0.46	4.97	0.34
QC3	0.55	0.88	1700.43	13.50	1.04	4.84	-0.44	5.39	0.45
QC4	0.58	0.93	1796.46	13.45	0.99	4.68	-0.47	5.82	0.47
QC5	0.70	1.13	2569.50	13.51	0.93	4.57	-0.37	5.37	0.72
QC5 - QC1	0.04	0.10	347.16	0.28	-0.09	3.72	-0.05	7.92	0.61

Table 1.1 Continued

Panel C: Portfolio Excess return and Alphas (Quality based on GPOA)

	QC	Raw Return	Excess Return	CAPM Alpha	3-factor Alpha	5-factor Alpha	q-factor Alpha	Adjusted *R2*
QC1	**-0.01**	**0.72**	**0.36**	**-0.21**	**-0.20**	**-0.21**	-0.15	80.37%
	(-5.08)	(4.13)	(2.03)	(-2.93)	(-2.60)	(-2.22)	(-1.26)	
QC2	**0.01**	**0.94**	**0.58**	0.00	-0.05	-0.08	-0.04	88.41%
	(2.84)	(5.21)	(3.19)	(0.00)	(-0.85)	(-1.11)	(-0.53)	
QC3	**0.01**	**0.83**	**0.47**	-0.11	**-0.20**	**-0.25**	**-0.25**	88.14%
	(5.12)	(4.61)	(2.59)	(-1.72)	(-3.52)	(-3.94)	(-3.30)	
QC4	**0.02**	**1.03**	**0.68**	0.11	0.05	-0.02	-0.08	88.72%
	(7.49)	(5.86)	(3.80)	(1.62)	(0.93)	(-0.29)	(-1.00)	
QC5	**0.04**	**1.23**	**0.88**	**0.34**	**0.36**	**0.30**	**0.26**	80.34%
	(15.58)	(7.36)	(5.23)	(4.78)	(4.74)	(3.21)	(2.44)	
QC5 - QC1	**0.05**	**0.52**	**0.52**	**0.56**	**0.57**	**0.51**	**0.41**	0.44%
	(31.47)	(3.97)	(3.97)	(4.32)	(4.23)	(2.98)	(1.96)	

Panel D: Portfolio Characteristics - (Quality based on Ordinal Measure)

	Quality (GPOA)	MB	Size	Age (Year)	Beta	Volatility	Skewness	Kurtosis	Sharpe Ratio
QC1	0.39	1.09	1970.26	13.52	0.99	4.87	-0.23	5.23	0.26
QC2	0.29	0.92	1817.96	13.15	1.01	4.76	-0.24	4.58	0.42
QC3	0.28	0.90	1818.26	13.43	1.02	4.84	-0.55	5.51	0.34
QC4	0.32	0.99	1891.06	13.45	0.99	4.67	-0.49	4.98	0.50
QC5	0.42	1.19	2151.33	13.77	0.92	4.53	-0.42	5.48	0.67
QC5 - QC1	0.04	0.10	181.07	0.25	-0.07	3.66	-0.14	7.23	0.49

Table 1.2 Cheapness-Quality Sorted Portfolios Performance

This table shows the portfolio returns based on our Cheapness-Quality Measure (*CQ*, regression *residual*). The sample period covers from July 1957 to December 2020. At the end of each month, stocks are ranked in ascending order on the basis of their **Cheapness-Quality Measure** and are assigned to five portfolios based on the NYSE breakpoint. Portfolios are value-weighted and rebalanced at the end of each month. Panels A and C show the returns and alphas of portfolios sorted based on *CQ* Quality Ordinal Measure (CQ_{QOM})and *CQ* Gross-profit-over-asset (CQ_{GPOA}), respectively. The bottom row reports returns/alphas of an arbitrage portfolio that longs the *cheap-with-high-relative-quality* portfolio (*CQ*1) and shorts the *expensive-with-low-relative-quality* portfolio (*CQ*5). Returns and alphas are in monthly percentage, Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. Panels B and D report the characteristics of portfolios sorted based on CQ_{QOM} and CQ_{GPOA}, respectively. We report portfolios' corresponding *QC* Measure (QC_{QOM} and QC_{GPOA}), MB (defined as log (M/B) ratio) Size, Age, Market Beta, Volatility, Skewness, Kurtosis, and Sharpe ratio. Beta is the loading of the market excess return in CAPM. Volatility is the standard deviation of excess returns in percentage. Sharpe ratios are annualized. The adjusted R^2 is the R^2 of the Fama-French five-factor model.

Panel A: Portfolio Excess return and Alphas - (Quality based on Ordinal Measure)

	CQ	**Raw Return**	**Excess Return**	**CAPM Alpha**	**3-factor Alpha**	**5-factor Alpha**	**q-factor Alpha**	**Adjusted** *R2*
CQ1	**-0.11**	**1.28**	**0.92**	**0.22**	**0.19**	**0.23**	**0.26**	88.78%
	(-39.19)	(6.12)	(4.37)	(2.90)	(2.52)	(2.68)	(2.70)	
CQ2	**-0.04**	**1.16**	**0.80**	**0.22**	**0.20**	**0.18**	**0.16**	93.35%
	(-34.77)	(6.95)	(4.78)	(5.04)	(4.81)	(4.06)	(3.01)	
CQ3	**0.00**	**0.95**	**0.60**	0.05	0.04	-0.01	-0.04	94.84%
	(-6.99)	(5.81)	(3.58)	(1.23)	(1.00)	(-0.29)	(-1.02)	
CQ4	**0.03**	**0.83**	**0.47**	-0.07	-0.07	**-0.10**	**-0.11**	94.47%
	(35.21)	(5.12)	(2.87)	(-1.66)	(-1.75)	(-2.35)	(-2.36)	
CQ5	**0.11**	**0.65**	0.29	**-0.29**	**-0.29**	**-0.27**	**-0.27**	88.47%
	(39.96)	(3.68)	(1.63)	(-4.78)	(-4.75)	(-4.41)	(-3.53)	
CQ1-CQ5	**-0.22**	**0.63**	**0.63**	**0.51**	**0.48**	**0.50**	**0.53**	8.90%
	(-40.26)	(5.67)	(5.67)	(4.58)	(4.24)	(4.07)	(3.49)	

Panel B: Portfolio Characteristics - (Quality based on Ordinal Measure)

	Quality	**MB**	**Size**	**Age (Year)**	**Beta**	**Volatility**	**Skewness**	**Kurtosis**	**Sharpe Ratio**
CQ1	0.63	0.97	1048.63	11.36	1.21	5.70	-0.28	5.30	0.56
CQ2	0.66	0.98	2289.02	14.05	1.01	4.60	-0.34	5.19	0.61
CQ3	0.66	1.00	2688.78	14.80	0.95	4.30	-0.47	4.80	0.48
CQ4	0.66	1.04	2632.04	14.48	0.93	4.25	-0.33	4.44	0.38
CQ5	0.62	1.12	1410.99	11.88	1.01	4.74	-0.45	5.03	0.21
CQ1-CQ5	0.01	-0.15	-362.36	-0.52	0.21	3.11	0.34	5.97	0.70

Table 1.2 Continued

Panel C: Portfolio Excess return and Alphas (Quality based on GPOA)

	CQ	Raw Return	Excess Return	CAPM Alpha	3-factor Alpha	5-factor Alpha	q-factor Alpha	Adjusted $R2$
CQ1	**-0.11**	**1.22**	**0.87**	0.13	0.08	0.18	0.22	87.53%
	(-40.24)	(5.72)	(4.04)	(1.54)	(0.94)	(1.78)	(1.79)	
CQ2	**-0.04**	**1.12**	**0.76**	**0.17**	**0.13**	**0.13**	0.09	91.90%
	(-33.63)	(6.37)	(4.30)	(3.34)	(2.88)	(2.77)	(1.70)	
CQ3	**0.00**	**0.98**	**0.63**	**0.08**	0.07	0.03	0.02	94.53%
	(-5.92)	(6.11)	(3.84)	(1.96)	(1.71)	(0.77)	(0.48)	
CQ4	**0.03**	**0.87**	**0.52**	-0.02	-0.02	-0.05	-0.07	93.89%
	(34.28)	(5.32)	(3.09)	(-0.55)	(-0.56)	(-1.19)	(-1.46)	
CQ5	**0.11**	**0.63**	0.28	**-0.31**	**-0.30**	**-0.27**	**-0.26**	86.61%
	(41.06)	(3.47)	(1.49)	(-4.75)	(-4.67)	(-4.01)	(-3.08)	
CQ1-CQ5	**-0.22**	**0.59**	**0.59**	**0.44**	**0.38**	**0.44**	**0.48**	12.46%
	(-41.45)	(4.67)	(4.67)	(3.38)	(2.86)	(3.03)	(2.55)	

Panel D: Portfolio Characteristics - (Quality based on Ordinal Measure)

	Quality	MB	Size	Age (Year)	Beta	Volatility	Skewness	Kurtosis	Sharpe Ratio
CQ1	0.35	0.97	1036.48	11.39	1.27	6.02	-0.26	5.84	0.50
CQ2	0.34	0.98	2268.98	14.15	1.03	4.73	-0.36	5.43	0.56
CQ3	0.33	1.00	2711.09	15.01	0.95	4.32	-0.37	4.75	0.50
CQ4	0.34	1.05	2669.21	14.61	0.93	4.25	-0.37	4.53	0.42
CQ5	0.35	1.14	1466.83	11.96	1.01	4.79	-0.41	5.01	0.20
CQ1-CQ5	0.000	-0.17	-430.35	-0.57	0.26	3.60	0.44	7.41	0.57

Table 1.3 Comparison between QC Strategy and Quality Strategy

This table presents the comparison between *QC* strategy and quality investing strategy. We report portfolios' excess returns of the dependent double sorts conditional on *QC* Measure and quality measure. The sample period covers from July 1957 to December 2020. Left-hand of Panels A and B show the performance of *QC* strategy in each quality quintile. At the end of each month, stocks are ranked in ascending order first based on their quality measure. Within each quality quintile, we then sort stocks on their *QC* Measure, forming 25 portfolios. Right-hand of Panels A and B exhibit the performance of quality strategy in each *QC* quintile. At the end of each month, stocks are ranked in ascending order first based on the *QC* Measure. Within each *QC* quintile, we then sort stocks on their quality measure, forming 25 portfolios. Portfolios are value-weighted, and rebalanced at the end of at the end of each month. The rightmost column reports returns of an arbitrage portfolio that longs the high *QC* Measure (Quality) portfolios and shorts the low *QC* Measure (Quality) portfolios. Returns are in monthly percentages. Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates, and 5% statistical significance are indicated in bold.

Panel A: QC Portfolio Performance (Quality based on OM)

Panel A-1: Excess return

			QC			
Quality	QC1	QC2	QC3	QC4	QC5	QC5-1
Q1	-0.14	-0.10	0.28	0.53	**0.92**	**1.06**
	(-0.51)	(-0.33)	(1.02)	(1.81)	(3.35)	(5.43)
Q2	0.13	**0.54**	**0.52**	**0.59**	**1.05**	**0.92**
	(0.56)	(2.38)	(2.43)	(2.82)	(5.05)	(5.62)
Q3	0.23	**0.56**	**0.58**	**0.55**	**0.79**	**0.56**
	(1.13)	(2.68)	(2.80)	(2.77)	(4.01)	(3.41)
Q4	**0.38**	**0.57**	**0.63**	**0.65**	**0.99**	**0.61**
	(1.99)	(2.98)	(3.69)	(3.54)	(5.39)	(3.74)
Q5	**0.51**	**0.68**	**0.59**	**0.83**	**0.96**	**0.45**
	(2.92)	(3.91)	(3.31)	(4.81)	(5.62)	(3.25)

Panel A-2: CAPM alpha

			QC			
Quality	QC1	QC2	QC3	QC4	QC5	QC5-1
Q1	**-0.91**	**-0.95**	**-0.49**	-0.27	0.19	**1.11**
	(-5.44)	(-5.66)	(-3.18)	(-1.80)	(1.21)	(5.64)
Q2	**-0.57**	-0.18	-0.13	-0.06	**0.45**	**1.03**
	(-4.48)	(-1.61)	(-1.17)	(-0.64)	(4.21)	(6.29)
Q3	**-0.40**	-0.07	-0.04	-0.05	**0.23**	**0.63**
	(-3.48)	(-0.66)	(-0.40)	(-0.48)	(2.34)	(3.72)
Q4	**-0.22**	-0.01	0.06	0.09	**0.44**	**0.66**
	(-2.44)	(-0.12)	(0.70)	(1.09)	(4.07)	(4.17)
Q5	-0.05	0.14	0.08	**0.31**	**0.42**	**0.47**
	(-0.52)	(1.70)	(0.91)	(3.92)	(4.89)	(3.31)

Panel A-3: 5-factor alpha

			QC			
Quality	QC1	QC2	QC3	QC4	QC5	QC5-1
Q1	**-0.85**	**-0.86**	**-0.35**	**-0.27**	0.24	**1.10**
	(-4.74)	(-5.20)	(-2.57)	(-1.98)	(1.68)	(4.40)
Q2	**-0.51**	**-0.27**	**-0.23**	**-0.21**	**0.43**	**0.94**
	(-3.82)	(-2.52)	(-2.22)	(-2.17)	(3.87)	(5.04)
Q3	**-0.45**	-0.17	**-0.19**	**-0.20**	**0.29**	**0.73**
	(-3.37)	(-1.89)	(-2.08)	(-2.12)	(2.51)	(3.56)
Q4	**-0.22**	**-0.20**	-0.10	-0.03	**0.38**	**0.60**
	(-2.14)	(-2.18)	(-1.11)	(-0.35)	(2.76)	(2.93)
Q5	0.02	0.04	-0.07	**0.26**	**0.35**	0.33
	(0.19)	(0.54)	(-0.87)	(2.95)	(3.50)	(1.80)

Panel B: Quality Portfolio Performance (Quality based on OM)

Panel B-1: Excess return

			Quality			
QC	Q1	Q2	Q3	Q4	Q5	Q5-1
QC1	-0.13	0.14	0.41	0.39	**0.38**	**0.51**
	(-0.53)	(0.60)	(1.82)	(1.90)	(2.00)	(2.88)
QC2	0.23	0.32	0.37	0.39	**0.53**	0.31
	(0.82)	(1.24)	(1.74)	(1.81)	(2.73)	(1.57)
QC3	**0.62**	**0.56**	**0.58**	**0.62**	**0.62**	0.00
	(2.68)	(2.50)	(2.83)	(3.04)	(3.37)	(0.00)
QC4	**0.80**	**0.61**	**0.57**	**0.56**	**0.62**	-0.19
	(3.60)	(2.87)	(2.80)	(2.80)	(2.97)	(-1.12)
QC5	**1.00**	**0.87**	**0.92**	**1.04**	**0.96**	-0.05
	(4.56)	(4.58)	(5.18)	(5.33)	(5.15)	(-0.30)

Panel B-2: CAPM alpha

			Quality			
QC	Q1	Q2	Q3	Q4	Q5	Q5-1
QC1	**-0.86**	**-0.53**	**-0.27**	**-0.24**	-0.21	**0.66**
	(-5.72)	(-4.48)	(-2.40)	(-2.41)	(-1.95)	(3.67)
QC2	**-0.52**	**-0.41**	**-0.31**	**-0.28**	-0.06	**0.46**
	(-3.40)	(-3.11)	(-2.90)	(-2.92)	(-0.63)	(2.33)
QC3	-0.05	-0.08	-0.06	-0.02	0.04	0.09
	(-0.43)	(-0.69)	(-0.59)	(-0.23)	(0.47)	(0.58)
QC4	0.12	-0.03	-0.06	-0.05	0.06	-0.06
	(0.93)	(-0.34)	(-0.58)	(-0.62)	(0.56)	(-0.31)
QC5	**0.42**	**0.30**	**0.35**	**0.49**	**0.40**	-0.02
	(3.10)	(3.07)	(3.81)	(4.25)	(4.05)	(-0.10)

Panel B-3: 5-factor alpha

			Quality			
QC	Q1	Q2	Q3	Q4	Q5	Q5-1
QC1	**-0.86**	**-0.41**	-0.22	-0.21	-0.16	**0.70**
	(-4.93)	(-2.89)	(-1.67)	(-1.58)	(-1.18)	(3.77)
QC2	**-0.63**	**-0.47**	**-0.37**	**-0.25**	-0.05	**0.58**
	(-4.57)	(-3.47)	(-3.28)	(-2.38)	(-0.44)	(3.08)
QC3	-0.15	-0.18	-0.16	-0.13	0.04	0.19
	(-1.27)	(-1.61)	(-1.69)	(-1.47)	(0.41)	(1.17)
QC4	-0.03	-0.11	-0.21	-0.08	0.05	0.08
	(-0.22)	(-0.93)	(-1.67)	(-0.78)	(0.45)	(0.46)
QC5	**0.31**	**0.28**	**0.28**	**0.44**	**0.37**	0.06
	(2.25)	(2.28)	(2.63)	(2.79)	(3.60)	(0.38)

Table 1.3 Continued

Panel C: QC Portfolio Performance (Quality based on GPOA)

Panel C-1: Excess return

Quality	QC1	QC2	QC3	QC4	QC5	QC5-1
Q1	0.21	0.38	0.45	**0.50**	**0.83**	**0.62**
	(0.84)	(1.48)	(1.70)	(2.13)	(3.11)	(2.66)
Q2	0.22	0.36	**0.46**	**0.50**	**0.79**	**0.56**
	(1.11)	(1.85)	(2.31)	(2.36)	(4.32)	(3.58)
Q3	**0.39**	**0.64**	**0.57**	**0.50**	**0.94**	**0.55**
	(2.00)	(3.15)	(2.96)	(2.45)	(4.75)	(3.41)
Q4	**0.44**	**0.45**	**0.72**	**0.54**	**0.80**	**0.35**
	(2.42)	(2.19)	(3.85)	(2.63)	(4.01)	(2.18)
Q5	**0.58**	**0.67**	**0.84**	**0.98**	**0.96**	0.38
	(2.92)	(3.29)	(4.47)	(4.75)	(4.30)	(1.93)

Panel C-2: CAPM alpha

Quality	QC1	QC2	QC3	QC4	QC5	QC5-1
Q1	**-0.49**	**-0.30**	-0.20	-0.14	0.18	**0.66**
	(-3.09)	(-2.07)	(-1.12)	(-1.14)	(0.99)	(2.89)
Q2	**-0.33**	**-0.25**	-0.17	-0.11	**0.28**	**0.62**
	(-2.68)	(-2.61)	(-1.71)	(-1.05)	(2.62)	(3.78)
Q3	**-0.21**	0.03	-0.04	-0.09	**0.35**	**0.56**
	(-2.00)	(0.31)	(-0.46)	(-0.96)	(3.65)	(3.65)
Q4	-0.15	-0.18	0.12	-0.08	0.22	**0.37**
	(-1.51)	(-1.79)	(1.36)	(-0.72)	(1.95)	(2.35)
Q5	-0.03	0.07	**0.30**	**0.40**	**0.39**	**0.41**
	(-0.24)	(0.66)	(2.69)	(3.45)	(2.53)	(2.22)

Panel C-3: 5-factor alpha

Quality	QC1	QC2	QC3	QC4	QC5	QC5-1
Q1	-0.25	-0.23	**-0.42**	-0.12	**0.49**	**0.74**
	(-1.33)	(-1.66)	(-2.61)	(-0.83)	(2.18)	(2.10)
Q2	**-0.39**	**-0.32**	**-0.32**	**-0.21**	0.13	**0.52**
	(-2.80)	(-3.66)	(-3.77)	(-2.12)	(1.15)	(2.71)
Q3	**-0.27**	-0.06	**-0.23**	**-0.26**	**0.27**	**0.53**
	(-2.01)	(-0.66)	(-2.72)	(-2.22)	(2.16)	(2.59)
Q4	-0.02	-0.19	0.02	-0.08	0.17	0.19
	(-0.17)	(-1.59)	(0.22)	(-0.72)	(1.36)	(0.94)
Q5	0.05	0.09	0.17	**0.30**	**0.56**	0.51
	(0.39)	(0.79)	(1.48)	(2.61)	(2.80)	(1.78)

Panel D: Quality Portfolio Performance (Quality based on GPOA)

Panel D-1: Excess return

QC	Q1	Q2	Q3	Q4	Q5	Q5-1
QC1	0.41	0.38	**0.41**	**0.49**	0.41	0.00
	(1.87)	(1.91)	(2.02)	(2.41)	(1.91)	(0.02)
QC2	0.25	**0.55**	**0.60**	**0.45**	**0.65**	**0.40**
	(1.07)	(2.65)	(2.65)	(2.15)	(3.05)	(2.50)
QC3	**0.49**	**0.42**	**0.49**	**0.50**	**0.64**	0.15
	(2.27)	(1.97)	(2.25)	(2.49)	(3.54)	(1.00)
QC4	**0.62**	**0.53**	**0.63**	**0.63**	**0.83**	0.21
	(2.67)	(2.33)	(3.06)	(3.02)	(4.22)	(1.30)
QC5	**0.94**	**0.78**	**0.93**	**0.93**	**1.03**	0.09
	(4.14)	(4.02)	(5.21)	(4.97)	(4.39)	(0.50)

Panel D-2: CAPM alpha

QC	Q1	Q2	Q3	Q4	Q5	Q5-1
QC1	-0.20	-0.20	-0.21	-0.10	**-0.24**	-0.04
	(-1.41)	(-1.76)	(-1.91)	(-0.95)	(-2.15)	(-0.22)
QC2	**-0.44**	-0.07	-0.03	-0.17	0.05	**0.49**
	(-3.77)	(-0.61)	(-0.24)	(-1.60)	(0.49)	(3.03)
QC3	-0.15	-0.22	-0.14	-0.12	0.07	0.22
	(-1.22)	(-1.90)	(-1.29)	(-1.27)	(0.82)	(1.37)
QC4	-0.02	-0.10	0.03	0.04	**0.27**	0.29
	(-0.18)	(-0.75)	(0.22)	(0.35)	(2.60)	(1.81)
QC5	**0.42**	0.19	**0.36**	**0.37**	**0.46**	0.04
	(2.78)	(1.94)	(3.14)	(2.94)	(3.01)	(0.21)

Panel D-3: 5-factor alpha

QC	Q1	Q2	Q3	Q4	Q5	Q5-1
QC1	-0.13	-0.18	-0.12	-0.07	-0.23	-0.10
	(-0.77)	(-1.23)	(-0.87)	(-0.56)	(-1.70)	(-0.58)
QC2	**-0.34**	-0.10	-0.06	**-0.26**	-0.03	0.30
	(-2.51)	(-0.84)	(-0.45)	(-2.30)	(-0.30)	(1.91)
QC3	-0.21	**-0.36**	**-0.25**	**-0.24**	-0.01	0.20
	(-1.83)	(-3.26)	(-2.20)	(-2.34)	(-0.09)	(1.31)
QC4	0.04	-0.21	-0.14	-0.10	0.14	0.10
	(0.29)	(-1.58)	(-1.20)	(-0.87)	(1.25)	(0.68)
QC5	**0.48**	0.14	**0.30**	**0.30**	**0.65**	0.17
	(2.24)	(1.18)	(2.24)	(2.10)	(3.10)	(0.84)

Table 1.4 Comparison between CQ Strategy and Value Strategy

This table presents the comparison between *CQ* strategy and value investing strategy. We report portfolios' excess returns of the dependent double sorts conditional on *CQ* Measure and value measure. The sample period covers from July 1957 to December 2020. Left-hand of Panels A and B show the performance of *CQ* strategy in each value quintile. At the end of each month, stocks are ranked in ascending order first based on their value measure. Within each value quintile, we then sort stocks on their *CQ* Measure, forming 25 portfolios. Right-hand of Panels A and B exhibit the performance of value strategy in each *CQ* quintile. At the end of each month, stocks are ranked in ascending order first based on the *CQ* Measure. Within each *CQ* quintile, we then sort stocks on their value measure, forming 25 portfolios. Portfolios are value-weighted, and rebalanced at the end of each month. Alphas are the intercepts in various asset pricing models. The rightmost column reports returns of an arbitrage portfolio that longs the low *CQ* Measure (Log(M/B) ratio) and shorts the high *CQ* Measure (Log(M/B) ratio) portfolios. Alphas are in monthly percentages. Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates, and 5% statistical significance are indicated in bold.

Panel A: CQ Portfolio Performance (Quality based on OM)

Panel A-1: Excess return

MB	CQ					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-5
MB1	**1.34**	**1.20**	**1.11**	**0.93**	0.15	**1.19**
	(3.33)	(3.72)	(4.09)	(3.80)	(0.56)	(4.59)
MB2	**1.16**	**0.99**	**0.87**	**0.61**	0.27	**0.89**
	(4.60)	(4.23)	(4.48)	(3.27)	(1.20)	(6.14)
MB3	**1.30**	**0.90**	**0.64**	0.33	0.23	**1.07**
	(6.13)	(4.88)	(3.92)	(1.92)	(1.34)	(7.95)
MB4	**0.87**	**0.82**	**0.57**	**0.34**	0.08	**0.79**
	(4.16)	(4.67)	(3.33)	(2.06)	(0.40)	(5.90)
MB5	**0.64**	**0.74**	**0.63**	**0.40**	0.32	**0.32**
	(2.69)	(3.65)	(3.19)	(2.07)	(1.33)	(2.18)

Panel A-2: CAPM alpha

MB	CQ					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-5
MB1	0.43	0.42	**0.43**	0.29	**-0.47**	**0.90**
	(1.35)	(1.84)	(2.20)	(1.73)	(-2.51)	(3.43)
MB2	**0.42**	**0.37**	**0.35**	0.07	**-0.34**	**0.76**
	(2.54)	(2.38)	(2.73)	(0.61)	(-2.73)	(4.96)
MB3	**0.62**	**0.34**	0.13	-0.17	**-0.31**	**0.93**
	(5.07)	(3.30)	(1.40)	(-1.69)	(-3.19)	(7.01)
MB4	**0.22**	**0.24**	0.01	**-0.18**	**-0.49**	**0.71**
	(2.07)	(2.89)	(0.17)	(-2.57)	(-5.22)	(5.11)
MB5	-0.09	0.10	0.05	**-0.21**	**-0.34**	0.25
	(-0.79)	(1.08)	(0.53)	(-2.60)	(-2.40)	(1.70)

Panel A-3: 5-factor alpha

MB	CQ					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-5
MB1	0.44	0.30	0.19	0.19	**-0.68**	**1.11**
	(1.22)	(1.31)	(1.07)	(1.07)	(-4.14)	(3.53)
MB2	0.22	0.20	0.20	-0.12	**-0.46**	**0.68**
	(1.50)	(1.50)	(1.53)	(-1.09)	(-4.01)	(4.05)
MB3	**0.44**	0.17	-0.07	**-0.35**	**-0.50**	**0.94**
	(2.97)	(1.78)	(-0.87)	(-4.02)	(-5.20)	(5.57)
MB4	0.13	0.09	-0.11	**-0.33**	**-0.51**	**0.64**
	(1.09)	(1.16)	(-1.54)	(-4.31)	(-4.93)	(4.07)
MB5	0.08	**0.21**	0.11	-0.11	-0.08	0.16
	(0.84)	(2.56)	(1.30)	(-1.33)	(-0.55)	(0.89)

Panel B: MB Portfolio Performance (Quality based on OM)

Panel B-1: Excess return

	MB					
CQ	MB1	MB2	MB3	MB4	MB5	MB1-5
CQ1	**1.40**	**1.21**	**1.20**	**1.02**	**0.64**	**0.76**
	(3.46)	(3.83)	(4.79)	(4.68)	(2.54)	(2.37)
CQ2	**1.22**	**1.07**	**0.95**	**0.87**	**0.79**	0.43
	(4.48)	(4.83)	(5.01)	(4.89)	(3.99)	(1.85)
CQ3	**1.03**	**0.75**	**0.71**	**0.64**	**0.65**	0.38
	(4.56)	(3.77)	(4.32)	(3.69)	(3.43)	(1.87)
CQ4	**0.68**	**0.48**	**0.37**	**0.35**	**0.50**	0.18
	(2.89)	(2.58)	(2.24)	(2.08)	(2.56)	(0.89)
CQ5	0.25	0.20	0.27	0.05	0.36	-0.11
	(0.93)	(0.89)	(1.45)	(0.24)	(1.54)	(-0.46)

Panel B-2: CAPM alpha

	MB					
CQ	MB1	MB2	MB3	MB4	MB5	MB1-5
CQ1	0.47	0.40	**0.46**	**0.31**	-0.13	0.60
	(1.59)	(1.72)	(3.00)	(2.46)	(-1.09)	(1.88)
CQ2	**0.52**	**0.45**	**0.38**	**0.29**	0.16	0.36
	(2.67)	(3.00)	(3.59)	(3.28)	(1.84)	(1.51)
CQ3	**0.42**	0.23	**0.21**	0.09	0.07	0.35
	(2.80)	(1.70)	(2.08)	(0.96)	(0.82)	(1.74)
CQ4	0.07	-0.05	-0.13	**-0.18**	-0.09	0.16
	(0.42)	(-0.45)	(-1.23)	(-2.45)	(-1.06)	(0.77)
CQ5	**-0.38**	**-0.41**	**-0.31**	**-0.53**	**-0.28**	-0.10
	(-2.09)	(-3.30)	(-3.17)	(-5.85)	(-2.06)	(-0.39)

Panel B-3: 5-factor alpha

	MB					
CQ	MB1	MB2	MB3	MB4	MB5	MB1-5
CQ1	0.43	0.29	0.29	0.24	0.06	0.37
	(1.29)	(1.19)	(1.90)	(1.56)	(0.60)	(1.14)
CQ2	0.26	**0.34**	**0.25**	0.17	**0.23**	0.03
	(1.43)	(2.33)	(2.64)	(1.72)	(2.87)	(0.14)
CQ3	**0.27**	0.08	-0.01	-0.07	0.11	0.16
	(2.05)	(0.63)	(-0.09)	(-0.89)	(1.39)	(1.02)
CQ4	-0.10	**-0.22**	**-0.30**	**-0.26**	-0.05	-0.05
	(-0.74)	(-2.32)	(-3.78)	(-3.69)	(-0.67)	(-0.30)
CQ5	**-0.60**	**-0.58**	**-0.42**	**-0.55**	-0.07	**-0.53**
	(-3.53)	(-5.21)	(-3.89)	(-5.48)	(-0.56)	(-2.35)

Table 1.4 Continued

Panel C: CQ Portfolio Performance (Quality based on GPOA)

Panel C-1: Excess return

MB	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-5
MB1	**1.41**	**1.18**	**1.11**	**0.92**	0.17	**1.24**
	(3.55)	(3.58)	(4.26)	(3.59)	(0.66)	(4.82)
MB2	**1.19**	**1.00**	**0.82**	**0.64**	0.30	**0.89**
	(4.47)	(4.34)	(4.03)	(3.49)	(1.34)	(5.55)
MB3	**1.20**	**0.95**	**0.64**	0.30	0.27	**0.93**
	(5.43)	(5.48)	(3.72)	(1.69)	(1.51)	(6.44)
MB4	**0.79**	**0.77**	**0.58**	**0.36**	0.08	**0.71**
	(3.59)	(4.38)	(3.39)	(2.08)	(0.41)	(4.57)
MB5	**0.64**	**0.78**	**0.60**	**0.51**	0.28	**0.35**
	(2.62)	(3.78)	(3.08)	(2.57)	(1.16)	(2.10)

Panel C-2: CAPM alpha

MB	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-5
MB1	0.49	0.41	**0.45**	0.26	**-0.45**	**0.93**
	(1.57)	(1.70)	(2.47)	(1.47)	(-2.53)	(3.58)
MB2	**0.43**	**0.38**	0.28	0.12	**-0.31**	**0.75**
	(2.53)	(2.48)	(1.94)	(1.16)	(-2.56)	(4.52)
MB3	**0.48**	**0.40**	0.11	**-0.21**	**-0.29**	**0.77**
	(3.76)	(4.04)	(1.17)	(-1.97)	(-3.00)	(5.29)
MB4	0.09	**0.19**	0.03	**-0.18**	**-0.49**	**0.58**
	(0.78)	(2.28)	(0.41)	(-2.54)	(-4.90)	(3.56)
MB5	-0.12	0.13	0.01	-0.09	**-0.37**	0.25
	(-0.95)	(1.48)	(0.11)	(-1.01)	(-2.45)	(1.47)

Panel C-3: 5-factor alpha

MB	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-5
MB1	0.47	0.30	0.25	0.15	**-0.67**	**1.14**
	(1.27)	(1.30)	(1.44)	(0.85)	(-4.30)	(3.42)
MB2	0.25	0.23	0.10	-0.01	**-0.49**	**0.74**
	(1.61)	(1.71)	(0.71)	(-0.12)	(-4.37)	(4.01)
MB3	**0.36**	**0.22**	-0.06	**-0.36**	**-0.46**	**0.83**
	(2.28)	(2.55)	(-0.73)	(-4.29)	(-4.71)	(4.69)
MB4	0.06	0.03	-0.10	**-0.32**	**-0.42**	**0.48**
	(0.42)	(0.34)	(-1.43)	(-4.30)	(-4.11)	(2.59)
MB5	0.07	**0.23**	0.09	-0.01	-0.07	0.14
	(0.57)	(2.87)	(1.16)	(-0.16)	(-0.49)	(0.68)

Panel D: MB Portfolio Performance (Quality based on GPOA)

Panel D-1: Excess return

CQ	MB1	MB 2	MB 3	MB 4	MB 5	MB1-5
CQ1	**1.36**	**1.14**	**1.12**	**0.85**	**0.60**	**0.76**
	(3.29)	(3.46)	(4.42)	(3.74)	(2.41)	(2.30)
CQ2	**1.18**	**1.01**	**1.05**	**0.78**	**0.85**	0.33
	(4.57)	(4.43)	(5.68)	(4.36)	(4.17)	(1.53)
CQ3	**0.95**	**0.81**	**0.67**	**0.66**	**0.63**	0.32
	(4.09)	(4.08)	(4.22)	(3.77)	(3.22)	(1.52)
CQ4	**0.66**	**0.56**	**0.38**	**0.44**	**0.57**	0.10
	(2.90)	(3.11)	(2.24)	(2.60)	(2.94)	(0.47)
CQ5	0.22	0.21	0.26	0.10	0.33	-0.12
	(0.84)	(0.92)	(1.36)	(0.54)	(1.40)	(-0.49)

Panel D-2: CAPM alpha

CQ	MB1	MB 2	MB 3	MB 4	MB 5	MB1-5
CQ1	0.40	0.17	0.25	0.09	0.04	0.37
	(1.16)	(0.70)	(1.50)	(0.51)	(0.31)	(1.12)
CQ2	0.25	0.25	**0.35**	0.05	**0.27**	-0.02
	(1.40)	(1.79)	(3.50)	(0.58)	(3.16)	(-0.13)
CQ3	0.19	0.16	-0.01	-0.04	0.05	0.13
	(1.30)	(1.27)	(-0.07)	(-0.53)	(0.73)	(0.79)
CQ4	-0.15	-0.12	**-0.30**	**-0.20**	0.03	-0.18
	(-1.14)	(-1.45)	(-3.87)	(-2.87)	(0.42)	(-1.08)
CQ5	**-0.62**	**-0.53**	**-0.39**	**-0.46**	-0.12	**-0.50**
	(-3.66)	(-4.47)	(-3.40)	(-4.72)	(-0.97)	(-2.34)

Panel D-3: 5-factor alpha

CQ	MB1	MB 2	MB 3	MB 4	MB 5	MB1-5
CQ1	**1.02**	0.45	0.38	0.18	0.04	**0.98**
	(2.41)	(1.30)	(1.75)	(0.79)	(0.28)	(2.45)
CQ2	**0.51**	0.37	**0.41**	0.06	**0.24**	0.28
	(2.14)	(1.68)	(3.41)	(0.56)	(2.19)	(1.18)
CQ3	**0.39**	0.31	0.00	-0.01	-0.02	0.42
	(2.03)	(1.59)	(-0.01)	(-0.16)	(-0.29)	(1.80)
CQ4	0.14	-0.02	**-0.29**	**-0.27**	-0.10	0.24
	(0.86)	(-0.22)	(-3.20)	(-3.32)	(-0.98)	(1.11)
CQ5	-0.37	**-0.43**	**-0.36**	**-0.49**	-0.17	-0.20
	(-1.84)	(-2.82)	(-2.65)	(-4.34)	(-1.02)	(-0.76)

Table 1.5 Independent Double-sorted Portfolio Performance (QC & CQ)

This table shows the two-way portfolios' excess returns and asset pricing model alphas based on our Quality-Cheapness and Cheapness-Quality Measures. The sample period covers from July 1957 to December 2020. At the end of each month, stocks are ranked in ascending order on the basis of their ***QC*** **Measure** and ***CQ*** **Measure** independently. Then, we take the intersection of "*QC*" and "*CQ*" stocks and form 25 portfolios. Portfolios are value-weighted, and rebalanced at the end of each month. The rightmost column reports returns of an arbitrage portfolio that longs the *cheap-with-high-relative-quality* portfolio (*CQ*1) and shorts the *expensive-with-low-relative-quality* portfolio (*CQ*5), and the lowest row reports returns of an arbitrage portfolio that longs the *high-quality-low-relative-price* portfolio (*QC*5) and shorts the *low-quality-high-relative-price* portfolio (*QC*1). The lower right corner reports the returns of an arbitrage portfolio that longs the strong quality/low relative-price portfolio (*QC*5/*CQ*1) and shorts the weak quality/high relative-price portfolio (*QC*1/*CQ*5). Panel A shows the returns and alphas of portfolios sorted based on QC_{QOM} and CQ_{QOM}. Panel B shows the returns and alphas of portfolios sorted based on QC_{GPOA} and CQ_{GPOA}. Returns and alphas are in monthly percentages. Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates, and 5% statistical significance are indicated in bold.

Panel A: Portfolio Excess return and Alphas (Quality based on Ordinal Measure)

Panel A-1: Excess return

Quality	Cheapness					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-5
QC1	**0.58**	**0.60**	**0.38**	0.20	-0.03	**0.61**
	(2.09)	(2.86)	(1.99)	(1.07)	(-0.15)	(3.03)
QC2	**0.84**	**0.68**	**0.54**	**0.45**	0.21	**0.63**
	(3.48)	(3.09)	(2.54)	(2.30)	(0.99)	(4.12)
QC3	**0.93**	**0.72**	**0.66**	**0.67**	0.36	**0.57**
	(3.78)	(3.54)	(3.59)	(3.55)	(1.86)	(3.45)
QC4	**1.13**	**0.89**	**0.75**	**0.40**	0.25	**0.88**
	(4.70)	(4.81)	(3.85)	(2.13)	(1.27)	(5.58)
QC5	**1.39**	**1.13**	**0.85**	**0.73**	**0.65**	**0.74**
	(7.25)	(6.40)	(4.88)	(4.22)	(2.87)	(4.73)
QC5-1	**0.81**	**0.53**	**0.47**	**0.53**	**0.68**	**1.42**
	(4.34)	(3.11)	(2.94)	(3.52)	(3.83)	(10.08)

Panel A-2: CAPM alpha

Quality	Cheapness					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-5
QC1	-0.23	-0.05	**-0.20**	**-0.36**	**-0.60**	0.38
	(-1.33)	(-0.44)	(-2.01)	(-3.86)	(-6.47)	(1.89)
QC2	0.07	0.03	-0.07	-0.14	**-0.41**	**0.48**
	(0.58)	(0.26)	(-0.63)	(-1.54)	(-4.57)	(3.18)
QC3	0.17	0.10	0.07	0.10	**-0.23**	**0.40**
	(1.27)	(1.06)	(0.76)	(1.08)	(-2.44)	(2.34)
QC4	**0.42**	**0.31**	**0.18**	-0.15	**-0.33**	**0.75**
	(3.83)	(4.02)	(1.99)	(-1.62)	(-2.82)	(5.01)
QC5	**0.77**	**0.59**	**0.33**	**0.20**	0.07	**0.70**
	(8.19)	(6.08)	(3.47)	(2.06)	(0.49)	(4.68)
QC5-1	**1.00**	**0.65**	**0.53**	**0.57**	**0.67**	**1.37**
	(5.55)	(3.81)	(3.35)	(3.68)	(3.94)	(9.52)

Panel A-3: 3-factor alpha

Quality	Cheapness					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-5
QC1	-0.30	-0.11	**-0.22**	**-0.37**	**-0.60**	0.30
	(-1.81)	(-0.93)	(-2.17)	(-3.96)	(-6.07)	(1.50)
QC2	-0.05	-0.07	-0.19	**-0.19**	**-0.47**	**0.42**
	(-0.42)	(-0.70)	(-1.81)	(-2.18)	(-5.03)	(2.71)
QC3	0.05	0.01	-0.01	0.06	**-0.26**	0.31
	(0.39)	(0.11)	(-0.11)	(0.61)	(-2.80)	(1.76)
QC4	**0.32**	**0.25**	0.14	**-0.19**	**-0.37**	**0.69**
	(3.08)	(2.98)	(1.44)	(-2.12)	(-3.16)	(4.39)
QC5	**0.76**	**0.58**	**0.35**	**0.23**	0.11	**0.65**
	(8.04)	(6.15)	(3.66)	(2.25)	(0.85)	(4.55)
QC5-1	**1.06**	**0.70**	**0.57**	**0.60**	**0.71**	**1.37**
	(5.90)	(4.01)	(3.58)	(3.86)	(4.11)	(9.12)

Panel A-4: 5-factor alpha

Quality	Cheapness					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-5
QC1	-0.11	-0.06	-0.16	**-0.37**	**-0.69**	**0.58**
	(-0.55)	(-0.42)	(-1.27)	(-3.35)	(-6.72)	(2.65)
QC2	0.04	-0.06	**-0.23**	**-0.23**	**-0.46**	**0.50**
	(0.32)	(-0.52)	(-2.24)	(-2.36)	(-4.38)	(2.88)
QC3	0.11	0.01	-0.08	0.02	**-0.25**	0.36
	(0.81)	(0.07)	(-0.91)	(0.19)	(-2.40)	(1.90)
QC4	**0.24**	**0.21**	0.02	**-0.24**	**-0.32**	**0.56**
	(2.38)	(2.26)	(0.17)	(-2.23)	(-2.19)	(3.12)
QC5	**0.63**	**0.45**	**0.29**	0.18	0.19	**0.44**
	(6.66)	(4.40)	(2.52)	(1.63)	(1.24)	(2.73)
QC5-1	**0.74**	**0.52**	**0.44**	**0.55**	**0.88**	**1.32**
	(3.46)	(2.60)	(2.21)	(3.13)	(4.10)	(8.74)

Panel A-5: q-factor alpha

Quality	Cheapness					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-5
QC1	0.04	0.01	-0.11	**-0.31**	**-0.62**	**0.66**
	(0.16)	(0.08)	(-0.77)	(-2.50)	(-5.18)	(2.58)
QC2	0.04	-0.02	-0.26	**-0.28**	**-0.47**	**0.51**
	(0.24)	(-0.16)	(-1.84)	(-2.59)	(-3.85)	(2.44)
QC3	0.17	-0.03	-0.08	0.03	**-0.26**	0.42
	(0.94)	(-0.31)	(-0.84)	(0.29)	(-2.25)	(1.82)
QC4	**0.26**	**0.21**	-0.03	**-0.30**	**-0.35**	**0.61**
	(2.05)	(2.03)	(-0.22)	(-2.39)	(-2.29)	(2.83)
QC5	**0.63**	**0.38**	0.22	0.16	0.27	0.35
	(5.92)	(3.54)	(1.68)	(1.32)	(1.36)	(1.85)
QC5-1	**0.59**	0.37	0.33	**0.47**	**0.90**	**1.25**
	(2.25)	(1.69)	(1.38)	(2.35)	(3.48)	(7.12)

Table 1.5 Continued

Panel B: Portfolio Excess return and Alphas (Quality based on GPOA)

Panel B-1: Excess return

Quality	Cheapness CQ1	CQ2	CQ3	CQ4	CQ5	CQ 1-5
QC1	**0.82**	**0.60**	**0.44**	0.28	0.05	**0.77**
	(3.45)	(3.02)	(2.47)	(1.50)	(0.23)	(4.77)
QC2	**0.82**	**0.90**	**0.59**	**0.46**	0.14	**0.67**
	(3.23)	(4.46)	(3.08)	(2.44)	(0.69)	(4.35)
QC3	**0.81**	**0.66**	**0.50**	**0.50**	0.20	**0.61**
	(3.35)	(3.26)	(2.56)	(2.60)	(1.01)	(3.77)
QC4	**1.16**	**0.84**	**0.80**	**0.58**	0.33	**0.83**
	(5.03)	(4.21)	(4.26)	(3.32)	(1.60)	(4.76)
QC5	**1.30**	**1.05**	**0.96**	**0.84**	**0.61**	**0.68**
	(6.19)	(5.91)	(5.68)	(4.50)	(2.84)	(4.39)
QC5-1	**0.47**	**0.44**	**0.52**	**0.56**	**0.57**	**1.25**
	(2.97)	(2.71)	(3.52)	(3.34)	(3.14)	(7.12)

Panel B-2: CAPM alpha

Quality	Cheapness CQ1	CQ2	CQ3	CQ4	CQ5	CQ 1-5
QC1	0.07	-0.02	-0.12	**-0.25**	**-0.54**	**0.61**
	(0.57)	(-0.19)	(-1.25)	(-2.46)	(-4.97)	(3.57)
QC2	0.08	**0.28**	0.02	-0.09	**-0.45**	**0.53**
	(0.59)	(2.78)	(0.14)	(-1.03)	(-4.26)	(3.45)
QC3	0.07	0.04	-0.08	-0.08	**-0.40**	**0.47**
	(0.56)	(0.44)	(-0.92)	(-0.76)	(-4.26)	(2.86)
QC4	**0.44**	**0.27**	**0.21**	0.04	**-0.24**	**0.68**
	(3.71)	(2.51)	(2.38)	(0.43)	(-2.25)	(3.87)
QC5	**0.63**	**0.50**	**0.47**	**0.33**	0.03	**0.59**
	(5.59)	(5.03)	(5.22)	(3.01)	(0.26)	(3.93)
QC5-1	**0.55**	**0.52**	**0.59**	**0.57**	**0.57**	**1.16**
	(3.63)	(3.20)	(4.00)	(3.38)	(3.26)	(6.47)

Panel B-3: 3-factor alpha

Quality	Cheapness CQ1	CQ2	CQ3	CQ4	CQ5	CQ 1-5
QC1	0.03	-0.04	-0.16	**-0.25**	**-0.52**	**0.56**
	(0.26)	(-0.34)	(-1.48)	(-2.52)	(-4.67)	(3.12)
QC2	-0.04	**0.20**	-0.04	-0.15	**-0.50**	**0.46**
	(-0.32)	(2.12)	(-0.36)	(-1.65)	(-4.72)	(2.94)
QC3	-0.04	-0.09	**-0.17**	-0.14	**-0.47**	**0.42**
	(-0.37)	(-1.09)	(-2.02)	(-1.50)	(-5.16)	(2.46)
QC4	**0.35**	**0.19**	0.16	-0.02	**-0.27**	**0.62**
	(3.18)	(1.98)	(1.79)	(-0.24)	(-2.37)	(3.46)
QC5	**0.59**	**0.50**	**0.48**	**0.37**	0.07	**0.53**
	(5.20)	(4.75)	(5.30)	(3.26)	(0.51)	(3.57)
QC5-1	**0.56**	**0.53**	**0.63**	**0.62**	**0.59**	**1.12**
	(3.60)	(3.16)	(4.16)	(3.54)	(3.24)	(6.19)

Panel B-4: 5-factor alpha

Quality	Cheapness CQ1	CQ2	CQ3	CQ4	CQ5	CQ 1-5
QC1	0.06	-0.03	-0.15	**-0.32**	**-0.58**	**0.63**
	(0.34)	(-0.26)	(-1.30)	(-3.00)	(-4.88)	(3.23)
QC2	0.04	0.18	-0.11	**-0.21**	**-0.48**	**0.53**
	(0.27)	(1.88)	(-1.10)	(-1.99)	(-4.26)	(2.94)
QC3	0.05	-0.15	**-0.25**	-0.17	**-0.48**	**0.53**
	(0.38)	(-1.56)	(-2.67)	(-1.82)	(-4.61)	(2.91)
QC4	**0.36**	0.11	0.06	-0.06	**-0.37**	**0.72**
	(3.07)	(1.02)	(0.62)	(-0.72)	(-2.92)	(4.00)
QC5	**0.55**	**0.38**	**0.35**	**0.33**	0.13	**0.42**
	(4.28)	(3.45)	(3.67)	(2.34)	(0.77)	(2.30)
QC5-1	**0.49**	**0.42**	**0.50**	**0.65**	**0.70**	**1.12**
	(2.58)	(2.17)	(2.84)	(3.11)	(3.05)	(5.67)

Panel B-5: q-factor alpha

Quality	Cheapness CQ1	CQ2	CQ3	CQ4	CQ5	CQ 1-5
QC1	0.17	0.05	-0.10	**-0.30**	**-0.54**	**0.71**
	(0.95)	(0.33)	(-0.73)	(-2.29)	(-4.08)	(3.31)
QC2	0.13	0.21	-0.06	-0.18	**-0.45**	**0.58**
	(0.71)	(1.83)	(-0.54)	(-1.56)	(-3.41)	(2.62)
QC3	0.07	-0.14	**-0.29**	-0.16	**-0.47**	**0.54**
	(0.45)	(-1.22)	(-2.55)	(-1.47)	(-3.87)	(2.49)
QC4	**0.32**	0.00	-0.01	-0.09	**-0.38**	**0.71**
	(2.49)	(0.02)	(-0.06)	(-0.94)	(-2.47)	(3.45)
QC5	**0.54**	**0.27**	**0.30**	0.25	0.19	0.35
	(3.97)	(2.30)	(2.75)	(1.55)	(0.94)	(1.68)
QC5-1	0.37	0.22	0.40	**0.55**	**0.73**	**1.08**
	(1.65)	(0.98)	(1.91)	(2.22)	(2.76)	(5.15)

Table 1.6 Arbitrage Portfolios and Factors

This table shows the performance of Quality-Cheapness and Cheapness-Quality arbitrage portfolios ($QC5-QC1$ and $CQ1-CQ5$) conditional on various asset pricing model risk factors and traditional risk factors plus Quality-Cheapness factor (SMW) and Cheapness-Quality factor (CME). The sample period covers from July 1957 to December 2020. The dependent variables of panels A and C are the return of arbitrage portfolio $QC5-QC1$ based QC_{QOM} and QC_{GPOA}, respectively. The dependent variables of panels B and D are the return of arbitrage portfolio $CQ1-CQ5$ based on CQ_{QOM} and CQ_{GPOA}, respectively. Factors are constructed as the intersection of six value-weighted size and QC/CQ Measures portfolios. Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Quality-Cheapness Arbitrage Portfolio (Quality based on Ordinal Measure)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	CAPM	CAPM	FF3	FF3	FF5	FF5	q-factor	q-factor
Market Excess Return	-0.08669**	0.00463	-0.08064**	0.01915	-0.05366	0.00845	-0.05110	0.02016
	(-2.24)	(0.32)	(-2.19)	(1.11)	(-1.27)	(0.49)	(-1.11)	(1.05)
SMB			-0.06762	-0.08073**	-0.05686	-0.07842**		
			(-0.85)	(-1.97)	(-0.83)	(-2.34)		
HML			-0.05674	-0.00079	-0.13394	0.07954		
			(-0.70)	(-0.02)	(-1.50)	(1.52)		
RMW					0.03501	0.01756		
					(0.22)	(0.34)		
CMA					0.21446	-0.15113**		
					(1.38)	(-2.04)		
ME (q-factor)							-0.03203	-0.07677*
							(-0.41)	(-1.78)
A (q-factor)							0.06302	-0.02292
							(0.40)	(-0.47)
ROE (q-factor)							0.17644	0.03237
							(1.39)	(0.92)
SMW		1.01450***		1.02034***		1.02744***		1.02023***
		(23.41)		(25.19)		(25.73)		(24.64)
CME		0.08508*		0.09797**		0.09664**		0.10678**
		(1.87)		(2.28)		(2.34)		(2.38)
Constant	0.00708***	-0.00111	0.00732***	-0.00118*	0.00653***	-0.00134*	0.00561***	-0.00178**
	(5.83)	(-1.64)	(5.83)	(-1.67)	(4.04)	(-1.77)	(2.86)	(-2.03)
Observations	762	762	762	762	690	690	648	648
Adjusted R-squared	0.92%	79.59%	1.05%	79.90%	1.20%	81.39%	2.00%	81.62%

Panel B: Cheapness-Quality Arbitrage Portfolio (Quality based on Ordinal Measure)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	CAPM	CAPM	FF3	FF3	FF5	FF5	q-factor	q-factor
Market Excess Return	0.20794***	0.00996	0.20201***	0.00972	0.18987***	0.01053	0.19414***	0.00785
	(5.44)	(0.45)	(4.88)	(0.39)	(4.35)	(0.43)	(4.10)	(0.30)
SMB			0.07319	-0.01158	0.04272	-0.01396		
			(1.00)	(-0.32)	(0.65)	(-0.40)		
HML			0.06599	-0.01536	0.10007	-0.03220		
			(0.92)	(-0.44)	(1.23)	(-0.65)		
RMW					-0.05898	-0.00540		
					(-0.46)	(-0.09)		
CMA					-0.12415	0.03927		
					(-0.93)	(0.60)		
ME (q-factor)							0.04298	0.00497
							(0.52)	(0.13)
A (q-factor)							0.00851	-0.00427
							(0.07)	(-0.07)
ROE (q-factor)							-0.11345	0.03403
							(-1.22)	(0.96)
SMW		0.09024***		0.09100***		0.09650***		0.10466***
		(2.75)		(2.85)		(3.02)		(3.17)
CME		1.12393***		1.12716***		1.14379***		1.15946***
		(24.78)		(25.03)		(23.91)		(23.15)
Constant	0.00505***	-0.00302***	0.00478***	-0.00298***	0.00498***	-0.00357***	0.00526***	-0.00385***
	(4.58)	(-4.16)	(4.24)	(-3.87)	(4.07)	(-4.24)	(3.49)	(-4.00)
Observations	762	762	762	762	690	690	648	648
Adjusted R-squared	8.58%	70.69%	9.04%	70.64%	8.90%	71.60%	9.77%	72.35%

Table 1.6 Continued

Panel C: Quality-Cheapness Arbitrage Portfolio (Quality based on GPOA)

VARIABLES	(1) CAPM	(2) CAPM	(3) FF3	(4) FF3	(5) FF5	(6) FF5	(7) q-factor	(8) q-factor
Market Excess Return	-0.07248*	-0.01251	-0.07279*	0.00006	-0.05766	-0.00339	-0.05349	0.00127
	(-1.89)	(-0.68)	(-1.89)	(0.00)	(-1.34)	(-0.16)	(-1.13)	(0.06)
SMB			-0.01797	-0.06763*	-0.01499	-0.05782*		
			(-0.23)	(-1.74)	(-0.23)	(-1.92)		
HML			-0.02926	0.00239	-0.08998	0.03747		
			(-0.36)	(0.08)	(-0.95)	(0.88)		
RMW					-0.00608	0.06979		
					(-0.04)	(1.40)		
CMA					0.15915	-0.05641		
					(1.11)	(-1.03)		
ME (q-factor)							0.03707	-0.06753*
							(0.48)	(-1.88)
A (q-factor)							0.05870	0.01674
							(0.39)	(0.35)
ROE (q-factor)							0.18329	0.04373
							(1.49)	(0.95)
SMW		1.10331***		1.11081***		1.12309***		1.11666***
		(20.16)		(22.15)		(23.02)		(22.42)
CME		0.11865***		0.12876***		0.14247***		0.15078***
		(2.70)		(2.98)		(3.44)		(3.44)
Constant	0.00558***	-0.00213***	0.00569***	-0.00220***	0.00513***	-0.00271***	0.00409*	-0.00282***
	(4.32)	(-3.48)	(4.23)	(-3.61)	(2.98)	(-4.04)	(1.96)	(-3.75)
Observations	762	762	762	762	690	690	648	648
Adjusted R-squared	0.63%	79.32%	0.43%	79.53%	0.44%	81.52%	1.62%	81.75%

Panel D: Cheapness-Quality Arbitrage Portfolio (Quality based on GPOA)

VARIABLES	(1) CAPM	(2) CAPM	(3) FF3	(4) FF3	(5) FF5	(6) FF5	(7) q-factor	(8) q-factor
Market Excess Return	0.25669***	0.02918	0.24538***	0.02241	0.22153***	0.01809	0.22791***	0.01400
	(5.67)	(1.24)	(4.93)	(0.86)	(4.36)	(0.68)	(3.89)	(0.49)
SMB			0.15085*	0.05797	0.12819*	0.05900*		
			(1.66)	(1.50)	(1.68)	(1.70)		
HML			0.14272	0.02335	0.23444**	0.02148		
			(1.64)	(0.58)	(2.21)	(0.37)		
RMW					-0.03115	0.01829		
					(-0.22)	(0.28)		
CMA					-0.28257*	-0.02026		
					(-1.82)	(-0.27)		
ME (q-factor)							0.12842	0.08074**
							(1.27)	(2.16)
A (q-factor)							-0.00190	-0.00806
							(-0.01)	(-0.12)
ROE (q-factor)							-0.13418	0.02807
							(-1.26)	(0.68)
SMW		0.06205		0.05491		0.07118*		0.07151*
		(1.32)		(1.29)		(1.70)		(1.67)
CME		1.14469***		1.13294***		1.16015***		1.16479***
		(26.96)		(27.80)		(26.46)		(26.68)
Constant	0.00440***	-0.00258***	0.00381***	-0.00259***	0.00445***	-0.00312***	0.00480**	-0.00325***
	(3.38)	(-3.37)	(2.86)	(-3.28)	(3.03)	(-3.64)	(2.55)	(-3.24)
Observations	762	762	762	762	690	690	648	648
Adjusted R-squared	9.76%	77.13%	11.81%	77.28%	12.46%	78.66%	12.31%	79.17%

Table 1.7 Factor Performance

This table shows the Quality-Cheapness factor (SWM) and Cheapness-Quality (CME) factor's excess returns and asset pricing model alphas. The sample period covers from July 1957 to December 2020. Factors are value-weighted and rebalanced at the end of each month. The dependent variables of Panels A and B are the factors based on the regression of quality ordinal measure and GPOA, respectively. Columns (1) to (4) of each panel reports the results of Quality-Cheapness factors (SWM), and Columns (5) to (8) of each panel reports the results of Cheapness-Quality (CME) factors. Alphas are the intercepts in various asset pricing models. Returns and alphas are in monthly percentage, Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Quality based on Ordinal Measure

	SMW				CME			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAPM	FF3	FF5	q-factor	CAPM	FF3	FF5	q-factor
Market Excess	-0.10550***	-0.11508***	-0.07580*	-0.08749	0.18462***	0.17989***	0.16319***	0.16856***
	(-2.72)	(-2.79)	(-1.68)	(-1.59)	(6.53)	(5.61)	(4.50)	(3.94)
SMB		0.00567	0.01645			0.07476	0.04816	
		(0.05)	(0.23)			(0.89)	(0.81)	
HML		-0.06225	-0.22041**			0.07720	0.13423*	
		(-0.71)	(-2.26)			(1.20)	(1.96)	
RMW			0.02156				-0.04866	
			(0.11)				(-0.36)	
CMA			0.37223**				-0.17427	
			(2.49)				(-1.56)	
ME (q-factor)				0.04080				0.02911
				(0.39)				(0.33)
IA (q-factor)				0.08387				0.00345
				(0.51)				(0.03)
ROE (q-factor)				0.15600				-0.14129
				(1.09)				(-1.56)
Constant	0.00753***	0.00774***	0.00701***	0.00649***	0.00657***	0.00626***	0.00688***	0.00727***
	(6.53)	(6.39)	(4.16)	(3.02)	(7.76)	(7.21)	(5.97)	(5.14)
Observations	762	762	690	648	762	762	690	648
Adjusted R^2	1.75%	1.74%	3.39%	2.60%	10.80%	11.87%	12.25%	13.35%

Panel B: Quality based on GPOA

	SMW				CME			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAPM	FF3	FF5	q-factor	CAPM	FF3	FF5	q-factor
Market Excess	-0.07617**	-0.08889***	-0.07113*	-0.07445	0.20288***	0.20111***	0.17973***	0.18822***
	(-2.45)	(-2.65)	(-1.92)	(-1.57)	(6.31)	(5.25)	(4.29)	(3.71)
SMB		0.03540	0.03082			0.08027	0.05775	
		(0.36)	(0.49)			(0.80)	(0.83)	
HML		-0.04094	-0.13783			0.10734	0.19202**	
		(-0.52)	(-1.56)			(1.46)	(2.32)	
RMW			-0.06264				-0.03877	
			(-0.35)				(-0.25)	
CMA			0.22234*				-0.23973*	
			(1.78)				(-1.95)	
ME (q-factor)				0.08888				0.03548
				(0.89)				(0.33)
IA (q-factor)				0.03717				0.00300
				(0.24)				(0.02)
ROE (q-factor)				0.14499				-0.14820
				(1.24)				(-1.39)
Constant	0.00636***	0.00648***	0.00620***	0.00529**	0.00575***	0.00533***	0.00615***	0.00659***
	(5.67)	(5.40)	(3.71)	(2.57)	(6.06)	(5.54)	(4.76)	(3.98)
Observations	762	762	690	648	762	762	690	648
Adjusted R^2	1.03%	1.02%	1.88%	1.99%	9.91%	11.21%	12.11%	12.21%

Table 1.8 Factors' Reversal and Momentum Exposure

This table shows the factors exposure to the Reversal and Momentum factors controlling the Fama-French five risk factors. Columns (1) and (2) report the results of Quality-Cheapness factor (SMW), and Columns (3) and (4) report the results of Cheapness-Quality factor (CME). Detailed factor construction is explained in Table 1.7. Newey-West autocorrelation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	SMW		*CME*	
	(1)	(2)	(3)	(4)
Momentum factor	0.1231		-0.1784***	
	(1.40)		(-3.16)	
Reversal factor		-0.9034***		0.7282***
		(-12.22)		(29.89)
Constant	0.00654***	0.01080***	0.00540***	0.00912***
	(5.18)	(10.73)	(4.94)	(7.88)
Observations	762	762	762	762
Adjusted R-squared	5.20%	60.76%	20.14%	85.12%

Table 1.9 Factors' Future Growth Opportunities Exposure

This table shows the factors exposure to the Future Growth Opportunities variables controlling the Fama-French five risk factors. The future growth opportunity proxies include production growth, consumption growth, and GDP growth. Growth measures are adjusted for inflation. Variables are measured in AR(1) residuals. Panels A and B show the results of Quality-Cheapness factor (SMW) and Cheapness-Quality factor (CME), respectively. Detailed factor construction are explained in Table 1.7. Newey-West autocorrelation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Portfolio Excess return and Alphas (Quality based on Ordinal Measure)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Production Growth (1 Month)	0.3515**								
	(2.21)								
Future Production Growth (12 Months)		0.2650**							
		(2.11)							
Future Production Growth (12 Months)			-0.0466						
			(-0.36)						
Consumption Growth (1 Month)				0.5419					
				(1.45)					
Consumption Growth (12 Month)					0.1602				
					(0.77)				
Future Consumption Growth (12 Months)						0.3073**			
						(2.26)			
GDP Growth (1 Month)							1.0494**		
							(2.54)		
GDP Growth (12 Month)								0.2032	
								(0.79)	
Future GDP Growth (12 Months)									-0.2576
									(-1.07)
Constant	0.0070***	0.0071***	0.0069***	0.0071***	0.0070***	0.0069***	0.0070***	0.0070***	0.0070***
	(4.20)	(4.19)	(3.90)	(4.21)	(4.18)	(3.92)	(4.18)	(4.16)	(4.15)
Observations	762	762	751	762	732	732	762	762	757
Adjusted R^2	4.07%	4.01%	2.64%	3.55%	3.44%	3.34%	3.95%	3.31%	3.24%

Panel B: Portfolio Excess return and Asset Pricing Model Alphas (Quality based on GPOA)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Production Growth (1 Month)	-0.4248***								
	(-3.95)								
Production Growth (12 Month)		-0.3291***							
		(-3.54)							
Future Production Growth (12 Months)			0.0737						
			(0.71)						
Consumption Growth (1 Month)				-0.5508*					
				(-1.82)					
Consumption Growth (12 Month)					-0.1653				
					(-1.05)				
Future Consumption Growth (12 Months)						-0.0126			
						(-0.15)			
GDP Growth (1 Month)							-1.0759***		
							(-3.48)		
GDP Growth (12 Month)								-0.3456	
								(-1.55)	
Future GDP Growth (12 Months)									0.3218*
									(1.86)
Constant	0.0068***	0.0068***	0.0072***	0.0068***	0.0069***	0.0071***	0.0069***	0.0069***	0.0070***
	(6.13)	(6.02)	(5.98)	(5.96)	(5.99)	(5.96)	(5.97)	(5.98)	(6.06)
Observations	690	690	679	690	690	679	690	690	685
Adjusted R^2	14.47%	14.42%	11.51%	12.74%	12.52%	11.40%	13.55%	12.48%	12.92%

Table 1.10 Factors' Risk Exposure

This table shows the factors exposure to the **Market Risk** variables controlling the Market excess return. The independent variables include Liquidity (Pastor & Stambaugh's liquidity Innovations and modified Amihud illiquidity), Ted Spread, Credit Spread, Term Spread, the Volatility changes (changes in the CBOE S&P 500 Volatility Index (VIX)), and IVOL (the aggregate idiosyncratic volatility). Variables are measured in AR(1) residuals. Panels A and B show the results of Quality-Cheapness factor (*SMW*) and Cheapness-Quality factor (*CME*), respectively. Detailed factor construction are explained in Table 1.7. Newey-West autocorrelation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Results of Quality-Cheapness factor (*SMW*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Liquidity - P&S	0.0220						
	(0.64)						
Liquidity - Amihud		0.0077					
		(1.52)					
Ted Spread			0.0006				
			(0.06)				
Credit Spread				0.0663			
				(0.09)			
Term Spread					-0.1977		
					(-0.43)		
VIX Index						0.0014**	
						(1.98)	
IVOL							1.9193*
							(1.96)
Constant	0.00777***	0.00754***	0.00769***	0.00749***	0.00752***	0.00752***	0.00741***
	(4.12)	(6.14)	(6.57)	(3.83)	(6.53)	(6.53)	(6.61)
Observations	678	690	419	690	690	370	690
Adjusted R^2	2.74%	3.80%	4.31%	3.25%	3.29%	5.50%	5.40%

Panel B: Results of Cheapness-Quality factor (*CME*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Liquidity - P&S	-0.0152						
	(-0.70)						
Liquidity - Amihud		-0.0051					
		(-1.47)					
Ted Spread			-0.0079				
			(-1.03)				
Credit Spread				0.3588			
				(0.62)			
Term Spread					0.1638		
					(0.46)		
VIX Index						-0.0002	
						(-0.47)	
IVOL							-0.7796
							(-1.59)
Constant	0.00355***	0.00692***	0.00650***	0.00325***	0.00657***	0.00658***	0.00663***
	(3.31)	(7.68)	(7.77)	(3.16)	(7.78)	(7.77)	(7.97)
Observations	678	690	419	690	690	370	690
Adjusted R^2	11.53%	12.60%	13.85%	12.19%	12.17%	15.22%	12.81%

Table 1.11 Factors' Uncertainties Exposure

This table shows the factors exposure to the Uncertainty variables. The independent variables are the Financial Uncertainty, Macro Uncertainty, and Real Uncertainty from Jurado et al. (2015)). Panels A and B show the results of Quality-Cheapness factor (SMW) and Cheapness-Quality factor (CME), respectively. Detailed factor construction are explained in Table 1.7. Newey-West autocorrelation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Results of Cheapness-Quality factor (*SMW*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial Uncertainty (1 Month)	-0.0008 (-0.09)								
Financial Uncertainty (3 Month)		-0.0008 (-0.07)							
Financial Uncertainty (12 Month)			-0.0014 (-0.04)						
Macro Uncertainty (1 Month)				0.0068 (0.62)					
Macro Uncertainty (3 Month)					0.0062 (0.59)				
Macro Uncertainty (12 Month)						0.0092 (0.63)			
Real Uncertainty (1 Month)							-0.0053 (-0.42)		
Real Uncertainty (3 Month)								-0.0045 (-0.36)	
Real Uncertainty (12 Month)									-0.0072 (-0.40)
Constant	0.00274	0.00102	-0.01350	-0.00195	-0.00284	-0.00892	0.00677	0.00606	0.00516
	(0.35)	(0.10)	(-0.40)	(-0.31)	(-0.39)	(-0.73)	(0.98)	(0.73)	(0.35)
Observations	690	690	690	690	690	690	690	690	690
Adjusted R^2	3.3%	3.3%	3.3%	3.3%	3.3%	3.3%	3.3%	3.3%	3.3%

Panel B: Results of Cheapness-Quality factor (*CME*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial Uncertainty (1 Month)	0.0244*** (3.00)								
Financial Uncertainty (3 Month)		0.0309*** (3.05)							
Financial Uncertainty (12 Month)			0.0845*** (2.97)						
Macro Uncertainty (1 Month)				0.0113 (0.87)					
Macro Uncertainty (3 Month)					0.0092 (0.74)				
Macro Uncertainty (12 Month)						0.0075 (0.44)			

Real Uncertainty (1 Month)							0.0113		
							(0.68)		
Real Uncertainty (3 Month)								0.0084	
								(0.48)	
Real Uncertainty (12 Month)									-0.0041
									(-0.17)
Constant	-0.0152**	-0.0223**	-0.0761***	-0.0004	-0.0003	0.0000	-0.0003	0.0006	0.0105
	(-2.20)	(-2.45)	(-2.78)	(-0.05)	(-0.03)	(0.00)	(-0.03)	(0.04)	(0.51)
Observations	690	690	690	690	690	690	690	690	690
Adjusted R^2	14.8%	14.7%	14.4%	12.3%	12.3%	12.2%	12.3%	12.2%	12.1%

Table 1.12 Factors' Behavioral Exposure

This table shows the factors exposure to the behavioral variables controlling the Market excess return. The independent variables include Consumer Sentiment Index from University of Michigan. the Sentiment Index (sentiment index of Baker and Wurgler (2006) and its component), and the Casino profits (the profits in the casino industry in the previous quarter dividend by gross domestic product (GDP)). Variables are measured in AR(1) residuals. Detailed variable construction is provided in Panel B of Table A1. Panels A and B show the results of Quality-Cheapness factor (SMW) and Cheapness-Quality factor (CME), respectively. Detailed factor construction are explained in Table 1.7. Newey-West autocorrelation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Results of Quality-Cheapness factor (*SMW*)

	(1)	(2)	(3)	(4)	(5)	(6)
Consumer Sentiment	0.0009**					
	(2.10)					
Sentiment Index (orthogonal)		-0.0085				
		(-0.84)				
Sentiment Index (non-orthogonal)			-0.0132			
			(-1.08)			
Sentiment Index - NIPO				-0.0001		
				(-1.63)		
Sentiment Index - S					0.1392	
					(1.04)	
Casino Profits						-0.0485
						(-0.49)
Constant	0.0075***	0.0080***	0.0080***	0.0076***	0.0076***	0.0077***
	(6.32)	(6.03)	(6.03)	(6.20)	(6.38)	(5.92)
Observations	733	641	641	707	720	658
Adjusted R-squared	2.26%	1.10%	1.24%	1.11%	1.06%	1.59%

Panel B: Results of Cheapness-Quality factor (*CME*)

	(1)	(2)	(3)	(4)	(5)	(6)
Consumer Sentiment	-0.0002					
	(-0.60)					
Sentiment Index (orthogonal)		0.0039				
		(0.59)				
Sentiment Index (non-orthogonal)			0.0085			
			(1.18)			
Sentiment Index - NIPO				-0.0001		
				(-0.92)		
Sentiment Index - S					-0.1740*	
					(-1.84)	
Casino Profits						-0.0746
						(-0.90)
Constant	0.0066***	0.0069***	0.0069***	0.0068***	0.0068***	0.0067***
	(7.56)	(7.11)	(7.04)	(7.64)	(7.91)	(7.03)
Observations	733	641	641	707	720	658
Adjusted R-squared	10.45%	10.27%	10.45%	10.18%	10.24%	11.12%

Table 1.13 Downside Model

The table reports results of downside risk tests. We employ the alternative model of Henriksson and Merton (1981), where downside and upside betas are estimated from a regression of returns on the minimum of zero or the market return (downside beta) and the maximum of zero or the market return (upside beta). Regression specification is as follow:

$$r^e_{Factor,t} = \alpha + \beta_{Downside}\, Min\{0, r^e_{mkt,t}\} + \beta_{Upside} Max\{0, r^e_{mkt,t}\} + \varepsilon_t$$

Panel A shows our benchmark model regression results, Panels B and C report the results of benchmark model after controlling the Fama-French 5-factors and Hou-Xue-Zhang's q-factors, respectively. The intercepts are in monthly percentage, adjusted R 2 are in decimals, Newey-West autocorrelation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Base Model

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	*SMW*	*CME*	$QC5 - QC1$	$CQ1 - CQ5$	$QC5/CQ1 - QC1/CQ5$
Downside Beta (β_{down})	-0.1291*	0.1091*	-0.0961	0.1398*	-0.0385
	(-1.83)	(1.95)	(-1.38)	(1.75)	(-0.46)
Upside Beta (β_{up})	-0.0807	0.2640***	-0.0768	0.2796***	0.2019***
	(-1.23)	(4.66)	(-1.11)	(4.30)	(2.73)
Constant	0.0067***	0.0039**	0.0068***	0.0026	0.0096***
	(3.75)	(2.54)	(3.51)	(1.39)	(4.40)
Observations	762	762	762	762	762
Adjusted R-squared	1.66%	11.47%	0.80%	8.86%	1.30%

Panel B: Base Model controlling FF 3-factors

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	*SMW*	*CME*	$QC5 - QC1$	$CQ1 - CQ5$	$QC5/CQ1 - QC1/CQ5$
Downside Beta (β_{down})	-0.0875	0.0857	-0.0528	0.1339*	-0.0304
	(-1.17)	(1.61)	(-0.74)	(1.78)	(-0.37)
Upside Beta (β_{up})	-0.0261	0.1868***	-0.0023	0.1904***	0.1745**
	(-0.36)	(2.94)	(-0.03)	(2.70)	(2.23)
Constant	0.0051**	0.0063***	0.0044*	0.0053***	0.0095***
	(2.35)	(3.62)	(1.92)	(2.68)	(3.89)
Observations	690	690	690	690	690
Adjusted R-squared	5.12%	20.34%	4.11%	13.98%	1.36%

Panel C: Base Model controlling HXQ q-factors

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	*SMW*	*CME*	$QC5 - QC1$	$CQ1 - CQ5$	$QC5/CQ1 - QC1/CQ5$
Downside Beta (β_{down})	-0.1104	0.0906	-0.0510	0.1342	-0.0304
	(-1.18)	(1.37)	(-0.63)	(1.52)	(-0.32)
Upside Beta (β_{up})	-0.0642	0.2458***	-0.0506	0.2539***	0.1738**
	(-0.90)	(3.55)	(-0.69)	(3.35)	(2.29)
Constant	0.0057**	0.0045**	0.0056**	0.0031	0.0088***
	(2.44)	(2.22)	(2.28)	(1.32)	(3.56)
Observations	648	648	648	648	648
Adjusted R-squared	2.48%	13.99%	1.85%	9.94%	0.65%

CHAPTER 2 VALUE INVESTING, INDIVIDUALISM, AND POLITICAL RISK

2.1 Introduction

Benjamin Graham and David Dodd, in their 1934 book Security Analysis, argued that securities that fell out of favor with investors were sometimes undervalued in the stock market. They advocate a value investing strategy that buys underpriced securities (relative to their fundamentals) and captures high expected returns. Literature has extensively documented that value stocks (stocks with high book-to-market ratios, earnings yields, and dividend yields) outperform growth stocks (e.g., Fama and French, 1992b, 1998; Lakonishok, Shleifer, and Vishny, 1994; Porta *et al.*, 1997; among others). Meanwhile, there is an increasing trend to investigate quality investing strategy. Arbitrage portfolios that is long high-quality stocks and short low-quality stocks yield positive risk-adjusted returns see Piotroski, 2000; Piotroski and So, 2012; Novy-Marx, 2013; Asness, Frazzini, and Pedersen, 2019. Both quality investing and value investing strategies generate considerable profits.

In this essay, we examine whether country-specific culture, political risk, and institutional quality help explain the value and quality investing strategies. Prior studies show that it is challenging to understand quality and value premium solely on risk-based arguments. Researchers propose a competing explanation that focuses on behavioral considerations.[13] The quality and value premiums are also observed universal, and the

[13] Although Fama and French (1996) attempt to attribute the abnormal return of value stocks to financial distress risk, Lakonishok, Shleifer, and Vishny (1994) argue that risk does not explain the return difference between value and growth stocks. On the other hand, Daniel, Hirshleifer, and Subrahmanyam (1998) investigate the effect of investors' overconfidence or self-attribution bias on momentum profits. Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999) document that investors' initial underreaction to information would generate momentum returns.

profit magnitudes vary across countries (Chan, Hamao, and Lakonishok, 1991a; Fama and French, 1998; Chui, Titman, and Wei, 2010; Asness, Frazzini, and Pedersen, 2019). Motivated by existing works, in this study, we use international data to investigate whether the performance of quality and value investing strategies will be influenced by investor behavioral biases (overconfidence) or country institutional quality (risk level). Prior literature suggests that the overconfidence behavior could potentially influence investors' information processing and make investor mistakenly judge their abilities to predict the future. We apply this behavioral bias to quality and value investing strategies and test whether overconfident investors may overrate high-quality/growth stocks and underrate low-quality/value stocks, leading to larger magnitudes of quality premium and smaller magnitudes of the value premium. Chui, Titman, and Wei (2010) link investors' overconfidence with the individualism index developed by Hofstede (2001) and argue that a country's level of individualism is possibly correlated to the cultural biases of overoptimism and self-attribution bias). Following their empirical designs, we use the individualism index to present the countries' overconfidence levels. In addition to individualism, we recognize that countries' risk and uncertainty levels also play an essential role in global equity market performance. For example, there are frequent movements in equity prices associated with dramatic political events. Political and economic stability is one of the most important determinants of financial market development and quality. Investors receiving high-quality information will make predictions about market trends and companies' future performance more precisely, while investors with low-quality signals will find it more challenging to recognize the true value of the firm. Therefore, we conjecture that investors in low institutional quality countries perceive less reliable or delayed information and require higher quality and value premiums. We use the political risk components of the *International Country Risk Guide* (ICRG) to measure a country's risk level.

Our empirical results suggest that the variation in quality and value investing strategies' performance across counties is associated with the difference in countries' individualism levels. We find that the average monthly return of the quality investing strategy (long high quality and short low quality) in high individualism score countries is 27 basis points higher than the return in low individualism score countries. Besides, the average monthly returns of value investing strategy (value minus growth) in high individualism score countries are 101 basis points lower than that in low individualism score countries. Both differences in returns are statistically significant, especially the difference in the value premium. On the other hand, we observe that the monthly return of value investing strategy in high institutional quality countries is 65 basis points than that in low institutional quality countries. However, we find insignificant monthly return difference between countries with high- and low-institutional quality. When considering the effect of individualism, political risk, and other potential explanatory variables together, we find that the quality and value premiums are still significantly related to individualism, while individualism weakens the effect of political risk. Besides, the inclusion of a set of control variables does not affect the significance of individualism. We also examined whether this positive (negative) relationship between individualism and quality (value) premium is robust across non-east Asian countries. We show that the relationships remain unchanged when excluding East Asian countries from our sample.

This study contributes to the literature by supplementing the cross-country evidence of quality investing and value investing strategies, and understanding the potential causes of the cross-country differences, specifically from investor behavior and institutional quality perspectives. Our empirical evidence highlights the explanatory power of overconfidence, specifically individualism, on the cross-country quality and value spread. Besides, institutional quality's influence on quality and value premiums is weakened when we consider individualism and political risk together.

The remainder of this essay is organized as follows. Section 2.2 reviews the prior literature and presents our hypotheses. Section 2.3 describes the sample and data used in this study, and Section 2.4 documents our empirical designs and empirical results. Section 2.5 concludes.

2.2 Related Literature and Hypothesis Development

Behavioral finance literature has extensively documented that behavioral biases can influence investors' decision-making process. From behavioral perspectives, investors across countries may have difference investment habits, and this diversity could come from many aspects. Cultural traits would greatly influence the way people think and act and may lead to over- or under-reactions to the market information. Existing literature suggests a potential link between investor overconfidence (or self-attribution behavior) and mis-reaction to the information. Cognitive psychological studies provide evidence that individuals would be biased (overoptimism or overconfident) when evaluating their own abilities. Markus and Kitayama (1991) suggest that people in individualistic cultures tend to be more overconfident and positively perceive their abilities also see Heine *et al.*, 1999; Camerer and Lovallo, 1999. The upshot of this over-optimism is that individuals are fostered to overestimate the precision of their predictions Van den Steen, 2004.

The effect of overconfidence has been widely applied to security markets and used to explain short-run momentum and long-run reversal phenomena. Kyle and Wang (1997) and Odean (1998) suggest that investors would overestimate the precision of their information. Daniel, Hirshleifer, and Subrahmanyam (1998) further argue that overconfident investors would overestimate the accuracy of their own information relative to public information, hence putting more weight on, and consequently overreact to, private information. This statement is supported by a branch of overconfidence models in the literature see Bernardo and Welch, 2001; Chuang and Lee, 2006; Gervais and Odean, 2001; Scheinkman and Xiong, 2003. Besides, they also indicate that momentum profits could be related to investors' overconfidence and self-attribution bias. De Bondt and Thaler (1985, 1987) documented the evidence of long-term price reversals and proposed the over-reaction explanation of the return anomaly, supported by Cooper, Gutierrez Jr, and Hameed (2004).

The above evidence suggests that the overconfidence behavior could potentially influence investors' information processing and make investor mistakenly judge their abilities to predict the future. This behavioral bias would also apply to quality investing and value investing strategies. Overconfident investors tend to adjust to new information with delay (DHS 1998). They suggest that overconfident investors overestimate the precision of their private information signal and put less weight on public signals received by all investors. Moreover, when the public information confirms the direction of their private information (good news after buying or bad news after selling), the increased overconfidence will trigger further overreactions to the stock prices. We argue that overconfident investors may overlook the past stock performance and project past growth into the future. Quality investors aim to buy firms with good quality and short firms with poor quality. However, the definition of quality is too vague to be concluded. Companies are often judged to be ‘good’ or ‘bad’ based on their past performance, although past performance is not necessarily indicating the future. Therefore, investors’ perception of firm quality is heavily influenced by historical information. Overconfident investors presume that *good* companies will move to the next level in the future, while the performance of *bad* companies will become worse.

On the other hand, value, or out-of-favor, stocks have relatively poor past performance relative to growth stocks. When predicting future performance, overconfident investors who focus more on past information may have a favorable sentiment towards glamour stocks and avoid holding stocks with lackluster performance in the past. Therefore, value stocks become more underpriced, and growth stocks overprice on the contrary. Existing literature also documents that overconfident investors would mis-react to information and hold riskier assets as a result of underestimating the risk see Barber and Odean, 2001; Chuang and Lee, 2006; Hirshleifer and Luo, 2001.

This study examines whether the quality and value premiums are associated with behavioral biases, specifically investor overconfidence or overoptimism under the international framework. Inspired by the work of Chui, Titman, and Wei (2010), which suggests the potential link between "individualism" and investor overconfidence and self-attribution behavior, we apply the individualism index developed by Hofstede (2001) to proxy the level of overconfidence over 37 countries around the world. Under this framework, we assume that market investors in high-individualism countries may think highly of the high-quality/growth stocks and look down on low-quality/value stocks more than investors in low-individualism countries, which lead to larger magnitudes of quality premiums and smaller magnitudes of value premiums. Therefore, we raise the following hypotheses:

Hypothesis 1a: *Investors in a higher level of individualism (overconfidence) countries mis-react more to information and obtain higher* ***quality*** *premiums.*

Hypothesis 1b: *Investors in a higher level of individualism (overconfidence) countries mis-react more to information and obtain lower* ***value*** *premiums.*

From institutional quality perspectives, countries' risk and uncertainty levels also play an essential role in global equity market performance. The drastic movements of equity prices before and after dramatic political events are frequently observed in the stock market. Investors will react to political shocks and revise their expectations about a country's macroeconomic policies. Prior literature has extensively documented the relation between political uncertainty and equity prices Brogaard and Detzel, 2015; see Erb, Harvey, and Viskanta, 1996; Li and Born, 2006; Pantzalis, Stangeland, and Turtle, 2000; Santa - Clara and Valkanov, 2003. Besides, political and economic stability is one of the most important determinants of financial market development. Institutional structures such as the stage of economic development, the legal origin/judicial system, country uncertainty level, and political economy would also affect the quality of the financial market, information processing, and decision-making.

In the stock market, high-quality signals will help investors make more precise predictions about market trends and companies' future performance. However, companies in countries with unsound financial markets may provide misleading or false financial information at lower costs, which makes investors harder to recognize the true value of the firm. On the other hand, if investors distrust the market information, this lack of trust further impedes information diffusion and market efficiency. Li (2005) argues that less information quality can lead to increased risk premium and stock return volatility. Brevik and d'Addona (2010) studied the relationship between information quality and equity risk premium. They find that as the quality of information available to investors increase, the equity returns required by investors decrease. Furthermore, Callen, Khan, and Lu (2013) documented a negative correlation between accounting quality and delayed price adjustment to information, and high delay firms have significantly higher expected stock returns. see also Hou and Moskowitz, 2005; Ogneva, 2012. Therefore, we argue that whether there is a relationship between a country's institutional quality and the performance of value investing and quality investing strategies is worth investigating. We also propose the hypotheses:

Hypothesis 2a: *Investors from low institutional quality countries perceive less reliable or delayed information and require higher **quality** premiums than investors from high institutional quality countries.*

Hypothesis 2b: *Investors from low institutional quality countries perceive less reliable or delayed information and require higher **value** premiums than investors from high institutional quality countries.*

2.3 Data Selection and Summary Statistics

Firm-level stock returns and accounting information are obtained from COMPUSTAT global Security Daily database and Fundamentals Annual database (except for the U.S.). We use the stock return and accounting variable collected from CRSP Security Files and COMPUSTAT North America Databases for the U.S. sample. Our sample covers 37 countries from January 1991 to December 2019. The starting date of each country varies depending on the data availability of the COMPUSTAT global database. We winsorize returns at the 1^{st} and 99^{th} percentile within each year to filter out the suspicious stock returns and avoid the impact of extreme values. The quality and value portfolios formation process requires two key variables: *gross-profit-over-asset* (GPOA) and *market-to-book ratio* (MB). GPOA is calculated as the difference between revenue and cost of goods sold scaled by the total assets. MB is the natural logarithm of the ratio between firms' market equity and book equity, where book equity is defined as shareholder's equity minus preferred stock. We use stockholders' equity (SEQ) to measure the shareholders' equity. If stockholders' equity is not available, we use the summation of common equity and preferred stock.

Individualism is one of the six cultural dimensions suggested by Geert Hofstede.[14] Hofstede (2001) argues that individualism reflects the extent to which people believe in their own attributes and prefer to distinguish themselves from others. Chui, Titman, and Wei (2010), who use individualism as a proxy for overconfidence and self-attribution

[14] Hofstede's Cultural Dimensions include Power Distance Index (PDI), Individualism versus Collectivism (IDV), Masculinity versus Femininity (MAS), Uncertainty Avoidance Index (UAI), Long- versus Short-Term Orientation (LTOWVS), and Indulgence versus Restraint (IVR). More details can be found at https://www.mindtools.com/pages/article/newLDR_66.htm and https://geerthofstede.com/research-and-vsm/ dimension-data-matrix/.

bias, documented an empirical relationship between individualism and momentum across countries. Inspired by their work, we focus on the effect of individualism on the performance of value investing and quality investing strategies among countries. Besides Hofstede's individualism index, we also consider other cultural dimensions such as uncertainty avoidance (UAI) and Indulgence (IVR). Panel A of Table 2.1 provides the summary statistics of Hofstede's cultural dimension indices, and the across countries variations are reported in Table A6 of the Appendix.

The political risk would reflect the institutional quality of a country. In this study, the variables measuring countries' political uncertainty are taken from the political risk components of the *International Country Risk Guide* (ICRG), provided by the PRS Group. The ICRG political risk rating contains twelve variables, which include *Government Stability*, *Socioeconomic Conditions*, *Investment Profile*, *Internal Conflict*, *External Conflict*, *Corruption*, *Military in Politics*, *Religious Tensions*, *Law and Order*, *Ethnic Tensions*, *Democratic Accountability*, and *Bureaucracy Quality.* Each variable is assigned a risk point with a minimum of 0 points and a maximum of 4/6/12 points. The lower the risk point, the higher to political risk (lower institutional quality). To obtain a single overall institutional quality measure, we average those twelve political risk measures and convert the overall index into a standardized z-score.[15] We have 7559 country-month pairs observations. Panel B of Table 2.1 provides the summary statistics of ICRG political risk ratings as well as the overall political risk index.

[15] In detail, we rank the overall political risk index cross-sectionally each month and obtain $rank_{i,t} = rank(political\ risk\ index_{i,t})$. Then, the z-score of each country's overall political risk index is calculated as $z_{i,t} = (rank_{i,t} - \mu_t)/\sigma_t$, where μ_t and σ_t are the cross-sectional mean and standard deviation of ranks in that month, respectively.

In addition to the variable of interest, we include several country characteristics as control variables in our empirical model. We use country population growth, GDP growth, Market capital per GDP, Inflation, and MSCI global index returns. There are 6929 country-month pair observations for those country-level control variables. Panel C of Table 2.1 provides the summary statistics.

2.4 Empirical Design and Results

2.4.1 Methodology

We first need to build quality and value investing portfolios for each county included in our sample to test our hypotheses. All stocks in each country are ranked in ascending order based on their *gross-profit-over-asset* (GPOA*,* quality investing strategy) or *market-to-book ratio* (MB*,* value investing strategy) and are assigned to five portfolios at the end of each month. For quality investing strategy, stocks in the bottom one-fifth GPOA category are assigned to the low-quality portfolio, and the stocks in the top one-fifth GPOA category are assigned to the high-quality portfolio. The quality arbitrage portfolio is an investment strategy that longs the high-quality portfolio and shorts the low-quality portfolio (High-quality-minus-low-quality). For value investing strategy, stocks in the bottom or top one-fifth MB category are assigned to the value or growth portfolio. The value arbitrage portfolio is an investment strategy that longs the value portfolio and shorts the growth portfolio (Value-minus-growth). Returns on these portfolios are measured next month. Portfolios are equal-weighted and rebalanced every month.

Next, we investigate the relationship between individualism and quality/value premiums to test Hypothesis 1. Based on the country's individualism index score, we classify countries into the high individualism group (above median) and low individualism group (below median). Within each individualism group, we then form a country-average portfolio, which is a portfolio that puts equal weight on each country-specific quality or value arbitrage portfolio.

We then proceed to our Hypothesis 2, which examines the effect of institutional quality on the performance of quality and value investing strategies. We separate countries into a high political risk (low institutional quality) group and a low political risk (high institutional quality) group based on their overall political risk index score. We then form country-average portfolios on quality investing and value investing arbitrage portfolios within each political risk group.

To further understand the determinants of cross-country performance of quality and value investing strategies, we conduct the panel regression controlling several possible alternative explanatory variables of quality and value premiums. We regress country quality and value premiums on the individualism dummy, political risk dummy, and a set of control variables:

$$\begin{aligned} Quality_{i,t}/Value_{i,t} = \alpha\ + \beta_1 D_{Individualism_i}\ + \beta_2 D_{Political\ Risk_{i,t}} \\ + Controls + Year\ FE\ + \varepsilon_{i,t} \end{aligned} \quad (1)$$

where $Quality_{i,t}$ and $Value_{i,t}$ are returns on the quality arbitrage portfolio and value arbitrage portfolio in country *i* month *t*, respectively. $D_{Individualism_i}$ is the individualism dummy that equals one if the country's individualism index score is higher than the median and equals 0 otherwise. Similarly, $D_{Political\ Risk_{i,t}}$ is the political risk dummy that equals one if the country's political risk index score is lower than the median and equals 0 otherwise (a lower score of the political risk index indicates a higher political risk). Control variables include other potential determinants such as uncertainty avoidance (UAI) and Indulgence (IVR) of the cultural dimensions, country population growth, GDP growth, Market capital per GDP, Inflation, and MSCI global index returns. Robust standard errors are used to calculate the t-statistics.

2.4.2 Empirical Results

Table 2.2 presents the average monthly returns (in percentage) of the high-/low-quality portfolios, value/growth portfolios, and quality/value arbitrage portfolios for each of the 37 countries. The results in Table 2.2 suggest that 31 out of 37 countries have positive quality premiums.[16] Countries with the highest quality premiums are Denmark (3.05%), South Korea (0.90%), South Africa (0.78%), the United Kingdom (0.77%), and Switzerland (0.75%). For value investing strategy, all but four countries (Bangladesh, Denmark, Finland, and New Zealand) have positive value premiums. Countries with the highest value premiums are Romania (3.47%), South Korea (2.19%), Indonesia (0.78%), Greece (1.76%), and China (1.757%). The quality and value premiums vary across countries. The cross-country monthly average quality premium is 0.39%, and the cross-country monthly average value premium is 0.88%.

Panel A of Table 2.3 represents the average monthly returns (%) on individualism-sorted country-average portfolios. We show a positive relationship between individualism level and quality premium. The average monthly quality premium in countries with higher individualism scores is 0.37% with a t-statistic of 3.80, while the quality premium in countries with lower individualism scores is 0.10% per month with a t-statistic of 1.09. The spread between high- and low-individualism country-average quality portfolios is 0.27%, with a t-statistic of 2.33. Besides, we find that the difference

[16] China, Hong Kong, Japan, Netherlands, Pakistan, Romania, and Taiwan have negative quality premiums.

is majorly driven by the higher expected returns for high-quality portfolios in high-individualism level countries. This difference suggests that peoples in high individualism countries (with a higher level of overconfidence) require higher returns on high-quality portfolios. The empirical results are consistent with Hypothesis 1a that investors in a higher level of individualism (overconfidence) countries obtain higher quality premiums.

For the value investing strategy, we find a negative correlation between individualism and value premium. The average monthly value premium in countries with higher individualism scores is 0.49%, with a t-statistic of 2.35. However, the value premium in countries with lower individualism scores is 1.48% per month with a t-statistic of 8.32. The spread between high- and low-individualism country-average value portfolios is -1.01 %, with a highly significant t-statistic of -5.46. In this case, value stocks have lower expected returns in high-individualism countries than in low-individualism courtiers, while the growth stocks have higher expected returns in high-individualism countries than in low-individualism courtiers. These differences lead to the negative spread of the value premium between high- and low-individualism countries. Again, this empirical result supports our Hypothesis 1b that investors in a higher level of individualism (overconfidence) countries obtain lower value premiums.

The previous test shows that individualism is related to cross-country quality and value investing strategies performance. Next, we examine the effect of political risk on quality and value premiums. Panel B of Table 2.3 represents the average monthly returns (%) on political risk-sorted country-average portfolios. We find that there is a negative relationship between political risk level and quality premium. The average monthly quality premium in countries with higher political risk scores is 0.16% with a t-statistic of

1.73, while the quality premium in countries with lower political risk scores is 0.30% per month with a t-statistic of 3.38. The spread between high- and low-political risk country-average quality portfolios is -0.14%, with an insignificant t-statistic of -1.28. This empirical result is inconsistent with our Hypothesis 2a that investors from low institutional quality countries require higher quality premiums than investors from low market institutional countries. On the other hand, we find a positive correlation between political risk level and value premium. The average monthly value premium in countries with higher political risk scores is 1.31%, with a t-statistic of 7.03. The value premium in countries with lower political risk is 0.66% per month with a t-statistic of 3.39. The spread between high- and low-political risk country-average value portfolios is 0.65 %, with a highly significant t-statistic of 3.78. Value stocks have much higher expected returns in high-political risk countries than in low-political risk courtiers, while the growth stocks' expected returns are almost indifferent in both high- and low-political risk countries. These differences lead to the positive spread of the value premium between high- and low-political risk countries. The empirical results support Hypothesis 2b that investors in countries with low institutional quality require higher value premiums than those from high market quality countries.

Table 2.4 exhibits the panel regression of quality premium determinants across countries. Columns (1) and (2) report the regression results of quality arbitrage portfolio returns on individualism dummy with and without the year fixed effects, respectively. We find that the coefficients on the individualism dummy are high significant no matter with or without the year fixed effects (the significant level at 1%), suggesting a positive relationship between individualism and quality premiums. This regression result is consistent with our portfolio analysis. When adding uncertainty avoidance and indulgence dummies as potential explanatory variables, we show in column (3) that the coefficient on individualism is still positively significant (at 1%), and the coefficients on uncertainty avoidance and indulgence are both insignificant. The coefficient magnitudes are also smaller relative to the coefficient of individualism. In column (4), when we regress quality premiums on the political risk dummy and year fixed effect, the coefficient on the political risk dummy is negative and marginally significant (at 10%). However, in column (5), we put the individualism dummy and political risk dummy together and find that the coefficient on the individualism dummy is still positively significant, while the significance of the political risk dummy disappears. We argue that the effect of political risk on quality investing strategy is subsumed by the effect of individualism, suggesting a stronger relationship between individualism and quality investing strategy. Finally, we put all potential explanatory variables with a set of control variables, including country population growth, GDP growth, Market capital per GDP, Inflation, and MSCI global index returns. Column (6) indicates that the coefficient on the individualism dummy is still significantly positive when those control variables are included in the regression. The relationship between individualism and quality premium is robust in various settings, however, the effect of political risk on the quality premium is subsumed by the effect of individualism.

Since the individualism level and the quality premiums are both relatively low in East Asian countries. To test the extent to which our results are robust to the counties outside of East Asia, we build an EastAsian dummy and include it in Equation (1). The East Asian dummy equals one if the country falls into China, Hong Kong, Japan, South

Korea, and Taiwan in our sample. Column (7) of Table 2.4 represents the regression result for the quality arbitrage portfolio. The coefficient of the individualism dummy is robust after including the EastAsian dummy, and the EastAsian dummy is insignificant itself.

Table 2.5 reports the panel regression of value premium determinants across countries. Similar to Table 2.4, Columns (1) and (2) report the regression results of value arbitrage portfolio returns on individualism dummy with and without year fixed effects, respectively. As expected, we find a negatively significant relationship between individualism and value premium, consistent with the results of our portfolio analysis. If we include uncertainty avoidance and indulgence dummies into the regression, the coefficient on the individualism dummy is still negatively significant at the 1% level, and the coefficient on the uncertainty avoidance dummy is insignificant. Interestingly, the coefficient on the indulgence dummy is also negatively significant at the 5% level. We then regress value premiums on political risk dummy and year fixed effect and report the results in column (4). The coefficient on the political risk dummy is positively significant at the 10% level. However, when we regress the individualism dummy and political risk dummy together, the political risk dummy loses its significance again, while the individualism dummy is still positively significant. Finally, we put all potential explanatory variables with a set of control variables, and column (6) shows that the coefficient on the individualism dummy remains negatively significant when those control variables are included in the regression. Surprisingly, the effect of indulgence is partially subsumed, and the coefficient is significant at 10%. Based on these empirical results, we conclude that the relationship between individualism and value premium is robust in various specifications. Nevertheless, the effect of political risk on the quality premium is subsumed again by the effect of individualism. Besides, the indulgence cultural dimension may also play a weak role in explaining the cross-country variation of value investing strategy performance. We also conduct the test on whether the results are robust to the counties outside of East Asia for our value arbitrage portfolio. Column (7) of Table 2.5 suggests that although the EastAsian dummy is positively significant, the relationship between individualism and value premium still exists and is significant at the 1% level.

2.4.3 Robustness Check

In the first essay, we proposed a regression-based approach to identify the quality-cheapness (*QC*) strategy with quality as priority and the cheapness-quality (*CQ*) strategy with cheapness as priority. Both strategies take quality and value into account. In this section, we present the robustness check with the *QC* and *CQ* strategies and provide additional evidence to support the main results provided in Section 2.4.2.

Panel A of Table 2.6 represents the average *QC* and *CQ* premiums (%) on individualism-sorted country-average portfolios. Similarly, we show a positive relationship between individualism level and *QC* premium. The average monthly *QC* premium in countries with higher individualism scores is 0.59% with a t-statistic of 4.21, while the quality premium in countries with lower individualism scores is 0.28% per month with a t-statistic of 3.72. The spread between high- and low-individualism country-average quality portfolios is 0.30%, with a t-statistic of 2.03. For the *CQ* investing strategy, we find a negative correlation between individualism and value premium, which is consistent with the patterns of value investing strategy. The average monthly value premium in countries with higher individualism scores is 0.31%, (t = 2.39), while the *CQ* premium in countries with lower individualism scores is 0.92% per month with a t-statistic of 8.04. The spread between high- and low-individualism country-average value portfolios is -0.61 %, with a highly significant t-statistic of -4.17. These empirical results further support our Hypothesis 1 that investors in a higher level of individualism (overconfidence) countries obtain higher quality premium and lower value premium.

Next, we examine the effect of political risk on *QC* and *CQ* premiums. Panel B of Table 2.6 represents the average *QC* and *CQ* premiums (%) on political risk-sorted country-average portfolios. We find that there is still a negative relationship between political risk level and *QC* premium. The average monthly quality premium in countries with higher political risk scores is 0.36% with a t-statistic of 4.75, while the quality premium in countries with lower political risk scores is 0.50% per month with a t-statistic of 3.79. The spread between high- and low-political risk country-average quality portfolios is -0.14%, with an insignificant t-statistic of -1.02. On the other hand, we find a positive correlation between political risk level and *CQ* premium. The average monthly value premium in countries with higher political risk scores is 0.79%, with a t-statistic of 7.08. The value premium in countries with lower political risk is 0.45% per month with a t-statistic of 3.70. The spread between high- and low-political risk country-average value portfolios is 0.34%, with a highly significant t-statistic of 2.77. Both results are consistent with the main results provided in Panel B of Table 2.3.

Table 2.7 exhibits the panel regression of *QC* premium determinants across countries. Columns (1) and (2) report the regression results of quality arbitrage portfolio returns on individualism dummy with and without the year fixed effects, respectively. We find that the coefficients on the individualism dummy are high significant no matter with or without the year fixed effects (the significant level at 1%), suggesting a positive relationship between individualism and quality premiums. This regression result is consistent with our portfolio analysis. When adding uncertainty avoidance and indulgence dummies as potential explanatory variables, we show in column (3) that the coefficient on individualism is still positively significant (at 1%), and the coefficients on uncertainty avoidance and indulgence are both insignificant. The coefficient magnitudes are also smaller relative to the coefficient of individualism. In column (4), when we regress quality premiums on the political risk dummy and year fixed effect, the coefficient on the political risk dummy is negative and marginally significant (at 10%). However, in column (5), we put the individualism dummy and political risk dummy together and find that the coefficient on the individualism dummy is still positively significant, while the significance of the political risk dummy disappears. We argue that the effect of political risk on quality investing strategy is subsumed by the effect of individualism, suggesting a stronger relationship between individualism and quality investing strategy. Finally, we put all potential explanatory variables with a set of control variables, including country population growth, GDP growth, Market capital per GDP, Inflation, and MSCI global index returns. Column (6) indicates that the coefficient on the individualism dummy is still significantly positive when those control variables are included in the regression. The relationship between individualism and quality premium is robust in various settings, however, the effect of political risk on the quality premium is subsumed by the effect of individualism.

Table 2.8 reports the panel regression of value premium determinants across countries. Similar to Table 2.7, Columns (1) and (2) report the regression results of value arbitrage portfolio returns on individualism dummy with and without year fixed effects, respectively. As expected, we find a negatively significant relationship between individualism and value premium, consistent with the results of our portfolio analysis. If we include uncertainty avoidance and indulgence dummies into the regression, the coefficient on the individualism dummy is still negatively significant at the 1% level, and the coefficient on the uncertainty avoidance dummy is insignificant. Interestingly, the coefficient on the indulgence dummy is also negatively significant at the 5% level. We then regress value premiums on political risk dummy and year fixed effect and report the results in column (4). The coefficient on the political risk dummy is positively significant at the 10% level. However, when we regress the individualism dummy and political risk dummy together, the political risk dummy loses its significance again, while the individualism dummy is still positively significant. Finally, we put all potential explanatory variables with a set of control variables, and column (6) shows that the coefficient on the individualism dummy remains negatively significant when those control variables are included in the regression. Surprisingly, the effect of indulgence is partially subsumed, and the coefficient is significant at 10%. Based on these empirical results, we conclude that the relationship between individualism and value premium is robust in various specifications. Nevertheless, the effect of political risk on the quality premium is subsumed again by the effect of individualism. Besides, the indulgence cultural dimension may also play a weak role in explaining the cross-country variation of value investing strategy performance.

2.5 Conclusion

This study examines the explanatory power of countries' cultural traits and institutional quality on the quality and value investing strategies in an international environment. Using data from 1991 to 2019 across 37 countries in our sample, we find that countries with higher individualism scores generally have higher quality premiums and lower value premiums than countries with lower individualism scores. Besides, countries with higher political risk would have higher value premiums, while the difference in quality premium is insignificant between high and low political risk countries. In conclusion, we find the explanatory power of overconfidence on the cross-country quality and value spread, and the effect of institutional quality was weakened when we take both individualism and political risk into consideration.

Table 2.1 Descriptive statistics

This table provides information on the major statistical attributes of the variables used in this essay. Data are from 1991 to 2019 across 37 countries. Panel A shows the characteristics of Hofstede's cultural dimension variables, including the individualism index, uncertainty avoidance index, and the indulgence index. Panel B provides a statistical summary of the ICRG Political Risk variables and the overall political risk index. Panel C displays the statistical attributes of country-level control variables.

Variable	Countries w/Valid Data	Mean	Median	Std. Dev.	5th Percentile	95th Percentile
Panel A: Hofstede's Cultural Dimension Variables						
Individualism	37	47.57	46.00	24.99	14.00	91.00
Uncertainty Avoidance	37	60.46	59.00	24.62	8.00	112.00
Indulgence	35	45.81	45.54	19.53	0.00	77.68
Panel B: ICRG Political Risk Variables (Panel)						
Government Stability	7559	7.86	8.00	1.65	4.50	11.00
Socioeconomic Conditions	7559	7.66	8.00	1.99	2.50	11.00
Investment Profile	7559	9.66	10.00	2.05	5.00	12.00
Internal Conflict	7559	9.60	10.00	1.54	5.50	12.00
External Conflict	7559	9.97	10.00	1.28	6.50	12.00
Corruption	7559	3.55	3.50	1.26	1.00	6.00
Military in Politics	7559	4.66	5.00	1.36	1.50	6.00
Religious Tensions	7559	4.74	5.00	1.43	1.00	6.00
Law and Order	7559	4.51	5.00	1.19	2.00	6.00
Ethnic Tensions	7559	4.18	4.00	1.28	1.00	6.00
Democratic Accountability	7559	4.97	5.50	1.41	1.00	6.00
Bureaucracy Quality	7559	3.15	3.00	0.83	1.00	4.00
Political Risk - Overall index	7559	0.00	0.02	0.66	-1.40	1.17
Panel C: Country-level Control Variables (Panel)						
Population growth	6929	0.85	0.76	0.69	-0.54	2.39
GDP growth	6929	0.06	0.06	0.11	-0.18	0.33
Market Capital per GDP	6929	0.23	0.25	0.41	-1.71	0.55
Inflation	6929	3.05	2.24	3.39	-0.92	13.88
MSCI Global Index Return	7559	0.00	0.01	0.04	-0.11	0.09

Table 2.2 Quality and Value Premiums by Country

This table provides the quality investing and value investing strategy portfolio returns across 37 countries. The sample period covers from January 1991 to December 2019. At the end of each month, all stocks in each country are ranked in ascending order on the basis of their *gross-profit-over-asset (GPOA)* or *market-to-book ratio (MB)* and are assigned to one of five portfolios. Stocks in the bottom one-fifth are assigned to the low-quality or value portfolio, and stocks in the top one-fifth are assigned to the high-quality or growth portfolio, respectively. Portfolios are equal-weighted and rebalanced every month. Returns on these portfolios are measured one month after ranking and displayed in monthly percentages.

		Quality Investing (Gross-profit-over-asset)			Value Investing (Market-to-book ratio)		
Country Code	**Country Name**	**Low Quality**	**High Quality**	**HighQ minus LowQ**	**Value**	**Growth**	**Value minus Growth**
AUS	Australia	0.19%	0.70%	0.51%	1.41%	-0.15%	1.56%
BGD	Bangladesh	-0.21%	0.36%	0.56%	-0.38%	-0.19%	-0.19%
BRA	Brazil	1.46%	1.68%	0.22%	1.98%	1.54%	0.44%
CHL	Chile	0.29%	0.42%	0.13%	0.52%	0.35%	0.18%
CHN	China	0.97%	0.44%	-0.53%	1.52%	-0.23%	1.76%
DNK	Denmark	-1.04%	2.01%	3.05%	-0.65%	0.40%	-1.06%
FIN	Finland	-0.36%	0.28%	0.64%	0.08%	0.26%	-0.18%
FRA	France	0.01%	0.32%	0.31%	0.65%	-0.05%	0.70%
DEU	Germany	-0.06%	0.40%	0.46%	0.37%	0.02%	0.35%
GRC	Greece	0.17%	0.28%	0.11%	1.42%	-0.34%	1.76%
HKG	Hong Kong	0.31%	0.08%	-0.23%	1.09%	-0.25%	1.34%
IND	India	0.76%	1.18%	0.42%	1.72%	0.34%	1.38%
IDN	Indonesia	1.48%	1.58%	0.10%	2.70%	0.89%	1.81%
ISR	Israel	-0.30%	0.30%	0.60%	0.99%	-0.23%	1.22%
ITA	Italy	-0.18%	0.40%	0.58%	0.66%	0.06%	0.60%
JPN	Japan	0.30%	0.23%	-0.07%	0.98%	-0.40%	1.38%
MYS	Malaysia	0.25%	0.56%	0.31%	1.05%	-0.09%	1.14%
NLD	Netherlands	-0.60%	-0.60%	-0.01%	-0.39%	-0.62%	0.23%
NZL	New Zealand	0.81%	1.03%	0.23%	0.74%	1.17%	-0.43%
NOR	Norway	-0.19%	0.45%	0.64%	0.08%	-0.21%	0.29%
PAK	Pakistan	1.39%	1.19%	-0.20%	1.66%	0.70%	0.96%
PHL	Philippines	0.43%	0.71%	0.28%	1.06%	0.02%	1.04%
POL	Poland	0.07%	0.67%	0.60%	0.60%	0.02%	0.58%
ROU	Romania	2.32%	1.87%	-0.45%	3.76%	0.29%	3.47%
RUS	Russia	-0.30%	0.01%	0.32%	0.38%	-0.74%	1.12%
SGP	Singapore	0.41%	0.66%	0.25%	1.27%	-0.03%	1.30%
ZAF	South Africa	0.98%	1.76%	0.78%	1.91%	0.71%	1.20%
KOR	South Korea	-0.39%	0.52%	0.90%	1.40%	-0.78%	2.19%
ESP	Spain	-0.58%	0.02%	0.60%	-0.03%	-0.16%	0.13%
SWE	Sweden	-0.43%	0.23%	0.66%	0.05%	-0.02%	0.07%
CHE	Switzerland	-0.21%	0.53%	0.75%	0.31%	0.25%	0.05%
TWN	Taiwan	0.37%	0.18%	-0.19%	0.98%	-0.33%	1.30%
THA	Thailand	0.77%	0.88%	0.11%	1.81%	0.12%	1.69%
TUR	Turkey	1.17%	1.65%	0.48%	1.80%	0.72%	1.08%
GBR	United Kingdom	-0.02%	0.74%	0.77%	0.73%	0.32%	0.40%
USA	United States	0.88%	1.03%	0.15%	1.07%	0.92%	0.15%
VNM	Vietnam	0.37%	0.84%	0.47%	1.26%	-0.13%	1.39%
Average		0.31%	0.69%	0.39%	0.99%	0.11%	0.88%

Table 2.3 Quality and Value premiums, Individualism, and Institutional Quality

This table reports average monthly quality and value profits (%) for individualism-separated portfolios (Panel A) and institutional quality-separated portfolios (Panel B). A country's individualism and institutional quality level are classified by Hofstede's individualism index and ICRG's political risk index, respectively. The country-average portfolio is a portfolio that puts equal weight on each country-specific quality or value portfolio in this portfolio. At the end of each month, all countries in our sample are allocated into two groups, from low (bottom 50%) to high (top 50%), based on their individualism index and overall political risk index scores. Countries with low individualism scores are classified into the low individualism group. On the other hand, countries with low political risk scores are attributed to the high political risk group. Country-average portfolios are formed in each individualism-sorted or political risk-sorted group. The test period is from January 1991 to December 2019. The corresponding t-statistics are in parentheses below returns. Profits with 5% or higher statistical significance are indicated in bold.

Panel A: Countries separated based on Individualism

	Quality Investing (Gross-profit-over-asset)			**Value Investing (Market-to-book ratio)**		
	Low Quality	**High Quality**	**HighQ minus LowQ**	**Value**	**Growth**	**Value minus Growth**
Low Individualism	0.44%	0.54%	0.10%	**1.32%**	-0.16%	**1.48%**
	(1.30)	(1.84)	(1.09)	(3.53)	(-0.53)	(8.32)
High Individualism	0.41%	**0.78%**	**0.37%**	**0.92%**	0.44%	**0.49%**
	(1.31)	(2.92)	(3.80)	(3.04)	(1.40)	(2.35)
High minus Low	-0.03%	0.24%	**0.27%**	-0.40%	**0.61%**	**-1.01%**
	(-0.11)	(1.01)	(2.33)	(-1.38)	(2.45)	(-5.46)

Panel B: Countries separated based on Political Risk

	Quality Investing (Gross-profit-over-asset)			**Value Investing (Market-to-book ratio)**		
	Low Quality	**High Quality**	**HighQ minus LowQ**	**Value**	**Growth**	**Value minus Growth**
Low Risk	0.17%	0.47%	**0.30%**	**0.73%**	0.07%	**0.66%**
	(0.52)	(1.70)	(3.38)	(2.24)	(0.22)	(3.39)
High Risk	**0.66%**	**0.82%**	0.16%	**1.48%**	0.17%	**1.31%**
	(2.17)	(3.18)	(1.73)	(4.46)	(0.64)	(7.03)
High minus Low	**0.49%**	**0.35%**	-0.14%	**0.75%**	0.10%	**0.65%**
	(2.22)	(2.23)	(-1.28)	(3.38)	(0.55)	(3.78)

Table 2.4 Determinants of Quality Premium across Countries: Panel Regressions

This table shows the regression results of country-specific monthly quality portfolio returns on Hofstede's cultural dimension dummies (1=high, 0=low), ICRG's political risk index dummy (1=high risk, 0=low risk), and a set of control variables. Columns (1) and (2) report the regression results of quality portfolio returns on individualism dummy with and without year fixed effects, respectively. Column (3) includes uncertainty avoidance and indulgence dummies. Column (4) tests the explanatory power of the political risk index, and column (5) examines the combined effect of individualism and political risk. Column (6) considers additional explanatory variables. This set of variables includes country population growth, GDP growth, Market capital per GDP, Inflation, and MSCI global index returns. East Asian is a dummy variable that equals one if the country is located in East Asia and equals 0 otherwise. Robust standard errors adjusted t-statistics are reported below coefficients. The asterisks ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	**Quality Arbitrage Portfolio (HighQ minus LowQ)**						
Individualism	0.0057***	0.0048***	0.0048***		0.0046***	0.0042***	0.0043***
	(4.26)	(4.27)	(4.75)		(3.83)	(3.18)	(2.85)
Uncertainty Avoidance			0.0005			0.0013	0.0005
			(0.48)			(0.85)	(0.36)
Indulgence			0.0001			0.0005	-0.0001
			(0.07)			(0.52)	(-0.09)
Political Risk (overall)				-0.0021*	-0.0005	-0.0015	-0.0013
				(-1.90)	(-0.57)	(-1.30)	(-1.11)
Population growth						-0.0000	-0.0003
						(-0.03)	(-0.36)
GDP growth						0.0085	0.0098
						(1.27)	(1.49)
Market Capital / GDP						-0.0005	-0.0005
						(-0.64)	(-0.78)
Inflation						0.0001	0.0001
						(0.71)	(0.60)
Global Index Return (MSCI)						-0.0256*	-0.0256*
						(-1.76)	(-1.76)
EastAsian							-0.0014
							(-0.40)
Constant	0.0008	-0.0013	-0.0016	0.0018	-0.0010	-0.0019	-0.0010
	(0.90)	(-0.84)	(-0.90)	(1.16)	(-0.66)	(-0.89)	(-0.38)
Year Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Robust Standard Error	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,559	7,559	7,161	7,559	7,559	6,555	6,555
Number of countries	37	37	35	37	37	34	34
R-square	0.37%	1.34%	1.39%	1.07%	1.34%	1.60%	1.60%

Table 2.5 Determinants of Value Premium across Countries: Panel Regressions

This table shows the regression results of country-specific monthly value portfolio returns on Hofstede's cultural dimension dummies (1=high, 0=low), ICRG's political risk index dummy (1=high risk, 0=low risk), and a set of control variables. Columns (1) and (2) report the regression results of value portfolio returns on individualism dummy with and without year fixed effects, respectively. Column (3) includes uncertainty avoidance and indulgence dummies. Column (4) tests the explanatory power of the political risk index, and column (5) examines the joint effect of individualism and political risk. Column (6) considers additional explanatory variables. This set of variables includes country population growth, GDP growth, Market capital per GDP, Inflation, and MSCI global index returns. EastAsian is a dummy variable that equals one if the country is located in East Asia and equals 0 otherwise. Robust standard errors adjusted t-statistics are reported below coefficients. The asterisks ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	**Value Arbitrage Portfolio (Value minus Growth)**						
Individualism	-0.0104***	-0.0094***	-0.0095***		-0.0086***	-0.0091***	-0.0067***
	(-4.79)	(-6.01)	(-7.16)		(-5.64)	(-5.17)	(-2.85)
Uncertainty Avoidance			-0.0005			-0.0011	-0.0006
			(-0.37)			(-0.77)	(-0.51)
Indulgence			-0.0033**			-0.0030*	-0.0016
			(-2.14)			(-1.73)	(-0.86)
Political Risk (overall)				0.0044***	0.0023	-0.0003	0.0009
				(2.60)	(1.57)	(-0.14)	(0.41)
Population growth						-0.0011	-0.0002
						(-0.64)	(-0.12)
GDP growth						-0.0129	-0.0129
						(-0.93)	(-0.90)
Market Capital / GDP						-0.0012	-0.0018
						(-0.77)	(-1.10)
Inflation						0.0007	0.0008
						(0.96)	(1.07)
Global Index Return (MSCI)						0.0460***	0.0459***
						(2.67)	(2.67)
EastAsian							0.0068**
							(2.48)
Constant	0.0137***	0.0100**	0.0114***	0.0041	0.0080	0.0091	0.0038
	(8.85)	(2.08)	(2.63)	(0.54)	(1.54)	(1.41)	(0.52)
Year Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Robust Standard Error	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,559	7,559	7,161	7,559	7,559	6,555	6,555
Number of countries	37	37	35	37	37	34	34
R-square	1.00%	3.55%	3.83%	2.89%	3.60%	4.43%	4.58%

Table 2.6 QC and CQ premiums, Individualism, and Institutional Quality

This table reports average monthly quality and value profits (%) for individualism-separated portfolios (Panel A) and institutional quality-separated portfolios (Panel B). A country's individualism and institutional quality level are classified by Hofstede's individualism index and ICRG's political risk index, respectively. The country-average portfolio is a portfolio that puts equal weight on each country-specific quality or value portfolio in this portfolio. At the end of each month, all countries in our sample are allocated into two groups, from low (bottom 50%) to high (top 50%), based on their individualism index and overall political risk index scores. Countries with low individualism scores are classified into the low individualism group. On the other hand, countries with low political risk scores are attributed to the high political risk group. Country-average portfolios are formed in each individualism-sorted or political risk-sorted group. The test period is from January 1991 to December 2019. The corresponding t-statistics are in parentheses below returns. Profits with 5% or higher statistical significance are indicated in bold.

Panel A: Countries separated based on Individualism

	QC Investing (Quality-Cheapness Measure)			**CQ Investing (Cheapness-Quality Measure)**		
	Low QC	**High QC**	**HighQC minus LowQC**	**Low CQ**	**High CQ**	**LowCQ minus HighCQ**
Low Individualism	0.44%	0.54%	0.10%	**1.32%**	-0.16%	**1.48%**
	(1.30)	(1.84)	(1.09)	(3.53)	(-0.53)	(8.32)
High Individualism	0.41%	**0.78%**	**0.37%**	**0.92%**	0.44%	**0.49%**
	(1.31)	(2.92)	(3.80)	(3.04)	(1.40)	(2.35)
High minus Low	-0.03%	0.24%	**0.27%**	-0.40%	**0.61%**	**-1.01%**
	(-0.11)	(1.01)	(2.33)	(-1.38)	(2.45)	(-5.46)

Panel B: Countries separated based on Political Risk

	QC Investing (Quality-Cheapness Measure)			**CQ Investing (Cheapness-Quality Measure)**		
	Low QC	**High QC**	**HighQC minus LowQC**	**Low CQ**	**High CQ**	**LowCQ minus HighCQ**
Low Risk	0.17%	0.47%	**0.30%**	**0.73%**	0.07%	**0.66%**
	(0.52)	(1.70)	(3.38)	(2.24)	(0.22)	(3.39)
High Risk	**0.66%**	**0.82%**	0.16%	**1.48%**	0.17%	**1.31%**
	(2.17)	(3.18)	(1.73)	(4.46)	(0.64)	(7.03)
High minus Low	**0.49%**	**0.35%**	-0.14%	**0.75%**	0.10%	**0.65%**
	(2.22)	(2.23)	(-1.28)	(3.38)	(0.55)	(3.78)

Table 2.7 Determinants of QC Premium across Countries: Panel Regressions

This table shows the regression results of country-specific monthly *QC* portfolio returns on Hofstede's cultural dimension dummies (1=high, 0=low), ICRG's political risk index dummy (1=high risk, 0=low risk), and a set of control variables. Columns (1) and (2) report the regression results of *QC* portfolio returns on individualism dummy with and without year fixed effects, respectively. Column (3) includes uncertainty avoidance and indulgence dummies. Column (4) tests the explanatory power of the political risk index, and column (5) examines the combined effect of individualism and political risk. Column (6) considers additional explanatory variables. This set of variables includes country population growth, GDP growth, Market capital per GDP, Inflation, and MSCI global index returns. East Asian is a dummy variable that equals one if the country is located in East Asia and equals 0 otherwise. Robust standard errors adjusted t-statistics are reported below coefficients. The asterisks ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	**QC Arbitrage Portfolio (HighQC minus LowQC)**						
Individualism	0.0020*	0.0022**	0.0027**		0.0022*	0.0034*	0.0034*
	(1.74)	(2.03)	(2.20)		(1.84)	(1.93)	(1.72)
Uncertainty Avoidance			-0.0001			-0.0006	-0.0006
			(-0.13)			(-0.34)	(-0.29)
Indulgence			-0.0007			-0.0001	-0.0000
			(-0.56)			(-0.06)	(-0.01)
Political Risk (overall)				-0.0009	0.0000	0.0005	0.0004
				(-0.74)	(0.00)	(0.30)	(0.27)
Population growth						-0.0011	-0.0012
						(-1.04)	(-1.05)
GDP growth						0.0073	0.0073
						(1.10)	(1.08)
Market Capital / GDP						0.0009	0.0009
						(0.69)	(0.68)
Inflation						0.0003	0.0003
						(1.58)	(1.51)
Global Index Return (MSCI)						0.0097	0.0097
						(0.82)	(0.82)
EastAsian							-0.0005
							(-0.14)
Constant	0.0031***	0.0020	0.0019	0.0035**	0.0020	-0.0014	-0.0014
	(4.26)	(1.13)	(0.94)	(2.43)	(1.07)	(-0.23)	(-0.22)
Year Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Robust Standard Error	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,559	7,559	7,161	7,559	7,559	6,555	6,555
Number of countries	37	37	35	37	37	34	34
R-square	0.08%	1.08%	1.17%	1.01%	1.08%	1.44%	1.44%

Table 2.8 Determinants of CQ Premium across Countries: Panel Regressions

This table shows the regression results of country-specific monthly *CQ* portfolio returns on Hofstede's cultural dimension dummies (1=high, 0=low), ICRG's political risk index dummy (1=high risk, 0=low risk), and a set of control variables. Columns (1) and (2) report the regression results of *CQ* portfolio returns on individualism dummy with and without year fixed effects, respectively. Column (3) includes uncertainty avoidance and indulgence dummies. Column (4) tests the explanatory power of the political risk index, and column (5) examines the joint effect of individualism and political risk. Column (6) considers additional explanatory variables. This set of variables includes country population growth, GDP growth, Market capital per GDP, Inflation, and MSCI global index returns. EastAsian is a dummy variable that equals one if the country is located in East Asia and equals 0 otherwise. Robust standard errors adjusted t-statistics are reported below coefficients. The asterisks ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	**CQ Arbitrage Portfolio (LowCQ minus HighCQ)**						
Individualism	-0.0078***	-0.0065***	-0.0075***		-0.0066**	-0.0079***	-0.0080***
	(-3.74)	(-2.63)	(-2.73)		(-2.58)	(-4.43)	(-3.69)
Uncertainty Avoidance			-0.0016			-0.0019	-0.0014
			(-0.57)			(-1.07)	(-0.65)
Indulgence			0.0009			0.0003	0.0013
			(0.37)			(0.18)	(0.56)
Political Risk (overall)				0.0015	0.0005	-0.0008	-0.0003
				(0.64)	(0.20)	(-0.48)	(-0.14)
Population growth						-0.0006	-0.0003
						(-0.55)	(-0.25)
GDP growth						-0.0231***	-0.0235***
						(-3.01)	(-3.04)
Market Capital / GDP						-0.0003	-0.0012
						(-0.17)	(-0.76)
Inflation						-0.0004*	-0.0004*
						(-1.84)	(-1.68)
Global Index Return (MSCI)						-0.0263*	-0.0264*
						(-1.92)	(-1.93)
EastAsian							0.0039
							(1.02)
Constant	0.0097***	0.0127***	0.0129***	0.0097*	0.0122**	0.0197***	0.0180**
	(5.20)	(2.92)	(2.63)	(1.92)	(2.40)	(2.81)	(2.42)
Year Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Robust Standard Error	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,559	7,559	7,161	7,559	7,559	6,555	6,555
Number of countries	37	37	35	37	37	34	34
R-square	0.21%	1.56%	1.62%	1.41%	1.54%	2.07%	2.13%

CHAPTER 3 UNDERSTANDING QUALITY PREMIUM

3.1 Introduction

Prior literature documents that high-quality firms are expected to earn higher future returns than low-quality firms. An investment strategy called quality investing that longs high-quality firms and shorts low-quality firms generate positively significant excess and abnormal returns, robust to various firm quality measures (e.g., Piotroski, 2000; Piotroski and So, 2012; Novy-Marx, 2013; Asness, Frazzini, and Pedersen, 2014; Asness, Frazzini, and Pedersen, 2019). Empirically, existing studies find that firms' quality is positively related to the market-to-book ratios and negatively related to the market risk. For high-quality firms, they have higher expected returns, higher mark-to-book ratios, and lower market beta (safer). Meanwhile, low-quality firms have lower expected returns, lower market-to-book ratio, and higher market beta (riskier). However, the risk-return tradeoff theory suggests that high risk is associated with high expected returns. In other words, risky stocks should have higher expected returns than safe stocks. The risk-return tradeoff theory could not explain the quality premium because quality (safe) stocks have higher expected returns than junk (risky) stocks. On the other hand, empirical studies find that high market-to-book ratio portfolios have low expected returns. Nevertheless, high-quality portfolios have high expected returns and high market-to-book ratio at the same time.

These two interesting inconsistencies arouse our interest in understanding what quality investing is and how we understand the quality premium. Existing studies make great efforts to explain the quality premium. Piotroski and So (2012) suggest that quality premium is driven by the expectation errors correlated with historical financial information. Novy-Marx (2013) argues that the quality spread is not consistent with rational pricing. Asness, Frazzini, and Pedersen (2019) propose three possible explanations, including (a) the imperfect quality measure, (b) hidden risk component uncaptured by the quality measure, and (c) limited market efficiency. They rule out the first two explanations and attribute the quality premium partially to the market inefficiency explanation. All the existing works suggest that it is challenging to associate the quality premium with risk-based explanations.

This essay aims to explain quality premium from the rational perspective. Campbell *et al.* (2018) view the volatility risk from long-term investors' perspective. They argue that the co-movement with volatility is priced in the stock returns. Assets with high sensitivities to market volatility would hedge against the long-term fluctuations of investment opportunities, including declines in expected returns and increases in volatility. Long-term investor's desire to hedge volatility helps explain various cross-sectional asset returns, especially the value premium. Growth stocks help long-term investors hedge against the declines in the expected stock return because growth firms carry growth options that are valuable during high volatility periods. Therefore, growth firms perform well during hard times and naturally have low average returns. Bansal *et al.* (2014) link volatility news to the long-run consumption shocks and develop a framework where cash flow, discount rate, and volatility risk could determine risk premia. They demonstrate that volatility risk generates significant positive risk premiums and helps explain the value premium.

Existing works highlight the importance of volatility risk, an additional risk component, in explaining many patterns in cross-sectional asset returns. Inspired by the Bansal *et al.* (2014) and Campbell *et al.* (2018), we introduce the volatility risk in explaining the quality-return relationship and argue that high-quality firms and low-quality firms react differently to volatility risk. High-quality firms have high profitability, earnings, and price. During the high volatility period, it is challenging for those good firms to keep the sustainability of high performance. In other words, there is a limited upside potential but significant downside potential for those high-quality firms (downside potential outweighs the upside potential). Therefore, volatility is a risk for high-quality firms, and we assume high-quality firms are more sensitive to volatility, especially during the high volatility period. On the other hand, low-quality firms have low profitability, earnings, and price. During the high volatility period, the downside potential is limited while there is a lot of room for improvement for those low-quality firms. Hence, volatility is not bad news to low-quality firms, and we conjecture that low-quality firms are less sensitive to volatility, or even have negative sensitivities to the volatility. Investors who realize the volatility risk to high-quality firms would request additional compensation for bearing that risk. Therefore, the expected returns for those high-quality firms would be higher. Meanwhile, as volatility is not a bad thing for low-quality firms due to the upside potential, investors do not ask for additional compensation for high volatility, and the expected returns for low-quality firms would be lower. The asymmetric reactions of high-quality and low-quality stocks to the volatility lead to the quality premium, and the magnitude of value premium would be even larger during the high volatility period. We conduct portfolio and regression analyses to provide empirical evidence supporting our conjectures.

Our empirical results suggest that high-quality portfolios and low-quality portfolios have asymmetric sensitivities to the market volatility, and the level of volatility risk indeed could influence the magnitudes and significance of the quality premium. We find that low-quality portfolios have negative sensitivity to volatility (volatility beta) and high-quality portfolios have positive sensitivity to volatility. This evidence supports our conjecture that high-quality firms and low-quality firms react to volatility differently. In the conditional double sorting, we find that in the lowest volatility beta group, the quality return spread is 54 basis points per month, while the quality spread in the highest volatility beta group is 25 basis points per month. The magnitude of quality premium is much lower in the high volatility risk level than in the low volatility risk level. Moreover, the GPOA-based quality arbitrage portfolios are only positively significant in the lowest volatility risk group, and it is positively insignificant in the remaining volatility risk groups. The conditional two-way sorting results suggest that the quality premium is significantly reduced after we consider the effect of volatility risk. Reversely, controlling the effect of GPOA barely influence the spread of volatility risk, suggesting that GPOA and volatility risk capture different firm characteristics. Further Fama-MacBeth analysis on the cross-sectional regression suggests that the coefficients on volatility beta are positive using various testing assets. This result implies that low-quality firms have negative volatility risk premiums, while high-quality firms have positive volatility premiums. We further test whether the volatility risk could serve as a risk factor to explain the quality spread. We find that volatility risk factor could partially explain the quality premium, and the explanatory power is significantly larger during the high market volatility period.

This study contributes to the literature by providing a risk-based explanation of the quality premium, while most existing literature attributes the quality premium to behavioral explanations. Our empirical evidence highlights the explanatory power of volatility risk on the source of quality premium and suggests that volatility risk has different effects on high-quality and low-quality firms.

The remainder of this essay is organized as follows. Section 3.2 reviews the prior literature and presents our hypotheses. Section 3.3 describes the sample and data used in this study and the empirical designs, and Section 3.4 documents our empirical results. Section 3.5 concludes.

3.2 Literature Review and Hypothesis development

Existing literature has extensively explored the quality characteristics of a company and stock returns. As an extension of the traditional value investing strategy, the quality investing strategy focuses on firms' fundamental performance, which may contain both value and growth characteristics of a stock. However, the quality of a firm is too vague to be defined straightforwardly. Existing studies used various measures to proxy firm quality, and they consistently find a positively significant return premium between high-quality firms and low-quality firms. For example, Piotroski (2000) combines nine fundamental indicators (covering the areas of firms' profitability, financial leverage/liquidity, and operating efficiency) and defines an F-score that differentiates high book-to-market stocks into high-quality and low-quality. He suggests that high BM firms with strong financial performance would significantly out perfume firms with high

B/M ratios alone. Piotroski and So (2012) further argue that the accounting-based value strategy remarkably outperforms the traditional value strategies. Moreover, Novy-Marx (2013) uses gross profitability as the quality measure and finds that controlling profitability could dramatically improve the value strategy performance. He finds that value and profitability strategies are negatively correlated. Therefore, the combination of two strategies reduces overall volatility but avoids doubling the risk. Besides, considering quality characteristics help traditional value investors find quality stocks at a reasonable price. Asness, Frazzini, and Pedersen (2019) propose a comprehensive quality measure (which captures the profitability, growth, safety, and payout characteristics of a firm) and distinguish between quality stocks from junk stocks. Above mentioned studies measure quality based on information available in accounting statements, while Jagannathan and Zhang (2020) propose a return-based method to identify high-quality stocks and find that high-quality firms perform better than other firms during stressful times.

On the other hand, valuation theory suggests that firms with high-quality (profitability) would have higher price (market-to-book ratio). Empirically, many studies documented that high-quality firms earn higher expected returns than low-quality firms, as well as having a much higher market-to-book ratio. Nevertheless, high market-to-book ratio firms (growth firms) are expected to earn lower expected returns than low market-to-book ratio firms (value firms). These empirical findings lead to the inconsistency of the valuation model.

Existing literature attempts to explain the above inconsistencies from behavioral perspectives. Piotroski and So (2012) suggest that quality premium is driven by the expectation errors correlated with historical financial information. Novy-Marx (2013) argues that the quality spread is not consistent with rational pricing. Asness, Frazzini, and Pedersen (2019) propose three possible explanations, including (a) the imperfect quality measure, (b) hidden risk component uncaptured by the quality measure, and (c) limited market efficiency. They rule out the first two explanations and attribute the quality premium partially to the market inefficiency explanation. All existing works suggest that it is hard to explain the quality premium using risk-based explanations.

To explain the source of quality spread from rational perspectives, we introduce volatility risk into the relationship between firm quality and the expected returns. Existing literature highlights the importance of volatility risk in explaining asset returns. Campbell *et al.* (2018) view the volatility risk from long-term investors' perspective. They argue that the co-movement with volatility is price in the stock returns. Assets with high sensitivities to market volatility hedge against the long-term fluctuations of investment opportunities, including declines in expected returns and increases in volatility. Long-term investor's desire to hedge volatility help explaining various cross-sectional asset returns, especially the value premium. Growth stocks help long-term investors hedge against the declines in the expected stock return because growth firms carry growth options that are valuable during high volatility periods. Therefore, growth firms perform well during hard times and naturally have low average returns. Bansal *et al.* (2014) link volatility news to the long-run consumption shocks and develop a framework where cash flow, discount rate and volatility risk could determine risk premia. They demonstrate that volatility risk generates significant positive risk premium and helps explain the value premium.

We argue that investors using fundamental analysis will pay serious attention to the volatility risk, because it could largely influence firms' future performance. For those high-quality firms with high profitability, earnings level, and prices, whether they could maintain their good performance in the uncertain future would be crucial when investors make investment decisions. Volatility would not be good news to those high-quality firms, because the higher the volatility, the more challenging it is to maintain good performance. In other words, the downside potential outweighs the upside potential for those good firms. Therefore, high-quality firms are more sensitive to volatility. On the other hand, volatility may have different effects on low-quality firms, because the upside potential outweighs the downside potential for those firms. There is much room for improvement for those low-quality firms compared to the high-quality firms. Hence, low-quality firms are less sensitive to the volatility, or even move negatively with the market volatility. We raise the following hypothesis:

Hypothesis 1: *High-quality firms are more sensitive to market volatility, and low-quality firms are less sensitive to market volatility.*

The asymmetric reaction to the volatility of high-quality and low-quality firms may help explain the quality premium. We conjecture that high-quality firms are more sensitive to volatility because volatility is considered a risk to those firms. Once the market investors recognize this characteristic, they will require additional compensation for bearing that risk, and the expected returns for high-quality firms are higher due to the volatility risk. Meanwhile, low-quality firms are less sensitive to volatility, and investors do not request additional compensation for the volatility risk. Therefore, we conjecture that asymmetric sensitivity to volatility drives the quality premium and propose the following hypothesis:

Hypothesis 2: *The quality premium will be reduced after considering the effect of volatility risk.*

3.3 Data and Empirical Design

In this section, we conduct portfolio analysis and regression analysis to investigate the unconditional and conditional performance of quality sorted portfolios and the effect of volatility risk on explaining the quality premium.

We collect stock returns and accounting information from the Center for Research in Security Prices (CRSP) daily and monthly stock files, and COMPUSTAT North America Fundamentals Quarterly and Annual databases. Our sample includes all available common stocks which have a CRSP share code of 10 or 11 or have a COMPUSTAT issue code of 0. We exclude stocks listed and traded on OTC exchanges. Following Shumway (1997), delisted stocks are assumed to have a -30% delisting return if their delisting return is missing. We match the accounting data for which the fiscal year ends anywhere in the calendar year t-1with the market information for June of the calendar year t to avoid look-ahead bias. The panel ranges from July 1957 to December 2020.

In this essay, we use a firm's *gross-profit-over-asset* (GPOA) to measure its quality. GPOA is calculated as the difference between revenue and cost of goods sold scaled by the total assets. MB is the natural logarithm of the ratio between firms' market equity and book equity, where book equity is defined as shareholder's equity minus preferred stock.[17] We winsorize firms' GPOA at the 1st and 99th percentile within each year to filter out the suspicious profitability measure and avoid the impact of extreme values. To measure the volatility risk, we conduct the following regression:

$$Return_{i,t} = \alpha + \boldsymbol{\beta} \times Market\ Volatility_{t-1} + \theta \times Market\ Return_t + \varepsilon_{i,t} \qquad (1)$$

where $Return_{i,t}$ is the firm excess return in month t, $Market\ Volatility_{t-1}$ is the rolling standard deviation of market index in month t-1, $Market\ Return_t$ is the market excess return in month t. The regression has a rolling window 5 years, with a restriction of minimum 3 years of monthly return observations. The β coefficient is the firm's sensitivity to volatility, or volatility risk.

We first assign stocks based solely on the GPOA or the volatility risk (unconditional single sorting) to prove the existence of quality spread and volatility risk spread. Next, we perform conditional double sorting (first on volatility risk then on GPOA, and first on GPOA then on consistence) to further understand the relationship between GPOA and volatility risk. Thirdly, we conduct cross-sectional regressions of selected testing assets to examine the volatility risk premium. Finally, we investigate whether the volatility risk factor could explain the quality premium.

3.3.1 Portfolio Strategy

At the end of each June, stocks are ranked in ascending order based on their GPOA and then we assign stocks into one of five portfolios. We calculate the monthly portfolio return as the value-weighted average returns of all stocks in the portfolio and

[17] We use stockholders' equity (SEQ) to measure the shareholders' equity. If stockholders' equity is not available, we use the summation of common equity (CEQ) and preferred stock (PSTK) instead.

rebalance portfolios every June. Next, we regress monthly portfolio returns of each GPOA-sorted portfolio as well as the long-short arbitrage portfolio on standard risk-factors used in various asset pricing models, which include the CAPM of Sharpe (1964), Sharpe (1964), and Mossin (1966) with the market factor (MKT); the Fama-French three-factor model of Fama and French (1993) with market (MKT), size (SMB), and value (HML) factors; and the Fama-French five-factor model of Fama and French (2015) with Fama and French three-factors plus the profitability (RMW) and investment (CMA) factors. The intercepts from the time-series regressions of monthly excess returns on these risk factors indicate whether the GPOA-sorted portfolios can generate abnormal returns (alphas). Regressions are specified below. Specification (2) stands for CAPM and Fama-French three-factor models. Specification (3) corresponds to Fama-French five-factor model.

$$r_t^e = \alpha + \beta^{MKT}\, MKT_t + \beta^{SMB}\, SMB_t + \beta^{HML}\, HML_t + \varepsilon_t \qquad (2)$$

$$r_t^e = \alpha + \beta^{MKT}\, MKT_t + \beta^{SMB}\, SMB_t + \beta^{HML}\, HML_t + \beta^{RMW} RMW_t + \beta^{CMA} CMA_t + \varepsilon_t \quad (3)$$

We then proceed to the performance of GOPA sorted portfolios after considering the effect of volatility risk. We first rank stocks in ascending order and sort five portfolios based on the firm’s volatility beta. Within each volatility beta quintile, we further sort five portfolios based on GPOA, forming twenty-five portfolios (Conditional double-sorting). Portfolio returns are the value-weighted average monthly returns of all stocks in the portfolio and are recalculated every June. We regress monthly portfolio returns of each GPOA-sorted portfolio as well as the long-short arbitrage portfolio on various asset pricing models to examine whether GPOA-sorted portfolios still generate abnormal returns across volatility risk groups. As a robustness test, we also conduct the conditional double-sorting on volatility beta after controlling the effect of GPOA to rule out the possibility that GPOA and volatility beta are capturing the same stock characteristic.

3.3.2 Cross-Sectional Regression

In this subsection, we conduct the two-step Fama and MacBeth (1973) cross-sectional regressions to further understand the relationship between GPOA and volatility risk. In this test, we use three groups of testing assets, including (1) Fama-French twenty-five size and BM portfolios; (2) five quality-sorted plus five size-sorted portfolios (total ten assets); and (3) ten quality-sorted plus ten size-sorted portfolios (total twenty assets). The first step is a time-series regression, where we regress testing assets' expected excess returns on the market volatility and market excess returns to estimate the volatility beta and market beta. Regression is specified below:

$$Return_{i,t+1} = \alpha_i + \boldsymbol{\beta_{vol,i}} \times Market\ Volatility_t + \beta_{mkt,i} \times Market\ Return_{t+1} + \varepsilon_{i,t} \quad (4)$$

where $Return_{i,t+1}$ is the excess return of testing assets in month t+1. This regression gives us firms' estimated exposures to market volatility and market excess returns. A rolling window of five years with minimum three years' observations are used to measure the volatility beta and market beta.

In the next step, we conduct the cross-sectional regression using the following specification:

$$Return_{i,t} = \lambda_{0,t} + \boldsymbol{\lambda_{vol,t}} \times \widehat{\boldsymbol{\beta}}_{vol,t} + \boldsymbol{\lambda_{mkt,t}} \times \widehat{\boldsymbol{\beta}}_{mkt,t} + \epsilon_{i,t} \quad (5)$$

where $\lambda_{vol,t}$ is the price of volatility risk in month t, and $\lambda_{mkt,t}$ is the price of market risk in month t. We proceed with taking the time-series average of the estimated risk $\lambda_{vol,t}$ and $\lambda_{mkt,t}$, and obtain the average price of risk $\hat{\lambda}$:

$$\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_t \tag{6}$$

In order to test whether the above estimated average price of risks are significantly different from zero, we calculate the standard errors by Newey and West (1987) adjusted for six lags.

3.3.3 Factor Analysis

To better understand the source of quality premium, we design the factor analysis and construct the volatility risk factor, which is the arbitrage portfolio between the high volatility beta portfolio (VB5) and low volatility beta portfolio (VB1). Next, we investigate whether the volatility risk factors have comparative explanatory power on the quality spread as the traditional risk factors. We regress the quality spread on risk factors used in traditional asset pricing models and the volatility risk factor. Asset pricing models include the CAPM of Sharpe (1964), Sharpe (1964), and Mossin (1966) with the market factor (MKT); the Fama-French three-factor model of Fama and French (1993) with market (MKT), size (SMB), and value (HML) factors and the Fama-French five-factor model of Fama and French (2015) with Fama and French three-factors plus the profitability (RMW) and investment (CMA) factors. Regressions are specified in Section 3.3.1. Specification (2) stands for CAPM and Fama-French three-factor models. Specification (3) corresponds to Fama-French five-factor model.

3.4 Empirical Results

Table 3.1 shows the result of unconditional single sorting on GPOA. We report the value-weighted GPOA, excess returns, asset pricing model alphas, market beta, and MB ratio of five GPOA-sorted portfolios. The excess return is calculated as the difference between the raw return and the one-month Treasury bill. Consistent with Novy-Marx (2013), we find a strong positive relationship between the GPOA and average returns, as well as the alphas. The high GPOA portfolio earns an average monthly excess return of 0.83% (t=5.10) in the subsequent month, and it generates positive and significant alphas with respect to different asset pricing models. On the other hand, the low GPOA portfolio has an average monthly excess return of 0.49% (t=2.42) and negatively significant alphas. Furthermore, GPOA5 has a much higher MB ratio and volatility beta than GPOA1, although GPOA5 has a lower market beta than GPOA1. More interestingly, the volatility beta is positive for high-quality portfolios and negative for low-quality portfolios, implying that the volatility risk has different effects on high- and low-quality firms. This result supports our Hypothesis 1 that high-quality firms are more sensitive to market volatility than low-quality firms.

Consequently, the long-short portfolio based on GPOA (GPOA5 − GPOA1) yields significant positive excess returns and asset pricing model alphas: the average monthly excess return of the GPOA arbitrage portfolio is 0.34% with t-statistics of 2.53. We can reject the null hypothesis that there is no return difference between high-quality and low-quality portfolio. Moreover, the alphas for the long-short arbitrage portfolio are positive and highly significant as well: 0.42% (t=3.06) for the CAPM, 0.69% (t=6.74) for Fama-French three-factor model, 0.55% (t=5.33) for Fama-French four-factor model, and

0.42% (t=3.99) for Fama-French five-factor model. Likewise, we can reject the null hypothesis that there is no alpha difference between high- and low-quality portfolios.

Table 3.2 shows the result of unconditional single sorting on volatility beta. We report the value-weighted volatility beta, excess returns, asset pricing model alphas, market beta, and MB ratio of five volatility beta-sorted portfolios. The high volatility beta portfolio earns an average monthly excess return of 1.06 % (t=4.06) in the subsequent month, and it generates positive alphas with respect to different asset pricing models. On the other hand, the low volatility beta portfolio has an average monthly excess return of 0.07% (t=0.22) and negatively significant alphas. Furthermore, high volatility beta portfolio has a slightly lower MB ratio and market beta than the low volatility beta portfolio. Consequently, the long-short portfolio based on volatility beta (VolBeta5 − VolBeta1) yields significant positive excess returns and asset pricing model alphas: the average monthly excess return of the volatility beta arbitrage portfolio is 0.99% with t-statistics of 2.32. We can reject the null hypothesis that there is no return difference between high volatility risk and low volatility risk portfolios. Moreover, the alphas for the long-short arbitrage portfolio are positive and highly significant as well: 0.99% (t=2.25) for the CAPM, 1.08% (t=2.36) for Fama-French three-factor model, 1.07% (t=2.35) for Fama-French four-factor model, and 1.12% (t=2.38) for Fama-French five-factor model. Likewise, we can reject the null hypothesis that there is no alpha difference between high-quality and low-quality portfolios. It is worth noting that the magnitude of volatility spread is significantly higher than the quality premium.

Tables 3.3 and 3.4 present the conditional double sorting results on GPOA and volatility beta. Table 3.3 shows the performance of GPOA sorted portfolios conditional on volatility beta. We find that in the lowest volatility beta group, the high GPOA portfolio (GPOA5) earns an average monthly excess return of 0.41% (t=1.23) in the subsequent month, and it generates negative CAPM model alpha. Moreover, the low GPOA portfolio has an average monthly excess return of -0.13 % (t=-0.35) and negatively significant CAPM model alpha of -0.89% (t= -3.14). The excess return difference between GPOA5 and GPOA1 is positively significant (0.54% with t=2.67), as well as the CAPM model alpha. Although, we cannot reject the null hypothesis that there is no return and alpha difference between GPOA5 and GPOA1. The quality premium still exists in the low volatility beta group. Meanwhile, in the highest volatility beta group, the high GPOA portfolio earns an average monthly excess return of 1.33% (t=4.78) in the subsequent month, while the low GPOA portfolio has an average monthly excess return of 1.08% (t=3.47). The excess return difference between GPOA5 and GPOA1 is now insignificant (0.25% with t=1.37), as well as the CAPM model alpha. Therefore, we cannot reject the null hypothesis that there is no return nor alpha difference between GPOA5 and GPOA1. We also find the quality premium (return spread between GPOA5 and GPOA) only remains significant in the low volatility beta quintile and is largely reduced in other volatility beta quintiles. The differences provide additional evidence that volatility risk may play a role in explaining the quality premium. Table 3.4 shows the performance of volatility beta sorted portfolios conditional on GPOA level. The excess return differences between VB5 and VB1 range from 0.69% to 1.29% per month, and most of the spreads are significant (four out of five quintiles). The CAPM alphas have similar patterns to the excess returns. We find that the return difference of volatility-based arbitrage portfolios is barely influenced by the effect of GPOA, suggesting that the volatility beta and GPOA may capture different characteristics of the firms. The conditional double sorting results is supportive to our Hypothesis 2 that the quality premium is less significant after considering the effect of volatility risk.

To prove that our empirical results are robust to different quality measures, we use the quality z-score proposed by Asness, Frazzini, and Pedersen (2019) to proxy firm quality and examine if the quality premium between high-quality z-score portfolio and low-quality z-score portfolio will be reduced after controlling the effect of volatility risk. Table 3.5 presents the results. Panel A of Table 3.5 shows the performance of quality z-score sorted portfolios conditional on volatility beta. We find that the results based on quality z-score are similar to the results based on GPOA. The excess return differences between portfolios Z5 and Z1 range from 0.11% to 0.63% per month, and most of the spreads are insignificant (four out of five quintiles). Panel B of Table 3.5 shows the performance of volatility beta sorted portfolios conditional on quality z-score. The excess return differences between portfolios VB5 and VB1 range from 0.72% to 1.64% per month, and all the spreads are significant. These results suggest that our findings are robust to different quality measures.

We next proceed with the cross-sectional test to further understand the relationship between quality premium and volatility risk. To conduct the Fama-MacBeth cross-sectional regression, we use three different groups of testing assets, including Fama-French twenty-five size and BM portfolios, five quality-sorted plus five size-sorted portfolios (total ten assets), and ten quality-sorted plus ten size-sorted portfolios (total twenty assets). Table 3.6 exhibits the results. Column (1) reports the cross-sectional regression results of Fama-French twenty-five size and BM portfolios' expected excess returns on the market index volatility and market excess returns. We find that the volatility beta loading is 0.00124 and significant at the 10% level, suggesting the average volatility risk premium is positive for those testing assets. Column (2) reports the cross-sectional regression results of five quality-sorted plus five size-sorted portfolios. For this group of assets, the average volatility risk loading is 0.00388 with a significance level of 1%. Similar for the ten quality-sorted plus ten size-sorted portfolios, column (3) shows that the average volatility risk loading is 0.00539 with a significance level of 1%. This test implies that the average volatility risk loading is positive for the overall market. Therefore, the volatility risk premium is positive for high-quality portfolios and negative for low-quality portfolios.

Finally, we examine whether the volatility risk factor could explain the quality spread and compare its explanatory power with the traditional asset pricing models. Panel A of Table 3.7 presents the explanatory power of volatility risk factor on the GPOA arbitrage portfolio (GPOA5 – GPOA1). Column (1) shows the CAPM model, and column (2) shows that when we regress the quality premium on volatility risk factor alone, the loading on volatility risk factor is 0.07985 and significant at 10%. Meanwhile, the alpha of the regression is 0.284%, which is 0.154% smaller than the CAPM alpha. In column (3), we regress quality premium on volatility risk factor and the market excess return, and the loading on volatility risk factor remains significant (0.07907 with t=1.90). Columns (4) and (5) present the regression results using Fama-French 3-factor model with and without the volatility risk factor. In this model, the volatility risk factor loses its significance after controlling HML and SMB factors. Interestingly, the volatility risk factor regains its significance in the Fama-French 5-factor model, and we report the results in columns (6) and (7). Column (7) shows that the loading on volatility risk factor is 0.04168 and significant at the 5% level. This test suggests that the volatility risk factor could partially explain the quality premium.

We further subdivide the sample into the high market volatility period and low market volatility period. If the monthly market index volatility is in the top 30% of the full sample, then this month is classified into the high market volatility period, and vice versa. Panel B of Table 3.7 presents the explanatory power of volatility risk factor on the GPOA arbitrage portfolio (GPOA5 – GPOA1) during the high market volatility period. We find that the explanatory power of volatility risk factor increases dramatically during the high market volatility period. The loadings of volatility risk factor are positive and significant across various asset pricing models and the alpha becomes insignificant after adding the volatility risk factor. We conclude that the volatility risk has a greater influence on high- and low-quality firms during the high market volatility period, therefore has more explanatory power during this period.

3.5 Conclusion

This essay provides a possible risk-based explanation of the quality premium and examines whether the volatility risk could explain the relationship between quality and expected returns. Our empirical results suggest that volatility could influence the magnitudes and significance of the quality premium. After controlling the effect of volatility risk, the quality premium is significantly reduced in most cases. However, controlling the quality barely influences the effect of volatility risk, suggesting that quality and volatility risk captures different sources of stock returns. Moreover, we find that firms with higher quality and lower quality will react differently to the market volatility. High-quality firms have positive volatility beta and volatility risk premium, while low-quality firms have negative volatility beta and volatility risk premium. Furthermore, we find that the volatility risk factor could partially explain the source of the quality premium, especially during the high market volatility period, suggesting volatility risk has a greater influence on high- and low-quality firms during the high market volatility period.

Table 3.1 Gross-Profit-over-Asset single sorting

This table shows the portfolio returns based on GPOA. The sample period covers from July 1957 to December 2020. At the end of each June, stocks are ranked in ascending order on the basis of their **GPOA** and are assigned to one of ten portfolios. Portfolios are value-weighted and rebalanced every June. The risk factors include the returns of the market (MKT), size (SMB), book-to-market (HML), profitability (RMW), and investment (CMA) portfolios. The bottom row reports returns/alphas of an arbitrage portfolio that longs the high GPOA portfolio (GPOA5) and shorts the low-GPOA portfolio (GPOA1). Returns and alphas are in monthly percentage, Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

	GPOA	**Excess return**	**CAPM alpha**	**3-factor alpha**	**4-factor alpha**	**5-factor alpha**	**Volatility Beta**	**Market Beta**	**Log(m/b)**
GPOA1	**0.07**	**0.49**	**-0.20**	**-0.37**	**-0.27**	**-0.19**	**-0.55**	1.09	0.46
	(11.70)	(2.42)	(-2.15)	(-4.74)	(-3.22)	(-2.35)	(-3.04)		
GPOA2	**0.17**	**0.56**	-0.05	**-0.14**	**-0.15**	**-0.15**	**-0.27**	0.95	0.62
	(29.62)	(3.47)	(-0.75)	(-2.70)	(-3.02)	(-2.98)	(-2.46)		
GPOA3	**0.30**	**0.66**	0.02	-0.02	-0.02	-0.08	-0.04	1.00	0.88
	(70.50)	(4.01)	(0.41)	(-0.35)	(-0.52)	(-1.47)	(-0.36)		
GPOA4	**0.44**	**0.67**	0.00	0.08	**0.13**	0.03	0.18	1.05	1.25
	(108.56)	(3.93)	(-0.04)	(1.57)	(2.49)	(0.52)	(1.56)		
GPOA5	**0.69**	**0.83**	**0.22**	**0.32**	**0.28**	**0.23**	0.09	0.95	1.60
	(137.29)	(5.10)	(3.10)	(5.20)	(4.78)	(3.44)	(0.76)		
G5 - G1	**0.63**	**0.34**	**0.42**	**0.69**	**0.55**	**0.42**	**0.65**	-0.14	1.14
	(103.04)	(2.53)	(3.06)	(6.74)	(5.33)	(3.99)	(2.61)		

Table 3.2 Volatility Risk single sorting

This table shows the portfolio returns based on volatility risk. The sample period covers from July 1957 to December 2020. At the end of each June, stocks are ranked in ascending order on the basis of their **volatility risk** (volatility beta) and are assigned to one of ten portfolios. Portfolios are value-weighted and rebalanced every June. The risk factors include the returns of the market (MKT), size (SMB), book-to-market (HML), profitability (RMW), and investment (CMA) portfolios. The bottom row reports returns/alphas of an arbitrage portfolio that longs the high volatility beta portfolio (VolBeta5) and shorts the low volatility beta portfolio (VolBeta1). Returns and alphas are in monthly percentage, Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

	VolBeta	**Excess return**	**CAPM alpha**	**3-factor alpha**	**4-factor alpha**	**5-factor alpha**	**Beta**	**Log(m/b)**
VolBeta1	**-5.23**	0.07	**-0.62**	**-0.69**	**-0.59**	**-0.62**	1.19	1.04
	(-20.96)	(0.22)	(-2.47)	(-2.59)	(-2.24)	(-2.27)		
VolBeta2	**-1.48**	0.39	-0.16	-0.19	**-0.20**	**-0.28**	0.94	1.02
	(-13.42)	(1.93)	(-1.59)	(-1.85)	(-2.01)	(-2.50)		
VolBeta3	**0.62**	**0.63**	**0.10**	0.08	**0.11**	-0.01	0.90	0.99
	(6.21)	(3.99)	(2.02)	(1.53)	(2.21)	(-0.13)		
VolBeta4	**2.76**	**0.74**	0.17	0.15	0.17	0.16	0.99	0.99
	(17.44)	(4.30)	(1.73)	(1.53)	(1.77)	(1.63)		
VolBeta5	**6.79**	**1.06**	0.37	0.40	**0.49**	**0.50**	1.18	0.99
	(20.07)	(4.06)	(1.73)	(1.83)	(2.22)	(2.19)		
VB5 - VB1	**12.02**	**0.99**	**0.99**	**1.08**	**1.07**	**1.12**	-0.01	-0.05
	(23.92)	(2.32)	(2.25)	(2.36)	(2.35)	(2.38)		

Table 3.3 Performance of GPOA Conditional on Volatility Risk

This table examines the performance of GPOA after controlling the effect of volatility risk. We report portfolios' excess returns and CAPM alpha in Panels A and B, respectively. The sample period is from July 1957 to December 2020. At the end of each month, stocks are ranked in ascending order first based on their volatility beta. Within each volatility beta quintile, we then sort stocks on the GPOA, forming 25 portfolios. Portfolios are value-weighted, and rebalanced every June. Alphas are the intercepts in various asset pricing models. The rightmost column reports return of an arbitrage portfolio that longs the high GPOA portfolio and shorts the low GPOA portfolios. Returns and alphas are in monthly percentages. Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the average returns and alphas, and 5% above statistical significance are indicated in bold.

Panel A: Excess return

Volatility Beta	**GPOA**					
	GPOA1	GPOA2	GPOA3	GPOA4	GPOA5	G5-G1
VB1	-0.13	-0.10	0.09	0.31	0.41	**0.54**
	(-0.35)	(-0.30)	(0.27)	(0.94)	(1.23)	(2.67)
VB2	0.44	0.34	0.42	**0.45**	**0.55**	0.12
	(1.82)	(1.63)	(1.94)	(1.97)	(2.57)	(0.70)
VB3	**0.62**	**0.45**	**0.63**	**0.62**	**0.76**	0.14
	(3.31)	(2.69)	(3.48)	(3.52)	(4.24)	(1.04)
VB4	**0.74**	**0.58**	**0.62**	**0.77**	**0.97**	0.23
	(3.85)	(3.27)	(3.33)	(3.87)	(5.12)	(1.57)
VB5	**1.08**	**0.89**	**1.06**	**0.93**	**1.33**	0.25
	(3.47)	(3.38)	(3.59)	(3.55)	(4.78)	(1.37)

Panel B: CAPM alpha

Volatility Beta	**GPOA**					
	GPOA1	GPOA2	GPOA3	GPOA4	GPOA5	G5-G1
VB1	**-0.89**	**-0.79**	**-0.60**	-0.36	-0.25	**0.64**
	(-3.14)	(-2.91)	(-2.29)	(-1.47)	(-1.00)	(3.17)
VB2	-0.19	-0.18	-0.15	-0.12	0.02	0.21
	(-1.33)	(-1.27)	(-1.18)	(-0.91)	(0.14)	(1.20)
VB3	0.05	-0.04	0.07	0.06	**0.24**	0.19
	(0.47)	(-0.44)	(0.91)	(0.78)	(2.52)	(1.36)
VB4	0.18	0.03	0.04	0.17	**0.40**	0.22
	(1.33)	(0.27)	(0.35)	(1.34)	(3.15)	(1.50)
VB5	0.36	0.23	0.35	0.25	**0.66**	0.30
	(1.31)	(1.02)	(1.46)	(1.13)	(2.72)	(1.66)

Table 3.4 Performance of Volatility Risk Conditional on GPOA

This table examines the performance of volatility risk after controlling the effect of GPOA. We report portfolios' excess returns and CAPM alpha in Panels A and B, respectively. The sample period is from July 1957 to December 2020. At the end of each month, stocks are ranked in ascending order first based on their GPOA. Within each GPOA quintile, we then sort stocks on the volatility beta, forming 25 portfolios. Portfolios are value-weighted, and rebalanced every June. Alphas are the intercepts in various asset pricing models. The rightmost column reports return of an arbitrage portfolio that longs the high volatility beta portfolio and shorts the low volatility beta portfolios. Returns and alphas are in monthly percentages. Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the average returns and alphas, and 5% above statistical significance are indicated in bold.

Panel A: Excess return

GOPA	**Volatility Beta**					
	VB1	VB2	VB3	VB4	VB5	VB5 – VB1
GPOA1	-0.19	0.45	**0.49**	**0.76**	**1.09**	**1.29**
	(-0.48)	(1.92)	(2.53)	(3.93)	(3.62)	(2.62)
GPOA2	-0.10	0.29	**0.48**	**0.59**	**0.95**	**1.05**
	(-0.30)	(1.41)	(2.80)	(3.39)	(3.65)	(2.52)
GPOA3	0.14	**0.51**	**0.63**	**0.67**	**1.07**	**0.93**
	(0.41)	(2.37)	(3.36)	(3.67)	(3.62)	(2.12)
GPOA4	0.31	0.33	**0.61**	**0.76**	**1.00**	0.69
	(0.97)	(1.44)	(3.51)	(3.74)	(3.78)	(1.70)
GPOA5	0.44	**0.54**	**0.83**	**0.97**	**1.42**	**0.99**
	(1.32)	(2.56)	(4.63)	(4.72)	(4.63)	(2.15)

Panel B: CAPM alpha

GOPA	**Volatility Beta**					
	VB1	VB2	VB3	VB4	VB5	VB5 – VB1
GPOA1	**-0.94**	-0.17	-0.07	0.19	0.38	**1.31**
	(-2.88)	(-1.20)	(-0.62)	(1.44)	(1.49)	(2.53)
GPOA2	**-0.78**	-0.24	-0.03	0.07	0.29	**1.06**
	(-2.95)	(-1.85)	(-0.29)	(0.52)	(1.31)	(2.47)
GPOA3	**-0.52**	-0.05	0.06	0.08	0.36	0.88
	(-2.05)	(-0.36)	(0.73)	(0.65)	(1.48)	(1.95)
GPOA4	-0.38	-0.25	0.04	0.15	0.30	0.68
	(-1.63)	(-1.85)	(0.41)	(1.21)	(1.33)	(1.63)
GPOA5	-0.21	0.00	**0.31**	**0.38**	**0.74**	**0.95**
	(-0.86)	(-0.02)	(3.15)	(2.71)	(2.76)	(2.02)

Table 3.5 Performance of Quality z-score Conditional on Volatility Risk

This table examines the performance of quality z-score (Asness, Frazzini, and Pedersen, 2019) after controlling the effect of volatility risk. We report portfolios' excess returns and CAPM alpha in Panels A and B, respectively. The sample period is from July 1957 to December 2020. At the end of each month, stocks are ranked in ascending order first based on their volatility beta. Within each volatility beta quintile, we then sort stocks on the quality z-score, forming 25 portfolios. Portfolios are value-weighted, and rebalanced every June. Alphas are the intercepts in various asset pricing models. The rightmost column reports return of an arbitrage portfolio that longs the high-quality z-score portfolio and shorts the low-quality z-score portfolios. Returns and alphas are in monthly percentages. Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the average returns and alphas, and 5% above statistical significance are indicated in bold.

Panel A: Conditional on Volatility Beta - Excess Returns

Volatility Beta	**Quality z-score**					
	Z1	Z2	Z3	Z4	Z5	Z5-Z1
VB1	-0.13	-0.10	0.09	0.31	0.41	**0.54**
	(-0.35)	(-0.30)	(0.27)	(0.94)	(1.23)	(2.67)
VB2	0.44	0.34	0.42	**0.45**	**0.55**	0.12
	(1.82)	(1.63)	(1.94)	(1.97)	(2.57)	(0.70)
VB3	**0.62**	**0.45**	**0.63**	**0.62**	**0.76**	0.14
	(3.31)	(2.69)	(3.48)	(3.52)	(4.24)	(1.04)
VB4	**0.74**	**0.58**	**0.62**	**0.77**	**0.97**	0.23
	(3.85)	(3.27)	(3.33)	(3.87)	(5.12)	(1.57)
VB5	**1.08**	**0.89**	**1.06**	**0.93**	**1.33**	0.25
	(3.47)	(3.38)	(3.59)	(3.55)	(4.78)	(1.37)

Panel B: Conditional on Quality z-score - Excess Returns

Quality z-score	**Volatility Beta**					
	VB1	VB2	VB3	VB4	VB5	VB5 – VB1
Z1	**-0.89**	**-0.79**	**-0.60**	-0.36	-0.25	**0.64**
	(-3.14)	(-2.91)	(-2.29)	(-1.47)	(-1.00)	(3.17)
Z2	-0.19	-0.18	-0.15	-0.12	0.02	0.21
	(-1.33)	(-1.27)	(-1.18)	(-0.91)	(0.14)	(1.20)
Z3	0.05	-0.04	0.07	0.06	**0.24**	0.19
	(0.47)	(-0.44)	(0.91)	(0.78)	(2.52)	(1.36)
Z4	0.18	0.03	0.04	0.17	**0.40**	0.22
	(1.33)	(0.27)	(0.35)	(1.34)	(3.15)	(1.50)
Z5	0.36	0.23	0.35	0.25	**0.66**	0.30
	(1.31)	(1.02)	(1.46)	(1.13)	(2.72)	(1.66)

Table 3.6 Volatility Risk Premium

This table reports the results of Fama-MacBeth cross-sectional regressions. The sample period is from July 1957 to December 2020. The regression has a rolling window of 5 years with a restriction of minimum 3 years' observations. Columns (1), (2), and (3) present the results with Fama-French 25 size and BM portfolios, 5 quality-sorted and 5 size-sorted portfolios, and 10 quality-sorted and 10 size-sorted portfolios, respectively.

	(1)	(2)	(3)
Testing Assets	FF 25 portfolios	Quality5 + Size5 10 portfolios	Quality10 + Size10 20 portfolios
$\hat{\lambda}_{mkt}$	-0.00262	-0.00286	-0.01007***
	(-0.85)	(-0.61)	(-2.62)
$\hat{\lambda}_{vol}$	0.00124*	0.00388***	0.00539***
	(1.96)	(3.01)	(4.08)
Constant	0.00974***	0.00910**	0.01660***
	(3.74)	(2.15)	(4.83)
Observations	19,050	7,620	15,240
R-squared	0.33411	0.49807	0.38275
Number of groups	762	762	762

Table 3.7 Factor Analysis

This table shows the performance of quality premium (GPOA5 − GPOA1) conditional on various asset pricing model risk factors and traditional risk factors plus volatility risk factor. The sample period is from July 1957 to December 2020. The dependent variables of panels A and B are the return of quality arbitrage portfolio. Panels A and B show the results in full sample and high market volatility subsample, respectively. Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	CAPM	Vol Risk	CAPM	FF3	FF3	FF5	FF5
Market excess return	-0.12984**		-0.12892***	-0.23161***	-0.22881***	-0.19400***	-0.19291***
	(-2.56)		(-2.72)	(-5.74)	(-5.89)	(-5.76)	(-5.87)
Volatility Risk Factor		0.07985*	0.07907*		0.02758		0.04168**
		(1.76)	(1.90)		(1.11)		(2.24)
HML				-0.80632***	-0.79771***	-0.91549***	-0.88855***
				(-11.46)	(-11.75)	(-11.05)	(-11.51)
SMB				-0.03607	-0.04254	0.10218**	0.09494**
				(-0.88)	(-0.99)	(2.12)	(1.97)
RMW						0.57780***	0.58523***
						(7.13)	(7.51)
CMA						0.22374**	0.19379*
						(2.12)	(1.88)
Constant	0.00438***	0.00284**	0.00359***	0.00712***	0.00682***	0.00420***	0.00373***
	(2.97)	(2.07)	(2.60)	(6.58)	(6.56)	(3.99)	(3.65)
R-squared	0.02461	0.01741	0.04172	0.40158	0.40296	0.50747	0.51169
Observations	762	762	762	762	762	690	690

Panel B: High Market Volatility Subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	CAPM	Vol Risk	CAPM	FF3	FF3	FF5	FF5
Market excess return	-0.22393*		-0.22778**	-0.33141***	-0.32513***	-0.25306***	-0.24919***
	(-1.92)		(-2.30)	(-4.07)	(-4.46)	(-4.55)	(-5.05)
Volatility Risk Factor		0.16419**	0.16685**		0.07894**		0.08354***
		(2.07)	(2.55)		(2.18)		(3.20)
HML				-0.87420***	-0.83736***	-1.09245***	-1.04232***
				(-7.37)	(-7.73)	(-8.68)	(-9.24)
SMB				-0.06588	-0.08469	0.14706*	0.12986
				(-0.92)	(-1.14)	(1.73)	(1.59)
RMW						0.67598***	0.68169***
						(5.74)	(6.19)
CMA						0.19575	0.17229
						(1.27)	(1.19)
Constant	0.00679*	-0.00510	-0.00301	0.00731***	0.00277	0.00341	-0.00131
	(1.87)	(-1.01)	(-0.68)	(2.79)	(0.93)	(1.63)	(-0.50)
R-squared	0.06025	0.06399	0.12631	0.45679	0.47056	0.58230	0.59787
Observations	228	228	228	228	228	220	220

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APPENDIX

Appendix A. Quality Ordinal Measure Constructions

We measure a firm's quality from profitability, growth, safety, and payout four aspects. For profitability, we average ordinal-measures of gross profits over assets, return on equity, return on assets, cash flow over assets, gross margin, and the fraction of earnings composed of cash:

$$\text{Profitability} = o(ogpoa + oroe + oroa + ocfoa + ogmar + oacc) \qquad \text{(A1)}$$

Growth is measured as the five-year growth in residual profitability measures scaled by the split-adjusted number of share outstanding:[18]

$$\text{Growth} = o(o\Delta\ \text{gpoa} + o\Delta\ \text{roe} + o\Delta\ \text{roa} + o\Delta\ \text{cfoa} + o\Delta\ \text{gmar}) \qquad \text{(A2)}$$

We use beta, leverage, bankruptcy risk (O-Score and Z-Score), and ROE volatility to value safety. Here, beta is the negative market beta estimated in Frazzini and Pedersen (2014).

$$\text{Safety} = o(obab + olev + oo + oz + oevol) \qquad \text{(A3)}$$

Payout is measured by considering net equity issuance, net debt issuance, and total net payout over profits.

$$\text{Payout} = o(o\text{eiss} + o\text{diss} + o\text{npop}) \qquad \text{(A4)}$$

[18] Please refer to the Table A1 in Appendix for detailed quality variable constructions.

Finally, we combine the four component measures into a single measure, make the aggregate ordinal-measure of it, and obtain:

$$\text{Quality Ordinal Measure} = o(\text{Profitability} + \text{Growth} + \text{Safety} + \text{Payout}) \qquad \text{(A5)}$$

Figure A1 Timeline of Data Alignment

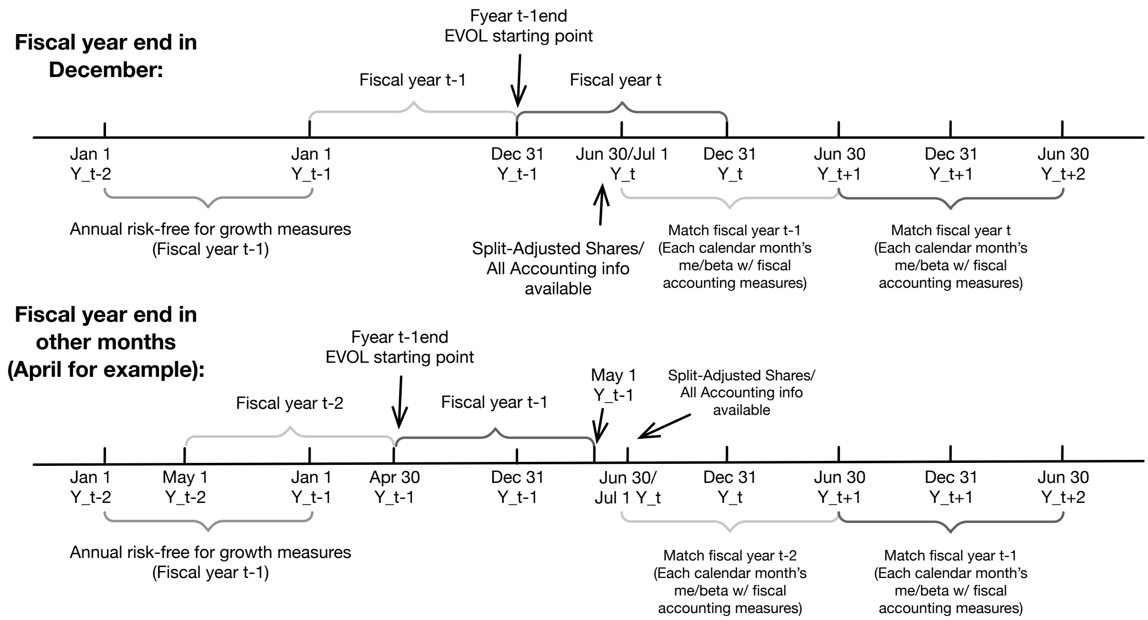

Table A1. Variable Descriptions

This table shows the detailed variable definition and construction. Following Asness, Frazzini, and Pedersen (2019), our quality variable definitions are based on Altman (1968); Ohlson (1980), Ang et al. (2006b); Daniel and Titman (2006); Penman (2007); Campbell et al. (2008); Novy-Marx (2012); Frazzini and Pedersen (2014); and Asness and Frazzini (2013); All accounting variables are based on the most recent information available as of June 30th of each year (Detailed alignments are shown in Figure A1). Variable names in calculation correspond to CRSP and Compustat data items (annual). Time subscripts refer to years.

Group	**Variable**	**Descriptions**	**Calculation/Source of Data**
Profitability	GPOA	Gross Profits Over Assets: revenue minus costs of goods sold divided by total assets	$(REV\ T - COGS)/AT$
	ROE	Return On Equity: net income divided by book-equity	IB/BE
	ROA	Return On Asset: net income divided by total assets	IB/AT
	CFOA	Cash Flow Over Assets: net income plus depreciation minus changes in working capital and capital expenditures divided by total assets	$(NB + DP - \Delta WC - CAPX)/AT.$
	GMAR	Gross Margin: revenue minus costs of goods sold divided by total sales	$(REV\ T - COGS)/SALE.$
	ACC	Low Accruals: depreciation minus changes in working capital	$-(\Delta WC - DP)/AT.$
Growth	$\Delta gpoa$	Five-year growth in residual gross profits over assets	$gpt - rfatt{-}1 - gpt{-}5 - rfatt{-}6/att{-}5$
	Δroe	Five-year growth in residual return on equity	$ibt - rfbet{-}1 - ibt{-}5 - rfbet{-}6/bet{-}5$
	Δroa	Five-year growth in residual return over assets	$ibt - \kappa fat{-}1 - ibt{-}5 - rfat{-}6/at{-}5$
	$\Delta cfoa$	Five-year growth in residual cash flow over assets	$(cft - rfat{-}1) - cft{-}5 - rfat{-}6/att{-}5$
	$\Delta gmar$	Five-year growth in gross margin	$(gp_t - gp_{t-5})/\mathrm{sale}_{t-5}$
Safety	BAB	Low Beta: minus market beta (product of the rolling one-year daily standard deviation and the rolling five-year three-day correlations. rolling five-year three-day correlations)	$-\left[\hat{\beta}_i^{ts} = \rho \frac{\hat{\sigma}_\iota}{\widehat{\sigma_m}}\right]$
	LEV	Low Average: minus total debt (the sum of long-term debt, short-term debt, minority interest, and preferred stock) over total assets	$-(DLTT + DLC + MIBT + PSTK)/AT.$
	EVOL	Low Earnings Volatility: standard deviation of quarterly ROE over the past 60 quarters	

	Z	retained earnings, earnings before interest and taxes, market equity, and sales, all over total assets	Z = (1.2WC+1.4RE+3.3EBIT+0.6ME+SALE)/AT
Payout	EISS	minus one-year percentage change in split-adjusted number of shares	$-\log(\text{SHROUT\_ADJ}_t/\text{SHROUT\_ADJ}_{t-1})$
	DISS	minus one-year percentage change in total debt	$-\log(TOTD_t/TOTD_{t-1})$.
	NPOP	the sum of total net payout over the past 5 yrs divided by total profits over the past 5 yrs	
Mid-step Variables	WC	Working Capital: current assets minus current liabilities minus cash and short-term instruments plus short-term debt and income taxes payable	$ACT - LCT - CHE + DLC + TXP$
	SHEQ	Shareholders' Equity: stockholders' equity,	SEQ
		the sum of common equity and preferred stock,	$CEQ + PSTK$
		and total assets minus the sum of total liability and minority interest due to availability	$AT - (LT + MIB)$
	PST	Preferred Stock: with the priority of PSTKRV, PSTKL, and PSTK.	
	BE	Book Equity: shareholders' equity minus preferred stock.	$SHEQ - PST$
	ADJ ASSET	Adjusted Total Assets: total assets plus 10% of the difference between book equity and market equity	$AT + 0.1 \times (ME - BE)$.
	CPI	Consumer Price Index	
	TLTA	Book value of debt (DLC + DLTT) divided by ADJASSET	$(DLC + DLTT)/ADJASSET$
	WCTA	Current assets minus current liabilities scaled by adjusted assets	$(ACT - LCT)/ADJASSET$
	CLCA	Current liabilities divided by current assets	LCT/ACT
	OENEG	Dummy equal to 1 if total liabilities exceed total assets	$1(LT > AT)$
	NITA	Net income over assets	IB/AT

	FUTL	Pre-tax income over total liabilities	PT/LT
	INTWO	Dummy equal to one if net income is negative for the current and prior fiscal year	$1(MAX\{IBt, IBt-1\} < 0)$.
	CHIN	Vhanges in net income	$(IB_t - IB_{t-1})/(\lvert IB\rvert_t + \lvert IB_{t-1}\rvert)$
	INTWO	Dummy equal to one if net income is negative for the current and prior fiscal year	$1(MAX\{IBt, IBt-1\} < 0)$.
Macroeconomic	PROD	Long-run Production growth, proxied by the growth of industrial production index	$INDPRO_t/INDPRO_{t-12} - 1$
	CONSUMP	Consumption growth, proxied by the growth of log consumption index. Consumption index is interpolated to monthly frequency.	$CONSUMP_t/CONSUMP_{t-1} - 1$
	GDP_{GR}	GDP growth, proxied by the growth of Real GDP. Real GDP is interpolated to monthly frequency.	$RealGDP_t/RealGDP_{t-1} - 1$
	GDP_{GAP}	GDP gap, proxied by the difference between the actual gross domestic product (GDP) and the potential GDP	$GDPActual - GDPPotential$
Risk-related	Amihud_{modify}	Amihud (2002) illiquidity measure modified by Acharya and Pedersen (2005)	$c^i_t = \min 0.25 + 0.30 ILLIQ^i_t P^M_{t-1}, 30.00$
	Δ VXO	Changes in the VXO index (the implied volatility of S&P 100 index options)	Chicago Board Options Exchange Database
	CREDIT	Credit Spread, proxied by the Moody's BAA bond yield in excess of 10-year Treasury yield	Federal Reserve Economic Data
	TERM	Term Spread, proxied by 10-year treasury yield in excess of 3-month treasury rate	Federal Reserve Economic Data
	TED	Ted Spread, proxied by the difference between the three-month LIBOR and the three-month Treasury bill	Federal Reserve Economic Data
	Risk-Aversion Index	A measure of time-varying risk aversion proposed in Bekaert et al. (2019)	https: //www.nancyxu.net/risk-aversion-index
	IVOL	Aggregate idiosyncratic volatility	
	CAPE	Cyclically Adjusted PE Ratio (CAPE Ratio) by Robert Shiller	http: //www.econ.yale.edu/~shiller/data.htm
Uncertainty	Time-varying Uncertainty	A measure of time-varying uncertainty proposed in Bekaert et al. (2019)	https: //www.nancyxu.net/risk-aversion-index
	Financial, Macro, Real Uncertainty	Financial, Macro, and Real Uncertainty Index from Jurado et al. (2015)	https://www.sydneyludvigson.com

Behavioral	Casino	Quarterly time series of profits for the casino industry scaled by nominal gross domestic product (GDP).	(REVTQ - COGSQ)/GDP(Nominal)
	Sentiment Index	The sentiment index in Baker and Wurgler (2006)	http://people.stern.nyu.edu/jwurgler/
	Consumer Sentiment	University of Michigan Consumer Sentiment Index	http://www.sca.isr.umich.edu

Table A2. Quality Measure-Sorted Portfolios Performance

This table shows the portfolio quality, raw returns, excess returns, asset pricing model alphas, and portfolio characteristics. The sample period covers from July 1957 to December 2020. At the end of each month, stocks are ranked in ascending order on the basis of their quality ordinal measure (QOM) or gross-profit-over-asset (GPOA) and are assigned to one of five portfolios based on NYSE breakpoint. Portfolios are value-weighted, and rebalanced at the end of each month. Panels A and C shows the returns and alphas of portfolios sorted based on quality ordinal measure (QOM) and gross-profit-over-asset (GPOA), respectively. The bottom row reports returns/alphas of an arbitrage portfolio that longs the strong-quality portfolio (Q5) and shorts the weak-quality portfolio (Q1). Returns and alphas are in monthly percentage, Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. Panels B and D reports the characteristics of portfolios sorted based on quality ordinal measure (QOM) and gross-profit-over-asset (GPOA), respectively. We report portfolios' log (M/B) Ratio, Size, Age, Market Beta, Volatility, Skewness, Kurtosis, and Sharpe ratio. Beta is the loading of the market portfolio in CAPM. Volatility is the standard deviation of excess returns in percentage. Sharpe ratios is annualized. The adjusted R^2 is the R^2 of the Fama-French five-factor model.

Panel A: Portfolio Excess return and Alphas - (Quality based on Ordinal Measure)

	Quality	Raw Return	Excess Return	CAPM Alpha	3-factor Alpha	5-factor Alpha	q-factor Alpha	Adjusted *R*2
Q1	**0.15**	**0.73**	0.38	**-0.34**	**-0.46**	**-0.34**	**-0.33**	93.73%
	(48.87)	(3.17)	(1.61)	(-3.72)	(-5.34)	(-4.80)	(-3.67)	
Q2	**0.35**	**0.94**	**0.58**	-0.03	**-0.13**	**-0.13**	-0.12	94.03%
	(99.36)	(4.99)	(3.06)	(-0.54)	(-2.64)	(-2.55)	(-1.64)	
Q3	**0.53**	**0.86**	**0.51**	-0.07	**-0.13**	**-0.13**	**-0.14**	95.01%
	(174.36)	(5.01)	(2.90)	(-1.68)	(-3.36)	(-3.32)	(-2.91)	
Q4	**0.71**	**0.97**	**0.62**	0.05	0.04	0.00	-0.02	95.83%
	(264.83)	(6.06)	(3.79)	(1.41)	(1.24)	(0.04)	(-0.60)	
Q5	**0.90**	**1.05**	**0.69**	**0.15**	**0.22**	**0.18**	**0.19**	96.29%
	(504.21)	(6.62)	(4.29)	(3.37)	(6.17)	(5.03)	(4.36)	
Q5 - Q1	**0.75**	**0.31**	**0.31**	**0.49**	**0.68**	**0.52**	**0.52**	64.57%
	(273.68)	(2.33)	(2.33)	(3.90)	(6.17)	(5.52)	(4.30)	

Panel B: Portfolio Characteristics - (Quality based on Ordinal Measure)

	MB	Size	Age (Year)	Beta	Volatility	Skewness	Kurtosis	Sharpe Ratio
Q1	0.62	603.17	10.65	1.24	5.87	-0.48	5.62	0.22
Q2	0.64	1217.14	13.55	1.06	4.90	-0.53	5.51	0.41
Q3	0.77	1602.41	14.07	1.00	4.54	-0.50	5.06	0.39
Q4	1.01	2403.90	14.41	0.98	4.42	-0.35	4.68	0.48
Q5	1.40	4296.42	13.69	0.93	4.23	-0.40	4.57	0.57
Q5 - Q1	0.79	3693.24	3.05	-0.31	3.22	0.01	5.41	0.34

Table A2 Continued

Panel C: Portfolio Excess return and Alphas (Quality based on GPOA)

	GPOA	Raw Return	Excess Return	CAPM Alpha	3-factor Alpha	5-factor Alpha	q-factor Alpha	Adjusted *R2*
GPOA1	**0.07**	**0.79**	**0.44**	-0.15	**-0.29**	**-0.15**	**-0.26**	89.38%
	(17.97)	(4.06)	(2.22)	(-1.82)	(-4.65)	(-2.48)	(-2.92)	
GPOA 2	**0.18**	**0.80**	**0.45**	-0.11	**-0.20**	**-0.20**	**-0.19**	90.75%
	(51.43)	(4.66)	(2.58)	(-1.46)	(-3.21)	(-3.10)	(-2.38)	
GPOA 3	**0.28**	**0.98**	**0.62**	0.04	0.00	-0.05	0.01	91.67%
	(83.05)	(5.63)	(3.52)	(0.74)	(0.07)	(-0.91)	(0.20)	
GPOA 4	**0.41**	**0.96**	**0.60**	0.00	0.07	0.07	**0.15**	92.58%
	(113.25)	(5.46)	(3.37)	(-0.09)	(1.45)	(1.25)	(2.01)	
GPOA 5	**0.67**	**1.12**	**0.76**	**0.20**	**0.30**	**0.20**	**0.16**	91.26%
	(129.61)	(6.49)	(4.34)	(2.75)	(4.85)	(3.17)	(2.18)	
GPOA 5 - 1	**0.60**	**0.32**	**0.32**	**0.35**	**0.59**	**0.35**	**0.42**	48.67%
	(148.03)	(2.58)	(2.58)	(2.69)	(6.53)	(3.85)	(3.15)	

Panel D: Portfolio Characteristics - (Quality based on GPOA)

	MB	Size	Age (Year)	Beta	Volatility	Skewness	Kurtosis	Sharpe Ratio
GPOA 1	0.53	1259.60	11.84	1.01	4.91	-0.50	5.20	0.31
GPOA 2	0.68	2108.68	14.93	0.96	4.53	-0.45	5.61	0.34
GPOA 3	0.92	2165.72	13.94	1.00	4.62	-0.43	4.81	0.46
GPOA 4	1.23	2478.62	13.79	1.05	4.86	-0.44	4.73	0.43
GPOA 5	1.63	1927.60	12.46	0.97	4.58	-0.34	4.73	0.57
GPOA 5 - 1	1.10	668.01	0.61	-0.05	3.04	0.04	3.70	0.37

Table A3. MB-Sorted Portfolios Performance

This table shows the portfolio log(M/B) ratio, raw returns, excess returns, asset pricing model alphas, and portfolio characteristics. The sample period covers from July 1957 to December 2020. At the end of each month, stocks are ranked in ascending order on the basis of their Cheapness Measure and are assigned to one of five portfolios. Portfolios are value-weighted, and rebalanced at the end of each month. The risk factors include the returns of the market (MKT), size (SMB), book-to-market (HML), profitability (RMW/ROE), and investment (CMA/INV) portfolios. Panel A shows the returns and alphas of portfolios sorted based on log(M/B) ratio. The bottom row reports returns/alphas of an arbitrage portfolio that longs the value portfolio (MB1) and shorts the growth portfolio (MB5). Returns and alphas are in monthly percentage, Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. Panel B reports the characteristics of portfolios sorted based on log(M/B) ratio. We report portfolios' Size, Age, Market Beta, Volatility, Skewness, Kurtosis, and Sharpe ratio. Beta is the loading of the market portfolio in CAPM. Volatility is the standard deviation of excess returns in percentage. Sharpe ratios is annualized. The adjusted R^2 is the $R^2$of Fama-French five-factor model.

Panel A: Portfolio Excess return and Alphas

	MB	**Raw Return**	**Excess Return**	**CAPM Alpha**	**3-factor Alpha**	**5-factor Alpha**	**q-factor Alpha**	**Adjusted** *R2*
MB1	**-0.28**	**1.22**	**0.86**	0.19	-0.13	0.03	0.29	84.22%
	(-10.57)	(5.08)	(3.59)	(1.27)	(-1.31)	(0.25)	(1.60)	
MB 2	**0.21**	**1.09**	**0.73**	0.18	-0.03	0.02	0.09	89.86%
	(8.39)	(5.84)	(3.93)	(1.85)	(-0.54)	(0.35)	(0.80)	
MB 3	**0.55**	**0.99**	**0.63**	0.11	-0.03	-0.10	-0.05	90.83%
	(19.87)	(6.30)	(3.97)	(1.33)	(-0.46)	(-1.56)	(-0.61)	
MB 4	**0.93**	**0.87**	**0.51**	-0.04	-0.07	**-0.16**	**-0.18**	93.11%
	(31.48)	(5.39)	(3.14)	(-0.70)	(-1.32)	(-3.07)	(-2.84)	
MB 5	**1.82**	**0.92**	**0.57**	-0.03	**0.10**	0.05	-0.03	96.68%
	(45.60)	(5.06)	(3.05)	(-0.54)	(2.62)	(1.11)	(-0.45)	
MB 5 - MB 1	**-2.09**	0.30	0.30	0.22	**-0.23**	-0.01	0.32	62.37%
	(-64.16)	(1.58)	(1.58)	(1.14)	(-2.03)	(-0.09)	(1.45)	

Panel B: Portfolio Characteristics

	Size	**Age (Year)**	**Beta**	**Volatility**	**Skewness**	**Kurtosis**	**Sharpe Ratio**
MB 1	560.37	12.72	1.17	6.23	0.40	8.59	0.48
MB 2	1179.32	14.47	0.96	4.79	-0.27	6.63	0.53
MB 3	1794.31	14.84	0.91	4.36	-0.34	5.62	0.50
MB 4	2700.18	13.81	0.96	4.42	-0.57	5.32	0.40
MB 5	3735.81	11.08	1.04	4.79	-0.38	4.58	0.41
MB 5 - MB 1	-3175.44	1.64	0.13	4.61	1.06	10.84	0.22

Table A4. Independent Double-sorted Portfolio Performance (Quality ordinal measure & Market-to-Book)

This table shows the two-way portfolios' excess returns and asset pricing model alphas based on traditional quality (quality ordinal measure) and value (market-to-book ratio) measures. The sample period covers from July 1957 to December 2020. At the end of each month, stocks are ranked in ascending order on the basis of their quality ordinal measure and market-to-book ratio independently. Then, we take the intersection of "quality" and "value" stocks and form 25 portfolios. Portfolios are value-weighted, and rebalanced at the end of each month. The explanatory variables are the returns of the market (MKT), size (SMB), book-to-market (HML), profitability (RMW/ROE), and investment (CMA/INV) portfolios. The rightmost column reports return of an arbitrage portfolio that longs the Value portfolio (MB1) and shorts the Growth portfolio (MB5), and the lowest row reports returns of an arbitrage portfolio that longs the high-quality portfolio (Q5) and shorts the low-quality portfolio (Q1). The lower right corner reports the returns of an arbitrage portfolio that longs the high-quality/value portfolio (Q5/MB1) and shorts the low-quality/growth portfolio (Q1/MB5). Returns and alphas are in monthly percentages. Newey-West auto-correlation corrected t-statistics with a lag length of 6 periods are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

Panel A: Excess return

Quality	MB					MB 1-5
	MB 1	MB 2	MB 3	MB 4	MB 5	
Q1	**0.72**	0.47	0.39	0.22	0.33	0.40
	(2.40)	(1.89)	(1.89)	(0.98)	(1.08)	(1.53)
Q2	**0.83**	**0.78**	**0.47**	**0.47**	**0.59**	0.24
	(3.56)	(4.04)	(2.52)	(2.35)	(2.36)	(1.15)
Q3	**0.95**	**0.76**	**0.45**	**0.41**	0.41	**0.55**
	(4.20)	(4.10)	(2.74)	(2.23)	(1.78)	(2.83)
Q4	**1.07**	**0.89**	**0.79**	**0.49**	**0.57**	**0.49**
	(4.63)	(4.92)	(4.73)	(2.95)	(2.87)	(2.37)
Q5	**1.16**	**1.01**	**0.88**	**0.73**	**0.65**	**0.51**
	(5.39)	(5.19)	(5.19)	(4.58)	(3.68)	(2.64)
Q5-Q1	**0.44**	**0.54**	**0.50**	**0.51**	0.33	**0.85**
	(2.17)	(3.47)	(3.87)	(3.63)	(1.59)	(3.24)

Panel B: CAPM alpha

Quality	MB					MB 1-5
	MB 1	MB 2	MB 3	MB 4	MB 5	
Q1	-0.06	-0.20	**-0.26**	**-0.47**	**-0.49**	0.43
	(-0.30)	(-1.65)	(-2.26)	(-4.00)	(-2.79)	(1.65)
Q2	0.17	**0.22**	-0.09	-0.15	-0.13	0.30
	(1.11)	(2.05)	(-0.87)	(-1.59)	(-1.10)	(1.49)
Q3	**0.32**	**0.22**	-0.06	**-0.17**	**-0.27**	**0.58**
	(2.17)	(2.22)	(-0.59)	(-2.13)	(-2.82)	(2.97)
Q4	**0.45**	**0.37**	**0.27**	-0.06	-0.06	**0.51**
	(2.79)	(2.90)	(2.68)	(-0.73)	(-0.72)	(2.42)
Q5	**0.57**	**0.47**	**0.38**	**0.22**	0.09	**0.48**
	(3.66)	(3.47)	(3.67)	(2.84)	(1.19)	(2.41)
Q5-Q1	**0.63**	**0.68**	**0.64**	**0.69**	**0.58**	**1.08**
	(3.34)	(4.67)	(5.01)	(5.33)	(3.14)	(4.24)

Panel C: 3-factor alpha

Quality	MB					MB 1-5
	MB 1	MB 2	MB 3	MB 4	MB 5	
Q1	**-0.42**	**-0.44**	**-0.41**	**-0.56**	**-0.37**	-0.05
	(-2.81)	(-4.62)	(-4.08)	(-5.03)	(-2.44)	(-0.26)
Q2	-0.14	0.02	**-0.23**	**-0.21**	-0.04	-0.10
	(-1.30)	(0.19)	(-2.65)	(-2.33)	(-0.35)	(-0.65)
Q3	0.02	0.02	**-0.18**	**-0.20**	-0.13	0.16
	(0.25)	(0.31)	(-2.16)	(-2.70)	(-1.59)	(1.18)
Q4	0.16	0.16	0.12	-0.08	0.07	0.10
	(1.36)	(1.70)	(1.52)	(-1.05)	(1.08)	(0.67)
Q5	**0.30**	**0.29**	**0.27**	**0.19**	**0.23**	0.08
	(2.42)	(2.63)	(2.96)	(2.67)	(3.69)	(0.53)
Q5-Q1	**0.72**	**0.74**	**0.67**	**0.75**	**0.60**	**0.69**
	(3.68)	(5.02)	(5.19)	(5.90)	(3.48)	(3.37)

Panel D: 5-factor alpha

Quality	MB					MB 1-5
	MB 1	MB 2	MB 3	MB 4	MB 5	
Q1	-0.19	**-0.31**	**-0.38**	**-0.53**	**-0.35**	0.16
	(-1.08)	(-2.85)	(-3.51)	(-4.55)	(-2.94)	(0.77)
Q2	-0.07	0.05	**-0.32**	**-0.26**	-0.03	-0.03
	(-0.55)	(0.60)	(-3.65)	(-2.77)	(-0.27)	(-0.19)
Q3	0.15	0.06	**-0.24**	**-0.33**	**-0.21**	**0.36**
	(1.01)	(0.67)	(-2.48)	(-4.33)	(-2.43)	(1.98)
Q4	0.23	0.15	0.00	**-0.18**	-0.03	0.26
	(1.51)	(1.48)	(0.04)	(-2.44)	(-0.38)	(1.38)
Q5	**0.30**	0.23	**0.21**	0.05	**0.17**	0.13
	(2.24)	(1.83)	(2.34)	(0.65)	(2.76)	(0.85)
Q5-Q1	**0.49**	**0.55**	**0.59**	**0.58**	**0.52**	**0.65**
	(2.49)	(3.59)	(4.31)	(4.54)	(3.60)	(3.49)

Panel E: q-factor alpha

Quality	MB					MB 1-5
	MB 1	MB 2	MB 3	MB 4	MB 5	
Q1	0.09	-0.22	**-0.40**	**-0.62**	**-0.46**	0.55
	(0.41)	(-1.55)	(-3.36)	(-4.51)	(-2.81)	(1.77)
Q2	0.19	0.12	**-0.34**	**-0.31**	-0.09	0.28
	(1.06)	(1.03)	(-3.14)	(-2.73)	(-0.61)	(1.18)
Q3	**0.42**	0.10	-0.21	**-0.36**	**-0.36**	**0.77**
	(2.10)	(0.77)	(-1.78)	(-4.03)	(-3.56)	(3.06)
Q4	**0.46**	0.18	0.08	**-0.24**	-0.09	**0.55**
	(2.28)	(1.35)	(0.77)	(-2.98)	(-1.08)	(2.27)
Q5	**0.51**	**0.44**	**0.33**	0.10	0.12	**0.39**
	(3.01)	(2.69)	(2.89)	(1.23)	(1.61)	(1.99)
Q5-Q1	0.42	**0.65**	**0.73**	**0.72**	**0.58**	**0.97**
	(1.75)	(3.86)	(4.91)	(4.76)	(3.32)	(3.57)

Table A5. Portfolio Performance in Good and Bad Market

This table shows the average monthly excess returns of *QC*, *CQ*, and market portfolios in good and bad market conditions. The full sample period covers from July 1957 to December 2020. We define good market time as the months in which the market index return is higher than or equal to the time-series average market returns. Bad market time is defined as the months in which the market index return is lower than the time-series average market returns. Returns with t-statistics of 5% statistical significance are indicated in bold.

		***QC*5 – *QC*1**	***CQ*1-*CQ*5**	**Market Excess Returns**
Quality Ordinal Measure	Good Market	**0.46%**	**1.16%**	**3.63%**
		(2.55)	(7.23)	(29.77)
	Bad Market	**0.90%**	-0.03%	**-3.12%**
		(4.41)	(-0.19)	(-17.90)
Gross-profit-over-asset	Good Market	0.30%	**1.20%**	**3.63%**
		(1.63)	(6.61)	(29.77)
	Bad Market	**0.78%**	-0.16%	**-3.12%**
		(4.06)	(-0.89)	(-17.90)

Table A6. Cultural Dimensions Across Countries

This table reports Hofstede's Individualism Index, Uncertainty Avoidance Index, and Indulgence Index for each of 37 countries in our sample.

Country Name	**Individualism Index**	**Uncertainty Avoidance Index**	**Indulgence Index**
Pakistan	14	70	0.00
Indonesia	14	48	37.72
Taiwan	17	69	49.11
Korea South	18	85	29.46
Vietnam	20	30	35.49
China	20	30	23.66
Singapore	20	8	45.54
Thailand	20	64	45.09
Bangladesh	20	60	19.64
Chile	23	86	68.00
Hong Kong	25	29	16.96
Malaysia	26	36	57.14
Romania	30	90	19.87
Philippines	32	44	41.96
Greece	35	112	49.55
Turkey	37	85	49.11
Brazil	38	76	59.15
Russia	39	95	19.87
Japan	46	92	41.74
India	48	40	26.12
Spain	51	86	43.53
Israel	54	81	N/A
Poland	60	93	29.24
Finland	63	59	57.37
South Africa white	65	49	N/A
Germany	67	65	40.40
Switzerland	68	58	66.07
Norway	69	50	55.13
France	71	86	47.77
Sweden	71	29	77.68
Denmark	74	23	69.64
Italy	76	75	29.69
New Zealand	79	49	74.55
Netherlands	80	53	68.30
Great Britain	89	35	69.42
Australia	90	51	71.43
U.S.A.	91	46	68.08

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PUBLICATIONS AND PRESENTATIONS

“Two-Dimension Value Investing Strategy” with Xiaoguang Jiang, Presented at 2020 Financial Management Association Annual Meeting, and 2021 Eastern Finance Association Annual Meeting.

“Independence of U.S. bank regulators and the politics of bank regulation” with Karen Y. Jang, Presented at 2020 Southern Finance Association Annual Meeting, 2020 Eastern Finance Association Annual Meeting, and 2021 Financial Management Association Annual Meeting.

“Language, Uncertainty, and Foreign Direct Investment” with A. M. Parhizgari, Marcos Velazquez, and Le Zhao, Presented at 2021 Eastern Finance Association Annual Meeting, 2021 Southwest Finance Association Annual Meeting, 2021 World Finance Conference, 2021 Global Finance Conference, and 2021 Academy of International Business.