Priority of Investment Strategy, Value or Quality?

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Abstract

We propose and identify two novel investment strategies, the quality-cheapness (QC) investing strategy with quality as a priority and the cheapness-quality (CQ) investing strategy with cheapness as a priority. We show that the QC (CQ) strategy notably outperforms the quality (value) strategy, priority matters. QC and CQ strategies exhibit different return distributions and risk exposures, although they perform almost equally well regarding return spreads, suggesting different sources of return spreads and potential synergy. Furthermore, macroeconomic growth, liquidity risk, uncertainty, downside risk, and sentiment partially explain the return spreads in the QC strategy but little in the CQ strategy.

Keywords: Priority of investment strategy, Value investing, Quality, Return drivers.
JEL: G11, G12, G14

Priority of Investment 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 Introduction

Valuation theory suggests a positive relationship between value and quality; i.e., high-quality firms tend to have high valuation. There is plentiful evidence that both value investing strategy (e.g., Fama and French, 1992, 1998; Lakonishok, Shleifer, and Vishny, 1994; Porta, Lakonishok, Shleifer, and Vishny, 1997; among others) and quality investing strategy (e.g., Piotroski, 2000; Piotroski and So, 2012; Novy-Marx, 2013, 2014; Asness, Frazzini, and Pedersen, 2019; Jagannathan and Zhang, 2020) yield positive risk-adjusted returns. However, the value strategy is short quality, whereas the quality strategy is short value (cheapness).[1] Although academics and practitioners recognize the merits of value and quality, there is no consensus on which is of first-order importance. Few studies examine the relative importance.

We propose and identify two novel investment strategies that consider both value and quality yet with distinct priorities: Quality-Cheapness (hereafter QC) strategy and Cheapness-Quality (hereafter CQ). Taking quality as a priority, the QC strategy goes long high-quality

[1] Value and cheapness are exchangeable in this study.

stocks without paying premium prices and short low-quality stocks with relatively high prices. On the other hand, taking cheapness as a priority, the CQ strategy goes long cheap stocks with relatively high-quality and short expensive stocks with relatively low-quality.

Our investment 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 studies show that quality and cheapness are negatively correlated, suggesting that 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 five 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 ten years) > seven
10. No more than two years of declining earnings over the previous ten years

Consistent with valuation theory, the first five factors are cheapness 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 insights, considering both quality and value. However, valuation theory, empirical studies, and the stock screens all remain silent on which one (quality or value) is the priority.

The investment gurus appear to have a discrepancy in the priority of value and quality. Warren Buffett favors quality, saying once in a letter to his shareholders, “It is far better to buy a wonderful company at a fair price than a fair company at a wonderful price.”[2] Frazzini et al. (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 stock. On the other hand, in a recent interview with the Wall Street Journal, Joel Greenblatt emphasizes the importance of cheapness, saying, “We buy — at all times — the cheapest stocks we can find.” There is no consensus on the priorities of quality and value.

We present a regression-based approach to identify the two investment strategies. Our approach is in a similar to that of 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’s stock returns on its quality. It is worth noting that the dependent variable of our regression is stock returns instead of valuation ratios, as in Bhojraj and Lee (2002), Rhodes-Kropf, Robinson, and Viswanathan (2005), and Bartram and Grinblatt (2018). Our regression approach relies heavily on valuation theory which guides us to identify QC firms and CQ firms. We take the regression fitted value as a measure of the QC and the residual as a measure of CQ. Conceptually, the QC (CQ) measure is similar to the “fundamental” return component (“residual” return component) in Daniel and Titman (2006) and Da et al. (2014). A high value of QC indicates high-quality with a relatively low price since the estimated slope coefficient is positively associated with the book-to-market ratio. A high value of CQ indicates an expensive price with relatively low-quality.[3]

We conduct portfolio analyses using both single- and double-sort. Indeed priority matters. We find that high QC (low CQ) portfolios generate higher excess returns and risk-adjusted

[2]From the Chairman’s Letter, Berkshire Hathaway, Inc., Annual Report, 1989.
[3]For derivation, please see the detailed discuss in subsection 3.2.

returns on average. Our QC and CQ strategies yield markedly high return spreads and outperform quality and value strategies, respectively. For example, the return spread in the QC strategy (66 basis points per month) is more than twice as high as that in the quality strategy (31 basis points per month). The return spread in the CQ strategy (63 basis points per month) is also more than twice as high as that in the value strategy (30 basis points per month). The Sharpe ratio in the QC strategy (0.61) and CQ strategy (0.70) are much higher than those in the quality strategy (0.37) and value strategy (0.22). The superior performance of the QC (CQ) strategy is plausible because it avoids long expensive high-quality (inferior cheap) firms and short cheap low-quality (superior expensive)firms.

We find that the QC and CQ strategies exhibit different return distributions and risk exposures, although they have similar return spreads. The QC strategy has a negative market beta , whereas the CQ strategy shows a convex function (nonlinear right-sided smile) of market excess returns. The negative market beta of the QC strategy indicates that its superior performance mainly comes from market downturns, echoing quality shining in challenging times. The nonlinear right-sided smile pattern of the CQ strategy suggests that it enjoys high returns when the market is high and has limited losses when the market is low.

Using dependent double sorts, we show that the QC (CQ)strategy subsumes the return spread in the quality (value) strategy. By contrast, the quality (value) strategy does not subsume the return spread in the QC (CQ) strategy. This evidence further supports the superior performance of the QC and CQ strategies. The positive return spreads and negative correlation between QC and CQ strategies suggest that a simple combination of the two should be closer to the efficient frontier than either strategy alone. The $QCCQ$ strategy, based on independent double-sorted portfolios of QC and CQ (taking priorities into account), generates a return spread of 142 basis points per month compared to the return spread of 85 basis points per month for the quality-value strategy based on independent double-sorted quality and value portfolios (not taking priority into account). In sum, priority matters.

We construct two factors to further understand the proposed investing strategies: Quality-Cheapness factor (hereafter, QCF) and Cheapness-Quality factor (hereafter, CQF), following Fama and French (1993), Asness et al. (2013), and Asness et al. (2019). [4] As expected, these factors are highly correlated with return spreads in the QC and CQ strategies. We find that the short-term reversal factor largely explains QCF (adjusted R^2 = 58%) and CQF (adjusted R^2 = 84%), whereas traditional asset pricing factors have very low 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 QCF and CQF are associated with the these three aspects. Our evidence suggests that investment growth opportunity, liquidity risk, uncertainty, and downside risk are associated with CQF but not QCF. Behavioral variables have some limited explanatory power for both QCF and CQF.

The remainder of this paper is organized as follows. Section 2 reviews the related literature on both value- and quality-investing strategies. Section 3 discusses the data and the methodology used. Section 4 and 5, we presents QC, CQ, $QCCQ$ formation, portfolio strategies, and the performance analysis of the QCF and CQF. Section 6 examines the potential sources of returns in the QCF and CQF. Section 7 concludes.

2 Related Literature

This study is closely related to and builds on two prior contributions of investment strategies: value investing strategy (e.g.,Graham and Dodd, 1934) and quality investing strategy (e.g.,Novy-Marx, 2013; Asness, Frazzini, and Pedersen, 2019). The history of value investing strategy can be traced back to Graham and Dodd's (1934) Security Analysis. The core concept of this strategy is to buy undervalued securities (relative to their intrinsic value) through fundamental analysis. Both academics and practitioners show great interest

[4] Please refer to Section 5 for details of the factor constructions.

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, 1991; and Fama and French, 1992), and value stocks outperform growth stocks (e.g., Fama and French, 1992, 1998; Lakonishok, Shleifer, and Vishny, 1994; and Porta, Lakonishok, Shleifer, and Vishny, 1997).

Despite numerous studies on value premiums, there is no consensus on the source of the value premium. On the one hand, Fama and French (1992, 1998, 2005) posit that the value premium is associated with financial distress risk. On the other hand, Lakonishok et al. (1994) and Porta et al. (1997) argue that value premiums arise because of market inefficiencies for various behavioral and institutional reasons.

A quality investing strategy that goes long high-quality stocks and short low-quality stocks seeks to identify firms with outstanding quality characteristics. The quality strategy is highly different from the value strategy, although it can be viewed as an alternative value strategy.

Piotroski (2000) constructs a quality measure, F-SCORE, based on nine accounting-based signals to identify higher quality firms among firms trading at low share prices relative to book value. Piotroski (2000) shows that firms with low F-SCORE have the strongest deterioration in fundamentals, and firms with the high F-SCORE have the strongest improvement in fundamentals, suggesting that information from accounting statements can improve value investing. Piotroski and So (2012) show that value and quality sorting strategies based on combined ranks perform better than a 50/50 combination of value and quality portfolios. Furthermore, Novy-Marx (2013) uses gross profitability as a quality measure and finds that controlling profitability could dramatically improve value strategy performance. Additionally, he finds that value and profitability strategies are negatively correlated. Asness et al. (2019) propose a comprehensive quality measure that captures the profitability, growth, safety, and payout characteristics of a firm and distinguishes between quality stocks and junk stocks. They find that stocks with high-quality substantially outperform stocks with low-quality. 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.

The determinants of the quality premium seem inconsistent with time-varying risk explanations. Piotroski (2000) and Piotroski and So (2012) suggest an inefficient market story: a firm's past financial performance is not timely and is not fully reflected in its market price. In addition, Asness et al. (2019) provide evidence consistent with the behavioral explanation that quality stocks are under priced while junk stocks are overpriced, although they propose three potential hypotheses for quality premiums.

This study contributes to the literature on investment strategies. In contrast to the studies mentioned above, our investment strategies consider both quality and value but with different priorities, and our regression-based method relies on information from both the stock market and firms' fundamentals.

3 Data and Methodology

This section describes the data sources used and then discusses the regression-based approach to identify the QC and CQ strategies in this study.

3.1 Data and Quality Measures

Stock returns are collected from the Center for Research in Security Prices (CRSP) daily and monthly stock files. Accounting data are from the COMPUSTAT North America Fundamentals Annual, and Fundamentals Quarterly databases. The VIX index is obtained from the Chicago Board Options Exchange Database. The macroeconomic variables of real GDP and real Personal Consumption Expenditures are from the Federal Reserve Economic

Data. We also use the Financial and Macro Uncertainty index from Jurado et al. (2015), the sentiment index from Baker and Wurgler (2006), and the University of Michigan Consumer Sentiment Index. Casino profit is measured as quarterly casino industry profits (revenue minus the cost of goods sold) scaled by the nominal GDP.[5] Our sample includes all the available common stocks traded in NYSE, AMEX, and Nasdaq.[6] Following Shumway (1997), delisted stocks are assumed to have a -30% delisting return if their delisting return is missing. We align accounting variables at the end of the fiscal year ending anywhere in the calendar year $t-1$ to June of the calendar year t. Detailed variable construction and timeline are shown in Panel A of Table A1 and Figure A1 of Internet Appendix 2. The sample period runs from July 1957 to December 2020.

Following the literature, we use the logarithm of the book-to-market ratio as an indicator of value (cheapness)); that is, high (low) book-to-market stocks are value (growth) stocks. We present two quality measures because the proposed strategies rely on quality. First, we choose quality variables based on firms' information related to profitability, growth, payout, and safety, as in Asness et al. (2019), to construct an ordinal composite measure of quality. Second, we use the gross-profits-over-asset ($GPOA$) utilized by Novy-Marx (2013) as an alternative quality measure. We report the empirical results using quality based on an ordinal measure in the main text. For robustness, we also report the empirical results using quality based on $GPOA$ measure in the Internet Appendix 2. Following Polk et al. (2006), we take three steps to construct the ordinal composite measure of quality. First, we rank firms each month based on each quality variable we choose and then divide the rank by the total number of firms to yield the percentile rank for each quality variable. Second, we average the available percentile ranks within each group (profitability, growth,payout, and safety) for a firm and then re-rank firms based on the group average each month to

[5]We include the two components of sentiment index (equity share in new issues and number of IPOs) by Baker and Wurgler (2006) as those two components are related to liquidity. The casino industry has a North American Industry Classification Code (NAICS) of 713210. Those variables are measured in AR1 residual. See Table A1 in Internet Appendix 2 for sources of volatility, liquidity, uncertainty, and behavioral variables.

[6]Common stocks have a CRSP share code of 10 or 11, or a COMPUSTAT issue code (TPCI) of 0.

form the group percentile rank. Third, we average the group percentile ranks for each firm and then re-rank the firms based on the average of the group percentile rank to form an ordinal composite measure of quality. There are several advantages of using an ordinal composite measure. First, it reduces the impact of outliers because the ordinal measure does not generate extreme values. Second, averaging the ordinal measures on available quality variables conveniently handles the potential missing data for quality variables. Third, ordinal measures circumvent the hardwired link between the magnitudes of quality variables.[7]

3.2 Methodology

We propose a similar cross-sectional regression framework inspired by valuation theory (e.g., Fama and French, 2006) and the methodologies of Bhojraj and Lee (2002), Rhodes-Kropf et al. (2005), Daniel and Titman (2006), Da et al. (2014), and Bartram and Grinblatt (2018) .

$$\text{Return}_{i,t} = \alpha_{i,t} + \beta \times \text{Quality}_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $\text{Return}_{i,t}$ is the current month's stock return and $\text{Quality}_{i,t}$ is the quality measure available in the current month.[8] Notably, the dependent variable in Equation (1) is the stock return instead of the market-to-book ratio. This specification shows that a high regression slope coefficient is associated with a high book-to-market ratio or low price. We argue that a high fitted value indicates high quality with a relatively low price, and a high value of residual follows expensive with relatively low quality. *QC* strategy goes long firms with high fitted value and short firms with low fitted value, taking quality as a priority yet considering value. The *CQ* strategy goes long firms with low residuals and short firms with high residuals,

[7] Detailed quality ordinal measures construction is provided in Internet Appendix 1.

[8] We add the interaction terms between firm quality and industry dummy to alter the slope for each industry. Adding industry dummy allow us to take the characteristics of industries into consideration and captures unobservable cross-industry effects. Industry dummies are based on 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.

prioritizing cheapness while considering the quality.

To understand how it works, we start with Gordon growth model,

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

where P, D, R, and G denote stock price, expected dividend, expected return and growth, respectively. A simple step of algebra and proxy for expected growth deliver

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

where λ denotes the dividend payout ratio, and ROE denotes the return on equity.[9] 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).

It is clear that the coefficient β is positively related to the book-to-market ratio from Equation (1) and(3); a high value of β indicates low price, ceteris paribus. Therefore the high fitted value in Equation (1) indicates high quality with a relatively low price, and a high value of residual follows expensive with relatively low quality. This regression framework enables us to identify QC and CQ strategies, considering quality and cheapness with different priorities.

We add an industry dummy to the regression to consider the industry effect:

$$\text{Return}_{i,t} = \alpha_{i,t} + (\beta \ + \theta \text{D}_{Industry}) \text{Quality}_{i,t} + \varepsilon_{i,t} \tag{4}$$

where $\text{D}_{Industry}$ denotes a dummy variable that indicates a firm's industry.[10] We form the QC, CQ, and $QCCQ$ strategies based on Equation (4).

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

[10] 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.

4 Performance of QC, CQ, and $QCCQ$ strategies

In this section, we construct portfolios based on our QC, CQ, and $QCCQ$ strategies and test their performance. We demonstrate that the QC (CQ) strategy performs much better than the quality (value) strategy and that the $QCCQ$ strategy also performs much better than the strategy combining quality and value.

4.1 Single-Sorts

We expect that a high QC (low CQ) portfolio yields higher returns. At the end of each month, stocks are sorted into quintile portfolios in ascending order based on their QC or CQ measure and the NYSE breakpoints. We calculate the monthly portfolio return as the value-weighted average returns of all stocks in each portfolio and rebalance the portfolios every month. Next, we regress monthly portfolio excess returns of each QC/CQ-sorted portfolio and the return spreads of long-short arbitrage portfolio on widely used risk factors in asset pricing models, which include the Capital Asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) with the market factor (MKT); the Fama-French three-factor (FF3) model with market (MKT), size (SMB), and value (HML) factors (Fama and French, 1993); the Fama-French five-factor (FF5) model with the profitability (RMW) and investment (CMA) factors in addition to Fama and French three-factors (Fama and French, 2015); and the Hou-Xue-Zhang q-factor (HXZ q-factor) model with market (MKT), size (ME), investment (IA), and profitability (ROE) factors (Hou et al., 2015).

4.1.1 QC strategy

Table 1 reports the monthly value-weighted average QC measure, average raw and excess returns, alphas of time series regressions of portfolio returns on various asset pricing models, Newey-West heteroskedasticity and autocorrelation-corrected t-statistics, adjusted R-squared for the FF5 model, quality, log (M/B) ratio, size, age, beta, volatility, skewness, kurtosis, and the Sharpe ratio for each quintile portfolio and strategy portfolio. The excess return is calculated as the difference between the portfolio raw return and the one-month Treasury bill rate.

Panel A of Table 1 shows that QC portfolios' average raw returns, excess returns, and abnormal returns (alphas) monotonically increase with the QC measure, which is consistent with the quality strategy pattern. The top quintile portfolio ($QC5$) earns an average raw return of 130 basis points (t-statistic=7.88) and an excess return of 94 basis points (t-statistic=5.71) in the subsequent month. It generates positive and significant alphas (ranging from 35 to 42 basis points) for different asset pricing models. The bottom quintile portfolio ($QC1$) has an average raw return of 64 basis points (t-statistic=3.70) and an excess return of 29 basis points (t-statistic=1.61) for the subsequent month. It generates negative and significant alphas, ranging from -31 to -21 basis points with respect to different asset pricing models. The adjusted R-squared values based on FF5 are at least 80% for each quintile portfolio.

We now focus on the QC strategy, the long-short portfolio ($QC5 - QC1$). The QC strategy yields a significantly positive return spread of 66 basis points with a t-statistic of 5.47 in the following month. Controlling for various risk factors, the alphas for the QC strategy are positive and highly significant: 71 basis points (t-statistic=5.83) for the CAPM, 73 basis points (t-statistic=5.83) for the FF3 model, 65 basis points (t-statistic=4.04) for the FF5 model, and 56 basis points (t-statistic=2.86) for the HXZ q-factor model. These results show that the QC strategy with quality as a priority yields superior performance. We notice that the adjusted R-square is small (1.20%) for the arbitrage portfolio, suggesting that the commonly used asset pricing models have very limited explanatory power for QC strategy return spread, although it explains QC quintile portfolio returns to a large extent.

Panel B of Table 1 reports the characteristics of the QC quintile portfolios and QC strategy. Generally,the top quintile portfolio ($QC5$) tends to have high quality, high market-to-book ratio, large size, low beta, low volatility, low skewness, high kurtosis, and high Sharpe ratio. The relatively high return and low risk of the QC strategy produces a remarkably high Sharpe ratio (0.61). The negative beta of the QC strategy suggests that the QC strategy yields relatively high returns when the market is in a downturn.

When quality is measured as $GPOA$, as in Novy-Marx (2013), the results are reported in Panels A and B of Table A2 in Internet Appendix 2. We find that the results are qualitatively similar to those in Table 1, suggesting the robustness of the superior performance of the QC strategy.

4.1.2 CQ strategy

For the CQ strategy with cheapness as a priority, Table 2 reports the performance and characteristics of the CQ quintile portfolios and CQ strategy in a similar format as in Table 1. Panel A of Table 2 reveal that CQ portfolios' average raw returns and excess returns monotonically decrease with the CQ measure, which is consistent with the value strategy pattern. The alphas generally decrease with the CQ measure for various asset pricing models. The bottom quintile portfolio ($CQ1$) earns an average raw return of 128 basis points (t-statistic=6.12) and an excess return of 92 basis points (t-statistic=4.37) in the subsequent month and generates positive and significant alphas (ranging from 19 to 26 basis points) with respect to different asset pricing models. On the other hand, the top quintile portfolio ($CQ5$) has an average monthly raw return of 65 basis points (t-statistic=3.68), an excess return of 29 basis points (t-statistic=1.63), and significantly negative alphas, ranging from -29 to -27 basis points.

The CQ strategy, the long-short portfolio ($CQ1 - CQ5$), yields a significantly positive return spread of 63 basis points (t-statistic=5.67) in the following month. Similarly, the alphas for the CQ strategy from various asset pricing models are positive and highly significant: 51 basis points (t-statistic=4.58) for the CAPM, 48 basis points (t-statistic=4.24) for the FF3 model, 50 basis points (t-statistic=4.07) for the FF5 model, and 53 basis points (t-statistic=3.49) for the HXZ q-factor model.

Panel B of Table 2 reports the characteristics of the CQ quintile portfolios and CQ strategy. As expected, CQ increases monotonically with the market-to-book ratio, reflecting cheapness as a priority. $CQ1$ tends to have higher quality, lower age, higher beta and volatility than $CQ5$ does. The CQ strategy has a beta of 0.21, indicating that the $CQ1$ portfolio exposes a higher market risk than the $CQ5$ portfolio. The Sharpe ratio of the QC strategy is 0.70, which is remarkably high.

Similarly, we construct CQ quintile portfolios and strategy measuring quality based on $GPOA$, as in Novy-Marx (2013), and report the results in Panels A and B in Table A3 in Internet Appendix 2. The performance and characteristics of the CQ quintile portfolios and CQ strategy in Table A3 are consistent with those in Table 2. Therefore, the superior performance of the CQ measure is robust to the different quality aspects.

Figure 1 provides monthly return spread comparison on the QC strategy vs the quality strategy, the CQ strategy vs the value strategy, and the $QCCQ$ strategy vs the value-quality strategy. The first four columns of Figure 1 show the superior performance of QC and CQ strategies comparing to the performance of quality and value strategies. The return spread of QC (CQ) strategy is more than twice as high as that in quality (value) strategy.[11] We argue that the superior performance of the QC (CQ) strategy not only considers the quality and cheapness effect but also takes priority into account.

Notably, the average return spread in the CQ strategy is comparable to that in QC strategy, showing that the CQ strategy (cheapness as priority) performs equivalently well as the QC strategy (quality as priority) in terms of return spread. However, the QC and CQ strategies show different return distributions and risk exposures. The former has a negative market beta and negative skewness, whereas the latter has a positive market beta and positive skewness. The higher return with negative market beta of the QC strategy indicates that its superior performance mainly comes from market downturns, consistent

[11]The performance of quality strategy and value strategy is reported in Tables A4 and A5 in Internet Appendix 2.

with quality shining in challenging times. The higher return with a positive market beta and positive skewness of the CQ strategy suggests that the CQ strategy enjoys high returns when the market is high and has limited loss when the market is low. These results suggest that the sources of the return spreads of QC and CQ strategies vary across business cycles, although they have similar average return spreads.

[Insert Table 2]

[Insert Figure 1]

4.2 Dependent Double-Sort

Our QC and CQ strategies that emphasize priority are built upon quality and value strategies (e.g., Fama and French, 1992; Novy-Marx, 2013; Piotroski and So, 2012; and Asness et al., 2019). One is curious whether the QC (CQ) strategy is subsumed by the quality (value) strategy or vice versa.

We conduct dependent double sorts to examine this question. We first sort stocks into quintile portfolios in ascending order each month on the quality measure. Then within each quality quintile, we sort the stocks into quintile portfolios on the QC measure, forming 25 portfolios. In this dependent double sorts, we examine whether the quality strategy subsumes the return spread in the QC strategy. By changing the order of the dependent double sorts, we examine whether the QC strategy subsumes the return spread in the quality strategy. Similarly, we conduct a dependent double sorts between the CQ and value measures to examine whether the CQ and value strategies are subsumed.

4.2.1 QC strategy vs. quality strategy

We present a performance comparison analysis between the QC and quality strategies based on the dependent double-sorting portfolios in Table 3.

Panel A of Table 3 reports the double-sort results conditional on quality. In the last column of the panel, we show that the QC strategy in each quality quintile still generates significantly positive return spreads, ranging from 45 to 106 basis points, and abnormal returns in various asset pricing models.[12] The QC return spread decreases with the quality measure. The average monthly return spread of the QC strategy is 72 basis points, even higher than that of the QC strategy based on the unconditional single sort. This result indicates that the quality strategy cannot subsume the QC strategy.

The last column of Panel B presents the performance of the quality strategy for each QC quintile portfolio. In contrast, Quality strategy return spreads in each QC quintile tend to be small and even negative with average monthly return spread of 12 basis points across QC quintiles. The return spreads of quality strategy are statistically insignificant in each QC quintile except for $QC1$. A similar pattern is found for the alphas. This result shows that the QC strategy subsumes return spreads in the quality strategy and confirms that the QC strategy is superior to the quality strategy.

As a robustness check, we conduct dependent double-sort using quality based on $GPOA$ as in Novy-Marx (2013) and report the results in Panels A and B of Table A6. We find that the results are qualitatively similar to those in Table 3. We claim that the QC strategy subsumes return spreads in the quality strategy, while quality strategy does not subsume return spreads in the QC strategy, and confirm the robust superior performance of the QC strategy.

[Insert Table 3]

[12]We also show that the QC strategy in each quality quintile still generates significantly positive alphas, ranging from 46 to 117 basis points, across various asset pricing models. For details, please see Table A7 in Internet Appendix 2.

4.2.2 CQ strategy vs. value strategy

We now turn to examine whether the CQ strategy and value strategy are subsumed by each other. We present a performance comparison analysis based on dependent double-sort portfolios.

We first sort stocks into quintile portfolios in ascending order based on the value measure (market-to-book). We then sort stocks on their CQ measures within each value quintile, forming 25 portfolios. Table 4 reports the results. The last column of Panel A shows that the CQ strategy in each value quintile generates significantly positive return spreads. The average monthly return spreads of the CQ strategy across value quintiles are remarkably high at 85 basis points. The return spreads of conditional CQ strategies decrease with market-to-book, with 119 basis points in $MB1$ and 32 basis points in $MB5$. The alphas of CQ strategies in various asset pricing models range from 64 basis points to 135 basis points across different quality quintiles.[13] This result indicates that the CQ strategy subsumes the return spread of the value strategy.

Panel B in Table 4 presents the performance of the value strategy for each CQ quintile portfolio. In contrast to the results in Panel A, the return spreads of the value strategy in each CQ quintile tend to be small, even negative, and statistically insignificant, except for $CQ1$. The alphas of the value strategy are significant only for $CQ5$. This result indicates that the value strategy does not subsume the return spread in the CQ strategy.

For robustness check, we conduct dependent double-sort (quality is based on $GPOA$ as in Novy-Marx (2013)) and report the results in Panels A and B of Table A8 in Internet Appendix 2. We confirm that the CQ strategy subsumes return spreads in the value strategy while the value strategy cannot subsume return spreads in the CQ strategy, and show the robust superior performance of the CQ strategy.

[Insert Table 4]

[13] Please see Table A9 in Internet Appendix 2 for details.

4.3 Independent Double-Sorts

Piotroski and So (2012) and Novy-Marx (2014) argue that the quality-value strategy based on independent double-sort on value and quality performs better than a simple 50/50 value and quality portfolio. We construct the $QCCQ$ strategy based on independent double sorts on QC and CQ and compare it with the quality-value strategy based on independent double sorts on quality and value.

Twenty-five portfolios are formed by independent quintile sorting of QC and CQ. The $QCCQ$ strategy is long portfolio $QC5/CQ1$ (high-quality stocks with relatively low price and cheap stocks with relatively high-quality) and short portfolio $QC1/CQ5$ (low-quality firms with relatively high price and expensive stocks with relatively low-quality) as following. Portfolio returns are the value-weighted average monthly returns of all stocks in the portfolio, and portfolios are rebalanced every month.

The independent double-sort results are provided in Table 5. The rightmost column ($CQ1$-$CQ5$) of each panel reports the average monthly return spreads or alpha spreads of the portfolio that longs the bottom quintile portfolio ($CQ1$) and shorts the top quintile portfolio ($CQ5$) across QC portfolios. Each panel's bottom row ($QC5$-$QC1$) reports the average monthly return spreads or alpha spreads of the portfolio that longs the top quintile portfolio ($QC5$) and shorts the bottom quintile portfolio ($QC1$) across CQ portfolios. The $QCCQ$ strategy is also a self-financing portfolio that longs stocks in $QC5$ and $CQ1$ intersected portfolios and shorts stocks in $QC1$ and $CQ5$ intersected portfolios. The bottom-right cell of each panel reports the corresponding average monthly return spreads or alpha spreads of the $QCCQ$ strategy.

The $QCCQ$ strategy yields a significantly positive return spread, 142 basis points with a t-statistic of 10.08, alpha spreads of 137 basis points with a t-statistic of 9.52, 137 basis points with a t-statistic of 9.12, 132 basis points with a t-statistic of 8.74, and 125 basis points with a t-statistic of 7.12 corresponding to the CAPM, FF3 model, FF5 model, and HXZ q-factor model, respectively. The $QCCQ$ strategy remarkably outperforms the quality-value combining strategy which also yields a significantly positive return spread (85 basis points) and alpha spreads (ranging from 69 to 132 basis points).[14]

In a robustness check when quality is based on $GPOA$, as in Novy-Marx (2013)), Table A11 in Internet Appendix 2 reports the results. We confirm that the $QCCQ$ strategy generates a significantly positive return spread and is superior to the quality-value strategy. The last two columns of Figure 1 show the superior performance of the $QCCQ$. We argue that the superior performance of the $QCCQ$ strategy considers not only quality and value effects but also priorities.

[Insert Table 5]

4.4 Time-Series Performance and Business Cycle

The above analysis shows that the QC, CQ, and $QCCQ$ strategies exhibit superior performance. In particular, QC and CQ strategies generate similar average return spreads but with discrepant return distributions and risk exposures. A natural question is whether QC and CQ strategies perform equally well across business cycles. To answer this question, we conduct three additional exercises. First, we plot the monthly average return spreads of the QC (CQ) strategy and market excess return over the period from 1957:07 to 2020:12 in Figure A2 (A3) in Internet Appendix 2. The most striking feature in Figure A2 is that the return spreads of the QC strategy are remarkably higher than the market excess return in recessions, and they are negatively correlated, consistent with the negative market beta of QC strategy, suggesting that the QC strategy may serve as a hedge for downside risk. Figure A3 confirms that the CQ strategy return spreads are positively correlated with market excess returns in recessions, although the return spreads of the CQ strategy are not as low as market excess returns. Figure A4 shows the performance of the $QCCQ$ strategy during

[14] The detailed results of quality-value combining strategy performance are reported in Table A10 in Internet Appendix 2.

the expansions and recessions. As expected, the $QCCQ$ strategy shares the characteristics of the QC and CQ strategies: it coheres to the market's excess returns in expansions, and hedges for downside risk in recessions.

Second, we plot the return spreads of the QC, CQ, and $QCCQ$ strategies against the market excess returns. Figure 2 provides a bird's eye view of the performance of QC, CQ, and $QCCQ$ strategies. It confirms that negative market beta of QC strategy, showing remarkable hedging effect. The CQ strategy exhibits a nonlinear and right-sided smile pattern with respect to market excess returns, suggesting that the CQ strategy enjoys high returns when the market excess returns are high. The $QCCQ$ strategy balances QC and CQ strategies, exhibiting a smile pattern. This finding confirms that the negative market beta of the QC strategy shows a remarkable hedging effect.

[Insert Figure 2]

Third, we examine the return spreads of QC and CQ strategies and market excess returns in a good market (market excess return is above its mean) and a bad market (market excess return is below its mean) and report the results in Table 6. Indeed, we find that CQ (CQ) average monthly return spreads in a bad market is 90 (-3) basis points compared with the related market excess return of negative 312 basis points, confirming the tremendous hedging effect of QC strategy and limited loss of CQ strategy. On the other hand, in a good market, the average monthly return spreads of QC (CQ) is 46 (116) basis points compared with the related market excess return of 363 basis points, supporting that the CQ strategy enjoys a relatively high return in a good market. We find a qualitatively similar results when the quality is based on the $GPOA$, and the results are reported in Table A12 in Internet Appendix 2.

[Insert Table 6]

5 Factor Analysis of QC and CQ Strategies

5.1 Factor Construction and Performance

To better understand the superior performance of QC and CQ strategies, we construct two sets of factors, QC factor (QCF) and CQ factor (CQF) following (Fama and French, 1993) and (Asness et al., 2019). QC (CQ) factors are constructed as the intersection of six value-weighted portfolios formed on the size and QC (CQ) measures. We assign stocks to two size-sorted portfolios and then three QC (CQ) portfolios within each size portfolio at the end of each month. The size breakpoint is the median of the NYSE market equity. The portfolios are value-weighted, and rebalanced monthly. The return on QCF is the value-weighted average return on two high-QC portfolios minus the average return on two low-QC portfolios:

$$\begin{aligned} QCF = & \frac{1}{2}\left(\text{Small } QC_{\text{High}} + \text{Big } QC_{\text{High}}\right) \\ & - \frac{1}{2}\left(\text{Small } QC_{\text{Low}} + \text{Big } QC_{\text{Low}}\right) \end{aligned} \tag{5}$$

Similarly, the return on CQF is the average returns on two low-CQ portfolios minus the average returns on two high-CQ portfolios:

$$\begin{aligned} CQF \; = & \frac{1}{2}\left(\text{Small } CQ_{\text{Low}} + \text{Big } CQ_{\text{Low}}\right) \\ & - \frac{1}{2}\left(\text{Small } CQ_{\text{High}} + \text{Big } CQ_{\text{High}}\right) \end{aligned} \tag{6}$$

We regress the return spreads of the QC and CQ strategies on various risk factors in the CAPM, FF3, FF5, and HXZ q-factor modeld, and these asset pricing models are augmented with QCF and CQF. We expect the QCF (CQF) to have more explanatory power for the QC (CQ) strategy. Panels A and B of Table 7 present the regression results. Panel A shows that commonly used asset pricing models have little explanatory power for the QC strategy. The adjusted R-squared values are 0.92%, 1.05%, 1.20%, and 2.00% for CAPM, FF3 model, FF5 model, and HXZ q-factor model respectively. As expected, adding QCF

and CQF yields remarkably high explanatory power for the QC strategy; the adjusted R-squared values of the augmented CAPM, FF3 model, FF5 model, and HXZ q-factor model increase to 79.59%, 79.90%, 81.39%, and 81.62%, respectively. It is not surprising that the loadings of QCF and CQF are significantly positive, and the magnitude of QCF loading is much higher than that of CQF loading.

Panel B shows that commonly used asset pricing models have low explanatory power for the CQ strategy. The adjusted R-squared values of the CAPM, FF3 model, FF5 model, and HXZ q-factor model are 8.58%, 9.04%, 8.90%, and 9.77% respectively. As expected, adding QCF and CQF yields remarkably high explanatory power for the CQ strategy. The adjusted R-squared values of the augmented CAPM, FF3, FF5, and HXZ q-factor models increase to 70.69%, 70.64%, 71.60%, and 72.35%, respectively. The loadings of QCF and CQF are significantly positive, and the magnitude of the CQF loading is much higher than the magnitude of the QCF loading.

Panels A and B of Table A13 in Internet Appendix 2 present the regression results when quality is measured based on the $GPOA$, and the patterns are qualitatively similar. We verify that the QCF and CQF could explain our QC and CQ strategies to a large extent, in addition to the commonly used risk factors.

[Insert Table 7]

We now examine the performance of the QCF and CQF. Table 8 reports the alphas and risk factor loadings with respect to the CAPM, FF3 model, FF5 model, and HXZ q-factor model. Columns (1) to (4) show the factor coefficients, alphas, and adjusted R-squared values for the QCF. Columns (5) to (8) show the factor coefficients, alphas, and adjusted R-squared values for the CQF. Both QCF and CQF yield statistically significant and positive alphas for each asset pricing model considered, suggesting abnormal returns in QCF and CQF, consistent with the performance in the QC and CQ strategies.

As expected, positive (negative) loadings on fundamental factors, such as RMW, CMA, and ROE, and negative (positive) loadings on the value factor HML and the market factor MKT are exhibited in the regression of QCF (CQF), indicating a negative correlation between QCF and CQF (hedge effect). The adjusted R-squared values range from 1.74% to 3.39% for QCF and 10.80% to 13.35% for CQF across the asset pricing models. Commonly used risk factors tend to have low explanatory powers for QCF and CQF, particularly for QCF..

Table A14 in Internet Appendix 2 reports the performance of the QCF and CQF (quality is based on the $GPOA$). The results are qualitatively similar, confirming that QCF and CQF yield statistically significant and positive alphas while commonly used asset pricing models have limited explanatory power for these two factors.

[Insert Table 8]

5.2 QCF and CQF vs. Momentum and Reversal

Existing literature documents the connection between the value effect, momentum, and short-run reversal. Asness et al. (2013) find significant comovement in value and momentum, negatively correlated with each other within and across diverse asset classes (Also see Daniel and Titman, 2006). Da et al. (2014) show that stock returns unexplained by "fundamentals" are more likely to reverse in the short-run, suggesting that the value positively correlates with reversal. Few study explores the association between quality effect and momentum or short-run reversal. We argue that momentum is positively (negatively) associated with QCF (CQF), and a short-run reversal is negatively (positively) associated with QCF (CQF) since both QC strategy and momentum strategies exhibit the tendency of firms with recent good (bad) performance to continue overperforming (underperforming) in the near future. The CQ strategy and short-run reversal strategy show the tendency of firms with cheap (expensive) prices to reverse in the near future. We examine these associations in this subsection.

We run the time-series regressions of QCF (CQF) returns on the momentum factor or the short-run reversal factor with and without FF5.[15] The results are presented in Table 9. As expected, we find that the momentum factor is positively (negatively) correlated with the QCF (CQF). Columns (1) and (2) of Panel A report the regression results of the QCF on the momentum factor without and with FF5. The coefficients of the momentum factor are 0.147 (t-statistic of 1.800) without FF5, and 0.123 (t-statistic of 1.404) with FF5. The adjusted R-squared values are 3.01% without FF5 and 5.20% with FF5. Columns (1) and (2) of Panel B show the regression results of the CQF on the momentum factor without and with FF5. Without FF5, the coefficient of the momentum factor is -0.213, with a t-statistic of -4.146. The negative relationship between momentum and CQF is robust with FF5, which produces a coefficient of -0.178 and a t-statistic of -3.159. The adjusted R-squared values are 12.35% without FF5 and 20.14% with FF5. We notice that the momentum factor explains the greater variation in CQF than in QCF.

On the other hand, the reversal factor is negatively (positively) correlated with the QCF (CQF). The strong negative correlation between the reversal factor and QCF is reported in Columns (3) and (4) of Panel A. Without FF5, the coefficient of the reversal factor is -0.845, with a t-statistic of -10.768. Adding FF5 to the reversal factor, the coefficient of reversal is -0.903, and the t-statistic is -12.219. The adjusted R-squared values are 57.63% without FF5 and 60.76% with FF5, indicating that the reversal factor explains much more of the variation in QCF than the momentum factor. Columns (3) and (4) of Panel B confirms the positive relationship between reversal factor and CQF. The coefficients are 0.741 (t-statistic of 36.678) and 0.728 (t-statistic of 29.887) for regressions without and with FF5, respectively. The adjusted R-squared values are 84.22% without FF5 and 85.12% with FF5, indicating that the reversal factor explains much more variation in the CQF than the momentum factor.

In summary, our results show that both the momentum and reversal factors capture

[15]Momentum and short-run reversal factors are obtained from Ken French's web site at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/.

substantial variations in the newly proposed factors, and the reversal factor appears to have much greater explanatory power than the momentum factor for the QCF and CQF.

[Insert Table 9]

6 Exploring Potential source of return spreads in QC and CQ Strategies

Although both reversal and momentum factors are associated with QCF and CQF, they reveal little economic intuition about the source of returns in QCF and CQF. To understand the determinants of the factors' abnormal returns, we explore the potential factor divers from the following five dimensions: liquidity, macroeconomic growth, uncertainties, downside risk, and behavioral.[16]

6.1 Liquidity risk

Existing studies have revealed that short-term reversals are consistent with incomplete liquidity provision (e.g., Campbell et al., 1993; Avramov et al., 2006; Nagel, 2012; and Da et al., 2014). Da et al. (2014) conduct a comprehensive study identifying the causes of short-term return reversals and provide strong empirical evidence that liquidity shocks are likely to drive the reversals of recent losers, whereas investor sentiment is more likely to drive reversals of recent winners.[17] Since QCF and CQF are highly correlated with short-run reversal, we examine whether QCF and CQF are associated with liquidity risk. Following Da et al., 2014, we measure liquidity risk using the realized S&P 500 index volatility and the volatility index VIX. We run the time-series regression of QCF (CQF) returns on lagged liquidity risk measures with and without FF5 and report the regression results in Table 10. We do not

[16] Detailed variable constructions are provided in Panel B of Table A1 in Internet Appendix 2.

[17] Alternatively, existing studies also interpret reversal as result of market inefficiency. Please see subsection 6.5 for details.

find evidence that QCF is sensitive to any liquidity risk variables that we consider, with or without FF5. By contrast, both liquidity risk measures positively correlate with CQF with or without FF5. The coefficient of lagged VIX index (scaled by 100) is 0.050 (t-statistic of 2.385) without FF5, and 0.040 (t-statistic of 1.889) with FF5, and the coefficient of lagged S&P 500 index volatility is 0.033 (t-statistic of 1.880) without FF5, and 0.029 (t-statistic of 1.792) with FF5. This evidence suggests that a high return of CQF may partially serve as compensation for liquidity risk, consistent with the liquidity risk based explanation. Our result is not surprising since our CQF is similar in spirit to the residual return in Da et al. (2014).

[Insert Table 10]

6.2 Macroeconomic Growth

A critical insight from Merton's ICAPM, the Intertemporal Capital Asset Pricing Model (Merton, 1973), is that assets are not only exposed to market risk factor but also state variables that capture future investment opportunities over time. Chen et al. (1986) find that innovations in macroeconomic variables which are associated with future investment opportunities are risks that are priced in the stock market. To understand risk sources in HML and SMB, Fama and French (1992, 1993, 1995, 1998) argue that HML and SMB act as state variables in the context of Merton's ICAPM. Liew and Vassalou (2000) show that HML and SMB are related to future GDP growth implying that these portfolios act as state variables that describe the future state of the economy (Vassalou (2003)). Motivated by these studies, we examine whether the QCF and CQF are related to the future growth of macroeconomic variables. The analysis in Section 4 shows that the QC strategy performs better and has a negative market beta, suggesting a hedge effect. We conjecture that the QCF is negatively associated with future economic growth. On the other hand, since the CQ strategy exhibits convexity and a right-sided smile to market return, we presume that

CQF is positively associated with future economic growth.

We measure macroeconomic growths using GDP and consumptions. GDP growth is measured as the annual growth rate of real gross domestic product, and consumption growth is constructed as the annual growth rate of personal consumption expenditures.[18] Following Liew and Vassalou (2000), we first run a univariate forecast regression of future economic growth on past returns in the QCF (CQF) using quarterly and monthly data as below.

$$g_{t,t+4} = \alpha + \beta FactorRet_{t-1,t} + e_{t,t+4} \tag{7}$$

$$g_{t,t+12} = \alpha + \beta FactorRet_{t-1,t} + e_{t,t+12} \tag{8}$$

where g is the one-year ahead growth rate of the economy, the GDP growth rate or consumption growth rate. $FactorRet$ is the return of QCF or CQF.

Since both QCF and CQF are related to other risk factors and existing literature shows that FF3 factors are positively associated with future economic growth (e.g., Liew and Vassalou, 2000), one may question whether other risk factors induce the association between QCF (CQF) and future economic growths. To address this concern, we run a multivariate regression, including FF5, in addition to QCF (CQF).

Table 11 presents the regression results for GDP growth and consumption growth using quarterly frequency data. Columns (1) and (2) of Panel A show that in both univariate and multivariate forecast regressions, the coefficient on QCF is negative as expected but statistically insignificant. Nevertheless, Columns (3) and (4) suggest that CQF is significantly and positively related to future GDP growth, and the coefficients are 0.217 (t-statistic of 4.253) without FF5 and 0.157 (t-statistic of 2.721) with FF5. Panel B of Table 11 presents

[18] We measure annual growth rate of real GDP and real consumption using both quarterly frequency and monthly frequency dataset. With the quarterly data, growth rate is measured as the change between four quarters ahead and the current quarter, divided by the value of the current quarter. With the monthly interpolated data, of growth rate is measured as the change between 12 months ahead and the current month, divided by the value of current month. Following Guo and Whitelaw (2006), we interpolate the quarterly GDP data into a monthly frequency.

the regression results for consumption growth. Similarly, we find that QCF is insensitive to the future consumption growth, whereas CQF is positively and significantly associated with future consumption growth. The CQF coefficients are 0.107 (t-statistic of 2.786) in the univariate regression and 0.069 (t-statistic of 1.781) in the multivariate regression with FF5. Our results show that CQF contains information about future economic growth, supporting a risk-based explanation that CQF may serve as a state variable in Merton's (1973) CAPM. However, little evidence of such an explanation is found in QCF.

Table A15 in Internet Appendix 2 confirms the significantly positive relationship between the CQF and future economic growth the results using monthly frequency data. The positive and statistically significant relationship between CQF and future economic growth is robust and unlikely to be induced by the known positive relationship between the Fama-French five factors and future economic growth.

[Insert Table 11]

6.3 Uncertainty

It is well known that uncertainty varies during business cycles and rises sharply in recessions (e.g., Bansal and Yaron, 2004; Bloom, 2009, 2014; Jurado et al., 2015). Bloom (2014) argues that uncertainty has an asymmetric impact on firms with different productivity levels and that productive firms are less aggressive in expanding and unproductive firms are less aggressive in contracting when uncertainty is high. We examine whether uncertainty is associated with QCF and CQF because both QC and CQ strategies acquire productive capacity cheaply.

Utilizing Financial uncertainty and Macro uncertainty from Jurado et al. (2015) as our uncertainty measures, we run the univariate time-series regression of QCF (CQF) returns on uncertainty measures and the multivariate regression, including FF5. Table 12 presents the regression results. In general, the QCF factor is not sensitive to any uncertainty variables.

On the other hand, CQF has significant coefficients on financial uncertainty: 0.024 (t-statistic of 2.998), 0.031 (t-statistic of 3.048), and 0.084 (t-statistic of 2.971) for one-month, three-month, and twelve-month financial uncertainty, respectively. We argue that the QCF factor may not relate to uncertainty risk; however, financial uncertainty risk would partially explains the returns of CQF.

[Insert Table 12]

6.4 Downside Risk

Lettau et al. (2014) posit that the downside risk capital asset pricing model (DR-CAPM) can jointly rationalize the cross section of equity, equity index options, commodities, sovereign bonds and currency returns, thus offering a unified risk view of these asset classes. We retrospect the time-series performance analysis of our strategies against the market index in Section 4.4 which shows that our QC and CQ strategies perform differently in the downside and upside markets. This subsection examines whether the QCF and CQF are associated with the downside risk. We adopt Henriksson and Merton (1981) downside risk capital asset pricing model:

$$r_{Factor,t} = \alpha + \beta_{Downside} \min\{0, r^e_{mkt,t}\} + \beta_{Upside} \max\{0, r^e_{mkt,t}\} + \varepsilon_t \tag{9}$$

where $r_{factor,t}$ is the return of QCF/CQF, $r^e_{mkt,t}$ is the market excess return, $\min\{0, r^e_{mkt,t}\}$ is the minimum function that returns the minimum value of zero or market excess return, and $\max\{0, r^e_{mkt,t}\}$ is the maximum function that returns the maximum value of zero or market excess return. Table 13 reports the performance of the downside risk model for the QCF and CQF, respectively. QCF shows a negative downside beta (marginally significant) and an upside beta (insignificant). The downside beta is -0.129, larger (in magnitude) than the upside beta, -0.081, which implies that QCF potentially moves more against the market during market downturns. The coefficients of CQF reveal opposite characteristics. Both the downside beta and upside beta are significantly positive. The upside beta (0.264) is larger than the downside beta (0.109). These results are consistent with our finding in Figure 2b that the return spread of the CQ strategy exhibits a right-sided smile with respect to the market excess return. The CQF co-moves with the market during good times and moves slightly against the market during bad times. Furthermore, we find that the alpha (abnormal return) for CQF is much smaller than that in the CAPM model, FF3, FF5, and HXZ q-factor models. The above empirical evidence suggests that the downside risk model could partially explain the abnormal returns in the CQF that are not captured by the commonly used asset pricing models we tested in Table 8. In summary, downside risk may serve as an alternative explanation for the source of the CQF's abnormal returns.

[Insert Table 13]

6.5 Behavioral Drivers

Previous studies also attribute quality and value premiums to market inefficiency for behavioral reasons (e.g., Lakonishok et al., 1994; Porta et al., 1997; Asness et al., 2019; Piotroski and So, 2012). We now explore the behavioral explanation of factor performance. We consider various behavioral proxies, including the consumer sentiment index from the University of Michigan, the sentiment index of Baker and Wurgler (2006), and its two components: equity share in new issues (S) and number of IPOs (NIPO). We also follow Asness et al. (2020) to consider the lottery demand proxied by casino profits in the U.S.

Panel A of Table 14 shows that Consumer Sentiment is positively associated with the QCF factor, and this relationship is significant with FF5 factors (0.001 with t-statistics of 2.548). The number of IPOs is significantly and negatively associated with QCF without and with FF5. Panel B of Table 14 shows that the equity share in the new issues component of the Sentiment Index has negative and significant exposure to the $CQQF$ factor. The coefficients are -0.221 (t-statistic of -2.120) and -0.188 (t-statistic of -1.720), without and with FF5. These results suggest that some behavioral variables are related to returns in QCF and CQF but only have limited explanatory power.

[Insert Table 14]

7 Conclusion

In this study, we propose and identify two novel investment strategies: a quality-cheapness (QC) strategy with quality as a priority and a cheapness-quality (CQ) strategy with cheapness as a priority. Both QC and CQ strategies consider quality and cheapness but with different priorities. Empirically we show priority matters.

We find that the return spreads in our QC (CQ) strategy are significantly higher than those in the quality (value) strategy. Although QC strategy and CQ strategy perform almost equally well in terms of average return spread, we show that they exhibit different return distributions and risk exposures, suggesting various sources of returns and potential synergy in QC and CQ strategies, which is confirmed in our two-dimensional $QCCQ$ strategy.

We find that commonly used asset pricing models (CAPM, FF3 model, FF5 model, and HXZ q-model) have limited explanatory power for the return spreads of our strategies. The momentum and short-term reversal factors, particularly short-term reversal factor, explain the return spreads of our strategies to a large extent. Further tests show that investment growth opportunity, liquidity risk, uncertainty, and downside risk are associated with CQF but not QCF. Some behavioral variables have limited explanatory power for both the QCF and CQF. We recognize that we provide a limited understanding, although this study examines the determinants of the return spreads of QC and CQ strategies from different perspectives. Further research on this topic is warranted.

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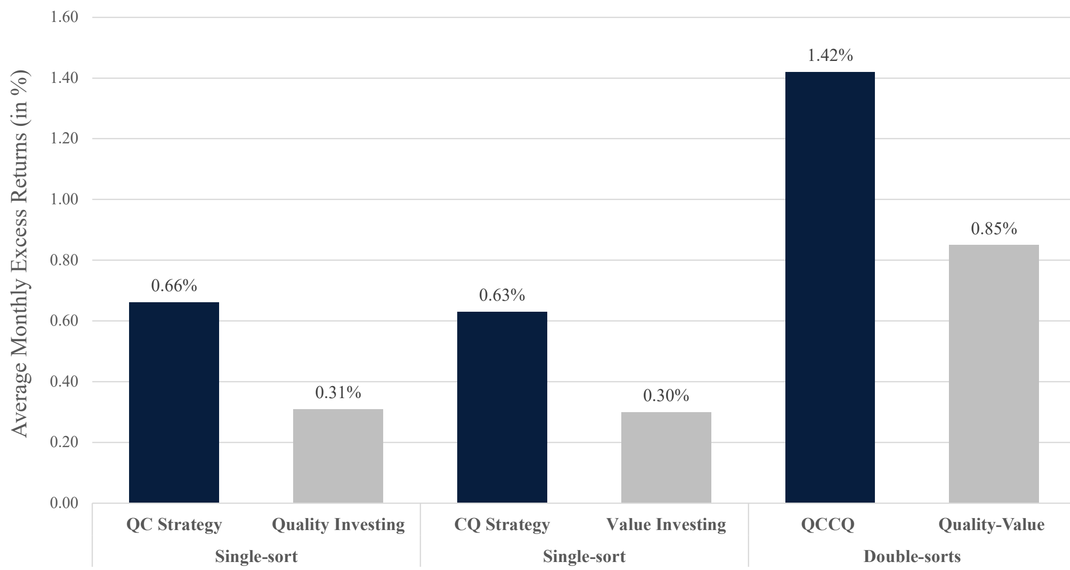
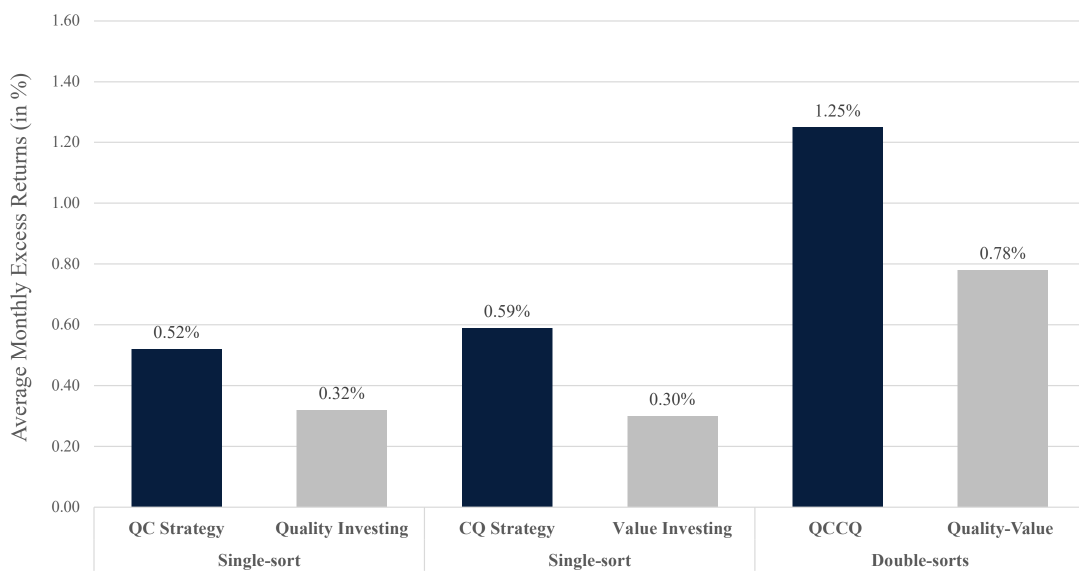


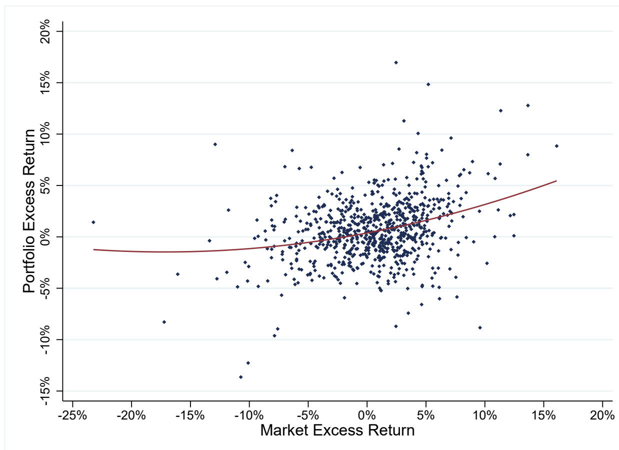
(a) Quality based on Ordinal Measure



(b) Quality based on Gross-profit-over-asset

Figure 1: Comparison of Investment Strategies.
This figure shows monthly return spread comparison between (1) QC strategy and quality investing strategy (left two histograms); (2) CQ strategy and value investing strategy (middle two histograms); and (3) $QCCQ$ strategy and quality-value strategy (right two histograms). Figure 1a shows the comparison of strategies where quality is based on ordinal measure, and Figure 1b exhibits the results of strategies where quality is based on gross-profit-over-asset.

(a) QC **Strategy**



(b) CQ **Strategy**

(c) $QCCQ$ **Strategy**

Figure 2: Time Series Plot of Return Spread of Investment Strategies Against Market Excess Returns.
In this figure, we plot monthly return spread of investment strategies against market excess return.

Table 1: Quality-Cheapness Sorted Portfolio Performance

This table shows the monthly portfolio returns and asset pricing model alphas based on our Quality-Cheapness Measure (*QC* based on ordinal measure). The sample period runs from July 1957 to December 2020. At the end of each calendar month, stocks are ranked in ascending order on the basis of their Quality-Cheapness Measure and are assigned to quintile portfolios based on NYSE breakpoint. Portfolios are value-weighted, and refreshed every month. The Alphas are the intercepts of time-series regressions of *QC* portfolio excess returns on various asset pricing models including CAPM, FF3 Model, FF5 Model, and HXZ q-factor Model. Panel A shows the returns and alphas of *QC* portfolios. The bottom row reports return spreads/alphas of *QC* strategy. Returns and alphas are in percentage, Newey-West auto-correlation corrected t-statistics with a lag length of 6 are given in parentheses, and 5% statistical significance is indicated in bold. Panel B reports the characteristics of *QC* portfolios and *QC* strategy. We report portfolios' raw quality measure (ordinal measure), MB (defined as log market-to-book ratio), Size (in Million Dollars), Age (in years), 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 adjusted 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**	**FF3 Alpha**	**FF5 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**	**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 2: Cheapness-Quality Sorted Portfolio Performance

This table shows the monthly portfolio returns and asset pricing model alphas based on our Cheapness-Quality Measure (CQ based on ordinal measure). The sample period runs from July 1957 to December 2020. At the end of each calendar month, stocks are ranked in ascending order on the basis of their Cheapness-Quality Measure and are assigned to quintile portfolios based on NYSE breakpoint. Portfolios are value-weighted, and refreshed every month. The Alphas are the intercepts of time-series regressions of CQ portfolio excess returns on various asset pricing models including CAPM, FF3 Model, FF5 Model, and HXZ q-factor Model. Panel A shows the returns and alphas of CQ portfolios. The bottom row reports return spreads/alphas of CQ strategy. Returns and alphas are in percentage, Newey-West auto-correlation corrected t-statistics with a lag length of 6 are given in parentheses, and 5% statistical significance is indicated in bold. Panel B reports the characteristics of CQ portfolios and CQ strategy. We report portfolios' raw quality measure (ordinal measure), MB (defined as log market-to-book ratio), Size (in Million Dollars), Age (in years), 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 adjusted 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**	**FF3 Alpha**	**FF5 Alpha**	**q-factor Alpha**	**Adjusted R^2**
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**	**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 3: Comparison between *QC* Strategy and Quality Strategy

This table presents the comparison between *QC* strategy and quality strategy. We report excess returns of portfolios based on the dependent double sorts. The sample period runs from July 1957 to December 2020. Panel A shows the performance of *QC* strategy in each quality quintile. At the end of each calendar month, stocks are ranked in ascending order first based on their quality ordinal measure. Within each quality quintile, we then sort stocks on their *QC* Measure, forming 25 portfolios. Panel B exhibits the performance of quality strategy in each *QC* quintile. At the end of each calendar month, stocks are ranked in ascending order first based on the *QC* Measure. Within each *QC* quintile, we then sort stocks on their quality ordinal measure, forming 25 portfolios. Portfolios are value-weighted, and refreshed every month. Newey-West auto-correlation corrected t-statistics with a lag length of 6 are given in parentheses, and 5% statistical significance are indicated in bold.

Panel A: Conditional on Quality

	QC					
Quality	QC1	QC2	QC3	QC4	QC5	QC5-QC1
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 B: Conditional on QC

	Quality					
QC	Q1	Q2	Q3	Q4	Q5	Q5-Q1
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)

Table 4: Comparison between CQ Strategy and Value Strategy

This table presents the comparison between CQ strategy and value strategy. We report excess returns of portfolios based on the dependent double sorts. The sample period runs from July 1957 to December 2020. Panels A shows the performance of CQ strategy in each value quintile. At the end of each calendar 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. Panel B exhibits the performance of value strategy in each CQ quintile. At the end of each calendar 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 refreshed every month. Newey-West auto-correlation corrected t-statistics with a lag length of 6 are given in parentheses, and 5% statistical significance are indicated in bold.

Panel A: Conditional on MB

	CQ					
MB	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-CQ5
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 B: Conditional on CQ

	MB					
CQ	MB1	MB2	MB3	MB4	MB5	MB1-MB5
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)

Table 5: Independent Double-sorted Portfolio ($QCCQ$) Performance

This table shows the monthly portfolio returns and asset pricing model alphas based on our QC and CQ Measures. The sample period runs from July 1957 to December 2020. At the end of each calendar month, stocks are ranked in ascending order on the basis of their QC and CQ independently. Then, we take the intersection of "QC" and "CQ" stocks and form 25 portfolios. Portfolios are value-weighted, and refreshed every month. The rightmost column reports reports return spreads/alphas of CQ strategy, and the bottom two rows reports reports return spreads/alphas of QC strategy. The lower right corner reports the reports return spreads/alphas of $QCCQ$ strategy. Returns and alphas are in monthly percentages. Newey-West auto-correlation corrected t-statistics with a lag length of 6 are given in parentheses, and 5% statistical significance are indicated in bold.

Panel A: Excess return

QC	**CQ**					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-CQ5
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 B: CAPM Alpha

QC	**CQ**					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-CQ5
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 C: FF3 Alpha

QC	**CQ**					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-CQ5
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 D: FF5 Alpha

QC	**CQ**					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-CQ5
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 E: HXZ q-factor Model Alpha

QC	**CQ**					
	CQ1	CQ2	CQ3	CQ4	CQ5	CQ1-CQ5
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 6: Performance QC and CQ Strategies in Good and Bad Market

This table shows the average monthly return spreads of QC strategy, CQ strategy, and market excess returns in good and bad market conditions. The full sample period runs 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 Strategy	CQ Strategy	Market Excess Return
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)

Table 7: Portfolios and Factors of QC Strategy and CQ Strategy

This table shows the performance of QC strategy and CQ strategy. We run time-series regression of $QC(CQ)$ strategy returns on various risk factors and compare traditional commonly used risk factor with Quality-Cheapness factor (QCF) and Cheapness-Quality factor (CQF). The sample period runs from July 1957 to December 2020. Newey-West auto-correlation corrected t-statistics with a lag length of 6 are given in parentheses. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Return Spread of QC strategy (Quality based on Ordinal Measure)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	CAPM	CAPM	FF3	FF3	FF5	FF5	q-factor	q-factor
Market Excess	-0.087**	0.005	-0.081**	0.019	-0.054	0.008	-0.051	0.020
	(-2.241)	(0.316)	(-2.188)	(1.106)	(-1.270)	(0.490)	(-1.109)	(1.048)
SMB			-0.068	-0.081**	-0.057	-0.078**		
			(-0.848)	(-1.973)	(-0.833)	(-2.343)		
HML			-0.057	-0.001	-0.134	0.080		
			(-0.697)	(-0.024)	(-1.496)	(1.521)		
RMW					0.035	0.018		
					(0.218)	(0.336)		
CMA					0.214	-0.151**		
					(1.380)	(-2.038)		
ME (q-factor)							-0.032	-0.077*
							(-0.410)	(-1.778)
IA (q-factor)							0.063	-0.023
							(0.403)	(-0.469)
ROE (q-factor)							0.176	0.032
							(1.392)	(0.922)
QCF		1.014***		1.020***		1.027***		1.020***
		(23.412)		(25.194)		(25.735)		(24.640)
CQF		0.085*		0.098**		0.097**		0.107**
		(1.869)		(2.279)		(2.340)		(2.379)
Constant	0.007***	-0.001	0.007***	-0.001*	0.007***	-0.001*	0.006***	-0.002**
	(5.827)	(-1.637)	(5.833)	(-1.670)	(4.042)	(-1.771)	(2.860)	(-2.027)
Observations	762	762	762	762	690	690	648	648
Adjusted R^2	0.92%	79.59%	1.05%	79.90%	1.20%	81.39%	2.00%	81.62%

Panel B: Return Spread of CQ strategy (Quality based on Ordinal Measure)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	CAPM	CAPM	FF3	FF3	FF5	FF5	q-factor	q-factor
Market Excess	0.208***	0.010	0.202***	0.010	0.190***	0.011	0.194***	0.008
	(5.436)	(0.450)	(4.879)	(0.387)	(4.345)	(0.427)	(4.102)	(0.305)
SMB			0.073	-0.012	0.043	-0.014		
			(1.004)	(-0.325)	(0.648)	(-0.403)		
HML			0.066	-0.015	0.100	-0.032		
			(0.917)	(-0.435)	(1.233)	(-0.645)		
RMW					-0.059	-0.005		
					(-0.459)	(-0.095)		
CMA					-0.124	0.039		
					(-0.925)	(0.597)		
ME (q-factor)							0.043	0.005
							(0.519)	(0.131)
IA (q-factor)							0.009	-0.004
							(0.068)	(-0.075)
ROE (q-factor)							-0.113	0.034
							(-1.224)	(0.956)
QCF		0.090***		0.091***		0.096***		0.105***
		(2.745)		(2.850)		(3.025)		(3.168)
CQF		1.124***		1.127***		1.144***		1.159***
		(24.777)		(25.035)		(23.912)		(23.154)
Constant	0.005***	-0.003***	0.005***	-0.003***	0.005***	-0.004***	0.005***	-0.004***
	(4.584)	(-4.155)	(4.242)	(-3.866)	(4.074)	(-4.242)	(3.486)	(-4.000)
Observations	762	762	762	762	690	690	648	648
Adjusted R^2	8.58%	70.69%	9.04%	70.64%	8.90%	71.60%	9.77%	72.35%

Table 8: Performance of QCF and CQF

This table shows the alphas of Quality-Cheapness factor (QCF) and Cheapness-Quality factor (CQF) based on various asset pricing models. The sample period runs from July 1957 to December 2020. QCF and CQF are value-weighted and refreshed every calendar month. Columns (1) to (4) of each panel reports the performance of Quality-Cheapness factor (QCF), and Columns (5) to (8) of each panel reports the performance of Cheapness-Quality factor (CQF). Newey-West auto-correlation corrected t-statistics with a lag length of 6 are given in parentheses. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	QCF				CQF			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	CAPM	FF3	FF5	q-factor	CAPM	FF3	FF5	q-factor
Market Excess	-0.106***	-0.115***	-0.076*	-0.087	0.185***	0.180***	0.163***	0.169***
	(-2.721)	(-2.786)	(-1.679)	(-1.587)	(6.530)	(5.610)	(4.502)	(3.945)
SMB		0.006	0.016			0.075	0.048	
		(0.055)	(0.232)			(0.888)	(0.807)	
HML		-0.062	-0.220**			0.077	0.134*	
		(-0.707)	(-2.260)			(1.204)	(1.958)	
RMW			0.022				-0.049	
			(0.112)				(-0.364)	
CMA			0.372**				-0.174	
			(2.493)				(-1.564)	
ME (q-factor)				0.041				0.029
				(0.388)				(0.326)
IA (q-factor)				0.084				0.003
				(0.508)				(0.027)
ROE (q-factor)				0.156				-0.141
				(1.089)				(-1.562)
Constant	0.008***	0.008***	0.007***	0.006***	0.007***	0.006***	0.007***	0.007***
	(6.526)	(6.392)	(4.165)	(3.022)	(7.759)	(7.207)	(5.974)	(5.140)
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%

Table 9: Reversal and Momentum Exposure

This table reports the time-series regression results of QCF/CQF on Reversal or Momentum with or without the Fama-French five risk factors. Panel A reports the results for Quality-Cheapness factor (QCF), and Panel B reports the results for Cheapness-Quality factor (CQF). Newey-West autocorrelation corrected t-statistics with a lag length of 6 are given in parentheses. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Quality-Cheapness factor (QCF)

	(1)	(2)	(3)	(4)
Momentum factor	0.147*	0.123		
	(1.800)	(1.404)		
Reversal factor			-0.845***	-0.903***
			(-10.768)	(-12.219)
Constant	0.006***	0.006***	0.011***	0.010***
	(4.852)	(3.900)	(10.941)	(9.612)
Control FF5	No	Yes	No	Yes
Observations	762	690	762	690
Adjusted R-squared	3.01%	5.20%	57.63%	60.76%

Panel B: Cheapness-Quality factor (CQF)

	(1)	(2)	(3)	(4)
Momentum factor	-0.213***	-0.178***		
	(-4.146)	(-3.159)		
Reversal factor			0.741***	0.728***
			(36.678)	(29.887)
Constant	0.009***	0.008***	0.004***	0.004***
	(9.507)	(7.196)	(11.182)	(9.928)
Control FF5	No	Yes	No	Yes
Observations	762	690	762	690
Adjusted R-squared	12.35%	20.14%	84.22%	85.12%

Table 10: Liquidity Exposure

This table reports the time-series regression results of QCF/CQF on Liquidity risk measures with or without the Fama-French five risk factors. Panel A reports the results for Quality-Cheapness factor (QCF), and Panel B reports the results for Cheapness-Quality factor (CQF). Newey-West autocorrelation corrected t-statistics with a lag length of 6 are given in parentheses. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Quality-Cheapness factor (QCF)

	(1)	(2)	(3)	(4)
Lagged VIX ($\times$100)	-0.002	-0.002		
	(-0.074)	(-0.060)		
Lagged S&P500 volatility			-0.007	-0.012
			(-0.428)	(-0.682)
Constant	0.007	0.008	0.008***	0.009***
	(1.488)	(1.560)	(3.463)	(3.566)
Control FF5	No	Yes	No	Yes
Observations	370	370	700	690
Adjusted R-squared	0.00%	6.19%	0.03%	4.17%

Panel B: Cheapness-Quality factor (CQF)

	(1)	(2)	(3)	(4)
Lagged VIX ($\times$100)	0.050**	0.040*		
	(2.385)	(1.889)		
Lagged S&P500 volatility			0.033*	0.029*
			(1.880)	(1.792)
Constant	-0.005	-0.004	0.003	0.003
	(-1.332)	(-1.123)	(1.463)	(1.280)
Control FF5	No	Yes	No	Yes
Observations	370	370	700	690
Adjusted R-squared	1.89%	17.48%	1.28%	13.87%

Table 11: Future Economic Growth and Past Factor Returns

This table shows the univariate and multivariate forecast regression results of one-year ahead real GDP growth and real consumption growth on past QCF/CQF with or without Fama-French five risk factors. Panels A and B reports results of future real GDP growth and future consumption growth, respectively. Newey-West autocorrelation corrected t-statistics with a lag length of 6 are given in parentheses. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Future GDP Growth

	(1)	(2)	(3)	(4)
	Future GDP (t, t+4)			
QCF (t)	-0.032	0.004		
	(-1.272)	(0.125)		
CQF (t)			0.217***	0.157***
			(4.253)	(2.721)
Constant	0.064***	0.063***	0.059***	0.060***
	(13.753)	(12.315)	(13.779)	(12.220)
Control FF5	No	Yes	No	Yes
Observations	254	230	254	230
Adjusted R-squared	-0.01%	3.35%	7.48%	6.70%

Panel B: Future Consumption Growth

	(1)	(2)	(3)	(4)
	Future Consumption (t, t+4)			
QCF (t)	-0.014	0.007		
	(-0.657)	(0.352)		
CQF (t)			0.107***	0.069*
			(2.786)	(1.781)
Constant	0.032***	0.029***	0.029***	0.028***
	(9.870)	(8.676)	(9.503)	(8.515)
Control FF5	No	Yes	No	Yes
Observations	254	230	254	230
Adjusted R-squared	0.01%	3.79%	3.75%	5.08%

Table 12: Uncertainty Exposure

This table reports the time-series regression results of QCF/CQF on uncertainty measures with or without the Fama-French five risk factors. Panel A reports the results for Quality-Cheapness factor (QCF), and Panel B reports the results for Cheapness-Quality factor (CQF). Financial Uncertainty and Macro Uncertainty are from Jurado et al. (2015). Newey-West autocorrelation corrected t-statistics with a lag length of 6 are given in parentheses. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Results of Quality-Cheapness factor (QCF)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Financial Uncertainty (1 Month)	0.009	-0.001										
	(1.067)	(-0.086)										
Financial Uncertainty (3 Month)			0.012	-0.001								
			(1.062)	(-0.074)								
Financial Uncertainty (12 Month)					0.034	-0.001						
					(1.015)	(-0.040)						
Macro Uncertainty (1 Month)							0.017	0.007				
							(1.622)	(0.623)				
Macro Uncertainty (3 Month)									0.015	0.006		
									(1.484)	(0.591)		
Macro Uncertainty (12 Month)											0.020	0.009
											(1.303)	(0.629)
Constant	-0.002	0.008	-0.004	0.008	-0.027	0.008	-0.004	0.003	-0.005	0.002	-0.011	-0.001
	(-0.224)	(1.059)	(-0.441)	(0.789)	(-0.825)	(0.256)	(-0.614)	(0.345)	(-0.634)	(0.256)	(-0.807)	(-0.098)
Control FF5	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	726	690	726	690	726	690	726	690	726	690	726	690
Adjusted R-squared	0.08%	3.25%	0.07%	3.25%	0.07%	3.25%	0.13%	3.29%	0.10%	3.28%	0.06%	3.29%

Table 12 Continued

Panel B: Results of Cheapness-Quality factor (CQF)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Financial Uncertainty (1 Month)	0.012	0.024***										
	(1.339)	(2.998)										
Financial Uncertainty (3 Month)			0.016	0.031***								
			(1.421)	(3.048)								
Financial Uncertainty (12 Month)					0.045	0.084***						
					(1.519)	(2.971)						
Macro Uncertainty (1 Month)							0.002	0.011				
							(0.161)	(0.870)				
Macro Uncertainty (3 Month)									0.002	0.009		
									(0.133)	(0.740)		
Macro Uncertainty (12 Month)											0.001	0.008
											(0.034)	(0.437)
Constant	-0.003	-0.015**	-0.007	-0.022**	-0.036	-0.076***	0.006	-0.000	0.006	-0.000	0.007	0.000
	(-0.419)	(-2.203)	(-0.720)	(-2.455)	(-1.278)	(-2.780)	(0.715)	(-0.053)	(0.672)	(-0.035)	(0.544)	(0.003)
Control FF5	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	726	690	726	690	726	690	726	690	726	690	726	690
Adjusted R-squared	0.52%	14.75%	0.55%	14.71%	0.53%	14.42%	-0.13%	12.34%	-0.13%	12.28%	-0.14%	12.18%

Table 13: Downside Risk

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

$$r_{Factor,t} = \alpha + \beta_{Downside} \min\{0, r^e_{mkt,t}\} + \beta_{Upside} \max\{0, r^e_{mkt,t}\} + \varepsilon_t$$

where $r_{factor,t}$ is the return of QCF/CQF, $r^e_{mkt,t}$ is the market excess return, $\min\{0, r^e_{mkt,t}\}$ is a minimum function that returns the minimum value of 0 or market excess return, and $\max\{0, r^e_{mkt,t}\}$ is a maximum function that returns the maximum value of 0 or negative market excess return. Newey-West autocorrelation corrected t-statistics with a lag length of 6 are given in parentheses. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)
Dependent Variable	QCF	CQF
Downside Beta ($\beta_{Downside}$)	-0.129*	0.109*
	(-1.831)	(1.946)
Upside Beta (β_{Upside})	-0.081	0.264***
	(-1.232)	(4.658)
Constant	0.007***	0.004**
	(3.747)	(2.541)
Observations	762	762
Adjusted R-squared	1.66%	11.47%

Table 14: Behavioral Exposure

This table reports the time-series regression results of QCF/CQF on behavioral measures with or without the Fama-French five risk factors. 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 in online Appendix. Panel A reports the results for Quality-Cheapness factor (QCF), and Panel B reports the results for Cheapness-Quality factor (CQF). Newey-West autocorrelation corrected t-statistics with a lag length of 6 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 (QCF)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Consumer Sentiment	0.001	0.001**								
	(1.536)	(2.548)								
Sentiment Index			-0.007	-0.008						
			(-0.728)	(-0.737)						
Sentiment Index - NIPO					-0.000**	-0.000**				
					(-2.029)	(-2.037)				
Sentiment Index - S							0.161	0.143		
							(1.220)	(1.052)		
Casino Profits									-0.035	0.009
									(-0.344)	(0.088)
Constant	0.007***	0.007***	0.008***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(5.848)	(4.284)	(5.711)	(3.825)	(5.897)	(3.896)	(6.072)	(3.917)	(5.508)	(3.928)
Control FF5	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	733	690	641	641	707	666	720	666	658	658
Adjusted R-squared	0.37%	4.43%	0.03%	2.73%	0.20%	2.76%	0.10%	2.63%	-0.14%	3.46%

Panel B: Results of Cheapness-Quality factor (CQF)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Consumer Sentiment	0.000	-0.000								
	(0.465)	(-1.261)								
Sentiment Index			0.002	0.002						
			(0.225)	(0.382)						
Sentiment Index - NIPO					0.000	-0.000				
					(0.032)	(-0.896)				
Sentiment Index - S							-0.221**	-0.188*		
							(-2.120)	(-1.720)		
Casino Profits									-0.099	-0.100
									(-1.206)	(-1.142)
Constant	0.008***	0.007***	0.008***	0.007***	0.008***	0.007***	0.008***	0.007***	0.008***	0.007***
	(8.540)	(6.027)	(7.943)	(5.688)	(8.416)	(5.855)	(8.720)	(5.968)	(8.065)	(5.847)
Control FF5	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	733	690	641	641	707	666	720	666	658	658
Adjusted R-squared	-0.09%	12.42%	-0.12%	11.52%	-0.14%	11.38%	0.72%	11.82%	0.01%	12.64%