Norwegian School of Economics
Bergen, Fall 2019

Industries and the Cash Conversion Cycle Effect

An Empirical Investigation of Industries as the Driver of the Return Spread

Kristoffer Ø. Hagevik and Andreas S. Røst

Supervisor: Darya Yuferova

Master thesis, Economics and Business Administration

Major: Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgements

We wish to express our sincere appreciation to our supervisor Darya Yuferova for giving us thorough and constructive guidance throughout the process of writing our thesis. Her feedback has truly been valuable. In addition, we thank the Norwegian School of Economics for providing access to databases and literature that have been important for our research. Finally, we thank each other for a great and enjoyable partnership. This has been a rewarding learning experience.

Norwegian School of Economics

Bergen, December 2019

Kristoffer Ø. Hagevik

Andreas S. Røst

Abstract

This thesis investigates whether there is a cash conversion cycle (CCC) effect in the industry component of stock returns. Using a panel of U.S. stock returns from July 1976 to December 2015, we find that a zero-investment portfolio with a long position in the lowest CCC decile and a short position in the highest CCC decile earns annual abnormal returns of 4%–7%. As the CCC varies considerably between industries, we check whether this portfolio systematically loads on specific industries. However, by constructing industry strategies that buy industries with low average CCCs and sell industries with high average CCCs instead of individual stocks, we do not find evidence of an industry CCC effect. As the CCC also varies considerably within industries, the portfolio of the strategy that buys and sells individual stocks does in fact appear to be well-diversified. The CCC effect therefore seems to be driven by individual stocks, but the underlying driver of this remains a puzzle.

Keywords – Cash conversion cycle, Asset pricing, Industry risk

Contents

List of Figures

List of Tables

1 Introduction

The cash conversion cycle (CCC) is the time between a firm pays for its inputs and receives the payment from the sale of its outputs (Berk & DeMarzo, 2017). While the CCC has long been a topic within working capital management, it has been rather understudied in an asset pricing context. However, in a recent paper, Wang (2019) finds that firms with low CCCs outperform firms with high CCCs. By constructing a zero-investment portfolio with a long position in low-CCC stocks and a short position in high-CCC stocks, he documents annual abnormal returns of 5%–7%. Since a higher CCC typically implies a higher dependence on external financing (Raddatz, 2006; Tong & Wei, 2011), Wang (2019) contradicts conventional economic theory regarding risk and return. Instead, Wang presents evidence that this return spread due to mispricing.

In this thesis, we add to Wang (2019) by investigating if this novel anomaly can be attributed to individual stocks or industries. Because the level of the CCC varies substantially between industries, we suspect that the low-minus-high CCC strategy systematically buys industries characterized by low CCCs and sells industries characterized by high CCCs. If this is the case, the low-minus-high strategy will predominantly buy and sell stocks from a small number of industries, which results in low diversification. Therefore, we do not rule out that this portfolio bets on outperforming industries instead of outperforming individual stocks, and that this drives the CCC effect. This reasoning is analogous to Moskowitz and Grinblatt (1999), who find that the momentum strategy is no longer profitable when controlling for industries. We check whether the same is true for the CCC strategy.

In order to establish the CCC effect, we first replicate Wang (2019) by using a panel of stock returns and accounting data for firms listed on The New York Stock Exchange (NYSE), The Nasdaq Stock Market (Nasdaq) and The American Stock Exchange (Amex) from July 1976 to December 2015. Each month, we sort stocks into deciles based on the stocks' CCC, which we adjust by the industry medians. We then create a zero-investment portfolio with a long position in the lowest decile financed with a short position in the highest decile and test how this portfolio performs over time. We refer to this as the individual strategy. Our results are profoundly similar to Wang, with abnormal returns of 4.8%–7.4% per annum. Noteworthy, the abnormal returns increase as we add more conventional systematic risk factors, as the portfolio generally loads negatively on these factors. We refer to the results from the individual strategy as the individual CCC effect.

Our industry analysis consists of implementing what we refer to as true and random industry strategies. These strategies are motivated by Moskowitz and Grinblatt (1999). When we investigate if there exists a CCC effect in the industry component of stock returns, referred to as the industry CCC effect, we want to use an unadjusted measure of the CCC as opposed to the intra-industry adjusted measure used by Wang (2019). Therefore, we first test whether the results from the individual strategy using these two different CCC measures as sort criteria differ, before we proceed with the industry analysis and a discussion of the results.

In our test of the individual strategy using the alternative, unadjusted sorting criterion, we find that the factor loadings change slightly, but we still earn statistically significant annual abnormal returns of 4.1%–6.6%. Importantly, we find that the difference in abnormal returns from the two sorts is statistically indistinguishable from zero. We therefore use this CCC sort in our industry analysis.

The true industry strategy buys industries with low average CCCs and sells industries with high average CCCs. We implement this strategy for several narrow and broad industry classifications. If there truly exists an industry CCC effect, the portfolios formed by this strategy should earn abnormal returns. However, we find that for the majority of the industry classifications, the abnormal returns we earn are statistically indistinguishable from zero, regardless of which asset pricing model we use. Moreover, the few statistically significant abnormal returns become insignificant once we add the CCC factor that controls for the individual CCC effect. Hence, our results from this strategy do not provide evidence for the existence of an industry CCC effect.

We proceed by implementing the random industry strategy. This strategy is an extension of the true industry strategy, where we substitute each stock in the industry portfolios with other stocks that have the closest CCC values. Hence, we create random industry portfolios. If there exists an industry CCC effect, this portfolio may not earn statistically significant abnormal returns. Nevertheless, we find that the majority of the equal-weighted portfolios for all industry classifications earn statistically significant abnormal returns. The results for the value-weighted portfolios are more ambiguous, as many of them do not earn statistically significant returns. However, with overwhelmingly significant results for the equal-weighted portfolios, and somewhat conflicting results for the value-weighted portfolios, we still do not find evidence of an industry CCC effect. Finally, when we add the CCC factor, the abnormal returns of most portfolios decrease substantially. This is evidence of a strong individual CCC effect.

By looking at statistics from the different investment strategies, we find that all industries are represented in both the long and short portfolios formed by the individual strategy. This is true for both CCC sorts. This indicates that the portfolios formed by this strategy are in fact more diversified than what could be expected, and is evidence of large CCC variability also within industries. Since all industries have both low- and high-CCC stocks, the random industry strategy portfolios are also well-diversified. On the other hand, the true industry strategy is substantially less diversified, indicating that the relationship between industries measured by their mean CCC is relatively stable across the sample period. The CCC effect therefore seems to be driven by individual stocks.

Our research is interesting for a number of reasons. First, Wang (2019) presents a mispricing explanation for the CCC effect. As mispricing should not occur in efficient markets, we try to find whether the CCC effect can be attributed to bets on individual stocks or industries. This is of both academic and professional interest. From an academic perspective, it is an important addition to the debate about market efficiency and asset pricing models. For investment professionals, it broadens the understanding of investment strategies and portfolio formation by following a top-down investment approach, where investors, in brief, buy industries instead of individual stocks. Since we do not find evidence of an industry CCC effect, our results indicate that a top-down investment approach is not attractive.

This thesis is structured as follows. In chapter 2, we present relevant literature. Chapter 3 introduces the data and present descriptive statistics. Next, in chapter 4, we outline our hypotheses and methodology. Chapter 5 presents our replication of Wang (2019). Then our analysis follows in chapter 6. In section 6.1, we construct the low-minus-high portfolio based on the unadjusted CCC sort. In section 6.2, we present the results from the true and random industry strategies. We discuss our overall findings in section 6.3. We further perform relevant robustness checks in chapter 7. Finally, in chapter 8, we summarize our findings and conclude.

2 Literature Review

In this chapter, we present the literature that is relevant for our research. To be able to provide a thorough understanding of the CCC effect, we will first review literature related to anomalies and how asset pricing models have developed in line with the research on the subject. We also present the accrual anomaly since the CCC is based on accrual accounting (Gentry, Vaidyanathan & Lee, 1990). Next, we present the literature on the CCC and concentrate primarily on the CCC effect, as it is most relevant for our thesis. Finally, we review studies that examine if anomalies can be explained by industries, which is relevant for our contribution to the literature on the CCC in an asset pricing context.

2.1 Anomalies

Market anomalies are known as cases when stock returns contradict predictions of asset pricing models (Schwert, 2003). This could happen due to stock mispricing, misspecified models or data mining (Engelberg, McLean & Pontiff, 2018). In this section, we present these explanations in detail before we proceed to review how asset pricing models have developed in line with the discovery of new anomalies. Among the anomalies we discuss is the accrual anomaly, which is relevant because CCC is based on accrual accounting (Gentry et al., 1990).

Firstly, anomalies could be a result of mispricing that occurs due to biased expectations, where the average investor, for various reasons, systematically believes that some stocks will perform better than others (Engelberg et al., 2018). Then, on days when new information arrives, particularly on earnings announcement days (EADs), investors are surprised, and prices adjust accordingly. Secondly, anomalies could be the result of misspecified models that fail to account for unobserved types of systematic risk (Engelberg et al., 2018). By assuming that an asset pricing model accounts for all systematic risk factors, one might conclude that an added variable generates abnormal returns, while in reality, it only reflects compensation from unobserved risks (Bodie, Kane & Marcus, 2018). Whether anomalies are due to model misspecification or mispricing can be hard to determine and is often subject to discussion.

A final explanation for anomalies could be data mining (Engelberg et al., 2018; Bodie et al., 2018). By testing enough variables on a given sample, it is not unlikely that some have predictive power on stock returns (Fama, 1998; Engelberg et al., 2018). However, it is not necessarily true in reality. Evidence that might support this is that some anomalies, such as the size factor, have faded rather quickly after discovery (Bodie et al., 2018). Moreover, a way to check for data mining bias is to research anomalies on new data samples.

2.1.1 Asset Pricing Models and Anomalies

The capital asset pricing model (CAPM) (Sharpe, 1964; Lintner, 1965; Mossin, 1966) can be regarded as one of the first models within asset pricing theory (Fama & French, 2004). According to the CAPM, differences in the cross-section of stock returns are only explained by differences in stocks' volatility relative to the market, measured by their market betas. Hence, other variables should not have any explanatory power when added to the model. However, there is no lack of empirical studies that contradict the CAPM. For instance, Basu (1977) finds that firms with low price-to-earnings (P/E) ratios on average perform better than the CAPM predicts, while firms with high P/E ratios perform worse than predicted. In addition, Banz (1981) finds evidence that firms with small market capitalizations perform better than predicted. Moreover, Rosenberg, Reid and Landstein (1985) find that the CAPM does not explain the outperformance of firms with high book-to-market (B/M) values.

Due to the empirical shortcomings of the CAPM, Fama and French (1993) introduce the three-factor model, where they add factors for small-minus-big (SMB) market capitalization and high-minus-low (HML) B/M value to the original CAPM equation (Fama & French, 2004). These factors function as proxies for unobserved, systematic sources of risk (Bodie et al., 2018). This argument implies that the market is efficient and that the CAPM is misspecified. Despite the three-factor model's recognition within the asset pricing literature, numerous variables become significant in explaining stock returns when added to the model. For instance, Jegadeesh and Titman (1993) find that stocks that have generated returns in excess of the market in the past three to twelve months continue to do well in the following months. They find the opposite for stocks that have performed poorly. The three-factor model does not explain the return spread (Fama & French, 1996). Whether this anomaly, known as the momentum factor (up-minus-down, UMD), is due to mispricing or model misspecification is not resolved, but the literature suggests a mispricing explanation (Barberis, Shleifer & Vishy, 1998; Hong & Stein 1998). Nevertheless, Carhart (1997) expands the Fama–French three-factor model by adding the momentum factor, which increases the model's explanatory power. Furthermore, following evidence by Titman, Wei and Xie (2004) and Novy-Marx (2013), Fama and French (2015) add a profitability factor (RMW) as well as an investment factor (CMA) to the three-factor model. RMW is long stocks with *robust* operating profitability and short stocks with *weak* operating profitability, while CMA is long stocks of firms that invest *conservatively* and short stocks of firms that invest *aggressively*. Although this five-factor model, and the other models described above, increase the predictability of stock returns, new anomalies are frequently discovered.

2.1.2 The Accrual Anomaly

Sloan (1996) documents that investors can earn abnormal returns by buying stocks with low accruals and short-selling stocks with high accruals. This anomaly is particularly interesting for our thesis since the CCC is based on accrual accounting (Gentry et al., 1990). A firm's earnings can be divided into an accrual component and a cash flow component (Dechow, Khimich & Sloan, 2015). If the accrual component of a firm's earnings is high, a relatively large portion of the firm's earnings is realized through future cash flows. Similarly, if the days receivables outstanding (DRO) component of a firm's CCC is large, the firm spends a long time to collect its payments, or equivalently, realize its sales. Moreover, if a firm holds much inventory on hand, the days inventory component of a firm's CCC is large. If this inventory is financed with cash on hand, accruals increase, all else equal. Finally, if a firm has little account payables, the days payable outstanding component (DPO) of the CCC is low, implying a higher CCC. Similarly, low amounts of account payables increase accruals. Hence, there is a positive relationship between CCC and accruals.

Sloan (1996) finds that U.S. firms with a relatively large accrual component of earnings are less likely to have strong future earnings performances. Moreover, he finds that a zero-investment portfolio with a long position in low-accrual stocks and a short position in high-accrual stocks earns most of the abnormal returns on EADs. This indicates that stocks with low accruals are underpriced and stocks with high accruals are overpriced. Sloan argues that this happens because the lower earnings persistence of high-accrual firms is unexpected by the market, and thus, the market is inefficient. Extending on this, Bradshaw, Richardson and Sloan (2001) find that analysts do not predict the weaker earnings persistence of high-accrual firms in their earnings forecasts.

2.2 The Cash Conversion Cycle

The cash conversion cycle (CCC) is the time between a firm pays for its inputs and receives the payment from the sale of the outputs (Berk & DeMarzo, 2017), and is used as a measure of working capital management. It has three components, calculated as days inventory outstanding (DIO) plus days receivable outstanding (DRO) minus days payable outstanding (DPO). For a period of n days, it is calculated as

$$\text{CCC} = n \cdot \left(\frac{\text{Average inventory}}{\text{COGS}} + \frac{\text{Average receivables}}{\text{Revenues}} - \frac{\text{Average payables}}{\text{COGS}} \right) \tag{2.1}$$

where COGS is cost of goods sold. The sum of the two first components is the operating cycle, which is the time between a firm takes delivery of its inputs and receives the payment from the sale of its outputs. It is equal to the CCC if the firm does not buy inventory on credit. The CCC is negative if DPO exceeds the operating cycle, indicating that a firm has efficient inventory management and receives payments from its customers before it has to pay its suppliers.

Previous research on the CCC has primarily focused on corporate performance and capital structure. For instance, Jose, Lancaster and Stevens (1996), Shin and Soenen (1998) and Deloof (2003) find evidence that there is a negative relationship between CCC and profitability. Raddatz (2006) documents that a higher CCC is associated with higher dependence on external financing. In addition, Kieschnick, Laplante and Moussawi (2013) argue that poor working capital management, measured by CCC, increases the probability of financial distress due to higher financial costs. However, in an asset pricing context, the CCC has received little attention. A notable exception is Wang (2019), who investigate the asset pricing implications of the CCC.

Wang (2019) finds that a zero-investment portfolio of U.S. stocks that has a long position in low-CCC firms and a short position in high-CCC firms earns statistically significant abnormal returns of 5–7% per annum after controlling for risk factors in the Fama–French (1993) three-factor model, the Fama–French–Carhart four-factor model (Carhart, 1997), the Fama–French (2015) five-factor model, the Hou, Xue and Zhang (2015) q-factor model and the Stambaugh–Yuan (2017) mispricing-factor model. Except for modest loadings on the market, the zero-investment portfolio is either uncorrelated with or has negative loadings on the systematic risk factors in the models. Moreover, the CCC spread is higher for small firms, although it remains statistically significant for all size groups.

Wang (2019) provides evidence that the positive CCC effect is not a result of higher systematic risk. As the zero-investment portfolio generally is either uncorrelated with or has negative loadings on the standard systematic risk factors, he controls for other systematic risk factors as well. However, the results persist. Moreover, Wang finds that the CCC effect is not explained by higher funding risk. By controlling for different funding risk measures identified by He, Kelly and Manela (2017), Adrian, Etula and Muir (2014), Frazzini and Pedersen (2014) and Hu, Pan and Wang (2013), in addition to the Fama–French five factors (Fama & French, 2015), Wang (2019) finds weak evidence that high-CCC firms, not low-CCC firms, are more correlated with funding risk. This is consistent with Raddatz (2006) and Tong and Wei (2011).

Instead, Wang (2019) provides evidence that the CCC effect is a result of mispricing. He finds that the CCC has predictive power on future profitability, and that a large part of the low-minus-high portfolio return is earned on EADs. This indicates that investors have biased expectations, like with the accrual anomaly, and is consistent with the reasoning Engelberg et al. (2018) use for mispricing evidence.

2.3 Anomalies and Industry Effects

Research on the performance of stock return anomalies when controlling for industry effects have resulted in interesting contributions to the understanding of return anomalies. In this section of our thesis, we will review some of these contributions.

Chou, Ho and Ko (2012) provide evidence that the size effect (SMB) is significant only for firms that have market capitalizations smaller than the industry average. Conversely, they find that there is a positive relationship between market capitalization and stock returns for companies that are larger than the industry average. However, the negative relationship between size and return for small firms dominates the positive relationship between size and return for large firms, resulting in an overall positive SMB effect. Moreover, Chou et al. also document a within-industry effect for the value factor (HML) and an across-industry effect for the momentum factor (UMD). They do not find any relationship between the size factor and industries.

Moskowitz and Grinblatt (1999) perform a more comprehensive analysis of the industry effects on the momentum strategy. Among other things, they find that replicating the standard momentum strategy on industry portfolios rather than on individual stocks earns statistically significant abnormal returns equal to that of the standard momentum strategy, indicating that there is a significant industry component that is driving momentum. On the other hand, when they substitute stocks in the industry portfolios with stocks from other industries that have approximately the same return, thereby creating "random" industries with the same momentum characteristic, they do not find such abnormal returns, providing further evidence that industries explain momentum.

One of the implications of Moskowitz and Grinblatt (1999) is that standard momentum strategy portfolios are not necessarily well-diversified. The reason is that winners from the cross-section tend to belong to one industry, while losers tend to belong to another industry, meaning that the portfolio will be skewed towards certain industries. This insight is highly relevant for our analysis as we hypothesize that this is also true for the low-minus-high CCC portfolio. More specifically, if firms in the lowest CCC decile are mainly from the same industry, and the same is true for the highest CCC decile, an investor's portfolio will be skewed towards a small number of industries. Hence, the portfolio has low diversification and is exposed to industry risk. Should this be true, a mispricing explanation may still be relevant, as investors should not be compensated for exposure to unsystematic risk as this can freely be diversified away.

3 Data

In this chapter, we present our data sources, data cleansing and descriptive statistics. We replicate Wang (2019) and highlight any deviations.

3.1 Data Sources and Data Cleansing

In this section, we present the data sources and data cleansing process. We obtain monthly stock data from The Center for Research in Security Prices[1] (2019) and quarterly and annual accounting data from Compustat (2019). Our sample consists of all firms that are incorporated in the U.S. and trade on the NYSE, Nasdaq or Amex. We exclude all securities that are not common shares (share code other than 10 or 11). Moreover, we exclude all financial firms, following Wang (2019) (SIC code starting with 6). This removes around 2,500 unique firms and more than 400,000 firm-month observations. If firms are missing book equity values, we fill this in (Davis, Fama & French, 2000), using data obtained from French (2019). Finally, if a delisting return is missing and performance-related, we set the delisting return to –30% (Shumway, 1997).

Furthermore, we obtain the Fama–French three factors (Fama & French, 1993), the momentum factor (Carhart, 1997), the Fama–French five factors (Fama & French, 2015), the risk-free rate and the NYSE size breakpoints from French (2019) and the Stambaugh–Yuan mispricing factors (Stambaugh & Yuan, 2017) from Stambaugh (2019). We obtain the Fama–French industry classifications from French (2019) and the official SIC industry classification from the U.S. Department of Labor (2019). We use all four digits of the SIC codes to assign firms to industries.

We match the quarterly accounting data from quarter t to stock returns in quarter $t + 2$, following Wang (2019), to ensure that the information is available in the market. For annual accounting data, we follow Fama and French (1992) and match accounting data from year t to stock returns from July of year $t + 1$ to June of year $t + 2$. Our sample of stock returns begins in July 1976 and ends in December 2015. Our sample of

[1] Hereafter referred to as CRSP.

quarterly accounting data starts in the first calendar quarter of 1976 and ends in the second calendar quarter of 2015, while our sample of annual accounting data starts in the calendar year of 1975 and ends in the calendar year of 2014.

The CCC is equal to days inventory outstanding (DIO) plus days receivables outstanding (DRO) minus days payable outstanding (DPO). Each quarter t, we calculate CCC_t measured in days as

$$CCC_t = 365 \cdot \left(\frac{1}{2} \cdot \frac{invtq_t + invtq_{t-1}}{cogsq_t} + \frac{1}{2} \cdot \frac{rectq_t + rectq_{t-1}}{revtq_t} - \frac{1}{2} \cdot \frac{apq_t + apq_{t-1}}{cogsq_t} \right) \quad (3.1)$$

where $invtq_t$ is inventories in quarter t, $rectq_t$ is account receivables in quarter t, apq_t is account payables in quarter t, $cogsq_t$ is cost of goods sold in quarter t and $revt_t$ is revenues in quarter t. Because we use quarterly items from the income statement, the CCC components should be multiplied by 90 days instead of 365 days. However, since Wang (2019) uses 365 days, and we replicate his findings, we also use 365 days.

We exclude observations with missing CCC, missing current month returns, missing last-month market capitalization and missing or negative book equity. This reduces our sample with around 1,300 unique firms and more than 400,000 firm-month observations. Furthermore, we exclude observations where quarterly revenues divided by lagged total assets is lower than 2.5% in order to avoid extreme observations caused by low revenues. This further reduces our sample with more than 200 unique firms and close to 40,000 firm-month observations.

Our final sample consists of more than 11,000 unique firms with close to 1.3 million firm-months observations. In comparison, Wang (2019) uses a larger sample, consisting of more than 13,000 unique firms and more than 1.3 million firm-month observations. We are not sure what causes this deviation. One reason may be that we have accessed the CRSP and Compustat databases at a different time compared to Wang, and that there have been some changes in between.

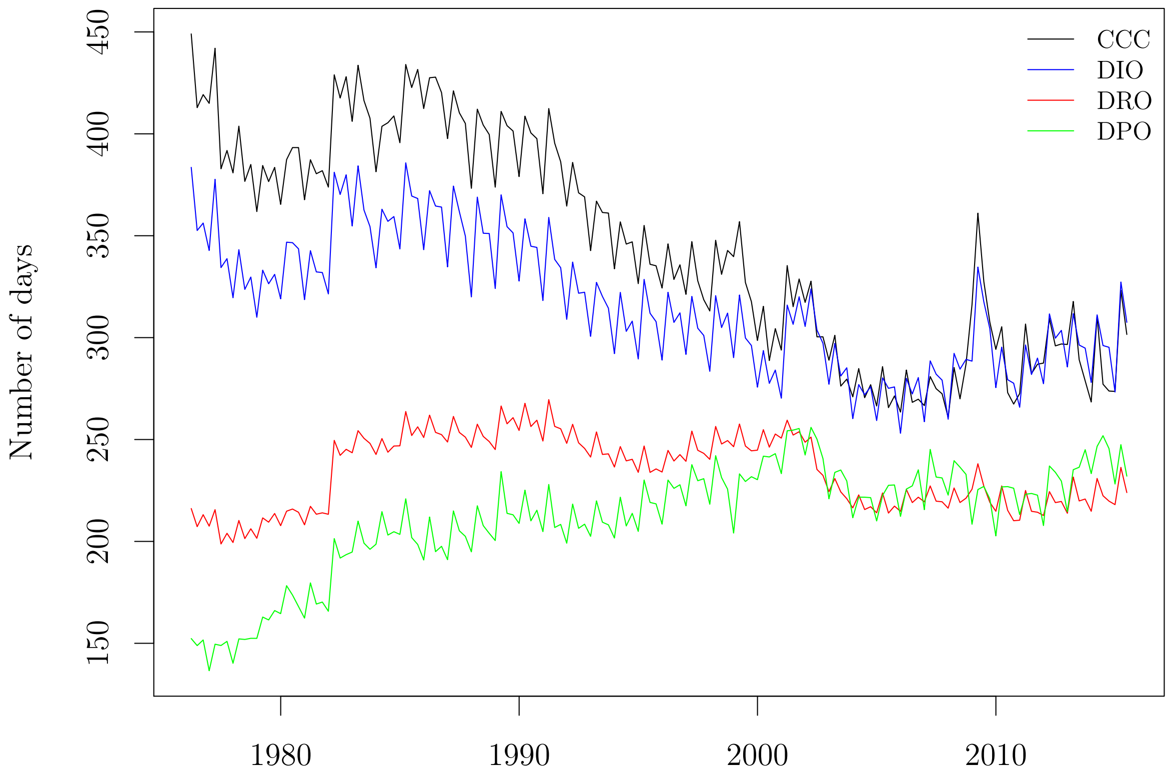
3.2 Descriptive Statistics

In this section, we present descriptive statistics of the sample. Figure 1 presents the average CCC, DIO, DRO and DPO per quarter during the sample period. Our results are consistent with Wang (2019). Each quarter, we calculate the average from the cross-section and winsorize all variables at the 1% level for both tails to mitigate the effect of outliers, following Wang. The CCC decreased from the 1980s to mid-2000s primarily because of a decrease in the DIO, which throughout the sample period has been the largest component. Also contributing to this trend is the increase in the DPO. Post mid-2000s, the DRO and the DPO have remained stable while the CCC has risen together with the DIO. Furthermore, the CCC of the average firm seems to repeat a certain seasonal trend. Over the sample period, the CCC is the highest at the end of the first quarter, in the middle at the end of the second and third quarter, and the lowest at the end of the fourth quarter. On average, the CCC is almost 1.1 times higher at the end of the first quarter compared to the end of the fourth quarter. The three components of CCC also exhibit this pattern.

Table 1 presents statistics for each of the Fama–French 48 industries. The sample consists of a total of 44 industries, as the four industries related to financial services are excluded. We follow Wang (2019), where we, quarter by quarter, calculate the median CCC, DIO, DRO and DPO as well as the first and third quartile CCC. We then calculate the time series means of these statistics. Our time series means are consistent with Wang (2019), however, our quartiles are more extreme on both ends for most of the industries. We do not know what causes this deviation. However, we are not particularly concerned with this, as we do not use the level of the CCC directly in our analyses. Instead, we use the CCC to rank stocks and assign them to deciles based on this ranking.

The CCC varies significantly both across and within industries. The industry with the lowest average CCC is petroleum and natural gas with seven days, while tobacco products is the highest with 657 days, nearly two years. The industry with the lowest CCC variability is restaurants, hotels and motels with an interquartile range of 91 days, while the interquartile range in the beer and liquor industry is 667 days, nearly two years.

Figure 1: Average CCC, DIO, DRO and DPO over the sample period.



This figure presents the average cash conversion cycle (CCC), days inventory outstanding (DIO), days receivables outstanding (DRO) and days payable outstanding (DPO) over the sample period from the first calendar quarter of 1976 to the second calendar quarter of 2015. Each quarter, we calculate the means from the cross-section. All variables are winsorized at the 1% level on both tails to mitigate the effect of outliers.

The CCC component that has the highest variability between industries is the DIO.

The sum of the number of firms in all industries is more than 13,000, which is higher than the total number of unique firms. The reason for this is that some firms have changed the SIC code during the sample period and are thus counted more than once. Business services has the highest number of firms (2,239), while tobacco products has the lowest number of firms (15). Seven of the 44 industries have less than 50 firms, while 27 industries have more than 150 firms.

Table 2 presents the mean and standard deviation of some major asset pricing variables and asset characteristics. We follow Wang (2019) and adjust the CCC by the industry-median CCC of that particular month. At the beginning of each month, we sort stocks into deciles based on the industry-adjusted CCC. We then calculate the statistics from the whole

Table 1: Industry summary statistics.

This table presents summary statistics of the sample grouped by the Fama-French 48 industries. The sample consists of a total of 44 industries, as the four industries related to financial services are excluded. CCC is the cash conversion cycle, DIO is days inventory outstanding, DRO is days receivables outstanding, DPO is days payable outstanding, and Q_1 and Q_3 are the first and third CCC quartile, respectively. $Q_3 - Q_1$ is the interquartile range of CCC. The CCC, DIO, DRO, DPO, Q_1, Q_3 and $Q_3 - Q_1$ are measured in days. Each quarter, we calculate the median CCC, DIO, DRO and DPO, and the first and third quartile of the CCC across firms within each industry. We then calculate the time series means of these statistics.

	Industry	Number of firms	CCC	DIO	DRO	DPO	Q_1	Q_3	$Q_3 - Q_1$
1	Petroleum and natural gas	525	7	73	243	314	−382	170	552
2	Restaurants, hotels and motels	331	10	35	41	75	−32	59	91
3	Entertainment	241	61	55	130	144	−71	241	312
4	Communication	530	75	32	217	198	−66	191	257
5	Transportation	292	90	31	167	106	24	153	130
6	Personal services	222	113	49	167	121	−2	236	238
7	Utilities	273	123	117	154	151	62	186	125
8	Coal	27	159	96	179	127	48	210	162
9	Healthcare	424	174	21	235	101	76	259	183
10	Printing and publishing	144	206	136	206	165	72	403	331
11	Business services	2239	207	22	270	134	77	343	266
12	Food products	188	223	229	126	127	146	325	179
13	Retail	767	250	343	27	153	118	417	299
14	Business supplies	132	259	220	179	131	187	367	179
15	Other	811	267	126	239	152	102	459	357
16	Shipbuilding, railroad and equipment	28	271	239	173	136	133	317	184
17	Shipping containers	60	273	243	186	145	189	348	160
18	Candy and soda	30	276	301	146	160	61	378	316
19	Non-metallic and industrial metal mining	81	287	263	206	157	118	401	284
20	Automobiles and trucks	171	314	234	219	145	201	457	256
21	Precious metals	43	315	373	172	240	56	420	364
22	Wholesale	754	318	283	188	149	161	505	344
23	Construction	181	326	166	245	131	182	796	614
24	Rubber and plastic products	144	342	274	213	147	235	437	202
25	Steel works	171	351	291	201	137	253	484	231
26	Agriculture	53	353	332	168	142	100	676	576
27	Chemicals	245	375	311	239	174	259	506	246
28	Construction materials	282	386	307	214	124	257	533	276
29	Fabricated products	56	398	271	260	153	273	485	212
30	Consumer goods	233	417	370	213	161	267	610	342
31	Beer and liquor	41	420	375	192	181	144	811	667
32	Computers	585	435	357	271	189	268	617	349
33	Pharmaceutical products	604	443	447	237	181	217	706	490
34	Textiles	81	446	342	230	126	351	533	182
35	Defense	26	453	310	247	131	227	559	332
36	Electronic equipment	777	474	397	243	168	319	659	340
37	Recreation	148	487	399	251	155	303	673	370
38	Apparel	151	509	444	217	134	388	639	251
39	Electrical equipment	458	515	418	255	161	376	692	316
40	Aircraft	63	520	405	229	144	387	650	263
41	Machinery	408	541	433	259	159	397	735	338
42	Medical equipment	454	608	543	252	170	407	824	417
43	Tobacco products	15	622	632	107	164	275	769	494
44	Measuring and control equipment	298	657	548	276	163	453	857	404
	Average	313	326	270	202	153	173	479	306

sample and for each of the deciles and report the time series means of these statistics. *CCC* is the industry-adjusted CCC, *Beta* is the stock's beta computed using monthly

Table 2: Summary statistics.

This table presents summary statistics of the sample. The first and second column reports the mean and standard deviation (SD) of each variable. The next ten columns report the mean of each CCC decile, from the lowest to the highest. *CCC* is the industry-adjusted CCC, *Beta* is the stock's beta computed using monthly returns over the past previous five years with a minimum number of 24 months as in Fama and French (1992), *Size* is the natural logarithm of the market capitalization at the end of last month, *BM* is the natural logarithm of the equity book value divided by the market capitalization as in Fama and French (2008a), *Accruals* is calculated as in Sloan (1996), *WorkingCap* is current assets minus current liabilities divided by total assets, *STDebt* and *LTDebt* is short-term debt and long-term debt divided by total assets, respectively, *TotalLev* is total liabilities divided by total assets, *XFIN* is external financing and is calculated as in Bradshaw, Richardson and Sloan (2006), *GrossProfit* is revenues less cost of goods sold divided by lagged total assets, following Novy-Marx (2013), *CBOP* is cash-based operating profitability and is calculated as in Ball, Gerakos, Linnainmaa and Nikolaev (2016), *ProfitMargin* is operating income after depreciation divided by revenues, *ROA* is operating income after deprecation divided by lagged total assets and *ROE* is operating income after depreciation divided by total assets less total liabilities. All variables are constructed using quarterly data, except from *BM* and *XFIN*, which are constructed using annual data. We winsorize all variables at the 1% level on both tails except for *Beta*, *Size* and *BM*. Each month, we sort stocks into deciles based *CCC*. We then calculate the means and standard deviations from the cross-section and take the time series means of these statistics.

Variables	Mean	SD	Low 1	2	3	4	5	6	7	8	9	High 10
CCC	35	337	−491	−204	−123	−66	−18	21	73	149	277	732
Beta	1.18	0.71	1.313	1.224	1.189	1.133	1.103	1.105	1.124	1.162	1.197	1.217
Size	12.09	1.98	12.05	12.20	12.26	12.31	12.32	12.31	12.20	11.99	11.77	11.48
BM	−0.53	0.92	−0.847	−0.670	−0.597	−0.538	−0.495	−0.465	−0.443	−0.426	−0.411	−0.389
Accruals	−0.01	0.05	−0.013	−0.008	−0.008	−0.008	−0.008	−0.007	−0.007	−0.005	−0.004	−0.005
CashHolding	0.15	0.17	0.238	0.176	0.151	0.136	0.126	0.122	0.125	0.128	0.135	0.143
WorkingCap	0.28	0.22	0.237	0.250	0.249	0.237	0.235	0.248	0.279	0.318	0.367	0.432
STDebt	0.05	0.07	0.038	0.039	0.041	0.042	0.042	0.044	0.047	0.050	0.055	0.068
LTDebt	0.18	0.16	0.161	0.167	0.173	0.186	0.193	0.193	0.185	0.177	0.161	0.157
TotalLev	0.48	0.20	0.480	0.499	0.494	0.500	0.497	0.493	0.482	0.468	0.441	0.420
XFIN	0.02	0.14	0.065	0.029	0.019	0.017	0.014	0.013	0.014	0.016	0.018	0.031
GrossProfit	0.10	0.08	0.100	0.114	0.109	0.102	0.098	0.097	0.097	0.101	0.102	0.091
CBOP	0.03	0.09	0.021	0.023	0.024	0.027	0.034	0.034	0.031	0.030	0.029	0.024
ProfitMargin	0.01	0.33	−0.090	−0.001	0.032	0.048	0.056	0.058	0.050	0.037	0.013	−0.064
ROA	0.02	0.04	0.008	0.020	0.023	0.023	0.023	0.022	0.020	0.018	0.015	0.006
ROE	0.04	0.10	0.028	0.050	0.054	0.054	0.054	0.052	0.045	0.041	0.032	0.016

returns over the past previous five years with a minimum number of 24 months as in Fama and French (1992), *Size* is the natural logarithm of the market capitalization at the end of last month, *BM* is the natural logarithm of the equity book value divided by the market capitalization as in Fama and French (2008a), *Accruals* is calculated as in Sloan (1996), *WorkingCap* is current assets minus current liabilities divided by total assets, *STDebt* and *LTDebt* is short-term debt and long-term debt divided by total assets, respectively, *TotalLev* is total liabilities divided by total assets, *XFIN* is external financing calculated as in Bradshaw, Richardson and Sloan (2006), *GrossProfit* is revenues less cost of goods sold divided by lagged total assets, following Novy-Marx (2013), *CBOP* is cash-based operating profitability calculated as in Ball, Gerakos, Linnainmaa and Nikolaev (2016), *ProfitMargin* is operating income after depreciation divided by revenues, *ROA* is operating income after deprecation divided by lagged total assets and *ROE* is operating income after depreciation divided by total assets less total liabilities. *BM* and *XFIN* are constructed using annual accounting data, while the other variables are constructed using quarterly data. We winsorize all variables at the 1% level on both tails except for *Beta*, *Size* and *BM*. We also present the correlation matrix of our sample in Table 3. Our results are consistent with Wang (2019).

Stocks with high CCCs tend to be smaller firms with higher book-to-market ratios. The book-to-market ratio increases monotonically from the lowest to the highest CCC decile. As expected, the CCC is positively correlated with accruals and short-term debt, while it is negatively correlated with cash holding and total leverage, of which account payables is one of the components. Although the correlations are relatively modest in size, they are highly statistically significant. The highest correlation is between the CCC and working capital. From the low 1 decile to the high 10 decile, *WorkingCap* increases from 24% to 43%, which is close to 0.9 standard deviations. Consistent with the literature on CCC and profitability, we see that the CCC is negatively correlated with the variables measuring firm profitability. However, with the exception of *GrossProfit*, we see clear non-monotonic relations between the CCC deciles and these variables, where the firms in the mid-deciles have higher profitability than the firms in the low and high deciles. In conclusion, these statistics indicate that firms with high CCCs need larger investments in working capital, have lower cash holdings and rely more on short-term debt financing.

Table 3: Correlation between variables.

This table presents the correlation between the variables in Table 2 over the sample period.

	CCC	*Beta*	*Size*	*BM*	*Accruals*	*Cash-Holding*	*Working-Cap*	*ST-Debt*	*LT-Debt*	*Total-Lev*	*XFIN*	*Gross-Profit*	*CBOP*	*Profit-Margin*	*ROA*	*ROE*
CCC	1.00															
Beta	−0.09	1.00														
Size	−0.14	0.11	1.00													
BM	0.14	−0.11	−0.37	1.00												
Accruals	0.02	−0.01	0.04	−0.05	1.00											
CashHolding	−0.14	0.26	0.02	−0.20	−0.02	1.00										
WorkingCap	0.24	0.11	−0.16	−0.01	0.13	0.63	1.00									
STDebt	0.08	−0.08	−0.21	0.07	0.01	−0.30	−0.34	1.00								
LTDebt	−0.01	−0.11	0.12	0.02	−0.01	−0.39	−0.38	0.04	1.00							
TotalLev	−0.14	−0.09	0.09	−0.06	−0.07	−0.47	−0.62	0.38	0.70	1.00						
XFIN	0.00	0.10	−0.12	−0.14	0.05	0.14	0.07	0.02	0.04	0.00	1.00					
GrossProfit	−0.16	−0.05	−0.03	−0.24	0.10	−0.02	0.07	−0.02	−0.19	−0.01	−0.08	1.00				
CBOP	−0.01	−0.00	0.10	−0.03	−0.31	0.05	0.02	−0.07	−0.02	−0.08	−0.23	0.15	1.00			
ProfitMargin	−0.08	−0.12	0.25	0.01	0.15	−0.23	−0.10	−0.02	0.09	0.07	−0.38	0.32	0.27	1.00		
ROA	−0.08	−0.13	0.35	−0.09	0.21	−0.19	−0.04	−0.07	0.07	0.00	−0.38	0.43	0.29	0.79	1.00	
ROE	−0.08	−0.12	0.31	−0.10	0.17	−0.19	−0.09	−0.04	0.18	0.13	−0.30	0.33	0.22	0.60	0.80	1.00

4 Methodology

In this chapter, we present the methodology of our analysis. We first replicate Wang (2019) in order to establish whether the CCC anomaly exists in our sample. We refer to this strategy as the individual strategy. As the CCC varies considerably across industries, we expect that this individual strategy loads on specific industries and hypothesize that the industry component of stock returns may account for a non-trivial part of the CCC effect. Therefore, we also present methods to control for industries, following Moskowitz and Grinblatt (1999). We refer to these methods as true and random industry strategies. Further, in order to control for the individual CCC effect, we present how we construct a CCC factor that we add to the analysis of the true and random industry strategies. Finally, we present our robustness testing.

4.1 The Individual Strategy

In this section, we present the methodology of Wang (2019) to establish the CCC anomaly. We refer to this as the individual strategy. At the beginning of each month, we buy the stocks in the lowest CCC decile and sell the stocks in the highest CCC decile to create a zero-investment portfolio. We lag the CCC of each stock with two quarters to make sure the financial information is available in the market, meaning that the CCC for the first calendar quarter is used for portfolio formation at the beginning of July, August and September, and so forth. We then test how this portfolio performs relative to the risk-free rate and by controlling for the Fama–French (1993) three-factor model (4.1), the Fama–French–Carhart four-factor model (Carhart, 1997) (4.2), the Fama–French (2015) five-factor model (4.3) and the Stambaugh–Yuan (2017) mispricing-factor model (4.4). We refer to this profit as the individual CCC effect. The respective models are presented below. Note that R_{pt} and $MktRf_t$ are the returns of the portfolio and the market in excess of the risk-free rate, respectively.

$$R_{pt} = \alpha_{pt} + \beta_{pM} MktRf_t + \beta_{ps} SMB_t + \beta_{ph} HML_t + \epsilon_{pt} \tag{4.1}$$

$$R_{pt} = \alpha_{pt} + \beta_{pM} MktRf_t + \beta_{ps} SMB_t + \beta_{ph} HML_t + \beta_{pu} UMD_t + \epsilon_{pt} \tag{4.2}$$

$$R_{pt} = \alpha_{pt} + \beta_{pM} MktRf_t + \beta_{ps} SMB_t + \beta_{ph} HML_t + \beta_{pr} RMW_t + \beta_{pc} CMA_t + \epsilon_{pt} \tag{4.3}$$

$$R_{pt} = \alpha_{pt} + \beta_{pM} MktRF_t + \beta_{ps} SMB_t + \beta_{pm} MGMT_t + \beta_{pp} PERF_t + \epsilon_{pt} \tag{4.4}$$

Models (4.1)–(4.3) are explained in section 2.1.1. However, the Stambaugh–Yuan (2017) mispricing-factor model (4.4) includes factors that we have previously not explained. Stambaugh and Yuan add a management (MGMT) factor and a performance (PERF) factor that are both based on clusters of anomalies. The cluster of MGMT includes variables that a firm's management can influence directly, such as net stock issues, composite equity issues, accruals, net operating assets, asset growth and investment to assets. The cluster of PERF includes variables that are more related to performance, such as distress, O-score, momentum, gross profitability and return on assets.

We use two different measures of the CCC to construct the individual strategy portfolio. The first is the industry-adjusted CCC used by Wang (2019), which is constructed by subtracting the industry median CCC every month from each stock's CCC of the corresponding month. Following Wang, we use the Fama–French 48 industry classification to calculate the industry medians. The second measure of the CCC is the unadjusted CCC. Since we study potential industry effects, we want to use a measure of the CCC that is not already industry-adjusted. However, the CCC effect established by Wang builds on the industry-adjusted sort. Therefore, it is necessary to analyze if the individual strategy based on the unadjusted CCC gives approximately the same results as the industry-adjusted CCC before we proceed to use this sort in our industry analysis. To analyze this, we first compare the results of the individual strategy based on the unadjusted sort to the results in our replication, which is based on the industry-adjusted sort. Then, we construct a portfolio that is long the low-minus-high portfolio based on the industry-adjusted CCC sort, and short the low-minus-high portfolio based on the unadjusted sort. We test if this portfolio earns statistically significant abnormal returns. Consequently, we test if we find evidence to reject the following null hypothesis in favor of the alternative:

***H*$_0$*: The unadjusted CCC sort gives different results compared to the industry-adjusted CCC sort.*

***H*$_A$*: The unadjusted CCC sort does **not** give different results compared to the industry-adjusted CCC sort.*

4.2 The industry strategies

In this section, we present our methodology for controlling for the industry component of stock returns. Motivated by Moskowitz and Grinblatt (1999), we construct true and random industry strategies, which are based on buying and selling portfolios of industries instead of portfolios of individual stocks that do not take industries into account.

4.2.1 The True Industry Strategy

The true industry strategy is based on buying the industries with the lowest average CCC and selling the industries with the highest average CCC. We create industry portfolios based on different industry classifications, which include both narrow and broad definitions[2]. These industry classifications include the Fama–French industry classifications[3], the official SIC classification and the classification applied by Moskowitz and Grinblatt (1999). We apply several industry definitions because they are, to a great extent, based on discretionary assessments, which can potentially lead to different results. In addition, there is a trade-off between narrow and broad industry classifications. The more narrow the definition, the more precisely industries are described. On the other hand, the higher the number of industries, the fewer observations per industry. By including several definitions in the analyses, we take both of these effects into consideration.

We further exclude stocks from the industries titled *Other*. We do this because this industry is likely to contain stocks that operate in very different businesses and do not necessarily have a common exposure to certain risk factors or share distinct industry characteristics. We therefore reason that it makes little economic sense to include *Other* in the industry analysis, and hence choose to exclude it.

[2]With narrow, we mean classifications that include many and precisely defined industries, whereas with broad, we mean classifications that include few and loosely defined industries.

[3]We use seven Fama–French industry classifications. These include 48, 38, 30, 17, 12, 10 and 5 different industries.

Having created the industry portfolios, we buy the n industries with the lowest average unadjusted CCC and sell the n industries with the highest average unadjusted CCC. Moskowitz and Grinblatt (1999) use $n = 3$ for a total of 20 industries, equivalent to 15%. We follow the 15% rule and choose an integer value of n according to the number of industries in the different industry classifications. If there exists a CCC effect in the industry component of stock returns (hereafter referred to as an industry CCC effect) that accounts for much of the total CCC effect, we expect that this strategy will earn significant abnormal returns close to the individual CCC effect. We therefore propose the following null and alternative hypotheses:

> $\boldsymbol{H_0}$*: The true industry strategy earns significant abnormal returns, implying that there is an industry CCC effect.*
>
> $\boldsymbol{H_A}$*: The true industry strategy does* ***not*** *earn significant abnormal returns, implying that there is no industry CCC effect.*

4.2.2 The Random Industry Strategy

The random industry strategy is an extension of the true industry strategy. Within a given industry I, we substitute stocks with other stocks[4] that have the closest unadjusted CCC value, thereby creating a random industry I^* that has virtually the same average CCC as industry I. We then buy the n random industries that have the lowest average unadjusted CCC and sell the n random industries that have the highest average unadjusted CCC. If there is an industry CCC effect that accounts for a substantial part of the total CCC effect, we expect that this strategy may *not* earn statistically significant abnormal returns, as we no longer have true industry portfolios. We therefore suggest the following null and alternative hypotheses:

> $\boldsymbol{H_0}$*: The industry CCC effect accounts for a substantial part of the total CCC effect, and the random industry strategy may* ***not*** *earn significant abnormal returns.*
>
> $\boldsymbol{H_A}$*: The industry CCC effect does not account for a substantial part of*

[4] The stocks can be from the same industry or not.

the total CCC effect, and the random industry strategy may earn significant abnormal returns.

4.3 The CCC Factor

Finally, we construct an individual CCC factor using a bivariate sort that we add to the equations presented in section 4.1 in some of the regressions in the industry analysis. We create this CCC factor by following the methods of Fama and French (1993; 2015) and Wang (2019). Using the median market capitalization of firms listed on the NYSE as breakpoint, we first sort firms into two groups based on their market capitalization. Then, for both the small and big market capitalization groups, we sort firms into three additional CCC portfolios. Firms below the 30th CCC percentile for NYSE stocks are assigned to a low-CCC portfolio, firms above the NYSE 70th CCC percentile are assigned to a high-CCC portfolio, while firms in between are assigned to a medium-CCC portfolio. Analogous to Moskowitz and Grinblatt (1999) who use the unadjusted momentum factor, we use the unadjusted CCC to construct the CCC factor. The CCC factor is constructed by taking the average of the low-CCC portfolio returns of both size groups, minus the average returns of the high-CCC portfolio of both size groups. Each of the four portfolios are value-weighted. By adding this CCC factor to the abovementioned industry strategies, we control for the individual CCC effect. If the true industry strategy earns abnormal returns even when controlling for the CCC factor, it is evidence that these abnormal returns are truly driven by an industry CCC effect. For the random industry strategy, we add the CCC factor to see if potential abnormal returns can be attributed to the individual CCC effect.

4.4 Robustness Testing

In order to establish the validity of our results, we finally test the robustness of our findings from the industry analysis. The robustness checks we perform are, to a great extent, motivated by Wang (2019). We first examine if the results hold in two subperiods. The first period starts in June 1976 and ends in December 1995, while the second period starts in January 1996 and ends in December 2015. Thus, the two periods have approximately the same length, with 234 and 240 months, respectively. Second, we check if the results change when we exclude low-priced stocks, which we define as stocks priced lower than $5 in the month prior to portfolio formation, following Wang. Stocks with such pricing are commonly referred to as penny stocks (SEC, 2019). Although the level of stock prices in theory is irrelevant, penny stocks are often associated with low liquidity, high volatility and other issues (Liu, Rhee and Zhang, 2015). We thus find it reasonable to exclude those stocks in our robustness checks.

5 Replication

In this chapter, we present our replication of Wang (2019) to establish whether there exists a CCC effect in our sample. Specifically, we test if a zero-investment portfolio that buys the lowest CCC decile and shorts the highest CCC decile earns statistically significant abnormal returns.

As described in section 4.1, for every month in our sample, we sort stocks into deciles based on the level of their CCCs adjusted by the industry median[5]. Following Wang (2019), we then calculate both the equal-weighted and value-weighted time series means of the monthly returns in each decile. Further, we test how these decile portfolios perform relative to the risk-free rate and when controlling for the Fama–French (1993) three-factor model, the Fama–French–Carhart four-factor model (Carhart, 1997), the Fama–French (2015) five-factor model and the Stambaugh–Yuan (2017) mispricing-factor model. Note that Wang (2019) also includes the Hou, Xue and Zhang (2015) *q*-factor model in his analysis. We do not have access to the factors in this model. The abnormal returns of these time series tests and the average return of each decile in excess of the risk-free rate are reported in Panel A of Table 4. We also include the results for the low-minus-high CCC portfolio, which is long the lowest CCC decile and short the highest CCC decile. Panel B presents the original results of Wang (2019).

The lowest CCC deciles earn sizeable and highly statistically significant abnormal returns in all tests. The abnormal returns decrease more or less monotonically from the lowest to the highest CCC decile. This indicates that the CCC effect does not only exist among the extremities of our sample. We discuss this further in section A1 of the appendix. Most interestingly, the low-minus-high CCC portfolio earns economically non-trivial abnormal returns that are highly statistically significant. The abnormal returns in the different tests range between 0.40%–0.61% per month, or approximately 4.82%–7.37% per annum. Hence, it is evident that low-CCC firms outperform high-CCC firms, indicating that there exists a strong CCC effect in our sample. Moreover, compared to the equal-weighted abnormal returns, the value-weighted abnormal returns are higher for most tests, but

[5]Our results are robust if we adjust the CCC by the industry mean.

Table 4: Individual strategy time series tests.

Panel A presents the excess returns and abnormal returns (in percentage) for both equal-weighted (EW) and value-weighted (VW) portfolios sorted by the industry-adjusted CCC. At the beginning of each month, from July 1976 to December 2015, we sort all stocks into deciles based on the industry-adjusted CCC two quarters ago and calculate the average return from the cross-section. We then report the average excess return, Fama–French three-factor abnormal return (Fama & French, 1993), Fama–French–Carhart four-factor abnormal return (Carhart, 1997), Fama–French five-factor abnormal return (Fama & French, 2015) and Stambaugh–Yuan mispricing-factor abnormal return (Stambaugh & Yuan, 2017) of the time series tests, from the low 1 to high 10 deciles. The rightmost column reports the average excess return and abnormal returns for the zero-investment portfolio with a long position in the low 1 decile and a short position in the high 10 decile. Panel B presents the result from Wang (2019).

Panel A: Replication

Model		Low 1	2	3	4	5	6	7	8	9	High 10	Low–minus–high
Excess return	EW	1.098***	1.058***	1.113***	1.043***	0.886***	0.901***	0.894***	0.888***	0.778***	0.663**	0.434***
		(3.47)	(3.71)	(4.17)	(4.02)	(3.55)	(3.60)	(3.47)	(3.31)	(2.80)	(2.26)	(4.43)
	VW	0.732***	0.542**	0.564**	0.691***	0.473**	0.494**	0.592***	0.524***	0.479**	0.362	0.369**
		(3.10)	(2.50)	(2.41)	(3.16)	(2.29)	(2.50)	(2.90)	(2.61)	(2.14)	(1.50)	(2.56)
Fama–French three-factor	EW	0.236**	0.196**	0.275***	0.200**	0.053	0.065	0.070	0.032	−0.111	−0.201*	0.437***
		(1.98)	(2.02)	(3.16)	(2.44)	(0.70)	(0.81)	(0.80)	(0.38)	(−1.12)	(−1.68)	(4.69)
	VW	0.250***	0.009	−0.025	0.124	−0.098	−0.060	0.015	−0.046	−0.165*	−0.249**	0.499***
		(2.67)	(0.11)	(−0.28)	(1.44)	(−1.38)	(−0.81)	(0.17)	(−0.54)	(−1.87)	(−2.35)	(3.42)
Fama–French–Carhart four-factor	EW	0.413***	0.422***	0.439***	0.365***	0.220***	0.243***	0.245**	0.218**	0.090	0.011	0.402***
		(3.21)	(3.93)	(4.71)	(4.45)	(2.84)	(2.82)	(2.57)	(2.39)	(0.85)	(0.08)	(3.93)
	VW	0.272***	0.064	−0.013	0.124	−0.104	−0.059	0.046	−0.035	−0.117	−0.237**	0.509***
		(2.74)	(0.78)	(−0.14)	(1.45)	(−1.46)	(−0.77)	(0.51)	(−0.40)	(−1.26)	(−2.09)	(3.17)
Fama–French five-factor	EW	0.513***	0.350***	0.375***	0.269***	0.086	0.121	0.146	0.104	−0.026	−0.070	0.582***
		(4.21)	(2.83)	(3.58)	(2.79)	(0.89)	(1.24)	(1.39)	(1.07)	(−0.22)	(−0.49)	(5.87)
	VW	0.279***	0.026	0.052	0.175*	−0.145**	−0.119	0.015	−0.196**	−0.273***	−0.334***	0.614***
		(2.81)	(0.34)	(0.55)	(1.92)	(−2.00)	(−1.57)	(0.17)	(−2.25)	(−2.89)	(−2.96)	(3.96)
Stambaugh–Yuan mispricing-factor	EW	0.603***	0.494***	0.464***	0.359***	0.216**	0.268**	0.286**	0.237*	0.115	0.106	0.497***
		(3.95)	(3.41)	(3.80)	(3.36)	(2.09)	(2.41)	(2.28)	(1.96)	(0.80)	(0.64)	(4.60)
	VW	0.226*	0.008	−0.024	0.174*	−0.128	−0.083	0.112	−0.081	−0.180*	−0.262**	0.488***
		(1.90)	(0.10)	(−0.21)	(1.86)	(−1.63)	(−1.05)	(1.12)	(−0.87)	(−1.80)	(−2.19)	(2.70)

Panel B: Original results

Model		Low 1	2	3	4	5	6	7	8	9	High 10	Low–minus–high
Excess return	EW	1.035***	1.029***	1.032***	1.024***	0.951***	0.888***	0.934***	0.883***	0.745***	0.535*	0.500***
		(3.27)	(3.66)	(3.83)	(3.97)	(3.77)	(3.51)	(3.58)	(3.28)	(2.66)	(1.85)	(5.15)
	VW	0.800***	0.573***	0.654***	0.616***	0.628***	0.628***	0.606***	0.576***	0.520**	0.398*	0.402***
		(3.50)	(2.66)	(2.76)	(2.91)	(3.08)	(3.16)	(3.07)	(2.76)	(2.32)	(1.70)	(2.94)
Fama–French three-factor	EW	0.157	0.170*	0.176**	0.173**	0.103	0.044	0.091	0.020	−0.141	−0.328***	0.484***
		(1.26)	(1.70)	(2.02)	(2.29)	(1.28)	(0.55)	(1.08)	(0.22)	(−1.41)	(−2.75)	(5.23)
	VW	0.312***	0.042	0.053	0.038	0.048	0.072	0.040	−0.024	−0.125	−0.202**	0.514***
		(3.77)	(0.54)	(0.67)	(0.52)	(0.62)	(1.00)	(0.49)	(−0.30)	(−1.52)	(−2.01)	(3.78)
Fama–French–Carhart four-factor	EW	0.366***	0.387***	0.359***	0.332***	0.283***	0.224***	0.267***	0.227***	0.077	−0.091	0.458***
		(3.11)	(4.37)	(4.61)	(4.89)	(3.98)	(3.14)	(3.54)	(2.87)	(0.86)	(−0.84)	(4.85)
	VW	0.330***	0.093	0.082	0.037	0.011	0.028	0.007	0.047	−0.077	−0.174*	0.504***
		(3.90)	(1.18)	(1.01)	(0.48)	(0.15)	(0.39)	(0.09)	(0.60)	(−0.92)	(−1.70)	(3.63)
Fama–French five-factor	EW	0.425***	0.298***	0.278***	0.239***	0.139*	0.096	0.169**	0.119	−0.054	−0.200*	0.625***
		(3.55)	(2.98)	(3.18)	(3.15)	(1.72)	(1.19)	(2.00)	(1.31)	(−0.54)	(−1.68)	(6.83)
	VW	0.296***	0.040	0.139*	0.041	−0.063	0.061	−0.074	−0.074	−0.222***	−0.290***	0.586***
		(3.47)	(0.50)	(1.71)	(0.54)	(−0.82)	(0.83)	(−0.92)	(−0.93)	(−2.69)	(−2.82)	(4.18)
Stambaugh–Yuan mispricing-factor	EW	0.564***	0.448***	0.377***	0.337***	0.254***	0.242***	0.297***	0.261***	0.101	−0.006	0.570***
		(4.21)	(4.27)	(4.01)	(4.09)	(2.97)	(2.88)	(3.34)	(2.70)	(0.93)	(−0.04)	(5.65)
	VW	0.245***	0.037	0.056	−0.017	−0.020	0.082	−0.034	0.072	−0.133	−0.225**	0.470***
		(2.61)	(0.43)	(0.64)	(−0.22)	(−0.24)	(1.05)	(−0.39)	(−0.86)	(−1.49)	(−2.06)	(3.14)

t statistics based on heteroscedasticity-consistent standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

have lower statistical significance. Finally, our results are very similar to Wang (2019), both in terms of the size of the coefficients and the statistical significance of our results.

Panel A of Table 5 reports the factor loadings and abnormal returns of both the equal-weighted and value-weighted low-minus-high CCC portfolios. Interestingly, the portfolio is either uncorrelated with or has negative loadings on most factors. For instance, the coefficient for the value factor (HML) is negative and highly statistically significant in all the models where it is included. This implies that the portfolio is long growth firms and short value firms, consistent with the correlation we find between the CCC and B/M, as reported in Table 3. Furthermore, the coefficient of the profitability factor (RMW) is negative. This is somewhat surprising given the extensive literature that finds a negative relationship between profitability and the CCC (Jose et al., 1996; Shin & Soenen, 1998; Deloof, 2003). Nevertheless, our coefficients are consistent with Wang (2019), who also documents that the returns of the low-CCC portfolios are more correlated with the returns of less profitable firms, even though low-CCC firms are more profitable on average.

Furthermore, the coefficient for the size factor (SMB) is only significant in the Fama–French (2015) five-factor model. The direction of the coefficient implies that the portfolio is long large firms and short small firms, measured by their market capitalization. This is also consistent with the correlation between the CCC and size, and suggests that the return of low-CCC firms are correlated with the return of large firms. The only positive loadings indistinguishable from zero are on the market in four cases, with modest coefficients of 0.055–0.092.

The abnormal returns the different portfolios earn, as displayed in Table 4, as well as the magnitude, direction and significance of the coefficients on the factor loadings, as reported in Table 5, are profoundly similar to Wang (2019). Therefore, we conclude that our replication is successful and there is strong evidence supporting the existence of the CCC effect.

Table 5: Factor loadings and abnormal returns of individual strategy portfolio.

Panel A presents the factor loadings and abnormal returns (in percentage) of both equal-weighted (EW) and value-weighted (VW) zero-investment portfolios with a long position in the lowest industry-adjusted CCC decile and a short position in the highest industry-adjusted CCC decile. MktRf is the market factor, SMB is the small minus big size factor, HML is the high minus low value factor, UMD is the up minus down momentum factor, RMW is the robust profitability minus weak profitability factor, CMA is the conservative investment minus aggressive investment factor, MGMT is a factor that arises from six anomaly variables that represent quantities that firm managements can affect directly, and PERF is a factor that arises from five anomaly variables that are more related to performance and less directly controlled by management. Panel B presents the results from Wang (2019).

Panel A: Replication

	Fama–French three-factor		Fama–French–Carhart four factor		Fama–French five-factor		Stambaugh–Yuan mispricing-factor	
	EW	VW	EW	VW	EW	VW	EW	VW
MktRf	0.084***	−0.091**	0.092***	−0.093**	0.055**	−0.120***	0.075***	−0.085*
	(3.33)	(2.51)	(3.56)	(−2.37)	(2.19)	(−3.01)	(2.59)	(−1.66)
SMB	0.003	0.048	−0.002	0.050	−0.106***	−0.024	−0.058	0.020
	(0.07)	(0.81)	(−0.04)	(0.83)	(−2.86)	(−0.40)	(−1.39)	(0.32)
HML	−0.190***	−0.302***	−0.176***	−0.307***	−0.156***	−0.231***		
	(−4.06)	(−4.20)	(−3.97)	(−4.25)	(−2.86)	(−3.03)		
UMD			0.039	−0.012				
			(0.99)	(−0.21)				
RMW					−0.305***	−0.173*		
					(−5.90)	(−1.79)		
CMA					−0.025	−0.151		
					(−0.31)	(−1.25)		
MGMT							−0.183***	−0.221**
							(−3.87)	(−2.48)
PERF							0.030	0.070
							(0.72)	(1.14)
Constant	0.437***	0.499***	0.402***	0.509***	0.582***	0.614***	0.497***	0.488***
	(4.69)	(3.42)	(3.93)	(3.17)	(5.87)	(3.96)	(4.60)	(2.71)
N	474	474	474	474	474	474	474	474
R^2	0.123	0.078	0.130	0.079	0.211	0.092	0.111	0.043
Adjusted R^2	0.118	0.072	0.122	0.071	0.202	0.083	0.104	0.035
Residual Std. Error	2.004 (df = 470)	3.027 (df = 470)	1.999 (df = 469)	3.030 (df = 469)	1.906 (df = 468)	3.011 (df = 468)	2.020 (df = 469)	3.088 (df = 469)

Panel B: Original results

	Fama–French three-factor		Fama–French–Carhart four factor		Fama–French five-factor		Stambaugh–Yuan mispricing-factor	
	EW	VW	EW	VW	EW	VW	EW	VW
MktRf	0.104***	−0.060*	0.110***	−0.058*	0.072***	−0.078**	0.082***	−0.039
	(4.82)	(−1.88)	(5.00)	(−1.78)	(3.23)	(−2.28)	(3.30)	(−1.06)
SMB	0.009	−0.013	0.005	−0.014	−0.090***	−0.062	−0.040	−0.036
	(0.27)	(−0.28)	(0.16)	(−0.30)	(−2.73)	(−1.23)	(−1.15)	(−0.70)
HML	−0.173***	−0.261***	−0.162***	−0.257***	−0.112***	−0.202***		
	(−5.12)	(−5.26)	(−4.67)	(−5.03)	(−2.63)	(−3.08)		
UMD			0.030	0.012				
			(1.42)	(0.37)				
RMW					−0.280***	−0.103		
					(−6.74)	(−1.62)		
CMA					−0.082	−0.115		
					(−1.28)	(−1.17)		
MGMT							0.019	0.084**
							(0.80)	(2.32)
PERF							−0.201***	−0.156***
							(−5.22)	(−2.72)
Constant	0.484***	0.514***	0.458***	0.504***	0.625***	0.586***	0.570***	0.470***
	(5.23)	(3.78)	(4.85)	(3.63)	(6.83)	(4.18)	(5.65)	(3.14)
R^2	0.131	0.052	0.132	0.050	0.205	0.056	0.131	0.023

t statistics based on heteroscedasticity-consistent standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 Analysis

In this chapter, we analyze whether there exists a non-trivial CCC effect in the industry component of stock returns. Since we use an unadjusted CCC sort in this analysis, while Wang (2019) uses an industry-adjusted CCC sort, we first test if the CCC effect also exists for the individual strategy using the unadjusted sort. Then, after finding evidence that supports this, we implement the true and random industry strategies, motivated by Moskowitz and Grinblatt (1999).

6.1 The Individual Strategy with the Unadjusted CCC Sort

In our analysis of the unadjusted CCC, we do the same sorting and tests as in Chapter 5, but do not subtract the industry median from the CCC. Hence, we now evaluate whether the CCC predicts stock returns without using an intra-industry measure of the asset characteristic. The results may differ if the two measures provide different information. However, in order to use the unadjusted CCC sort in the industry analysis, the two sorts have to give approximately the same results. We therefore test if we find evidence to reject the null hypothesis from section 4.1, which says that the unadjusted and industry-adjusted CCC sorts give different results.

Table 6 presents the abnormal returns for the different CCC deciles when using the unadjusted CCC sort. The excess returns and abnormal returns of the low-minus-minus portfolio are all highly economically and statistically significant, with a return spread of 0.34%–0.55% per month (4.06%–6.62% per annum). However, with the exception of the Stambaugh–Yuan (2017) mispricing-factor model, all the returns are lower than for the low-minus-high portfolio created based on the industry-adjusted CCC. All returns also have lower t statistics. The prominent near-monotonic trend of decreasing abnormal returns from the low 1 decile to the high 10 decile is also less evident as compared to the industry-adjusted sort.

As displayed in Table 7, some of the factor loadings also change when we use the

Table 6: Time series tests of the individual strategy with unadjusted CCC.

This table presents the excess returns and abnormal returns (in percentage) for both equal-weighted (EW) and value-weighted (VW) portfolios sorted by the unadjusted CCC. At the beginning of each month, from July 1976 to December 2015, we sort all stocks into deciles based on the unadjusted CCC two quarters ago and calculate the average return from the cross-section. We then report the average excess return, Fama–French three-factor abnormal return (Fama & French, 1993), Fama–French–Carhart four-factor abnormal return (Carhart, 1997), Fama–French five-factor abnormal return (Fama & French, 2015) and Stambaugh–Yuan mispricing-factor abnormal return (Stambaugh & Yuan, 2017) from the time series tests, from the low 1 to high 10 deciles. The rightmost column reports the average excess return and abnormal returns for the zero-investment portfolio with a long position in the low 1 decile and a short position in the high 10 decile.

Model		Low 1	2	3	4	5	6	7	8	9	High 10	Low–minus–high
Excess return	EW	0.964***	1.066***	1.019***	0.994***	0.893***	1.001***	0.943***	0.927***	0.895***	0.622**	0.342***
		(3.272)	(4.317)	(4.097)	(3.754)	(3.341)	(3.661)	(3.410)	(3.300)	(3.130)	(2.103)	(2.954)
	VW	0.675***	0.731***	0.579***	0.379*	0.524**	0.571**	0.573**	0.536**	0.480**	0.342	0.333**
		(2.985)	(3.797)	(2.973)	(1.740)	(2.286)	(2.416)	(2.402)	(2.244)	(2.020)	(1.426)	(2.041)
Fama–French three-factor	EW	0.137	0.288***	0.230***	0.142	0.028	0.117	0.053	0.027	0.021	−0.228*	0.365***
		(1.084)	(3.329)	(2.636)	(1.601)	(0.332)	(1.358)	(0.578)	(0.303)	(0.210)	(−1.872)	(3.126)
	VW	0.180*	0.257***	0.056	−0.185**	−0.069	−0.052	−0.092	−0.126	−0.140	−0.256**	0.436**
		(1.790)	(3.032)	(0.753)	(−2.334)	(−0.769)	(−0.561)	(−1.039)	(−1.371)	(−1.345)	(−2.258)	(2.545)
Fama–French–Carhart four-factor	EW	0.321**	0.447***	0.417***	0.337***	0.205**	0.306***	0.256**	0.195**	0.198*	−0.017	0.338***
		(2.312)	(4.834)	(4.301)	(3.807)	(2.469)	(3.122)	(2.438)	(2.211)	(1.901)	(−0.127)	(2.785)
	VW	0.164	0.166*	0.057	−0.127	−0.033	0.010	−0.014	−0.062	−0.058	−0.246**	0.409**
		(1.457)	(1.917)	(0.742)	(−1.638)	(−0.390)	(0.111)	(−0.159)	(−0.607)	(−0.549)	(−1.989)	(2.083)
Fama–French five-factor	EW	0.424***	0.423***	0.340***	0.254**	0.128	0.197*	0.082	0.057	0.068	−0.107	0.531***
		(3.131)	(4.375)	(3.058)	(2.287)	(1.189)	(1.786)	(0.736)	(0.582)	(0.607)	(−0.743)	(4.248)
	VW	0.208*	0.181**	0.052	−0.126	0.038	−0.026	−0.138	−0.204**	−0.244**	−0.344***	0.552***
		(1.930)	(2.049)	(0.640)	(−1.586)	(0.429)	(−0.255)	(−1.422)	(−2.089)	(−2.151)	(−2.836)	(2.991)
Stambaugh–Yuan mispricing-factor	EW	0.566***	0.498***	0.477***	0.385***	0.246**	0.316**	0.256*	0.162	0.200	0.038	0.528***
		(3.596)	(4.258)	(3.821)	(3.204)	(2.230)	(2.332)	(1.850)	(1.422)	(1.528)	(0.228)	(4.299)
	VW	0.214*	0.171*	0.060	−0.123	−0.020	−0.040	−0.123	−0.076	−0.118	−0.311**	0.525**
		(1.776)	(1.819)	(0.737)	(−1.389)	(−0.217)	(−0.372)	(−1.257)	(−0.717)	(−1.017)	(−2.332)	(2.506)

t statistics based on heteroscedasticity-consistent standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

unadjusted CCC sort. In contrast to the industry-adjusted sort, the low-minus-high portfolio does not load negatively on the HML factor, and is in most cases uncorrelated with the factor. Although not statistically significant, the HML coefficients from the different models are also smaller in magnitude. Instead, the portfolio from the unadjusted sort loads negatively on the SMB factor, particularly the equal-weighted portfolio. The magnitudes of the SMB coefficients are also larger. In most cases, the returns of the portfolio from the industry-adjusted sort are uncorrelated with the returns of the SMB factor. Finally, the returns of the portfolio from the unadjusted sort are generally uncorrelated with the market. The equal-and value-weighted portfolios from the industry-adjusted CCC sort have modest positive and modest negative loadings on the market, respectively.

Table 8 reports the results for an equal- and value-weighted portfolio that buys the low-minus-high portfolio based on the industry-adjusted CCC sort, and shorts the

Table 7: Factor loadings and abnormal returns of individual strategy portfolio with unadjusted CCC.

This table presents the factor loadings and abnormal returns (in percentage) of both equal-weighted (EW) and value-weighted (VW) zero-investment portfolios with a long position in lowest unadjusted CCC decile and a short position in the highest unadjusted CCC decile. MktRf is the market factor, SMB is the small-minus-big size factor, HML is the high-minus-low value factor, UMD is the up-minus-down momentum factor, RMW is the robust-minus-weak profitability factor, CMA is the conservative-minus-aggressive investment factor, MGMT is a factor that arises from six anomaly variables that represent quantities that firm managements can affect directly, and PERF is a factor that arises from five anomaly variables that are more related to performance and less directly controlled by management.

	Fama–French three-factor		Fama–French–Carhart four factor		Fama–French five-factor		Stambaugh–Yuan mispricing-factor	
	EW	VW	EW	VW	EW	VW	EW	VW
MktRf	0.033	−0.077	0.039	−0.071	−0.006	−0.103*	0.0003	−0.076
	(1.111)	(−1.562)	(1.256)	(−1.317)	(−0.203)	(−1.879)	(0.009)	(−1.187)
SMB	−0.124**	−0.073	−0.128***	−0.077	−0.230***	−0.158**	−0.209***	−0.195***
	(−2.576)	(−1.099)	(−2.607)	(−1.128)	(−4.735)	(−2.253)	(−4.290)	(−2.763)
HML	−0.059	−0.144*	−0.048	−0.133	0.048	−0.062		
	(−1.103)	(−1.742)	(−0.912)	(−1.529)	(0.685)	(−0.650)		
UMD			0.031	0.030				
			(0.980)	(0.439)				
RMW					−0.298***	−0.189*		
					(−3.819)	(−1.690)		
CMA					−0.153	−0.134		
					(−1.489)	(−0.914)		
MGMT							−0.134**	−0.129
							(−2.489)	(−1.422)
PERF							−0.026	0.017
							(−0.690)	(0.251)
Constant	0.365***	0.436**	0.338***	0.409**	0.531***	0.552***	0.528***	0.525**
	(3.126)	(2.545)	(2.785)	(2.083)	(4.248)	(2.991)	(4.299)	(2.506)
N	474	474	474	474	474	474	474	474
R^2	0.023	0.019	0.026	0.020	0.095	0.037	0.056	0.030
Adjusted R^2	0.017	0.013	0.017	0.012	0.086	0.026	0.048	0.022
Residual Std. Error	2.497 (df = 470)	3.531 (df = 470)	2.497 (df = 469)	3.532 (df = 469)	2.408 (df = 468)	3.506 (df = 468)	2.457 (df = 469)	3.514 (df = 469)

t statistics based on heteroscedasticity-consistent standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

equivalent portfolio based on the unadjusted CCC sort. We observe that regardless of which model we control for, the abnormal returns are statistically indistinguishable from zero. This implies that the returns of the two portfolios are not significantly different, and thus supports the rejection of our null hypothesis of dissimilar returns.

Table 4 and Table 6 indicate that adjusting the CCC for the industry median provides slightly higher estimates of profits. However, as we find that the difference in abnormal returns between the two CCC measures is statistically indistinguishable from zero, we reject the null hypothesis that the unadjusted CCC sort does not earn statistically significant abnormal returns similar to the industry-adjusted CCC sort. Consequently, we use the unadjusted sort in the following industry analysis. Finally, it is also worth noting that our findings are in contrast to Moskowitz and Grinblatt (1999), who find that momentum profits disappear after demeaning.

Table 8: Time series tests of the return difference of the industry-adjusted and the unadjusted portfolios.

This table presents the excess return and abnormal returns (in percentage) of both the equal-weighted and value-weighted zero-investment portfolio that has a long position in the low-minus-high portfolio using the industry-adjusted CCC sort and a short position in the low-minus-high portfolio using the unadjusted CCC sort. Each month, we calculate the return from the cross-section and then report the average excess returns, the Fama–French three-factor abnormal returns (Fama & French, 1993), the Fama–French–Carhart four-factor (Carhart, 1997) abnormal returns, the Fama–French five-factor abnormal returns (Fama & French, 2015) and the Stambaugh–Yuan mispricing-factor abnormal returns (Stambaugh & Yuan, 2017).

	Excess return	Fama–French three-factor	Fama–French–Carhart four-factor	Fama–French five-factor	Stambaugh–Yuan mispricing-factor
Equal-weighted	0.093	0.072	0.064	0.051	−0.030
	(1.193)	(1.012)	(0.853)	(0.695)	(−0.390)
Value-weighted	0.036	0.063	0.100	0.062	−0.037
	(0.315)	(0.543)	(0.866)	(0.511)	(−0.296)

t statistics based on heteroscedasticity-consistent standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.2 Controlling for Industries

In this section, we present our analysis of the potential industry CCC effect. We start by studying the true industry strategy before we proceed to examine the random industry strategy. These strategies are based on industry portfolios, as described in section 4.2. The industry portfolios are constructed by assigning firms to industries using established industry classifications, such as the Fama–French industry classifications, the official SIC classification and the classification applied by Moskowitz and Grinblatt (1999). In total, we use nine different industry classifications and thus end up with nine equal-weighted and nine value-weighted portfolios.

6.2.1 True Industry Portfolios

We start analyzing the potential industry CCC effect by implementing the true industry strategy. If there is evidence against our null hypothesis, implying that there is no industry CCC effect, the portfolios created from this strategy should not earn statistically significant abnormal returns.

The true industry strategy is a long-short strategy that buys the n industry portfolios with the lowest average CCC and sells the n industry portfolios with the highest average

CCC. As described in section 4.2.1, we follow Moskowitz and Grinblatt (1999) and choose n so that n divided by the total number of industries is 15%. Nevertheless, our results are not very sensitive to reasonable values of n. Furthermore, we exclude stocks assigned to the industry titled *Other* for all industry classifications. We do this because this industry is likely to contain stocks that operate in very different businesses and do not necessarily have a common exposure to certain risk factors or share distinct industry characteristics. We therefore reason that it makes little economic sense to include *Other* in the industry analysis, and hence choose to exclude it. Nonetheless, our results do not change if we include *Other*.

We suspect that the CCC varies substantially between industries due to the nature of their businesses, as indicated in Table 1. Thus, we do not rule out that the individual CCC strategy is systematically skewed towards certain industries. If this is true, the true industry strategy should also earn positive abnormal returns. If the CCC effect is primarily driven by an industry CCC effect, those abnormal returns should be close to those abnormal returns of the individual strategy. The results are reported in Table 9.

For virtually all industry classifications, the true industry strategy does not earn positive and statistically significant abnormal returns, regardless of which model we apply, as presented in Panel A[6]. This is true for both the equal-weighted and value-weighted portfolios. The only exceptions are the equal- and value-weighted portfolios based Fama–French 38 industry classification (FF38) as well as the value-weighted portfolio based on the Fama–French 12 industry classification (FF12). The FF38 equal-weighted portfolio earns statistically significant abnormal returns when controlled for the Fama–French five-factors (Fama & French, 2015), while the FF38 and FF12 value-weighted portfolios earn statistically significant abnormal returns when controlled for the Stambaugh–Yuan mispricing-factors (Stambaugh & Yuan, 2017). The only one of these portfolios that earns statistically significant abnormal returns at the one percent level is the FF38 equal-weighted portfolio, while the other portfolios only earn statistically significant abnormal returns at the ten percent level. Moreover, once we control for the CCC factor, as presented in Panel B, the statistically significant positive abnormal returns disappear.

[6] The results do not change if we use the median or industry-adjusted mean instead of the unadjusted mean as the sorting criterion.

Table 9: True industry strategy time series tests.

This table presents the average excess returns and abnormal returns (in percentage) for both equal-weighted (EW) and value-weighted (VW) true industry strategy portfolios for different industry classifications. Each month, for each industry classification, we calculate the average industry CCC based on the stocks' unadjusted CCC two quarters ago. We then buy the 15% industries with the lowest average CCC in equal amounts and sell the 15% industries with the highest average CCC in equal amounts, constructing a zero-investment portfolio. Following that we calculate the average return from the cross-section and report the average excess return, Fama–French three-factor abnormal return (Fama & French, 1993), Fama–French–Carhart four-factor abnormal return (Carhart, 1997), Fama–French five-factor abnormal return (Fama & French, 2015) and Stambaugh–Yuan mispricing-factor abnormal return (Stambaugh & Yuan, 2017) of the time series tests in Panel A. In Panel B we add the CCC constructed as described in section 4.3 to the Fama–French (2015) five-factor model and the Stambaugh–Yuan (2017) mispricing-factor model. FF48, FF38, FF30, FF17, FF12, FF10 and FF5 are the Fama–French 48, 38, 30, 17, 12, 10 and 5 industry classifications, MG is the industry classification in Moskowitz and Grinblatt (1999) and SIC is the official SIC industry classification.

Model		FF48	FF38	FF30	FF17	FF12	FF10	FF5	MG	SIC
Panel A: Excess returns and models without CCC factor										
Excess return	EW	−0.027	0.069	0.032	−0.074	−0.184	−0.243	−0.170	0.058	−0.638
		(−0.213)	(0.438)	(0.214)	(−0.315)	(−0.598)	(−0.794)	(−0.888)	(0.270)	(−0.996)
	VW	−0.198	−0.090	−0.086	0.058	0.115	0.017	−0.007	0.193	−0.719
		(−1.610)	(−0.545)	(−0.634)	(0.237)	(0.437)	(0.064)	(−0.038)	(0.918)	(−1.148)
Fama–French three-factor	EW	−0.115	0.102	−0.066	0.174	−0.146	−0.189	−0.273	0.079	−0.329
		(−0.894)	(0.656)	(−0.415)	(0.866)	(−0.488)	(−0.636)	(−1.547)	(0.398)	(−0.652)
	VW	−0.231*	0.064	−0.067	0.318	0.260	0.144	−0.261	0.113	−0.457
		(−1.807)	(0.391)	(−0.458)	(1.430)	(0.995)	(0.538)	(−1.370)	(0.545)	(−0.942)
Fama–French–Carhart four-factor	EW	−0.077	0.151	−0.027	−0.047	−0.179	−0.246	−0.303	−0.091	−0.357
		(−0.548)	(0.935)	(−0.164)	(−0.216)	(−0.565)	(−0.785)	(−1.637)	(−0.446)	(−0.661)
	VW	−0.258*	0.036	−0.126	0.015	0.128	0.013	−0.272	−0.053	−0.450
		(−1.921)	(0.218)	(−0.859)	(0.066)	(0.431)	(0.043)	(−1.327)	(−0.260)	(−0.881)
Fama–French five-factor	EW	−0.037	0.263*	0.065	0.032	−0.120	−0.189	−0.293	−0.115	−0.166
		(−0.275)	(1.668)	(0.395)	(0.145)	(−0.370)	(−0.594)	(−1.334)	(−0.546)	(−0.311)
	VW	−0.166	0.193	−0.006	0.128	0.425	0.303	−0.112	−0.051	−0.347
		(−1.187)	(1.165)	(−0.038)	(0.557)	(1.528)	(1.075)	(−0.541)	(−0.233)	(−0.667)
Stambaugh–Yuan mispricing-factor	EW	0.105	0.443***	0.259	0.116	0.213	0.116	−0.318*	−0.033	−0.050
		(0.651)	(2.635)	(1.390)	(0.463)	(0.598)	(0.330)	(−1.667)	(−0.140)	(−0.068)
	VW	−0.076	0.314*	0.080	0.164	0.530*	0.371	−0.153	0.061	−0.285
		(−0.489)	(1.882)	(0.493)	(0.625)	(1.682)	(1.158)	(−0.733)	(0.260)	(−0.399)
Panel B: Models with CCC factor										
Fama–French five-factor + CCC	EW	−0.296**	0.013	−0.206	−0.371*	−0.582*	−0.646**	−0.632***	−0.417**	−0.461
		(−2.270)	(0.080)	(−1.249)	(−1.823)	(−1.804)	(−2.037)	(−2.887)	(−2.056)	(−0.780)
	VW	−0.505***	−0.153	−0.338**	−0.398*	−0.180	−0.319	−0.599***	−0.413**	−0.582
		(−4.077)	(−0.973)	(−2.438)	(−1.803)	(−0.682)	(−1.195)	(−3.414)	(−1.966)	(−1.010)
Stambaugh–Yuan mispricing-factor + CCC	EW	−0.108***	0.222	0.027	−0.174	−0.148	−0.237	−0.587***	−0.227	−0.305
		(−0.665)	(1.284)	(0.139)	(−0.726)	(−0.413)	(−0.668)	(−3.041)	(−0.969)	(−0.391)
	VW	−0.355**	0.019	−0.196	−0.220	0.012	−0.160	−0.577***	−0.185	−0.486
		(−2.538)	(0.115)	(−1.295)	(−0.859)	(0.040)	(−0.537)	(−3.024)	(−0.801)	(−0.638)

t statistics based on heteroscedasticity-consistent standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This implies that there is no industry CCC effect once we control for the individual CCC effect.

In contrast to the findings above, there are two portfolios that earn statistically significant negative abnormal returns, though only at the ten percent level, as shown in Panel

A. These are the value-weighted portfolio based on the Fama–French 48 industry classification (FF48) controlled for Fama–French three-factors (Fama & French, 1993) and the Fama–French–Carhart four factors (Carhart, 1997), and the equal-weighted portfolio based on the Fama–French 5 industry classification (FF5) controlled for the Stambaugh–Yuan mispricing-factor (Stambaugh & Yuan, 2017). The magnitude of these negative abnormal returns is generally smaller than the magnitude of the statistically significant positive abnormal returns.

In summary, the majority of the portfolios earn abnormal returns that are statistically indistinguishable from zero in most models. Some portfolios earn statistically significant abnormal returns, however, these profits disappear once we control for the individual CCC effect by adding the CCC factor. Hence, the true industry strategy results provide sufficient evidence to reject our null hypothesis that there is an industry CCC effect. We discuss potential reasons for this further in section 6.3.

6.2.2 Random Industry Portfolios

We proceed to analyze the performance of the portfolios that follow the random industry strategy. If there is evidence against our null hypothesis for this strategy, implying that there is no industry CCC effect, these portfolios may earn statistically significant abnormal returns.

The random industry strategy is an extension of the true industry strategy. The difference is that within each of the portfolios in the true industry strategy, we substitute each stock with other stocks[7] that have the closest CCC value. Consequently, we construct random industry portfolios that have approximately the same CCC distribution as the true industry portfolios, but do not consist of stocks from the same industries. Hence, if the CCC effect is driven by industries, this strategy may not earn statistically significant abnormal returns. On the other hand, if the CCC effect is driven by individual stocks, this strategy may earn statistically significant abnormal returns.

Panel A of Table 10 presents the excess and abnormal returns for the five models for each

[7]The stocks can be from the same industry or not.

Table 10: Random industry strategy time series tests.

This table presents the average excess returns and abnormal returns (in percentage) for both equal-weighted (EW) and value-weighted (VW) random industry strategy portfolios for different industry classifications. Each month, for each industry classification, we calculate the average industry CCC based on the stocks' CCC two quarters ago. We then buy the 15% industries with the lowest average CCC in equal amounts and sell the 15% industries with the highest average CCC in equal amounts, constructing a zero-investment portfolio. Following that, for each of the selected industries, we substitute each stock with another stock that has the closest CCC value, thereby creating random industries that have approximately the same CCC distribution as the true industries. We then calculate the average return from the cross-section and report the average excess return, Fama–French three-factor abnormal return (Fama & French, 1993), Fama–French–Carhart four-factor abnormal return (Carhart, 1997), Fama–French five-factor abnormal return (Fama & French, 2015) and Stambaugh–Yuan mispricing-factor abnormal return (Stambaugh & Yuan, 2017) of the time series tests in Panel A. In Panel B we add the CCC constructed as described in section 4.3 to the Fama–French five-factor (2015) model and the Stambaugh–Yuan (2017) mispricing-factor model. FF48, FF38, FF30, FF17, FF12, FF10 and FF5 are the Fama–French 48, 38, 30, 17, 12, 10 and 5 industry classifications, MG is the industry classification in Moskowitz and Grinblatt (1999) and SIC is the official SIC industry classification.

Model		FF48	FF38	FF30	FF17	FF12	FF10	FF5	MG	SIC
Panel A: Excess returns and models without CCC factor										
Excess return	EW	0.263***	0.080	0.128	0.360***	0.257*	0.385**	0.140	0.265*	0.239
		(2.781)	(0.836)	(1.230)	(3.165)	(1.654)	(2.287)	(1.642)	(1.752)	(0.982)
	VW	0.063	0.082	0.250*	0.100	0.113	0.061	−0.043	0.118	0.051
		(0.510)	(0.497)	(1.821)	(0.812)	(0.594)	(0.318)	(−0.361)	(0.681)	(0.180)
Fama–French three-factor	EW	0.319***	0.084	0.131	0.332***	0.306**	0.446***	0.146*	0.324**	0.225
		(3.311)	(0.870)	(1.224)	(3.022)	(1.976)	(2.653)	(1.741)	(2.088)	(0.907)
	VW	0.227*	0.267	0.396***	0.169	0.257	0.211	0.080	0.167	0.257
		(1.857)	(1.615)	(2.889)	(1.374)	(1.340)	(1.078)	(0.646)	(0.936)	(0.920)
Fama–French–Carhart four-factor	EW	0.324***	0.133	0.165	0.378***	0.308*	0.431**	0.198**	0.254	0.186
		(2.918)	(1.278)	(1.480)	(3.405)	(1.868)	(2.417)	(2.282)	(1.602)	(0.727)
	VW	0.128	0.203	0.284**	0.186	0.191	0.137	0.113	0.137	0.099
		(1.062)	(1.206)	(1.983)	(1.387)	(0.996)	(0.705)	(0.911)	(0.730)	(0.325)
Fama–French five-factor	EW	0.461***	0.136	0.277**	0.448***	0.466***	0.597***	0.159*	0.493***	0.158
		(4.623)	(1.332)	(2.318)	(3.666)	(2.957)	(3.454)	(1.683)	(2.944)	(0.629)
	VW	0.283**	0.387**	0.461***	0.216	0.268	0.166	0.058	0.167	0.208
		(2.084)	(2.260)	(3.135)	(1.623)	(1.358)	(0.798)	(0.451)	(0.850)	(0.721)
Stambaugh–Yuan mispricing-factor	EW	0.379***	0.136	0.215*	0.390***	0.501***	0.617***	0.251***	0.340**	0.164
		(3.111)	(1.206)	(1.813)	(3.186)	(2.949)	(3.141)	(2.821)	(1.978)	(0.626)
	VW	0.231*	0.363**	0.395***	0.284**	0.206	0.167	0.095	0.254	0.133
		(1.739)	(1.998)	(2.582)	(2.004)	(0.990)	(0.799)	(0.732)	(1.224)	(0.425)
Panel B: Models with CCC factor										
Fama–French five-factor + CCC	EW	0.359***	−0.013	0.134	0.386***	0.214	0.371**	0.220**	0.326**	−0.009
		(3.467)	(−0.130)	(1.066)	(3.142)	(1.350)	(2.109)	(2.395)	(2.010)	(−0.034)
	VW	0.007	0.038	0.175	0.001	−0.031	−0.129	0.187	−0.119	−0.150
		(0.050)	(0.218)	(1.229)	(0.010)	(−0.157)	(−0.628)	(1.425)	(−0.660)	(−0.514)
Stambaugh–Yuan mispricing-factor + CCC	EW	0.261**	0.002	0.067	0.313**	0.266	0.403**	0.302***	0.167	0.046
		(2.089)	(0.018)	(0.548)	(2.442)	(1.572)	(2.013)	(3.165)	(0.926)	(0.174)
	VW	−0.002	0.067	0.156	0.108	−0.032	−0.058	0.207	0.027	−0.133
		(−0.013)	(0.358)	(1.082)	(0.769)	(−0.146)	(−0.261)	(1.497)	(0.139)	(−0.386)

t statistics based on heteroscedasticity-consistent standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of the industry classifications[8]. Most of the equal-weighted portfolios earn statistically significant positive abnormal returns, while some have returns indistinguishable from zero. Few value-weighted portfolios have statistically significant abnormal returns at

[8]The results do not change if we use the median as the sorting criterion.

the five percent level. Applying the Fama–French 12, 10 and 5 industry classifications, the industry classification in Moskowitz and Grinblatt (1999) and the official SIC industry classification, which all contain relatively few industries, do not produce any statistically significant abnormal for the value-weighted portfolios. Moreover, the industry classifications in FF38 and SIC do not produce any statistically significant abnormal returns for the equal-weighted portfolios.

In Panel B of Table 10, we add the CCC factor to the Fama–French (2015) five-factor model and the Stambaugh–Yuan (2017) mispricing-factor model[9]. In tests not reported here, all of the portfolios have high and statistically significant loadings on the CCC factor, except for the portfolios based on the Fama–French 5 industry classification, which have modest, statistically significant negative loadings. Consequently, both the magnitudes and statistical significance of the abnormal returns decrease in most cases. Some of the abnormal returns of the equal-weighted portfolios are still highly statistically significant, implying that there are other variables not accounted for in the models that explain the profits of the random industry strategy. None of the value-weighted portfolios achieve abnormal returns statistically indistinguishable from zero. Altogether, the addition of the CCC factor is evidence of an individual CCC effect.

Unlike the true industry strategy, it is not straightforward to conclude whether the random industry strategy indicates that the industry component of stock returns drive the CCC effect. The tests indicate that several of the equal-weighted portfolios produce statistically significant abnormal returns across models. Although generally smaller than those achieved by the individual CCC strategy, most of these abnormal returns are economically significant. On the other hand, none of the value-weighted portfolios consistently achieve statistically significant abnormal returns when controlling for several asset pricing models, and not a single value-weighted portfolio achieve such profits when we add the CCC factor. Moskowitz and Grinblatt (1999) only use value-weighted portfolios in their analysis of the random industry strategy. In this regard, it is worth commenting that there are positive and negative aspects of both equal- and value-weighted portfolios. Fama and French (2008b) argue that value-weighted portfolios are often dominated by a few big stocks,

[9] The results are the same for the other asset pricing models with the addition of the CCC factor.

which may distort the interpretation of anomalies. However, firms with small market capitalization can be very influential in equal-weighted portfolios (Hou, Xue and Zhang, 2018). In addition, Fama (1998) argues that value-weighted portfolios might provide a better understanding of anomalies as they are better at capturing the total wealth effect on investors. Nevertheless, many studies rely on equal-weighted portfolios (Hou et al., 2018).

Altogether, as several portfolios achieve statistically abnormal returns, there seems to be enough evidence to reject the null hypothesis that the industry CCC effect accounts for a substantial part of the CCC effect. In fact, the addition of the CCC factor provides evidence of an individual CCC effect.

6.3 Discussion of the CCC Strategies

The results from the true and random industry strategies provide enough evidence to reject our null hypotheses that there exists an industry CCC effect. In this section, we discuss potential reasons for why this is the case. Important for this discussion, we also provide statistics of the long and short portfolios in the four different strategies presented. These strategies include the industry-adjusted and unadjusted CCC sorts for the individual strategy, and the true and random industry strategies. For the industry strategies, we only report statistics from the Fama–French 48 industries.

Table 11 presents the statistics for the long and short portfolios in the four strategies mentioned above. We report the mean, minimum, first quartile, median, third quartile and maximum industry-adjusted CCC and CCC, respectively, of each portfolio. We also report the total number of observations, unique stocks and unique industries in each of the portfolios.

The CCC statistics vary considerably between the long and short portfolios, though more for the individual strategies compared to the industry strategies. The reason for this is naturally that the portfolios in the individual strategies consist only of the most extreme stocks in terms of the industry-adjusted CCC and the unadjusted CCC, while the portfolios in the industry strategies use the average industry CCC as the criterion. As

Table 11: Strategy statistics.

This table presents statistics of the long and short portfolio for each of the four strategies presented; the individual strategy using the industry-adjusted CCC sort, the individual strategy using the unadjusted CCC sort, the true industry strategy and the random industry strategy. For the industry strategies we, use the Fama–French 48 industry classification to construct the portfolios. We report the mean, minimum, first quartile, median, third quartile and maximum industry-adjusted CCC and unadjusted CCC, respectively, of each portfolio. We also report the total number of observations, number of unique stocks and number of unique industries in each of the portfolios.

	Industry-adjusted CCC						CCC								
	Mean	Min	Q_1	Median	Q_3	Max	Mean	Min	Q_1	Median	Q_3	Max	Obs.	Stocks	Industries
Individual CCC-adjusted															
Long portfolio	−514	−1924	−581	−389	−312	−193	−195	−1848	−384	−74	98	926	128009	4157	44
Short portfolio	762	255	479	616	919	2235	1114	173	813	1013	1327	2586	127941	3751	44
Individual CCC															
Long portfolio	−427	−1924	−567	−314	−164	146	−289	−1848	−386	−137	−55	106	128016	3569	44
Short portfolio	723	−440	419	604	919	2235	1160	641	880	1026	1328	2586	127943	3382	44
True industry															
Long portfolio	−30	−1924	−88	0	97	2235	28	−1848	−39	62	174	2586	204456	3317	17
Short portfolio	87	−1687	−172	0	233	2235	673	−1730	405	597	846	2586	146966	2256	18
Random industry															
Long portfolio	-247	-1924	-340	-199	-80	2235	28	-1848	-39	62	174	2586	204456	7520	43
Short portfolio	325	-1687	55	231	480	2235	673	-1730	405	597	846	2586	146966	6843	43

a consequence of this, high-CCC and low-CCC stocks may be included in the long and short portfolios, respectively, which reduces the difference in the CCC distribution of the portfolios. For example, stocks with the maximum CCC (that is winsorized at the 1% level) are included in both the long and short industry portfolios.

Another noteworthy observation is the difference in terms of diversification between the true industry portfolios and the portfolios from the other strategies. The true industry portfolios have a lower number of unique stocks and fewer industries represented, while both the individual strategy portfolios and the random industry strategy portfolios have all industries represented[10]. Interestingly, all industries are represented in both the long and short portfolios of the individual strategies, which indicates that these portfolios are more diversified than the CCC variability across industries presented in Table 1 suggests a priori. Isolated, this indicates industries do not drive the CCC effect in these strategies, at least not entirely, which is consistent with the results from the industry strategy analyses.

Finally, if we require that each industry has at least 15 observations per month, the true industry strategy earns statistically significant abnormal returns for the Fama–French

[10]The total number of industries in FF48 is 44, as we exclude four industries related to financial services. In the industry analysis the total number of industries is 43, as we also exclude *Other*.

38 and 30 industry classifications. However, once we control for the CCC factor, these abnormal returns disappear. Again, this implies that there is no industry CCC effect once we control for the individual CCC effect. The results are presented in section A2 of the appendix.

7 Robustness Test

In this chapter, we present the robustness of our analysis on the industry CCC effect. We first examine if our results for the true and random industry strategy hold in two subperiods. Then, we check if the results change when we exclude low-priced stocks, which we define as stocks priced lower than $5 in the month prior to portfolio formation. These robustness checks are only performed on the Fama–French 48 and 12 industry classifications[11]. Note that we also report our robustness checks on our replication of Wang (2019). However, we choose not to comment too extensively on this to limit the scope of our discussion.

Motivated by Wang (2019), the first subperiod starts in June 1976 and ends in December 1995, while the other subperiod starts in January 1996 and ends in December 2015. For these two subperiods there are 234 and 240 months, respectively. The results of the two subperiods are reported in Panel A and Panel B of Table 12. We observe that the results from the true industry strategy, for both industry classifications, are generally consistent with our findings in 6.2.1 in both periods. The value-weighted portfolio based on the FF48 industry classification are slightly more negative and statistically significant in the second subperiod for some models. Otherwise, the results are similar to our findings in 6.2.1, both in magnitude and statistical significance.

Furthermore, when studying the random industry strategies, we observe that the abnormal returns of the equal-weighted portfolios for both the Fama–French 48 and 12 industry classifications are substantially more significant in the first subperiod relative to the second. Both the magnitude and statistical significance of the first subperiod are more consistent with the results from section 6.2.2. Moreover, the abnormal returns for the value-weighted portfolio based on the FF48 industry classification are no longer statistically reliable when we split the sample into subperiods. In both subperiods, the results for the value-weighted portfolio based on the FF12 industry classification are generally consistent with the results from section 6.2.2.

[11]We choose the Fama–French 48 and 12 industry classification so that we check the robustness for one narrow and one broad industry classification.

Table 12: Robustness test.

This table presents the robustness of the tests in the previous analyses of the individual strategy, the true industry strategy and the random industry strategy for both equal-weighted (EW) and value-weighted portfolios. Column three and four are the individual EW and VW portfolios from the industry-adjusted CCC sort, respectively, column four and five are the individual EW and VW portfolios from the unadjusted CCC sort, respectively, column six and seven are the true industry EW and VW portfolios based on the Fama–French 48 industry classification (FF48), respectively, column eight and nine are the true industry EW and VW portfolios based on the Fama–French 12 industry classification (FF12), respectively, column 10 and 11 are the random industry EW and VW portfolios based on FF48, respectively and the two rightmost columns are the random industry EW and VW portfolios based on FF12. The table reports (in percentage) the average excess return, Fama–French three-factor abnormal return (Fama & French, 1993), Fama–French–Carhart four-factor abnormal return (Carhart, 1997), Fama–French five-factor abnormal return (Fama & French, 2015) and Stambaugh–Yuan mispricing-factor abnormal return (Stambaugh & Yuan, 2017) of the time series tests. Panel A uses a sample of stock returns from 1995 and before. Panel B uses a sample of stock returns from 1996 and later. Panel C excludes stock returns where the stock prices the previous month below $5.

	Individual Industry-adjusted CCC		Individual Unadjusted CCC		True industry FF48		True industry FF12		Random industry FF48		Random industry FF12	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Panel A: 1995 and before												
Excess return	0.628***	0.344**	0.645***	0.393*	0.073	−0.037	−0.307	0.190	0.404***	0.109	0.451**	0.186
	(6.593)	(1.998)	(4.382)	(1.670)	(0.497)	(−0.213)	(−0.861)	(0.557)	(3.585)	(0.645)	(2.049)	(0.751)
Fama–French	0.676***	0.501***	0.718***	0.430**	0.054	−0.184	−0.233	−0.044	0.475***	0.277	0.512**	0.308
three-factor	(6.983)	(2.664)	(5.616)	(1.700)	(0.379)	(−0.984)	(−0.758)	(−0.140)	(3.762)	(1.623)	(2.361)	(1.073)
Fama–French–	0.652***	0.432**	0.634***	0.222	−0.058	−0.381*	−0.344	−0.316	0.518***	0.109	0.478**	−0.007
Carhart four-factor	(6.423)	(2.161)	(4.764)	(0.825)	(−0.373)	(−1.912)	(−1.076)	(−1.024)	(3.922)	(0.627)	(2.137)	(−0.028)
Fama–French–	0.620***	0.313	0.658***	0.068	0.032	−0.334	−0.353	−0.349	0.492***	0.102	0.641***	0.074
five-factor	(5.524)	(1.495)	(4.330)	(0.246)	(0.186)	(−1.630)	(−1.077)	(−1.054)	(3.434)	(0.495)	(2.601)	(0.243)
Stambaugh–Yuan	0.589***	0.142	0.749***	0.312	0.042	−0.292	−0.283	−0.288	0.487***	0.260	0.835***	0.342
mispricing factor	(5.324)	(0.667)	(4.893)	(0.946)	(0.224)	(−1.116)	(−0.797)	(−0.789)	(2.938)	(1.277)	(3.343)	(1.030)
Panel B: 1996 and after												
Excess return	0.245	0.394*	0.046	0.275	−0.124	−0.355**	−0.064	0.041	0.221	−0.027	0.387*	0.079
	(1.450)	(1.706)	(0.261)	(1.211)	(−0.609)	(−2.022)	(−0.129)	(0.103)	(1.400)	(−0.158)	(1.665)	(0.268)
Fama–French	0.185	0.448**	−0.006	0.321	−0.251	−0.367**	−0.084	0.260	0.266*	0.068	0.339	0.186
three-factor	(1.342)	(2.102)	(−0.037)	(1.487)	(−1.232)	(−2.043)	(−0.169)	(0.662)	(1.829)	(0.381)	(1.568)	(0.634)
Fama–French–	0.125	0.452**	−0.048	0.318	−0.196	−0.350*	−0.145	0.185	0.281*	−0.001	0.375	0.126
Carhart four-factor	(0.860)	(1.970)	(−0.301)	(1.328)	(−0.903)	(−1.957)	(−0.280)	(0.425)	(1.673)	(−0.006)	(1.517)	(0.424)
Fama–French–	0.296*	0.455**	0.045	0.275	−0.263	−0.335*	−0.279	0.426	0.431***	0.170	0.429*	0.256
five-factor	(1.897)	(2.056)	(0.237)	(1.252)	(−1.204)	(−1.703)	(−0.518)	(1.003)	(2.795)	(0.903)	(1.844)	(0.771)
Stambaugh–Yuan	0.179	0.434*	0.035	0.311	−0.060	−0.184	0.112	0.559	0.344*	0.063	0.464*	−0.001
mispricing factor	(1.122)	(1.681)	(0.212)	(1.190)	(−0.239)	(−0.959)	(0.203)	(1.274)	(1.712)	(0.347)	(1.667)	(−0.003)
Panel C: Excluding low-priced stocks												
Excess return	0.420***	0.365**	0.394***	0.33**	−0.046	−0.242**	−0.057	0.199	0.313***	0.122	0.291**	0.142
	(4.142)	(2.513)	(3.364)	(2.009)	(−0.397)	(−1.963)	(−0.193)	(0.796)	(3.421)	(0.907)	(2.272)	(0.780)
Fama–French	0.458***	0.495***	0.434***	0.434**	−0.128	−0.243*	−0.104	0.207	0.373***	0.291**	0.360***	0.300
three-factor	(4.873)	(3.379)	(3.663)	(2.521)	(−1.061)	(−1.935)	(−0.353)	(0.825)	(4.214)	(2.180)	(2.818)	(1.637)
Fama–French–	0.434***	0.509***	0.395***	0.408**	−0.124	−0.282**	−0.040	0.160	0.336***	0.254*	0.384***	0.187
Carhart four-factor	(4.448)	(3.140)	(3.197)	(2.065)	(−1.008)	(−2.178)	(−0.132)	(0.604)	(3.533)	(1.879)	(2.931)	(1.039)
Fama–French–	0.664***	0.612***	0.640***	0.552***	−0.062	−0.218	−0.008	0.359	0.516***	0.340**	0.494***	0.329*
five-factor	(7.135)	(3.915)	(5.341)	(2.973)	(−0.512)	(−1.599)	(−0.026)	(1.292)	(5.502)	(2.481)	(3.812)	(1.795)
Stambaugh–Yuan	0.592***	0.490***	0.618***	0.525**	0.072	−0.116	0.448	0.503*	0.421***	0.401***	0.559***	0.259
mispricing factor	(5.996)	(2.677)	(5.142)	(2.484)	(0.537)	(−0.796)	(1.338)	(1.754)	(4.116)	(2.681)	(4.162)	(1.267)

t statistics based on heteroscedasticity-consistent standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results of our second robustness check, where we exclude low-priced stocks, are reported in Panel C of Table 12. The abnormal returns of the true industry strategy based on the FF48 industry classification are consistent with our original findings. However, it is worth noting that for the random industry strategy, the value-weighted portfolio now earns economically and statistically significant abnormal returns. Finally, we see that the results for the portfolios that are based on the FF12 industry classification are consistent with our findings in section 6.2.1 and 6.2.2. The sizes of the abnormal returns are slightly lower, but the statistical significance of the coefficients remains more or less unchanged.

Table 12 also reports our robustness checks for our replication of Wang (2019) and our individual analysis using the unadjusted CCC sort. The most noteworthy finding from these checks is that the CCC effect appears to be somewhat stronger, both in terms of magnitude and statistical significance, in the first subperiod compared to the second. This indicates that the CCC effect has faded slightly over the last two decades. Another potential explanation is that the subperiods include fewer observations.

In summary, we find that some of the results from our robustness checks deviate from our original findings in sections 6.2.1 and 6.2.2. However, we still consider our original findings to be robust as our robustness checks are overall consistent with our previous results.

8 Conclusion

In this thesis, we investigate whether there is a CCC effect in the industry component of stock returns. We find that the individual CCC strategy using an industry-median adjusted CCC sort achieves annual abnormal returns of 4.8%–7.4%. The individual CCC strategy using an unadjusted CCC sort achieves slightly weaker annual abnormal returns of 4.1%–6.6%, however, the difference in returns is statistically indistinguishable from zero. Noteworthy, the individual CCC strategy portfolios are either uncorrelated with or have negative loadings on most conventional risk factors.

While we find clear evidence of an individual CCC effect, we find no evidence of an industry CCC effect. In most of the tests in the true industry analysis, the portfolios earn abnormal returns statistically indistinguishable from zero. Moreover, the few statistically significant abnormal returns become insignificant once we control for the individual CCC effect by adding the CCC factor. The results are robust to different sorting criteria and industry classifications. In the random industry analysis, the majority of the equal-weighted portfolios for most industry classifications earn statistically significant abnormal returns. The results for the value-weighted portfolios are more ambiguous, as many of them do not earn statistically significant returns. Nevertheless, when we add the CCC factor, the abnormal returns of most portfolios decrease substantially, indicating that there is an individual CCC effect and no industry CCC effect.

We observe that all industries are represented in both the long and short portfolio of the individual strategy, regardless of which CCC sort. This indicates that the individual CCC strategy is in fact more diversified than what we expected a priori. Although the CCC varies considerably across industries, it also varies considerably within industries.

In summary, we do not find that there is a CCC effect in the industry component of stock returns. One practical implication of this is that a top-down CCC strategy approach, where investors buy and sell industries instead of individual stocks, is not attractive. The CCC effect seems to be driven by individual stocks, but the underlying driver of this remains a puzzle and is subject for future research.

References

Adrian, T., Etula, E., & Muir, T. (2014). Financial intermediaries and the cross-section of asset returns. *The Journal of Finance*, *69*(6), 2557–2596.

Ball, R., Gerakos, J., Linnainmaa, J. T., & Nikolaev, V. (2016). Accruals, cash flows, and operating profitability in the cross section of stock returns. *Journal of Financial Economics*, *121*(1), 28–45.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, *49*(3), 307–343.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance*, *32*(3), 663–682.

Berk, J. & DeMarzo, P. (2017). *Corporate Finance – 4th Global Edition*. London, United Kingdom: Pearson, 4 edition.

Bodie, Z., Kane, A., & Marcus, A. (2018). *Investments, Eleventh Edition*. New York, United States of America: McGraw-Hill Education, 11 edition.

Bradshaw, M. T., Richardson, S. A., & Sloan, R. G. (2001). Do analysts and auditors use information in accruals? *Journal of Accounting Research*, *39*(1), 45–74.

Bradshaw, M. T., Richardson, S. A., & Sloan, R. G. (2006). The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of Accounting and Economics*, *42*(1–2), 53–85.

Campbell, J. Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2001). Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk. *The Journal of Finance*, *56*(1), 1–43.

Carhart, M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57–82.

Chou, P., Ho, P., & Ko, K. (2012). Do industries matter in explaining stock returns and asset-pricing anomalies? *Journal of Banking Finance*, *36*(2), 355–370.

Davis, J. L., Fama, E., & French, K. (2000). Characteristics, covariances, and average returns: 1929 to 1997. *The Journal of Finance*, *55*(1), 389–406.

Dechow, P. M., Khimich, N. V., & Sloan, R. G. (2015). *The Accrual Anomaly*, chapter 2, (pp. 23–61). John Wiley & Sons, Ltd.

Deloof, M. (2003). Does working capital management affect profitability of belgian firms? *Journal of Business Finance Accounting*, *30*(3–4), 573–588.

Engelberg, J., McLean, R. D., & Pontiff, J. (2018). Anomalies and news. *The Journal of Finance*, *73*(5), 1971–2001.

Evans, J. L. & Archer, S. H. (1968). Diversification and the reduction of dispersion: An empirical analysis. *The Journal of Finance*, *23*(5), 761–767.

Fama, E. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, *49*(3), 283–306.

Fama, E. & French, K. (1992). The cross-section of expected stock returns. *The Journal of Finance*, *47*(2), 427–465.

Fama, E. & French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

Fama, E. & French, K. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, *51*(1), 55–84.

Fama, E. & French, K. (2004). The capital asset pricing model: Theory and evidence. *Journal of Economic Perspectives*, *18*(3), 25–46.

Fama, E. & French, K. (2008a). Average returns, b/m, and share issues. *The Journal of Finance*, *63*(6), 2971–2995.

Fama, E. & French, K. (2008b). Dissecting anomalies. *The Journal of Finance*, *63*(4), 1653–1678.

Fama, E. & French, K. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22.

Frazzini, A. & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1–25.

French, K. (2019). Kenneth R. French – Data Library. Retrived September 30, 2019, from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Gentry, J. A., Vaidyanathan, R., & Lee, H. W. (1990). A weighted cash conversion cycle. *Financial Management*, *19*(1), 90–99.

He, Z., Kelly, B., & Manela, A. (2017). Intermediary asset pricing: new evidence from many asset classes. *Journal of Financial Economics*, *126*(1), 1–35.

Hong, H. & Stein, J. C. (1998). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, *54*(6), 2143–2184.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, *28*(3), 650–705.

Hou, K., Xue, C., & Zhang, L. (2018). Replicating anomalies. *The Review of Financial Studies*. forthcoming.

Hu, G., Pan, J., & Wang, J. (2013). Noise as information for illiquidity. *The Journal of Finance*, *68*(6), 2341–2382.

Jegadeesh, N. & Titman, S. (1993). Returns to buying winners and selling losers, implications for stock market efficiency. *The Journal of Finance*, *48*(1), 65–91.

Jose, M. L., Lancaster, C., & Stevens, J. (1996). Corporate returns and cash conversion cycles. *Journal of Economics and Finance*, *20*(1), 33–46.

Kieschnick, R., Laplante, M., & Moussawi, R. (2013). Working capital management and shareholders' wealth. *Review of Finance*, *17*(5), 1827–1852.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, *47*(1), 13–37.

Liu, Q., Rhee, S. G., & Zhang, L. (2015). Limits-to-arbitrage in us penny stocks: An overlooked segment of us equity markets. *Asian Finance Association (AsianFA) Conference Paper*.

Moskowitz, T. & Grinblatt, M. (1999). Do industries explain momentum? *The Journal of Finance*, *54*(4), 1249–1290.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica*, *34*(4), 768–783.

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

Raddatz, C. (2006). Liquidity needs and vulnerability to financial underdevelopment. *Journal of Financial Economics*, *80*(3), 677–722.

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management*, *11*(3), 9–16.

Schwert, W. G. (2003). Anomalies and market efficiency. In G. Constantinides, M. Harris, & R. Stulz (Eds.), *Handbook of the Economics of Finance*, volume 1, Part B chapter 15, (pp. 939–974). Elsevier.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), 425–442.

Shin, H. & Soenen, L. (1998). Efficiency of working capital management and corporate profitability. *Financial Practice Education*, *8*(2), 37–45.

Shumway, T. (1997). The Delisting Bias in CRSP Data. *The Journal of Finance*, *52*(1), 327–340.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, *71*(3), 289–315.

S&P Global Market Intelligence. (2019). Compustat Daily Updates – Fundamentals Quarterly. Retrived September 30, 2019, from https://wrds-web.wharton.upenn.edu/wrds/ds/compd/fundq/index.cfm?navId=83.

Stambaugh, R. (2019). Robert F. Stambaugh – Data Library. Retrived September 30, 2019, from http://finance.wharton.upenn.edu/~stambaug/.

Stambaugh, R. & Yuan, Y. (2017). Mispricing factors. *The Review of Financial Studies*, *30*(4), 1270–1315.

The Center for Research in Security Prices. (2019). CRSP Monthly Stock. Retrived September 30, 2019, from https://wrds-web.wharton.upenn.edu/wrds/ds/crsp/stock_a/msf.cfm?navId=128.

Titman, S., Wei, K., & Xie, F. (2004). The other side of value: The gross profitability premium. *The Journal of Financial and Quantitative Analysis*, *39*(4), 677–700.

Tong, H. & Wei, S. (2011). The composition matters: capital inflows and liquidity crunch during a global economic crisis. *The Review of Financial Studies*, *24*(6), 2023–2052.

U.S. Department of Labor (2019). SIC Division Structure. Retrived October 10, 2019, from https://www.osha.gov/pls/imis/sic_manual.html.

U.S. Securities and Exchange Commission (2019). Penny Stock Rules. Retrived October 19, 2019, from https://www.sec.gov/fast-answers/answerspennyhtm.html.

Wang, B. (2019). The cash conversion cycle spread. *Journal of Financial Economics*, *133*(2), 472–497.

Appendix

A1 Looking Beyond Low-minus-High

As described in chapter 5, we observe a monotonically decreasing trend in abnormal returns from the lowest to the highest CCC decile. We find this observation interesting because it indicates that the CCC effect may exist for other individual strategy portfolios than that created with the low 1 and high 10 deciles. In this section, we look beyond this low-minus-high portfolio.

There is a number of ways to form other zero-investment portfolios. We limit our analysis to 15 portfolios following a systematic pattern where we end up towards the mid-deciles. Due to the monotonically decreasing trend we observe, we expect that the CCC effect also exists for portfolios based on other deciles, but that both the size and statistical significance of the abnormal returns will decrease as we move away from the lowest and highest CCC decile. We therefore propose the following null and alternative hypotheses:

> $\boldsymbol{H_0}$**:** *The CCC effect only exists for the low-minus-high portfolio, and thus, other portfolios earn statistically insignificant abnormal returns.*
> $\boldsymbol{H_A}$**:** *The CCC effect does not only exist for the low-minus-high portfolio, and thus, other portfolios also earn statistically significant abnormal returns.*

To test the hypotheses above, we first form one-and-one portfolios consisting of a long position in one decile and a short position in another decile. The first portfolio among these is the already reported low-minus-high CCC portfolio, the next consists of a long position in decile 2 and a short position in decile 9, the third a long position in decile 3 and a short position decile 8, and so on. We do this also for portfolios consisting of two-and-two, three-and-three, four-and-four and five-and-five deciles. We buy the long deciles in equal amounts and sell the short deciles in equal amounts. The results of the tests are presented in Table A1.1.

The abnormal returns gradually and consistently decrease when moving towards or

Table A1.1: Alternative individual strategy portfolios.

This table presents abnormal returns (in percentage) for both equal-weighted (EW) and value-weighted (VW) zero-investment portfolios with a long position in the decile(s) to the left of the minus sign and a short position in the decile(s) to the right of the minus sign. We have an equal investment in each decile. At the beginning of each month, from July 1976 to December 2015, we sort all stocks into deciles based on the industry-adjusted CCC two quarters ago and calculate the average return from the cross-section. We then report the Fama–French three-factor abnormal return (Fama & French, 1993), Fama–French–Carhart four-factor abnormal return (Carhart, 1997), Fama–French five-factor abnormal return (Fama & French, 2015) and Stambaugh–Yuan mispricing-factor abnormal return (Stambaugh & Yuan, 2017) from the time series tests.

	Fama–French three-factor		Fama–French–Carhart four factor		Fama–French five-factor		Stambaugh–Yuan mispricing-factor	
	EW	VW	EW	VW	EW	VW	EW	VW
One-and-one portfolios								
(1) − (10) (Low-minus-high)	0.437***	0.499***	0.402***	0.509***	0.582***	0.614***	0.497***	0.488***
	(4.688)	(3.420)	(3.928)	(3.173)	(5.869)	(3.957)	(4.602)	(2.705)
(2) − (9)	0.307***	0.174	0.332***	0.181	0.376***	0.299**	0.379***	0.188
	(4.374)	(1.424)	(4.536)	(1.437)	(5.161)	(2.396)	(4.840)	(1.347)
(3) − (8)	0.244***	0.021	0.221***	0.022	0.271***	0.248*	0.227***	0.057
	(3.957)	(0.161)	(2.957)	(0.156)	(4.280)	(1.887)	(2.989)	(0.379)
(4) − (7)	0.131**	0.109	0.120*	0.078	0.124*	0.160	0.073	0.062
	(2.228)	(0.983)	(1.925)	(0.672)	(1.898)	(1.366)	(1.124)	(0.452)
(5) − (6)	−0.013	−0.038	−0.023	−0.046	−0.035	−0.026	−0.051	−0.045
	(−0.234)	(−0.388)	(−0.413)	(−0.452)	(−0.646)	(−0.271)	(−0.901)	(−0.425)
Two-and-two portfolios								
(1, 2) − (9, 10)	0.372***	0.336***	0.367***	0.345***	0.479***	0.456***	0.438***	0.338***
	(6.074)	(3.432)	(5.767)	(3.391)	(7.485)	(4.551)	(6.453)	(2.892)
(2, 3) − (8, 9)	0.275***	0.097	0.277***	0.101	0.324***	0.274***	0.303***	0.123
	(5.362)	(1.013)	(5.126)	(1.031)	(6.005)	(2.940)	(5.237)	(1.115)
(3, 4) − (7, 8)	0.187***	0.065	0.170***	0.050	0.197***	0.204**	0.150***	0.060
	(4.201)	(0.690)	(3.451)	(0.49)	(4.041)	(2.096)	(2.963)	(0.522)
(4, 5) − (6, 7)	0.059	0.035	0.048	0.016	0.044	0.067	0.011	0.009
	(1.505)	(0.486)	(1.189)	(0.214)	(1.062)	(0.915)	(0.255)	(0.103)
Three-and-three portfolios								
(1, 2, 3) − (8, 9, 10)	0.329***	0.231***	0.318***	0.237***	0.410***	0.387***	0.368***	0.245**
	(6.636)	(2.767)	(5.96)	(2.685)	(7.933)	(4.656)	(6.499)	(2.358)
(2, 3, 4) − (7, 8, 9)	0.227***	0.101	0.224***	0.094	0.257***	0.236***	0.226***	0.103
	(5.677)	(1.270)	(5.450)	(1.115)	(5.871)	(2.942)	(5.200)	(1.091)
(3, 4, 5) − (6, 7, 8)	0.121***	0.031	0.106***	0.018	0.120***	0.127*	0.083**	0.025
	(3.515)	(0.421)	(2.738)	(0.233)	(3.222)	(1.783)	(2.096)	(0.296)
Four-and-four portfolios								
(1, 2, 3, 4) − (7, 8, 9, 10)	0.280***	0.201***	0.269***	0.198**	0.338***	0.330***	0.294***	0.199**
	(6.970)	(2.766)	(6.190)	(2.483)	(7.666)	(4.427)	(6.321)	(2.132)
(2, 3, 4, 5) − (6, 7, 8, 9)	0.167***	0.066	0.162***	0.059	0.184***	0.170***	0.157***	0.066
	(5.089)	(1.002)	(4.725)	(0.845)	(5.118)	(2.658)	(4.307)	(0.863)
Five-and-five portfolios								
(1, 2, 3, 4, 5) − (6, 7, 8, 9, 10)	0.221***	0.153**	0.210***	0.149**	0.264***	0.259***	0.225***	0.150*
	(6.531)	(2.475)	(5.655)	(2.230)	(7.023)	(4.215)	(5.609)	(1.932)

t statistics based on heteroscedasticity-consistent standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

adding mid-deciles to the portfolio. For the portfolios that include the low 1 and high 10 deciles, the return spread decreases from the previously reported 0.40%–0.61% per month (4.82%–7.37% per annum) for the low-minus-high portfolio, to 0.15%–0.26% per month (1.80%–3.17%) for the portfolio that includes all deciles. This is an economically significant reduction. Furthermore, there is a stark contrast between the low-minus-high portfolio and the other portfolios in terms of equal-weighted versus value-weighted abnormal returns. For the low-minus-high portfolio, the value-weighted abnormal returns are all higher than the equal-weighted abnormal returns, except for when controlling for the Stambaugh–Yuan mispricing factors (Stambaugh & Yuan, 2017). For the other portfolios, all value-weighted portfolios have lower abnormal returns, and nearly all those that do not include the low 1 or high 10 deciles have returns that are statistically insignificant. On the other hand, we observe that for the one-and-one portfolios, the equal-weighted portfolios earn highly statistically significant, though decreasing returns all the way up to the $(3) - (8)$ portfolio, and in some models for the $(4) - (7)$ portfolio. We observe the same pattern of decreasing, though still statistically significant, abnormal returns for the two-and-two, three-and-three and four-and-four portfolios.

In summary, we earn non-trivial abnormal returns that are highly statistically significant for a range of equal-weighted portfolios. This is also true for the value-weighted portfolios that include the low 1 and high 10 deciles. We therefore find strong evidence to reject our null hypothesis that the CCC effect only exists for the low-minus-high CCC decile portfolio. This implies that the CCC effect in our sample is very strong. This reflects the monotonic trend we observe in chapter 5.

A2 The True Industry Strategy with Restriction

In this section of the appendix, we discuss the results of the true industry strategy when we require that each industry has at least 15 observations every month[12], which reduces the level of idiosyncratic risk. Besides from this restriction, the true industry strategy is implemented as described in section 4.2.1. We only show the results from the portfolios

[12] While Evans and Archer (1968) show that portfolios of eight to ten stocks achieve most of the benefits from diversification, Campbell, Lettau, Malkie and Xu (2001) find that the marginal diversification benefit from adding new firms to a portfolio has decreased over time. We therefore consider 15 firms per industry per month to be a suitable restriction, however, our results are not sensitive to other values.

based on the Fama–French 38 and 30 industry classifications, as these are the only ones that earn statistically significant abnormal returns. The restriction reduces the average number of industries per month with seven and four, respectively. We add the CCC factor to this model to see if potential abnormal returns persist even after controlling for the individual CCC effect. If that is the case, there is evidence supportive of an industry CCC effect. The results are reported in Table A2.1.

In Panel A of Table A2.1, we observe that the equal-weighted portfolio based on the Fama–French 38 industry classification (FF38) earns abnormal returns of approximately 0.40% per month, while the Fama–French 30 industry classification (FF30) earns abnormal returns of approximately 0.26% per month. These returns are also highly statistically significant, implying that there exists an industry CCC effect. However, when controlling for the individual CCC effect, as observed from models (2) and (4), these returns become statistically indistinguishable from zero. Hence, there is evidence supporting that the abnormal returns earned in model (1) and (3) cannot be attributed to an industry CCC effect.

Furthermore, Panel B shows the results for the value-weighted portfolios for the FF38 and FF30 industry classifications. Similar to the equal-weighted portfolios, these portfolios earn highly statistically significant returns of 0.33% and 0.24% per month, respectively. Nevertheless, also these returns become statistically insignificant once controlling for the individual CCC factor. Hence, an industry CCC effect is not the driving force for these abnormal returns.

In summary, when we require that each industry has at least 15 firms per month, the portfolios based on FF38 and FF30 earn statistically and economically significant abnormal returns when controlling for the Fama–French (2015) five-factor model. This indicates that there exists an industry CCC effect. However, when controlling for the individual CCC effect by including the CCC factor in the model, these returns are no longer statistically significant[13]. Hence, in line with our findings from section 6.2.1, we reject our null hypothesis that there is an industry CCC effect.

[13] We get the same result of statistically significant profits without the CCC factor, and statistically insignificant profits with the CCC factor in other asset pricing models as well.

Table A2.1: True industry strategy with restriction.

This table presents the factor loadings and abnormal returns (in percentage) of the true industry strategy using the Fama–French 38 industry classification (FF38) and the Fama–French 30 industry classification (FF30). We require that each industry has at least 15 observations every month. Each month, for each industry classification, we calculate the average industry CCC based on the stocks' unadjusted CCC two quarters ago. We then buy the 15% industries with the lowest average CCC in equal amounts and sell the 15% industries with the highest average CCC in equal amounts, constructing a zero-investment portfolio. Following that, we calculate the average return from the cross-section. Models (1) and (3) are the Fama–French (2015) five-factor model, and models (2) and (4) are the Fama–French five-factor model plus the CCC factor. The CCC factor is constructed as described in section 4.3. Panel A and Panel B report the time series tests of the equal-weighted and value-weighted portfolios, respectively.

Panel A: Equal-weighted portfolios

	FF38		FF30	
	(1)	(2)	(3)	(4)
MktRf	−0.011	0.083***	−0.079***	−0.008
	(−0.348)	(2.907)	(−2.852)	(−0.288)
SMB	−0.445***	−0.313***	−0.247***	−0.147***
	(−7.988)	(−5.734)	(−5.234)	(−3.179)
HML	0.062	0.022	0.153**	0.124**
	(0.806)	(0.346)	(2.312)	(1.964)
RMW	−0.116*	0.027	−0.112	−0.005
	(−1.709)	(0.451)	(−1.621)	(−0.063)
CMA	−0.013	0.092	−0.054	0.026
	(−0.117)	(0.867)	(−0.549)	(0.274)
CCC		0.700***		0.529***
		(10.355)		(7.925)
Constant	0.398***	0.072	0.235**	−0.011
	(2.897)	(0.585)	(2.065)	(−0.103)
N	474	474	474	474
R^2	0.173	0.328	0.147	0.285
Adjusted R^2	0.164	0.319	0.138	0.276
Residual Std. Error	2.749 (df = 468)	2.481 (df = 467)	2.237 (df = 468)	2.051 (df = 467)
F statistic	19.530*** (df = 5; 468)	37.951*** (df = 6; 467)	16.135*** (df = 5; 468)	31.035*** (df = 6; 467)

Panel B: Value-weighted portfolios

	FF38		FF30	
	(5)	(6)	(7)	(8)
MktRf	−0.127***	−0.007	−0.157***	−0.061
	(−3.217)	(−0.207)	(−4.107)	(−1.716)
SMB	−0.456***	−0.289***	−0.226***	−0.092
	(−7.466)	(−4.984)	(−3.901)	(−1.586)
HML	−0.023	−0.073	−0.010	−0.050
	(−0.280)	(−1.078)	(−0.135)	(−0.740)
RMW	−0.116	0.064	0.003	0.148
	(−1.144)	(0.746)	(0.039)	(1.789)
CMA	0.194	0.328***	0.277***	0.385
	(1.510)	(2.891)	(2.650)	(4.185)
CCC		0.887***		0.712***
		(11.258)		(6.800)
Constant	0.326**	−0.087	0.240***	−0.091
	(2.033)	(−0.619)	(1.702)	(−0.740)
N	474	474	474	474
R^2	0.196	0.381	0.207	0.38
Adjusted R^2	0.188	0.373	0.199	0.372
Residual Std. Error	3.148 (df = 468)	2.766 (df = 467)	2.596 (df = 468)	2.299 (df = 467)
F statistic	22.843*** (df = 5; 468)	47.877*** (df = 6; 467)	24.455*** (df = 5; 468)	47.613*** (df = 6; 467)

t statistics based on heteroscedasticity-consistent standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A3 Variable and Industry Classification Definitions

Table A3.1: Variable definitions.

This table presents the definitions of the variables used in this thesis. All variables are constructed using quarterly data, except from *BM* and *XFIN*, which are constructed using annual data. We omit the subscript when all the subscripts are t. Panel A presents the variables from CRSP and Compustat. Panel B presents the variables we calculate.

Panel A

Variable	Description
actq	Total current assets
apalchy	Accounts payable and accrued liabilities increase (decrease)
apq	Total account payables
at	Total assets (annual filing)
atq	Total assets (quarterly filing)
cheq	Cash and short-term investments
cogsq	Cost of goods sold
dlcq	Total current debt
dltis	Long-term debt issuance
dltr	Long-term debt reduction
dlttq	Total long-term debt
dpq	Total depreciation and amortization
dvt	Total dividends
invtq	Total inventories
lctq	Total current liabilities
lt	Total liabilities (annual filing)
ltq	Total liabilities (quarterly filing)
oiadpq	Operating income after depreciation
prc	Stock price
prstkc	Purchase of common and preferred stock
pstk	Total preferred stock capital
pstkl	Preferred stock liquidation value
pstkrv	Preferred stock redemption value
rectq	Total receivables
revtq	Total revenues
shrout	Number of shares outstanding
sstk	Sale of common and preferred stock
txditc	Deferred taxes and investment tax credit
txpq	Income taxes payable
xrdq	Research and delevopment expense
xsgaq	Selling, general and administrative expenses

Table A3.1: Variable definitions (continued).

Panel B

Variable	Description	Formula
CCC	Cash conversion cycle measured in days	$DIO + DRO - DPO$
DIO	Days inventory outstanding	$365 \cdot (1/2) \cdot (invtq_t + invtq_{t-1})/cogsq_t$
DRO	Days receivables outstanding	$365 \cdot (1/2) \cdot (rectq_t + rectq_{t-1})/revtq_t$
DPO	Days payable outstanding	$365 \cdot (1/2) \cdot (apq_t + apq_{t-1})/cogsq_t$
$Beta$	Stocks' beta computed using monthly returns over the past previous five years with a minimum number of 24 months as in Fama and French (1992)	
$Size$	Natural logarithm of market capitalization at the end of last month	$\ln(prc \cdot shrout)$
B	Equity book value, calculated as in Fama and French (2008a)	$at - lt + txditc -$ preferred equity[a]
BM	Natural logarithm of book-to-market value as in Fama and French (2008a)	$\ln(B/(prc \cdot shrout))$
$Accruals$	Accruals scaled by lagged total assets as in Sloan (1996)	$[\Delta actq_t - \Delta cheq_t - (\Delta lctq_t - \Delta dlcq_t - txpq_t)$ $-dpq_t]/atq_{t-1}$
$CashHolding$	Cash scaled by total assets	$cheq/atq$
$WorkingCap$	Working capital scaled by total assets	$(actq - lctq)/atq$
$STDebt$	Short-term debt scaled by total assets	$dlcq/atq$
$LTDebt$	Long-term debt scaled by total assets	$dlttq/atq$
$TotalLev$	Liabilities scaled by total assets	ltq/atq
$XFIN$	External financing scaled by total assets as in Bradshaw et al. (2006)	$(sstk - dvt - prstkc + dltis - dltr)/at$
$GrossProfit$	Gross profit scaled by lagged total assets as in Novy-Marx (2013)	$(revtq_t - cogsq_t)/atq_{t-1}$
$CBOP$	Cash-based operating profitability scaled by lagged total assets as in Ball et al. (2016)	$[revtq_t - cogsq_t - xsgaq_t + xrdq_t$ $-(\Delta rectq_t + \Delta invtq_t) - apalchy_t]/atq_{t-1}$
$ProtifMargin$	Operating income after depreciation divided by total revenues	$oiadq/revtq$
ROA	Operating income after depreciation divided by total assets	$oiadq/atq$
ROE	Operating income after depreciation divided by total assets less total liabilities	$oiadq/(atq - ltq)$

[a] Preferred equity is (1) *pstkl*, (2) *pstkrv*, (3) *pstk* or (4) zero, depending on availability.

Table A3.2: Fama–French 48 industry classification.

This table presents the SIC codes of the Fama–French 48 industry classification.

	Industry	SIC codes
1	Agriculture	0100–0299, 0700–0799, 0910–0919, 2048
2	Food products	2000–2046, 2050–2063, 2070–2079, 2090–2092, 2095, 2098, 2099
3	Candy and soda	2064–2068, 2086, 2087, 2096, 2097
4	Beer and liquor	2080, 2082–2085
5	Tobacco products	2100-2199
6	Recreation	0920–0999, 3650–3652, 3732, 3930, 3931, 3940–3949
7	Entertainment	7800-7833, 7840, 7841, 7900, 7910, 7911, 7920–7933, 7940–7949, 7980, 7990–7999
8	Printing and publishing	2700–2749, 2770, 2771, 2780–2799
9	Consumer goods	2047, 2391, 2392, 2510–2519, 2590–2599, 2840–2844, 3160, 3161, 3170–3172, 3190–3199, 3229, 3260, 3262, 3263, 3269, 3230, 3231, 3630–3639, 3750, 3751, 3800, 3860, 3861, 3870–3873, 3910, 3911, 3914, 3915, 3960–3962, 3991, 3995
10	Apparel	2300-2390, 3020, 3021, 3100, 3111, 3130, 3131, 3140–3149, 3150, 3151, 3963–3965
11	Healthcare	8000–8099
12	Medial equipment	3693, 3840–3849, 3850, 3851
13	Pharmaceutical products	2830, 2831, 2833–2836
14	Chemicals	2800–2829, 2850–2899
15	Rubber and plastic products	3031, 3041, 3050–3053, 3060–3099
16	Textiles	2200–2284, 2290–2295, 2297–2299, 2393–2095, 2397–2399
17	Construction metals	0800-0899, 2400-2439, 2450–2459, 2490–2499, 2660, 2661, 2950–2952, 3200, 3210, 3211, 3240, 3241, 3250–3259, 3261, 3264, 3270–3275, 3280, 3281, 3290–3293, 3295–3299, 3420–3429, 3430–3433, 3440-3442, 3446, 3448, 3449, 3450–3452, 3490–3499, 3996
18	Construction	1500–1511, 1520–1549, 1600–1799
19	Steel works	3300, 3310–3317, 3320–3325, 3330–3341, 3350-3357, 3360–3379, 3390-3399
20	Fabricated products	3400, 3443, 3444, 3460–3479
21	Machinery	3510–3536, 3538, 3540–3569, 3580–3582, 3585, 3586, 3589–3599
22	Electrical equipment	3600, 3610–3613, 3620, 3621, 3623–3629, 3640–3646, 3648, 3649, 3660, 3690–3692, 3699
23	Automobiles and trucks	2296, 2396, 3010, 3011, 3537, 3647, 3694, 3700, 3710, 3711, 3713–3716, 3790–3792, 3799
24	Aircraft	3720–3725, 3728, 3729
25	Shipbuilding, railroad and equipment	3730, 3731, 3740–3743
26	Defense	3480–3489, 3760–3769, 3795
27	Precious metals	1040–1049
28	Non-metallic and industrial metal mining	1000–1039, 1050–1119, 1400-1499
29	Coal	1200–1299
30	Petroleum and natural gas	1300, 1310–1339, 1370–1389, 2900–2912, 2990–2999

Table A3.2: Fama–French 48 industry classification (continued).

	Industry	SIC codes
31	Utilities	4900, 4910, 4911, 4920–4925, 4930–4932, 4939–4942
32	Communication	4800, 4810-4813, 4820–4822, 4830–4841, 4880-4892, 4899
33	Personal services	7020, 7021, 7030–7033, 7200, 7210–7212, 7214–7217, 7219–7221, 7230, 7231, 7240, 7241, 7250, 7260–7299, 7395, 7500, 7510–7515, 7520–7549, 7600, 7622–7623, 7329–7631, 7690–7699, 8100–8499, 8600–8699, 8800-8899
34	Business services	2750–2759, 3993, 4220-4229, 7218, 7300, 7310–7342, 7350–7353, 7359–7374, 7375–7385, 7389–7394, 7396–7397, 7399, 7519, 8700, 8710–8713, 8720, 8721, 8730–8734, 8740–8748, 8900-8911, 8920–8999
35	Computers	3570–3579, 3680–3689, 3695, 7373
36	Electronic equipment	3622, 3661–3666, 3669–3679, 3810, 3812
37	Measuring and control equipment	3811, 3820–3827, 3829–3839
38	Business supplies	2520–2549, 2600-2369, 2670–2699, 2760, 2761, 3950–3955
39	Shipping containers	2440–2449, 2640–2659, 3220, 3221, 3410–3412
40	Transportation	4000-4013, 4040–4049, 4100, 4110–4121, 4130, 4131, 4140–4142, 4150, 4151, 4170–4173, 4190–4199, 4200, 4210–4231, 4240–4249, 4500–4700, 4710–4712, 4720–4749, 4780, 4782–4785, 4789
41	Wholesale	5000, 5010–5015, 5020–5023, 5030–5060, 5063–5065, 5070–5078, 5080–5088, 5090–5094, 5099, 5100, 5110-5113, 5020–5122, 5130–5172, 5180–5182, 5190–5199
42	Retail	5200, 5210–5231, 5250, 5251, 5260, 5261, 5270, 5271, 5300, 5310, 5311, 5320, 5330, 5331, 5334, 5340–5349, 5390–5400, 5410–5412, 5420–5469, 5490–5500, 5510–5579, 5590–5700, 5710–5722, 5722, 5730–5736, 5750–5799, 5900, 5910–5912, 5920–5932, 5940–5999
43	Restaurants, hotels and motels	5800–5829, 5890-5899, 7000, 7010–7019, 7040–7049, 7213
44	Banking	6000, 6010–6036, 6040–6062, 6080–6082, 6090–6100, 6110–6113, 6120–6199
45	Insurance	6300, 6310–6331, 6350, 6351, 6360, 6361, 6370–6379, 6390–6411
46	Real estate	6500, 6510,6512–6515, 6517–6532, 6540–6541, 6550–6553, 6590–6599, 6610, 6611
47	Trading	6200-6299, 6700, 6710–6726, 6730–6733, 6740–6779, 6790–6795, 6798, 6799
48	Other	Other

Table A3.3: Fama–French 38 industry classification.

This table presents the SIC codes of the Fama–French 38 industry classification.

	Industry	SIC codes
1	Agriculture, forestry and fishing	0100–0999
2	Mining	1000–1299
3	Oil and gas extraction	1300–1399
4	Non-metallic minerals excluding fuels	1400–1499
5	Construction	1500–1799
6	Food and kindred products	2000–2099
7	Tobacco products	2100–2199
8	Textile mill products	2200–2299
9	Apparel and other textile products	2300–2399
10	Lumber and wood products	2400–2499
11	Furniture and fixtures	2500–2599
12	Paper and allied products	2600–2661
13	Printing and publishing	2700–2799
14	Chemicals and allied products	2800–2899
15	Petroleum and coal products	2900–2999
16	Rubber and miscellaneous plastics products	3000–3099
17	Leather and leather products	3100–3199
18	Stone, clay and glass products	3200–3299
19	Primary metal industries	3300–3399
20	Fabricated metal products	3400–3499
21	Machinery excluding electrical	3500–3599
22	Electrical and electronic equipment	3600–3699
23	Transportation equipment	3700–3799
24	Instruments and related products	3800–3879
25	Miscellaneous manufacturing industries	3900–3999
26	Transportation	4000–4799
27	Telephone and telegraph communication	4800–4829
28	Radio and television broadcasting	4830–4899
29	Electric, gas and water supply	4900–4949
30	Sanitary services	4950–4959
31	Steam supply	4960–4969
32	Irrigation systems	4970–4979
33	Wholesale	5000–5199
34	Retail stores	5200–5999
35	Finance, insurance and real estate	6000–6999
36	Services	7000–8999
37	Public administration	9000–9999
38	Other	Other

Table A3.4: Fama–French 30 industry classification.

This table presents the SIC codes of the Fama–French 30 industry classification.

	Industry	SIC codes
1	Food poducts	0100–02999, 0700–0799, 0910–0919, 2000-2046, 2048, 2050–2068, 2070–2079, 2086, 2087, 2090–2092, 2095–2099
2	Beer and liquor	2080, 2082–2085
3	Tobacco products	2100–2199
4	Recreation	0920–0999, 3650–3652, 3732, 3930, 3931, 3940–3949, 7800–7833, 7840, 7841, 7900, 7910, 7911, 7920–7933, 7940–7949, 7980, 7990–7999
5	Printing and publishing	2700-2759, 2770, 2771, 2780–2799, 3993
6	Consumer goods	2047, 2391, 2392, 2510–2519, 2590–2599, 2840–2844, 3160, 3161, 3170–3172, 3190–3199, 3229–3231, 3260, 3262, 3263, 3269, 3630–3639, 3750, 3751, 3800, 3860, 3861, 3870–3873, 3910, 3911, 3914, 3915, 3960–3962, 3991, 3995
7	Apparel	2300–2390, 3020, 3021, 3100–3111, 3130, 3131, 3140–3151, 3963–3965
8	Healthcare, medical equipment and pharmaceutical products	2830, 2831, 2833–2836, 3693, 3840–3849, 3850, 3851, 8000–8099
9	Chemicals	2800–2829, 2850–2879, 2890–2899
10	Textiles	2200–2284, 2290–2295, 2297–2299, 2393–2395, 2397–2399
11	Construction and construction materials	0800–0899, 1500–1511, 1520–1549, 1600–1799, 2450–2459, 2490–2499, 2660, 2661, 2950–2952, 3200, 3210, 3211, 3240, 3241, 3250–3259, 3261, 3264, 3270–3275, 3280, 3281, 3290–3293, 3295–3299, 3420–3429–3433, 3440–3442, 3446, 3448–3452, 3490–3499, 3996
12	Steel works	3300, 3310–3317, 3320–3325, 3330–3341, 3350–3357, 3360–3379, 3390–3399
13	Fabricated products and machinery	3400, 3443, 3444, 3460–3479, 3510–3536, 3538, 3540–3569, 3580–3582, 3585, 3586, 3589, 3599
14	Electrical equipment	3600, 3610–3613, 3620, 3621, 3623–3629, 3640–3646, 3648, 3649, 3660, 3690, 3691, 3699
15	Automobiles and trucks	2296, 2396, 3010, 3011, 3537, 3647, 3694, 3700, 3710, 3711, 3713–3716, 3790, 3792, 3799
16	Aircraft, ships and railroad equipment	3720, 3721, 3723, 3725, 3728–3731, 3740–3743
17	Precious metals, non-metallic and industrial metal mining	1000–1119, 1400–1499
18	Coal	1200–1299
19	Petroleum and natural gas	1300, 1310–1339, 1370–1382, 1389, 2900–2912, 2990–2999
20	Utilities	4900, 4910, 4911, 4920–4925, 4930–4932, 4939, 4940–4942
21	Communication	4800, 4810–4813, 4820–4822, 4830–4841, 4880–4892, 4899
22	Personal and business services	7020, 7021, 7200, 7210–7212, 7214–7221, 7230, 7231, 7240, 7241, 7250, 7251, 7260–7300, 7310–7342, 7349–7353, 7359–7372, 7374–7385, 7389–7397, 7399, 7500, 7510–7549, 7600, 7620, 7622, 7623, 7629–7631, 7640, 7641, 7690–7699, 8100–8499, 8600–8700, 8710–8713, 8720, 8721, 8730–8734, 8740–8748, 8800–8911, 8920–8999

Table A3.4: Fama–French 30 industry classification (continued).

	Industry	SIC codes
23	Business equipment	3570–3579, 3622, 3661, 3662–3666, 3669–3689, 3695, 3810–3812, 3820–3839, 7373
24	Business supplies and shipping containers	2400–2449, 2520–2549, 2600–2659, 2670–2699, 2760, 2761, 3220, 3221, 3410–3412, 3950–3955
25	Transportation	3400–4013, 4040–4049, 4100, 4110–4121, 4130, 4131, 4140–4142, 4150, 4151, 4170–4173, 4190–4200, 4210–4231, 4240–4249, 4400–4700, 4710–4712, 4720–4749, 4780, 4782–4785, 4789
26	Wholesale	5000, 5010–5015, 5020–5023, 5030–5060, 5063–5065, 5070–5078, 5080–5088, 5090–5094, 5099, 5100, 5110–5113, 5120–5122, 5130–5172, 5180–5182, 5190–5199
27	Retail	5200, 5210–5231, 5250, 5251, 5260, 5261, 5270, 5271, 5300, 5310, 5311, 5320, 5330, 5331, 5334, 5340–5349, 5390–5400, 5410–5412, 5420–5469, 5490–5500, 5510–5579, 5590–5700, 5710–5722, 5730–5736, 5750–5799, 5900, 5910–5912, 5920–5932, 5940–5990, 5992–5995, 5999
28	Restaurants, hotels and motels	5800–5829, 5890–5899, 7000, 7010–7019, 7040–7049, 7213
29	Banking, insurance, real estate and trading	6000, 6010–6036, 6040–6062, 6080–6082, 6090–6100, 6110–6179, 6190–6300, 6310–6331, 6350, 6351, 6360, 6361, 6370–6379, 6390–6411, 6500, 6510, 6512–6515, 6517–6532, 6540, 6541, 6550–6553, 6590–6599, 6610, 6511, 6700, 6710–6726, 6730–6733, 6740–6779, 6790–6795, 6798, 6799
30	Other	Other

Table A3.5: Fama–French 17 industry classification.

This table presents the SIC codes of the Fama–French 17 industry classification.

	Industry	SIC codes
1	Food	0100–0299, 0700–0799, 0900–0999, 2000–2048, 2050–2068, 2070–2080, 2082–2087, 2090–2092, 2095–2099, 5140–5159, 5180–5182, 5191
2	Mining and minerals	1000–1049, 1060–1069, 2080–1099, 1200–1299, 1400–1499, 5050–5052
3	Oil and petroleum products	1300, 1310–1329, 1380–1382, 1389, 2900–2912, 5170–5172
4	Textiles, apparel and footwear	2200–2284, 2290–2399, 3020, 3021, 3100–3111, 3130, 3131, 3140–3151, 3963–3965, 5130–5139
5	Consumer durables	2510–2519, 2590–2599, 3060–3099, 3630–3639, 3650–3652, 3860, 3861, 3870–3873, 3910, 3911, 3930, 3931, 3940–3949, 3960–3962, 5020–5023, 5064, 5094, 5099
6	Chemicals	2800–2829, 2860–2879, 2890–2899, 5160–5169
7	Drugs, soap, perfumes and tobacco	2100–2199, 2830, 2831, 2833, 2834, 2840–2844, 5120–5122, 5194
8	Construction and construction materials	0800–0899, 1500–1511, 1520–1549, 1600-1799, 2400–2459, 2490–2499, 2850–2859, 2950–2952, 3200, 3210, 3211, 3240, 3241, 3250–3259, 3261, 3264, 3270–3275, 3280, 3281, 3290–3293, 3420–3433, 3440–3442, 3446, 3448–3452, 5030–5039, 5070–5078, 5198, 5210, 5211, 5250, 5251
9	Steel works	3300, 3310–3317, 3320–3325, 3330–3341, 3350–3357, 3360–3369, 3390–3399
10	Fabricated products	3410–3412, 3443, 3444, 3460–3499
11	Machinery and business equipment	3510–3536, 3540–3582, 3585, 3586, 3589–3600, 3610–3613, 3620–3629, 3670–3695, 3699, 3810–3812, 3820–3839, 3950–3955, 5060, 5063, 5065, 5080, 5081
12	Automobiles	3710, 3711, 3714, 3716, 3750, 3751, 5010–5015, 5510–5521, 5530, 5531, 5560, 5561, 5570, 5571, 5590–5599
13	Transportation	3713, 3715, 3720, 3721, 3724, 3725, 3728, 3730–3732, 3740–3743, 3760–3769, 3790, 3795, 3799–4013, 4100, 4110–4121, 4130, 4131, 4140–4142, 4150, 4151, 4170–4173, 4190–4200, 4210–4231, 4400–4499, 4500–4700, 4710–4712, 4720–4742, 4780, 4783, 4785, 4789
14	Utilities	4900, 4910, 4911, 4920–4925, 4930–4932, 4939–4942
15	Retail stores	5260, 5261, 5270, 5271, 5300, 5330, 5334, 5390–5400, 5410–5412, 5420, 5421, 5430, 5431, 5440, 5441, 5450, 5451, 5460, 5461, 5490–5499, 5540, 5541, 5550, 5551, 5600–5700, 5710–5722, 5730–5736, 5750, 5800–5813, 5890, 5900, 5910–5912, 5920, 5921, 5930–5932, 5940–5949, 5960–5963, 5980–5990, 5992–5995, 5999
16	Banks, insurance companies and other financials	6010–6023, 6025, 6026, 6028–6036, 6040–6062, 6080–6082, 6090–6100, 6110–6129, 6140–6163, 6172, 6199–6300, 6310–6312, 6320–6324, 6330, 6331, 6350, 6351, 6360, 6361, 6370, 6371, 6390–6411, 6500, 6510, 6512–6515, 6517–6519, 6530–6532, 6540, 6541, 6550–6553, 6611, 6700, 6710–6726, 6730–6733, 6790, 6792, 6794, 6795, 6798, 6799
17	Other	Other

Table A3.6: Fama–French 12 industry classification.

This table presents the SIC codes of the Fama–French 12 industry classification.

	Industry	SIC codes
1	Consumer, non-durables	0100-0999, 2000–2399, 2700–2749, 2770–2799, 3100–3199, 3940–3989
2	Consumer, durables	2500–2519, 2590–2599, 3630–3659, 3710, 3711, 3714, 3716, 3750, 3751, 3750, 3751, 3792, 3900–3939, 3990–3999
3	Manufacturing	2520–2589, 2600–2699, 2750–2769, 3000–3099, 3200–3569, 3580–3629, 3700–3709, 3712, 3713, 3715, 3717–3749, 3752–3791, 3793–3799, 3830–3839, 3860–3899
4	Oil, gas and coal extraction and products	1200–1399, 2900–2999
5	Chemicals and allied products	2800-2829, 2840–2899
6	Business equipment	3570–3579, 3660–3692, 3694–3699, 3810–3829, 7370–7379
7	Telephone and television transmission	4800–4899
8	Utilities	4900–4949
9	Wholesale, retail and some services	5000–5999, 7200–7299, 7600–7699
10	Healthcare, medical equipment and drugs	2830–2839, 3693, 3840–3859, 8000–8099
11	Finance	6000–6999
12	Other	Other

Table A3.7: Fama–French 10 industry classification.

This table presents the SIC codes of the Fama–French 10 industry classification.

	Industry	SIC codes
1	Consumer, non-durables	0100–0999, 2000–2399, 2700–2749, 2770–2799, 3100–3199, 3940–3989
2	Consumer, durables	2500–2519, 2590–2599, 3630–3659, 3710–3711, 3714, 3716, 3750, 3751, 3792, 3900–3939, 3990–3999
3	Manufacturing	2520–2589, 2600–2699, 2750–2769, 2800–2829, 2840–2899, 3000–3099, 3200–3569, 3580–3629, 3700–3709, 3712, 3713, 3715, 3717–3749, 3752–3791, 3793–3799, 3830–3839, 3860–3899
4	Oil, gas and coal extraction and products	1200–1399, 2900–2999
5	Business equipment	3570–3579, 3622, 3660–3692, 3694–3699, 3810–3839, 7370–7379, 8730–8734
6	Telephone and television transmission	4800–4899
7	Wholesale, retail and some services	5000–5999, 7200–7299, 7600–7699
8	Healthcare, medical equipment and drugs	2830–2839, 3693, 3840–3859, 8000–8099
9	Utilities	4900–4949
10	Other	Others

Table A3.8: Fama–French 5 industry classification.

This table presents the SIC codes of the Fama–French 5 industry classification.

	Industry	SIC codes
1	Consumer	0100-0999, 2000–2399, 2500–2519, 2590–2599, 2700–2749, 2770–2799, 3100–3199, 3630–3659, 3710, 3711, 3714, 3716, 3750, 3751, 3792, 3900–3999, 5000–5299, 7200–7299, 7600–7699
2	Manufacturing	1200–1399, 2520–2589, 2600–2699, 2750–2769, 2800–2829, 2840–3099, 3200–3569, 3580–3629, 3700–3709, 3712, 3713, 3715, 3717–3749, 3752–3791, 3793–3799, 3830–3839, 3860–3899, 4900–4949
3	High-tech	3570–3579, 3622, 3660–3692, 3694–3699, 3810–3839, 4800–4899, 7370–7379, 7391, 8730–8734
4	Healthcare	2830–2839, 3693, 3840–3859, 8000–8099
5	Other	Other

Table A3.9: Moskowitz and Grinblatt industry classification.

This table presents the SIC codes of the industry classification in Moskowitz and Grinblatt (1999).

	Industry	SIC codes (first two digits)
1	Mining	10–14
2	Food	20
3	Apparel	22, 23
4	Paper	26
5	Chemical	28
6	Petroleum	29
7	Construction	32
8	Primary metals	33
9	Fabricated metals	34
10	Machinery	35
11	Electrical equipment	36
12	Transport equipment	37
13	Manufacturing	38, 39
14	Railroads	40
15	Other transportation	41–47
16	Utilities	49
17	Department stores	53
18	Retail	50–52, 54–59
19	Financial	60–69
20	Other	Other

Table A3.10: The official SIC industry classification.

This table presents the SIC codes of the official SIC industry classification.

	Industry	SIC codes (first two digits)
1	Agriculture, forestry and fishing	01, 02, 07–09
2	Mining	10, 12–14
3	Construction	15–17
4	Manufacturing	20–39
5	Transportation, communications, electric, gas and sanitary services	40–49
6	Wholesale trade	50, 51
7	Retail trade	52–59
8	Finance, insurance and real estate	60–65, 67
9	Services	70, 72, 73, 75, 76, 78–84, 86–89
10	Public administration	91–97, 99
11	Other	Other