The Cash Conversion Cycle Spread*

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Abstract

The cash conversion cycle (CCC) refers to the time span between the outlay of cash for purchases to the receipt of cash from sales. It is a widely used metric to gauge the effectiveness of a firm's management and intrinsic need for external financing. This paper shows that a zero-investment portfolio that buys stocks in the lowest CCC decile and shorts stocks in the highest CCC decile earns 5 to 7% alphas per year. The CCC effect is prevalent across industries and remains even for large capitalization stocks. The CCC effect is distinct from the known return predictors. The returns of high-CCC stocks are more sensitive to the health of the financial intermediaries than low-CCC stocks. This suggests that the CCC-based strategy cannot be explained by the financial intermediary leverage risk.

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1. Introduction

The cash conversion cycle (CCC) of a firm is equal to the time it takes to sell inventory and collect receivables less the time it takes to pay the firm's payables. It represents the number of days a firm's cash is tied up within the operation of the business. The CCC captures a fundamental feature of a firm's operation: it explicitly recognizes that the four basic business activities—purchasing/production, sales, collection, and payment—create flows within the working capital accounts that are non-instantaneous. It is a widely used metric to gauge the effectiveness of a firm's management and intrinsic need for external financing (Ross, Westerfield, and Jaffee, 2002, p. 755; Raddatz, 2006; Braun and Raddatz, 2008; Tong and Wei, 2011). This paper investigates the asset pricing implications of CCC.

The CCC is interesting for several reasons. First, technological reasons, such as the length of the time in the production process and the mode of operation, are important determinants of CCC.[1] An average US publicly listed firm finances its total assets with 27% of working capital. The ratio of working capital to total assets varies significantly across firms: from 22% for the firms in the lowest CCC decile to 42% for the firms in the highest CCC decile. Hence, understanding how the CCC relates to firms' costs of capital is important. Second, firms with a higher CCC have a higher need to finance their working capital and rely more on short-term debt. If funding liquidity deterioration makes it difficult for them to raise funds or causes them to suffer losses in rolling over their maturing debt they can have higher exposure to aggregate funding risk (Tong and Wei, 2011; He and Xiong, 2012). Firms with a higher CCC finance their working capital with more short-term debt; firms with higher short-term debt perform worse during financial crisis periods (Duchin, Ozbas, and Sensoy, 2010; Almeida, Campello, Laranjeira, and Weisbenner, 2012).

[1] See Raddatz (2006) and Tong and Wei (2011) for more discussions.

Investigating the CCC's asset pricing implications can shed light on whether and how funding risk is priced in the cross-section (Adrian, Etula, and Muir, 2014; He, Kelly, and Manela, 2017).[2]

Using the panel of US stock returns over the 1976 to 2015 period, we find a strong negative correlation between a firm's CCC and its subsequent returns. Sorting stocks into CCC deciles, we find that the excess returns of both equal-weighted (EW) and value-weighted (VW) portfolios decrease almost monotonically when the CCC increases. A zero-investment portfolio that buys stocks in the lowest CCC decile and shorts stocks in the highest CCC decile earns a monthly excess return of 0.500% for an EW portfolio and 0.402% for a VW portfolio. The long-short portfolio has negative loadings on most of the widely used factors, notably the value factor of Fama and French (1993) and the profitability factor of Fama and French (2015). Adjusting the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the recent Fama and French (2015) five-factor model, the Hou, Xue, and Zhang (2015) *q*-factor model, and the Stambaugh and Yuan (2017) mispricing-factor model does not change the return spread of the low-CCC minus high-CCC portfolio much. If anything, the adjustments increase the spread. For example, the Fama and French five-factor alphas are 0.625% and 0.586% for the EW and VW portfolios, respectively, both higher than the unadjusted returns.

The CCC's predictive power for returns is prevalent. First, the results hold when we control for a large number of known return predictors. Second, the results also hold in both subperiods: one that starts in July 1976 and ends in December 1995, and another that starts in January 1996

[2] Another widely used external finance dependence measure is the measure proposed by Rajan and Zingales (1998). Rajan and Zingales (1998) compute their measure as capital expenditure minus cash flow from operations divided by capital expenditure. We find that this measure is inversely correlated with future stock returns, but its predictive power disappears after controlling for firm profitability. This is consistent with the criticism put forth by Fisman and Love (2007) who find that the Rajan and Zingales (1998) measure may capture growth opportunity and challenge this measure's validity in measuring external finance dependence. Tong and Wei (2011) present evidence that CCC performs better in explaining the cross-sectional firm performance during the 2007-2009 financial crisis: High-CCC firms performed worse than low-CCC firms, but Rajan and Zingales's measure is not significantly related to firm performance in the crisis period.

and ends in December 2015. Third, the results hold in all of the industries based on the Fama-French five-industry classification. Fourth, the results hold in all size quintiles where the size breakpoints are based on stocks listed in the New York Stock Exchange (NYSE). Fifth, the CCC effect persists for at least three years after portfolio formation.

After establishing the robustness of the CCC's predictive power for returns, we test whether the CCC effect is most consistent with a risk or mispricing explanation. We show that standard risk-return models (including conditional CAPM) do not explain the effect. The most directly related risk is perhaps the intermediary leverage risk. The intermediary asset pricing theories argue that financial intermediaries are marginal investors and their marginal value of wealth is a plausible pricing kernel.[3] High-CCC firms are more dependent on external financing (Raddatz, 2006; Tong and Wei, 2011).[4] We find that, relative to low-CCC stocks, high-CCC stocks' returns are more sensitive to the financial intermediary sector risk factor proposed by He, Kelly, and Manela (2017).[5] However, our finding that low-CCC stocks earn higher returns than high-CCC stocks is opposite to the prediction from these models.[6] The low-CCC minus high-CCC portfolio therefore cannot be explained by the financial intermediary leverage risk.

[3] See Brunnermeier and Pedersen (2009), He and Krishnamurthy (2012, 2013), Adrian and Shin (2014), and Brunnermeier and Sannikov (2014).

[4] Raddatz (2006) reports that financial development reduces the volatility of output in sectors with high CCC. Using a sample of manufacturing firms, Tong and Wei (2011) show that stock performance during the 2007-2009 crisis was inversely related to CCC. This is consistent with our finding.

[5] We find no evidence that stock return sensitivity to the Adrian, Etula, and Muir (2014) factor is correlated with CCC. The existing models differ in their prediction on whether leverage is pro-cyclical or counter-cyclical. Brunnermeier and Sannikov (2014) and He and Krishnamurthy (2012, 2013) predict that leverage is counter-cyclical, but Brunnermeier and Pedersen (2009) and Adrian and Shin (2014) predict that leverage is pro-cyclical. Adrian, Etula, and Muir (2014), and He, Kelly, and Manela (2017) propose two different factors based the above different models. However, empirically, the two factors are positively correlated. He, Kelly, and Manela (2017) provide evidence that their factor performs better in pricing many asset classes.

[6] Relative to other asset classes such as derivative contracts or foreign exchange, equity has greater direct participation by households. He, Kelly, and Manela (2017) acknowledge that equity is the asset class where they least expect good performance by the pricing kernel of their intermediary balance sheet factor.

We find consistent evidence for the mispricing explanation. First, CCC predicts future earnings even after controlling for past earnings. Investors do not seem to fully incorporate the CCC's earnings implication in their expectation: Earnings announcements for low-CCC firms are associated with significantly higher abnormal returns than high-CCC firms. Second, consistent with limits to arbitrage (Shleifer and Vishny, 1997), we find that the CCC effect is stronger among stocks that are harder to value and harder to arbitrage.

Although a textbook measure, surprisingly the CCC has been relatively understudied. The literature on the CCC has focused primarily on the effects of the CCC on firm profitability. For example, Shin and Soenen (1998) and Deloof (2003) provide evidence that a firm's profitability is inversely related to its CCC. Kieschnick, Laplante, and Moussawi (2013) find that the marginal dollar invested in net operating capital is worth less than the incremental dollar held in cash. Raddatz (2006) and Tong and Wei (2011) use the CCC as a measure for the dependence on external financing for working capital. Dechow, Kothari, and Watts (1998) investigate how CCC moderates the ability of accruals to predict future earnings. Some studies (e.g., Shin and Soenen, 1998) have examined the *contemporaneous* relationship between the CCC and stock returns. While, we investigate whether the CCC predicts future stock returns after controlling for profitability.

Related but different from our paper, a small number of studies have investigated how firms' inventory behavior affects asset pricing. Belo and Lin (2012), Jones and Tuzel (2013), and Chen (2016) model inventory as a factor of production and argue that inventory growth is inversely associated with expected returns. On the empirical side, Thomas and Zhang (2002) and Belo and Lin (2012) confirm that inventory increases negatively predicts returns. Chen, Frank, and Wu (2005) and Alan, Gao, and Gaur (2014) investigate how days inventory outstanding (DIO) predicts future stock returns. DIO is one component of the CCC. Chen, Frank and Wu (2005) examine manufacturing firms and find a non-monotonic relationship between DIO and future stock returns. These authors focus on the valuation effect of DIO rather than its return prediction, and they match DIO of year t to returns from January of year t+1 to December of year t+1. Therefore, their strategy is not implementable because the information needed to calculate DIO is not available at the beginning of year t+1. Alan, Gao, and Gaur (2014) examine 399 retailers and in total obtain 36,164 firm-month observations. Our sample is significantly more comprehensive: it covers more than 13,000 unique firms and more than 1.3 million firm-month observations. Our study also differs from the above studies by examining the CCC of which DIO is just one component. We also find that days receivables outstanding—another component of CCC—predicts future stock returns.

2. Data

We compute CCC as:

$$CCC = 365 * \left(\frac{Avg.\,Inventories}{COGS} + \frac{Avg.\,Accounts\ Receivables}{Sales} - \frac{Avg.\,Accounts\ Payables}{COGS}\right). \quad (1)$$

We calculate the CCC with data from the Compustat quarterly file. Average inventory, average accounts receivables, and average accounts payables are calculated as the average of the beginning quarter and end of quarter levels. COGS (i.e., costs of goods sold) and Sales (i.e., total revenue) are aggregated over the same quarter. The CCC has three components: days inventory outstanding (DIO), days receivables outstanding (DRO), and days payables outstanding (DPO). The CCC is measured in days. It can be negative if DPO is longer than the sum of DIO and DRO.[7]

We obtain monthly stock returns from the Center for Research in Security Prices (CRSP) and quarterly and annual accounting data from Compustat. Our sample starts with all firms traded on

[7] One reason is that firms generate revenue from customers before they have to pay their suppliers. Many well-known firms have negative CCC and consistently so for many years. In the last quarter of our sample, negative CCC firms include Apple, Exxon Mobil, Coca Cola, Verizon, Visa, McDonalds, Delta Air Lines, Hilton, Hertz, and New York Times among many others.

NYSE, Amex, and NASDAQ. We exclude securities other than common shares, and firms in the financial industry (SIC codes between 6000 and 6999). We adjust the stock returns by delisting. If a delisting return is missing and the delisting is performance related, we set the delisting return to -30% (Shumway, 1997). We skip a quarter to match the quarterly accounting data to the CRSP monthly returns. For example, accounting data ended at January, February, or March are matched to returns from July to September.[8] We follow Fama and French (1992) and match the annual accounting data to monthly stock returns. Specifically, the annual accounting variables in year t are matched to monthly returns from July of year t+1 to June of year t+2. The sample consists of firms that have non-missing current month returns, market value of equity at the end of the last month, non-missing book-to-market, and non-missing CCC.

Our analysis of stock returns begins in July 1976 using the March 1976 quarterly accounting data, and ends on December 2015 using the June 2015 quarterly accounting data. There are 474 months in our sample. To avoid extreme values caused by small sales, we exclude quarters where a firm's quarterly sales/lagged total assets is lower than 2.5%, and winsorize the CCC at the 1% level for both tails to mitigate the effect of outliers.

Fig. 1 presents the average CCC over time. The decreasing pattern in the CCC is evident in the figure and is almost purely driven by a similar trend in the average DIO. The decreasing trend in DIO from the early 1980s to the early 2000s is consistent with Blanchard and Simon (2000), Kahn, McConnell, and Perez-Quiro (2001), and Chen, Frank and Wu (2005). This is consistent with the operation management literature that attributes this decreasing trend to the adoption of modern

[8] In choosing the lag between quarterly accounting data and returns, existing studies have used two months (Campbell, Hilscher, and Szilagyi, 2008) to four months (Avramov, Chordia, Jostova, and Philipov, 2013). Novy-Marx (2013) and Hou, Xue, and Zhang (2015) assume that quarterly accounting data are available after the quarterly earnings announcement. In our sample, 98.8% firms have reported their quarter t's earnings by the end of quarter t+1. Our results are very similar if we skip one more month. For example, in our main Fama-MacBeth regression analyses (Table 5), if we skip one more month, the Fama-MacBeth coefficient of the CCC is -0.159 (t=-6.07) in column (1) of Table 5, and -0.187 (t=-7.72) in column (5) of Table 5.

inventory management tools and methods, such as just-in-time and electronic data interchange, that were put into use mostly in the early 1980s after advances in information technology (Rajagopalan and Malhotra, 2001). However, we find that the decreasing trend in the CCC stops after the early 2000s. DRO and DPO comove with each other. This is not surprising: accounts receivables of one firm must be accounts payables somewhere else. Before 2000, DRO is slightly longer than DPO. This spread indicates that an average public firm offers trade credit to other firms.[9] The difference shows a decreasing trend and completely disappears after the early 2000s. Investigating the underlying reasons for these patterns is beyond the scope of this paper. We speculate that these patterns might be driven by the improving efficiency in the payment system, or by the change in the composition of public firms.

Table 1 reports the summary statistics for the CCC for each of the Fama and French 48 industries, sorted from the industry with the shortest CCC to the industry with the longest CCC. We first calculate, quarter by quarter, the median CCC, the first quartile of the CCC (Q1), the third quartile of the CCC (Q3), the median DIO, the median DRO, and the median DPO and then calculate the time-series means for each of these statistics.

The CCC varies significantly both across industries and within industries. In the Restaurants, Hotels, Motels industry, the CCC is only eight days, while in the Measuring and Control Equipment industry, it is near to two years (633 days). The three components also vary significantly across industries. The difference between Q3 and Q1 is the smallest in the Transportation industry (16 days) and the largest in the Computer industry (378 days). Many scholars have argued that the differences across industries in the length of the CCC are mainly

[9] Petersen and Rajan (1997) show evidence that firms with better access to credit offer more trade credit. Our finding that an average public firm offers more credit than they take in is indirectly consistent with Petersen and Rajan (1997), if public firms, on average, are less financially constrained.

technological (Ramey, 1989). In the remaining analysis, we adjust a firm's CCC by its industry median CCC. However, in most of the text, we still refer to the industry median adjusted CCC as the CCC.[10]

Table 2 presents the summary statistics for the main variables in the analysis.[11] We winsorize the CCC and other accounting variables (all variables in Table 2 except *Beta*, *Size*, *BM*, $R_{t\text{-}1}$, $R_{t\text{-}12,t\text{-}2}$, $R_{t\text{-}60,t\text{-}13}$, *ILLIQ*, and *IVOL*) month by month at the 1% level for both tails to mitigate the effect of outliers. The Mean column and the STD column report the mean and standard deviations of each variable. The Corr column reports the pairwise correlation between each variable and the industry-adjusted CCC. The next ten columns report the average of each variable within each CCC decile. We sort stocks into deciles at the beginning of each month. We first calculate the statistics from the cross-section of each month, and then calculate the time-series means of these cross-sectional statistics.

Beta is a stock's beta computed using monthly returns over the previous five years, as in Fama and French (1992). *Size* is the log of the market value of the firm's outstanding equity at the end of month t-1. *BM* is the log of the firm's book value of equity divided by its market value of equity, where the book-to-market ratio is computed following Fama and French (2008); we fill in the missing book equity values with data from Davis, Fama and French (2002);[12] firms with negative book values are excluded from the analysis. $R_{t\text{-}1}$ is the stock's return in month t-1, which is a control for the short-term reversal effect. $R_{t\text{-}12,t\text{-}2}$ is the stock's cumulative return from the start of month t-

[10] We adjust the CCC by industry median because median is less influenced by outliers. Our results are robust if we adjust the CCC by industry mean. Results are available upon request.

[11] See the Appendix for the detailed definitions of the major variables. We construct all the accounting variables using the quarterly data except *AssetGrowth*, *SalesGrowth*, *XFIN* (*external finance*), *Dividend*, and *OrgCap*. We use annual data for *AssetGrowth*, *XFIN*, *SalesGrowth*, and *Dividend* because they are lumpy or seasonal. Hou, Xue, and Zhang (2015) also construct their investment factor using annual data. The annual Compustat data provides longer history of data to construct *OrgCap*. Our results are very similar if we construct all these variables using quarterly data.

[12] Data are available from Kenneth French's website.

12 to the end of month *t*-2, which is a control for the momentum effect (Jegadeesh and Titman, 1993). $R_{t\text{-}60,t\text{-}13}$ is the stock's cumulative return from the start of month *t*-60 to the end of month *t*-13, which is a control for the long-term reversal effect (DeBont and Thaler, 1985). *ILLIQ* is the Amihud's (2002) illiquidity measure, computed using daily data in month *t*-1. *IVOL* is the standard deviation of the stock's daily idiosyncratic returns (relative to the Fama and French (1993) three-factor model) over month *t*-1, as in Ang, Hodrick, Xing, and Zhang (2006).

AssetGrowth is the percentage of total asset growth between two consecutive fiscal years, as in Cooper, Gulen, and Schill (2008). *CBOP* is the cash-based operating profitability measure proposed by Ball, Gerakos, Linnainmaa, and Nikolaev (2016). We use CBOP as our measure of profitability because Ball, Gerakos, Linnainmaa, and Nikolaev (2016) show that CBOP outperforms other profitability measures in explaining the cross-section of stock returns. *Accruals* is calculated following Sloan (1996).

Besides these widely used asset pricing variables, we also consider a few other firm characteristics that might be correlated with the CCC. *WorkingCapital* is working capital divided by total assets, where working capital is the difference between total current assets minus total current liabilities. *LTDebt* and *STDebt* are long-term debt and short-term debt, both divided by total assets. *OpLev* is the operating leverage variable that is computed as cost of goods sold and selling, general, and administrative (SG&A) expenses scaled by total assets (Novy-Marx, 2011). *CashHolding* is cash and short-term investment divided by total assets. *OrgCap* is the capitalized SG&A expenses measure proposed by Eisfeldt and Papanikolaou (2013). *Z-Score* is a bankruptcy risk measure that is calculated following Altman (1968).[13] *XFIN* is the external finance measure by Bradshaw, Richardson, and Sloan (2006). *NOA* is the net operating assets measure of

[13] Results are similar if we use Ohlson's (1980) O-Score model, or the distress probability measure developed by Campebll, Hilscher, and Szilagyi (2008).

Hirshleifer, Hou, Teoh, and Zhang (2004), which is calculated as the cumulative difference between operating income and free cash flow. *PPE* is an asset tangibility measure calculated as net property, plant, and equipment divided by total assets. We also consider the components of profitability and accruals. We decompose profitability in two ways. First, we decompose *ROE* based on the DuPont analysis (Soliman, 2008). *ROE* is earnings before interests and taxes divided by total equity. *AssetTurnover* is sales divided by total assets. *ProfitMargin* is earnings before interests and taxes divided by total sales. *TotalLev* is total liabilities divided by total assets. Second, following Ball, Gerakos, Linnainmaa, and Nikolaev (2015), we break profitability into seven components: gross profitability which is equal to revenue minus cost of goods sold (Novy-Marx, 2013), reported SG&A (the Compustat XGSA item minus R&D expenses), R&D, depreciation, interest expenses, tax expenses, and other expenses, all divided by the lagged total assets. We break accruals into four components: change in inventory, change in receivables, change in accounts payables, and other accruals, again all divided by the lagged total assets.

The CCC is negatively correlated with past stock returns ($R_{t\text{-}1}$, $R_{t\text{-}12,t\text{-}2}$, $R_{t\text{-}60,t\text{-}13}$), CBOP and ROE. The CCC is positively correlated with Accruals and BM. All of these correlations are consistent with the previous studies that find that firms with shorter CCC perform better (Shin and Soenen, 1998, and Deloof, 2003). Although the correlations are highly statistically significant, the magnitudes are modest. For example, from decile 1 to decile 10, CBOP decreases by 0.8%, which is less than 12% of one standard deviation of CBOP. From the DuPont decomposition, we find that high-CCC firms have lower asset turnover and lower profit margin, but they also have lower leverage. The CCC's correlation with ROE is modest. The CCC's negative correlation with profitability measures mainly comes from its positive correlation with cost of goods sold (see the correlation between CCC and gross profitability). But high-CCC firms have lower SG&A, low

R&D, and low depreciation. Thus, firms' net income is not very strongly correlated with the CCC. One possible reason is that cost of goods sold, SG&A, R&D, and fixed assets are technologically substitutable inputs. Different firms adopt different technology.

The highest correlation is between the CCC and working capital: firms with higher CCC have more working capital. From decile 1 to decile 10, working capital increases by 20.9% of total assets, which is around one standard deviation of working capital. Related, higher CCC firms are less tangible. From decile 1 to decile 10, PPE decreases by 12% of total assets. In terms of financing, high-CCC firms rely more on short-term debt as indicated by the positive correlation between CCC and STDebt. The CCC is also strongly and negatively correlated with operating leverage, cash holdings, depreciation expenses, and taxes. The absolute correlation coefficients between the CCC and other variables are all below 0.10.

To summarize, the CCC is most strongly correlated with firms' short-term operation and financing activities such as working capital, cash holdings, and short-term leverage. This is consistent with the view that firms with higher CCC rely more on external financing for working capital (Raddatz, 2006; Tong and Wei, 2011).

3. Main results

In this section, we conduct the asset pricing tests of the CCC. In Section 3.1, we test using decile portfolio sorts. In Section 3.2, we test using the Fama-MacBeth regression methodology.

3.1 Time-series tests

We conduct the decile-sort test as follows: At the start of each month, beginning in July 1976 and ending in December 2015, we sort stocks into deciles based on CCC. We then compute the average return of each CCC-decile portfolio over the next month, both equal-weighted and value-weighted. This gives us a time series of monthly returns for each CCC decile. We use these time-series returns to compute the average return of each decile over the entire sample period. In Table 3, we report the average return of each decile in excess of the risk-free rate; the Fama-French three-factor alpha (Fama and French, 1993), the Fama-French-Carhart four-factor alpha (following Carhart (1997), the return adjusted by the three factors of Fama and French (1993) and by a momentum factor), the Fama-French five-factor alpha (Fama and French, 2015, 2016), the *q*-theory factors (Hou, Xue, and Zhang, 2015, 2016), and the mispricing factors (Stambaugh and Yuan, 2017).[14] In the right-most column (Low-minus-High), we report the difference between the returns of the two extreme decile portfolios. Low-minus-High is a zero-investment portfolio that buys the stocks in the lowest CCC decile and shorts the stocks in the highest CCC decile.

The results in the Low-minus-High column show that stocks with low-CCC outperform stocks with high-CCC. In most cases, factor adjustments increase the magnitude of the alphas except that the Fama-French three-factor alpha and the Fama-French-Carhart four-factor alpha of the equal-weighted Low-minus-High are slightly smaller than the excess return of the Low-minus-High. The excess returns and alphas of the equal-weighted returns are slightly stronger than that of the value-weighted returns. Moreover, the economic magnitudes of the excess returns and the alphas of the Low-minus-High portfolios are sizable and are in the range of 0.40% to 0.64% per month. This implies that on average, the stocks in the lowest CCC deciles outperform the stocks in the highest CCC deciles by 5 to 7% per year.

Table 4 reports the factor loadings for the Low-minus-High portfolios in the four asset pricing models, and for both the equal- and value-weighted returns. The most important observation is that the Low-minus-High portfolios have negative loadings on most of the factors. The loading on

[14] Data for the Fama and French three factors and Fama and French five factors are downloaded from Kenneth French's website. The Stambaugh and Yuan's factors are downloaded from Yu Yuan's website. Hou, Xue, and Zhang's factors are directly from Lu Zhang. We appreciate that the authors made the data available to us.

HML is negative, consistent with the positive correlation between CCC and BM that is in Table 1. The loadings on the profitability factor in the Fama-French five-factor model (the RMW factor), and the profitability factor in the Hou, Xue, and Zhang model (the ROE factor) are negative. In Table 1, we show that the CCC is negatively correlated with firms' profitability. The negative loadings on the profitability factors suggest that, although on average the firms in the low-CCC portfolio are more profitable, their returns are more closely correlated with the less profitable firms. In the Stambaugh and Yuan mispricing-factor model, the Low-minus-High portfolio loads negatively on the MGMT factor (a factor that arises from six anomaly variables which all represent quantities that firm managements can affect rather directly). The loadings on other factors do not reveal a consistently strong pattern.

Fig. 2 presents a graphical view of the results in Table 3. It plots the equal-weighted (top panel) and value-weighted (bottom panel) Fama-French five-factor alphas on the ten CCC-decile portfolios. The figure makes clear another aspect of the results in Table 3, namely, that the alphas on the ten portfolios decline in a near monotonic fashion as we move from the lowest CCC-decile portfolio to the highest CCC-decile portfolio.

3.2 Fama-MacBeth tests

One advantage of the Fama-MacBeth regression test is that it allows us to examine the predictive power of the CCC while controlling for known return predictors. We implement the Fama-MacBeth regressions in the usual way. Each month, starting from July 1976 and ending in December 2015, we run a cross-sectional regression of stock returns (in percentage) in that month on the CCC. In the Fama-MacBeth regressions, the CCC is measured in number of years. Table 5 reports the time-series averages of the coefficients on the independent variables. Different columns in the table correspond to different regression specifications which differ in the control variables they include. Panel A presents results for all stocks, and Panel B presents results for all-but-microcaps. Microcaps are stocks with market capitalization below the 20^{th} percentile of the NYSE market capitalization distribution (Fama and French, 2008). These stocks account for only 3% of the total market capitalization, but include around 60% of all stocks (Fama and French, 2008). The results for all-but-microcaps can check whether the results are affected by these small firms.

The results in the table confirm the findings based on the time-series portfolio analysis. In Column (1) of Panel A, we include the CCC as the single return predictor. The coefficient on the CCC is -0.181. The average CCC (in years) is -1.203 and 1.921 for the lowest and the highest CCC portfolios, respectively. This implies a return spread of 0.565%, which is equal to -0.181*(-1.203-1.921). The magnitude of the return spread is similar to the alphas in the time-series portfolio analysis. The coefficient on the CCC is highly statistically significant, as indicated by the *t*-value which is close to seven. The results are slightly weaker but remain strong if we remove the microcaps.

The CCC variable retains significant predictive power even after we include the major known predictors of returns. In Column (2), we include beta, market capitalization (Size), and book-to-market (BM). In Column (3), we add the past month return (R_{t-1}), the cumulative return from month *t*-12 to month *t*-2 ($R_{t-12,t-2}$), the cumulative return from month *t*-60 to *t*-13 ($R_{t-60,t-13}$), an illiquidity measure (ILLIQ), and an idiosyncratic volatility measure (IVOL). In Column (4), we add AssetGrowth and the cash-based operating profitability (CBOP) measure. In Column (5), we further add Accruals. The coefficients on these control variables are similar to those in the literature. Accruals alone is significantly and negatively related to future stock returns but loses its statistical significance in Column (5). This is consistent with Ball, Gerakos, Linnainmaa, and Nikolaev (2016) which also show that the CBOP measure subsumes the predictive power of accruals for returns.

The table shows that the results are somewhat stronger after we control for these major known return predictors.[15]

3.3 Firm size and the effect of CCC

Table 6 reports the results by size quintiles. For each month, we group all stocks into size quintiles based on the NYSE breakpoints. Within each size quintile, we further sort stocks into CCC quintiles. The table reports the Fama-French five-factor alpha for the 25 portfolios: equal-weighted returns in Panel A and value-weighted returns in Panel B. We also report the alpha for each size quintile of the low-CCC minus high-CCC portfolios. The results show that the CCC effect exists in all five size quintiles. The effect is weaker among large firms (quintile 4 and quintile 5) than among small firms (quintile 1 and quintile 2), although the effect is not monotonic with respect to size. The difference in low-minus-high between size quintile 1 and size quintile 5 is not statistically significant, but the difference in low-minus-high between the smallest two size quintiles and the largest two size quintiles is 0.287% (t=3.14) for equal-weighted portfolios and 0.320 (t=3.18) for value-weighted portfolios.

3.4 Robustness

We examine the robustness of the results. The six panels in Table 7 correspond to six different robustness checks. The four right-most columns report the Fama-French five-factor alphas for the low-CCC minus high-CCC portfolios based on either equal- or value-weighted returns, and the

[15] The alphas in Table 3 and the coefficients on the CCC from the Fama-MacBeth regression are all statistically significant, even by the standards suggested by Harvey, Liu, and Zhu (2016) and Harvey (2017). Harvey (2017) proposes an alternative statistical significance analysis approach known as the minimum Bayes factor which delivers a Bayesian p-value. The minimum t-value in the Fama-MacBeth regression analysis and the Fama-French five-factor alpha analysis is 4.18. This is considered as significant at the 5% level even when the prior belief on the probability that the null (the CCC is unrelated to future stock return) is true is only 5%. See the t-statistic thresholds for minimum Bayes factors in Table III of Harvey (2017).

coefficient on the CCC from Fama-MacBeth regressions using the same specification as in Column (5) of Table 5, one for all stocks and one for all-but-microcaps.[16]

First, we check whether our results hold not only in the full sample, but also in each of two subperiods: one that starts in July 1976 and ends in December 1995, and another that starts in January 1996 and ends in December 2015. These two subperiods are approximately equal in length: 234 months in the first subperiod and 240 months in the second subperiod. The first panel of Table 7 confirms that our main results hold in both subperiods: the long-short portfolios have significantly positive alphas in both subperiods. The coefficients on the CCC from the Fama-MacBeth regressions are also significant in both subperiods.

In the second robustness check, we test whether our results hold after excluding low-priced stocks. The second panel of Table 7 shows that, when we exclude stocks whose prices fall below \$5 in the month before portfolio construction, the equal- and value-weighted Fama-French five-factor alphas remain significant. Both the magnitude of the alphas and the *t*-values are similar to that of the results based on all stocks. The coefficient on the CCC from the Fama-MacBeth regression is -0.184 (t=-7.72), and it is -0.155 (t=-5.47) if we exclude microcaps, both of which are also statistically significant.

In the third robustness check, we run the analysis separately for the firms with different inventory valuation methods. Because of accounting treatment differences, two otherwise identical firms can have different CCC values if they adopt different inventory valuation methods, although the difference is not economic but purely accounting. We conduct the analysis for three groups of firms: First-In First-Out (FIFO), Last-In First-Out (LIFO), and all others. The data on the firms'

[16] In all later tests, we choose to report the alphas based on the Fama and French (2015) five-factor model rather than the *q*-factor model by Hou, Xue, and Zhang (2015) or the mispricing-factor model by Stambaugh and Yuan (2017) because, as shown in Table 3, the Fama and French five-factor model explains the variation of the Low-minus-High portfolio better than other models. Our results are qualitatively similar if we use either of the other two models.

inventory valuation methods are from Compustat (item INVVAL). FIFO and LIFO are the two most widely used inventory valuation methods. The results show that the CCC effect exists even within firms with the same inventory valuation method.[17]

The fourth robustness check is a cross-sectional analysis of the stocks in each of the Fama and French five-industry categorizations. In each of the five industries, we find that low CCC predicts higher stock returns than high CCC. It is statistically significantly so in all the five industries based on the Fama-MacBeth regression methodology, and in most of the long-short portfolio alphas. These results show that the CCC's predictive power for returns is pervasive across industries.

Fifth, we check the robustness by varying the way we construct CCC. We first construct a rolling CCC based on data for the four most recent quarters. We calculate the average inventory, average accounts receivables, average payables, average costs of goods sold, and average sales over the four quarters, and then calculate the rolling CCC. This process removes any possible seasonality in the CCC. These results show that the CCC's return predictive power remains. The CCC's return predictive power also remains if we use the CCC from annual data or without industry adjustment.

Lastly, we investigate whether our results hold if we use quarterly data and industry-adjusted characteristics to construct factors. Previous studies find that industry adjustment and using more recent data can sometimes improve return prediction (Novy-Marx, 2013, 2015; Hou, Xue, and Zhang, 2015). The first row of this panel reports the results of replacing the HML, RMW and CMA factors by their industry-adjusted version. The factors are constructed following Fama and

[17] The results for LIFO firms should be read with caution, because the number of LIFO firms has been decreasing. In the end of our sample period, we only have around 150 firms with LIFO method. There are other inventory valuation methods such as Specific Identification, and Average Cost. We do not do separate analysis because the number of firms using these methods are too small for cross-sectional asset pricing analysis.

French (1993, 2015) but based on industry-adjusted characteristics.[18] In the second row, we replace these factors by their quarterly version. In the third row, we do industry adjustment and also quarterly data. In the Fama-MacBeth regressions, we use industry-adjusted annual accounting variables in the first row, unadjusted quarterly accounting variables in the second row, and unadjusted quarterly accounting variables with industry fixed effects in the third row. Industries are all defined as the Fama-French 48 industries. These have very little effect on the results.

Tables 3 and 4 and Fig. 2 look at whether the CCC in quarter t predicts a stock's returns in quarter t+2. We now examine whether the CCC can predict returns beyond quarter t+2. Thus, we sort stocks into decile portfolios at quarter $t+j$ based on the CCC of quarter t, and examine j up to 12. We also conduct the analysis when $j=1$, which is the first quarter after the quarter when the CCC is measured. When j=1, this is not a tradable strategy because the accounting information for the computation of the CCC is announced with a delay. Nevertheless, the analysis provides information on how the market reacts to the information for the CCC. Fig. 3 illustrates the results. The top chart corresponds to equal-weighted alphas, the medium chart corresponds to value-weighted alphas, and the bottom chart corresponds to the coefficients on the CCC of the Fama-MacBeth regressions. The alphas that correspond to the $t+j$ label on the horizontal axis are calculated with the Fama-French five-factor model of a long-short portfolio that each month buys stocks that were in the lowest CCC-decile j quarters previously and shorts stocks that were in the highest CCC-decile j quarters previously.

The figure shows that the CCC has predictive power for at least 12 quarters after the portfolio construction. High-CCC firms earn lower returns than low-CCC firms in quarter t+1, suggesting

[18] Novy-Marx (2013) proposes a factor model where factors are created based on industry-adjusted characteristics. We download the data from Novy-Marx's website. The data end in December 2012. Using this model, the alpha of the CCC strategy is 0.654 (t=6.07) and 0.593 (t=3.55) for EW and VW portfolios, respectively.

that the market reads high-CCC as negative information. The CCC's predictive power becomes weaker when *j* becomes larger, but even after three years (*j*=12), the CCC's return predictive power remains.

3.5 Controlling for other factors

Is the predictive power of the CCC distinct from other firm characteristics which also predict returns? We consider the following characteristics: external financing (XFIN), operating leverage, organizational capital, Z-score, and the standardized unexpected earnings (SUE, a measure for the post-earnings announcement effect). As Table 2 shows, the CCC has different relations with different components of profitability and accruals. We therefore also examine whether the decomposition of profitability and accruals can explain the effect of the CCC.

In Panel A and B of Table 8, we conduct the test with the Fama-MacBeth regression (one for all stocks, and one for all-but-microcaps), and in Panel C of Table 8, we conduct double portfolio sorts. In Panel A and B, we include all of the variables in Column (5) of Table 5 but do not report their coefficients for the sake of space. In Columns (1) through (7) of Panel A and B, we add XFIN, operating leverage, organizational capital, Z-score, SUE, NOA, asset turnover, and profit margin. The results in these columns show that controlling for these factors has very little effect on the coefficient on the CCC. In Columns (8) and (9), we control for the components of the profitability and accruals. We decompose profitability—following Ball, Gerakos, Linnainmaa, and Nikolaev (2015)—into seven components: gross profitability, reported SG&A, R&D expenses, depreciation expenses, interest expenses, tax expenses, and other expenses. We decompose accruals into four components: change in receivables, change in inventory, change in account payables, and other accruals.[19]

Fama-MacBeth regressions allow us to examine the predictive power of the CCC while controlling for known predictors, but they have a limitation: they assume that the relationship between stock returns and the various predictors is linear. To implement the double sort analysis, we use the following procedure. Suppose that we want to know whether the predictive power of the CCC is subsumed by control variable X. At the beginning of each month, we sort stocks into quintiles based on X. Within each X quintile, we again sort stocks into quintiles based on the CCC. The returns of the five CCC-quintile portfolios are then averaged across different quintiles of the control variable X. More precisely, if $r_{i,j}$ is the return of the portfolio of stocks in the i'th quintile of X and j's quintile of CCC, we compute, for j=1, …, 5,

$$\overline{r_j} = \frac{r_{1,j}+\cdots+r_{5,j}}{5}. \tag{2}$$

We then compute

$$\overline{r_1} - \overline{r_5} = \frac{(r_{1,1}-r_{1,5})+\cdots+(r_{5,1}-r_{5,5})}{5} \tag{3}$$

as a measure of the return of the low-CCC minus high-CCC portfolio, while controlling for variable X.

We report the results of this exercise in Panel C of Table 8. Each row corresponds to a specific control variable. Within each row, we report the Fama and French five-factor alphas of the five CCC-quintile portfolios on both an equal-weighted and value-weighted basis—in other words, $\overline{r_1}$, $\overline{r_2}$, $\overline{r_3}$, $\overline{r_4}$, and $\overline{r_5}$, defined above, adjusted for the Fama-French five-factors—and, in the Low-

[19] Thomas and Zhang (2002) find a negative correlation between changes in inventory and future stock returns. The coefficient on changes in inventory in Column (9) is positive. This is because we also have asset growth in the same model. Change in inventory is part of asset growth. If we remove asset growth, the coefficient on changes in inventory is indeed negative. Our results are similar if we also control for inventory growth (Belo and Lin, 2012).

High column of each row, the five-factor alpha of the low-CCC minus high-CCC portfolio, in other words, $\overline{r_1} - \overline{r_5}$ adjusted for the five factors. The control variables we consider are AssetGrowth, CBOP, Accruals, XFIN, operating leverage (OpLev), organizational capital (OrgCap), Z-score, SUE, NOA, asset turnover, profit margin, and all the profitability components and the accrual components.

The Low-High column in Panel C is the most important one. It shows that, consistent with the Fama-MacBeth regression results in Panel A and B, the CCC variable retains significant predictive power for returns even after controlling for known return predictors.

3.6 CCC factor

We next construct a factor that captures the effect of the CCC and compare it with the Fama-French five factors (Fama and French, 2015) and the *q*-factors (Hou, Xue, and Zhang, 2015). We follow Fama and French (1993, 2015) to construct the CCC factor. We first sort stocks by size into two groups depending on whether its market capitalization is below or above the median NYSE size breakpoint. We then perform an independent sort based on the CCC into three sub-groups: low CCC (i.e., below the 30th NYSE percentile), high CCC (i.e., above the 70th NYSE percentile), and medium CCC (i.e., between the 30th percentile and 70th percentile). The CCC factor is constructed by taking the average of the two low CCC portfolios minus the average of the two high CCC portfolios. All portfolios are value weighted. As in previous analysis, we use the industry-median adjusted CCC from the quarterly Compustat and the portfolios are rebalanced quarterly.

Panel A of Table 9 presents the average monthly returns, standard deviations and *t*-values for the CCC factor, the five factors of Fama and French (2015), and the investment factor and the ROE factor of Hou, Xue, and Zhang (2015). The CCC factor's mean return is 0.255%, which is comparable to SMB, HML and CMA, but smaller than RMW, and the I/A and ROE factors. Its standard deviation is the smallest among all the factors, leading to one of the highest *t*-values.

In Panel B, we use spanning regressions to judge whether other factors explain the CCC factor and whether the CCC factor has any explanatory power on other factors. We consider the Fama-French three factors, Fama-French five factors, the Hou, Xue, and Zhang factors, and Fama-French three factors augmented with the CCC factor. Ball, Gerakos, Linnainmaa, and Nikolaev (2016) and Fama and French (2017) find that a cash-based operating profitability factor better captures average returns than the RMW factor. We therefore also consider a five-factor model where we replace RMW by the cash-based operating profitability factor which is also constructed based on the same procedures as Fama and French (1993, 2015). Each candidate factor is regressed on other factors of a model. If the intercept in a spanning regression is non-zero, that factor adds to the model's explanation of average returns (Fama, 1998; Barillas and Shanken, 2017).

All the factor models leave sizable alphas on the CCC factor. The lowest alpha is from the five-factor model using cash-based operating profitability to construct the profitability factor. The alpha of the CCC factor from this model is 0.256% (t=4.59), which is very close to the mean of the CCC factor. These statistically significant alphas indicate that, relative to other models, the CCC factor contains useful information about expected returns. When we regress other factors on the Fama-French three factors, the alphas of these factors remain statistically significant. This is also true when we augment the three-factor model with the CCC factor. The augmented model actually delivers higher alphas than the Fama-French three-factor model, except for the cash-based operating profitability factor. Overall, these results suggest that the CCC factor is distinct from other factors and it contains useful information about expected returns.

3.7 Which components of CCC?

The CCC has three components: DIO, DRO, and DPO. Which components play the role of return prediction? Table 10 reports the results of the Fama-MacBeth regressions (Panel A) and the decile portfolio sorts (Panel B). We also analyze the role of operating cycle—the sum of DIO and DRO—which on its own is also a widely used measure of working capital management efficiency (Ross, Westerfield, and Jaffee, 2002, p. 755). The results show that the return predictive power comes mainly from DIO and DRO. The role of DPO does not predict returns after considering DIO and DRO. An interesting observation is that although DPO does not provide additional return predictive power, the operating cycle's return predictive power is not enhanced relative to the CCC. For example, in Fama-MacBeth regression, the operating cycle has a t-value of -7.50 (the last column of Table 10), and the CCC has a t-value of -8.88 (the last column of Panel A of Table 5).

4. Is the CCC effect due to risk or mispricing?

4.1 Tests of risk-based explanations

The results so far show that standard models of risk have difficulty in explaining the variation in returns associated with the CCC effect. If anything, the CCC's low-high portfolio is either uncorrelated with these factors or has negative loadings on these factors.[20] Now, we estimate a conditional CAPM model:

$$r_{t+1} = \alpha + (b_0 + b_1 DY_t + b_2 DEF_t + b_3 TERM_t + b_4 TB_t) r_{mkt,t+1} + b_{SMB} SMB_{t+1} + b_{HML} HML_{t+1} + b_{RMW} RMW_{t+1} + b_{CMA} CMA_{t+1} + \varepsilon_{t+1}, \quad (4)$$

[20] We also check whether the low-CCC minus high-CCC portfolio return is correlated with the five macroeconomic variables analyzed by Chen, Roll, and Ross (1986)—the growth rate of industrial production, unexpected inflation, change in expected inflation, default premium, and the term premium. We regress the low-CCC minus high-CCC portfolio return on these five macroeconomic variables and the Fama-French five factors. None of the coefficients on these five macroeconomic variables is statistically different from zero.

where r_{t+1} is the monthly low-CCC minus high-CCC portfolio return; $r_{mkt,t+1}$ is the excess return of the value-weighted CRSP market index; and SMB_t, HML_t, RMW_t, and CMA_t are the other four Fama-French five factors. DY_t, DEF_t, $TERM_t$, and TB_t are the dividend yield of the S&P 500 index, the yield spread between Baa-rated and Aaa-rated corporate bonds, the yield spread between 10-year T-bonds and 3-month T-bills, the yield of a T-bill with three months to maturity, and ε_{t+1} is an error term. α and b_1, b_2, b_3, and b_4 are parameters which we will estimate. The data for *DY* are from Robert Shiller's website; and the data for *DEF*, *TERM*, and *TB* are from the Federal Reserve. If the conditional CAPM can explain the CCC effect, then the estimated alpha should be indistinguishable from zero. We find that the alpha from the regression is 0.598% (t=6.59) for the equal-weighted portfolio and 0.538% (t=3.87) for the value-weighted portfolio, respectively. b_3 is -0.065 (t=-3.29) for the equal-weighted portfolio and -0.063 (t=-2.10) for the value-weighted portfolio, suggesting that the low-CCC minus high-CCC portfolio return is less sensitive to the market return when the beginning period TERM is higher. b_1, b_2, and b_4 are all indistinguishable from zero. These results suggest that time-varying risk from a conditional CAPM model does not explain the CCC effect.

Next, we investigate whether the low-CCC and high-CCC return spread can be explained by funding risk. Firms with a longer CCC rely more on external financing for working capital via short-term debt. There are at least two reasons that their performance might be more sensitive to the health of the financial intermediary sector. First, funding liquidity deterioration may make it difficult for firms to get external financing and they may suffer losses in rolling over their maturing debt (Almeida, Campello, Laranjeira, and Weisbenner, 2012). High-CCC firms may suffer more because they are more reliant on external financing (Tong and Wei, 2011). Second, High-CCC firms finance their working capital by borrowing more short-term debt than low-CCC firms. As shown by He and Xiong (2012), short-term debt exacerbates rollover risk.

We measure the health of the financial intermediary sector by the factors proposed by He, Kelly, and Manela (2017). Table 11 reports the results. At the monthly frequency, high-CCC firms' returns are more sensitive to the intermediary capital risk factor of He, Kelly, and Manela (2017). This is consistent with the literature that finds that firms with higher CCC or that rely on more short-term debt financing performed worse during the 2007-2009 crisis (Duchin, Ozbas, and Sensoy, 2010; Tong and Wei, 2011; Almeida, Campello, Laranjeira, and Weisbenner, 2012). However, the significant results largely disappear at the quarterly frequency; for the intermediary leverage factor of Adrian, Etula, and Muir (2014); or other proxies for funding risk—the betting against beta factor of Frazzini and Pedersen (2014), the change in the noise measure by Hu, Pan, and Wang (2013), the TED spread change, and the change in the VIX.

The intermediary asset pricing models argue that financial intermediaries are marginal investors, and stocks whose returns are more positively correlated with the marginal value of wealth of the financial intermediary sector should earn higher returns (Brunnermeier and Pedersen, 2009; He and Krishnamurthy, 2012, 3013; Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2012, 2013; Adrian and Shin, 2014). High-CCC stocks' returns are more positively correlated with the intermediary capital ratio factor of He, Kelly, and Manela (2017). Therefore, based on He and Krishnamurthy (2012, 2013) and He, Kelly, and Manela (2017), high-CCC stocks are riskier than low-CCC stocks, and should deliver higher returns. This is opposite to our finding.

Overall, there is no evidence that systematic risk can explain the low-CCC minus high-CCC return spread: We find some weak evidence that high-CCC firms' returns are more positively correlated with measures of funding risk and are basically uncorrelated with other measures of systematic risks. The finding that high-CCC firms' returns are more positively correlated with the intermediary capital ratio factor of He, Kelly, and Manela (2017) shows that the low-CCC minus high-CCC return spread cannot be explained by the intermediary asset pricing risk.

4.2 Tests of mispricing-based explanations

We examine whether our results are consistent with the mispricing arguments. The CCC is a measure of management's efficiency in using working capital and is correlated with firm profitability. Investors might not fully account for the CCC's implication on profitability and be surprised by the subsequent earnings realizations.

First, we examine whether the CCC provides predictive power for earnings after we control for other known earnings predictors including past earnings. We use the cross-sectional profitability model of Fama and French (2000, 2006) and Hou, van Dijk, and Zhang (2012) to estimate the following cross-sectional regressions with quarterly accounting data:

$$E_{i,t} = \alpha + \beta_{Low}LowCCC_{i,t-1} + \beta_{High}HighCCC_{i,t-1} + \beta_1 AT_{i,t-1} + \beta_2 Dividend_{i,t-1} + \beta_3 DDiv_{i,t-1} + \beta_4 E_{i,t-1} + \beta_5 NegE_{i,t-1} + \beta_6 Accruals_{i,t-1} + \varepsilon_{i,t}, \quad (5)$$

where $E_{i,t}$ denotes the earnings divided by total assets of firm *i* in quarter *t*. LowCCC and HighCCC indicate the lowest CCC decile and the highest CCC decile, respectively. AT is the natural logarithm of firm *i*'s total assets, Dividend is dividend paid in the previous year divided by total assets, DDiv is a dummy for dividend payer, NegE is a dummy for firms with negative earnings, and Accruals is computed following Sloan (1996). All explanatory variables are measured as of quarter t-1. If the CCC contains information about future earnings beyond its correlation with current earnings, we expect that β_{Low} to be positive and β_{High} to be negative.

Table 12 reports the results. We estimate Eq. (5) with the Fama-MacBeth regression. We define earnings as CBOP.[21] Consistent with our expectation, the coefficient on LowCCC is positive and the coefficient on HighCCC is negative, even after controlling for past earnings. These coefficients indicate that the CCC does provide independent information on the future profitability of firms.

Second, although the profitability results in Table 12 are consistent with mispricing, we cannot be sure that investors cannot expect this and are surprised by the subsequent earnings realizations. To test the relationship between subsequent operating performance and stock return reactions, we examine stock returns around earnings announcements after portfolio formation. This is a widely used method to examine whether anomalies are the result of biased expectations (Sloan, 1996; La Porta, Lakonishok, Shleifer, and Vishny, 1997; Engelberg, McLean, and Pontiff, 2017).[22] We predict that if the CCC effect is explained by risk, the mean returns on earnings announcement days (EADs) should be similar to the mean returns on non-EADs. If mispricing is the explanation, the prediction is that for high-CCC (low-CCC) firms, the EAD returns will tend to be lower (higher) than the non-EAD returns as investors are surprised by the subsequent unanticipated bad (good) news.

To test these competing predictions, we obtain EADs from the quarterly Compustat and I/B/E/S. Following DellaVigna and Pollet (2009), we keep the earlier of the two dates in the instance where dates from Compustat and IBES are not in accordance. We show results for the entire 1983-2015 sample period. We define CAR as the size-decile-adjusted returns to earnings in

[21] Results are similar if we define earnings as income before extraordinary items.
[22] One caveat of this test is that, as pointed out by Engelberg, McLean and Pontiff (2017), although different anomaly returns around earnings announcement days are most consistent with mispricing, they could also be consistent with dynamic risk models, which allow for time-varying risk premia and time-varying betas (Patton and Verado, 2012; Savor and Wilson, 2016).

the five days around the announcement (t-2, t+2). We obtain the size-decile portfolio returns directly from CRSP.

Table 13 presents the results of the Fama-MacBeth regressions of CAR on CCC and a number of controls used in Table 5. For CAR in quarter t, the CCC and other accounting variables are measured in quarter t-2, and other measures based on stock prices are measured at the end of quarter t-1. In Column (1), the coefficient on the CCC is -0.072 (t=-2.63). The absolute magnitude of the coefficient on the CCC becomes larger when controlling for other factors. The coefficient on the CCC is -0.150 (t=-4.84) in Column (5) when we control for all of the factors in Table 5. On average, the difference in the CCC between decile 1 and decile 10 is 1,140 days (3.12 years). The coefficient on the CCC implies a -0.225% to -0.468% difference between the two extreme deciles. The alpha for the long-short strategy in Table 3 is around 0.60% per month. On average, earnings announcements occur four times a year. This indicates that roughly one-eighth to one-quarter of the abnormal returns of the long-short trading strategy are realized around EADs. This is comparable to a typical anomaly. Engelberg, McLean, and Pontiff (2017) study 97 stock market anomalies, and find that relative to non-EADs, daily anomaly returns are six times higher on EADs and three times higher in the three days around EADs. This implies that around one-tenth to one-sixth of anomaly returns are realized around EADs. The results provide support to the mispricing explanation that investors do not fully incorporate the CCC's profitability implication into their earnings forecasts and are therefore surprised when earnings are realized.

4.3 The role of limits to arbitrage

The above evidence shows that the CCC effect is mostly consistent with mispricing. Thus, we should expect the return spread should be the largest (the mispricing is the greatest) for those stocks that are the most difficult to value or the most difficult to arbitrage (Shleifer and Vishny, 1997).

The findings in Table 6 show that the CCC effect is stronger for small firms than for large firms, consistent with the limits to arbitrage. We now explore the CCC effect varies with other measures of limits to arbitrage.

Following Baker and Wurgler (2006), we investigate the role of these limits to arbitrage measures: (1) trading friction measures: idiosyncratic volatility (*IVOL*), illiquidity (ILLIQ), firm age (Age), and analysts coverage (Analysts); (2) a profitability measure CBOP; (3) a dividend policy measure (Dividend); (4) tangibility measures: PPE/assets (PPE) and R&D/assets (R&D); and (5) growth opportunity measures: absolute sales growth rate, external finance (XFIN), and absolute asset growth. As argued by Baker and Wurgler (2006) and other studies in the literature, firms with high idiosyncratic volatility, high illiquidity, young age, small number of analysts following, low profitability, low dividend, low tangible assets, and high R&D are difficult to value or arbitrage. Baker and Wurgler (2006) also argue that the difficulty in valuing is higher for less stable firms. We measure stable firms as firms with low external finance, low absolute sales growth rate, and low absolute asset growth.

For each limits-to-arbitrage variable X, we first sort all of the stocks into five quintiles based on X except Dividend and R&D for which we sort stocks into three groups. Many firms have zero dividends or R&D. For dividend and R&D, we sort firms into three groups: the first group contains firms with zero dividends (or R&D), and firms with positive dividends (or R&D) are sorted into two equal-sized groups. Then within each X group, we further sort stocks into CCC quintiles and calculate the Fama-French five-factor alpha—on both an equal-weighted and a value-weighted basis for low-CCC minus high-CCC portfolios for each X group. Repeating this each month provides a time series of returns for each X group. We also conduct a test on whether the long-short alphas differ between the two extreme X quintiles.

The most important column in Table 14 is the "Large-Small" column which reports the difference in the long-short strategy between the small and the large X groups. The "Expected Sign" column reports the expected sign of the "Large-Small" column. Although the long-short alphas do not always change monotonically with the measures of limits to arbitrage, the Large-Small estimates always have the signs predicted by limits to arbitrage and are statistically significant in 9 out of the 11 cases we consider for both the equal- and the value-weighted returns. Therefore, the results in Table 13 provide strong support for limits to arbitrage.

4.4 Discussion

The above results show that low-CCC firms' earnings announcements are associated with significantly higher returns than those of high-CCC firms. The CCC effect is also stronger among stocks that are harder to value and harder to arbitrage. These two tests are consistent with a mispricing interpretation of the CCC effect. However, we also find that the CCC predicts returns for at least three years after the date of the portfolio formation (Fig. 3). This is hard to be explained by mispricing because the effects of limit to arbitrage and other trading frictions are unlikely to persist for this long. Although we do not find evidence to support the risk-based interpretation, the results do not rule out the possibility that some risks could also contribute towards the CCC spread. Therefore, we caution that these results are not conclusive to exclude one or the other interpretation. It is possible that both forces are in effect.

5. Conclusions

This paper investigates the asset pricing implications of the CCC. Despite being a textbook measure, the literature has relatively understudied the CCC. We find that low-CCC firms earn higher returns than high-CCC firms. The CCC effect is distinct from other known return predictors. Relative to high-CCC stocks, low-CCC stock returns are less sensitive to the intermediary capital ratio factor proposed by He, Kelly, and Manela (2017). Our findings suggest that the low-CCC minus high-CCC portfolio cannot be explained by the intermediary leverage risk.

We also show that the CCC has a strong and positive correlation with the working capital ratio of a firm. Firms with a higher CCC fund their operations with more short-term debt. It is known that firms with more short-term debt are more sensitive to a financial downturn (Duchin, Ozbas, and Sensoy, 2010; Tong and Wei, 2011; Almeida, Campello, Laranjeira, and Weisbenner, 2012). This sensitivity might be why the high-CCC stocks react more strongly to the intermediary capital ratio factor of He, Kelly, and Manela (2017) than the low-CCC stocks.

Our findings also reveal a few stylized facts about the CCC. The CCC decreased from the early 1980s to the early 2000s, and stopped decreasing afterwards. The time-series change in the CCC is mainly explained by the change in days inventory outstanding. Days receivables outstanding was longer than days payables outstanding before 2000 and the difference disappears after 2000. We leave the questions on how these trends affect corporate financing activities, such as cash holding (Bates, Kahle, and Stulz, 2009) and debt maturity (Custodio, Ferreira, and Laureano, 2013) to future research.

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Appendix

Table A.1. Definitions of variables

This table discusses the definitions of the main variables used in the paper. All the variables are constructed using quarterly data except *AssetGrowth*, *SalesGrowth*, *XFIN*, *Dividend*, and *OrgCap*. Time subscripts are omitted when they are all at *t*.

Variable	Description
CCC	=DIO+DRO-DPO.
DIO	$=365*0.5*(INVTQ_t+INVTQ_{t-1})/COGSQ_t$.
DRO	$=365*0.5*(RECTQ_t+RECTQ_{t-1})/REVTQ_t$
DPO	$=365*0.5*(APQ_t+APQ_{t-1})/COGSQ_t$.
OperatingCycle	=(DIO+DRO).
Beta	Following Fama and French (1992), we estimate betas from the past five years of monthly data, with the requirement that at least 24 months of data is available.
BM	The natural logarithm of the ratio of total book value of equity to total market capitalization. Book value is measured as in Fama and French (2008).
Size	Market capitalization at the end of last month measured as a natural logarithm.
MOM	Cumulative return from month *t*-12 to month *t*-2.
REV	Short-term reversal. Return of month *t*-1.
LTREV	Long-term reversal. Cumulative return from month *t*-60 to month *t*-13.
ILLIQ	Illiquidity measure as in Amihud (2002) based on daily data over month *t*-1.
IVOL	Idiosyncratic volatility as in Ang, Hodrick, Xing, and Zhang (2006).
AG	$=(AT_t-AT_{t-1})/AT_{t-1}$., as measured in Cooper, Gulen, and Schill (2008).
GrossProfit	$=(REVTQ_t-COGSQ_t)/ATQ_{t-1}$, following Novy-Marx (2013).
CBOP	$=[(REVTQ_t-COGSQ_t-XSGAQ_t+XRDQ_t)-(\Delta RECTQ_t-\Delta INVTQ_t-\Delta XPPQ_t+\Delta(DRCQ_t+DRLTQ_t)+\Delta APQ_t)]/ATQ_{t-1}$, following Ball, Gerakos, Linnainmaa, and Nikolaev (2016).
Accruals	=ΔACTQ-ΔCHEQ-[ΔLCTQ-ΔDLCQ-ΔTXPQ]-DPQ divided by lagged ATQ (Sloan, 1996).
WorkingCapital	=(ACTQ-LCTQ)/ATQ.
STDebt	=DLCQ/ATQ.
LTDebt	=DLCTTQ/ATQ.
XFIN	=(SSTK-DV-PRSTKC+DLTIS-DLTR)/AT (Bradshaw, Richardson, and Sloan, 2006).
OpLev	Operating Leverage=(COGSQ+XSGAQ)/ATQ, following Novy-Marx (2011).
CashHolding	=CHEQ/ATQ.
OrgCap	$=OrgCap_{it} = (1-\delta_0) * OrgCap_{it-1} + \frac{SGA_{it}}{cpi_t}$, where cpi_t is the CPI at year *t*. The initial stock of organizational capital is calculated as $\frac{SGA_{it}}{g+\delta_0}$. We set δ_0 to 15% and g to 10%, following Eisfeldt and Papanikolaou (2013).
ZScore	=(3.3*PIQ+REVTQ+1.4*REQ+1.2*(ACTQ-LCTQ))/ATQ, as measured in Altman (1968).
PPE	=PPENTQ/ATQ.
SUE	Change in split-adjusted quarterly earnings per share (EPSPXQ divided by AJEXQ) from its value four quarters ago divided by the standard deviation of this change in quarterly earnings over the prior eight quarters (six quarters minimum).
NOA	=[(ATQ-CHEQ)-(ATQ-DLCQ-DLTTQ-MIBQ-PSTKQ-CEQQ)]/ATQ, following Hirshleifer, Hou, Teoh, and Zhang (2004).
Age	The number of years since a firm shows in the CRSP file.
Analysts	Number of analysts following a firm, from I/B/E/S.
Dividend	=DIV/AT.
R&D	=XRDQ/ATQ.
SalesGrowth	$=(REVT_t-REVT_{t-1})/REVT_{t-1}$.
ROE	$=OIADPQ_t/(ATQ_{t-1}-LTQ_{t-1})$.
AssetTurnover	$=REVTQ_t/ATQ_{t-1}$.
ProfitMargin	$=OIADPQ_t/REVT_t$.
TotalLev	=LTQ/ATQ.

Table 1. CCC by industry

This table reports the summary statistics for the CCC (in days) by the Fama-French 48-industry classification. We sort industries by their average CCC. The CCC is the cash conversion cycle. DIO, DRO, and DPO are days inventory outstanding, days receivables outstanding, and days payables outstanding, respectively. Q1, Q3, and Q3-Q1 report the 25th percentile, 75th percentile, and the difference between the 75th and 25th percentile of CCC across firms in each industry. We first calculate these statistics for each industry in each quarter and report the time-series means of these cross-sectional statistics.

	CCC	DIO	DRO	DPO	Q1	Q3	Q3-Q1
Restaurants, Hotels, Motels	8	35	38	78	-5	14	20
Petroleum and Natural Gas	19	68	237	288	-15	53	69
Entertainment	52	45	140	149	-8	102	110
Communication	72	28	210	199	44	98	55
Transportation	85	30	161	105	77	93	16
Personal Services	114	59	168	128	47	167	120
Utilities	119	111	152	149	97	140	43
Others	147	25	247	145	126	172	46
Coal	150	88	174	123	100	193	93
Healthcare	170	22	231	105	147	189	42
Business Services	199	27	269	141	159	240	81
Food Products	220	227	125	126	206	236	30
Printing and Publishing	233	143	213	167	131	319	188
Retail	245	335	31	152	222	270	48
Candy & Soda	249	281	146	163	194	304	109
Business Supplies	262	220	182	131	238	283	45
Shipping Containers	270	238	184	147	227	317	90
Non-Metallic and Industrial Metal Mining	273	243	201	157	223	310	87
Shipbuilding, Railroad Equipment	290	263	164	142	229	350	121
Precious Metals	304	338	174	216	240	360	120
Agriculture	306	274	154	125	219	369	149
Automobiles and Trucks	312	241	218	149	275	346	71
Wholesale	316	285	193	155	278	349	72
Rubber and Plastic Products	331	265	214	145	303	358	56
Construction	332	172	242	130	286	378	92
Steel Works	347	288	201	137	324	371	47
Beer & Liquor	350	326	173	172	242	397	155
Chemicals	360	300	237	175	336	384	48
Construction Materials	374	299	211	125	350	397	47
Fabricated Products	390	268	251	156	354	424	69
Computers	420	353	266	193	240	618	378
Consumer Goods	429	379	215	162	390	468	78
Defense	433	291	247	130	333	505	172
Textiles	433	336	227	126	410	456	46
Pharmaceutical Products	447	474	234	199	381	491	110
Electronic Equipment	466	393	241	171	387	548	161
Recreation	495	406	252	156	426	566	141
Electrical Equipment	513	424	254	167	440	584	143
Apparel	514	447	218	136	466	560	94
Aircraft	524	419	230	146	478	558	79
Machinery	536	434	259	162	483	587	104
Medical Equipment	596	531	256	175	552	632	80
Tobacco Products	613	613	102	158	428	782	354
Measuring and Control Equipment	633	526	274	161	577	680	104

Table 2. Data summary

This table presents the summary statistics for the sample: the mean and standard deviation of each variable, and their pairwise correlations with CCC (the first three columns). We winsorize the CCC and other accounting variables (all variables in Table 2 except Beta, Size, BM, R_{t-1} $R_{t-12,t-2}$, $R_{t-60,t-13}$, ILLIQ, and IVOL) month by month at the 1% level for both tails to mitigate the effect of outliers. The next ten columns report the means of each variable by CCC decile. For each month, we sort all stocks into ten deciles based on the CCC. We compute the means, standard deviations, and correlations from the cross-sectional month by month and report the time-series averages of the monthly cross-sectional statistics. The variables are defined in the Appendix. In this table, CCC is adjusted by industry median.

	Mean	STD	Corr	Low 1	2	3	4	5	6	7	8	9	High 10
Major asset pricing variables													
CCC	42	313	1	-439	-192	-115	-60	-14	26	79	153	280	701
Beta	1.20	0.77	-0.01	1.347	1.250	1.207	1.166	1.128	1.138	1.157	1.186	1.227	1.231
Size	12.09	1.99	-0.11	12.10	12.24	12.23	12.29	12.33	12.34	12.20	11.97	11.77	11.46
BM	-0.55	0.89	0.13	-0.865	-0.676	-0.603	-0.559	-0.530	-0.510	-0.488	-0.465	-0.435	-0.394
R_{t-1}	0.01	0.15	-0.01	0.016	0.015	0.015	0.015	0.014	0.014	0.014	0.013	0.012	0.009
$R_{t-12,t-2}$	0.16	0.59	-0.07	0.205	0.205	0.190	0.178	0.167	0.167	0.145	0.139	0.111	0.065
$R_{t-60,\ t-13}$	0.76	1.95	-0.03	0.783	0.824	0.813	0.800	0.743	0.756	0.750	0.751	0.702	0.664
ILLIQ	9.75	95.92	0.02	12.173	8.576	8.315	8.418	7.380	6.862	8.571	9.317	10.273	17.614
IVOL	0.03	0.02	0.04	0.032	0.028	0.027	0.026	0.026	0.025	0.026	0.028	0.030	0.033
AssetGrowth	0.21	0.54	-0.03	0.317	0.239	0.215	0.211	0.196	0.191	0.195	0.193	0.193	0.200
CBOP	0.02	0.07	-0.04	0.026	0.026	0.027	0.028	0.027	0.028	0.025	0.024	0.023	0.017
Accruals	-0.01	0.05	0.04	-0.013	-0.008	-0.008	-0.007	-0.007	-0.007	-0.006	-0.005	-0.004	-0.005
Other characteristics													
WorkingCap	0.27	0.22	0.27	0.213	0.235	0.238	0.232	0.227	0.239	0.275	0.315	0.361	0.422
STDebt	0.05	0.18	0.11	0.043	0.041	0.042	0.043	0.043	0.045	0.049	0.052	0.057	0.074
LTDebt	0.08	0.17	-0.02	0.167	0.173	0.178	0.190	0.198	0.198	0.187	0.176	0.162	0.161
OpLev	0.32	0.21	-0.20	0.326	0.423	0.381	0.360	0.342	0.334	0.316	0.289	0.262	0.210
CashHolding	0.14	0.17	-0.10	0.222	0.166	0.145	0.134	0.122	0.118	0.123	0.126	0.130	0.133
OrgCap	1.21	1.12	0.01	1.296	1.370	1.213	1.112	1.059	1.057	1.127	1.228	1.305	1.299
Z-Score	0.62	1.53	0.07	-0.173	0.562	0.663	0.707	0.743	0.756	0.768	0.765	0.753	0.633
XFIN	0.03	0.14	-0.01	0.066	0.031	0.024	0.022	0.019	0.019	0.021	0.023	0.027	0.042
NOA	0.61	0.20	0.20	0.503	0.552	0.589	0.610	0.629	0.638	0.637	0.643	0.653	0.673
PPE	0.31	0.22	-0.18	0.323	0.310	0.329	0.348	0.363	0.354	0.310	0.273	0.242	0.199
DuPont analysis													
ROE	0.01	0.17	-0.04	0.018	0.010	0.006	0.004	0.006	0.005	0.013	0.010	0.008	0.011
AssetTurnover	0.34	0.21	-0.11	0.342	0.444	0.402	0.377	0.356	0.346	0.329	0.306	0.281	0.220
ProfitMargin	0.02	0.04	-0.07	0.009	0.020	0.022	0.022	0.022	0.022	0.019	0.018	0.014	0.006
TotalLev	0.49	0.20	-0.10	0.507	0.516	0.508	0.509	0.509	0.505	0.494	0.474	0.449	0.435
Break-up profitability													
GrossProfit	0.10	0.07	-0.08	0.108	0.115	0.107	0.101	0.097	0.096	0.098	0.102	0.102	0.091
SG&A	0.08	0.06	-0.05	0.085	0.088	0.081	0.077	0.073	0.074	0.076	0.077	0.077	0.074
R&D	0.01	0.02	-0.06	0.014	0.009	0.007	0.006	0.005	0.005	0.006	0.007	0.008	0.008
Depreciation	0.01	0.01	-0.19	0.014	0.012	0.011	0.011	0.011	0.011	0.010	0.010	0.009	0.008
InterestExp	0.00	0.00	0.00	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
Tax	0.01	0.01	-0.10	0.008	0.009	0.009	0.009	0.008	0.008	0.008	0.007	0.006	0.004
OtherExp	0.00	0.02	0.01	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001	0.000	0.000	0.000
Break-up accruals													
ΔReceivables	0.01	0.04	-0.07	0.008	0.008	0.008	0.007	0.006	0.006	0.005	0.004	0.002	-0.003
ΔInventory	0.00	0.03	0.06	0.002	0.003	0.002	0.002	0.002	0.002	0.004	0.004	0.005	0.008
ΔPayable	0.00	0.03	-0.04	0.006	0.005	0.004	0.003	0.003	0.002	0.003	0.002	0.001	0.001
Other accruals	-0.01	0.03	0.07	-0.017	-0.014	-0.014	-0.014	-0.013	-0.013	-0.013	-0.012	-0.010	-0.008

Table 3. Time-series tests

This table reports average monthly excess returns and alphas (in percentage) on both an equal-weighted (EW) and value-weighted (VW) basis of stock portfolios sorted by industry-adjusted CCC. Each month, all stocks are sorted into deciles based on the industry-adjusted CCC two quarters ago. For each of the decile portfolios, Low 1 through High 10, we report the average excess return, Fama-French three-factor alpha, Fama-French-Carhart four-factor alpha, Fama-French five-factor alpha, Hou-Xue-Zhang *q*-factor alpha, and the Stambaugh-Yuan mispricing-factor alpha. The right-most column reports the excess returns and alphas of the Low-minus-High portfolios.

CCC deciles		Low 1	2	3	4	5	6	7	8	9	High 10	Low -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	EW	0.157	0.170	0.176	0.173	0.103	0.044	0.091	0.020	-0.141	-0.328	**0.484**
three-factor		(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-	EW	0.366	0.387	0.359	0.332	0.283	0.224	0.267	0.227	0.077	-0.091	**0.458**
Carhart four-factor		(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	EW	0.425	0.298	0.278	0.239	0.139	0.096	0.169	0.119	-0.054	-0.200	**0.625**
five-factor		(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)**
Hou-Xue-Zhang	EW	0.669	0.509	0.469	0.399	0.329	0.270	0.363	0.330	0.199	0.074	**0.595**
q-factor		(5.67)	(5.21)	(5.41)	(5.28)	(3.90)	(3.31)	(4.49)	(3.71)	(2.00)	(0.65)	**(6.03)**
	VW	0.375	0.093	0.172	0.032	-0.031	0.055	-0.047	-0.006	-0.170	-0.264	**0.639**
		(4.02)	(1.09)	(2.03)	(0.40)	(-0.39)	(0.75)	(-0.56)	(-0.07)	(-1.98)	(-2.45)	**(4.40)**
Stambaugh-Yuan	EW	0.564	0.448	0.377	0.337	0.254	0.242	0.297	0.261	0.101	-0.006	**0.570**
mispricing-factor		(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)**

Table 4. Factor loadings

This table reports the factor loadings of a long-short portfolio that, each month, buys stocks whose CCC is in the bottom decile and shorts stocks whose CCC is in the top decile. The CCC is adjusted by industry median. We report results for five models – the Fama-French three-factor model, the Fama-French-Carhart four-factor model, the Fama-French five-factor model, the Hou-Xue-Zhang *q*-factor model, and the Stambaugh-Yuan mispricing-factor model – and on both an equal-weighted (EW) and value-weighted (VW) basis. MktRf is the market factor; SMB is the size factor; HML is the value factor; UMD is the momentum factor; RMW is the robust profitability minus weak profitability factor; CMA is the conservative investment minus aggressive investment factor; I/A is the investment factor; ROE is the return-on-equity factor; MGMT is a factor that arises from six anomaly variables which all represent quantities that firm managements can affect rather directly; and PERF is a factor that arises from five anomaly variables that are more related to performance and less directly controlled by management.

		MktRf	SMB	HML	UMD	RMW	CMA	I/A	ROE	MGMT	PERF	R^2
Fama-French	EW	0.104	0.009	-0.173								
three-factor		(4.82)	(0.27)	(-5.12)								0.131
	VW	-0.060	-0.013	-0.261								
		(-1.88)	(-0.28)	(-5.26)								0.052
Fama-French-	EW	0.110	0.005	-0.162	0.030							
Carhart four-factor		(5.00)	(0.16)	(-4.67)	(1.42)							0.132
	VW	-0.058	-0.014	-0.257	0.012							
		(-1.78)	(-0.30)	(-5.03)	(0.37)							0.050
Fama-French	EW	0.072	-0.090	-0.112		-0.280	-0.082					
five-factor		(3.23)	(-2.73)	(-2.63)		(-6.74)	(-1.28)					0.205
	VW	-0.078	-0.062	-0.202		-0.103	-0.115					
		(-2.28)	(-1.23)	(-3.08)		(-1.62)	(-1.17)					0.056
Hou-Xue-Zhang	EW	0.103	-0.049					-0.210	-0.110			
q-factor		(4.54)	(-1.51)					(-3.98)	(-2.90)			0.126
	VW	-0.065	-0.060					-0.334	-0.106			
		(-1.93)	(-1.93)					(-4.29)	(-1.90)			0.038
Stambaugh-Yuan	EW	0.082	-0.040							0.019	-0.201	
mispricing-factor		(3.30)	(-1.15)							(0.80)	(-5.22)	0.131
	VW	-0.039	-0.036							0.084	-0.156	
		(-1.06)	(-0.70)							(2.32)	(-2.72)	0.023

Table 5. Fama-MacBeth regressions

This table reports the results of Fama-MacBeth regressions. The CCC is the industry-adjusted cash conversion cycle. The CCC is measured in number of years. The dependent variable is return (in percentage). All the accounting variables including CCC are winsorized month by month at the 1% level for both tails. Panel A presents results for all stocks, and Panel B presents results for all-but-microcaps. Microcaps are stocks with market capitalization below the 20th percentile of the NYSE market capitalization distribution. Variables are defined in the Appendix.

Panel A. All stocks

	(1)	(2)	(3)	(4)	(5)
CCC	**-0.181**	**-0.235**	**-0.214**	**-0.160**	**-0.216**
	(-6.89)	**(-9.74)**	**(-9.31)**	**(-6.26)**	**(-8.88)**
Beta		0.018	0.108	0.150	0.095
		(0.16)	(1.03)	(1.45)	(0.96)
Size		-0.079	-0.119	-0.124	-0.137
		(-1.74)	(-3.51)	(-3.68)	(-4.02)
BM		0.268	0.253	0.197	0.215
		(4.23)	(4.92)	(3.86)	(4.22)
R_{t-1}			-4.632	-4.680	-4.776
			(-12.20)	(-12.39)	(-12.46)
$R_{t-12,t-2}$			0.647	0.623	0.612
			(5.41)	(5.26)	(5.18)
$R_{t-60,t-13}$			-0.044	-0.027	-0.045
			(-2.70)	(-1.79)	(-2.88)
ILLIQ			0.006	0.006	0.006
			(2.97)	(2.65)	(2.51)
IVOL			-15.896	-14.978	-14.802
			(-5.52)	(-5.21)	(-5.13)
Asset Growth				-0.005	-0.005
				(-6.43)	(-5.82)
Cash-Based OP				3.176	3.875
				(7.02)	(9.87)
Accrual					0.743
					(1.40)
Intercept	1.319	2.368	2.991	3.020	3.170
	(4.92)	(3.78)	(6.54)	(6.62)	(6.84)
Average R^2	0.001	0.032	0.053	0.055	0.056

Panel B. All-but-microcaps

	(1)	(2)	(3)	(4)	(5)
CCC	**-0.152**	**-0.175**	**-0.153**	**-0.146**	**-0.153**
	(-4.59)	**(-6.16)**	**(-5.79)**	**(-5.23)**	**(-5.36)**
Beta		-0.031	0.025	-0.002	0.001
		(-0.21)	(0.20)	(-0.02)	(0.01)
Size		-0.080	-0.110	-0.126	-0.127
		(-1.98)	(-3.12)	(-3.48)	(-3.49)
BM		0.054	0.089	0.103	0.097
		(0.80)	(1.67)	(1.89)	(1.77)
R_{t-1}			-2.334	-2.482	-2.493
			(-5.40)	(-5.71)	(-5.72)
$R_{t-12,t-2}$			0.670	0.671	0.670
			(4.85)	(4.85)	(4.85)
$R_{t-60,t-13}$			-0.031	-0.037	-0.038
			(-1.99)	(-2.26)	(-2.35)
ILLIQ			1.747	1.853	1.859
			(2.04)	(2.17)	(2.19)
IVOL			-16.856	-17.479	-17.053
			(-4.25)	(-4.45)	(-4.35)
Asset Growth				-0.003	-0.003
				(-3.43)	(-3.18)
Cash-Based OP				3.128	2.863
				(7.20)	(5.58)
Accrual					-0.760
					(-1.25)
Intercept	1.193	2.336	2.860	3.084	3.090
	(4.85)	(3.84)	(5.31)	(5.35)	(5.34)
Average R^2	0.002	0.055	0.084	0.086	0.088

Table 6. Firm size and the effect of CCC

This table reports the results on how the CCC effect varies with firm size. For each month, we sort all the stocks into quintiles based on the market capitalization at the end of the previous month. We use the NYSE size breakpoints. Within each size quintile, we further sort stocks into quintiles based on industry-adjusted CCC. We report the Fama and French five-factor alphas of the 25 portfolios. We also report, for each size quintile, the low-CCC minus high-CCC portfolio alpha. Panel A reports the results on an equal-weighted basis and Panel B reports the results on a value-weighted basis.

	Small firms	2	3	4	Large firms
Panel A. equal-weighted alphas					
Low CCC	0.501	0.306	0.146	0.141	0.304
	(2.81)	(3.52)	(1.52)	(1.46)	(4.61)
2	0.451	0.148	0.037	-0.027	0.027
	(3.23)	(1.87)	(0.45)	(-0.32)	(0.43)
3	0.224	0.046	-0.056	0.076	-0.002
	(1.61)	(0.53)	(-0.70)	(0.92)	(-0.03)
4	0.256	0.051	-0.004	0.023	-0.019
	(1.87)	(0.63)	(-0.05)	(0.29)	(-0.26)
High CCC	-0.093	-0.368	-0.254	-0.123	-0.126
	(-0.60)	(-4.52)	(-2.77)	(-1.45)	(-1.81)
High-Low	**0.594**	**0.674**	**0.400**	**0.264**	**0.430**
	(6.70)	**(6.65)**	**(3.74)**	**(2.67)**	**(4.74)**
Panel B. value-weighted alphas					
Low CCC	0.160	0.317	0.137	0.146	0.215
	(1.27)	(3.54)	(1.43)	(1.50)	(2.82)
2	0.239	0.119	0.057	-0.012	0.111
	(2.29)	(1.50)	(0.69)	(-0.14)	(1.42)
3	-0.000	0.065	-0.064	0.088	-0.005
	(-0.00)	(0.76)	(-0.79)	(1.08)	(-0.06)
4	-0.025	0.041	0.009	0.018	0.004
	(-0.26)	(0.49)	(0.11)	(0.23)	(0.05)
High CCC	-0.400	-0.371	-0.268	-0.068	-0.179
	(-3.74)	(-4.63)	(-2.94)	(-0.78)	(-2.38)
High-Low	**0.559**	**0.689**	**0.405**	**0.214**	**0.394**
	(6.28)	**(6.67)**	**(3.78)**	**(2.11)**	**(3.43)**

Table 7. Robustness

The table presents the results of several robustness checks. The EW (VW) column reports the equal-weighted (value-weighted) Fama-French five-factor alphas of a long-short portfolio that, each month, buys (shorts) stocks with industry-adjusted CCC in the lowest (highest) decile. The other two columns report the coefficient on the CCC from the Fama-MacBeth regression with the same specification as in column (5) in Table 5: one for all stocks and the other for all-but-microcaps. In the Fama-MacBeth regressions, the CCC is measured in number of years. The first panel presents the results for two subperiods. In the second panel, we exclude stocks whose price falls below $5 in the month before portfolio construction. In the third panel, we conduct the analysis for firms with different inventory valuation methods: one for First-In First-Out (FIFO), one for Last-In First-Out (LIFO), and for all others. In the fourth panel, we conduct the analysis within each of the Fama-French five industries. The fifth panel reports the results where the CCC is calculated over the four most recent quarters, annual CCC, and CCC without industry adjustment. The last panel presents the results of constructing factors using industry-adjusted characteristics, quarterly data, and industry-adjusted quarterly data, respectively. In the Fama-MacBeth regressions, we add industry fixed effects for the industry-adjusted analysis.

		EW	VW	FM All stocks	FM All-but-microcaps
Subperiods	<=1995	0.600	0.473	-0.275	-0.239
		(5.22)	(2.73)	(-8.28)	(-6.16)
	>=1996	0.423	0.379	-0.156	-0.109
		(2.95)	(2.03)	(-4.45)	(-2.67)
Exclude low-priced stocks	Price>=$5	0.646	0.576	-0.184	-0.155
		(7.88)	(4.27)	(-7.72)	(-5.47)
Inventory valuation method	FIFO	0.619	0.717	-0.214	-0.147
		(5.12)	(3.65)	(-6.70)	(-3.54)
	LIFO	0.409	0.381	-0.261	-0.150
		(2.62)	(1.81)	(-4.69)	(-2.90)
	Others	0.705	0.598	-0.188	-0.132
		(4.95)	(3.07)	(-5.23)	(-3.24)
By industry	Consumer goods	0.708	0.359	-0.220	-0.111
		(5.32)	(1.54)	(-5.59)	(-2.60)
	Manufacturing	0.077	0.185	-0.119	-0.157
		(0.43)	(1.01)	(-2.63)	(-3.26)
	Hi-Tech	0.891	1.423	-0.344	-0.257
		(4.71)	(5.08)	(-7.14)	(-4.62)
	Healthcare	0.711	0.371	-0.144	-0.122
		(2.41)	(1.19)	(-2.12)	(-2.28)
	Other industries	0.729	1.223	-0.170	-0.178
		(3.34)	(4.39)	(-2.57)	(-1.97)
Different CCC measures	Past four-quarter	0.396	0.495	-0.158	-0.127
	rolling CCC	(4.44)	(3.45)	(-6.07)	(-4.27)
	Annual CCC	0.320	0.401	-0.311	-0.311
		(3.36)	(3.06)	(-3.04)	(-2.72)
	Unadjusted CCC	0.510	0.547	-0.164	-0.116
		(4.37)_	(3.19)	(-6.15)	(-3.59)
Factors and controls	Industry adjusted	0.439	0.403	-0.406	-0.367
	+ Annual	(4.21)	(2.69)	(-4.23)	(-3.35)
	Quarterly	0.624	0.501	-0.201	-0.145
		(6.71)	(3.54)	(-8.37)	(-5.09)
	Industry adjusted	0.507	0.450	-0.238	-0.162
	+ Quarterly	(5.05)	(3.11)	(-10.35)	(-5.99)

Table 8. Controlling for other characteristics

Panel A. Fama-MacBeth regressions – all stocks

This panel reports the results for the Fama-MacBeth regression after controlling for additional characteristics and for all stocks. The CCC is the industry-adjusted cash conversion cycle. The CCC is measured in number of years. All of these specifications have all of the variables in column (5) of Table 5. All the accounting variables including CCC are winsorized month by month at the 1% level for both tails. However, we only report the coefficient on the main variable CCC.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CCC	**-0.213**	**-0.205**	**-0.215**	**-0.218**	**-0.195**	**-0.180**	**-0.188**	**-0.192**	**-0.170**	**-0.176**
	(-8.25)	**(-7.88)**	**(-8.80)**	**(-8.96)**	**(-7.92)**	**(-7.09)**	**(-7.30)**	**(-7.91)**	**(-7.21)**	**(-7.21)**
XFIN	-0.450									
	(-2.08)									
OpLev		0.392								
		(2.61)								
OrgCap			0.134							
			(4.18)							
Z-score				0.119						
				(2.43)						
SUE					0.361					
					(10.29)					
NOA						-1.050				
						(-6.37)				
AssetTurnover							0.572			
							(4.65)			
ProfitMargin								8.711		
								(9.05)		
Gross Profit									10.258	
									(9.69)	
Reported SG&A									-7.867	
									(-7.09)	
R&D									4.080	
									(1.86)	
Depreciation									-3.422	
									(-1.01)	
Interest Expenses									-26.817	
									(-4.14)	
Tax									6.895	
									(2.36)	
Other Expense									-2.847	
									(-1.82)	
ΔReceivable										7.242
										(8.87)
ΔInventory										5.344
										(4.94)
ΔPayable										2.799
										(3.80)
Other Accrual										-3.869
										(-5.66)
Intercept	3.167	2.941	2.707	3.013	3.122	3.791	2.812	3.199	2.701	3.097
	(6.96)	(6.13)	(5.87)	(6.33)	(6.77)	(7.71)	(5.80)	(7.04)	(5.97)	(6.67)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average R^2	0.057	0.057	0.058	0.059	0.061	0.057	0.057	0.058	0.059	0.066

Panel B. Fama-MacBeth regressions – all-but-microcaps

This panel reports the results for the Fama-MacBeth regression after controlling for additional characteristics and for all-but-microcaps. Microcaps are stocks with market capitalization below the 20th percentile of the NYSE market capitalization distribution. The CCC is the industry-adjusted cash conversion cycle. The CCC is measured in number of years. All of these specifications have all of the variables in column (5) of Table 5. However, we only report the coefficient on the main variable CCC.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CCC	**-0.144**	**-0.144**	**-0.158**	**-0.159**	**-0.143**	**-0.122**	**-0.138**	**-0.145**	**-0.142**	**-0.128**
	(-4.94)	**(-4.78)**	**(-5.56)**	**(-5.50)**	**(-5.01)**	**(-4.18)**	**(-4.63)**	**(-5.12)**	**(-5.22)**	**(-4.50)**
XFIN	-0.319									
	(-1.24)									
OpLev		0.282								
		(1.66)								
OrgCap			0.085							
			(1.82)							
Z-score				0.112						
				(1.86)						
SUE					0.129					
					(6.98)					
NOA						-0.812				
						(-4.99)				
AssetTurnover							0.280			
							(2.11)			
ProfitMargin								5.323		
								(4.76)		
Gross Profit									4.224	
									(3.04)	
Reported SG&A									-2.837	
									(-1.70)	
R&D									6.153	
									(2.27)	
Depreciation									-3.576	
									(-0.94)	
Interest Expenses									12.523	
									(1.59)	
Tax									7.702	
									(2.15)	
Other Expense									0.503	
									(0.24)	
ΔReceivable										3.532
										(3.63)
ΔInventory										0.742
										(0.53)
ΔPayable										3.330
										(3.76)
Other Accrual										-3.577
										(-4.58)
Intercept	3.036	2.926	2.890	2.858	3.113	3.690	2.890	3.001	2.798	2.984
	(5.19)	(5.01)	(4.99)	(4.69)	(5.40)	(6.24)	(4.95)	(5.18)	(4.86)	(5.16)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average R^2	0.092	0.092	0.093	0.093	0.091	0.091	0.091	0.091	0.093	0.107

Panel C. Double sorts

This panel reports the results of double sorts. Each row corresponds to one control variable. For each control variable X, we sort all the stocks into quintiles based on X, and then further sort all the stocks into CCC quintiles. The CCC is industry adjusted. The returns of the five CCC-quintile portfolios are then averaged across different quintiles of the control variable X. Reported are the Fama-French five-factor alphas of these averaged CCC portfolios and also the low-CCC minus high-CCC portfolios.

	EW						VW					
	Low CCC	2	3	4	High CCC	Low-High	Low CCC	2	3	4	High CCC	Low-High
AssetGrowth	0.338	0.292	0.125	0.138	-0.107	**0.446**	0.127	0.144	0.003	-0.056	-0.255	**0.382**
	(3.49)	(3.71)	(1.62)	(1.66)	(-1.04)	**(7.71)**	(2.12)	(2.47)	(0.07)	(-0.94)	(-3.51)	**(4.13)**
CBOP	0.288	0.235	0.067	0.129	-0.139	**0.427**	0.105	0.076	-0.075	-0.159	-0.369	**0.474**
	(2.66)	(2.74)	(0.78)	(1.44)	(-1.35)	**(6.48)**	(1.64)	(1.21)	(-1.20)	(-2.48)	(-4.89)	**(5.14)**
Accruals	0.358	0.260	0.130	0.154	-0.111	**0.469**	0.175	0.093	-0.016	-0.099	-0.219	**0.394**
	(3.53)	(3.31)	(1.69)	(1.87)	(-1.08)	**(8.08)**	(3.04)	(1.52)	(-0.26)	(-1.77)	(-3.04)	**(4.11)**
XFIN	0.304	0.215	0.091	0.117	-0.110	**0.415**	0.101	0.055	-0.034	-0.054	-0.228	**0.329**
	(3.18)	(2.66)	(1.14)	(1.40)	(-1.05)	**(6.67)**	(1.66)	(0.93)	(-0.57)	(-0.87)	(-3.17)	**(3.55)**
Operating	0.304	0.168	0.117	0.031	-0.036	**0.340**	0.242	0.021	0.027	-0.155	-0.248	**0.489**
leverage	(2.84)	(2.02)	(1.43)	(0.37)	(-0.32)	**(5.18)**	(3.86)	(0.33)	(0.46)	(-2.28)	(-3.20)	**(5.28)**
OrgCap	0.342	0.280	0.149	0.122	-0.140	**0.481**	0.212	0.065	-0.013	0.022	-0.329	**0.541**
	(3.38)	(3.55)	(1.92)	(1.52)	(-1.37)	**(7.94)**	(2.64)	(1.22)	(-0.20)	(0.36)	(-5.18)	**(6.04)**
ZScore	0.287	0.305	0.146	0.119	-0.067	**0.354**	0.223	0.152	0.137	-0.034	-0.141	**0.364**
	(3.32)	(3.68)	(1.78)	(1.38)	(-0.61)	**(5.73)**	(4.22)	(2.56)	(2.20)	(-0.58)	(-1.86)	**(4.06)**
SUE	0.408	0.255	0.143	0.177	-0.065	**0.473**	0.180	0.020	-0.010	-0.000	-0.202	**0.382**
	(4.30)	(3.36)	(1.97)	(2.27)	(-0.68)	**(7.94)**	(3.39)	(0.37)	(-0.16)	(-0.01)	(-2.93)	**(4.38)**
NOA	0.253	0.204	0.164	0.146	-0.022	**0.275**	0.114	0.029	0.064	-0.015	-0.290	**0.404**
	(2.63)	(2.58)	(2.23)	(1.73)	(-0.20)	**(4.60)**	(2.24)	(0.54)	(1.19)	(-0.25)	(-4.22)	**(4.53)**
AssetTurnover	0.350	0.208	0.174	0.063	-0.044	**0.394**	0.246	0.002	0.029	-0.071	-0.227	**0.473**
	(3.56)	(2.62)	(2.25)	(0.78)	(-0.42)	**(6.54)**	(4.30)	(0.03)	(0.55)	(-1.19)	(-3.39)	**(5.26)**
ProfitMargin	0.304	0.247	0.129	0.172	-0.098	**0.403**	0.082	0.064	-0.059	-0.052	-0.302	**0.383**
	(3.28)	(2.93)	(1.56)	(2.05)	(-1.04)	**(7.20)**	(1.19)	(0.94)	(-0.90)	(-0.77)	(-3.96)	**(4.13)**
ΔReceivable	0.352	0.268	0.150	0.143	-0.160	**0.512**	0.219	0.116	0.025	-0.027	-0.236	**0.455**
	(3.43)	(3.33)	(1.98)	(1.75)	(-1.60)	**(8.49)**	(3.73)	(1.91)	(0.41)	(-0.49)	(-3.35)	**(4.73)**
ΔInventory	0.302	0.269	0.107	0.115	-0.096	**0.398**	0.154	0.123	0.007	-0.111	-0.215	**0.369**
	(3.13)	(3.39)	(1.39)	(1.43)	(-0.95)	**(7.06)**	(2.92)	(2.06)	(0.12)	(-1.89)	(-3.03)	**(4.25)**
ΔPayable	0.366	0.257	0.121	0.134	-0.126	**0.492**	0.200	0.097	-0.030	-0.042	-0.299	**0.498**
	(3.71)	(3.30)	(1.59)	(1.60)	(-1.21)	**(8.05)**	(3.79)	(1.71)	(-0.52)	(-0.73)	(-4.23)	**(5.66)**
Other	0.361	0.237	0.136	0.142	-0.082	**0.444**	0.162	0.085	-0.015	-0.034	-0.186	**0.348**
Accrual	(3.59)	(2.95)	(1.84)	(1.69)	(-0.79)	**(7.45)**	(2.94)	(1.45)	(-0.26)	(-0.60)	(-2.65)	**(3.74)**
Gross	0.344	0.239	0.141	0.155	-0.126	**0.469**	0.133	0.045	0.059	-0.092	-0.219	**0.353**
Profit	(3.38)	(3.03)	(1.87)	(1.88)	(-1.22)	**(7.86)**	(2.71)	(0.82)	(1.13)	(-1.62)	(-3.09)	**(4.05)**
Reported	0.308	0.257	0.096	0.101	-0.180	**0.488**	0.264	0.075	0.021	-0.023	-0.241	**0.505**
SG&A	(2.87)	(2.98)	(1.14)	(1.16)	(-1.67)	**(7.73)**	(4.30)	(1.09)	(0.37)	(-0.40)	(-3.26)	**(5.11)**
R&D	0.401	0.359	0.267	0.202	-0.042	**0.443**	0.169	0.103	0.091	-0.047	-0.280	**0.449**
	(3.91)	(4.26)	(3.32)	(2.38)	(-0.38)	**(6.82)**	(2.82)	(1.63)	(1.59)	(-0.79)	(-4.04)	**(4.79)**
Depreciation	0.301	0.292	0.143	0.109	-0.097	**0.398**	0.225	0.082	-0.001	-0.023	-0.202	**0.427**
	(3.17)	(3.76)	(1.85)	(1.29)	(-0.90)	**(6.62)**	(4.33)	(1.34)	(-0.01)	(-0.39)	(-3.03)	**(4.97)**
Interest	0.298	0.243	0.149	0.121	-0.131	**0.429**	0.188	0.063	0.018	-0.064	-0.254	**0.443**
Expenses	(3.03)	(3.21)	(1.93)	(1.47)	(-1.26)	**(7.21)**	(3.24)	(1.11)	(0.34)	(-1.02)	(-3.61)	**(4.71)**
Tax	0.307	0.233	0.115	0.158	-0.101	**0.408**	0.126	0.026	-0.039	-0.072	-0.289	**0.415**
	(3.33)	(2.83)	(1.45)	(1.90)	(-1.07)	**(7.07)**	(1.93)	(0.41)	(-0.67)	(-1.17)	(-3.89)	**(4.32)**
Other	0.284	0.244	0.093	0.105	-0.143	**0.427**	0.085	0.099	-0.002	-0.075	-0.288	**0.372**
expenses	(2.65)	(2.88)	(1.11)	(1.19)	(-1.34)	**(6.67)**	(1.52)	(1.48)	(-0.04)	(-1.21)	(-3.82)	**(3.98)**

Table 9. The CCC factor

Panel A shows the monthly average returns, standard deviations, and *t*-statistics of the monthly factors. CCC is the CCC factor. MktRf, SMB, HML, RMW and CWA are the Fama-French five factors, and I/A and ROE are the investment factor and profitability factor of Hou, Xue, and Zhang (2015). CBOP is the cash-based operating profitability factor. Panel B reports estimates from spanning regressions. The left-hand side variable is the monthly return on different factors. The explanatory variables are the Fama-French three factors, Fama-French five factors, q-factors, five-factor model using the CBOP factor instead of RMW, or the three factors augmented with the CCC factor.

Panel A. Summary statistics for monthly factor returns

	CCC	MktRf	SMB	HML	RMW	CMA	I/A	ROE	CBOP
Mean	0.255	0.601	0.236	0.282	0.329	0.283	0.356	0.597	0.370
STD	1.244	4.440	2.917	2.872	2.392	1.959	1.849	2.530	1.416
t-statistic	4.46	2.94	1.76	2.14	3.00	3.15	4.19	5.14	5.68

Panel B. Spanning regressions

	CCC				RMW		CMA		I/A		ROE		CBOP	
α	0.279	0.366	0.352	0.256	0.428	0.558	0.206	0.249	0.287	0.320	0.750	0.847	0.442	0.404
	(5.26)	(6.98)	(6.15)	(4.59)	(4.32)	(5.65)	(3.23)	(3.81)	(4.64)	(5.05)	(6.81)	(7.57)	(7.22)	(6.45)
Mktrf	0.040	0.014	0.033	0.030	-0.097	-0.078	-0.098	-0.091	-0.070	-0.065	-0.099	-0.085	0.004	-0.002
	(3.24)	(1.08)	(2.53)	(2.33)	(-4.19)	(-3.45)	(-6.51)	(-6.07)	(-4.85)	(-4.49)	(-3.83)	(-3.29)	(0.28)	(-0.10)
SMB	-0.013	-0.048	-0.025	0.003	-0.291	-0.297	0.055	0.053	-0.015	-0.016	-0.273	-0.277	-0.110	-0.108
	(-0.73)	(-2.53)	(-1.28)	(0.17)	(-8.50)	(-8.96)	(2.49)	(2.41)	(-0.69)	(-0.77)	(-7.15)	(-7.36)	(-5.19)	(-5.13)
HML	-0.159	-0.088		-0.097	0.102	0.027	0.435	0.411	0.407	0.388	-0.106	-0.161	-0.175	-0.153
	(-8.37)	(-3.59)		(-3.78)	(2.86)	(0.75)	(19.00)	(16.85)	(18.38)	(16.42)	(-2.69)	(-3.86)	(-7.97)	(-6.55)
CCC						-0.466		-0.154		-0.118		-0.346		0.137
						(-5.58)		(-2.78)		(-2.20)		(-3.66)		(2.59)
RMW		-0.143												
		(-6.00)												
CMA		-0.129		-0.102										
		(-3.51)		(-2.70)										
I/A			-0.215											
			(-7.01)											
ROE			-0.058											
			(-2.59)											
CBOP				0.099										
				(2.51)										
R^2	0.176	0.254	0.151	0.196	0.223	0.270	0.517	0.523	0.493	0.497	0.138	0.160	0.149	0.159

Table 10. Which components of CCC?

Panel A. Fama-MacBeth regressions

This panel reports the Fama-MacBeth regression results for days inventory outstanding (DIO), days receivables outstanding (DRO), and days payables outstanding (DPO). All are adjusted by the Fama-French 48 industry median. We also analyze the operating cycle which is the sum of DIO and DRO. DIO, DRO, DPO, and operating cycle are all measured in number of years. All the accounting variables including CCC, DIO, DRO, and DPO are winsorized month by month at the 1% level for both tails.

	(1)	(2)	(3)	(4)	(5)
DIO	**-0.222**				**-0.191**
	(-8.06)				**(-6.85)**
DRO		**-0.481**			**-0.401**
		(-6.64)			**(-5.71)**
DPO			**-0.098**		**0.064**
			(-1.89)		**(1.23)**
Operating Cycle				**-0.141**	
				(-7.50)	
Beta	0.098	0.103	0.093	0.095	0.100
	(0.99)	(1.04)	(0.94)	(0.95)	(1.01)
Size	-0.135	-0.134	-0.128	-0.135	-0.137
	(-3.98)	(-3.95)	(-3.77)	(-3.97)	(-4.05)
BM	0.196	0.203	0.192	0.196	0.206
	(3.89)	(4.02)	(3.87)	(3.90)	(4.11)
R_{t-1}	-4.774	-4.791	-4.767	-4.758	-4.798
	(-12.44)	(-12.47)	(-12.45)	(-12.43)	(-12.52)
$R_{t-12,t-2}$	0.608	0.612	0.627	0.607	0.598
	(5.14)	(5.17)	(5.30)	(5.14)	(5.06)
$R_{t-60,t-13}$	-0.047	-0.047	-0.047	-0.047	-0.046
	(-3.01)	(-2.99)	(-3.04)	(-3.03)	(-3.00)
ILLIQ	0.006	0.006	0.006	0.006	0.006
	(2.57)	(2.52)	(2.61)	(2.61)	(2.51)
IVOL	-14.387	-14.407	-14.544	-14.251	-14.318
	(-4.99)	(-5.01)	(-5.09)	(-4.95)	(-5.03)
Asset Growth	-0.005	-0.005	-0.005	-0.453	-0.005
	(-5.76)	(-5.74)	(-5.86)	(-5.69)	(-5.85)
Cash-Based OP	3.870	3.756	3.854	3.797	3.810
	(9.90)	(9.60)	(9.99)	(9.72)	(9.87)
Accruals	0.750	0.441	0.558	0.629	0.626
	(1.40)	(0.83)	(1.07)	(1.18)	(1.20)
Intercept	3.136	3.114	3.031	3.134	3.182
	(6.81)	(6.76)	(6.56)	(6.81)	(6.91)
Average R^2	0.056	0.056	0.056	0.058	0.058

Panel B. Decile portfolio sorts

This table reports the Fama and French five-factor alphas (in percentage), on both an equal-weighted (EW) and value-weighted (VW) basis of portfolios of stocks sorted on industry-adjusted CCC components. Each month, all stocks are sorted into deciles based on one of the four variables: days inventory outstanding (DIO), days receivables outstanding (DRO), days payables outstanding (DPO), and operating cycle. Operating cycle is equal to the sum of DIO and DRO. All are adjusted by the Fama-French 48 industry median. We lag them by two quarters by matching to CRSP returns. We report the Fama-French five-factor alpha for each of the decile portfolios. The right-most column reports the alphas of the Low-minus-High portfolios.

		Low 1	2	3	4	5	6	7	8	9	High 10	Low-High
DIO	EW	0.430	0.107	0.126	0.160	0.527	0.012	0.178	0.104	-0.073	-0.166	**0.596**
Inventory		4.264	1.209	1.381	1.850	4.021	0.140	2.092	1.194	-0.712	-1.344	**(6.89)**
	VW	0.217	0.037	0.043	-0.181	0.390	-0.045	-0.049	-0.068	-0.177	-0.166	**0.383**
		2.138	0.422	0.507	-2.149	3.722	-0.570	-0.688	-0.898	-2.004	-1.407	**(2.37)**
DRO	EW	0.234	0.301	0.343	0.226	0.149	0.115	0.167	0.097	0.058	-0.188	**0.422**
Receivables		2.409	3.185	4.166	2.634	1.729	1.444	1.805	1.065	0.505	-1.435	**(4.39)**
	VW	0.208	0.234	0.118	0.073	-0.016	-0.036	0.008	-0.069	-0.225	-0.294	**0.501**
		1.983	2.655	1.469	0.921	-0.209	-0.483	0.110	-0.956	-2.518	-2.811	**(3.26)**
DPO	EW	0.365	0.295	0.210	0.199	0.123	0.021	0.060	0.053	0.074	0.099	**0.266**
Payables		4.021	3.670	2.596	2.448	1.536	0.242	0.619	0.503	0.626	0.734	**(2.72)**
	VW	0.069	0.140	-0.038	-0.024	0.229	-0.036	0.062	0.046	-0.090	0.026	**0.042**
		0.591	1.428	-0.407	-0.326	2.672	-0.513	0.831	0.578	-1.143	0.321	**(0.28)**
Operating	EW	0.436	0.245	0.265	0.238	0.238	0.187	0.164	0.037	-0.067	-0.236	**0.672**
Cycle		(4.69)	(2.61)	(3.28)	(2.91)	(2.78)	(2.14)	(1.69)	(0.41)	(-0.60)	(-1.89)	**(7.71)**
	VW	0.206	0.199	0.170	-0.041	0.073	0.008	0.013	-0.165	-0.257	-0.325	**0.531**
		(2.03)	(2.17)	(1.89)	(-0.54)	(1.05)	(0.11)	(0.17)	(-1.93)	(-2.96)	(-2.96)	**(3.40)**

Table 11. Funding risk

This table presents the results on the analysis of funding risk. We regress the low-CCC minus high-CCC portfolio return (equal-weighted in Panel A and value-weighted in Panel B) on a funding risk measure and the Fama-French five factors. In column (1) through (7), we consider these funding risk measures: primary dealers' capital ratio factor of He, Kelly and Manela (2017) (both monthly and quarterly), the Adrian, Etula, and Muir (2014) leverage factor, the betting against beta factor (BAB) of Frazzini and Petersen (2014), the change in the noise measure of Hu, Pan, and Wang (2013), the change in the TED spread, and the change in the VIX.

	Panel A. Equal-Weighted Portfolio							Panel B. Value-Weighted Portfolio						
	(1) HKM	(2) HKM Qtr	(3) AEM Qtr	(4) BAB	(5) Noise	(6) TED	(7) VIX	(1) HKM	(2) HKM Qtr	(3) AEM Qtr	(4) BAB	(5) Noise	(6) TED	(7) VIX
Intercept	0.563	1.902	2.088	0.650	0.552	0.551	0.550	0.544	1.999	1.878	0.603	0.554	0.565	0.504
	(6.17)	(5.21)	(5.93)	(7.01)	(4.86)	(3.29)	(5.02)	(3.84)	(4.20)	(4.12)	(4.24)	(3.15)	(5.21)	(2.99)
HKM	**-0.087**	**-0.074**						**-0.059**	**0.051**					
	(-4.09)	**(-1.63)**						**(-1.79)**	**(0.85)**					
AEM			-0.013							0.002				
			(-0.59)							(0.06)				
BAB				-0.045							-0.032			
				(-1.56)							(-0.72)			
ΔNoise					-0.032							-0.065		
					(-0.25)							(-0.32)		
ΔTED						-0.008							-0.005	
						(-1.23)							(-1.23)	
ΔVIX							0.014							0.071
							(0.50)							(1.61)
Mktrf	0.178	0.152	0.064	0.073	0.076	-0.055	0.093	-0.005	-0.120	-0.057	-0.077	-0.043	0.075	0.010
	(5.25)	(2.10)	(1.40)	(3.29)	(2.59)	(-1.32)	(2.74)	(-0.10)	(-1.27)	(-0.97)	(-2.25)	(-0.94)	(2.75)	(0.19)
SMB	-0.105	-0.084	-0.087	-0.081	-0.086	-0.046	-0.086	-0.072	-0.092	-0.091	-0.055	-0.033	-0.088	-0.038
	(-3.22)	(-1.23)	(-1.26)	(-2.42)	(-2.17)	(-0.79)	(-2.26)	(-1.42)	(-1.03)	(-1.01)	(-1.08)	(-0.54)	(-2.32)	(-0.65)
HML	-0.059	-0.133	-0.182	-0.101	-0.156	-0.274	-0.146	-0.165	-0.172	-0.130	-0.194	-0.337	-0.139	-0.286
	(-1.34)	(-1.53)	(-2.19)	(-2.34)	(-2.99)	(-3.56)	(-2.95)	(-2.42)	(-1.52)	(-1.21)	(-2.92)	(-4.16)	(-2.78)	(-3.75)
RMW	-0.284	-0.344	-0.343	-0.256	-0.290	-0.053	-0.291	-0.106	-0.098	-0.098	-0.086	-0.017	-0.297	-0.043
	(-6.95)	(-4.72)	(-4.67)	(-5.79)	(-5.72)	(-0.69)	(-5.95)	(-1.67)	(-1.03)	(-1.03)	(-1.27)	(-0.22)	(-6.05)	(-0.57)
CMA	-0.095	-0.028	-0.001	-0.067	-0.067	-0.136	-0.060	-0.124	-0.088	-0.111	-0.104	-0.096	-0.069	-0.115
	(-1.51)	(-0.24)	(-0.01)	(-1.04)	(-0.89)	(-1.23)	(-0.84)	(-1.26)	(-0.56)	(-0.72)	(-1.05)	(-0.83)	(-0.97)	(-1.04)
Adj-R^2	0.240	0.309	0.298	0.217	0.280	0.107	0.272	0.072	0.074	0.069	0.067	0.120	0.274	0.110
Observations	474	146	146	474	335	359	359	474	146	146	474	335	359	359

Table 12. Earnings prediction

This table reports the Fama-MacBeth regression coefficients of the following regression:

$$E_{i,t} = \alpha + \beta_{Low}LowCCC_{i,t-1} + \beta_{High}HighCCC_{i,t-1} + \beta_1 AT_{i,t-1} + \beta_2 Div_{i,t-1} + \beta_3 DDiv_{i,t-1} + \beta_4 E_{i,t-1} + \beta_5 NegE_{i,t-1} + \beta_6 Acc_{i,t-1} + \varepsilon_{i,t}$$

where $E_{i,t}$ denotes the earnings of firm *i* in quarter *t*. Earnings is defined as cash-based operating profitability. LowCCC and HighCCC indicate the lowest CCC decile and the highest CCC decile, respectively. The CCC is industry adjusted. AT is the natural logarithm of the firm's total assets, Div is dividend paid in the previous year divided by total assets, DDiv is a dummy for dividend payer, NegE is a dummy for firms with negative earnings, and Accruals is accruals computed following Sloan (1996).

	(1)	(2)
LowCCC	**0.106**	**0.109**
	(2.00)	**(2.35)**
HighCCC	**-2.548**	**-1.112**
	(-15.07)	**(-6.19)**
AT		0.304
		(15.22)
Dividend		16.426
		(9.86)
DDiv		-0.115
		(-2.14)
E		14.317
		(14.64)
NegE		-3.078
		(-45.73)
Accruals		16.895
		(25.27)
Intercept	2.502	1.512
	(31.24)	(11.29)
Average R^2	0.003	0.125

Table 13. Earnings announcement returns

This table presents the Fama-MacBeth coefficients for the regressions where the dependent variable is the five-day cumulative abnormal returns around earnings announcement days. The cumulative abnormal return is the raw returns adjusted by size-decile portfolio returns. We run the cross-sectional regression quarter by quarter. Reported are the statistics calculated from the time series of the cross-sectional regression coefficients. The CCC is the industry-adjusted cash conversion cycle, measured in number of years. Other variables are defined in the Appendix.

	(1)	(2)	(3)	(4)	(5)
CCC	**-0.072**	**-0.145**	**-0.135**	**-0.139**	**-0.150**
	(-2.63)	**(-5.12)**	**(-4.76)**	**(-4.94)**	**(-4.84)**
Beta		-0.131	-0.107	-0.099	-0.071
		(-2.28)	(-1.89)	(-1.76)	(-1.28)
Size		-0.113	-0.069	-0.072	-0.079
		(-5.94)	(-4.26)	(-4.39)	(-4.37)
BM		0.204	0.183	0.165	0.149
		(5.25)	(4.72)	(4.27)	(3.65)
R_{t-1}			-0.453	-0.473	-0.384
			(-1.69)	(-1.75)	(-1.44)
$R_{t-12,t-2}$			0.232	0.240	0.225
			(3.11)	(3.16)	(2.79)
$R_{t-60,t-13}$			-0.032	-0.021	-0.035
			(-1.87)	(-1.25)	(-1.87)
ILLIQ			0.024	0.022	0.018
			(1.56)	(1.52)	(1.28)
IVOL			-3.991	-3.483	-3.212
			(-1.40)	(-1.22)	(-1.10)
Asset Growth				-0.250	-0.265
				(-3.82)	(-3.79)
CBOP					1.479
					(3.01)
Accruals					0.130
					(0.20)
Intercept	0.436	2.095	1.491	1.535	1.578
	(8.82)	(8.18)	(6.00)	(6.18)	(5.88)
Average R^2	0.001	0.007	0.018	0.019	0.021

Table 14. Limits to arbitrage

This table presents the results on limits to arbitrage. For each limits-to-arbitrage variable X, we first sort all the stocks into five quintiles based on X except dividend and R&D for which we sort stocks into three groups. A large number of firms have zero dividends or zero R&D. For dividend and R&D, we sort firms into three groups: the first group contains firms with zero dividends (or R&D), and firms with positive dividends (or R&D) are sorted into two equal-sized groups. Then within each X group, we further sort stocks into CCC quintiles and calculate the Fama-French five-factor alpha—on both an equal-weighted (EW) and value-weighted (VW) basis—of low-CCC minus high-CCC portfolios for each X group. The CCC is industry adjusted. The "Large-Small" column reports the difference in the low-CCC minus high-CCC portfolios between the large X quintile and the small X quintile. The "Exp. Sign" column shows the expected sign of the Large-Small column based on limits to arbitrage.

		EW						VW					
	Exp. Sign	Small X	2	3	4	Large X	Large -Small	Small X	2	3	4	Large X	Large -Small
Panel A. Trading frictions and information frictions													
IVOL	+	0.129	0.275	0.471	0.612	0.758	**0.629**	0.135	0.522	0.678	0.465	0.969	**0.834**
		(2.10)	(3.37)	(4.66)	(5.26)	(4.36)	**(3.46)**	(1.23)	(3.47)	(3.58)	(2.02)	(2.93)	**(2.42)**
ILLIQ	-	0.394	0.489	0.537	0.616	0.652	**0.258**	0.348	0.429	0.485	0.542	0.659	**0.311**
		(4.95)	(5.42)	(4.96)	(5.00)	(4.40)	**(1.54)**	(3.43)	(4.73)	(4.27)	(4.06)	(4.33)	**(1.72)**
Age	-	0.780	0.584	0.492	0.319	0.127	**-0.654**	0.594	0.841	0.981	0.442	0.179	**-0.415**
		(5.67)	(4.54)	(4.17)	(3.27)	(1.72)	**(-4.14)**	(2.67)	(3.46)	(5.07)	(2.33)	(1.56)	**(-1.69)**
Analysts	-	0.804	0.589	0.695	0.532	0.327	**-0.476**	0.829	0.608	0.666	0.504	0.308	**-0.522**
		(5.67)	(4.80)	(6.07)	(5.00)	(3.45)	**(-2.72)**	(4.61)	(3.97)	(5.15)	(4.25)	(2.67)	**(-2.57)**
Panel B. Profitability													
CBOP	-	0.840	0.445	0.456	0.207	0.188	**-0.652**	0.707	0.708	0.520	0.155	0.281	**-0.426**
		(4.95)	(3.72)	(4.06)	(1.81)	(1.48)	**(-3.01)**	(2.81)	(3.75)	(3.06)	(0.92)	(1.48)	**(-1.36)**
Panel C. Dividend policy													
Dividend	-	0.557	0.474	0.276			**-0.281**	0.636	0.668	0.002			**-0.633**
		(5.79)	(4.88)	(4.03)			**(-2.50)**	(3.28)	(4.02)	(0.02)			**(-2.97)**
Panel D. Tangibility													
PPE	-	0.683	0.821	0.424	0.454	0.177	**-0.506**	1.001	0.866	0.276	0.382	-0.171	**-1.171**
		(5.45)	(6.99)	(3.71)	(3.88)	(1.50)	**(-2.88)**	(4.40)	(4.43)	(1.55)	(2.44)	(-1.22)	**(-4.27)**
R&D	+	0.373	0.350			0.605	**0.232**	0.260	0.559			0.527	**0.266**
		(5.06)	(3.31)			(4.70)	**(1.57)**	(2.35)	(3.81)			(2.48)	**(1.07)**
Panel E. Gross opportunity													
Abs	+	0.298	0.232	0.421	0.482	0.892	**0.594**	0.127	0.275	0.299	0.626	0.961	**0.835**
(Sales growth)		(2.97)	(2.32)	(3.81)	(4.07)	(6.36)	**(3.49)**	(0.83)	(1.60)	(1.76)	(2.98)	(3.99)	**(2.94)**
XFIN	+	0.296	0.102	0.386	0.618	0.676	**0.380**	0.244	0.417	0.728	0.170	0.917	**0.674**
		(3.32)	(1.02)	(3.39)	(4.93)	(4.45)	**(2.24)**	(1.64)	(2.54)	(3.97)	(0.82)	(3.62)	**(2.36)**
Abs	+	0.138	0.455	0.185	0.550	0.991	**0.853**	0.120	0.132	0.158	0.401	0.845	**0.724**
(Asset growth)		(1.34)	(4.58)	(1.69)	(4.66)	(7.01)	**(5.08)**	(0.73)	(0.78)	(1.03)	(1.91)	(3.81)	**(2.69)**

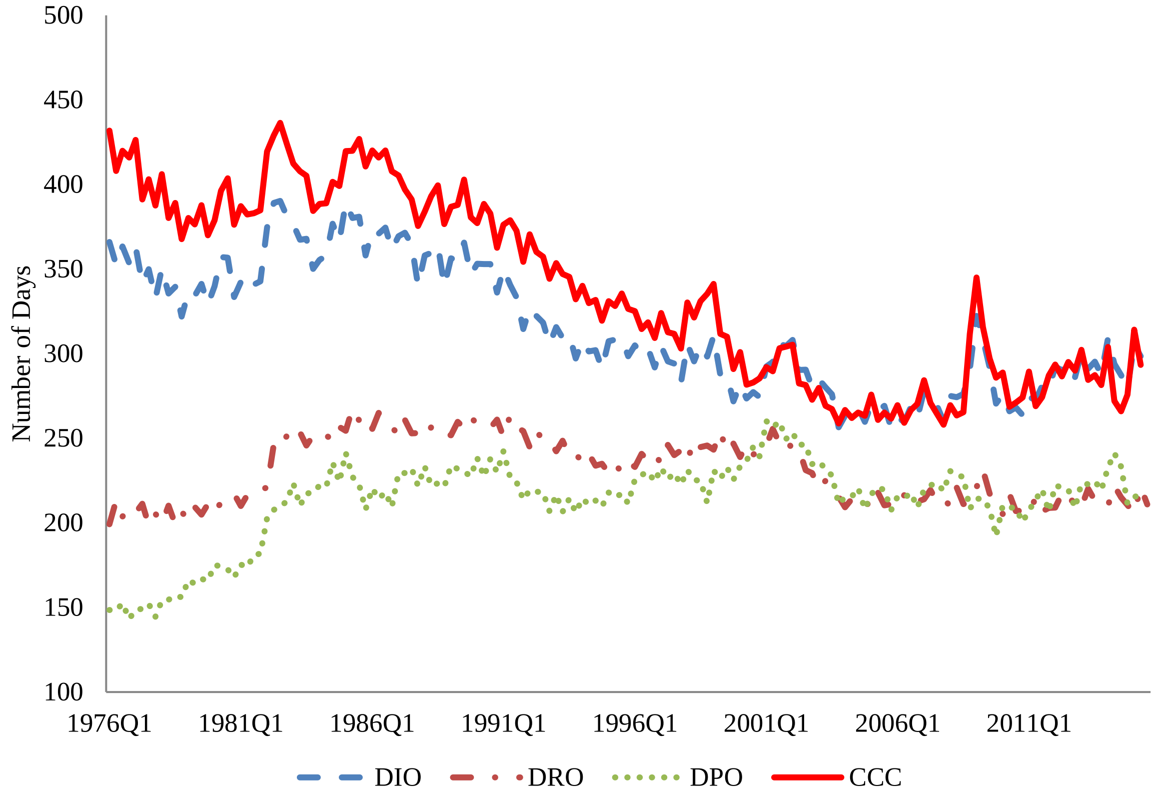
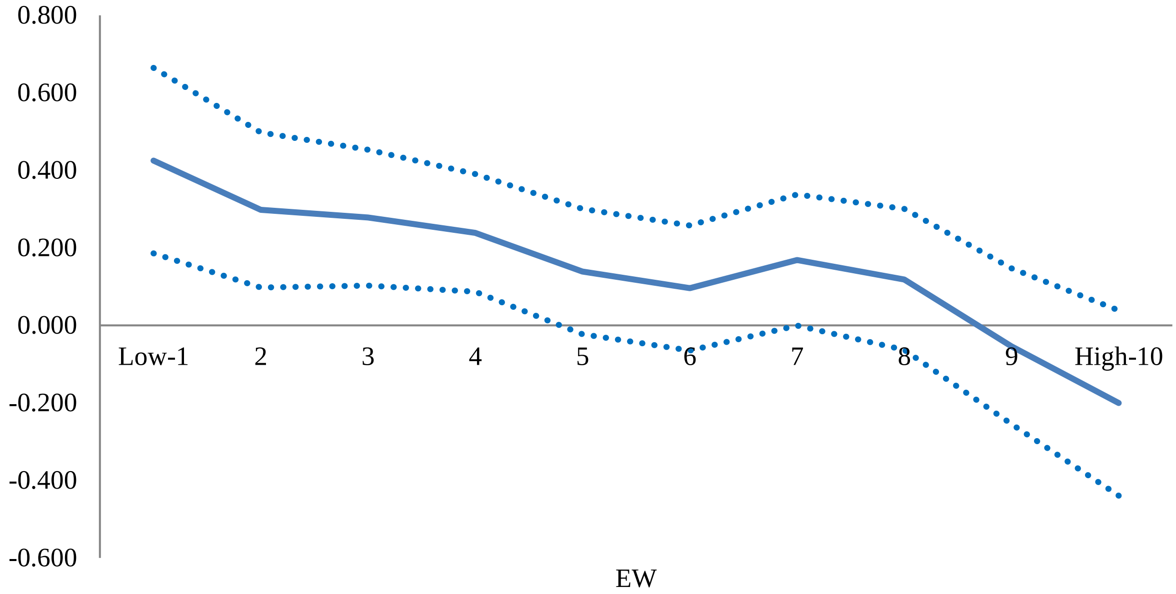


Figure 1. The average CCC over time

This figure reports the time-series average of the cash conversion cycle (CCC) and its components: days inventory outstanding (DIO), days receivables outstanding (DRO), and days payables outstanding (DPO). The sample period is from 1976Q1 to 2015Q2. The CCC, DIO, DRO, and DPO are winsorized at the 1% level for both tails but not industry-adjusted.



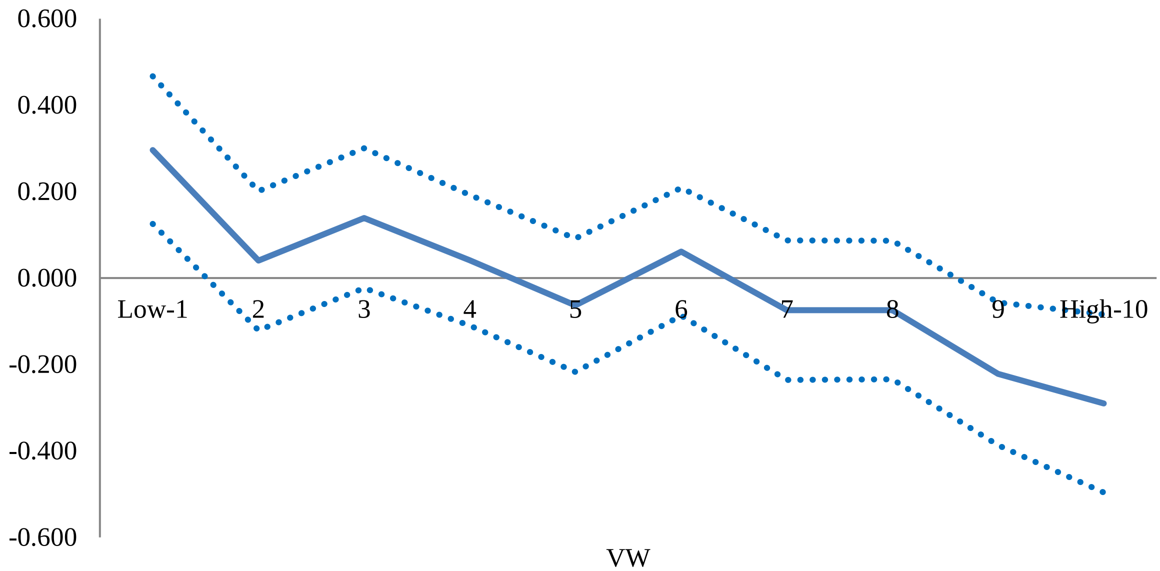


Figure 2. Performance of CCC deciles
Each month, we sort all stocks into deciles by industry-adjusted CCC and record the average return of each decile on both an equal-weighted (EW) and value-weighted (VW) basis. Using the time series of average returns, we compute the Fama-French five-factor alphas for the deciles and plot them in the figure. The top panel is for equal-weighted returns; the bottom panel is for value-weighted returns. The vertical axis is the monthly alpha, in percent; the horizontal axis marks the decile portfolio, from decile 1 (low-CCC) on the left to decile 10 (high-CCC) on the right.

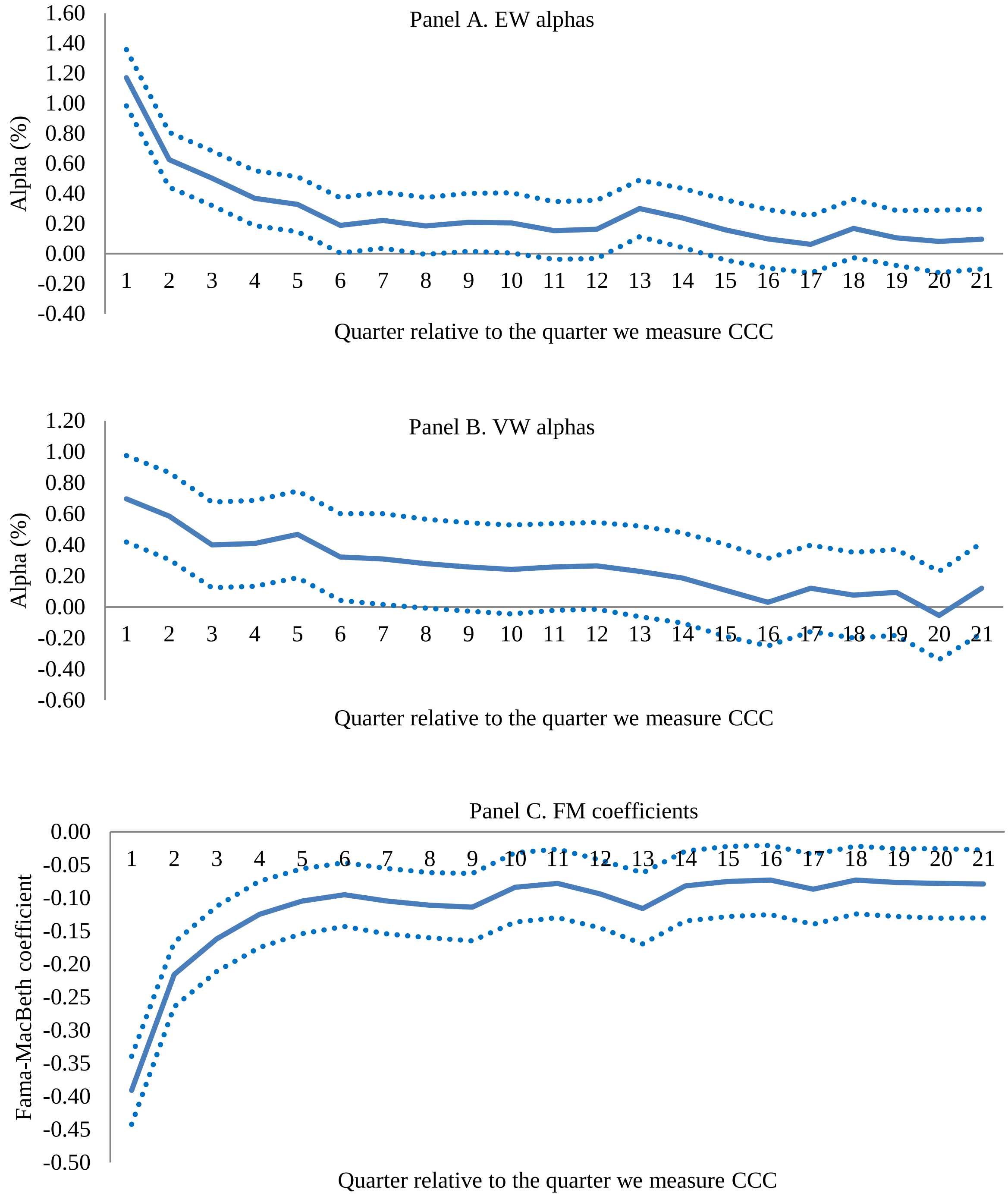


Figure 3. How does the CCC effect decline over time?

This figure plots the Fama-French five-factor alphas for both an equal-weighted (EW, Panel A) and value-weighted (VW, Panel B) basis of a long-short portfolio that buys (shorts) stocks that were in the lowest (highest) industry-adjusted CCC decile at some point in the past. Panel C reports the coefficient on the industry-adjusted CCC from the Fama-MacBeth regressions with the same specification as in column (5) in Table 5. The results for quarter $t+j$ are based on the CCC measured in quarter t. The dotted lines are the 95% confidence intervals (two standard deviations from the solid lines). The results when $j=2$ are the main results reported in the paper.