Equity Market Risk, Working Capital and Accruals Quality

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Abstract

The relation between market risk and fundamentals is not yet completely understood. We investigate the role of working capital ratio (WCR) in the evaluation of market risk measured by Value-at-Risk (VaR). We find a strong positive relation between WCR and VaR. We show that the positive sign of the relation between WCR and VaR is due to a low quality of the accruals component of the WCR. In addition, we find that the WCR gives a significant advantage to investors in estimating portfolio market risk especially during the crisis period.

Keywords: working capital, risk management, Value-at-Risk, financial crises, accruals quality, information risk.

JEL classification: G17, G28, G32, M40, M41.

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1 Introduction

The importance of financial risk management became more visible during and after the subprime mortgage crisis. In particular tools to measure market risk are of paramount importance to the financial survival of investors and ultimately of the financial system itself. Due to its simplicity and ease of interpretation Value-at-Risk (VaR) has been the measure of choice to estimate market risk. Despite its known disadvantages, as the well known lack of coherence as a measure of risk (see Artzner et al. (1999)), VaR has been widely used by the financial industry and regulators. Simple VaR methods as historical simulation and RiskMetrics have been playing a fundamental role in estimating market risk. These methods are of reduced form in the sense that they model risk based on information extracted from past prices alone. Our goal in this article is to show that financial statements information can significantly improve the evaluation of market risk even when using a simple measure of risk as VaR.

There has been interest in the relation between firm or market characteristics and stock returns. Banz (1981) pioneer in this area, shows that firms with lower total market value have on average higher risk adjusted returns. Stattman (1980), and Rosenberg et al. (1985) find a positive relationship between average return and book-to-market for U.S. stocks while Chan et al. (1991) find the equivalent result for the Japanese stock market. Fama and French (1992) include market capitalization and book-to-market when studying stock returns. More recently, Andersen et al. (2012) stress the need for a better understanding of the possible relationships between market risk and macroeconomic fundamentals. Most of this work has concentrated on investigating relations between firm characteristics and stock mean returns.

But given that VaR is a quantile of the returns distribution it is licit to expect that there might also be interesting relations between firm or market variables and market risk. In fact, Halbleib and Pohlmeier (2012), and Dias (2013) show that market capitalization can play a relevant role in risk management, in particular in the estimation of VaR.

The analysis of financial statements information is useful to evaluate the performance of a firm according to different dimensions such as profitability, growth, liquidity and solvency (Beaver et al., 1970; Beaver and Manegold, 1975; Penman, 2013; Ou and Penman, 1989). Liquidity and solvency are important for analysing the risk of a firm. Both measure the ability of a firm to repay its debts when these are due, although liquidity focusses on short-term debt while solvency relates to long-term debt.

Since VaR is computed for short time horizons as one day, 10 days, or at most in some cases one year, we choose liquidity as an accounting measure related to the short-term ability of a firm to repay its debt. Accounting liquidity can be computed from a wide range of financial ratios. Following research on the use of accounting-based risk measures, namely (Beaver et al., 1970; Beaver and Manegold, 1975), we use the working capital ratio (WCR) as a short-term performance measure.

In this paper we answer two questions. First we investigate if there is a relation between the short term liquidity of firms, measured by the WCR, and market risk measured by VaR. Second, we test if taking WCR into account improves the estimation of portfolio VaR.

The WCR is defined as the ratio between working capital and total assets. The working capital is obtained as the difference between current assets (cash and cash equivalents, receivables, inventories and other asset accruals) and current liabilities (payables, short term loans and other liability accruals). Working capital measures the liquidity of a firm as its ability to pay short-term liabilities, when they are due, with the current assets available. To obtain the WCR the working capital is divided by the firm total assets (non-current assets and current assets) in order to take into consideration the size of the firm. Altman (1968) argues that firms with recurrent operating losses will have a lower WCR. Therefore firms with low WCR could face liquidity problems and not be able to repay their short-term liabilities when these are due.

At first we would expect to observe a negative relation between WCR and VaR. Firms with higher WCR would have a lower VaR indicating a lower market risk. However the empirical analysis conducted reveals a positive correlation between WCR and VaR. In light of this counterintuitive result we investigate the reasons behind the positive sign of this relationship. A possible reason could be the existence of estimation errors affecting the quality of the accrual components of the working capital (the numerator of the WCR).

Accounting research has long investigated whether accruals quality is a priced risk factor (Francis et al., 2005; Core et al., 2008; Zhang and Wilson, 2018). Research concluding that accruals quality is a proxy for information risk states that firms with low accruals quality tend to have higher cost of capital. Therefore, these firms are perceived by the market as riskier than firms with high accruals quality (Francis et al., 2005; Hsu et al., 2019). Although high WCR is an indicator of high liquidity, if a firm has high WCR but the accruals included in the working capital have low quality, due to estimation errors, then we would expect that market investors perceive such firm as riskier and thus the VaR is higher. Therefore we would expect that a firm with high WCR including a high proportion of low quality accruals would be perceived as riskier. That would explain the positive correlation between WCR and VaR.

Concerning the estimation of VaR there are different possible approaches. VaR is a quantile of the distribution of the returns on a stock or portfolio. One approach consists of estimating VaR by forecasting the distribution of the returns and then computing the appropriate quantile. Another approach consists of modeling directly the quantile using the so-called regression quantile method introduced by Chernozhukov and Umantsev (2001) and further developed by Engle and Manganelli (2004). The first approach includes non-parametric, semi-parametric and fully parametric models for VaR. The non-parametric approach is the historical simulation introduced by Boudoukh et al. (1998) which consists on estimating VaR as the empirical quantile of the returns distribution. The prime example of a semi-parametric model is the filtered historical simulation (FHS) introduced and developed by Barone-Adesi et al. (1998) and Barone-Adesi et al. (1999). The stock returns are modeled by a time series model, typically a GARCH type model, and then an empirical quantile is computed on the residuals of the filtered returns. RiskMetrics (1996) is a typical example of a fully parametric model as well as the filtered extreme value theory model of McNeil and Frey (2000).

Extensive work has been done that explicitly or implicity compare the performance of different VaR estimation models. Important references include Barone-Adesi et al. (2002), Bao et al. (2003, 2006), Brooks et al. (2005), Kuester et al. (2006) and Pritsker (1997, 2006). From these studies the FHS method stands out as a relatively simple method often outperforming other more sophisticated methods. In addition, Giannopoulos and Tunaru (2005) show that the FHS method has desirable theoretical properties. Hence, in our study we use the FHS method to estimate VaR.

We conduct our study using data of firms from the S&P 500 equity index. We follow Bates et al. (2009) and exclude financial firms and utilities. Financial firms are omitted because their business operating cycle is different from non-financial firms (financial firms do not have to buy inventory and convert it into sales). In addition financial firms have to meet capital requirements imposed by regulators. This means that in this case the WCR does not reflect the firms' ability to meet their short term obligations rendering WCR an unsuitable measure of liquidity. Similarly firms from the utilities sector are excluded in our study because regulatory authorities can impose the level of cash this firms must hold.

Our result shows that the quality of working capital accruals, contained in the WCR, give a significant advantage to investors in estimating portfolio market risk. Indeed, the estimation of portfolio VaR can be improved taking WCR into consideration especially during the financial crisis. These findings have important practical implications for investors who can take advantage of WCR in estimating risk at high probability levels during times of financial constrains when accurate and conservative risk estimates are pivotal for financial survival.

The remainder of the article is organized as follows. Section 2 describes the methodology used for the WCR, on the evaluation of the quality of accruals, the VaR estimation method, and the backtesting methodology. Section 3 presents the data and the in-sample analysis of the relation between WCR and VaR. Section 4 explains the sign of the relation between WCR and VaR. Section 5 presents the results on the role of WCR in the estimation of VaR for financial risk management. Section 6 concludes the article.

2 Methodology

One of the components of the working capital are the accruals. The evaluation of the accruals quality plays an essential role in our study.

2.1 Evaluation of accruals quality

The usefulness of the accounting information in market capital research is strongly affected by the characteristics of the accounting system adopted by the firms. The USA accounting standards (US General Accepted Accounting Principles) require firms to adopt an accrual-basis accounting (in the preparation of their income statement and balance sheet) because it is claimed to provide more accurate information about a firm's business events and better performance measurements than a cash-basis accounting system (FASB, 2010) (see Statement of Accounting Concepts No. 8, FASB 2010, paragraph OB17).

According to the accrual-basis accounting system a firm records business transactions when they occur regardless of the timing of cash inflows or outflow, and earnings are computed matching expenses with their corresponding revenues. Therefore accrual accounting is assumed to overcome both timing and matching problems which characterize cash accounting (Dechow, 1994). Timing problems relate to cash flows that are not simultaneous with the business event yielding those cash flows. For instance, a purchase occurs in the second quarter, but cash is paid in the third quarter. Matching problems arise when cash inflows and cash outflows occurring from a business event do not take place in the same reporting period. For example, cash to acquire plant and equipment is usually spent several reporting periods before the cash inflows received from selling the goods produced using these plant and equipment. As a consequence, these cash outflows and inflows do not match in time.

In order to achieve a matching between expenses and revenues and correct the timing of the cash flows, firms record accrual adjustments. For example when a firm sells on credit it records a revenue and a receivable for the same amount. The receivable represents an accrual that accelerates the recognition of future cash flow in earnings. Therefore accruals can be seen as items that affect the accounting results by shifting or adjusting the recognition of cash flows over time. Moreover, for the purpose of this paper, we must distinguish short-term accruals from long-term accruals (Guay and Sidhu, 2001). Short-term accruals refer to the non-cash items of the working capital, hence called working capital accruals. Examples of this type of accruals are: accounts receivable, inventory, and accounts payable. This type of accruals postpone or anticipate the operating cash flow of one accounting period (such as a fiscal year or a fiscal quarter) and they reverse within one period. On the contrary, long-term accruals affect earnings in the long run and they typically arise from the capitalization process. An example of long-term accruals is the depreciation.

Although the accruals system improves the measurement of a firm's performance, its implementation requires judgements and estimates. These judgements and estimates can contain errors distorting the relevance and reliability of the accounting numbers. For example, if the cash collected from a receivable is less than the amount of the receivable (original estimate), then an entry should record the right amount of cash received and the correction of the estimation error. According to Dechow and Dichev (2002) these estimation errors represent 'noise' that decreases the usefulness and the quality of accruals.

Francis et al. (2005) assume that accruals quality can be used as a proxy for information risk in capital markets. On the basis of this assumption they investigate whether accruals quality is related with cost of debt and equity. They find that firms with lower accruals quality have higher cost of debt and equity, confirming the role of accruals quality as a risky factor. Francis et al. (2005) starts off a debate about the role of accruals quality in assessing firms' risk and even its possible use in the bank sector to evaluate SMEs' risk; see also García-Teruel et al. (2014).

Following the assumption made by Francis et al. (2005), we investigate if the level of accruals quality of the working capital items is a risk factor that can shed light on the positive relationship between WCR and VaR. In order to proceed, we need to define and estimate an adequate measure of accruals quality. Over the last two decades, accounting scholars have developed several definitions and measures of accruals quality related to both short and long-term accruals, separately and jointly; for a comprehensive review see Dechow et al. (2010). However for the accounting variable considered in this paper (working capital), the most appropriate measure of accruals quality is the one suggested by Dechow and Dichev (2002). Their accruals quality measure focuses on short-term accruals and measures how much working capital accruals correspond to cash flow realizations. A weak correspondence is evidence of low accruals quality. Empirically, they measure accruals quality as the standard deviation of the residuals from a firm-specific regression of changes in working capital without cash items (between one year and the previous) on previous, present, and future year operating cash flows. We use the same model specification as Dechow and Dichev (2002) but with quarterly data:

$$\Delta WC_t = b_0 + b_1 \times CFO_{t-1} + b_2 \times CFO_t + b_3 \times CFO_{t+1} + \epsilon_t, \tag{1}$$

where ΔWC_t is the change from $t-1$ to t in the working capital (without cash items), CFO_t is the cash flow from operations at time t, and $b_1, b_3 \in (0,1)$ and $b_2 \in (-1,0)$ are coefficients to be estimated. The error term ϵ_t expresses the variation in the working capital that is not reflected in the cash flows from operations. According to the Dechow and Dichev (2002) model the standard deviation of the residuals provide a proxy for the quality of the accruals. A high standard deviation indicates low quality. Once the standard deviation of the residuals is estimated, we can inspect the relation between this measure of accruals quality and VaR. In Section 4 we show the results of both the specific-firm time series regression and the correlation between accruals quality and VaR.

2.2 VaR estimation method

The $100\alpha\%$ VaR is the negative of the quantile of probability $1-\alpha$ of the returns distribution. In most applications α varies between 95% and 99% but α can also take the value of 99.9% as for instance it is required for operational risk by the Basel II Accord. Formally, for a confidence level $\alpha \in (0,1)$, the $100\alpha\%$ VaR for period $t+h$, conditional on the information available up to time t, is given by

$$\mathrm{VaR}_{t+h}^{\alpha} = -Q_{1-\alpha}(R_{t+h}|\mathcal{F}_t) = -\inf\{r \in \mathbb{R} : P(R_{t+h} \leq r|\mathcal{F}_t) \geq 1-\alpha\}, \tag{2}$$

where R_t is the random variable representing the return in period t, $Q_\alpha(\cdot)$ denotes the quantile of probability α and $\mathcal{F}_t$ represents the information available at time t. Estimating VaR is equivalent to estimating a quantile of the unknown distribution of returns for period $t+h$.

The VaR estimation methods used in this paper are historical simulation and filtered historical simulation (FHS). The historical simulation method (without filtering) uses simply the empirical quantiles obtained from past data. The FHS method was introduced by Barone-Adesi et al. (1998) to compute portfolio risk measures. The most common implementation of the FHS method consist of filtering the returns on stocks with a GARCH type model, introduced by Bollerslev (1986), in order to take into account volatility dynamics and compute VaR based on the empirical distribution of the innovations. Despite its relative simplicity FHS often outperforms more sophisticated fully parametric or (semi-parametric) extreme value theory models; see McNeil and Frey (2000). The good performance of FHS has been documented in the literature in articles where several methods are compared as for instance in Kuester et al. (2006) and Dias (2013).

In order to estimate VaR we assume that the returns can be defined as a location scale process conditional on the set of information available at time t:

$$r_{t+h} = E(R_{t+h}|\mathcal{F}_t) + \epsilon_{t+h} = \mu_{t+h} + \sigma_{t+h}\, z_{t+h}, \tag{3}$$

where μ_{t+h} is the expected return for the period $t+h$ given the information available at time t, σ_{t+h} is the conditional scale, ϵ_{t+h} is an error term and z_{t+h} has a zero location, unit scale probability density function $f_Z(\cdot)$. The $100\alpha\%$ VaR forecast for the period $t+h$ conditional on the information available at time t is then

$$\text{VaR}^{\alpha}_{t+h} = -\left(\mu_{t+h} + \sigma_{t+h} Q_{1-\alpha}(Z)\right), \tag{4}$$

where Q_α is the α quantile of $f_Z(\cdot)$.

Different VaR methods assume different specifications for the conditional location μ_{t+h}, conditional scale σ_{t+h}, and probability density $f_Z(\cdot)$. An outline of the VaR methods used in this study follows.

2.2.1 Historical Simulation

The simplest method of estimating VaR (see for instance Christoffersen (2012)) is to use the empirical quantile of the return distribution. This method is usually called (see Kuester et al. (2006)) the naive historical simulation. The theoretical justification for this estimator is that if we assume that the process of the returns is stationary then the empirical distribution is a consistent estimator of the unobserved future distribution function. This method assumes that both the mean and the scale in model (3) are constant.

In order to define the estimator consider a sample of past ω returns $(r_t, r_{t-1}, \ldots, r_{t-w+1})$ and the ordered sample $(r_{(1)}, r_{(2)}, \ldots, r_{(\omega)})$, where $r_{(1)} \leq r_{(2)} \leq \ldots \leq r_{(\omega)}$ are the so-called ordered statistics. The historical simulation $100\alpha\%$ VaR for period $t+1$ is given by

$$\widehat{\text{VaR}}_{t+1}^{\alpha} = -\hat{Q}_{1-\alpha}(r_t, r_{t-1}, \ldots, r_{t-w+1}) = -r_{([(1-\alpha)\times\omega])} \tag{5}$$

where [.] represents the integer part of a real number. As an example, if we consider a sample of return observations with size $\omega = 1,000$, then the 90% VaR estimate is the negative of the 100-*th* sample statistic, $\widehat{\text{VaR}}_{t+1}^{0.9} = -r_{(100)}$.

A more sophisticated approach consists of using the empirical distribution $f_Z(\cdot)$ in model (3) and equation (4). This method is known as filtered historical simulation.

2.2.2 Filtered historical simulation (FHS)

In this study we also use a FHS method where the location and scale in equation (3) are time varying by considering a conditional mean function of past information described by an ARMA(p, q) model of the form

$$\mu_t = \mu + \sum_{i=1}^{p} \phi_i (r_{t-i} - \mu) + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}, \tag{6}$$

where $\phi(z) = 1 - \phi_1 z - \ldots - \phi_p z^p$ and $\theta(z) = 1 - \theta_1 z - \ldots - \theta_q z^q$ have no common roots and no roots inside the unit circle. We use a time varying scale parameter following a GARCH(r, s) process

$$\sigma_t^2 = c_0 + \sum_{i=1}^{r} c_i \epsilon_{t-i}^2 + \sum_{j=1}^{s} d_j \sigma_{t-j}^2, \tag{7}$$

where $c_0 > 0$, $c_i \geq 0$, $d_j \geq 0$ as introduced in Bollerslev (1986).

After filtering the data the empirical quantile is calculated from the filtered standardized residuals $z_t = (r_t - \mu_t)/\sigma_t$. The conditional VaR estimate is then obtained by replacing the empirical quantile in equation (4).

2.3 Testing the performance of the VaR model

Using the methods described in the previous section applied to a rolling window of observations of size w we obtain sequences of out-of-sample VaR estimates $\{\widehat{\text{VaR}}_t^{\alpha}\}_{t=\omega+1,\ldots,T}$. Next we test the quality of these VaR forecasts. We have to compare the ex-ante VaR forecasts with the ex-post realized returns. This exercise is called backtesting and we follow here the procedure in Christoffersen (1998). In the case where the VaR estimates are in sample the performance of the VaR model can be equally evaluated with the tests described in this section.

Assume that we are using daily returns. Given $100\alpha\%$ VaR forecasts we would expect to observe $100(1-\alpha)$ return losses larger than the forecasted VaR every 100 days. The losses larger than the forecasted VaR are called violations.

Consider a sequence of past VaR forecasts $\{\widehat{\text{VaR}}_t^{\alpha}\}_{t=\omega+1,\ldots,T}$ and a sequence of realized returns $\{r_t\}_{t=\omega+1,\ldots,T}$. In order to implement Christoffersen's backtesting procedure we start by defining the hit sequence $\{I_t\}_{t=1+\omega,\ldots,T}$ of VaR violations where

$$I_t = \begin{cases} 1 & \text{if} \quad r_t < -\text{VaR}_t, \\ 0 & \text{if} \quad r_t \geq -\text{VaR}_t. \end{cases} \tag{8}$$

We expect VaR violations to be independent and uniformly spread through time. The implication is that accordingly I_t will have a Bernoulli distribution with parameter $1-\alpha$, where α usually varies between 95% and 99% depending on the confidence level required for the VaR.

2.3.1 Testing the unconditional coverage

The simplest test checks if the percentage of violations is significantly different from the corresponding VaR level $1-\alpha$. This procedure is called the unconditional coverage test.

Denote the number of zeros in the hit sequence by T_0, and the number of ones by T_1. We call $\hat{\pi}$ the observed ratio of violations, $\hat{\pi} = T_1/T$. A likelihood ratio test is given by

$$\mathrm{LR}_{\mathrm{uc}} = -2\ln\left[L(1-\alpha)/L(\hat{\pi})\right], \tag{9}$$

where $L(\cdot)$ is the likelihood function of an iid Bernoulli sequence. Replacing with the appropriate function we obtain the expression for the likelihood ratio test

$$\mathrm{LR}_{\mathrm{uc}} = -2\ln\left[\alpha^{T_0}(1-\alpha)^{T_1}/\left\{(1-T_1/T)^{T_0}(T_1/T)^{T_1}\right\}\right] \overset{a}{\sim} \chi^2_1, \tag{10}$$

which asymptotically has a chi-square distribution with one degree of freedom.

2.3.2 Testing the independence of the violations

The unconditional coverage test checks if the number of violations is what we would expect given a level α for the VaR. But given that financial returns often show volatility clusters, VaR violations are also likely to cluster over time. This is an important fact. It is more dangerous for the financial stability of a portfolio to have ten VaR violations during two weeks than to have the same ten violations occurring over a period of one year. Hence, it is relevant to test the hypothesis of independence of the VaR violations.

The Christoffersen (1998) test of independence for VaR violations assumes, under the hypothesis of dependence, that the hit sequence can be described by a first-order Markov process with transition probability matrix

$$\Pi_1 = \begin{bmatrix} 1-\pi_{01} & \pi_{01} \\ 1-\pi_{11} & \pi_{11} \end{bmatrix}, \tag{11}$$

where π_{11} is the probability that tomorrow's return is a violation given that today is a violation, and π_{01} is the probability that tomorrow's return is a violation given that today is not a violation.

Given a sample of size T the likelihood function of the first-order Markov process is

$$L(\Pi_1) = (1-\pi_{01})^{T_{00}}\pi_{01}^{T_{01}}(1-\pi_{11})^{T_{10}}\pi_{11}^{T_{11}}, \tag{12}$$

where T_{ij}, $i, j = 0, 1$, is the number of observations in the hit sequence with a j following an i. The maximum likelihood estimates of the transition probabilities are

$$\hat{\pi}_{01} = \frac{T_{01}}{T_{00}+T_{01}} \qquad \text{and} \qquad \hat{\pi}_{11} = \frac{T_{11}}{T_{10}+T_{11}}.$$

Given a sample of returns it can happen that $T_{11} = 0$. In this case the likelihood function is simply

$$L(\hat{\Pi}_1) = (1-\hat{\pi}_{01})^{T_{00}}\,\hat{\pi}_{01}^{T_{01}}. \tag{13}$$

Under the null hypothesis of independence $\pi_{01} = \pi_{11} = \pi$ and the transition matrix is

$$\hat{\Pi} = \begin{bmatrix} 1-\hat{\pi} & \hat{\pi} \\ 1-\hat{\pi} & \hat{\pi} \end{bmatrix}, \tag{14}$$

where $\hat{\pi} = T_1/T$ is the estimator for the ratio of violations as in the unconditional coverage test. The likelihood function in the case of independence is then given by

$$L(\hat{\Pi}) = (1-\hat{\pi})^{T_{00}+T_{10}}\,\hat{\pi}^{T_{01}+T_{11}}. \tag{15}$$

The likelihood ratio

$$\mathrm{LR}_{\mathrm{ind}} = -2\ln\left[L(\hat{\Pi})/L(\hat{\Pi}_1)\right] \overset{a}{\sim} \chi^2_1 \tag{16}$$

can be used to test the independence hypothesis that $\pi_{01} = \pi_{11}$. The likelihood ratio has an asymptotic chi-square distribution with one degree of freedom.

2.3.3 Testing the conditional coverage

Christoffersen (1998) tests simultaneously if the number of violations is correct and if the VaR violations are independent. This means testing if $\pi_{01} = \pi_{11} = 1-\alpha$. Christoffersen uses the likelihood ratio test

$$\mathrm{LR}_{\mathrm{cc}} = -2\ln\left[L(1-\alpha)/L(\hat{\Pi}_1)\right] \overset{a}{\sim} \chi^2_2 \tag{17}$$

which has an asymptotic chi-square distribution with two degrees of freedom. $L(1-\alpha)$ is the same as the likelihood used in equation (9). In practice it is worth noting that

$$\mathrm{LR}_{\mathrm{cc}} = \mathrm{LR}_{\mathrm{uc}} + \mathrm{LR}_{\mathrm{ind}}, \tag{18}$$

the conditional coverage likelihood ratio test statistic is the sum of the two likelihood ratios from the unconditional coverage and independence tests.

2.3.4 The three color scheme from Basel II

In practice VaR models are classified by the regulators according to a three color scheme devised by the Basel Committee on Banking Supervision (1996). According to this criteria a VaR model is acceptable if it falls in the "green zone", it is disputable if it falls in the "yellow zone" and it is seriously flawed if it belongs to the "red zone".

The color classification of a VaR model is a function of its number of violations. A model is in the green zone if the number of violations of the 99% VaR is below the 95% quantile of a binomial distribution with probability of success 0.01. The model is in the yellow zone if the number of violations is between the 95% and the 99.99% quantiles of the same binomial distribution. A model is classified in the red zone if the number of violations is above the 99.99% quantile. We add this classification to the backtesting procedure in our study in order to know how the models perform to the eyes of the regulators.

According to the colors criteria from the regulator point of view the smaller the number of violations the better the model is. That is not necessarily the case from the financial institution point of view. A number of violations much smaller than the expected number αT means that the VaR is being overestimated, the regulatory capital is overestimated and there is an economic cost from the loss of investment opportunity on the excessive regulatory capital.

3 Data and the relation between WCR and VaR

We consider the firms included in the S&P 500 equity index. Firms from the financial and utilities sectors are excluded resulting in a sample with 387 firms. The sample covers the period from January 2, 1998 to June 30, 2015. The data, collected from Bloomberg, are quarterly observations of working capital and total assets, and daily stock prices for each firm. The ratio between working capital and total assets gives the observations on WCR. Table 1 reports the summary statistics of the daily logarithmic returns on the 387 firms grouped by WCR. Firms are split into ten groups according to their WCR ranking. For

Table 1: Summary statistics for the WCR and returns by group.

Group	WCR Mean	WCR Std. Dev.	Returns (%) Mean	Returns (%) Std. Dev.	Returns (%) Skewness	Returns (%) Kurtosis	VaR Mean	VaR Std. Dev.
Lower Decile	-0.0595	0.0736	0.0286	2.2854	-1.020	40.07	2.886	1.821
2nd Decile	0.0007	0.0460	0.0272	2.2755	-0.698	37.87	2.957	1.855
3rd Decile	0.0390	0.0525	0.0278	2.3093	-0.215	14.65	2.947	1.728
4th Decile	0.0840	0.0642	0.0348	2.2511	-0.565	22.35	2.911	1.663
5th Decile	0.1238	0.0789	0.0236	2.5017	-0.905	32.18	3.143	1.888
6th Decile	0.1716	0.0866	0.0364	2.3029	-0.642	23.86	2.917	1.718
7th Decile	0.2227	0.0855	0.0392	2.6730	0.063	79.97	3.269	2.041
8th Decile	0.2708	0.0931	0.0428	2.7641	2.102	135.0	3.382	1.974
9th Decile	0.3367	0.1251	0.0579	2.8918	0.843	65.19	3.535	2.205
Upper Decile	0.5107	0.1505	0.0588	3.1724	0.016	18.45	3.960	2.308
All stocks	0.1688	0.1912	0.0377	2.5608	0.086	54.43	3.193	1.959

Notes: Summary statistics of the WCR, daily returns (in percentage), and 95%VaR on ten groups and for all the stocks. The data covers the period from January 2, 1998 to June 30, 2015. The values of kurtosis listed are values for the excess kurtosis.

instance, the 10% of firms with lower average WCR are in group one (lower decile), and the 10% of firms with higher average WCR are in group ten (upper decile).

We observe that the mean return increases with WCR and so it does the standard deviation. This confirms the idea that firms with higher liquidity produce higher mean returns but with a higher variance. It is also interesting that firms in the lower WCR deciles have negative return skewness while firms in the upper deciles have positive skewness. The returns excess kurtosis is extremely high especially for firms in deciles seven, eight and nine.

By construction the average WCR increases with the WCR group but we observe that the variance within each group also increases with the decile. The values of VaR listed in Table 1 are in sample estimates computed using the historical simulation method at the 95% probability level. For each firm and quarter we estimate the 95%VaR. The average VaR for each group also increases with the decile of WCR as well as its variance. It is then interesting to compare WCR with VaR. Figure 1 has the scatter plot of the pairs WCR and 95%VaR for each firm.

It has been shown that economic recessions have an effect on firm and market volatility;

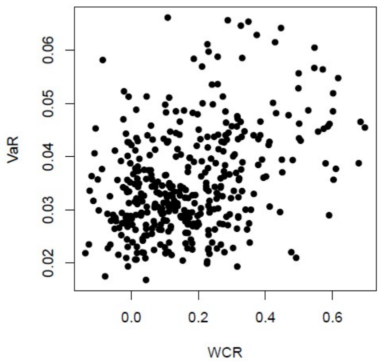

Figure 1: WCR versus 95%VaR for each of the 387 firms in the sample. The WCR and VaR are based on a sample covering the period from January 2, 1998 to June 30, 2015.

Table 2: The relation between WCR and VaR.

Period	(WCR,90%VaR)	(WCR,95%VaR)	(WCR,99%VaR)
1/1998 - 2/2001 (dotcom bubble)	0.565	0.565	0.503
3/2001 - 11/2001 (dotcom crash)	0.482	0.476	0.414
12/2001 - 11/2007 (before subprime crisis)	0.437	0.418	0.396
12/2007 - 6/2009 (subprime mortgage crisis)	0.075	0.074	0.068
7/2009 - 6/2015 (after subprime crisis)	0.129	0.138	0.162
All sample period	0.352	0.351	0.348

Notes: Linear correlation between WCR and VaR observed for each of the 387 firms in the sample during periods of economic expansion and contraction.

see Schwert (1989) and Bloom et al. (2012). Hence, we split the sample into different periods according to the dates published by the NBER Business Cycles Dating Committee[1]. The correlation between WCR and VaR for the different time periods at the probability levels of 90%, 95%, and 99% is listed in Table 2. We find that there is a strong positive relation between WCR and VaR. From the results we observe that the correlation between WCR and VaR decreases over time until the subprime mortgage crisis, being much lower during this period. After June 2009 the relation becomes stronger again suggesting a possible structural change in the negative trend observed in the correlation between WCR and VaR before the subprime crises.

WCR is a measure of liquidity of the firm as it reveals the ability of the firm to meet its

[1]Available at `http://www.nber.org/cycles.html`

short term obligations. Hence, our results seem to indicate that firms with higher liquidity are risker in the sense that their stock prices are more prone to suffer large losses. Given that the positive relation between WCR and VaR found is so strong we proceed in the next section investigating this puzzling result.

4 The positive relation between WCR and VaR

In order to understand why WCR and VaR are positively correlated we have to analyse the accruals component of the WCR, more specifically we have to investigate the quality of these accruals. In Section 2.1 we introduce the methodology used in this section to evaluate the accruals quality. Recall that we have to first regress the cash flows of a firm on the non-cash working capital for each firm, and then look at the dispersion of the residuals.

Table 3: Summary statistics

Panel A: Descriptive Statistics					
	Mean	SD	Lower quartile	Median	Upper quartile
Cash flow from operations (CFO)	0.035	0.037	0.016	0.031	0.048
Change in working capital (ΔWC)	0.002	0.028	-0.009	0.001	0.012
Total assets (in millions)	19,990	47,194	3,081	7,655	18,940
Panel B: Pearson coefficient of correlation					
	CFO_{t-1}	CFO_t	CFO_{t+1}		
ΔWC_t	0.152*	-0.657*	0.220*		
CFO_{t-1}		0.098*	0.201*		
CFO_t			0.096*		

Notes: Summary statistics of the variables used to estimate the accruals quality. Cash flow from operations (CFO), and change in working capital (ΔWC) are both divided by average total assets. The data consist of quarterly observations of each variable for each of the 387 firms covering the period from January 1, 1998 to June 30, 2015. SD stands for standard deviation.
* Significant at the 0.0001 level.

Panel A in Table 3 shows the descriptive statistics of the variables used in measuring the accruals quality. The data on the accounting variables (cash flows from operations, change in working capital without cash items, and total assets) were obtained by fiscal quarter from

Bloomberg covering the period between January 1, 1998 and June 30, 2015. We are interested in using WCR to improve the estimation of VaR which typically has to be computed for short time horizons. Hence, although previous research estimates accruals quality mostly on a yearly basis, we conduct a quarterly estimation. This is the shortest period of time on which firms have to report and it is more appropriate in the context of our research. In order to control for firm size effect, all the variables are scaled by the average total assets which is also in line with our liquidity ratio WCR. The descriptive statistics reported in Table 3 are consistent with those obtained in related literature where the same variables are used (Sloan, 1996; Dechow, 1994; Barth et al., 2001; Dechow and Dichev, 2002). The linear correlations between the variables used in the regression are provided in Panel B of Table 3. All the correlations are highly significant. We observe that the correlation between change in working capital and past and future cash flows is positive, while the correlation with the concurrent cash flows is negative. These results are in line with previous findings and theoretical assumptions about the properties of cash flows and accruals (Barth et al., 2001; Dechow, 1994).

Table 4 shows the results of fitting the Dechow and Dichev (2002) model, specified in equation (1), to the quarterly data of the 387 firms in our sample. Panel A presents the results from the firm-specific regressions and panel B exhibits the results from the pooled linear regression. The average of the results from the firm level regressions agrees with the results obtained from the pooled model. Indeed their adjusted R square is very close.

Focusing on the mean value of the coefficients, their signs across the firm specific and pooled regression are the same. These observations are in line with Dechow and Dichev (2002) results and theoretical assumptions. The current cash flow from operations negatively

Table 4: Regression of ΔWC on lagged cash flows from operations

Panel A: Firm-specific regressions				
	mean	Lower quartile	Median	Upper quartile
Intercept	0.013	0.004	0.012	0.021
t-stat	3.431	1.021	2.569	5.080
p-value	0.175	*0.000*	*0.012*	0.234
b_1	0.082	-0.002	0.075	0.166
t-stat	1.144	0.028	0.978	2.184
p-value	0.304	*0.027*	0.204	0.529
b_2	-0.621	-0.816	-0.660	-0.439
t-stat	-9.737	-12.550	-8.072	1.699
p-value	*0.021*	*0.000*	*0.000*	*0.000*
b_3	0.157	0.042	0.128	0.250
t-stat	2.001	0.577	1.807	3.200
p-value	0.231	*0.002*	*0.068*	0.412
Adjusted R^2	0.547	0.325	0.584	0.785
SD Residuals	0.012	0.007	0.010	0.015

Panel B: Pooled regression				
	Intercept	b_1	b_2	b_3
Coefficient	0.008	0.126	-0.530	0.201
t-statistic	38.350*	35.840*	-154.722*	55.836*
Adjusted R^2	0.548			
SD Residuals	0.019			

Notes: Results from the regressions of the change in working capital on past, current, and future cash flows from operations as per the Dechow and Dichev (2002) model using the firm quarterly observations.
* Significant at the 0.0001 level.

effect the change in working capital. Assuming constant earnings, an increase in the current cash flows is linked to a decreasing amount of the working capital. For example, assuming constant earnings, if a firm can shift payments to the future and anticipate the collection of receivables, it can increase the amount of cash flows and reduce the accruals recorded in the working capital. On the contrary past and future cash flows positively affect the current change in the working capital. This result is consistent with the theoretical expectations. For instance, a firm with high cash flows in the past is expected to have a decrease in the working capital due to both a lower amount of receivables to be collected and a higher amount of payables.

As for the significance of the coefficients, we observe that the concurrent cash flows from operations have a highly significant impact on the change in the working capital. On the contrary, the effect of past and future cash flows on the current working capital is significant at 5% level only for 25% of the firms in the sample.

Looking at the magnitude of the coefficients, we can observe that they are all in the correct range according to the theory. The boundary values of 1 for past and future cash flows, and -1 for concurrent cash flows occur in the absence of accruals and cash flow estimation errors. Our estimates are different from the boundary values, again in line with previous research, showing the presence of estimation errors affecting the relationship between cash flows and accruals over time.

From the firm specific regressions we obtain the standard deviations of the residuals for each firm, that according to the Dechow and Dichev (2002) model are a proxy for the accruals quality. The higher are the standard deviations, the lower is the quality of the accruals.

Table 5 shows the quartiles of the standard deviation of the residuals. The correlation

Table 5: Quality of the accruals

	minimum	lower quartile	median	upper quartile	maximum
SD of residuals	0.001286	0.007466	0.010503	0.014944	0.090560

Notes: Quartiles of the standard deviation of the residuals obtained from regressing the change in working capital on the cash flows for each firm. The higher the standard deviation of the residuals the lower the quality of the accruals.

between the standard deviation of the residuals, which measures the accruals quality, and the average WCR per firm is 36.95%. Hence, firms with high average WCR have low quality of accruals in their working capital. As a consequence, the correlation between the standard deviation of the residuals and the average VaR per firm is 30.70%. We can observe in Figure 2 the plot of the standard deviation of the residuals against the average VaR per firm.

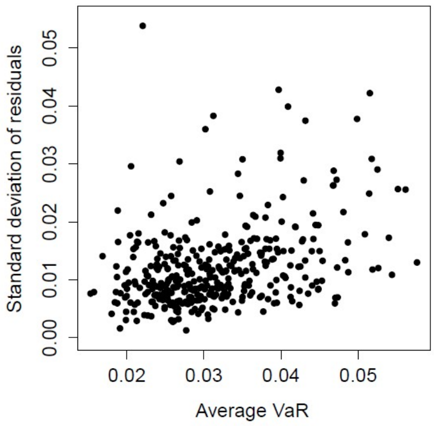

Figure 2: Standard deviation of the residuals, measure of accruals quality, versus the 95%VaR for each of the 387 firms in the sample.

The relation between the quality of accruals and market risk is undeniable. This result is consistent with previous research from Francis et al. (2005) who found a positive correlation between low accruals quality and risk. Therefore we argue that the apparently puzzling positive relationship that we found between WCR and VaR can be explained by the lower quality of the accruals. Given this fact it could be suggested that we use the quality of the accruals as a risk management tool instead of WCR. But while the data to compute WCR is readily available, the estimation of the accruals quality requires more data and the estimation of the Dechow and Dichev (2002) model which can introduce estimation errors. Hence, we investigate in the subsequent sections how WCR can be useful for risk management by improving the estimation of VaR.

5 Estimation of VaR

In this section we investigate the importance of considering WCR in the estimation of market risk measured by VaR from a risk management point of view. The 387 firms in the data sample are grouped into ten equally weighted portfolios according to the deciles of WCR. For instance, the firms with WCR between the 10% and the 20% WCR deciles constitute portfolio two. Given that recessions have an effect on firm volatility and possibly also on VaR we consider separately the periods of economic recession and expansion listed in Table 2.

We compute the VaR of the daily logarithmic returns for the ten WCR portfolios and for the equally weighted portfolio with all the firms. For each portfolio we compute the one day ahead (out of sample) VaR using a rolling window of $1,000$ past returns. In order to incorporate volatility time effects we use a filtered historical simulation VaR estimation method. This method of estimating VaR has shown a good performance when compared with other methods; see for instance Kuester et al. (2006) and Dias (2013). Also in line with these references we filter the returns using an AR(1)-GARCH(1,1) model. This model has been commonly used to filter daily returns on stocks from the S&P 500. The results in Table 1 show that the returns have skewness and large excess kurtosis. Hence, we use a skewed Student-t distribution to model the innovations of the AR-GARCH model. Using the filtered historical simulation method we obtain a sequence of out of sample VaR estimates for each portfolio that can be backtested in relation to the observed corresponding portfolio returns.

The $100\alpha\%$ VaR estimates should produce, on average, $100(1-\alpha)\%$ of return violations. Here we estimate VaR at the probability levels of 90%, 95%, and 99%. In the main text we present and analyze the results of the 99% VaR. We report the results for the 90% and 95% VaR in appendix.

Table 6 reports the results from estimating the 99%VaR and corresponding backtesting for the different time periods. $\overline{\text{VaR}}$ denotes the average VaR estimated in each portfolio. For the percentage number of violations reported the cases which fall in the green, yellow and red Basel II color classification have normal, italic and bold type face respectively. The backtesting results LR_{uc} are the p-values obtained from the unconditional coverage test from equation (10). LR_{ind} and LR_{cc} are the p-values of the independence test (see equation (16)) and conditional coverage test (see equation (18)) respectively.

We observe that before the crisis the average VaR increases with the WCR decile portfolio. During the crisis there is no significant trend but after the crisis the portfolios in the higher deciles have again higher average VaR. Not surprisingly during the crisis the average VaR is much higher than before or after the crisis. It is also interesting to remark that the average VaR after the crisis is higher than before the crisis for all the portfolios except for the portfolio above the tenth decile. Hence, the portfolios in our sample are risker than they were before the subprime mortgage crisis. The percentage of violations is very close to the target of 1% for all the portfolios before and after the crisis. During the crisis the model

Table 6: Performance of Filtered historical simulation VaR method

Decile	Lower	2nd	3rd	4th	5th	6th	7th	8th	9th	Higher	All
					Before the subprime mortgage crisis						
$\overline{\text{VaR}}$	2.12	2.27	2.28	2.11	2.47	2.33	2.47	2.65	2.74	3.33	2.28
% Viol.	1.24	1.17	0.96	1.10	0.96	0.82	1.10	0.89	1.10	0.96	1.38
LR_{uc}	0.37	0.51	0.89	0.69	0.89	0.49	0.69	0.68	0.69	0.89	0.16
LR_{ind}	0.48	0.18	0.12	0.53	0.58	0.64	0.16	0.61	0.53	0.89	0.44
LR_{cc}	0.52	0.34	0.29	0.76	0.85	0.71	0.35	0.81	0.76	0.85	0.28
					During the subprime mortgage crisis						
$\overline{\text{VaR}}$	5.58	5.12	5.27	4.96	5.37	4.67	5.04	5.06	4.86	5.74	5.12
% Viol.	1.58	*2.04*	1.58	*2.04*	*2.49*	*2.04*	*2.49*	*2.49*	*2.04*	1.36	*2.49*
LR_{uc}	0.25	0.05	0.25	0.05	0.01	0.05	0.01	0.01	0.05	0.03	0.01
LR_{ind}	0.61	0.51	0.61	0.51	0.43	0.51	0.43	0.43	0.51	0.66	0.43
LR_{cc}	0.45	0.12	0.45	0.12	0.02	0.12	0.02	0.02	0.12	0.69	0.02
					After the subprime mortgage crisis						
$\overline{\text{VaR}}$	2.80	2.93	2.81	2.82	3.01	2.95	2.94	2.92	2.91	3.20	2.84
% Viol.	1.12	1.12	1.05	1.19	0.99	1.19	0.99	1.05	1.19	1.12	1.05
LR_{uc}	0.63	0.63	0.81	0.46	0.97	0.46	0.97	0.81	0.46	0.63	0.81
LR_{ind}	0.52	0.52	0.54	0.49	0.57	0.49	0.57	0.54	0.49	0.52	0.54
LR_{cc}	0.72	0.72	0.81	0.60	0.85	0.61	0.85	0.81	0.60	0.72	0.81
					Full sample period						
$\overline{\text{VaR}}$	2.87	2.93	2.90	2.79	3.09	2.75	3.01	3.08	3.09	3.59	2.90
% Viol.	1.23	1.26	1.08	1.26	1.17	1.14	1.23	1.17	1.26	1.08	1.38
LR_{uc}	0.18	0.13	0.61	0.13	0.31	0.39	0.18	0.31	0.13	0.61	0.03
LR_{ind}	0.29	0.55	0.41	0.28	0.32	0.33	0.53	0.32	0.28	0.36	0.24
LR_{cc}	0.24	0.27	0.62	0.18	0.36	0.44	0.34	0.36	0.18	0.57	0.05

Notes: The table reports the results on backtesting 99%VaR estimates obtained by the filtered historical simulation method across the different portfolio deciles of WCR using a rolling window of 1,000 days. $\overline{\text{VaR}}$ denotes the average VaR. The percentage number of violations which fall in the green, yellow and red Basel II color classification have normal, italic and bold type face respectively. LR_{uc} are the p-values obtained from the unconditional coverage test in equation (10). LR_{ind} and LR_{cc} are the p-values of the independence test (see equation (16)) and conditional coverage test (see equation (18)) respectively.

underestimates VaR and the estimates follow in the Basel II yellow category for portfolios two to nine. The estimates for all the portfolios before and after the crisis fall in the green category. This shows the good performance of the filtered historical simulation method. The unconditional coverage test produces very high p-values before the crisis, after the crisis and for the all period. During the subprime crisis the p-values for this test can be as low as 1% due to the excessive number of violations. Despite the fact that VaR is underestimated during the crisis period, the independence test gives very high p-values for all portfolios and time periods. Hence, the filtering process is adequately modelling the persistence of large losses. The conditional test, which tests for both the correct number and independence of violations, gives very high p-values except for some of the portfolios during the crisis period again due to a large number of violations. Overall we conclude that the estimates of VaR are very good, although not exceptional during the subprime mortgage crisis period.

5.1 WCR in the estimation of VaR

We can now test if WCR is significant when estimating VaR. For the several time periods and levels of VaR probability we regress the average VaR on the WCR. We use simple OLS to perform the regressions. Table 7 has the estimated coefficients of the slope and corresponding standard error and significance. For the all sample the average VaR increases significantly with WCR. This is true for the three levels of VaR probability, 90%, 95%, and 99%. Looking at the different time periods separately we can see that before the crisis the increase of VaR as a function of the WCR is significant at 1% level for all the VaR levels. During the crisis there is no significant relation between VaR and WCR. But after the crisis, for the 99%VaR there is again a significant positive relation between VaR and WCR. Given that VaR is a

Table 7: Relation between Working Capital Ratio and VaR.

Sample period	90% VaR	95% VaR	99% VaR
Before the subprime crisis	0.078***	0.090***	0.102***
	(0.013)	(0.016)	(0.022)
During the subprime crisis	0.021	0.023	−0.011
	(0.020)	(0.022)	(0.038)
After the subprime crisis	0.015	−0.033	0.026**
	(0.009)	(0.028)	(0.010)
All sample	0.043***	0.050.***	0.053**
	(0.010)	(0.013)	(0.020)

Notes: This table reports the regression coefficient estimates (and standard errors in parentheses) of regressing the average VaR estimates for each portfolio (obtained using a 1000 day window) on the Working Capital Ratio portfolios. The explanatory variable Working Capital Ratio takes values 1 to 10 corresponding to the first to the tenth deciles.

* Significant at 10%

** Significant at 5%

*** Significant at 1%

measure of risk this results confirm that portfolios with stocks having higher WCR are riskier than portfolios with low WCR stocks. Perhaps surprisingly, during the subprime crisis there was no difference between the riskiness of stocks with different WCR. Our results agree with the well known expression "no place to hide" frequently used by the financial media during the crisis. It is also worthwhile to note that the standard deviation of the returns on each decile portfolio increases significantly with the WCR. In addition, knowing that out of crisis periods portfolios with higher WCR have a higher probability of incurring very large losses is a valuable piece of information for investors.

5.2 VaR of a portfolio with different WCR stocks

Assume that an investor has a portfolio with diverse stocks in terms of WCR and that she wants to estimate the risk of the portfolio. Should the calculations take WCR into consideration? To answer this question we compare the performance of the VaR estimates with and without taking WCR into consideration. First we estimate the VaR for the portfolio with all the stocks in our sample. Second we estimate the VaR for each of the ten decile portfolios and then take the average of the ten VaR values obtained. Finally we compare the performance of the 'Portfolio' VaR with the 'Average' VaR. We perform this calculations for the 90%, 95% and 99% VaR and for the different time periods.

The results are reported in Table 8. As before the filtered historical simulation method for estimating VaR performs very well according to the backtesting p-values. Across all periods and probability levels taking WCR into consideration produces lower percentage of violations than ignoring the WCR. This means that including WCR gives more conservative estimates of VaR. During the crisis periods the percentage of violations is closer to the target, depending on the VaR probability level, when considering the WCR. It is especially during the crisis period that WCR improves the estimation of VaR of a portfolio of stocks with different WCR. The effect of the WCR is even stronger for the case of the 99%VaR. This result is very important because it shows that considering WCR gives investors a significant advantage on estimating risk at high probability levels during the critical period of crisis when good estimates of risk are of the essence for financial survival.

6 Conclusion

The subprime mortgage crisis emphasized the need for better risk management in general and in particular for improved estimates of risk. In this study we analyse the relation between WCR and market risk, measure by VaR. The motivation to use WCR comes from the fact

Table 8: Performance of portfolio VaR estimates with and without taking into account WCR.

	Before subprime		During subprime		After subprime		Entire sample	
	Portfolio	Average	Portfolio	Average	Portfolio	Average	Portfolio	Average
				90% VaR				
$\overline{\text{VaR}}$	1.28	1.35	2.67	2.66	1.36	1.40	1.50	1.54
% Viol.	9.73	8.21	*13.1*	*12.9*	9.13	8.34	9.91	8.88
LR_{uc}	0.73	0.02	0.03	0.05	0.25	0.03	0.86	0.03
LR_{ind}	0.18	0.14	0.02	0.03	0.65	0.65	0.63	0.61
LR_{cc}	0.39	0.02	0.00	0.02	0.47	0.08	0.88	0.08
				95% VaR				
$\overline{\text{VaR}}$	1.60	1.72	3.62	3.60	1.91	1.93	2.00	2.06
% Viol.	5.17	4.07	7.48	7.48	4.76	4.30	5.29	4.61
LR_{uc}	0.75	0.09	0.02	0.02	0.67	0.20	0.43	0.30
LR_{ind}	0.12	0.12	0.02	0.02	0.10	0.18	0.52	0.55
LR_{cc}	0.28	0.27	0.01	0.01	0.24	0.18	0.60	0.49
				99% VaR				
$\overline{\text{VaR}}$	2.28	2.48	5.12	5.17	2.84	2.89	2.90	3.01
% Viol.	1.38	0.55	*2.49*	1.58	1.05	0.93	*1.38*	0.85
LR_{uc}	0.16	0.06	0.00	0.25	0.81	0.77	0.03	0.37
LR_{ind}	0.44	0.75	0.43	0.61	0.54	0.59	0.24	0.47
LR_{cc}	0.28	0.16	0.02	0.45	0.81	0.83	0.05	0.52

Notes: Estimation of VaR, using a 1,000 day window, for a portfolio with all stocks. The column portfolio has the estimates without considering WCR. The column average has the estimates from obtaining VaR for each of the ten portfolios with different WCR and then take the average of the ten VaR estimates. $\overline{\text{VaR}}$ denotes the average VaR for the sample period. LR_{uc}, LR_{ind} and LR_{cc} are the p-values of the unconditional coverage, independence and conditional coverage test respectively.

that this ratio is usually used as a measure of short term accounting liquidity. The WCR reveals the ability of a firm to pay its short-term obligations with the current assets taking into account the size of the firm. Assuming that investors perceive high liquidity as an indicator of future good performance then we would expect high WCR to be associated with low market risk. However our empirical results show a strong positive correlation between WCR and VaR.

There could be two possible explanations for this result. One explanation could be related to the difficulty in finding an optimal threshold for the working capital (Deloof, 2003). While a lack of liquidity can result in bankruptcy, excessive liquidity can damage the future firm profitability and growth (Ding et al., 2013) due to the loss of potential investment opportunities. A second more plausible explanation, which we pursue in this paper, is related to the information risk implicit in the accrual accounting process. Indeed we compute a proxy for the quality of the working capital accruals following Dechow and Dichev (2002), and we find a strong positive correlation between both low accruals quality and WCR, and VaR. This result leads us to conclude that firms with high WCR and low accruals quality have higher VaR. Therefore we confirm that the quality of accruals incorporated in the WCR is a risk factor priced by the market.

We use the relation found between WCR and VaR in the estimation of market risk from the risk management point of view. We use the filtered historical simulation method to estimate VaR which proves to be an effective method of estimating VaR according to the the backtesting results. We confirm that portfolios with high WCR have a higher VaR forecasts especially before and after the subprime mortgage crisis. During the crisis the relation between WCR and VaR is not clear which corroborates the use of the expression “no place to hide" by the financial media during this period. Interestingly while during the crisis we do not find such strong evidence of a relation between WCR and VaR it is during this period that considering WCR shows a higher improvement in the estimation of the portfolio riskiness. We conclude that the information about the accruals quality contained in the WCR gives a significant advantage to investors in estimating portfolio market risk especially during the crisis period.

The interpretation of the positive relationship between WCR and VaR due to excess of cash can be an issue worth exploring in the future. Here we show that it is useful to consider accounting information in the estimation of VaR and further work can explore the relationship between market risk and other accounting variables (e.g. profitability, leverage and growth) and firms' characteristics (e.g. size and operating cycle).

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Appendix

Table 9: Performance of Filtered historical simulation VaR method.

Decile	Lower	2nd	3rd	4th	5th	6th	7th	8th	9th	Higher	All
					Before the subprime mortgage crisis						
$\overline{\text{VaR}}$	1.40	1.49	1.51	1.57	1.61	1.60	1.72	1.87	1.96	2.44	1.60
% Viol.	4.76	5.24	5.17	4.69	5.38	4.89	4.76	4.83	5.31	4.96	5.17
LR_{uc}	0.67	0.67	0.75	0.58	0.50	0.86	0.67	0.76	0.58	0.95	0.75
LR_{ind}	0.61	0.13	0.26	0.05	0.01	0.07	0.14	0.35	0.73	0.69	0.12
LR_{cc}	0.80	0.30	0.51	0.12	0.03	0.19	0.31	0.62	0.81	0.92	0.28
					During the subprime mortgage crisis						
$\overline{\text{VaR}}$	3.62	3.52	3.61	3.46	3.70	3.24	3.57	3.77	3.45	4.03	3.62
% Viol.	**8.39**	**9.07**	6.57	*7.70*	*7.25*	*7.48*	*7.70*	**8.84**	*6.80*	*7.02*	*7.48*
LR_{uc}	0.00	0.00	0.14	0.02	0.04	0.03	0.02	0.00	0.09	0.06	0.02
LR_{ind}	0.01	0.00	0.04	0.02	0.26	0.02	0.02	0.01	0.03	0.02	0.01
LR_{cc}	0.00	0.00	0.04	0.00	0.07	0.01	0.00	0.00	0.03	0.02	0.00
					After the subprime mortgage crisis						
$\overline{\text{VaR}}$	1.76	1.97	1.94	1.85	2.02	1.79	1.91	2.04	1.93	2.12	1.91
% Viol.	4.56	4.90	4.50	4.63	4.70	4.83	4.70	4.83	4.56	5.09	4.76
LR_{uc}	0.43	0.85	0.36	0.51	0.59	0.76	0.59	0.76	0.43	0.85	0.67
LR_{ind}	0.01	0.08	0.45	0.60	0.11	0.09	0.11	0.66	0.13	0.54	0.10
LR_{cc}	0.03	0.22	0.50	0.70	0.24	0.23	0.24	0.86	0.23	0.81	0.24
					Full sample period						
$\overline{\text{VaR}}$	1.85	1.97	1.97	1.94	2.06	1.90	2.02	2.19	2.14	2.51	2.00
% Viol.	5.14	5.58	5.05	5.05	5.32	5.20	5.11	5.35	5.17	5.29	5.29
LR_{uc}	0.69	0.12	0.87	0.87	0.39	0.58	0.75	0.35	0.63	0.43	0.43
LR_{ind}	0.05	0.34	0.68	0.39	0.40	0.58	0.44	0.48	0.11	0.33	0.52
LR_{cc}	0.12	0.19	0.90	0.68	0.48	0.74	0.70	0.50	0.25	0.46	0.60

Notes: The table reports the results on backtesting 95%VaR estimates obtained by the filtered historical simulation method across the different portfolio deciles of WCR using a rolling window of 1,000 days. See also notes in Table 6.

Table 10: Performance of Filtered historical simulation VaR method.

Decile	Lower	2nd	3rd	4th	5th	6th	7th	8th	9th	Higher	All
Before the subprime mortgage crisis											
$\overline{\text{VaR}}$	1.08	1.17	1.17	1.18	1.24	1.24	1.36	1.51	1.59	1.95	1.28
% Viol.	9.93	9.17	10.1	9.52	9.66	9.17	9.31	9.10	9.45	8.97	9.73
LR_{uc}	0.93	0.29	0.85	0.54	0.66	0.29	0.38	0.25	0.48	0.18	0.73
LR_{ind}	0.10	0.61	0.13	0.47	0.01	0.33	0.10	0.11	0.59	0.62	0.18
LR_{cc}	0.25	0.50	0.32	0.64	0.03	0.36	0.17	0.15	0.67	0.36	0.39
During the subprime mortgage crisis											
$\overline{\text{VaR}}$	2.71	2.65	2.54	2.59	2.71	2.39	2.63	2.81	2.51	3.08	2.67
% Viol.	*14.0*	**14.9**	**15.1**	**14.7**	*14.2*	**15.4**	*14.0*	**14.9**	*12.6*	*13.1*	*13.1*
LR_{uc}	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.06	0.03	0.03
LR_{ind}	0.03	0.00	0.00	0.05	0.03	0.00	0.01	0.01	0.01	0.01	0.02
LR_{cc}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.01
After the subprime mortgage crisis											
$\overline{\text{VaR}}$	1.26	1.45	1.40	1.33	1.47	1.28	1.37	1.52	1.41	1.52	1.36
% Viol.	9.27	8.87	9.27	9.00	9.20	9.20	9.27	8.47	9.40	8.94	9.13
LR_{uc}	0.34	0.13	0.34	0.19	0.29	0.29	0.34	0.04	0.43	0.16	0.25
LR_{ind}	0.44	0.60	0.65	0.48	0.47	0.19	0.31	0.27	0.37	0.27	0.65
LR_{cc}	0.47	0.29	0.57	0.33	0.44	0.24	0.38	0.07	0.49	0.20	0.47
Full sample period											
$\overline{\text{VaR}}$	1.37	1.49	1.45	1.43	1.53	1.41	1.53	1.68	1.63	1.91	1.50
% Viol.	10.1	9.79	10.4	9.97	10.0	10.0	9.91	9.58	9.85	9.50	9.91
LR_{uc}	0.73	0.68	0.42	0.95	0.90	0.99	0.86	0.42	0.77	0.32	0.86
LR_{ind}	0.64	0.16	0.62	0.64	0.41	0.15	0.41	0.39	0.61	0.06	0.63
LR_{cc}	0.84	0.34	0.64	0.89	0.71	0.34	0.70	0.50	0.84	0.11	0.88

Notes: The table reports the results on backtesting 90%VaR estimates obtained by the filtered historical simulation method across the different portfolio deciles of WCR using a rolling window of 1,000 days. See also notes in Table 6.