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Research article

The impact of business conditions and commodity market on US stock returns: An asset pricing modelling experiment

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Abstract: In this paper, two comprehensive mathematical approaches: cubic piecewise polynomial function (CPPF) model and the Fourier Flexible Form (FFF) model are built into asset pricing models to explore the stock market risk, commodity market risk and overall business conditions in relation to US stock returns as a modelling experiment. A selection of knots and orders are applied on the models to determine the best fit coefficients, respectively, based on Akaike Information Criteria (AIC). The classic risk coefficient along with downside and upside counterparts are estimated in a non-linear time-weighted fashion and are subsequently adopted as risk factors to investigate the explanatory and predictive power to stock returns. It is found that time-weighted classic, downside and upside risk coefficients of all three domains provide significant explanatory power to current stock returns, while the predictive power appears to be weak. The findings fill the gap in literature, specifically on both investigating and pricing the time-weighted risk. This paper innovatively employs the Aruoba-Diebold-Scotti (ADS) real business index to measure the business conditions in macroeconomics context. The methodology proposed in this paper embeds advanced mathematical approaches to provide robust regression estimation. The application of proposed models enriches the dimension in pricing risk in stock market and wider financial market.

Keywords: stock returns; business conditions; commodity market; time-weighted risk; asset pricing

JEL Codes: G10, G12, C58

1. Introduction

Among numerous asset pricing models, market factor has long been the primary focus. Along with the fast-evolving asset pricing techniques, additional risk factors have been considered, while limited studies focused on two aspects: firstly, applying comprehensive quantitative approach to generate time weighted risk factor coefficients (e.g., time-weighted beta); secondly, little consideration has been given to introduce a risk factor which could measure the overall business condition in macroeconomics context. To bridge the gap in literature, in this study, to investigate how broad macroeconomic factors impact stock returns, comprehensive quantitative approaches are applied on two multi-factor models, namely the cubic piecewise polynomial function (CPPF) model and Fourier Flexible Form (FFF) model with various knots and orders employed to examine the significance of classic, downside and upside risks in relation to the US stock returns as an asset pricing modelling experiment. Adopting the CPPF and FFF models allows the beta estimates to be time-varying and to present the time-weighted relationship between variables at each point in time. This study innovatively considers a market portfolio, the Aruoba-Diebold-Scotti (ADS) real business index and a commodity price index simultaneously, as risk factors, where ADS index proxies overall business condition and commodity price index measures price level of essential goods. The Akaike information criteria (AIC) (Akaike, 1974) is adapted to uncover the most appropriate number of knots and orders for the sample. With the AIC, the best fit the classic, downside and upside risk estimates for both models are generated. These estimates are sorted into portfolios to examine the risk-return relationship. Fama-Macbeth regressions are performed to investigate the significance of the estimates cross-sectionally. We find that all three factors have significant impact on individual stock returns. Moreover, downside and upside estimates provide more explanatory power than classic estimates. However, the predictive power of all estimates is found to be poor.

This paper is arranged as follows: Section 2 provides literature reviews of both models, followed by Section 3 describes the data. Section 4 explains the econometric models and methodology. Section 5 provides the empirical results and analysis. Section 6 concludes.

2. Literature review

There has been a long history of literature suggesting that the market factor is not sufficient to explain the risk-return relationship of stocks. Rose (1951) pointed out that economic news and information can be quantified and treated as an additional risk factor for stock returns. Moreover, the APT model assumes asset returns follow a multi-factor return generating process (Ross, 1976).

Among numerous multi-factor asset pricing studies, macroeconomic variables are the most popular ones to be employed within this context. There are quite a number of studies that investigate the relationship between stock returns and inflation. For instance, in the studies by Bodie (1976), Jaffe and Mandelker (1976), Nelson (1976), Fama and Schwert (1977), Fama (1981), and Fama and Gibbons (1982), inflation is employed as a common factor, and all of them found a negative relationship between stock returns and inflation with strong evidence provided. Apart from inflation, other macroeconomic variables have been employed as a risk factor. Chen et al. (1986) showed that industrial production, the spread between long and short interest rates, expected and unexpected inflation and the spread between high and low grade bonds are significantly priced. They find that neither aggregate consumption nor oil price differences are priced separately.

Fama (1990) used the economic growth rate to proxy the shock to cash flows, and he showed that the variance of stock returns is well explained by the economic growth rate. In Chen's (1991) later study, more variables are employed. The results indicate that the lagged production growth rate and the market dividend to price ratio are significantly priced, and they are positively correlated with future market excess returns. Bilson et al (2001) attempted to use macroeconomic variables to proxy local risk factors in emerging markets to explain the volatility of stock returns, with moderate evidence found to support the hypothesis. Flannery and Protopapadakis (2002) employed seventeen macroeconomic factors as independent variables in a GARCH model, and found that the consumer price index (CPI), producer price index (PPI), monetary aggregate, balance of trade, unemployment rate and housing starts are significantly priced. Duca (2007) applied Granger causality teste on the stock market excess return and GDP, (GDP is a component of the ADS index) with the results showing strong evidence that GDP Granger causes excess market returns. Also, Gay (2008) failed to find any significant influence of exchange rates on stock returns in emerging markets.

Moreover, Gan et al. (2006), Rjoub et al. (2009) and Singh et al. (2011) employed various macroeconomic variables to explain the movement of their local stock markets with only weak evidence found to support their proposed ideas. Although there are large number of studies employing macroeconomic variables in asset pricing models, few studies employ a macroeconomic factor which can measure the real economy (business) from all aspects (GDP is a commonly accepted indicator, however, it fails to measure the employment rate and other key aspects). The reason for that is obvious, to measure all aspects of the economy, there are numerous variables to be employed, and there are few variables available which can measure all aspects.

The innovation in this study is that it employs the ADS business conditions index, which measures the real economy from most aspects. The index itself is measured over a daily frequency but is computed using a number of macroeconomic variables with various frequencies. The constituents of the ADS index have been extended and modified ever since it was proposed, and the components and computing method were last fixed in 2011.[1] There are six macro components of the ADS index. At a weekly frequency, there are initial jobless claims; at a monthly frequency, there are payroll employment, industrial production, personal income less transfer payments and manufacturing and trade sales; and at a quarterly frequency, real GDP (adjusted for inflation and deflation) is employed. It would be possible to employ individual macroeconomic factors rather than the ADS index. However, since each individual factor is measured over a different frequency, using the ADS index is an optimal choice.

Apart from macroeconomic variables, commodity prices as an indicator of the price level of essential goods have long been employed in asset pricing studies. For instance, Hirshleifer (1989) found that the variability of stock market returns would increase the premium of hedging in the commodity market. Buyuksahin et al. (2010) failed to find any evidence to support the co-movement between a commodity index and stock returns. Buyuksahin and Robe (2014) pointed out that the commodity index and stock prices are correlated more closely when hedge funds perform actively in the market, while the correlation is much lower during a financial crisis. Hong and Yogo (2012) argue that commodity future prices are a good predictor of commodity returns. However, there is only weak evidence that commodity prices are a significant factor in the stock market.

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[1]The ADS index was set to start on 29th February 1960, and was re-estimated on 18th August 2011 due to the full release of manufacturing and trade sales in US.

Moreover, as energy, especially crude oil becomes more valuable, oil prices become more of a focus in asset pricing. There are quite a few studies that focus on the relationship between the oil price and stock returns. Sadorsky (1999) finds a significant negative relationship between oil price shocks and the US stock market. Papapetrou (2001) pointed out that oil prices can affect both stock returns and the real economy, while stock returns only appear to have a weak influence on oil prices and the real economy. Miller and Ratti (2009) state that stock returns and oil prices are cointegrated, however, they failed to explain why stock returns and oil prices grew apart during several sub-periods. Kilian and Parker (2009) proposed that changes in stock prices differ significantly depending on whether the change of oil price is driven by supply or demand. They found that the change in stock prices is always consistent with the change in oil prices when it was driven by a drop in demand. However, when the change in oil price is driven by supply, stock prices move randomly and are difficult to predict. Notably, as one of the key macroeconomic factors, inflation, is not employed by the ADS index. This study therefore also employs a commodity price index as a risk factor to represent the whole commodity market and as a measure of inflation.

Although literature is sufficient on separate risk factors in relation to asset returns and multifactor asset pricing models are widely accepted, there is little consideration on time-weighted risk factors coefficients and their premia. This study is aiming to fill the gap by introducing two comprehensive multi-factor asset pricing models.

3. Data and data transformation

The data used in this study are taken from the CRSP database. This study focuses on the ordinary common stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ measured on a monthly frequency from January 1960 to December 2010.[2] American depositary receipts (ADR), real estate investment trust (REIT), closed-end funds, foreign firms and other securities which do not have a CRSP share code of 10 or 11 are excluded from the sample. Each stock is required to have at least 5 years of consecutive monthly adjusted return observations with at most 5 missing observations. The return of each stock is adjusted for stock splits, mergers and acquisitions, and dividends (dividends are subtracted from stock prices for adjustment), giving 13557 stocks. The value-weighted return of all listed stocks is taken as a measure of the market portfolio, and the one-month Treasury bill rate represents the risk-free rate.[3] Summary statistics of stocks are shown in Table 1.

The ADS index is collected from the Federal Reserve Bank of Philadelphia website. It is a dynamic daily index starting from 1st March 1960 to date. This index is derived from and updated by the aforementioned six macroeconomic variables to track the real business conditions of the US with a mean of zero.[4] Therefore, if the value of the ADS index is below zero, it means that at that point in time, the business conditions are worse than average, and vice versa. Since monthly data are used in this study, the last observation of each month of the ADS index is used.

[2]The NASDAQ data are only available from January 1972.

[3]Using the same criteria Ang et al. (2007) used and no filtering out outliers aims to follow their study.

[4]Subject to the availability of the variables when updating.

Table 1. Summary of stocks.

Stock Exchange	Number of Stocks	Percentage to whole Sample	Average Annualized Return	Standard Deviation
NYSE	2198	16.21%	10.59%	10.99%
NASDAQ	7636	56.33%	12.32%	20.13%
AMEX	1105	8.15%	10.98%	16.91%
NYSE & NASDAQ	1031	7.60%	14.12%	13.55%
NYSE & AMEX	556	4.10%	14.10%	13.72%
NASDAQ & AMEX	829	6.11%	11.24%	20.17%
NYSE & NASDAQ & AMEX	202	1.49%	14.61%	16.15%
Total Sample	13557	100%	12.08%	17.06%

Note: This table summarizes the constituents of US stocks, average annual returns and volatility, the sample size is from March 1960 to December 2010.

The commodity price index is provided by the Commodity Research Bureau and collected from Datastream. This index is a commodity spot price index measured at monthly frequency and has an initial value of zero in year 1967. In order to conduct the analysis, continuous compounded returns of the commodity price index are derived as follows:

$$CR_t = ln(CP_t) - ln(CP_{t-1}) \tag{1}$$

whereas CP_t is the continuously compounded return of the commodity price index at time *t*, CP_t is the commodity price index at time *t*, and ln is the natural logarithm.

4. Methodology and models

In this section, two comprehensive multi-factor asset pricing models CPPF and FFF models are introduced. The beauty of these two models attribute to their time-vary nature, which allow the risk factor coefficients to be time-weighted to reflective the true context of risk premia.

4.1. The CPPF model

The advantages of the CPPF approach are, firstly, data are flexibly adjusted without considering the sample size. Secondly, for research with particular focus on data smoothing and weighting, it allows time weight to be considered when estimating among various selected knots. Thirdly, apart from the time weight, the nature of the original data is retained and there are no extra functions or patterns to be built into the model which fits the purpose of this study. By using the CPPF model, all risk factors (excess return on the market portfolio xR_M,[5] excess return on the commodity market *xCR*,[6] and the ADS business index *ADS)* are divided into series depending on the numbers of knots selected. Up to 5 knots are employed (Huang et al., 2021) and the placement of knots follows the quintile method proposed by Stone (1986).

[5]Defined as the difference between the return of market portfolio R_M and risk free rate R_f.

[6]We define $xCR = CR - R_f$.

The models used in this study take full advantage of the CPPF approach, building on the classic market model. To estimate the coefficients of the risk factors for each stock, the augmented market model can be written as:

$$xR_i = \alpha_i + b_i \cdot (xR_M \odot S_N) + c_i \cdot (xCR \odot S_N) + d_i \cdot (ADS \odot S_N) + \varepsilon_i$$
$$N = 0,\ 1,\ 2,\ 3,\ 4,\ 5. \tag{2}$$

where ($xR_M \odot S_N$), ($xCR \odot S_N$) and ($ADS \odot S_N$) are all in dimension of (t×n), b_i, c_i and d_i are the OLS coefficients of market factor, commodity factor and ADS factor, respectively, measuring the co-movement between the risk factor and stock returns, and S_N is cubic piecewise polynomial matrix with N knots. The expression for S_N can be found in Equation A.1–A.6 in Appendix.

The OLS regression is applied to each stock to estimate the vectors of coefficients, with each coefficient vector having the dimension n×1. Subsequently, using the cubic piecewise polynomial matrix multiplied by the vectors of coefficients estimates, the time-varying coefficient estimates for each risk factor of a stock b_s, c_s, and d_s (B_s, C_s and D_s in vector form respectively) can be obtained, as follows:

$$B_{s,i} = S_N \cdot B_i \tag{3}$$

$$C_{s,i} = S_N \cdot C_i \tag{4}$$

$$D_{s,i} = S_N \cdot D_i \tag{5}$$

where B_i C_i and D_i are vector forms of b_i, c_i and d_i, respectively. It can be seen from Equations (3 to 5) that $B_{s,i}$, $C_{s,i}$ and $D_{s,i}$ are products of the piecewise polynomial matrix S_N with the dimension t×n and the coefficient vector with the dimension n×1. Therefore, regardless of the number of knots placed in the function, the dimension of $B_{s,i}$, $C_{s,i}$ and $D_{s,i}$ will always be t×1. In other words, the coefficient estimates are always time-varying. Since the number of knots varies from 0 to 5, there will be 6 groups of b_i, c_i and d_i for each stock, one for each corresponding number of knots. In order to find the best estimates of b_S^*, c_S^* and d_S^* for each stock, AIC is an appropriate indicator to decide the best fit of b_i, c_i and d_i.

To calculate the downside and upside estimates by using the CPPF model, the same approach to conducting b_S^*, c_S^* and d_S^* is followed, with Equation (2) is modified accordingly. As in Ang et al. (2006), the downside beta and upside estimates in this study are calculated as:

$$b_i^- = \frac{cov(\,xR_i, xR_M | xR_M < \overline{xR_M})}{var(\,xR_M | xR_M < \overline{xR_M})} \tag{6}$$

$$b_i^+ = \frac{cov(\,xR_i, xR_M | xR_M \geq \overline{xR_M})}{var(\,xR_M | xR_M \geq \overline{xR_M})} \tag{7}$$

$$c_i^- = \frac{cov(\,xR_i, xCR | xCR < \overline{xCR})}{var(\,xCR | xCR < \overline{xCR})} \tag{8}$$

$$c_i^+ = \frac{cov(xR_i, xCR | xCR \geq \overline{xCR})}{var(xCR | xCR \geq \overline{xCR})} \quad (9)$$

$$d_i^- = \frac{cov(xR_i, ADS | ADS < \overline{ADS})}{var(ADS | ADS < \overline{ADS})} \quad (10)$$

$$d_i^+ = \frac{cov(xR_i, ADS | ADS \geq \overline{ADS})}{var(ADS | ADS \geq \overline{ADS})} \quad (11)$$

where $\overline{xR_M}$, $\overline{xCR}$ and $\overline{ADS}$ are the average market excess return, average commodity market excess return and average ADS business index value, respectively, over the sample period, and all other notation remains the same. In light of Ang et al. (2006), dummy variables (vectors) $D_{1, xRM}$, $D_{2, xRM}$, $D_{1, xCR}$, $D_{2, xCR}$, $D_{1, ADS}$ and $D_{2, ADS}$, are created and employed for each stock. These dummy variables can be expressed as (time subscript *t* is used):

$$D_{1, xRM} = 1 \text{ and } D_{2, xRM} = 0 \text{ if } xR_{M,t} < \overline{xR_M} \quad (12)$$

$$D_{1, xCR} = 1 \text{ and } D_{2, xCR} = 0 \text{ if } xCR_t < \overline{xCR} \quad (13)$$

$$D_{1, ADS} = 1 \text{ and } D_{2, ADS} = 0 \text{ if } ADS_t < \overline{ADS} \quad (14)$$

and

$$D_{1, xRM} = 0 \text{ and } D_{2, xRM} = 0 \text{ if } xR_{M,t} < \overline{xR_M} \quad (15)$$

$$D_{1, xCR} = 0 \text{ and } D_{2, xCR} = 0 \text{ if } xCR_t < \overline{xCR} \quad (16)$$

$$D_{1, ADS} = 0 \text{ and } D_{2, ADS} = 0 \text{ if } ADS_t < \overline{ADS} \quad (17)$$

It can be seen from Equations (12) to (17) that $D_{1, xRM}$, $D_{1, xCR}$ and $D_{1, ADS}$ represent the downside stock market, commodity market and real business condition dummies, respectively, while $D_{2, xRM}$, $D_{2, xCR}$ and $D_{2, ADS}$ represent the upside ones, respectively.

The CPPF augmented market model can be written as:

$$xR_i = b_i^- \cdot (D_{1,xRM} \odot xR_M \odot S_N) + b_i^+ \cdot (D_{2,xRM} \odot xR_M \odot S_N) + c_i^- \cdot (D_{1,xCR} \odot xCR \odot S_N)$$
$$+ c_i^+ \cdot (D_{2,xCR} \odot xCR \odot S_N) + d_i^- \cdot (D_{1,ADS} \odot ADS \odot S_N) + d_i^+ \cdot (D_{2,ADS} \odot ADS \odot S_N) + \varepsilon_i \quad (18)$$
$$N = 0, 1, 2, 3, 4, 5.$$

It can be seen from Equation (18) that in order to avoid multi-collinearity, there is no constant term. The value of $D_{1, xRM} \odot xR_M$ is xR_M if the value of xR_M is below the mean, and zero otherwise. On the other hand, the value of $D_{2, xRM} \odot xR_M$ is xR_M if the value of xR_M is equal or above the mean, and zero otherwise.

The parameters b_i^-, c_i^- and d_i^- are the downside risk estimate coefficients while b_i^+, c_i^+ and d_i^+ are the upside risk estimate coefficients associated with stock *i*. In terms of the matrices, all of the estimates are column vectors with a dimension of n×1. Since the number of knots varies from 0 to 5, there will be 6 pairs of downside and upside vectors for each stock, with each pair of vectors having an associated AIC value. Among the 6 AICs, the lowest one indicates the best fitting pair of estimates, in addition, the associated best fitting time-varying downside and upside estimate coefficients for stock i, $b_{S,i}^{-*}$, $c_{S,i}^{-*}$, $d_{S,i}^{-*}$ and $b_{S,i}^{+*}$, $c_{S,i}^{+*}$, $d_{S,i}^{+*}$ ($B_{S,i}^{-*}$, $C_{S,i}^{-*}$, $D_{S,i}^{-*}$ and $B_{S,i}^{+*}$, $C_{S,i}^{+*}$, $D_{S,i}^{+*}$ in vector form) can be calculated as follows:

$$B_{S,i}^{-*} = S_N \cdot B_{S,i}^{-} \tag{19}$$

$$C_{S,i}^{-*} = S_N \cdot C_{S,i}^{-} \tag{20}$$

$$D_{S,i}^{-*} = S_N \cdot D_{S,i}^{-} \tag{21}$$

$$B_{S,i}^{+*} = S_N \cdot B_{S,i}^{+} \tag{22}$$

$$C_{S,i}^{+*} = S_N \cdot C_{S,i}^{+} \tag{23}$$

$$D_{S,i}^{+*} = S_N \cdot D_{S,i}^{+} \tag{24}$$

where $B_{S,i}^{-}$, $C_{S,i}^{-}$, $D_{S,i}^{-}$ and $B_{S,i}^{+}$, $C_{S,i}^{+}$, $D_{S,i}^{+}$ are the vector forms of b_i^-, c_i^-, d_i^- and b_i^+, c_i^+, d_i^+. As mentioned in the previous paragraph, regardless of the number of knots placed in the function, the dimension of $B_{S,i}^{-*}$, $C_{S,i}^{-*}$, $D_{S,i}^{-*}$ and $B_{S,i}^{+*}$, $C_{S,i}^{+*}$, $D_{S,i}^{+*}$ are always t×1.

4.2. The FFF model

As an alternative way of generating time-varying risk estimate coefficients, the FFF model is presented. The advantages of the FFF approach are: firstly, in the context of normal and high frequency data, the macroeconomic news announcement effect has been filtered by the periodic pattern of the FFF, therefore it is not essential to model the macroeconomic news announcement effect; secondly, the FFF approach creates a smooth pattern for volatility dynamics and changes; thirdly, the FFF approach is based on sound mathematics and the fitness of the periodicity of financial data is widely agreed. By using the FFF model, all risk factors are divided into series depending on the order number.

In light of Andersen and Bollerslev (1998), Andersen et al. (2000), Bollerslev et al. (2000), and Evans and Speight (2010a), the FFF market model employed in this study is given by:

$$\begin{aligned} xR_i = \alpha_i + \sum_{p=1}^{P}[\, b_{cos,p,i} \cdot (cos\frac{p2\pi}{N} n \cdot xR_M) + b_{sin,p,i} \cdot (sin\frac{p2\pi}{N} n \cdot xR_M)] + \sum_{p=1}^{P}[\, c_{cos,p,i} \\ \cdot (cos\frac{p2\pi}{N} n \cdot xCR) + c_{sin,p,i} \cdot (sin\frac{p2\pi}{N} n \cdot xCR)] + \sum_{p=1}^{P}[\, d_{cos,p,i} \\ \cdot (cos\frac{p2\pi}{N} n \cdot ADS) + d_{sin,p,i} \cdot (sin\frac{p2\pi}{N} n \cdot ADS)] + \varepsilon_i \end{aligned} \tag{25}$$

whereas α_i is the constant term, $b_{cos,p,i}$, $b_{sin,p,i}$, $c_{cos,p,i}$, $c_{sin,p,i}$, $d_{cos,p,i}$ and $d_{sin,p,i}$, are the coefficients to be estimated of each factor for stock i, N is the total number of observations of stock i, n is the order of observations with $n = \{1, 2, 3 \ldots T\}$, p is the order of the FFF model and the remaining notation remains the same. According to Andersen and Bollerslev (1998), the order of the FFF could vary from 1 to infinity. However, in order to improve the efficiency of the estimates, we follow their lead and chose 4 as the appropriate order. In this study, orders from 1 to 4 are considered.

The OLS regression is applied to each stock to obtain the estimated risk factor coefficient vector produced from Equation (25). The AIC is then computed for each regression. Since the orders of 1 to 4 are considered, there are 4 AICs for each stock. Taking advantage of the nature of the AIC, the regression that produces the lowest AIC gives the best fit. To calculate the best fitting time-varying coefficients $b_{F,i}^{*}$, $c_{F,i}^{*}$ and $d_{F,i}^{*}$ for each stock, the minimum AIC estimated vector for stock *i* are calculated as follows:

$$b_{F,i}^{*} = \sum_{p=1}^{P} (b_{cos,p,i} \cdot cos\frac{p2\pi}{N}n + b_{sin,p,i} \cdot sin\frac{p2\pi}{N}n) \tag{26}$$

$$c_{F,i}^{*} = \sum_{p=1}^{P} (c_{cos,p,i} \cdot cos\frac{p2\pi}{N}n + c_{sin,p,i} \cdot sin\frac{p2\pi}{N}n) \tag{27}$$

$$d_{F,i}^{*} = \sum_{p=1}^{P} (d_{cos,p,i} \cdot cos\frac{p2\pi}{N}n + d_{sin,p,i} \cdot sin\frac{p2\pi}{N}n) \tag{28}$$

In order to calculate the downside and upside estimates by using the above FFF model, the same procedure used above is followed. The dummy variables $D_{1,xRM}$, $D_{2,xRM}$, $D_{1,xCR}$, $D_{2,xCR}$, $D_{1,ADS}$ and $D_{2,ADS}$ used in Equation (18) are created and employed again for each stock in the new FFF model. The new model is defined as:

$$\begin{aligned} xR_i = &\sum_{p=1}^{P}[b_{cos,p,i}^{-} \cdot (cos\frac{p2\pi}{N}n \cdot xR_M \odot D_{1,xRM}) + b_{sin,p,i}^{-} \cdot (sin\frac{p2\pi}{N}n \cdot xR_M \odot D_{1,xRM})] \\ &+ \sum_{p=1}^{P}[b_{cos,p,i}^{+} \cdot (cos\frac{p2\pi}{N}n \cdot xR_M \odot D_{2,xRM}) + b_{sin,p,i}^{+} \cdot (sin\frac{p2\pi}{N}n \cdot xR_M \odot D_{2,xRM})] \\ &+ \sum_{p=1}^{P}[c_{cos,p,i}^{-} \cdot (cos\frac{p2\pi}{N}n \cdot xCR \odot D_{1,xCR}) + c_{sin,p,i}^{-} \cdot (sin\frac{p2\pi}{N}n \cdot xCR \odot D_{1,xCR})] \\ &+ \sum_{p=1}^{P}[c_{cos,p,i}^{+} \cdot (cos\frac{p2\pi}{N}n \cdot xCR \odot D_{2,xCR}) + c_{sin,p,i}^{+} \cdot (sin\frac{p2\pi}{N}n \cdot xCR \odot D_{2,xCR})] \\ &+ \sum_{p=1}^{P}[d_{cos,p,i}^{-} \cdot (cos\frac{p2\pi}{N}n \cdot ADS \odot D_{1,ADS}) + d_{sin,p,i}^{-} \cdot (sin\frac{p2\pi}{N}n \cdot ADS \odot D_{1,ADS})] \\ &+ \sum_{p=1}^{P}[d_{cos,p,i}^{+} \cdot (cos\frac{p2\pi}{N}n \cdot ADS \odot D_{2,ADS}) + d_{sin,p,i}^{+} \cdot (sin\frac{p2\pi}{N}n \cdot ADS \odot D_{2,ADS})] + \varepsilon_i \end{aligned} \tag{29}$$

Whereas $b_{cos,p,i}^{-}$, $b_{sin,p,i}^{-}$, $c_{cos,p,i}^{-}$, $c_{sin,p,i}^{-}$, $d_{cos,p,i}^{-}$, and $d_{sin,p,i}^{-}$, are the downside coefficients to be estimated for stock *i*, while $b_{cos,p,i}^{+}$, $b_{sin,p,i}^{+}$, $c_{cos,p,i}^{+}$, $c_{sin,p,i}^{+}$, and $d_{cos,p,i}^{+}$, and $d_{sin,p,i}^{+}$ are the upside coefficients to be estimated for stock *i*. For the same reason as for Equation (24), there is no conventional constant term in the model to avoid multi-collinearity. Since the order of the FFF examined varies from 1 to 4, there will be 4 groups of estimated risk factor coefficient vectors for each stock. The best fit time-varying downside and upside estimates for stock *i*, $b_{F,i}^{-*}$, $b_{F,i}^{+*}$, $c_{F,i}^{-*}$, $c_{F,i}^{+*}$, $d_{F,i}^{-*}$ and $d_{F,i}^{+*}$ can be calculated as follows:

$$b_{F,i}^{-*} = \sum_{p=1}^{P} (b_{cos,p,i}^{-} \cdot cos\frac{p2\pi}{N}n + b_{cos,p,i}^{-} \cdot sin\frac{p2\pi}{N}n) \quad (30)$$

$$b_{F,i}^{+*} = \sum_{p=1}^{P} (b_{cos,p,i}^{+} \cdot cos\frac{p2\pi}{N}n + b_{cos,p,i}^{+} \cdot sin\frac{p2\pi}{N}n) \quad (31)$$

$$c_{F,i}^{-*} = \sum_{p=1}^{P} (c_{cos,p,i}^{-} \cdot cos\frac{p2\pi}{N}n + c_{cos,p,i}^{-} \cdot sin\frac{p2\pi}{N}n) \quad (32)$$

$$c_{F,i}^{+*} = \sum_{p=1}^{P} (c_{cos,p,i}^{+} \cdot cos\frac{p2\pi}{N}n + c_{cos,p,i}^{+} \cdot sin\frac{p2\pi}{N}n) \quad (33)$$

$$d_{F,i}^{-*} = \sum_{p=1}^{P} (d_{cos,p,i}^{-} \cdot cos\frac{p2\pi}{N}n + d_{cos,p,i}^{-} \cdot sin\frac{p2\pi}{N}n) \quad (34)$$

$$d_{F,i}^{+*} = \sum_{p=1}^{P} (d_{cos,p,i}^{+} \cdot cos\frac{p2\pi}{N}n + d_{cos,p,i}^{+} \cdot sin\frac{p2\pi}{N}n) \quad (35)$$

It can be seen from Equation (30) to (35) that regardless the order of the model, $b_{F,i}^{-*}$, $b_{F,i}^{+*}$, $c_{F,i}^{-*}$, $c_{F,i}^{+*}$, $d_{F,i}^{-*}$ and $d_{F,i}^{+*}$ always have the dimension t×1.

5. Empirical results

Based on the methods explained in the previous section, the best estimates for both the CPPF model and the FFF model are obtained. To summarize the estimation details, distribution of the best fitting knots and orders are presented in Table 2a and Table 2b.

For the CPPF model, it can be seen from Table 2a that 7307 stocks (53.90% of the sample) construct b_S^*, c_S^* and d_S^*, when no knots are placed. When the number of knots varies from 1 to 4, a much lower number of best fit estimates are produced. However, 4223 stocks obtain the best estimates with 5 knots placed (31.15% of the sample). On the other hand, to construct downside and upside risk factor coefficients, unlike the classic risk factor coefficients, no knots are used for only 3923 stocks (28.94% of the sample). Similar to classic risk estimates, a much lower number of best fit estimates are produced when 1 to 4 knots are placed. Surprisingly, 5900 stocks obtain best fit estimates when 5 knots are placed (more than 40% of the sample).

For the FFF model, it is clear from Table 2b that to construct b_F^*, c_F^* and d_F^*, 8999 stocks used order 1 (66.38% of the sample). Stocks with orders 2, 3 and 4, however, produce a lower number of best estimates. It is considerably consistent when constructing downside and upside estimates.

Table 2a. Knots of CPPF model selected to construct best fit estimates.

Knots		0	1	2	3	4	5
Classic estimates	Number of Stocks	7307	587	288	328	824	4223
	Percentage of Whole sample	53.90 %	4.33 %	2.12 %	2.42 %	6.08%	31.15 %
Downside and upside estimates	Number of Stocks	3923	350	494	909	1981	5900
	Percentage of Whole sample	28.94 %	2.58 %	3.64 %	6.71 %	14.61 %	43.52 %

Note: This table reports the number and percentage of stocks with different knots to construct the best fit estimates of the CPPF model.

Table 2b. The order of the FFF model selected to construct best fit estimates.

Order		1	2	3	4
Classic estimates	Number of Stocks	8999	2164	1205	1189
	Percentage of Whole sample	66.38%	15.96%	8.89%	8.77%
Downside and upside estimates	Number of Stocks	9079	1414	742	2322
	Percentage of Whole sample	66.97%	10.43%	5.47%	17.13%

Note: This table reports the number and percentage of stocks in different order to construct the best fit estimates of the FFF model.

Furthermore, the relations among stock returns and classic, downside and upside estimates of both the CPPF model and the FFF model betas are examined. In order to present the relationship in a cross-sectional fashion, stocks at each point in time are cross-sectionally assigned to five portfolios according to the value of the risk estimates. Since the classic, downside and upside beta estimates are not independent of each other due to the nature of the calculation, to distinguish the effects among them, more statistics are introduced. Specifically, we consider, for the CPPF model, the relative estimates denoted by $(b_S^{-*}$-$b_S^*)$, $(c_S^{-*}$-$c_S^*)$ and $(d_S^{-*}$-$d_S^*)$ for the downside market, and $(b_S^{+*}$-$b_S^*)$, $(c_S^{+*}$-$c_S^*)$ and $(d_S^{+*}$-$d_S^*)$ for the upside market. Similarly, for the FFF model, $(b_F^{-*}$-$b_F^*)$, $(c_F^{-*}$-$c_F^*)$ and $(d_F^{-*}$-$d_F^*)$ for the downside market, and $(b_F^{+*}$-$b_F^*)$, $(c_F^{+*}$-$c_F^*)$ and $(d_F^{+*}$-$d_F^*)$ for the upside market are computed. Introducing these statistics aims to illustrate the impact of downside and upside estimates after controlling for classic estimates.

To sort the portfolio, at each point in time, all stocks are sorted into five quintiles according to the value of the target estimate. When stocks are sorted into 5 portfolios at each point of time (since monthly data are used in this study, and the whole sample is from March 1960 to December 2010, so there should be 610 time points), the equally weighted average of the estimate for each portfolio and the corresponding same period average annualized stock returns and average values of the risk estimates are calculated. The results of both models are summarized in Table 3 to Table 8.

5.1. Empirical results: the CPPF model

For the CPPF model, Table 3 presents the results pertaining to the relationship between annualized excess stock returns and estimates of market beta. It can be seen from Panel 1 that when stocks are sorted by b_S^*, portfolio 1 has an average b_S^* value of −0.40, while on the other hand, portfolio 5 shows an average b_S^* value of 2.15. Consistent with the classic literature, the average annualized return of each portfolio increases with b_S^*, portfolio 1 yields a return of 4.40% while portfolio 5 yields a return of 20.74%. The average b_S^{-*} and b_S^{+*} values of each portfolio follow the same trend as b_S^*, with average b_S^{-*} equaling −0.91 in portfolio 1 and increasing to 1.81 in portfolio 5. Similarly, average b_S^{+*} is −0.92 in portfolio 1 and increases to 2.01 in portfolio 5.

When stocks are sorted by b_S^{-*}, it can be seen from Panel 2 that the average returns generally drop from 14.02% to 8.19%, however from portfolio 2 to portfolio 4, returns

present a U-shaped pattern. When stocks are sorted by b_S^{+*}, both returns and b_S^* increase dramatically from portfolio 1 to portfolio 5, with a negligible drop in b_S^* in portfolio 2. b_S^{-*} slumps from 1.82 to −1.41 along with the increase of b_S^{+*}.

When controlling for b_S^*, returns drop from 14.39% to 7.27% when stocks are sorted by (b_S^{-*}-b_S^*). In contrast, it is clear from Panel 5 that returns increase gradually from 8.23% to 14.5% when stocks are sorted by (b_S^{+*}-b_S^*). It can be seen from Panel 6 that only b_S^{-*} increases from −1.79 to 2.11, while returns drop from 14.76% to 7.36%.

Table 3. Excess stock returns sorted by stock market factor loadings of CPPF model.

Panel 1 Stocks Sorted by b_S^*					Panel 2 Stocks Sorted by b_S^{-*}				
Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}	Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}
1 Low	4.40%	−0.40	−0.91	−0.92	1 Low	14.02%	1.06	−1.03	1.62
2	7.62%	0.62	0.91	0.55	2	9.62%	0.72	0.22	0.96
3	9.41%	0.99	1.29	1.06	3	10.40%	1.01	1.02	0.98
4	11.64%	1.44	1.53	1.51	4	11.56%	1.40	1.99	0.92
5 High	20.74%	2.15	1.81	2.01	5 High	8.19%	1.61	2.15	−1.94
High-Low	16.34%	2.55	2.72	2.93	High-Low	−5.83%	0.55	3.18	−3.56
Panel 3 Stocks Sorted by b_S^{+*}					Panel 4 Stocks Sorted by $(b_S^{-*} - b_S^*)$				
Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}	Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}
1 Low	5.23%	0.66	1.82	−0.39	1 Low	14.39%	1.98	−1.74	1.84
2	7.54%	0.63	1.13	0.10	2	13.54%	1.17	0.48	1.54
3	10.05%	0.95	0.97	0.91	3	9.88%	0.94	0.98	0.90
4	12.64%	1.43	1.03	1.85	4	8.71%	0.98	1.77	0.43
5 High	18.34%	2.13	−1.41	2.30	5 High	7.27%	−0.26	2.46	−1.39
High-Low	13.11%	1.47	−3.23	2.68	High-Low	−7.13%	−2.24	4.20	−3.24
Panel 5 Stocks Sorted by $(b_S^{+*} - b_S^*)$					Panel 6 Stocks Sorted by $(b_S^{-*} - b_S^*)$				
Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}	Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}
1 Low	8.23%	1.70	1.93	−2.06	1 Low	14.76%	1.64	−1.79	2.19
2	9.15%	1.07	1.61	0.31	2	12.88%	1.15	0.50	1.63
3	10.05%	0.94	0.97	0.91	3	9.94%	0.97	0.98	0.91
4	11.86%	1.08	0.64	1.66	4	8.85%	0.99	1.76	0.35
5 High	14.50%	−0.46	−1.47	2.24	5 High	7.36%	−1.06	2.11	−1.94
High-Low	6.28%	−2.16	−3.40	4.30	High-Low	−7.40%	−2.70	3.90	−4.13

Note: This table presents the relationship between excess stock returns and stock market factor loadings associated with the CPPF model. The column labeled "return" reports the annual average stock returns over the one-month T-bill rate. "High-Low" reports the difference between portfolio 5 and portfolio 1.

Table 3 presents the relationship between excess stock returns and estimates of commodity market risk. It can be seen from Panel 1 that when stocks are sorted by c_S^*, portfolio 1 has an average c_S^* value of −1.82. On the other hand, portfolio 5 shows an average c_S^* value of 1.78. Unlike Panel 1 in Table 3 the average annualized return of each portfolio declines along with the increase of c_S^*, portfolio 1 yields a return of 15.31% while portfolio 5 yields a return of 7.85%. The average c_S^{-*} and c_S^{+*} of each portfolio follows the same trend as c_S^*, the average c_S^{-*} is −1.43 in portfolio 1 and increases to 1.8 in portfolio 5. Similarly, the average c_S^{+*} is −1.52 in portfolio 1 and increases to 2.22 in portfolio 5.

When stocks are sorted by c_S^{-*}, it can be seen from Panel 2 that the average returns decrease from 16.66% to 5.82%. c_S^* presents a reversed U−shaped pattern along with the increase of c_S^{-*}, starting at −1.36 in portfolio 1 and finishing at 0.26 in portfolio 5, reaching a peak at 0.56 in portfolio 4. Moreover, c_S^{+*} drops dramatically from 1.71 to −1.94. When stocks are sorted by c_S^{+*}, returns increase dramatically from portfolio 1 to portfolio 5 and c_S^* increases gradually from portfolio 1 to portfolio 4, with a drop in portfolio 5. While c_S^{-*} slumps from 1.43 to −0.64 along with the increase of c_S^{+*}.

Table 4. Excess stock returns sorted by commodity market factor loadings of CPPF model.

Panel 1 Stocks Sorted by c_S^*					Panel 2 Stocks Sorted by c_S^{-*}				
Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}	Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}
1 Low	15.31%	−1.82	−1.43	−1.52	1 Low	16.66%	−1.36	−1.45	1.71
2	11.29%	−0.34	−1.29	−1.28	2	12.49%	−0.19	−1.30	0.49
3	10.17%	0.10	−0.57	−1.01	3	10.00%	0.07	0.05	0.15
4	9.18%	0.60	0.27	1.95	4	8.81%	0.56	1.61	−0.35
5 High	7.85%	1.78	1.80	2.22	5 High	5.82%	0.26	2.17	−1.94
High-Low	−7.46%	3.60	3.23	3.75	High-Low	−10.84%	1.62	3.62	−3.65
Panel 3 Stocks Sorted by c_S^{+*}					Panel 4 Stocks Sorted by ($c_S^{-*}-c_S^*$)				
Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}	Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}
1 Low	7.87%	−1.03	1.43	−1.41	1 Low	11.14%	1.83	−1.46	1.35
2	8.74%	−0.25	0.84	−1.06	2	10.80%	0.34	0.67	1.19
3	10.02%	0.07	−0.04	0.09	3	10.17%	0.10	1.18	1.09
4	12.45%	0.35	−0.48	1.72	4	10.14%	−0.09	1.50	0.15
5 High	14.71%	0.19	−0.64	1.92	5 High	11.53%	−1.83	1.94	−0.78
High-Low	6.84%	1.22	−2.07	3.33	High-Low	0.39%	−3.67	3.40	−2.12
Panel 5 Stocks Sorted by ($c_S^{+*}-c_S^*$)					Panel 6 Stocks Sorted by ($c_S^{-*}-c_S^{+*}$)				
Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}	Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}
1 Low	7.96%	1.58	1.61	−1.94	1 Low	14.36%	−0.85	−1.63	1.78
2	7.56%	0.26	0.67	−1.46	2	13.48%	0.13	−1.06	1.48
3	10.27%	0.07	−0.34	0.10	3	10.26%	0.05	0.02	0.10
4	13.60%	0.02	−0.87	1.56	4	8.02%	0.15	1.38	−1.35
5 High	14.39%	−1.58	−1.25	1.95	5 High	7.67%	−0.14	1.97	−1.71
High-Low	6.44%	−3.16	−2.86	3.89	High-Low	−6.69%	0.71	3.61	−3.49

Note: This table presents the relationship between excess stock returns and commodity market factor loadings associated with the CPPF model. The column labeled "return" reports the annual average stock returns over the one-month T-bill rate. "High-Low" reports the difference between portfolio 5 and portfolio 1.

To control for c_S^*, when stocks are sorted by $(c_S^{-*} - c_S^*)$, returns present a U−shaped pattern but with little change in its value, starting at 11.14% and finishing at 11.53%. In contrast, it is clear from Panel 5 that returns increase steadily from 7.96% to 14.39% with a negligible drop in portfolio 2 when stocks are sorted by $(c_S^{+*} - c_S^*)$. In Panel 6, $(c_S^{-*} - c_S^{+*})$ is employed for the same reason mentioned in Table 3. It can be seen from Panel 6 that only c_S^{-*} increases obviously from −1.63 to 1.97, while returns and c_S^{+*} are decreasing and it is difficult to trace the pattern of c_S^*.

Table 5 presents the relationship between excess stock returns and estimates of ADS risk. It can be seen from Panel 1 that when stocks are sorted by d_S^*, portfolio 1 has an average d_S^* value of −0.89 and portfolio 5 shows an average d_S^* value of 0.89. The average annualized return of each portfolio shows a U−shaped pattern along with the increase of d_S^*. Portfolio 1 yields a return of 10.6% while portfolio 5 is at a peak of 12.11%, and there is a slight drop in portfolio 2. The average d_S^{-*} and d_S^{+*} values of each portfolio follow the same trend as d_S^*, average d_S^{-*} is −0.79 in portfolio 1 and increases to 0.82 in portfolio 5. Also, average d_S^{+*} is −0.53 in portfolio 1 and increases to 1.23 in portfolio 5.

When stocks are sorted by d_S^{-*}, it can be seen from Panel 2 that average returns decrease from 16.93% to 4.83%. d_S^* and d_S^{+*} both increase gradually along with the increase of d_S^{-*}. When stocks are sorted by d_S^{+*}, both returns and d_S^* increase steadily from portfolio 1 to portfolio 5.

Table 5. Excess stock returns sorted by business conditions factor loadings of CPPF model.

Panel 1 Stocks Sorted by d_S^*					Panel 2 Stocks Sorted by d_S^{-*}				
Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}	Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}
1 Low	10.60%	−0.89	−0.79	−0.53	1 Low	16.93%	−0.04	−0.73	−0.34
2	10.15%	−0.02	−0.13	−0.20	2	13.32%	−0.01	−0.12	−0.07
3	10.28%	0.00	−0.03	0.57	3	10.15%	0.00	0.01	0.13
4	10.66%	0.01	0.48	0.77	4	8.55%	0.01	0.10	0.29
5 High	12.11%	0.89	0.82	1.23	5 High	4.83%	0.05	1.11	1.45
High-Low	1.51%	1.78	1.62	1.76	High-Low	−12.11%	0.09	1.84	1.79
Panel 3 Stocks Sorted by d_S^{+*}					Panel 4 Stocks Sorted by $(d_S^{-*} - d_S^*)$				
Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}	Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}
1 Low	4.54%	−0.06	1.60	−0.36	1 Low	14.52%	0.47	−0.59	1.61
2	8.95%	−0.01	0.85	−0.13	2	13.70%	0.01	−0.11	1.26
3	10.36%	0.00	0.25	0.01	3	10.47%	0.00	−0.01	1.19
4	12.24%	0.00	0.10	0.12	4	8.21%	−0.01	0.10	0.24
5 High	17.70%	0.07	−1.45	1.53	5 High	6.88%	−0.46	1.80	0.05
High-Low	13.15%	0.12	−3.05	1.89	High-Low	−7.64%	−0.93	2.39	−1.56
Panel 5 Stocks Sorted by $(d_S^{+*} - d_S^*)$					Panel 6 Stocks Sorted by $(d_S^{-*} - d_S^{+*})$				
Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}	Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}
1 Low	8.02%	0.61	−1.02	−1.23	1 Low	12.81%	0.01	−1.73	1.71
2	9.25%	0.00	0.59	−0.13	2	13.75%	−0.01	−0.11	1.29
3	10.28%	0.00	1.30	0.01	3	10.39%	0.00	−0.01	0.01
4	12.02%	−0.01	0.36	1.12	4	8.48%	0.00	1.09	−0.12
5 High	14.21%	−0.60	−1.07	1.61	5 High	8.34%	0.00	1.71	−1.55
High-Low	6.19%	−1.21	−0.05	2.85	High-Low	−4.47%	−0.01	3.45	−3.26

Note: This table presents the relationship between excess stock returns and business conditions factor loadings associated with the CPPF model. The column labeled "return" reports the annual average stock returns over the one-month T-bill rate. "High-Low" reports the difference between portfolio 5 and portfolio 1.

However, d_S^{-*} slumps from 1.6 to −1.45 along with the increase of d_S^{+*}. When stocks are sorted by $(d_S^{-*} - d_S^*)$, all returns, d_S^* and d_S^{+*} drop gradually while d_S^{-*} increases substantially. In contrast, it is clear from Panel 5 that returns increase steadily from 8.02% to 14.21% when stocks are sorted by $(d_S^{+*} - d_S^*)$. Meanwhile, d_S^* decreases along with the increase of d_S^{+*}, while d_S^{-*} presents a reversed U−shaped pattern. In Panel 6, $(d_S^{-*}-d_S^{+*})$ is employed to sort stocks. It can be seen from this panel that only d_S^{-*} increases obviously from −1.73 to 1.71, while returns and d_S^{+*} decrease in general and a U−shaped pattern is presented in d_S^*.

Overall, for stock market fluctuation and overall business conditions, beta and upside beta have a positive impact on stock returns, while downside beta shows a negative impact. For commodity market risk, as a measure of price level for essential goods, the beta shows a reverse impact on stock returns compared to the other two risk factors, while downside and upside beta follow the same impact on stock returns as the other two factors, which indicates that potential hedging in commodity market could be explored when systematic risk is considered symmetrically in stock market and overall business context.

5.2. Empirical result of the FFF model

A similar approach applies to the FFF-based estimates. Table A.1 to Table A.3 (in Appendix) present the risk-return relationship between annualized excess stock returns and estimates of stock market risk, commodity market risk and ADS index risk, respectively.

Although some patterns are not identical between both models, the relationship between returns and risk estimates are quite similar in general. It can be concluded that for both models, consistent with previous Huang et al's (2021) study, the conventional estimates of the stock market risk measures b_S^* and b_F^* do have a positive influence on stock returns, and are consistent with the classic literature of "high beta high return". However, the classic estimates of the commodity market risk measures c_S^* and c_F^* appear to have a negative impact on stock returns. The reason for that is most likely that risk in the stock market and commodity market are inversely related while ADS index risk measures d_S^* and d_F^* did not exhibit an obvious impact on stock returns. Furthermore, for the downside estimates, except $(c_S^{-*}-c_S^*)$, all have strong negative effects on stock returns. When downside risk estimates increase, stock returns decrease dramatically. There is no clear evidence that $(c_S^{-*} - c_S^*)$ has an impact on stock returns. Moreover, it is shown in Table 4 to Table A.9 that all the upside estimates (even when controlling for the classic estimates) have a strong positive impact on stock returns. When upside estimates increase, stock returns also increase substantially.

With these findings, the roles of downside and upside estimates are not simply components of classic estimates, but are new risk measures. Therefore, it is worthwhile examining the importance of downside and upside estimates as factors rather than factor loadings.

5.3. Fama-Macbeth regressions

In this section, in order to illustrate the impact of estimates of both models on driving stock returns from a cross-sectional regression point of view, a series of Fama-Macbeth regressions are performed which employ different combinations of the above estimates as independent variables.

In order to investigate possible multicollinearity, the correlation coefficient matrix of all estimates is presented in Table 6. It can be seen from Table 6 that none of the estimates are highly correlated with one another.[7] Between these estimates, the most correlated pair is b_S^* and d_S^* with a correlation coefficient at 0.43, followed by b_F^* and b_F^{+*}, and b_S^{-*} and c_S^{+*} at 0.38 and 0.33 respectively. Since none of the estimates is highly correlated with another, econometrically, all of them can be employed in Fama-Macbeth regression methodology.

Fama-Macbeth regressions are performed on possible combinations of estimates. The estimated coefficients are shown in Table 7 and Table 8 with Newey-West (1987) heteroscedastic robust standard errors with 12 lags employed to calculate the t−statistics and the R^2 values presented in the tables are adjusted R^2 values.

[7]Here we define high correlation as a correlation coefficient greater than 0.5 or less than −0.5.

Table 6. Correlation coefficients between factor loadings of both models.

	b_S^*	b_S^{-*}	b_S^{+*}	b_F^*	b_F^{-*}	b_F^{+*}	c_S^*	c_S^{-*}	c_S^{+*}	c_F^*	c_F^{-*}	c_F^{+*}	d_S^*	d_S^{-*}	d_S^{+*}	d_F^*	d_F^{-*}	d_F^{+*}
b_S^*	1.0000																	
b_S^-	0.0004	1.0000																
b_S^+	−0.0013	−0.1297	1.0000															
b_F^*	0.0073	0.0012	0.0025	1.0000														
b_F^-	0.0026	0.0077	−0.0035	0.2997	1.0000													
b_F^+	0.0035	−0.0041	0.0121	0.3774	−0.2454	1.0000												
c_S^*	−0.2451	−0.0101	0.0169	−0.0037	−0.0121	0.0060	1.0000											
c_S^-	−0.0003	−0.0116	0.0191	0.0005	−0.0004	0.0012	0.0010	1.0000										
c_S^+	−0.0013	0.3318	−0.0030	−0.003	0.0006	−0.0026	−0.0023	−0.0259	1.0000									
c_F^*	−0.0011	−0.0012	−0.0028	−0.0139	−0.0317	0.0111	0.0090	0.0013	0.0025	1.0000								
c_F^-	−0.006	−0.0044	−0.0024	0.0258	−0.1546	0.2540	0.0169	0.0009	0.0026	0.3038	1.0000							
c_F^+	0.0001	−0.0022	0.0016	−0.0444	0.0932	−0.1733	−0.0036	0.0002	0.0066	0.1358	−0.1648	1.0000						
d_S^*	0.4324	0.0022	−0.0045	−0.0001	0.0016	−0.0016	−0.2643	−0.0005	−0.0020	−0.0022	−0.0062	−0.0000	1.0000					
d_S^-	0.0001	0.0013	0.0004	−0.0002	−0.0027	0.0011	−0.0002	0.0007	0.0031	−0.0001	−0.0003	0.0003	0.0002	1.0000				
d_S^+	−0.003	0.0043	0.0525	0.0021	0.0009	0.0000	0.0058	0.0053	−0.0009	0.0014	−0.0003	0.0010	−0.0014	−0.0000	1.0000			
d_F^*	−0.0026	0.0026	0.0028	−0.0413	0.0017	−0.0346	−0.0035	−0.0009	0.0019	−0.1584	−0.0650	−0.0118	0.0076	0.0025	−0.0025	1.0000		
d_F^-	−0.0039	−0.0003	0.0004	0.0228	−0.0029	0.0258	0.0041	−0.0001	−0.0000	−0.0086	−0.0388	−0.0090	0.0123	0.0000	0.0000	0.0008	1.0000	
d_F^+	−0.001	0.0012	−0.0025	−0.008	0.0814	−0.0858	−0.0020	0.0004	0.0023	−0.0182	0.0649	−0.0371	0.0029	−0.0006	−0.0058	0.1207	0.0080	1.000

Note: This table reports the correlation coefficients between all factor loadings of the CPPF and the FFF models. To avoid repetition, only the lower triangle of the matrix is shown.

Table 7. Fama-Macbeth regression of CPPF model factor loadings.

	1	2	3	4	5	6	7	8
b_S^*	0.00336*** [3.38]		0.000435*** [3.09]			0.000631* [1.87]	0.00136*** [2.79]	
c_S^*	−0.000246 [−0.30]			0.00000587 [0.12]		−0.0000503 [−0.36]		0.0000986 [0.43]
d_S^*	−0.0329 [−0.63]				−0.00173 [−0.39]		−0.0104 [−0.66]	0.000218 [0.02]
b_S^{-*}		−0.00814*** [−6.55]		−0.000390*** [−3.63]	−0.000264* [−1.80]			0.00000105 [0.04]
b_S^{+*}		0.0110*** [10.69]		0.00103*** [4.05]	0.000438*** [3.24]			0.0000540*** [2.81]
c_S^{+*}		−0.00599*** [−6.34]	−0.000286*** [−4.57]		−0.000131*** [−3.65]		−0.0000179* [−1.68]	
c_S^{-*}		0.00485*** [6.43]	0.000397*** [3.35]		0.000234*** [2.60]		0.0000244** [2.46]	
d_S^{+*}		−0.251*** [−3.81]	−0.0137*** [−2.81]	−0.0206** [−2.02]		−0.00425 [−1.22]		
d_S^{-*}		0.217*** [6.24]	0.0199*** [4.00]	0.0235*** [3.91]		0.00291** [2.00]		
Cons	0.00417** [2.47]	0.00286* [1.72]	0.00795*** [3.05]	0.00760*** [3.00]	0.00834*** [3.26]	0.00795*** [3.25]	0.00692*** [2.90]	0.00842*** [3.24]
No. of Obs	2396262	2396262	2396262	2396262	2396262	2396262	2396262	2396262
Adjusted R^2	0.129	0.296	0.035	0.037	0.032	0.032	0.038	0.032

Note: This table reports the result of the Fama-Macbeth regression of the CPPF model factor loadings on excess stock returns. The t−statistics in the square brackets are calculated by using Newey-West (1987) heteroscedastic robust standard error with 12 lags. * denotes significance at the 10% level, ** denotes significance at the 5% level and ***denotes significance at the 1% level.

It can be seen from Table 7 that estimates of the CPPF-based cross-sectional model are employed in different possible combinations to examine the sensitivity of risk factor coefficients to stock returns. Among these eight regressions, regression 2 produces the highest adjusted R^2 value at 0.30, with all estimates highly significant at the 1% significance level. Regression 2 employs all the downside and upside estimates of the CPPF model to explain the movement of stock returns without considering the classic estimates. Among the independent variables in regression 2, d_S^{-*} and d_S^{+*} have coefficients of 0.251 and 0.217, respectively. Regression 1 aims to employ all the classic estimates to explain the movement of stock returns regardless of the downside and upside estimates. It produces the second highest R^2 value among the eight regressions, however, c_S^* and d_S^* are not significant even at the 10% significance level. Regression 3 employs downside and upside estimates of commodity market and ADS index risk to explain stock returns. All of the independent variables are significant at the 1% significance level. However, it produces a much lower R^2 value than regression 2 at 0.04.

It can be concluded that classic estimates do not have enough explanatory power on stock returns, and when dividing the market risk into downside and upside risk, downside and upside estimates have more explanatory power than classic ones. Regarding the importance of market risk, although commodity market and business risk do have a relationship with the stock market, market risk is still an essential element relating to stock returns.

Table 8. Fama-Macbeth regression of the FFF model factor loadings.

	1	2	3	4	5	6	7	8
b_F^*	0.00567*** [3.52]		0.00608*** [4.38]			0.00597*** [4.08]	0.00578*** [3.97]	
c_F^*	−0.00156 [−1.28]			0.00144 [−1.47]		−0.000992 [−0.95]		−0.00143 [−1.34]
d_F^*	−0.0301 [−0.37]				−0.0104 [−0.15]		−0.00434 [−0.06]	−0.0259 [−0.35]
b_F^{-*}		−0.0110*** [−8.17]		−0.00371*** [−5.35]	−0.00322*** [−5.04]			−0.00134*** [−2.99]
b_F^{+*}		0.0153*** [13.07]		0.00702*** [8.45]	0.00582*** [8.07]			0.00316*** [5.58]
c_F^{-*}		−0.00791*** [−7.95]	−0.00253*** [−6.83]		−0.00271*** [−5.64]		−0.00117*** [−4.38]	
c_F^{+*}		0.00661*** [7.35]	0.00267*** [6.33]		0.00276*** [5.70]		0.00142*** [5.57]	
d_F^{-*}		−0.277*** [−4.16]	−0.114*** [−4.52]	−0.143*** [−4.21]		−0.0856*** [−4.13]		
d_F^{+*}		0.242*** [6.80]	0.120*** [5.59]	0.109*** [5.60]		0.0745*** [5.07]		
Con	0.00929*** [4.45]	0.00716*** [3.85]	0.00721*** [3.12]	0.00688*** [3.18]	0.00928*** [4.40]	0.00728*** [3.27]	0.00917*** [4.13]	0.00909*** [4.23]
No. of Obs	2396262	2396262	2396262	2396262	2396262	2396262	2396262	2396262
Adjusted R^2	0.071	0.135	0.095	0.094	0.099	0.075	0.077	0.079

Note: This table reports the result of the Fama-Macbeth regression of the FFF model factor loadings on excess stock returns. The t−statistics in the square brackets are calculated by using Newey-West (1987) heteroscedastic robust standard error with 12 lags. * denotes significance at the 10% level, ** denotes significance at the 5% level and ***denotes significance at the 1% level.

It can be seen from Table 8 that estimates of the FFF model are employed in different combinations. Among these eight regressions, regression 2 produces the best fit with an adjusted R^2 value of 0.14, with all estimates significant at the 1% level.

It employs all the downside and upside risk estimated coefficients of the FFF model to explain the movement of stock returns without considering the classic betas. Among the independent variables in regression 2, d_F^{-*} and d_F^{+*} have coefficients of 0.277 and 0.242, respectively. Regression 3 produced the second best fit with an adjusted R^2 of 0.1. It employs the classic stock market beta with downside and upside commodity market and ADS index risk to explain stock returns, with all variables significant at the 1% level significance.

It can be concluded from Table 7 and Table 8 that when the estimates are separately employed in the Fama-Macbeth regression based on their original models, the downside and upside risk estimates of both models of all three risk factors are significantly priced and produce the best fit, while the classic estimates did not perform as well as downside and upside ones. Among the downside and upside risk estimates, the ones that employ ADS index risk explain stock returns the most. Downside and upside risk estimates of the CPPF model, employed as independent variables in Fama-Macbeth regression produced the best fit among all regressions.

For the sake of completeness, rather than dividing estimates into two groups based on their original models, all available estimates are employed in different combinations to perform Fama-Macbeth regressions, in order to examine whether putting estimates from both models together could enhance the cross-sectional explanatory power. The results of these exercises are shown in Table A.4 (in Appendix). It is obvious that when all estimates are employed, regression 7 produces the highest R^2 value of 0.38 among all regressions among Table 7 to Table A.10. However, the best fit does not make all estimates significant, particularly, d_S^* c_S^*, c_F^* and d_F^* which are not significant at the 10% significance level. Regression 2 employs all the downside and upside estimates of both models and produces the second best fit with an adjusted R^2 value of 0.35. All estimates of regression 2 are highly significant at the 1% significance level. The remaining regressions in Table A.10 produce low adjusted R^2 values with certain independent variables being not significant.

Notably, the classic estimates of the commodity market and ADS index risk of both models, c_S^*, d_S^*, c_F^* and d_F^*, have never been significant in any regression. In contrast, the downside and upside estimate of all three factors associated with both models are almost always significant. It can be concluded that from a cross-sectional point of view, downside and upside estimates are not only components of classic estimates, but also produce better explanatory power than classic estimates. The importance of downside and upside estimates show that explaining the movement of stock returns can be more precisely achieved by examining the downside and upside of risk factors individually rather than treating risk factors as a whole. Moreover, it also can be summarized that apart from stock market risk itself, commodity market and ADS index risk do have significant relations with stock returns. The downside risk estimates have a negative relationship with stock returns, while upside estimates show a positive one. Furthermore, between the CPPF model and the FFF model, with all estimates significant, the former one does produce a slightly better fit than the latter one.

Although there is no sign of multicollinearity between all available variables econometrically (bivariate correlations), the implication of employing risk estimates of the same risk factors from both models is still questionable. Nevertheless, it is clear that employing downside and upside estimates of both models produces a much higher adjusted R^2 value with all estimates significant. It is most likely that the CPPF model and the FFF model can complement each other, and the downside and upside risk estimated coefficients could capture something that the one of the other models could not.

Finally, consistent with the results of previous studies, the downside and upside estimates of market risk are highly significant, and have negative and positive relations with stock returns, respectively. More importantly, employing commodity market and ADS index risk in the regressions leads to a dramatic increase in adjusted R^2 values. It is obvious that commodity market risk and real business risk do have strong explanatory power on stock returns. While there could be other factors significantly driving stock prices, the above three factors are preferred because they measure the whole economy in a more comprehensive way.

5.4. The predictability of risk factor estimated coefficients

After revealing the relationship between realized stock returns and estimates of both models, the predictability of the risk factor coefficients is examined. As in earlier sections, the relative estimates associated with the CPPF model, denoted by $(b_S^{-*} - b_S^*)$, $(c_S^{-*} - c_S^*)$ and $(d_S^{-*} - d_S^*)$ for the downside market, and $(b_S^{+*} - b_S^*)$, $(c_S^{+*} - c_S^*)$ and $(d_S^{+*} - d_S^*)$ for the upside market, and repetitive measures associated with the FFF model. Moreover, the annualized average excess return of each stock are computed based on the following year's data. Furthermore, all stocks in the sample are assigned into five portfolios based on the mean of the target estimate. Finally, the equally weighted average of estimates and future one−year excess returns for each portfolio are computed. The results are shown in Tables 9 to Table 11 and Table A.5 to Table A.7 (in Appendix).

For the CPPF model, it can be seen from Table 9 that when stocks are sorted by b_S^*, b_S^{-*}, b_S^{+*}, $(b_S^{-*} - b_S^*)$ and $(b_S^{+*} - b_S^*)$, the highest future returns all appear in portfolio 3, and returns present a reversed U−shaped pattern. When stocks are sorted by $(b_S^{-*} - b_S^{+*})$, the reversed U−shaped pattern still exists. When stocks are sorted by estimates of the commodity market and ADS index risk, it is even more obvious from Table 10 and Table 11 that the reversed U-shaped pattern of future returns is present, and with portfolio 3 of each group producing the highest future return.

Table 9. Future excess stock returns sorted by stock market factor loadings of the CPPF model.

Panel 1 Stocks Sorted by b_S^*					Panel 2 Stocks Sorted by b_S^{-*}				
Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}	Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}
1 Low	8.69%	−1.01	−0.48	0.11	1 Low	7.45%	0.99	−1.37	1.61
2	17.44%	0.65	0.31	−0.13	2	20.86%	1.05	−0.72	1.13
3	21.64%	1.06	1.11	0.58	3	23.40%	1.09	1.08	0.98
4	18.31%	1.49	1.64	2.00	4	16.94%	1.06	1.75	0.77
5 High	7.76%	2.10	1.92	1.24	5 High	5.19%	1.12	1.92	−1.69
High-Low	−0.93%	3.11	2.41	1.12	High-Low	−2.26%	0.13	3.30	−3.30
Panel 3 Stocks Sorted by b_S^{+*}					Panel 4 Stocks Sorted by $(b_S^{-*}-b_S^*)$				
Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}	Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}
1 Low	6.68%	0.60	1.96	−0.54	1 Low	8.82%	1.79	−0.36	1.36
2	12.42%	1.05	1.55	−0.53	2	20.84%	1.33	0.55	1.15
3	21.47%	1.16	1.04	0.92	3	22.13%	1.03	1.06	0.98
4	20.60%	1.31	0.81	1.14	4	15.78%	0.82	1.58	0.41
5 High	12.66%	1.19	−1.85	1.81	5 High	6.27%	−1.67	1.93	−1.71
High-Low	5.98%	0.59	−3.81	2.35	High-Low	−2.55%	−3.46	2.30	−3.07
Panel 5 Stocks Sorted by $(b_S^{+*}-b_S^*)$					Panel 6 Stocks Sorted by $(b_S^{-*}-b_S^{+*})$				
Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}	Portfolio	Return	b_S^*	b_S^{-*}	b_S^{+*}
1 Low	6.86%	1.42	1.71	−1.50	1 Low	10.62%	1.42	−1.21	1.61
2	11.98%	1.19	1.43	−0.38	2	22.66%	1.32	0.53	1.64
3	22.23%	1.00	0.95	0.94	3	21.18%	0.97	1.02	0.91
4	21.85%	0.92	1.25	1.01	4	12.94%	0.90	1.34	−0.34
5 High	10.93%	−1.84	−1.20	1.73	5 High	6.43%	0.69	1.84	−1.04
High-Low	4.07%	−3.26	−2.91	3.23	High-Low	−4.19%	−0.73	3.06	−2.65

Note: This table presents the relationship between future excess stock returns and the stock market factor loadings associated with the CPPF model. The column labeled "return" reports the annual average future stock returns over the one−month T−bill rate. "High−Low" reports the difference between portfolio 5 and portfolio 1.

Table 10. Future excess stock returns sorted by commodity market factor loadings of the CPPF model.

Panel 1 Stocks Sorted by c_S^*					Panel 2 Stocks Sorted by c_S^{-*}				
Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}	Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}
1 Low	5.94%	−1.33	−0.01	−2.57	1 Low	7.35%	−0.43	−0.58	1.67
2	19.74%	−0.30	−1.93	−2.00	2	18.81%	−0.78	1.07	1.84
3	19.77%	1.11	0.79	0.60	3	20.88%	1.02	1.46	0.46
4	19.45%	1.58	−0.87	1.94	4	17.76%	−0.07	1.52	−1.57
5 High	8.94%	1.82	2.16	1.30	5 High	9.05%	1.63	2.10	−1.12
High-Low	3.00%	3.14	2.18	3.87	High-Low	1.70%	2.06	2.68	−2.79
Panel 3 Stocks Sorted by c_S^{+*}					Panel 4 Stocks Sorted by ($c_S^{-*}-c_S^*$)				
Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}	Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}
1 Low	6.54%	−1.07	1.97	−1.18	1 Low	8.76%	0.81	−0.53	0.82
2	19.90%	0.01	1.33	−0.55	2	18.31%	1.49	−0.16	1.56
3	21.53%	1.11	−0.11	0.14	3	21.77%	0.11	0.06	0.27
4	19.22%	−0.44	0.36	1.44	4	15.82%	−0.28	1.05	0.51
5 High	6.65%	−0.24	−1.41	1.76	5 High	9.17%	−1.77	1.69	−1.90
High-Low	0.11%	0.83	−3.38	2.94	High-Low	0.41%	−2.58	2.22	−2.72
Panel 5 Stocks Sorted by ($c_S^{+*}-c_S^*$)					Panel 6 Stocks Sorted by ($c_S^{-*}-c_S^{+*}$)				
Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}	Portfolio	Return	c_S^*	c_S^{-*}	c_S^{+*}
1 Low	6.70%	0.97	1.77	−0.45	1 Low	7.74%	−1.78	−0.17	1.78
2	18.18%	0.53	1.76	−0.17	2	18.21%	1.32	0.48	1.17
3	23.83%	0.14	−0.08	0.18	3	23.54%	1.16	1.00	0.05
4	18.50%	−0.29	0.18	1.33	4	17.55%	−1.20	1.20	−1.13
5 High	6.62%	−1.99	−1.49	1.51	5 High	6.80%	1.50	1.60	−1.27
High-Low	−0.08%	−2.96	−3.26	1.96	High-Low	−0.94%	3.28	1.77	−3.05

Note: This table presents the relationship between future excess stock returns and the commodity market factor loadings associated with the CPPF model. The column labeled "return" reports the annual average future stock returns over the one-month T-bill rate. "High-Low" reports the difference between portfolio 5 and portfolio 1.

For the FFF model, it can be seen from Table A.5 to Table A.7 (in Appendix) that the reversed U-shaped pattern on future returns on all groups of portfolios exists except when stocks are sorted by b_F^{+*} and $(b_F^{+*} - b_F^*)$. For the remaining groups, portfolio 1 or portfolio 5 constantly has the lowest future return.

It can be concluded from the results that the medium value estimates of the commodity market and ASD index risk lead to a high future return, while the top and bottom value estimates constantly lead to a low future return. Moreover, for estimates of stock market risk, there is very weak evidence that low upside estimates indicate a high future return on the FFF model. However, the estimates of the CPPF model do not support the evidence, the remaining estimates of stock market risk appear to be consistent with the estimates of the commodity market and ADS index risk.

Table 11. Future excess stock returns sorted by business conditions factor loadings of the CPPF model.

Panel 1 Stocks Sorted by d_S^*				
Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}
1 Low	11.42%	−0.69	−1.57	−1.07
2	18.47%	−0.02	−1.51	−0.69
3	23.10%	0.00	0.75	0.53
4	16.24%	1.01	−0.17	0.40
5 High	4.61%	1.58	−1.17	−1.22
High-Low	−6.81%	2.27	0.40	−0.15

Panel 2 Stocks Sorted by d_S^{-*}				
Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}
1 Low	9.31%	−0.07	−1.04	−2.10
2	18.05%	−0.02	−0.87	1.20
3	23.09%	0.00	−0.01	0.03
4	18.25%	1.03	0.74	−0.27
5 High	5.14%	1.14	1.68	−0.50
High-Low	−4.17%	1.21	2.72	1.60

Panel 3 Stocks Sorted by d_S^{+*}				
Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}
1 Low	8.07%	−0.19	−0.30	−1.79
2	15.46%	1.03	−0.87	−0.47
3	22.68%	−0.01	1.08	1.01
4	15.99%	1.31	1.72	1.40
5 High	11.64%	−0.04	−0.30	1.81
High-Low	3.57%	0.15	0.00	3.60

Panel 4 Stocks Sorted by $(d_S^{-*} - d_S^*)$				
Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}
1 Low	10.15%	1.13	−0.91	−1.16
2	17.54%	1.06	−0.84	−0.58
3	20.92%	−1.00	1.01	1.12
4	20.62%	−1.04	1.43	−0.86
5 High	4.61%	−1.26	1.86	−1.56
High-Low	−5.54%	−2.39	2.78	−0.40

Panel 5 Stocks Sorted by $(d_S^{+*} - d_S^*)$				
Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}
1 Low	8.08%	1.20	−0.50	−0.68
2	13.76%	1.05	−0.02	−0.47
3	23.44%	−1.00	1.14	1.00
4	17.44%	−1.05	0.95	1.40
5 High	11.13%	−1.32	−1.24	1.72
High-Low	3.05%	−2.52	−0.74	2.40

Panel 6 Stocks Sorted by $(d_S^{-*} - d_S^{+*})$				
Portfolio	Return	d_S^*	d_S^{-*}	d_S^{+*}
1 Low	10.88%	−1.06	−1.01	1.84
2	18.11%	−1.03	−1.01	0.49
3	22.84%	−0.03	1.01	0.01
4	17.10%	1.10	1.94	−0.53
5 High	4.91%	−1.04	2.52	−1.87
High-Low	−5.97%	0.02	3.54	−3.72

Note: This table presents the relationship between future excess stock returns and the business conditions factor loadings associated with the CPPF model. The column labeled "return" reports the annual average future stock returns over the one-month T-bill rate. "High-Low" reports the difference between portfolio 5 and portfolio 1.

5. Conclusions

From the cross−sectional point of view, the time−varying conventional estimates of stock market risk play important roles in determining stock returns. Specifically, b_S^* and b_F^* are found have a positive influence on stock returns — a result that is consistent with the classic literature. The classic estimates of commodity market risk c_S^* and c_F^* appear to have a negative impact on stock returns which appear to be a hedging market during economic downturn. The classic estimates of ADS index risk d_S^* and d_F^* did not show an obvious impact on stock returns. Furthermore, for all the downside estimates of both models, even when controlling for the classic estimates and upside estimates, there are strong negative impacts on stock returns. The findings indicate that stock returns are more sensitive to recessed business condition.

When estimates are treated as factors rather than factor loadings, this study finds that downside and upside estimates are not only components of classic estimates, but also produce better explanatory power than classic estimates. The evidence from downside and upside estimates shows that explaining the movement of stock returns can be enhanced by examining the downside and upside of risk factors individually rather than treating the risk symmetrically. Moreover, it can be summarized that apart from stock market risk, the commodity market and ADS index risks are found to have significant impacts on stock returns. The downside estimates have a negative relationship with stock returns, while upside estimates have a positive impact. Furthermore, between the CPPF model and the FFF model, with all estimates significant, the former one produces a better fit than the latter one. However, it is found that employing downside and upside estimates of both models can produce a much higher adjusted R^2 value with all estimates significant. This could be due to the complementary property of both models.

Finally, the predictive power of all classic, downside and upside estimate of both models is found to be poor. There is weak evidence that low upside estimates of stock market risk indicate a higher future return when the FFF model is employed.[8] However the estimates of the CPPF model do not support the evidence. The findings indicate that risks (as of stock market, overall business conditions and commodity market) are of significant exploratory power to contemporaneous stock returns, while being modest of predictive power.

Arguably, there are certain limitations in this study. Firstly, although both CPPF and FFF approaches are considered to be comprehensive time series data smoothing technique, the impact on financial economic inference of modelling will need to be further explored. Secondly, adjusted R^2 is used to differentiate goodness of fit of Fama-Macbeth regressions, while supplementary approaches e.g., GRS test (Gibbons et al., 1989) could have been employed to compare the modelling efficiency. Thirdly, this study uses ADS index and commodity price index to proxy overall business condition and price level, while alternative indices could have been considered for comparisons. Nonetheless, these lead to further research on asset pricing modelling.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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[8]See Panel 3, Table A.11.

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