Returns to public debt: The US federal budget deficit and the cross-section of equity returns

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Abstract

This paper investigates the implications for asset pricing of changes in the US federal budget deficit. A portfolio-based risk factor related to changes in the budget deficit is formulated and its cross-sectional properties analyzed. In contrast to economic intuition, the spread between portfolios exhibiting the highest risk related to changes in the budget deficit and those exhibiting the lowest risk is found to be significantly negatively priced. Standard asset pricing models in line with Fama and French (1992) and Carhart (1997) cannot explain this apparently anomalous pattern. The spread appears to generate high payoffs in bad states of the economy.

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1. INTRODUCTION

On Friday August 5, 2011 Standard & Poor's announced that it had downgraded the credit rating of the USA for the first time in history. One major reason for downgrading the nation's creditworthiness was the enormous US federal budget deficit which has increased continuously for several decades. In the wake of the downgrading of the US economy, the US federal budget deficit and its impact on domestic macroeconomic variables have generated a great deal of public debate. Changes in the federal budget deficit are also associated with different effects on the financial sphere from a micro perspective. There are some papers that study the association between the federal budget deficit variable and the stock market. Darrat and Brocato (1994) investigated the efficiency of the US stock market as it pertains to a number of major macro-finance variables. Their findings indicate that the stock market may be inefficient with regard to the federal budget deficit. Ewing (1998) examined whether the federal budget deficit has an impact on the stock markets of Australia and France. Consistent with the findings of Darrat and Brocato (1994), Ewing's results indicate that in both Australia and France the past deficit contains information about the future movements in the stock markets. The empirical findings from Darrat and Brocato (1994) and Ewing (1998), which may be summarized as indicating that changes in the budget deficit are Granger-causal for stock market returns, have been most recently confirmed by Laopodis (2009 & 2012) and Grobys (2013).

The purpose of this paper is to investigate the asset pricing implications of changes in the federal budget deficit. This paper is motivated by the growing body of literature that models the relation between macro-finance variables and expected returns.[2] Nevertheless, there has been no study undertaken that would investigate asset pricing implications of changes in the federal budget

[2] Relevant papers within this strand of literature include Bodie (1976), Fama (1981, 1990 & 1991), Geske and Roll (1983), Pearce and Roley (1983 & 1985), Flannery and Protopapadakis (2002).

deficit in a portfolio based approach in the spirit of Fama and French (2008). This paper contributes to prior literature in the following aspects: First, it generates a portfolio-based systematic risk factor based upon changes in the US federal budget deficit. A novel aspect of this paper is the proposed approach to generating a portfolio-based risk factor which involves employing cumulative impulse response functions based upon iteratively estimated VAR-models. Second, the study identifies whether traditional risk factors are capable of explaining the risk factor related to changes in the budget deficit. Third, the study examines the extent to which the new risk factor can help to explain the cross-section of equity returns.

The presence of Granger causality constitutes the employment of impulse response functions that in this context have an economic meaning. In a bivariate Vector-Autoregressive model the corresponding impulse response functions can be interpreted as measures of future return that firm i is expected to generate when the budget deficit is subject to a shock. In the first step of the empirical analysis, the portfolio-based procedure in the spirit of Fama and French (2008) is extended by first dividing a set of equity portfolios into 20 groups based on their cumulative impulse response to orthogonalized shocks in the budget deficit process. Subsequently, the current research examines the returns of quarterly rebalanced consecutive zero-cost strategies that are long on the group of equity portfolios exhibiting the highest negative cumulative impulse responses to shocks in the budget deficit process and short on the all other groups of equity portfolios. Since the cumulative impulse response functions depend also on the underlying forecast horizon, the zero-cost strategies are also investigated for different forecast horizons.

Then, the zero-cost strategy associated with the optimal forecast horizon corresponding to a long-term horizon of 23 periods is treated as a risk factor and investigated further. The result is an analysis of a sample spanning more than 30 years of quarterly data. The proposed sorting methodology reveals a strong interaction between cumulative impulse responses and future returns: The raw spread between the equity portfolio group (PG) comprising the equity portfolios exhibiting the highest negative and lowest cumulative impulse responses is -1.27% per quarter with heteroskedasticity robust *t*-value of -2.48. Risk-adjusting the spread by employing Carhart's (1997) four-factor model slightly increases the economic magnitude of the spread to -1.42% per quarter with heteroskedasticity robust *t*-value of -2.84 indicating statistical significance on any level. Even though this outcome may be referred to as anomaly because it suggests that investors are willing to pay a premium for bearing risk, the conducted spread appears to be negatively associated with the business cycle and appears to generate high payoffs in bad states of the economy.

Furthermore, it is investigated whether standard asset pricing models are able to explain the portfolios sorted by their deficit risk sensitivities. I employed the traditional CAPM derived from the work of Sharpe (1964), Lintner (1995) and Black (1972), Fama and French's (1993) three-factor model, and four-factor model specifications in line with Carhart (1997). It is found that none of these standard asset pricing models can explain the cross section of these test assets. Moreover, the cross-sectional risk premium of the deficit-related risk factor was found to be of economic importance ranging between -1.16% and -1.20% per quarter, depending on the model specification, with corresponding *t*-values varying between -2.07 and -2.10. Given the set of test-portfolios, the new risk factor alone is able to explain 73% of the cross-section of equity returns. Taken together, the results presented in this paper provide strong evidence that changes in the budget deficit appear to be of relevance for describing the cross-section of equity returns.

The remainder of this paper is organized as follows. The next section provides more details on the background to the paper. The third section presents the data and the results from the proposed new sorting methodology. As a result, I set up bivariate VAR-models for a large set of equity portfolios and implemented the corresponding cumulative impulse response functions for different forecast horizons. For each forecast horizon under consideration, the equity portfolios were sorted into 20 groups with respect to estimated cumulative impulse responses to shocks in the budget deficit return process. Then, various zero-cost strategies are investigated, depending on the respective forecast horizon, by buying the group of equity portfolios exhibiting the highest negative cumulative impulse responses and selling consecutively all other PGs. Then, the optimal zero-cost portfolio is employed for pricing the cross-section of equity returns. The last section concludes.

2. BACKGROUND

Flannery and Protopapadakis (2002) argue that macroeconomic variables are excellent candidates for systematic risk factors because macroeconomic changes may simultaneously have an impact on many companies' cash flows and may affect the risk-adjusted discount rate. Moreover, economic conditions may also have an effect on the number and types of real investment opportunities available. However, Chan et al. (1998) highlight that macroeconomic factors generally perform poorly in explaining variations in equity returns. In the academic literature, many papers have tried to identify reliable associations between macroeconomic variables and equity returns (Chen et al., 1986, Chang and Pinegar, 1989 & 1990, Fama, 1990 & 1991, Flannery and Protopapadakis, 2002). Darrat and Brocato (1994) particularly emphasize the role of the federal budget deficit as a macro-finance variable. They highlight that variation in the federal budget deficit can be considered an argument in the non-idiosyncratic risk structure that may be related to the whole stock universe. More precisely, Darrat and Brocato (1994) argue that deficit risk cannot be eliminated through diversification and consequently, this risk should be priced according to financial theory. In particular, the long-standing public policy concerns regarding chronic excessive federal spending, and the observed link between the size of the deficit and the business cycle, may constitute the belief that variation in the deficit factor could have a high information quotient for the rational investor.

Furthermore, Darrat and Brocato (1994) describe various channels through which changes in the federal budget deficit may affect investors' expectations concerning future cash flows and/or the discount rate. Both arguments are integral parts of the conventional discounted cash flow model. A simple discounted cash-flow model for stock price determination may be given by

$$P_{i,t} \left| \Omega_t \right. = E\left(\sum_{t=0}^{N} \frac{EPS_{i,t}}{\left(1+d_i\right)^t} \left| \Omega_t \right. \right) \tag{1}$$

where P_{it} denotes the stock price of firm *i* at time *t*, EPS_i denotes the earnings per share of firm *i*, d_i is the firm specific discount rate and *T* is the number of time periods taken into account. Equation (1) also shows that the expected earnings of a company depend on the current information set Ω_t of the investor at time *t*. The firm specific discount rate is the sum of the risk free rate and a firm specific risk premium. The theoretical belief that the expected sign of the budget deficit effect on stock returns is negative rests upon the assumption that deficits exert upward pressure on the nominal interest rate. However, an increase in the budget deficit can be occasioned by an increase in government spending, a decrease in government revenues (i.e., lowered taxes), or a mixture of both. All these policies are intended to stimulate the economy. It seems logical that if the government reduces the tax burden of companies, the profit of firms will increase, all else being equal. The same argumentation may hold if the government increases its public spending and, as a consequence, increases subventions for firms. Moreover, the government has also the option to decrease the tax burden of private households which, in turn, is also likely to result in an increased budget deficit. However, Elmendorf and Mankiw (1999) point out that conventional analysis concludes that this policy will stimulate consumption, at least from a short-term perspective. In turn, an increase in consumption will, *ceteris paribus*, lead to an increase in corporate profits.

Summing up, the theoretical belief that the expected sign of the budget deficit effect on stock returns is negative implies that a higher budget deficit leads to an increase in interest rates and, moreover, that the negative effect of an increased risk-free rate is larger than the positive effect of an increased value of expected earnings-per-share (EPS) on an individual firm level. However, anecdotal evidence contradicts this theoretical belief. The USA has been running an ever-increasing budget deficit for decades, while the risk-free rate has simultaneously declined. Even if we assume that the theory holds, the negative effect of rising interest rates would not occur instantaneously, but be subject to a time lag and, therefore, appear in uncertain future periods. Hence, the expected sign of the budget deficit effect on stock returns may be not unambiguous.[3]

Since changes in the budget deficit are understood as risk that has a long-term effect on the whole economy, it will also be assumed that firms that exhibit a high long-term sensitivity to the deficit risk are more risky than firms that exhibit a low long-term sensitivity to the deficit risk. Traditional economic theory suggests that the spread between firms that are more risky and firms that are less risky should be positive. The long-term effect of fiscal policy is well known in the

[3] Recent empirical findings from Laopodis (2012) and Grobys (2013) examined the impulse responses of the US stock market to shocks in the US-federal budget deficit variable. Their findings give empirical evidence for shocks in the budget deficit variable resulting in positive impulse responses of the US stock market. In Laopodis (2012) study, however, the impulse response function is positive only in the three months immediately after the shock occurred.

macroeconomic literature and most often referred to as the *multiplier effect*. In turn, shocks in the deficit process have a long-term effect on organizational cash flows. Therefore, rational investors will require a risk premium for holding stocks of companies whose expected generated returns are affected by public spending. That is because positive shocks to the budget deficit rate will increase the long-term cash flow of firms that exhibit a high positive long-term sensitivity to the deficit risk, whereas negative budget deficit shocks will decrease the cash flows of those firms over an extended period.[4] As a consequence, the spread between firms that exhibit a high long-term sensitivity to the deficit risk and firms that exhibit a low long-term sensitivity to the deficit risk should be positively priced because it reflects a systematic risk. In the parlance of Novy-Marx (2013), this reasoning is "consistent with risk based pricing".

In contrast to traditional portfolio-based risk factors such as *SMB* and *HML*, as proposed by Fama and French (1993), or the *MOM* factor, as proposed in Jegadeesh and Titman (1993) and Carhart (1997), the portfolio based risk factor related to deficit risk, as proposed in this study, is directly linked to the macro economy. Since changes in the budget deficit hit the whole economy at the same time, this risk cannot be diversified away (Darrat and Brocato 1994). For equities, it seems natural to consider changes in fundamental macro-finance variables to be major drivers of equity returns. Previous research has tried to identify reliable associations between macroeconomic variables and equity returns, but has concluded that macroeconomic factors generally perform poorly in explaining variations in equity returns (Chan et al. 1998; Flannery and Protopapadakis 2002). This paper breaks new ground in empirical asset pricing research and shows that the federal budget deficit as a macro-finance can assist in predicting future equity returns. While developing a new theoretical model is beyond the scope of this paper, it is

[4] Analogously, positive shocks to the budget deficit rate will decrease the long-term cash flow of firms that exhibit a high negative long-term sensitivity to the deficit risk, whereas negative budget deficit shocks will increase the cash flows of those firms over an extended period.

possible to state that any theory that attempts to explain the cross-section of equity returns should also be consistent with the empirical facts linking changes in the budget deficit and future equity returns.

3. DATA

To serve as proxies for the US federal budget deficit, I downloaded the series Federal Debt Held by Foreign & Institutional Investors (series: FDHBFIN), Federal Debt Held by Federal Reserve Banks (series: FDHBFRBN) and Federal Debt Held by Private Investors (series: FDHBPIN) from the Federal Reserve Bank of St. Louis.[5] The data series are available from the first quarter of 1970 onwards (here I use the form 1970:1 to designate years and quarters). I compound the proxy for the US federal budget deficit simply as the sum of these three series and then compound the corresponding quarterly returns. Furthermore, I obtained the following research equity portfolios from Kenneth French's website[6]: 100 value-weighted research equity portfolios formed on size and book-to-market ratio, 25 value-weighted research equity portfolios formed on size and momentum, 49 value-weighted research equity portfolios formed on industry, 25 value-weighted equity research portfolios sorted by size and short-term reversal and 25 value-weighted equity research portfolios sorted by size and long-term reversal. In total, I used 224 research value-weighted equity portfolios employed as input assets for the sorting methodology. From my perspective, operating with equity portfolio returns instead of individual stock returns makes sense in the context of this analysis for the following reasons: First, I avoid potential back-filling and survival biases as previously mentioned in the academic literature. Second, equity portfolios are not as "noisy" as individual stocks: Reduced noise in the return series may have a positive

[5] See http://research.stlouisfed.org/fred2/categories/106.
[6] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

effect on the accuracy of the parameter estimates for the impulse response functions. Third, operating with equal-weighted averages in PGs, consisting of value-weighted equity portfolios, eliminates via construction the risk that the results could be driven by outliers, such as microcaps, as defined by Fama and French (2008). Fourth, each of the equity portfolios employed to develop the sorting methodology itself contains a basket of value-weighted equities exhibiting the same characteristics. Consequently, these assets (equity portfolios) can be interpreted as proxies for firms that share similar characteristics. The corresponding data for the risk factors such as the market risk factor, *SMB*, *HML* and *MOM* and the risk-free rate data were also obtained from Kenneth French's website. I matched all data series against the data for the US federal budget deficit and compounded the quarterly returns. The overall data set accounts for 172 quarterly observations running from 1970:2 to 2012:4.

4. SORTS ON CUMULATIVE IMPULSE RESPONSE FORECASTS

For each equity portfolio i=1,..,224, I used a rolling time window of ten years of quarterly data starting in 1970:2 and estimated the following bivariate VAR-model:

$$\mathbf{Y}_{it} = \mathbf{c}_i + \mathbf{A}_{i2}\mathbf{Y}_{it-2} + \mathbf{A}_{i3}\mathbf{Y}_{it-3} + \mathbf{A}_{i4}\mathbf{Y}_{it-4} + \mathbf{E}_{it}, \tag{2}$$

Where $\mathbf{Y}_{it}$ is a 2×1 vector containing the proxy for changes in the federal budget deficit and the returns of equity portfolio i, $\mathbf{E}_{it}$ is a 2×1 vector of random variables with covariance matrix $\mathbf{\Sigma}_i$, $\mathbf{c}_i$ is a 2×1 vector of constants and $\mathbf{A}_{ip}$ with $p = 1,...,4$ denote 2×2 parameter matrices. I selected only equity portfolios that had no missing return entries in both the in-sample rolling time window spanning ten years of data and the out-of-sample holding period, that is, one quarter ahead. The current value of the budget deficit is not in the information set Ω_t of the investor because the updated figure for the current budget deficit takes about six to ten weeks to be released and become publically available. Therefore, the first lag of the VAR-model was skipped. In line with Lütkepohl and Krätzig (2004), a lag-order of p=4 is common practice when operating with quarterly data and also used in Darrat and Brocato (1994) and Grobys (2013), for instance. Next, I investigated the response of the returns of equity portfolio i to orthogonalized shocks in the budget deficit process of one standard deviation making use of the Wold-Moving Average (MA) representation of the process in equation (2), given by

$$\mathbf{Y}_{it} = \mathbf{\Theta}_{i0}\mathbf{\Psi}_{it} + \mathbf{\Theta}_{i1}\mathbf{\Psi}_{it-1} + \mathbf{\Theta}_{i2}\mathbf{\Psi}_{it-2} + \dots \qquad (3)$$

where $\mathbf{\Theta}_{ik} = \mathbf{\Phi}_{ik}\mathbf{P}_i$ and $\mathbf{\Psi}_{it} = \mathbf{P}_i^{-1}\mathbf{E}_{it}$ with k={1, 2,…}, $\mathbf{\Phi}_{iS} = \sum_{j=1}^{S} \mathbf{\Phi}_{iS-j}\mathbf{A}_{ij}$ and $\mathbf{\Phi}_{i0}$ is a 2×2 identity matrix. The matrix $\mathbf{P}_i$ is a lower triangular and denotes the Cholesky decomposition of the covariance matrix $\mathbf{\Sigma}_i$ of the residuals of equation (2) which is described in detail in Lütkepohl and Krätzig (2004, pp.165-171). Moreover, I used the Cholesky ordering method meaning that the first element, $y_{1,it}$ in the vector $\mathbf{Y}_{it}$ correspond to the budget deficit returns and the second element, $y_{2,it}$ corresponds to the returns of equity portfolio i. Then, I compounded the cumulative impulse response of the respective equity portfolio to orthogonalized shocks in the budget deficit process of one standard deviation. If equity portfolios are considered as proxies for firms, cumulative impulse response functions have a useful economic meaning. They measure the expected cumulative future return that a firm generates, given the investors' current information set Ω_t at time *t*, if an innovation corresponding to one standard deviation in the budget deficit process occurs. It might be assumed that firms exhibiting similar sensitivity to changes in the budget deficit would move together.[7]

Furthermore, I compounded the cumulative impulse response (CIR) functions for forecast horizons *k*=1,…,32. Then, for each forecast horizon *k*, I divided the overall sample of equity portfolios into 20 groups. Since the estimated cumulative impulse response functions showed non-linear patterns, I sorted all portfolios in order of highest negative to highest positive impulse responses to shocks in the deficit process. PG 1 contained the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas PG 20 contained the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses, whereas PG 10 contained equities exhibiting on average the least respond to shocks. Then, I compounded the corresponding zero-cost portfolios by buying PG 1 and consecutively selling PG 2 to 20, given the forecast horizon *k*. The strategies are updated at the beginning of each quarter. I used a rolling time window of ten years of quarterly data to estimate the VAR-models. For instance, the initial portfolio allocation starts in 1980:1, whereas the estimation procedure accounts for data from 1970:2 to 1979:4. The second allocation takes place in 1980:2 and accounts for data from 1970:3 to 1980:1 and so on. The overall portfolio allocation procedure covers the period from 1980:1 to 2012:4 corresponding to 132 quarterly observations. Furthermore, I employed Carhart's (1997) four-factor model to risk-adjust the zero-cost portfolios, depending on both the forecast horizon *k* and PG *i* by running the following OLS regressions for all *k*=1,…,32 and *i*=2,…,20 zero-cost portfolios:

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[7] When the US government determines a fiscal program to stimulate the economy, irrespective of whether that program involves direct subvention for firms or a lowered tax burden, the program is highly likely to continue for the duration of the period of government, so probably for at least four years ahead.

$$DEF_{ikt} = \alpha_{ik} + \beta_{1ik} MRF_t + \beta_{2ik} SMB_t + \beta_{3ik} HML_t + \beta_{4k} MOM_t + \varepsilon_{ikt} \quad (4)$$

In equation (4), DEF_{ikt} denotes the returns of the constructed zero-cost portfolio based on a cumulative impulse response forecast accounting for a forecast horizon of *k* and long/short strategy PG 1 – PG *i*, MRF_t denotes the market factor, SMB_t and HML_t are the common size and value related risk factors of Fama and French and MOM_t denotes the momentum factor in line with Carhart (1997). The residuals ε_{ikt} are assumed to follow a white noise process; β_{1ik}, β_{2ik}, β_{3ik} and β_{4ik} denote the sensitivity of DEF_{ikt} against these risk factors and α_{ik} corresponds to the risk-adjusted return of zero-cost portfolio *k* and long/short strategy (PG 1 – PG *i*).

The results are reported in Table I and II. Generally, it is evident that spreads appear to be negative on average. The CIRs appear to be non-linear. In Figure I shows the CIRs of the sorted portfolios for the last formation period running from 2002:4 to 2012:3 and a forecast-horizon of *k*=3. The corresponding out-of-sample returns for different strategy combinations are reported in the first column of Table I Panel A and Table II Panel A. The CIRs for the sorted portfolios are different, depending on the time-window and forecast-horizon while the shapes are typically the same. The higher the forecast horizon is chosen, the more extreme are the left- and right hand-tails of the distribution.

Moreover, the Carhart (1997) model is only limitedly able to explain the variation of the zero-cost portfolios. Considering Table II it is evident that a whole battery of zero-cost strategies appears to be statistically significant different from zero. The statistical significance of the raw excess returns tends to increase as the forecast horizon increases. For instance, considering a forecast horizon of *k*=16 we see that ten out of 19 zero-cost strategies generating raw-spreads that are statistically different from zero on a common 5% level. It is also evident that the magnitude of the spread generally increases as it is moved from strategy (PG 1 – PG 2) to (PG 1 – PG 10) and decreases as it is moved from strategy (PG 1 – PG 14) to (PG 1 – PG 20). This seems to be also reasonable because the average sensitivities are decreasing when moving from PG 1 to PG 10 and then again increasing as it is moved from PG 10 to PG 20. A forecast horizon of k=4 and strategy (PG 1 – PG 19) exhibits the highest statistical significance corresponding to a raw return of -1.44% per quarter with heteroskedasticity robust t-statistic of -3.04. The corresponding risk-adjusted return is -1.17% per quarter with heteroskedasticity robust t-statistic of -2.48 indicating statistical significance on a common 5% level. Table I shows that implementing this sorting methodology, based upon past information, leads to a whole battery of zero-cost strategies that are potential candidates for portfolio-based risk factors linked to the macroeconomic deficit risk. The empirical finding that generally longer forecast horizons lead to economically relevant and statistically significant zero-cost strategies may have arisen due to 'matching maturities': Given that new information arrives at time t, rational investors update their information set Ω_t while anticipating the long-term effect of innovations in the budget deficit return process. Once the US government has agreed a fiscal program to stimulate the economy, that program is highly likely to be pursued throughout the period of government. Because rational investors formulate their expectations according to this common long-standing assumption, they will require a risk premium that "matches maturities". However, from a theoretical point of view, the spreads between PG 1 and PG i where i={2,…,10} should be positive because PG 1 is "the most risky" portfolio compared to PG 2 to PG 10. Next, I investigate the asset pricing implications of the optimal spread for the cross-section of equity returns.

Even though Novy-Marx (2013) studied a different issue related to the profitability premium, he faced a similar problem because many different profitability measures have been discussed in the academic literature. Novy-Marx (2013, p.3) argued that "determining the best measure of economic productivity is, however, ultimately an empirical question." His study adopts the profitability measure that exhibits the highest statistical significance in the cross-sectional analysis of stock returns. Extending the statistical selection criterion applied by Novy-Marx (2013), the selection criteria used here for the optimal spread considers simply its statistical significance, too. Based upon this intuitive selection criteria, I find that a forecast horizon of *k*=23 and strategy (PG 1 – PG 10) with heteroskedasticity robust *t*-statistic corresponding to -2.84 and risk-adjusted economic magnitude of -1.42% per quarter appears to be the most informative spread from a statistical point of view.[8] Hence, this zero-cost portfolio will be investigated in more detail in the analysis below.

Hence, the *DEF* factor is a zero-cost portfolio that is long in PG 1 (e.g., the group exhibiting the highest negative cumulative impulse responses to a orthogonalized shock in the budget deficit return process of one standard deviation) and long in PG 10 (e.g., the group exhibiting the least response to a orthogonalized shock in the budget deficit process of one standard deviation). Table III illustrates the average excess returns and the average risk-adjusted returns for group *i*=1,…,20, given a forecast horizon of *k*=23. It can be seen that the excess returns are non-linear increasing when moving from PG 1 to PG 20. PG 1 and PG 2 generate average excess raw returns that are not statistically different from zero. Moving from PG 3 to PG 15, it is observed that the average raw excess returns of all PGs are statistically significant on at least a 5% significance level. PG 15 generates out-of-sample the largest average raw excess return with a

[8] Since the residuals of the regression equation for risk-adjusting the spread do not exhibit any autocorrelation, the heteroskedasticity robust estimates are reported. However, it may be worth noting that the Newey-West (1987) *t*-statistics are even higher and exhibit a corresponding *t*-value of -3.16.

magnitude of 2.50% per quarter with a corresponding heteroskedasticity robust *t*-statistic of 2.98. The risk-adjusted return spread between PG 1 and PG 10 is -1.42% per quarter with heteroskedasticity robust *t*-statistic of -2.84. I also perform the LM-test for first-order autocorrelation. The *p*-value of 0.47 suggests that the spread is independently distributed.

The next element of the process was to investigate the correlations between the *DEF* factor and the ten Fama and French industries. In doing so, I considered the sample period from 1980:1 to 2012:4 that corresponds to the portfolio allocation. The data for the risk factors and the industries were downloaded from Kenneth French's website and the correlation matrix is shown in Table IV. On the one hand, the *DEF* factor appears to be modestly correlated with the *SMB*, *HML*, *MOM* and market factor. On the other hand, the *DEF* factor appears to be modestly negatively correlated with the ten industries; and this roughly to the same extent like the *HML* factor.

5. THE BUDGET DEFICIT AND THE CROSS SECTION OF EQUITY RETURNS

5.1 Are traditional asset pricing models able to explain the test portfolios sorted by their sensitivities to shocks in the US federal budget deficit process?

The next step was to investigate both whether traditional asset pricing models are able to explain the test asset sorted by cumulative impulse responses to shocks in the budget deficit process, and to assess the asset pricing implications of the *DEF* factor. I employed the 20 groups of portfolios in excess returns sorted by cumulative impulse responses to shocks in the budget deficit process as test assets.[9] I ran ten cross-sectional regressions employing different risk factors in succession to price this set of test assets. These regressions involved the CAPM as derived from the work of Sharpe (1964), Lintner (1995) and Black (1972), Fama and French's (1993) three-factor model

[9] See Table III.

and Carhart’s (1997) four-factor model. The R-squared for each model specification and the Wald-test statistic for testing the pricing errors were also estimated. Owing to operating with excess returns, the constant in the Fama-MacBeth (1973) regressions can be considered a weak test of the pricing errors because a statistically significant intercept indicated a systematic pricing error of the respective model. I used the 132 quarterly observations running from 1980:1-2012:4 to estimate the Fama-MacBeth (1973) regressions and present the results in Table V. The first five cross-sectional regressions show that in a one-factor model specification, the *DEF* has the highest explanatory power. The *DEF* factor taken alone is capable of explaining 73% of the cross-sectional variation, whereas the CAPM model specification only explains 42%. Moreover, the corresponding Wald-test statistic is the lowest for the one-factor model specification accounting for the *DEF* factor alone. Interestingly, the one-factor model specification employing the *DEF* factor alone generates an even higher R-squared value than Fama and French’s (1993) three-factor, or Carhart’s (1997) four-factor model specifications, which produce R-squared values of 54% and 59%, respectively. Surprisingly, none of the traditional risk factors appears to be priced. Moreover, we can see that the risk premium related to the *DEF* factor exhibits a noteworthy stability; varying between -1.16% and -1.20% per quarter with *t*-values varying between -2.07 and -2.10 indicating statistical significance on a common 5% level. Comparing the properties of the time series sample averages for the period 1980:1 to 21012:4, it was evident that the value premium exhibited a time series sample average of 0.98% per quarter with corresponding *t*-statistic of 1.83 indicating only marginal significance on a 10% significance level. In contrast, the deficit risk-related premium exhibited a time series sample average of -1.23% per quarter with corresponding *t*-statistic of -2.48 indicating statistical significance on a common 5% level, and as a consequence, a higher stability than the value premium.

Furthermore, including the *DEF* factor in the different model specifications, leads to considerable dips in the Wald-test statistics for testing the pricing errors. For instance, when including the *DEF* factor in Fama and French's (1993) three-factor model specification, the Wald-test statistic drops from 20.81 to 16.94, whereas the R-squared increases from 54% to 74%. Even though the Wald-test statistics indicate apparently that all of these model specifications can price the test assets correctly from a statistical perspective, disregarding the *DEF* factor results in a lack of explanatory power.

5.2 Are the cross-sectional results robust?

Next, I checked whether the results were robust and estimated stochastic discount factor models by employing the Generalized Methods of Moments (GMM) technique as described in detail in Cochrane (2005). The moment conditions for the pricing kernels correspond to the cross-sectional model specifications as described in the previous section. Since I operated with portfolio-based risk factors in excess form, I followed Burnside (2007) and employd de-meaned factors in all stochastic discount factor models. The results are reported in Table VI. Again, I employed the same set of test assets as in the previous section to check both, to which extent traditional asset pricing models are able to explain the portfolios sorted by their cumulative impulse responses to shocks in the budget deficit process, and to investigate the marginal usefulness of the conducted *DEF* factor. Considering the pricing errors of standard asset pricing models, the GMM-estimation related to Fama and French (1993) three-factor model reveals that the pricing errors were cut into halves when the *DEF* factor is included in the stochastic discount factor model specifications. Furthermore, when comparing one-factor model specifications, the

DEF factor appears to exhibit the highest statistical significance with a *t*-value of -3.56. Even though the parameter estimates of the *DEF* factor become insignificant in the GMM-framework when the *DEF* factor is included in the Fama and French (1993) or Carhart (1997) model specification, the huge drops in the pricing errors indicate that the factor may be important for pricing the cross-section of equity returns.[10] Finally, when comparing traditional asset pricing models with the corresponding model specification that includes the *DEF* factor, it was evident that the CAPM model specification that accounts for *DEF* factor exhibited the lowest pricing errors corresponding to 4.88. Furthermore, considering this model specification in more detail, we see that the parameter estimated for both factors the market factor and the *DEF* factor are statistically significant on a common 5% level.

5.3 Anomaly or compensation for business cycle risk?

From a theoretical point of view, a possible explanation for why the spread related to the budget deficit risk is negative could be that this zero-cost portfolio generates high payoffs in "bad states" of the economy. In order to empirically investigate the association between the *DEF* factor and the business cycle, I followed Nyberg and Pöyry (2013) and categorized the periods from 1980:1 to 2012:4 as expansionary or recessionary based on the classifications made by the NBER. More precisely, based upon the NBER dating, I refer to the following periods as recessionary: January 1980 - July 1980, July 1981 - November 1982, July 1990 - March 1991, March 2001 - November 2001, and finally, December 2007 - June 2009. As a consequence, 17 out of 132 quarters were coded as recessionary periods. I regressed the *DEF* factor, as employed in the previous sections, on a constant and a dummyvariable indicating the recessionary periods.

[10] The insignificance of the *DEF* factor when included in the Fama and French (1993) or Carhart (1997) model specification could arise due to a multicollinerarity because the *DEF* factor appears to be slightly correlated with the *SMB* and *MOM* factor (see Table III).

Surprisingly, the estimated constant has a magnitude of -1.57 per quarter with corresponding *t*-statistic of -2.97 indicating statistically significance on any level. The parameter estimate related to the recession dummyvariable is 2.62% per quarter with *t*-statistic of 1.78 indicating statistically significance on at least a 10% level. I also checked the residuals of the regression. The *p*-value of the LM-test statistic concerning testing first-order autocorrelation is 0.94, whereas the *p*-value of the ARCH-LM-test statistic for testing conditional heteroskedasticity is 0.62, suggesting that the *DEF* factor is distributed as IID.[11] Next, I coded the initial quarter of the beginning of each recessionary period as an expansionary one, implying the assumption that the effect from the real economy to the financial sphere is lagged. This approach is similar to the one in Nyberg and Pöyry (2013) and results in 13 recessionary quarters in the sample. Then, I estimated the regression equation again, resulting in a parameter estimate of -1.40% per quarter for the constant with *t*-value of -2.34 and a parameter estimate of 4.01% per quarter for the recession dummy with corresponding *t*-value of 2.11 indicating statistically significance on a common 5% level. Again as before, I checked the residuals and did not find any evidence for autocorrelation or ARCH-effects. I consider these results as evidence for that the *DEF* factor appears to be indeed negatively associated with the business cycle, that is, in economic downturns, the payoff appears to be considerably higher than in “good states” of the economy.

[11] The tests are robust even when testing for higher order autocorrelation in the first and second order moments. In unreported results, I executed both tests by consecutively accounting for up to five lags. The *p*-value of all test statistics are clearly larger than 0.05.

6. DISCUSSION

Many papers have attempted to explain the value premium and to establish robust links between it and other factors. Most recently, Novy-Marx (2013) proposes a profitability premium that appears to be associated with the value premium. It may be worth mentioning that the raw excess return of Novy-Marx's (2013) profitability premium is 0.93 in quarterly terms with a *t*-statistic of 2.49. The deficit risk-related premium proposed in this paper, however, exceeds Novy-Marx's (2013) profitability premium in both economic magnitude and statistical significance. Furthermore, Novy-Marx's (2013) profitability premium and the value premium of Fama and French (1993) exhibit a correlation coefficient of -0.57, implying that a profitability strategy is a growth strategy and, hence may act to hedge value strategies. Regressing the deficit-related risk premium on the Carhart (1997) four-factor model shows that the sensitivities against the *HML* and market factor are statistically not different from zero. However, the loadings against the *SMB* and *MOM* factor are -0.23 and 0.23 with corresponding heteroskedasticity robust *t*-values of -2.02 and 3.06 indicates that this *DEF* factor tends to be invested in large caps and "winners". However, -1.42% per quarter of the spread cannot be explained by Carhart's (1997) four-factor model. Moreover, the orthogonality property between the *DEF* and *HML* factor implies, that this strategy could be employed to reduce the portfolio risk for value strategies.

Considering the cross-section of equity returns, it is apparent that the *DEF* factor has noteworthy asset pricing implications. The risk premium is statistically significantly negatively priced in the cross-section and exhibits a higher degree of stability over time in comparison to other risk factors. Interestingly, traditional *HML* and *SMB* factors do not appear to be priced, irrespective of the model specification chosen when running the cross-sectional Fama MacBeth (1973) regressions. Furthermore, there is some interpreting the empirical finding of Granger causality between changes in the budget deficit and stock returns as being 'disturbing' (see Laopodis 2009) because it would indicate market inefficiency. If changes to the budget deficit affect stock markets, then standard economic theory suggests that the expected sign of the budget deficit should be negative (e.g. Darrat and Brocato, 1994, Laopodis, 2009 & 2012) simply because higher deficits are assumed to lead to increased interest rates. A higher budget deficit should be expected to act through this interest rate channel to exert a negative effect on the stock market. However, the portfolio-based approach that is used to construct the *DEF* factor is long on the portfolio of equities exhibiting the highest negative cumulative impulse response to shocks in the budget deficit and short in an equity portfolio exhibiting the least sensitivity to shocks. Economic intuition suggests that this spread should be positive. However, the empirical analysis suggests that the spread is statistically significantly negative while generating large positive payoffs in "bad states" of the economy.

Furthermore, many papers related to empirical asset pricing research employ deciles or quintiles when conducting portfolio-based risk factor analysis. These studies typically use individual stocks instead of equity portfolios. It may be noteworthy that the average number of portfolios, taken into account for sorting the 20 PGs was roughly 196 meaning that each of the 20 groups sorted by cumulative impulse responses to shocks in the budget deficit return process contained an average of around ten equally-weighted portfolios that themselves were baskets of value-weighted equity portfolios. Operating with deciles or even quintiles lowers both the spread and its statistical significance. This is because in contrast to traditional sorts with respect to *size*, *momentum* or *book-to-market value*, the sorting procedure making use of cumulative impulse response forecasts of the equity portfolios is non-linear.[12]

[12] Moreover, Fama and French (1993, 1996, 2008) conducted their *SMB* and *HML* risk factor on sorts by market capitalization and book-to-market ratio respectively. The momentum risk factor employed in Carhart's (1997) four-

7. CONCLUSION

Macroeconomic variables are reasonable candidates for systematic risk factors, because macroeconomic changes simultaneously have an impact on many organizations in the economy (Flannery and Protopapadakis 2002). However, Chan et al. (1998) underlined that macroeconomic factors generally perform poorly in explaining variations in equity returns. Many papers have attempted to identify reliable associations between macroeconomic variables and equity returns. The current research established a significant and robust connection between the US federal budget deficit risk and equity returns. Shifts in the budget deficit have the ability to predict future returns. A zero-cost strategy for conducting a new risk factor related to deficit risk is proposed. This zero-cost portfolio is long on equity portfolios that exhibit the highest negative cumulative impulse responses to orthogonalized shocks in the budget deficit process and short on equity portfolios that exhibit the least cumulative impulse responses to orthogonalized shocks in the budget deficit returns. After risk adjustment, the sample average return of the spread that is used as a risk factor remains statistically significant at even a 1% significance level. This result provides strong evidence that this new risk factor related to budget deficit risk is negatively priced while generating large positive payoffs in bad states of the economy. The cross-sectional analysis shows also that the risk premium is of economic importance and is statistically

factor model uses cumulative past returns as sorting criteria which can easily be compounded by summing up past returns of the return series itself. Kolari et al. (2008) investigated the relation between the cross-section of US stock returns and foreign exchange rates and formulated a risk factor as zero-investment factor related to foreign exchange-rate sensitivities. Their study sorts portfolios with respect to their sensitivities against the exchange-rate time series ending up with 25 groups where Group 1 contained the stocks exhibiting the lowest sensitivity to changes in the exchange-rate, whereas Group 25 contained those stocks exhibiting the highest sensitivity to changes in the exchange-rate. The study also found a non-linear association. Apparently, non-linear patterns encourage making use of wider spreads. This study mirrors Kolari et al. (2008) in a non-linear association and, consequently, the risk factor is formed based upon 20 groups. Moreover, Kolari et al. (2008) sorted their 25 portfolios by their sensitivity to the exchange-rate time series which can be a suitable approach when the chosen time series lacks correlation. However, a macroeconomic time series such as quarterly changes in GDP or changes in the budget deficit rare typically higher-order auto-correlated, and therefore the econometric impulse response technique is more suitable to investigate stochastic interrelations between changes in the budget deficit and equity returns.

significant. In addition, the current research establishes a new avenue of asset pricing research that targets revealing the associations between the cross-section of equity returns and macro-fundamental variables in a traditional portfolio-based asset pricing approach. While developing a new theoretical model is beyond the scope of this paper, we conclude that any theory that attempts to explain the cross-section of equity returns should also be consistent with the empirical facts linking changes in the budget deficit and future equity returns.

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Table I: Zero-cost portfolios

For each quarter t, I estimated a bivariate VAR-model of lag order p=4 for all equity portfolios. Each VAR-model contains the changes of the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR-model I estimated the Wold-Moving-Average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables as described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the cumulative impulse response (CIR) functions accounting for a forecast horizon of k=1,…,32 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR-model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon k into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. Then, the zero-cost portfolio for forecast horizon k and portfolio group i is conducted by buying PG 1 and buying PG i and i=1,…,20. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategies were updated at the beginning of each quarter. The initial portfolio allocation started in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit are downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. In Table I the results for different long/short strategies are reported. Each strategy is short in PG 1 exhibiting the highest negative cumulative impulse responses. Panels A-C report the average raw excess returns. Heteroskedasticity robust t-statistics are given in parentheses.

Panel A

Strategy	Forecast horizon									
	3	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1-2	0.10	-0.20	0.07	0.32	-0.11	0.15	0.20	-0.13	0.20	-0.03
	(0.18)	(-0.49)	(0.16)	(0.80)	(-0.30)	(0.31)	(0.50)	(-0.36)	(0.48)	(-0.08)
1-3	-1.03*	-0.79	-0.52	-0.25	-0.47	-0.13	-0.72	-0.81*	-0.86	-0.66
	(-1.71)	(-1.44)	(-0.92)	(-0.50)	(-0.85)	(-0.23)	(-1.32)	(-1.87)	(-1.60)	(-1.36)
1-4	-0.25	-0.71	-0.36	-0.29	-0.74	-0.38	-0.69	-0.68	-0.48	-0.49
	(-0.48)	(-1.42)	(-0.67)	(-0.64)	(-1.32)	(-0.76)	(-1.27)	(-1.48)	(-1.03)	(-1.07)
1-5	-0.52	-0.49	-0.65	-0.38	-0.91	-0.09	-0.87	-0.49	-0.85	-0.57
	(-0.96)	(-1.23)	(-1.16)	(-0.72)	(-1.50)	(-0.16)	(-1.41)	(-1.00)	(-1.63)	(-1.28)
1-6	-0.56	-0.57	-0.41	-0.20	-0.70	-0.02	-0.74	-0.20	-0.58	-0.03
	(-1.00)	(-1.31)	(-0.69)	(-0.40)	(-1.02)	(-0.03)	(-1.12)	(-0.37)	(-1.01)	(-0.06)
1-7	-0.66	-0.92*	-0.65	-0.17	-1.00	0.38	-0.99	-0.41	-0.96*	-0.56
	(-1.23)	(-1.91)	(-1.00)	(-0.32)	(-1.51)	(0.61)	(-1.58)	(-0.71)	(-1.74)	(-0.98)
1-8	-0.95*	-1.10**	-0.50	-0.29	-0.79	-0.22	-0.75	-0.36	-0.76	-0.49
	(-1.65)	(-2.18)	(-0.84)	(-0.65)	(-1.33)	(-0.43)	(-1.24)	(-0.73)	(-1.38)	(-0.97)
1-9	-0.68	-0.90*	-0.88	-0.29	-0.78	0.06	-0.92	-0.62	-0.72	-0.13
	(-1.20)	(-1.66)	(-1.50)	(-0.62)	(-1.37)	(0.11)	(-1.64)	(-1.32)	(-1.44)	(-0.26)
1-10	-1.21*	-1.16**	-0.88	-0.53	-1.09*	-0.45	-1.14**	-0.69	-1.06**	-0.55
	(-1.95)	(-2.39)	(-1.49)	(-1.20)	(-1.85)	(-0.89)	(-2.11)	(-1.46)	(-2.20)	(-1.15)
1-11	-0.99	-0.65	-0.75	-1.04**	-1.15**	-0.64	-1.35**	-0.96*	-1.22**	-0.87*
	(-1.62)	(-1.23)	(-1.29)	(-2.37)	(-2.09)	(-1.30)	(-2.36)	(-1.93)	(-2.48)	(-1.73)
1-12	-0.82	-0.66	-0.96	-0.69	-1.05*	-0.72	-0.90	-0.82	-0.79	-0.69
	(-1.42)	(-1.49)	(-1.64)	(-1.43)	(-1.80)	(-1.35)	(-1.61)	(-1.54)	(-1.56)	(-1.33)
1-13	-0.49	-0.84*	-0.66	-0.39	-0.79	-0.26	-0.87	-0.67	-0.92*	-0.52
	(-0.81)	(-1.79)	(-1.13)	(-0.78)	(-1.36)	(-0.51)	(-1.60)	(-1.37)	(-1.88)	(-1.05)
1-14	-0.73	-1.23***	-1.24**	-0.70	-0.90	-0.46	-1.06*	-0.87*	-0.87*	-0.91*
	(-1.21)	(-2.87)	(-2.12)	(-1.46)	(-1.62)	(-0.95)	(-1.90)	(-1.86)	(-1.78)	(-1.93)
1-15	-0.58	-1.35***	-0.60	-0.66	-1.00*	-0.89*	-1.22*	-1.23***	-1.20**	-1.15**
	(-0.97)	(-2.94)	(-0.95)	(-1.52)	(-1.65)	(-1.74)	(-2.16)	(-2.59)	(-2.30)	(-2.45)
1-16	-0.86	-0.79	-0.64	-0.97**	-0.90	-0.63	-0.75	-0.92*	-0.79	-0.82*
	(-1.34)	(-1.47)	(-0.98)	(-2.21)	(-1.49)	(-1.28)	(-1.20)	(-1.87)	(-1.36)	(-1.74)
1-17	-0.80	-0.86	-1.00	-0.71	-1.12*	-0.37	-1.05	-0.61	-0.77	-0.56
	(-1.24)	(-1.59)	(-1.54)	(-1.38)	(-1.73)	(-0.65)	(-1.61)	(-1.10)	(-1.30)	(-1.07)
1-18	-0.68	-0.72	-0.98	-0.53	-1.12*	-0.35	-1.04*	-0.52	-0.98*	-0.38
	(-1.13)	(-1.31)	(-1.63)	(-1.12)	(-1.72)	(-0.72)	(-1.69)	(-1.02)	(-1.79)	(-0.78)
1-19	-0.70	-1.44***	-1.00	-0.76*	-0.90	-0.60	-0.87	-0.90*	-0.57	-0.74*
	(-1.00)	(-3.04)	(-1.42)	(-1.73)	(-1.30)	(-1.25)	(-1.32)	(-1.93)	(-0.97)	(-1.68)
1-20	-0.54	-1.19***	-0.81	-0.75*	-0.95	-0.51	-0.94	-0.85*	-0.83	-0.83*
	(-0.75)	(-2.60)	(-1.21)	(-1.69)	(-1.44)	(-1.09)	(-1.49)	(-1.85)	(-1.52)	(-1.83)

*Statistically significant on a 10% level
**Statistically significant on a 5% level
***Statistically significant on a 1% level

Panel B

Strategy	Forecast horizon									
	13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**
1-2	0.71	-0.03	0.16	-0.52*	0.93**	0.05	0.40	-0.40	0.13	-0.21
	(1.54)	(-0.06)	(0.38)	(-1.75)	(2.05)	(0.13)	(1.14)	(-1.11)	(0.38)	(-0.52)
1-3	-0.25	-0.78*	-0.88*	-1.01**	-0.39	-0.57	-0.67	-0.63	-0.89*	-0.43
	(-0.47)	(-1.68)	(-1.66)	(-2.25)	(-0.70)	(-1.35)	(-1.25)	(-1.37)	(-1.72)	(-1.00)
1-4	0.03	-0.59	-0.54	-0.79*	0.07	-0.53	-0.37	-0.62	-0.46	-0.44
	(0.06)	(-1.27)	(-1.10)	(-1.65)	(0.13)	(-1.28)	(-0.69)	(-1.42)	(-0.86)	(-1.01)
1-5	-0.46	-0.47	-0.77	-0.68	-0.24	-0.54	-0.75	-0.55	-1.01*	-0.25
	(-0.84)	(-1.00)	(-1.40)	(-1.44)	(-0.41)	(-1.29)	(-1.31)	(-1.19)	(-1.74)	(-0.59)
1-6	-0.24	-0.06	-0.80	-0.19	-0.18	0.23	-0.40	-0.02	-0.76	0.09
	(-0.40)	(-0.11)	(-1.37)	(-0.35)	(-0.27)	(0.50)	(-0.62)	(-0.05)	(-1.19)	(0.20)
1-7	-0.61	-0.69	-1.11**	-0.83	-0.45	-0.60	-0.95	-0.59	-1.02*	-0.46
	(-1.10)	(-1.21)	(-2.08)	(-1.45)	(-0.73)	(-1.13)	(-1.57)	(-1.10)	(-1.67)	(-0.87)
1-8	-0.23	-0.60	-0.78	-0.94*	-0.22	-0.76	-0.63	-0.78	-0.88	-0.50
	(-0.41)	(-1.12)	(-1.39)	(-1.77)	(-0.35)	(-1.51)	(-1.01)	(-1.51)	(-1.43)	(-0.99)
1-9	-0.56	-0.22	-1.06**	-0.71	-0.57	-0.49	-0.89	-0.51	-0.98*	-0.46
	(-1.09)	(-0.42)	(-2.06)	(-1.33)	(-0.99)	(-1.05)	(-1.60)	(-1.09)	(-1.73)	(-1.04)
1-10	-0.63	-0.75	-1.12**	-0.74	-0.52	-0.44	-1.01*	-0.59	-1.23**	-0.33
	(-1.32)	(-1.52)	(-2.27)	(-1.45)	(-0.96)	(-1.01)	(-1.85)	(-1.30)	(-2.32)	(-0.77)
1-11	-0.71	-0.79	-1.16**	-1.09**	-0.53	-0.90**	-1.09*	-0.91*	-1.22**	-0.81*
	(-1.36)	(-1.56)	(-2.28)	(-2.20)	(-0.89)	(-1.98)	(-1.89)	(-1.97)	(-2.15)	(-1.81)
1-12	-0.63	-0.83	-1.07**	-1.13**	-0.55	-0.86*	-0.87	-1.07**	-1.18**	-0.84
	(-1.24)	(-1.48)	(-2.12)	(-2.10)	(-0.92)	(-1.78)	(-1.55)	(-2.11)	(-2.10)	(-1.63)
1-13	-0.54	-0.51	-0.92*	-0.90*	-0.30	-0.84*	-0.67	-0.96**	-0.81	-0.75*
	(-1.10)	(-1.01)	(-1.92)	(-1.79)	(-0.55)	(-1.80)	(-1.25)	(-2.07)	(-1.49)	(-1.68)
1-14	-0.59	-1.02**	-0.92*	-1.32***	-0.35	-1.19***	-0.93	-1.17***	-1.09*	-0.87**
	(-1.18)	(-2.05)	(-1.68)	(-2.61)	(-0.57)	(-2.66)	-1.62	(-2.54)	(-1.91)	(-1.97)
1-15	-0.61	-0.94*	-1.09*	-1.16**	-0.47	-0.87**	-0.92	-0.88**	-1.08*	-0.58
	(-1.15)	(-1.87)	(-1.99)	(-2.42)	(-0.77)	(-2.01)	(-1.59)	(-2.03)	(-1.86)	(-1.32)
1-16	-0.43	-0.73	-1.04*	-0.84	-0.40	-0.63	-0.72	-0.83*	-1.05*	-0.57
	(-0.72)	(-1.47)	(-1.84)	(-1.60)	(-0.63)	(-1.31)	(-1.19)	(-1.73)	(-1.72)	(-1.21)
1-17	-0.48	-0.67	-0.89	-0.85	-0.34	-0.64	-0.79	-0.73	-0.91	-0.42
	(-0.80)	(-1.23)	(-1.48)	(-1.53)	(-0.51)	(-1.29)	(-1.24)	(-1.46)	(-1.43)	(-0.91)
1-18	-0.54	0.49	-1.04*	-0.89*	-0.45	-0.68	-0.82	-0.73	-1.04*	-0.82**
	(-1.03)	(-0.93)	(-1.91)	(-1.73)	(-0.73)	(-1.57)	(-1.37)	(-1.64)	(-1.69)	(-2.04)
1-19	-0.20	-0.73	-0.82	-1.09**	-0.29	-0.84**	-0.67	-0.90**	-0.83	-0.69*
	(-0.34)	(-1.55)	(-1.33)	(-2.28)	(-0.45)	(-2.16)	(-1.06)	(-2.25)	(-1.31)	(-1.80)
1-20	-0.44	-0.83*	-0.87	-1.07**	-0.26	-0.87*	-0.70	-0.92*	-0.94	-0.75*
	(-0.82)	(-1.71)	(-1.53)	(-2.08)	(-0.42)	(-1.97)	(-1.12)	(-2.03)	(-1.49)	(-1.76)

*Statistically significant on a 10% level
**Statistically significant on a 5% level
***Statistically significant on a 1% level

Panel C

Strategy	Forecast horizon									
	23	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
1-2	-0.03	-0.37	-0.07	-0.13	0.11	-0.47	0.46	-0.52	0.38	-0.56
	(-0.09)	(-0.93)	(-0.19)	(-0.32)	(0.32)	(-1.13)	(1.10)	(-1.41)	(0.93)	(-1.46)
1-3	-0.94*	-0.32	-0.96*	-0.31	-0.85*	-0.61	-0.49	-0.83*	-0.58	-0.60
	(-1.72)	(-0.69)	(-1.81)	(-0.62)	(-1.68)	(-1.29)	(-1.00)	(-1.74)	(-1.10)	(-1.24)
1-4	-0.51	-0.54	-0.60	-0.48	-0.46	-0.50	-0.08	-0.58	-0.26	-0.70
	(-1.03)	(-1.16)	(-1.22)	(-1.04)	(-0.91)	(-1.14)	(-0.16)	(-1.28)	(-0.51)	(-1.50)
1-5	-0.99*	-0.34	-0.97*	-0.39	-0.79	-0.55	-0.52	-0.67	-0.65	-0.49
	(-1.83)	(-0.73)	(-1.86)	(-0.81)	(-1.32)	(-1.23)	(-0.89)	(-1.46)	(-1.09)	(-1.03)
1-6	-0.86	-0.06	-0.89	0.19	-0.64	0.02	-0.26	-0.08	-0.35	-0.03
	(-1.37)	(-0.12)	(-1.44)	(0.36)	(-0.98)	(0.05)	(-0.40)	(-0.14)	(-0.55)	(-0.07)
1-7	-1.17**	-0.33	-1.22**	-0.28	-1.05*	-0.44	-0.76	-0.54	-1.04*	-0.56
	(-2.04)	(-0.61)	(-2.15)	(-0.51)	(-1.81)	(-0.83)	(-1.33)	(-1.00)	(-1.81)	(-1.00)
1-8	-0.89	-0.72	-1.06*	-0.66	-0.67	-0.71	-0.34	-0.86*	-0.53	-1.08**
	(-1.54)	(-1.40)	(-1.82)	(-1.32)	(-1.12)	(-1.54)	(-0.58)	(-1.70)	(-0.90)	(-2.16)
1-9	-1.07*	-0.34	-1.13**	-0.20	-0.83	-0.29	-0.63	-0.46	-0.83	-0.46
	(-1.99)	(-0.70)	(-2.12)	(-0.40)	(-1.48)	(-0.62)	(-1.13)	(-0.92)	(-1.48)	(-0.91)
1-10	-1.23**	-0.58	-1.33***	-0.47	-1.13**	-0.68	-0.87*	-0.88*	-0.98*	-0.82*
	(-2.48)	-1.33	(-2.74)	-1.05	(-2.21)	(-1.61)	(-1.77)	(-1.87)	(-1.99)	(-1.79)
1-11	-1.27**	-0.81*	-1.27*	-0.81*	-1.05*	-0.90*	-0.71	-1.07**	-0.71	-1.12**
	(-2.40)	(-1.70)	(-2.38)	(-1.65)	(-1.85)	(-1.95)	(-1.26)	(-2.14)	(-1.24)	(-2.25)
1-12	-1.12**	-0.91*	-1.21**	-0.82	-1.00*	-0.94*	-0.56	-1.04**	-0.69	-1.01*
	(-2.17)	(-1.77)	(-2.36)	(-1.54)	(-1.84)	(-1.87)	(-0.96)	(-1.96)	(-1.20)	(-1.90)
1-13	-0.88*	-0.66	-1.02*	-0.40	-0.82	-0.40	-0.47	-0.57	-0.67	-0.45
	(-1.67)	(-1.42)	(-1.94)	(-0.89)	(-1.51)	(-0.94)	(-0.89)	(-1.23)	(-1.26)	(-0.99)
1-14	-1.02*	-0.72	-1.04*	-0.52	-0.76	-0.65	-0.66	-0.74	-0.86*	-0.74
	(-1.89)	(-1.58)	(-1.93)	(-1.10)	(-1.39)	(-1.45)	(-1.29)	(-1.53)	(-1.70)	(-1.55)
1-15	-1.39***	-0.78*	-1.32**	-0.80*	-1.11*	-0.78*	-0.82	-0.90*	-0.99*	-0.85*
	(-2.78)	(-1.77)	(-2.49)	(-1.78)	(-1.95)	(-1.80)	(-1.43)	(-1.90)	(-1.73)	(-1.76)
1-16	-1.18**	-0.73	-1.20**	-0.62	-1.06*	-0.72	-0.68	-1.00**	-0.84	-1.02**
	(-2.06)	(-1.50)	(-2.07)	(-1.31)	(-1.75)	(-1.56)	(-1.16)	(-2.14)	(-1.41)	(-2.19)
1-17	-0.95	-0.67	-0.94	-0.64	-0.79	-0.74*	-0.38	-0.98**	-0.59	-1.05**
	(-1.58)	(-1.47)	(-1.56)	(-1.37)	(-1.31)	(-1.68)	(-0.63)	(-2.02)	(-0.99)	(-2.33)
1-18	-1.00*	-0.89**	-1.19**	-0.80**	-1.02*	-0.96**	-0.79	-1.11***	-0.98*	-1.08***
	(-1.72)	(-2.15)	(-2.04)	(-1.97)	(-1.72)	(-2.44)	(-1.37)	(-2.62)	(-1.71)	(-2.58)
1-19	-0.89	-0.82**	-0.88	-0.63	-0.64	-0.79**	-0.15	-0.96**	-0.31	-0.94**
	(-1.47)	(-1.98)	(-1.45)	(-1.54)	(-1.03)	(-2.03)	(-0.26)	(-2.23)	(-0.53)	(-2.24)
1-20	-1.01*	-0.83*	-1.08*	-0.79*	-0.89	-0.89**	-0.60	-1.02**	-0.78	-0.98**
	(-1.76)	(-1.88)	(-1.85)	(-1.87)	(-1.47)	(-2.14)	(-1.05)	(-2.27)	(-1.31)	(-2.25)

*Statistically significant on a 10% level
**Statistically significant on a 5% level
***Statistically significant on a 1% level

Table II: Risk-adjusted zero-cost portfolios

For each quarter *t*, I estimated a bivariate VAR-model of lag order *p*=4 for all equity portfolios. Each VAR-model contains the changes of the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR-model I estimated the Wold-Moving-Average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables as described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the cumulative impulse response (CIR) functions accounting for a forecast horizon of *k*=1,…,32 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR-model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon *k* into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. Then, the zero-cost portfolio for forecast horizon *k* and portfolio group *i* is conducted by buying PG 1 and buying PG *i* and *i*=1,…,20. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategies were updated at the beginning of each quarter. The initial portfolio allocation started in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit are downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. In Table I the results for different long/short strategies are reported. Each strategy is short in PG 1 exhibiting the highest negative cumulative impulse responses. Panels A-C report the risk-adjusted returns. For risk adjustment Carhart's (1997) four-factor model is employed. Heteroskedasticity robust *t*-statistics are given in parentheses.

Panel A

Strategy	Forecast horizon									
	3	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1-2	-0.10	-0.31	0.07	0.42	-0.32	0.43	0.13	-0.16	-0.07	-0.10
	(-0.19)	(-0.69)	(0.15)	(0.82)	(-0.82)	(0.65)	(0.30)	(-0.32)	(-0.13)	(-0.25)
1-3	-1.00	-1.15	-0.12	-0.37	-0.48	0.04	-0.74	-0.98	-1.13	-0.94
	(-1.35)	(-1.57)	(-0.18)	(-0.50)	(-0.88)	(0.05)	(-1.31)	(-1.64)	(-1.64)	(-1.48)
1-4	-0.06	-0.82	-0.08	-0.48	-0.61	-0.32	-0.65	-0.73	-0.46	-0.63
	(-0.10)	(-1.20)	(-0.14)	(-0.73)	(-1.04)	(-0.44)	(-1.08)	(-1.10)	(-0.95)	(-1.00)
1-5	-0.14	-0.20	-0.21	-0.67	-0.79	-0.02	-0.46	-0.37	-0.63	-0.65
	(-0.23)	(-0.49)	(-0.34)	(-0.94)	(-1.20)	(-0.02)	(-0.65)	(-0.72)	(-1.15)	(-1.43)
1-6	-0.37	-0.42	-0.07	-0.44	-0.78	-0.22	-0.93	-0.57	-0.90	-0.41
	(-0.56)	(-0.97)	(-0.10)	(-0.78)	(-0.86)	(-0.32)	(-1.03)	(-0.82)	(-1.28)	(-0.60)
1-7	-0.25	-0.70	-0.45	-0.32	-0.77	0.14	-0.92	-0.59	-1.10	-0.82
	(-0.43)	(-1.40)	(-0.50)	(-0.53)	(-0.89)	(0.21)	(-1.10)	(-0.91)	(-1.61)	(-1.20)
1-8	-0.73	-1.37**	-0.12	-0.07	-0.65	0.10	-0.51	-0.42	-0.72	-0.76
	(-1.11)	(-2.20)	(-0.16)	(-0.14)	(-1.02)	(0.20)	(-0.69)	(-0.92)	(-1.26)	(-1.57)
1-9	-0.43	-1.30*	-0.48	-0.40	-0.68	0.36	-0.76	-0.59	-0.65	-0.22
	(-0.63)	(-1.89)	(-0.74)	(-0.83)	(-1.04)	(0.68)	(-1.23)	(-1.27)	(-1.35)	(-0.49)
1-10	-1.51*	-1.17**	-0.43	-0.78	-0.91	-0.37	-0.98*	-0.77	-1.05**	-0.86*
	(-1.89)	(-2.24)	(-0.64)	(-1.57)	(-1.53)	(-0.64)	(-1.67)	(-1.48)	(-2.32)	(-1.78)
1-11	-1.14	-0.61	-0.33	-0.86	-0.71	-0.47	-0.98	-0.97*	-1.01*	-0.93
	(-1.30)	(-1.00)	(-0.54)	(-1.61)	(-1.26)	(-0.85)	(-1.44)	(-1.66)	(-1.98)	(-1.58)
1-12	-0.77	-0.63	-0.48	-0.84	-0.80	-0.49	-0.64	-0.89	-0.72	-0.72
	(-1.12)	(-1.36)	(-0.63)	(-1.47)	(-1.07)	(-0.72)	(-0.91)	(-1.36)	(-1.27)	(-1.23)
1-13	-0.15	-0.91	-0.24	-0.15	-0.69	-0.39	-0.72	-0.78	-0.79	-0.75
	(-0.18)	(-1.44)	(-0.32)	(-0.18)	(-1.03)	(-0.58)	(-1.02)	(-1.28)	(-1.32)	(-1.22)
1-14	-0.29	-1.06**	-0.80	-0.68	-0.69	-0.11	-0.77	-0.89*	-0.75	-1.07**
	(-0.35)	(-2.09)	(-1.20)	(-1.12)	(-1.20)	(-0.19)	(-1.20)	(-1.73)	(-1.45)	(-2.01)
1-15	-0.44	-1.21***	0.05	-0.72	-0.53	-0.65	-0.74	-1.22***	-0.96	-1.24***
	(-0.71)	(-2.73)	(0.06)	(-1.41)	(-0.63)	(-1.08)	(-0.90)	(-2.56)	(-1.36)	(-2.54)
1-16	-1.03	-0.50	-0.01	-0.79	-0.54	-0.41	-0.32	-0.85	-0.47	-0.84*
	(-1.40)	(-0.74)	(-0.01)	(-1.58)	(-0.68)	(-0.72)	(-0.37)	(-1.61)	(-0.65)	(-1.72)
1-17	-0.80	-0.71	-0.82	-0.54	-1.12	0.05	-1.11	-0.32	-0.95	-0.38
	(-1.07)	(-1.04)	(-1.07)	(-0.90)	(-1.62)	(0.08)	(-1.48)	(-0.51)	(-1.54)	(-0.61)
1-18	-0.50	-0.41	-0.60	-0.26	-1.07*	0.11	-1.06*	-0.28	-1.12**	-0.21
	(-0.65)	(-0.65)	(-0.99)	(-0.49)	(-1.74)	(0.22)	(-1.72)	(-0.47)	(-2.20)	(-0.36)
1-19	-0.80	-1.17**	-1.04	-0.60	-0.94	-0.09	-0.89	-0.67	-0.82	-0.70
	(-0.88)	(-2.48)	(-1.20)	(-1.21)	(-1.19)	(-0.18)	(-1.10)	(-1.36)	(-1.23)	(-1.52)
1-20	-0.53	-0.94**	-0.17	-0.33	-0.53	0.15	-0.43	-0.36	-0.48	-0.42
	(-0.65)	(-2.01)	(-0.23)	(-0.74)	(-0.71)	(0.29)	(-0.57)	(-0.92)	(-0.87)	(-1.07)

*Statistically significant on a 10% level
**Statistically significant on a 5% level
***Statistically significant on a 1% level

Panel B

Strategy	Forecast horizon									
	13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**
1-2	0.34	-0.07	-0.13	-0.72**	1.13**	-0.23	0.40	-0.57	0.17	-0.33
	(0.62)	(-0.12)	(-0.23)	(-2.17)	(2.10)	(-0.50)	(1.03)	(-1.27)	(0.4)5	(-0.64)
1-3	-0.55	-0.95	-1.24*	-1.34**	-0.26	-0.86	-0.63	-1.01	0.88	-0.76
	(-0.82)	(-1.57)	(-1.71)	(-2.21)	(-0.39)	(-1.59)	(-1.02)	(-1.61)	(1.46)	(-1.26)
1-4	0.11	-0.66	-0.44	-0.98	0.71	-0.60	0.15	-0.79	0.14	-0.62
	(0.22)	(-1.04)	(-0.85)	(-1.55)	(1.04)	(-1.09)	(0.24)	(-1.34)	(0.23)	(-1.00)
1-5	-0.39	-0.36	-0.73	-0.77*	0.33	-0.43	-0.25	-0.60	0.63	-0.20
	(-0.67)	(-0.68)	(-1.22)	(-1.66)	(0.44)	(-0.99)	(-0.34)	(-1.12)	(0.90)	(-0.47)
1-6	-0.64	-0.35	-1.09	-0.70	-0.00	0.02	-0.35	-0.34	0.69	-0.24
	(-0.87)	(-0.52)	(-1.63)	(-1.06)	(-0.00)	(0.05)	(-0.41)	(-0.64)	(0.79)	(-0.51)
1-7	-0.79	-0.91	-1.31**	-1.10	-0.07	-0.74	-0.69	-0.83	0.72	-0.66
	(-1.13)	(-1.35)	(-2.04)	(-1.63)	(-0.08)	(-1.16)	(-0.83)	(-1.28)	(0.84)	(-1.02)
1-8	-0.22	-0.60	-0.73	-1.11**	0.30	-0.94*	-0.24	-1.04*	0.59	-0.80
	(-0.38)	(-1.06)	(-1.22)	(-2.12)	(0.38)	(-1.75)	(-0.33)	(-1.70)	(0.88)	(-1.52)
1-9	-0.55	-0.16	-1.06**	-1.04**	-0.12	-0.67*	-0.53	-0.79*	0.58	-0.61*
	(-1.09)	(-0.33)	(-2.07)	(-2.10)	(-0.18)	(-1.75)	(-0.82)	(-1.88)	(0.83)	(-1.75)
1-10	-0.68	-0.93*	-1.17**	-0.86	-0.02	-0.46	-0.72	-0.75	0.98	-0.47
	(-1.42)	(-1.76)	(-2.36)	(-1.64)	(-0.02)	(-1.12)	(-0.99)	(-1.58)	(1.44)	(-1.18)
1-11	-0.72	-0.72	-1.15**	-1.35**	-0.13	-1.09**	-0.91	-1.15**	0.92	-1.00**
	(-1.24)	(-1.25)	(-2.06)	(-2.51)	(-0.17)	(-2.28)	(-1.41)	(-2.27)	(1.42)	(-2.15)
1-12	-0.65	-0.79	-1.00*	-1.39**	0.04	-1.10*	-0.33	-1.47**	0.74	-1.28*
	(-1.12)	(-1.23)	(-1.75)	(-2.17)	(0.05)	(-1.82)	(-0.42)	(-2.21)	(0.97)	(-1.95)
1-13	-0.47	-0.64	-0.71	-1.28**	0.46	-1.25**	-0.02	-1.41**	0.13	-1.14**
	(-0.80)	(-1.02)	(-1.25)	(-2.19)	(0.65)	(-2.16)	(-0.03)	(-2.41)	(0.20)	(-2.01)
1-14	-0.52	-1.02*	-0.61	-1.40**	0.51	-1.13**	-0.23	-1.21**	0.40	-0.59
	(-0.98)	(-1.75)	(-0.82)	(-2.47)	(0.60)	(-2.34)	(-0.28)	(-2.35)	(0.50)	(-1.44)
1-15	-0.39	-0.76	-0.90	-1.19**	0.19	-0.77*	-0.36	-0.88*	0.53	-0.43
	(-0.53)	(-1.42)	(-1.17)	(-2.31)	(0.21)	(-1.77)	(-0.41)	(-1.84)	(0.60)	(-0.98)
1-16	-0.20	-0.65	-1.06*	-0.64	0.16	-0.29	-0.34	-0.57	0.65	-0.34
	(-0.28)	(-1.24)	(-1.75)	(-1.03)	(0.21)	(-0.58)	(-0.47)	(-1.06)	(0.91)	(-0.74)
1-17	-0.70	-0.43	-1.13*	-0.75	0.13	-0.43	-0.69	-0.68	0.90	-0.37
	(-1.06)	(-0.67)	(-1.70)	(-1.09)	(-0.16)	(-0.78)	(-0.89)	(-1.12)	(1.22)	(-0.74)
1-18	-0.68	-0.17	-1.21**	-1.00*	-0.14	-0.71*	-0.60	-0.84*	0.87	-0.75*
	(-1.44)	(-0.30)	(-2.34)	(-1.98)	(-0.19)	(-1.79)	(-0.87)	(-1.90)	(1.12)	(-1.95)
1-19	-0.55	-0.56	-1.12	-1.09**	-0.12	-0.75**	-0.61	-0.83**	0.76	-0.54
	(-0.82)	(-1.12)	(-1.61)	(-2.26)	(-0.15)	(-2.07)	(-0.77)	(-2.04)	(0.99)	(-1.49)
1-20	-0.10	-0.29	-0.53	-0.67	0.62	-0.40	0.03	-0.54	0.21	-0.35
	(-0.16)	(-0.67)	(-0.85)	(-1.43)	(0.78)	(-1.12)	(0.04)	(-1.33)	(0.27)	(-1.04)

*Statistically significant on a 10% level
**Statistically significant on a 5% level
***Statistically significant on a 1% level

Panel C

Strategy	Forecast horizon									
	23	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
1-2	-0.29	-0.54	-0.21	-0.51	0.06	-0.52	0.48	-0.79*	0.46	-0.76
	(-0.54)	(-1.11)	(-0.46)	(-0.98)	(0.16)	(-0.98)	(0.98)	(-1.66)	(1.02)	(-1.48)
1-3	-1.25*	-0.62	-1.15*	-0.70	-0.95	-0.74	0.51	-1.11*	0.52	-0.66
	(-1.78)	(-0.98)	(-1.79)	(-1.07)	(-1.62)	(-1.14)	(0.91)	(-1.76)	(0.87)	(-1.03)
1-4	-0.28	-0.73	-0.20	-0.74	-0.02	-0.60	0.43	-0.72	0.22	-0.80
	(-0.56)	(-1.15)	(-0.38)	(-1.17)	(-0.03)	(-0.98)	(0.70)	(-1.27)	(0.35)	(-1.32)
1-5	-0.95*	-0.37	-0.66	-0.55	-0.40	-0.52	0.02	-0.75	0.19	-0.49
	(-1.73)	(-0.80)	(-1.21)	(-1.06)	(-0.55)	(-1.19)	(0.03)	(-1.56)	(0.26)	(-1.03)
1-6	-1.07	-0.43	-1.03	-0.19	-0.71	-0.17	0.27	-0.34	0.33	-0.27
	(-1.50)	(-0.87)	(-1.34)	(-0.35)	(-0.79)	(-0.36)	(0.30)	(-0.60)	(0.38)	(-0.52)
1-7	-1.17*	-0.55	-1.03	-0.60	-0.84	-0.63	0.39	-0.74	0.73	-0.71
	(-1.74)	(-0.86)	(-1.44)	(-0.92)	(-1.03)	(-0.97)	(0.47)	(-1.13)	(0.92)	(-1.10)
1-8	-0.97*	-1.05*	-0.96	-1.12**	-0.54	-0.89*	0.22	-1.11*	0.40	-1.13**
	(-1.70)	(-1.85)	(-1.60)	(-1.97)	(-0.77)	(-1.81)	(0.32)	(-1.92)	(0.57)	(-2.09)
1-9	-0.98*	-0.61	-0.88*	-0.51	-0.46	-0.43	0.49	-0.63	0.74	-0.60
	(-1.77)	(-1.48)	(-1.68)	(-1.16)	(-0.72)	(-1.12)	(0.69)	(-1.42)	(1.06)	(-1.50)
1-10	-1.42***	-0.83*	-1.37***	-0.81*	-0.97	-0.85**	0.64	-1.24***	0.73	-1.09**
	(-2.84)	(-1.94)	(-2.59)	(-1.78)	(-1.45)	(-2.16)	(0.95)	(-2.56)	(1.07)	(-2.37)
1-11	-1.19**	-1.19**	-1.02*	-1.37**	-0.67	-1.21**	0.26	-1.47***	0.06	-1.53***
	(-2.14)	(-2.26)	(-1.72)	(-2.45)	(-0.90)	(-2.40)	(0.34)	(-2.63)	(0.08)	(-2.63)
1-12	-0.74	-1.42**	-0.71	-1.40**	-0.45	-1.28**	0.29	-1.39**	0.16	-1.31*
	(-1.26)	(-2.16)	(-1.21)	(-2.04)	(-0.66)	(-2.02)	(0.36)	(-2.01)	(0.20)	(-1.93)
1-13	-0.45	-1.01*	-0.46	-0.51	-0.16	-0.14	0.21	-0.34	0.06	-0.08
	(-0.65)	(-1.71)	(-0.66)	(-1.01)	(-0.21)	(-0.33)	(0.28)	(-0.69)	(0.08)	(-0.18)
1-14	-0.64	-0.66	-0.54	-0.42	-0.18	-0.35	0.23	-0.44	0.44	-0.33
	(-0.92)	(-1.47)	(-0.78)	(-0.82)	(-0.24)	(-0.80)	(0.41)	(-0.82)	(0.79)	(-0.65)
1-15	-1.39***	-0.82*	-1.18**	-0.94*	-0.92	-0.74*	0.53	-0.91*	0.73	-0.75
	(-2.57)	(-1.70)	(-2.02)	(-1.85)	(-1.27)	(-1.81)	(0.72)	(-1.76)	(1.02)	(-1.48)
1-16	-1.17**	-0.55	-1.01	-0.52	-0.86	-0.41	0.43	-0.99**	0.55	-0.98**
	(-2.02)	(-1.08)	(-1.65)	(-1.03)	(-1.24)	(-0.94)	(0.63)	(-2.06)	(0.79)	(-2.06)
1-17	-1.22*	-0.88*	-1.05	-0.97*	-0.76	-0.87*	0.21	-1.23**	0.45	-1.12**
	(-1.98)	(-1.75)	(-1.63)	(-1.87)	(-1.02)	(-1.92)	(0.26)	(-2.26)	(0.56)	(-2.22)
1-18	-1.16*	-0.91**	1.19*	-0.88**	-0.87	-0.89**	0.60	-1.13**	0.78	-1.03**
	(-1.69)	(-2.26)	(-1.69)	(-2.06)	(-1.08)	(-2.20)	(0.76)	(-2.65)	(1.02)	(-2.44)
1-19	-1.16*	-0.78*	-1.02	-0.63	-0.70	-0.58	0.15	-0.82*	0.01	-0.74*
	(-1.76)	(-1.90)	(-1.48)	(-1.49)	(-0.90)	(-1.56)	(0.24)	(-1.86)	(0.02)	(-1.76)
1-20	-0.60	-0.51	-0.53	-0.58	-0.27	-0.46	0.02	-0.67*	0.15	-0.54
	(-1.01)	(-1.34)	(-0.84)	(-1.49)	(-0.36)	(-1.39)	(0.03)	(-1.66)	(0.20)	(-1.42)

*Statistically significant on a 10% level
**Statistically significant on a 5% level
***Statistically significant on a 1% level

Table III: Quarterly sorts conditioned on cumulative impulse responses to shocks in the US federal budget deficit process of one standard deviation

For each quarter *t*, I estimated a bivariate VAR-model of lag order p=4 for all equity portfolios. Each VAR-model contains the changes of the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR-model I estimated the Wold-Moving-Average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables as described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the cumulative impulse response (CIR) functions accounting for a forecast horizon of k=1,…,32 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR-model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon k into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategy was updated at the beginning of each quarter. The initial portfolio allocation started in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit were downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. Panel A shows the average raw excess returns, the average risk-adjusted return and the p-value of LM-tests for autocorrelation concerning the residuals of the corresponding risk-adjusted models for PG i with i=1,…,10. Panel B shows the corresponding estimates for PG i with i =11,…,20. Heteroskedasticity robust t-values are given in parentheses.

Panel A: Group 1 -10

Group	Average excess returns	Average risk-adjusted returns	LM-test (p-value)
1	1.10	-0.80*	0.24
	(1.49)	(-1.69)	
2	1.14	-0.51	0.00
	(1.57)	(-0.82)	
3	2.04***	0.45	0.74
	(2.80)	(0.82)	
4	1.61**	-0.52*	0.24
	(1.96)	(-1.84)	
5	2.09**	0.14	0.05
	(2.50)	(0.41)	
6	1.96**	0.27	0.70
	(2.43)	(0.50)	
7	2.27***	0.37	0.66
	(2.90)	(0.70)	
8	1.99**	0.17	0.13
	(2.36)	(0.58)	
9	2.17***	0.18	0.11
	(2.58)	(0.60)	
10	2.33***	0.62*	0.14
	(2.73)	(1.73)	

Panel B: Group 11-20 and (1-10)

Group	Average excess returns	Average risk-adjusted returns	LM-test (p-value)
11	2.37***	0.39	0.02
	(2.74)	(1.12)	
12	2.22***	-0.06	0.07
	(2.60)	(-0.20)	
13	1.98**	-0.35	0.43
	(2.40)	(-0.91)	
14	2.12**	-0.16	0.59
	(2.53)	(-0.46)	
15	2.50***	0.59**	0.95
	(2.98)	(2.04)	
16	2.28***	0.37	0.84
	(2.70)	(1.09)	
17	2.05**	0.42	0.57
	(2.42)	(1.19)	
18	2.10**	0.35	0.99
	(2.45)	(0.73)	
19	1.99**	0.36	0.82
	(2.24)	(0.72)	
20	2.11**	-0.20	0.95
	(2.25)	(-0.64)	
(1-10)	-1.23**	-1.42***	0.47
	(-2.48)	(-2.84)	

*Statistically significant on a 10% level
**Statistically significant on a 5% level
***Statistically significant on a 1% level

Table IV: Correlations between Risk factors and Industries

For each quarter *t*, I estimated a bivariate restricted VAR-model of lag order *p*=4 for all equity portfolios. Each VAR-model contains the returns of the US federal budget deficit and the respective equity portfolio. Then, for each VAR-model I estimated the Wold-Moving-Average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables as described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the cumulative impulse response (CIR) functions accounting for a forecast horizon of *k*=1,…,32 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR-model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon *k* into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. The optimal zero-cost portfolio accounting for a forecast horizon *k=23* is conducted by buying PG 1 and selling PG 10. This portfolio is referred to as *DEF*. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategy was updated at the beginning of each quarter. The initial portfolio allocation started in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit are downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website.

Correlation matrix of Risk factors and the 10 Fama and French industries

DEF	1	-0.36	-0.36	0.10	0.39	-0.30	-0.31	-0.32	-0.18	-0.36	-0.26	-0.35	-0.24	-0.35	-0.34
Market		1	0.43	-0.36	-0.19	0.75	0.80	0.91	0.60	0.87	0.75	0.84	0.74	0.53	0.90
SMB			1	-0.16	-0.24	0.25	0.46	0.40	0.16	0.45	0.17	0.46	0.14	0.01	0.39
HML				1	-0.21	-0.12	-0.02	-0.19	-0.09	-0.55	-0.23	-0.28	-0.40	0.06	-0.10
MOM					1	-0.14	-0.35	-0.21	-0.02	-0.20	-0.16	-0.15	0.00	-0.07	-0.22
NoDur						1	0.64	0.80	0.40	0.52	0.61	0.84	0.81	0.59	0.80
Durbl							1	0.84	0.45	0.69	0.58	0.74	0.48	0.39	0.82
Manuf								1	0.63	0.75	0.64	0.81	0.69	0.52	0.89
Enrgy									1	0.47	0.43	0.38	0.38	0.56	0.54
HiTech										1	0.65	0.72	0.58	0.37	0.71
Telcm											1	0.66	0.57	0.56	0.70
Shops												1	0.73	0.46	0.85
Hlth													1	0.49	0.71
Utils														1	0.59

Note: *MFF* denotes the excess market return, *SMB* (Small Minus Big) is the average return on a small portfolio minus the average return on a big portfolio, *HML* (High Minus Low) is the average return on a value portfolio minus the average return on a growth portfolio, whereas *MOM* is the average return on a high prior return portfolio minus the average return on a low prior return portfolio. A detailed description of these risk factors and the ten industry sectors is provided on Kenneth's French website.

Table V: Fama-MacBeth regressions

For each quarter *t*, I estimated a bivariate VAR-model of lag order *p*=4 for all equity portfolios. Each VAR-model contains the changes of the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR-model I estimated the Wold-Moving-Average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables as described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the cumulative impulse response (CIR) functions accounting for a forecast horizon of *k*=23 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR-model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon *k*=23 into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. The optimal zero-cost portfolio accounting for a forecast horizon *k=23* is conducted by buying PG 1 and selling PG 10. This portfolio is referred to as *DEF*. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategy was updated at the beginning of each quarter. The initial portfolio allocation started in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit are downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. I compounded the excess returns for all 20 PGs sorted by cumulative impulse responses and used these portfolios as test assets (see Table III). All cross-sectional OLS regressions included a constant term. The corresponding *t*-values are given in parentheses. Apart from the parameter estimates for the different asset pricing models, I also report the corresponding R-squared value, the test statistic of the Wald-test of the pricing errors, and the corresponding *p*-value. The corresponding data for the *MRF*, *SMB*, *HM,L* and *MOM* factor were also downloaded from Kenneth's French website.

Fama-MacBeth Regressions

Constant	MRF	SMB	HML	MOM	DEF	R-squared	Wald-test	p-value
-0.21 (-0.20	2.30* (1.70)					0.42	23.69	0.21
0.59 (0.75)		1.26* (1.66)				0.42	24.52	0.18
1.68** (2.36)			-1.25 (-0.76)			0.06	24.75	0.17
1.05 (1.45)				-2.94* (1.86)		0.44	22.82	0.25
1.20* (1.75)					-1.20** (-2.08)	0.73	18.99	0.46
1.15 (1.17)	0.70 (0.54)				-1.20** (-2.10)	0.73	18.99	0.39
-0.07 (-0.07)	1.23 (1.00)	1.23 (1.51)	1.51 (0.81)			0.54	20.81	0.23
1.06 (1.10)	0.56 (0.46)	0.57 (0.69)	0.42 (0.24)		-1.17** (-2.10)	0.74	16.94	0.39
0.10 (0.10)	1.15 (0.95)	1.06 (1.34)	1.22 (0.66)	-2.29 (-1.54)		0.59	20.12	0.21
1.08 (1.09)	0.55 (0.44)	0.55 (0.68)	0.42 (0.24)	-0.78 (-0.53)	-1.16** (-2.07)	0.74	16.90	0.32

*Statistically significant on a 10% level, **Statistically significant on a 5% level, ***Statistically significant on a 1% level.

Table VI: GMM-estimation

For each quarter *t*, I estimated a bivariate VAR-model of lag order *p*=4 for all equity portfolios. Each VAR-model contains the changes of the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR-model I estimated the Wold-Moving-Average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables as described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the cumulative impulse response (CIR) functions accounting for a forecast horizon of *k*=23 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR-model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon *k*=1,…,32 into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. The optimal zero-cost portfolio accounting for a forecast horizon *k=23* is conducted by buying PG 1 and selling PG 10. This portfolio is referred to as *DEF*. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategy was updated at the beginning of each quarter. The initial portfolio allocation started in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit are downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. I compounded the excess returns for all 20 PGs sorted by cumulative impulse responses and used these portfolios as test assets. The corresponding *t*-values are given in parentheses. Apart from the parameter estimates for the different asset pricing models, I also report the corresponding pricing errors, and the test statistic of the Wald-test and the corresponding *p*-value. The corresponding data for the *MRF*, *SMB*, *HM,L* and *MOM* factor were also downloaded from Kenneth's French website. Table VI reports the estimates for the second-stage GMM as described in detail in Cochrane (2005) using the statistical optimal weighting-matrix.

GMM-estimation

MRF	SMB	HML	MOM	DEF	Pricing errors	Wald-test	p-value
0.0367*** (3.17)					9.35	23.87	0.20
	0.0672*** (2.84)				2.71	23.86	0.20
		-0.0473 (-1.05)			48.91	26.90	0.11
			-0.0377* (-1.81)		31.24	21.26	0.32
				-0.0523*** (-3.56)	15.81	20.37	0.37
0.0255** (2.03)				-0.0279** (-2.06)	4.88	20.20	0.32
0.0438*** (2.57)	0.0190 (0.59)	0.0831** (2.42)			13.19	12.02	0.80
0.0413** (2.39)	-0.0026 (-0.07)	0.0795** (2.26)		-0.0210 (-1.48)	6.45	11.44	0.78
0.0403** (2.29)	0.0118 (0.35)	0.0802** (2.15)	-0.0067 (-0.44)		6.21	12.06	0.74
0.0409** (2.29)	-0.0035 (-0.10)	0.0789** (2.16)	-0.0014 (-0.10)	-0.0207 (-1.38)	6.10	11.39	0.72

*Statistically significant on a 10% level, **Statistically significant on a 5% level, ***Statistically significant on a 1% level.

Figure I: Non-linear cumulative impulse response (CIR) functions

For each quarter *t*, I estimated a bivariate VAR-model of lag order $p=4$ for all equity portfolios. Each VAR-model contains the changes of the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR-model I estimated the Wold-Moving-Average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables as described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the cumulative impulse response (CIR) functions accounting for a forecast horizon of $k=23$ quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR-model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon $k=1,\ldots,32$ into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. The optimal zero-cost portfolio accounting for a forecast horizon $k=23$ is conducted by buying PG 1 and selling PG 10. This portfolio is referred to as *DEF*. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategy was updated at the beginning of each quarter. The initial portfolio allocation started in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit are downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. I compounded the excess returns for all 20 PGs sorted by cumulative impulse responses and used these portfolios as test assets. Figure I illustrate the sorting procedure for $k=3$ based upon the in-sample time-window running from 2002:4 to 2012:3.The *x*-axis hosts the 224 input equity research portfolios sorted by the CIR function. Thereby, 100 Fama and French value-weighted equity research portfolios sorted by size and book-to-market ratio, 25 value-weighted equity research portfolios sorted by size and momentum, 49 value-weighted equity research portfolios sorted by industry, 25 value-weighted equity research portfolios sorted with respect to size and short-term reversal, and 25 value-weighted equity research portfolios sorted by size and long-term reversal are employed. The *y*-axis hosts the corresponding CIR forecast.