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Momentum and macroeconomic state variables

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Abstract We find strong evidence that momentum across asset classes is driven by macroeconomic state variables. By reacting to changes in the macroeconomic environment, the strategy performs particularly well in times of economic distress. This result is interesting for practitioners and academics alike the success of an investment strategy that simultaneously looks at relative momentum across currencies, bonds, real estate, commodities, and equities can be interpreted as a payoff for rational investors hedging against predictable changes in the investment opportunity set. Our results allow us to establish a link between momentum and more sophisticated predictive regressions.

Keywords Momentum · Macroeconomic factors · Trading strategy · Asset allocation · Two-way sorts

JEL Classification G12 · G14 · G15

1 Introduction

The objective of this article is to analyze the performance of return momentum across asset classes and to understand the economic forces driving it. We find a strong link between cross-asset class momentum and macroeconomic state variables. This moti-

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vates us to use the term "macro momentum" for a cross-sectional momentum strategy in global asset markets.

Employing a cross-sectional momentum strategy (with monthly rebalancing cycles and equally weighted long short wing portfolios), we obtain several key results. First, confirming and extending previous work, we find economically strong and statistically significant performance for this strategy in the period from January 1984 to April 2010. All results are stable across sub-periods and resistant to transaction costs or alternative momentum specifications. Second, we run predictive regressions using macroeconomic factors as a proxy for the state of the economy, similar to Fama and French (1989). We show out of sample that portfolios built on these rolling regressions yield a performance similar to our macro momentum strategy. Third, we use fitted returns from these predictive regressions to decompose momentum returns into their systematic and idiosyncratic parts. This decomposition provides strong evidence that macroeconomic factors are an important driver of return momentum across asset classes. Fourth, we show that once we allow for predictability in factor exposures, the outperformance of macro momentum drops to zero. This, of course, does not mean that one should not use these models for tactical asset allocation; it only means that this strategy is not for everyone. Investors that are able to take risk if the marginal utility from consumption is high will engage in these strategies. Finally, we analyze the performance of cross-asset class momentum over the business cycle. In times of recession, as defined by NBER, the economic momentum strategy performs particularly well, profiting from the rapid adjustments of asset class valuations to an economy that is shifting from growth to contraction.

One of our contributions is a deeper knowledge about return momentum effects in capital markets. Asness et al. (2013), as well as Moskowitz et al. (2012), rigorously document momentum in equities, bonds, commodities, and currencies, but concentrate on time-series momentum and cross-sectional momentum *within* an asset class. They expand and unify similar results long found for individual asset classes. While their analysis provides support for time-series momentum, it remains silent on the asset allocation characteristics of momentum *across* asset classes. Rey and Schmid (2007) provide strong evidence for the significance of the equity momentum effect even when adapting the strategy to circumvent market frictions. To our knowledge, the first references on the profitability of macro momentum, i.e., momentum *across* asset classes, are Ribeiro and Loeys (2006) and Blitz and Van Vliet (2008). Both papers present cross-sectional momentum, but work on shorter time horizons and use a more narrow set of assets than we do in this article. However, most importantly, previous articles made no attempt to relate the performance of macro momentum to macroeconomic predictability.[1] Consequently, they also do not consider predictable variation in risk premia in their performance analyses. While the existence of cross-sectional momentum in equities has been known since Jegadeesh and Titman (1993), our results provide further evidence that momentum investing across

[1] Cooper et al. (2004) deny such a link for equity momentum, but concentrate in their analysis on the forecasting ability of macroeconomic variables for momentum returns (whereas we study a contemporaneous link between across asset class momentum and macroeconomic variables).

asset classes, i.e., without a stock-picking element, can provide significantly positive alpha.

Our article is also related to the literature on asset rotation in a broader sense. Rapach et al. (2011) use a principal component analysis to extract information out of a large set of economic variables. The resulting factors are used successfully as predictors for industry portfolios and can be used for asset rotation. That analysis is similar to the regression forecasting approach we apply in this article in a cross-asset class context. Andreu et al. (2013) successfully apply momentum-based asset rotation strategies to countries and sectors using exchange traded funds. Another asset rotation strategy is introduced by Maio (2012a). This strategy invests in different equity portfolios depending on changes in the Fed funds rate and generates significant Sharpe ratio increases over a buy-and-hold strategy. Unlike Maio (2012a), who concentrates on an analysis of the forecasting power of the Fed funds rate, our forecasting strategy uses a broader set of economic forecasting variables. While we use a forecasting strategy based on economic variables in our cross-asset class setting, for equities often fundamentals-based sum-of-the-parts approaches are applied to achieve profitable investment strategies. Rather than the economics-based top–down approach employed in this article, a sum-of-the-parts analysis is a bottom–up approach (compare, e.g., Ferreira and Santa-Clara 2011).

The main contribution of this article is the analysis of the link between macroeconomic factors and momentum across asset classes. In the academic literature, there is a range of alternative explanations for the profitability of momentum investing that can be broadly split into two strands of research: market inefficiencies and time-varying risk premia. On the market inefficiency side, research focuses on behavioral arguments such as overconfidence, mental accounting, and prospect theory (see, e.g., DeBondt and Thaler 1985, 1987; Grinblatt and Han 2005; Frazzini 2006) or on the way information diffuses into the market (compare Hong and Stein 1999; Hong et al. 2000). Investment restrictions (see Qin 2009) and short-selling restrictions (see, e.g., Lamont and Stein 2004; Diamond and Verrecchia 1987) are seen as further drivers of inefficiency-based momentum. This article, however, concentrates on the link between momentum and time-varying risk premia. Moskowitz and Grinblatt (1999) find that momentum can be partially explained by industry factors. Their results can be interpreted as proxies for the time-varying risk premia required by investors for different industries. Liu and Zhang (2008) also associate momentum with macroeconomic factors by finding that equity momentum returns can be partially explained by the growth in industrial production.[2] An article by Maio (2013) links momentum to macroeconomic factors by finding that momentum returns can be priced by a factor related to CPI inflation. Chordia and Shivakumar (2002) find a strong link between equity momentum returns and time-varying risk premia. This link is established by using changing economic conditions as a proxy for time-varying risk premia. We extend these results with our research hypothesis that macro momentum should exhibit a particularly clear link with economic developments. The economic intuition for this hypothesis is that

[2] Liu and Zhang (2008) also provide evidence that refutes earlier claims by Griffin et al. (2003) that equity momentum is not linked to macroeconomic factors.

asset classes react in distinct—but often negatively correlated—ways to changes in the economic environment.

The remainder of this article is structured as follows. Section 2 gives an in-depth analysis of macro momentum. The link between macroeconomic factors and their power in forecasting asset returns is analyzed in Sect. 3. Evidence for a strong link between macroeconomic development and the performance of economic momentum is given in Sect. 4. Section 5 analyzes the performance of cross-sectional momentum after allowing for predictability in economic state variables. We conclude in Sect. 6.

2 Macro momentum

2.1 Data

We use Datastream to retrieve excess return data (proxying futures returns) for our analysis.[3] Our return time series range from December 1983 until April 2010. For equities, we use data for the S&P 500, FTSE 100, TOPIX, DJ Eurostoxx 50, and MSCI Emerging Markets index. Where data are not available, we use returns for the respective Datastream Total Market Index. Our commodity universe covers five subindices of the S&P GSCI: Light Energy, Energy, Agriculture, Industrial Metals, and Livestock. These indices are available for the whole timeframe of our analysis. For fixed income, we use eight total market indices from Datastream that cover German (as a proxy for the Euro area), U.S., U.K., and Japanese bonds in the 1–3-year- and 7–10-year maturity bands. These indices are available for the whole time period of our analysis. Real estate investments are proxied using the Datastream retail REIT Index for the Americas. The foreign exchange asset class is represented by the U.S. dollar exchange rate of the Euro, British pound, and Japanese yen. We determine the total return of a foreign exchange investment as the sum of the spot rate return and the 1-month money market rate earned in the non-USD leg of the trade. The excess return of the foreign exchange investment can be conveniently calculated as the sum of the spot price movement plus the ratio between the 1-month forward price and the spot price, i.e., the carry element. For the risk-free rate, we use the 1-month Libor rate associated with the base currency of the underlying asset. Summary statistics for the data can be found in Table 7 in the Appendix.

2.2 Methodology

We define macro momentum as trending in relative asset class returns. By this we mean, for example, the tendency of safe haven assets (bonds, U.S. dollars, Japanese yen) to outperform risky assets (equities, commodities) in times of economic stress. To define this concept precisely we start by calculating the log excess returns for each asset:

[3] This approximation is, of course, imperfect as there remains an ambiguity about index replication as well as leverage costs.

$$R_{t,i} = \ln\left(\frac{P_{t,i}}{P_{t-1,i}}\right) - r_{f,i,t-1} \tag{1}$$

where $r_{f,i,t-1}$ is the one-period (month) continuously compounded risk-free rate of return at time $t-1$ in the currency that asset i is denominated and $P_{t,i}$ is the price of asset i at time t. The prices $P_{t,i}$ are on a total return basis and include all dividend or interest payments the holder of the respective instrument would receive. We calculate the return over the last n periods to define the n-period return momentum:

$$M^n_{t,i} = \sum_{j=1}^{n} R_{t-j+1} \tag{2}$$

Our momentum strategy goes long (short) in assets with a momentum higher (lower) than the median return of all assets. The corresponding portfolio weights evolve according to:

$$v^{n,\mp}_{t,i} = \begin{cases} -1 & \text{if } M^n_{t,i} - \underset{i}{\text{median}}(M^n_{t,i}) < 0 \\ +1 & \text{if } M^n_{t,i} - \underset{i}{\text{median}}(M^n_{t,i}) \geq 0. \end{cases} \tag{3}$$

To ensure a cash-neutral investment portfolio—when there is an uneven number of assets in the investment universe—we apply the following normalization to the negative and positive weights:

$$w^{n,+}_{t,i} = \frac{v^{n,+}_{t,i}}{\sum v^{n,+}_{t,i}}, \quad w^{n,-}_{t,i} = -\frac{v^{n,-}_{t,i}}{\sum v^{n,-}_{t,i}} \tag{4}$$

The portfolio weights of all assets i in the momentum strategy are then the row vector $w^n_t = \left[w^{n,-}_{t,i}, w^{n,+}_{t,i}\right]$. Finally, to make the portfolio weights comparable across strategies and benchmarks, we normalize the expected returns of our investment portfolio to an ex ante annual volatility of 1 %:[4]

$$w^{n,\text{strat}}_{t,i} = \gamma^n_t w^n_{t,i}, \quad \gamma^n_t = \frac{1}{100 \cdot \sqrt{12 \cdot w^n_t \Omega_t w^{n\prime}_t}} \tag{5}$$

where Ω_t is the variance–covariance matrix of the asset excess returns in the investment universe (ordered with respect to $w^n_{t,i}$) estimated with the monthly returns available at time t. This normalization will help in later sections of this article to compare performance across different time periods. Furthermore, asset managers often apply this methodology to control the risk in their portfolios. Barroso and Santa-Clara (2012) scale portfolios by their expected volatility. This approach delivers a momentum portfolio performance with higher risk-adjusted returns. Furthermore, Barroso and Santa-Clara (2012) arrive through this scaling with expected volatility at return profiles

[4] This is standard in the investment industry as it maintains diversification across time (each month is equally important) and avoids the dangers of St.Petersburg-like strategies (doubling up).

which are preferable to investors with CRRA utility. In accordance with the literature on momentum, such as Jegadeesh and Titman (1993) and Blitz and Van Vliet (2008), we focus on long- and short-term momentum given by a 1-month momentum (i.e., $n = 1$) and a 12−1-month momentum $M_{t,i}^{12-1}$ that is defined as:

$$M_{t,i}^{12-1} = M_{t,i}^{12} - M_{t,i}^{1}. \tag{6}$$

We analyze these two momentum portfolios ($M_{t,i}^{12-1}$ and $M_{t,i}^{1}$) on a stand-alone basis, but we also analyze a portfolio that invests equally in both portfolios. The investment weights for this combined portfolio are defined as:

$$w_{t,i}^{\text{comb}} = \gamma_t^{\text{comb}} \left(\frac{1}{2} w_{t,i}^{1} + \frac{1}{2} w_{t,i}^{12-1} \right) \tag{7}$$

where γ_t^{comb} is the scaling factor for bringing the annualized portfolio target volatility to 1 %. This combined momentum strategy will be the base case for the remainder of this article.[5]

2.3 Results

Our empirical analysis provides strong evidence for the presence of momentum in a cross-asset class setting. Table 1 summarizes the results of the strategy implementation. We find that the 1-month and the 12−1-month macro momentum are profitable, with Sharpe ratios of 0.788 and 0.856, respectively. Both momentum timeframes, 1-month and 12−1-month, are successful in capturing market trends, illustrating that momentum strategies are profitable for a range of different look-back periods.[6] While Sharpe ratios[7] give an indication of the risk-return tradeoff, the t-statistics provide additional evidence for the extent of the statistical significance.[8] With t-statistics of

[5] Focusing on a particular momentum strategy leaves open the possibility of data mining. We address this issue in the next section.

[6] We find a large drawdown of our momentum strategy in 2009. This result is consistent with Danial and Moskowitz (2011), who find evidence for momentum crashes in periods immediately after significant market crashes. The authors attribute these drawdowns in momentum returns to the strong rebounds of the biggest losers after a market correction. We thank an anonymous referee for this point.

[7] We reluctantly follow the convention of presenting or even comparing Sharpe ratios. Strictly speaking, it is not permissible to compare investments using their Sharpe ratios (even when we abstract from non-normality). A Sharpe ratio is a stand-alone(!) measure that ignores an investment's portfolio contribution. For example, investors are willing to hold even negative Sharpe ratio assets if they show negative covariance with their remaining assets. This is the gist of modern portfolio theory. All that matters is the portfolio context. Low individual asset risk is attractive only if it co-varies little with the market portfolio and high returns are attractive only as long as they are not spanned by existing assets. A good example is the case of government bonds, which are held by nearly every investor due to their negative correlation with equities. They are essentially recession hedges. Our only defense for using Sharpe ratios is for comparability with the above-mentioned literature.

[8] Under the assumption of a world with a risk-free asset and without borrowing constraints, the portfolio with the maximum Sharpe ratio is the risky portfolio that mean-variance investors hold as part of their allocation between risky and risk-free assets. This is the result of the two-fund separation theorem by

Table 1 Performance of macro momentum

	1M macro momentum	12−1M macro momentum	Comb. macro momentum	S&P 500 excess returns	Normalized S&P 500 excess returns
Mean (p.a.)	0.843 %	0.920 %	1.133 %	6.021 %	0.381 %
Volatility (p.a.)	1.071 %	1.076 %	1.152 %	15.823 %	1.000 %
Min	−0.72 %	−0.96 %	−1.41 %	−24.10 %	−1.52 %
Max	1.17 %	1.10 %	1.60 %	12.40 %	0.78 %
Skewness	0.686	−0.120	0.021	−1.042	−1.042
Excess Kurtosis	2.700	0.455	2.532	3.447	3.447
t-stat	(3.679)***	(4.632)***	(5.156)***	(1.766)*	(1.766)*
Sharpe ratio	0.788	0.856	0.983	0.381	0.381

Descriptive statistics for a macro momentum strategy for the period 1984/1 to 2010/4 (316 data points). The t-statistic for the average (monthly) return comes from a regression of excess returns against a constant with HAC adjusted errors (HAC standard errors with Newey–West/Bartlett Window and 12 lags)

3.679 and 4.632, respectively, for the 1-month and 12−1-month macro momentum, we reject the null hypothesis of zero excess returns. A combination of both momentum portfolios results in a more profitable strategy payoff with a Sharpe-ratio of 0.983.[9] This is partially due to a low (average) correlation between the two return profiles of 0.24 for the sample period from 1984/1 to 2010/4.[10]

The positive cross-asset class momentum returns for the 1-month filter stand in contrast to the reversal in equity returns documented by Jegadeesh (1990), Lo and Mackinlay (1990), and Judice et al. (2010), and others for equity-based portfolios. For equities, the observed return reversals are frequently traced back to overreaction or cross-effects among the equities in the respective universe (compare, e.g., Lo and Mackinlay 1990). Liquidity considerations also play a role in equity return reversals, as documented by Pastor and Stambaugh (2003). Consistent with our results, in related work, Blitz and Van Vliet (2008) find profitable 1-month momentum strategies in their cross-asset class approach. The lack of reversals in the cross-asset class strategies might be linked to the generally larger liquidity in the included asset classes, which reduces the effect of reversals caused by transient price impact through trading. Furthermore, the effect of overreaction might be reduced here as the included asset classes are driven to a larger extent by macroeconomic developments than equities, which have a larger idiosyncratic return component. Finally, the cited articles that provide

Footnote 8 continued
Tobin (1958). Thus, we refrain from using mean-variance utility-based performance measures in our analysis, such as the ones used in Ferreira and Santa-Clara (2011) and Maio (2012a), as they do not reveal any relevant insight over and above the Sharpe ratio.

9 Our Sharpe ratio is close to time-series momentum in Moskowitz et al. (2012) for the same period, even though our universe is only a third (21 assets) of theirs (58 assets).

10 The regression strategy only covers the period 1988/1 to 2004/10 due to the need to calibrate the initial regression parameters during the first five years of the sample.

evidence for reversals look at daily or weekly return periods, which are shorter than the monthly return period we study, providing another explanation for the difference in results.

Comparing these returns with the S&P 500, which has a Sharpe ratio of 0.381 during this period, we conjecture that the returns from macro momentum provide a statistically significant increase in Sharpe ratio over a pure equity investment. The non-normal nature of the return data (excess kurtosis of 2.532) and their significant first-order autocorrelation of 0.14 (t-value of 2.60) do not allow us to employ the Memmel (2003) adjusted Jobson and Korkie (1981) test statistic for the equality of Sharpe ratios. Instead, we employ the bootstrapping technique by Ledoit and Wolf (2008) to formally test this hypothesis. For block-wise bootstrapping (to capture the autocorrelation) with an average block length of three months we arrive at a p value of 0.036. We therefore reject the null hypothesis of equal Sharpe ratios at the 95 % confidence level.[11] Combining both strategies also provides better Sharpe ratios in 89 % of all bootstrapped data sets when compared with a short-term (1-month) strategy and 85 % when compared with a long-term (12−1-month) strategy.

By not adjusting the momentum returns for the volatility of the respective assets in Eq. (3), we follow the established momentum strategy structure chosen by Blitz and Van Vliet (2008) and Jegadeesh and Titman (1993). However, this might cause results to be driven by equity returns, which have rather high volatilities when compared to the other asset classes in our universe. We rerun our momentum strategy without equities to determine how much of the performance can be attributed to equity asset allocation decisions. In unreported results we find that the performance persists even when we exclude equities from the investment universe. With a Sharpe ratio of 0.952 and a t-statistic of 4.887, we continue to obtain strong performance for the combined 1-month and 12−1-month strategy without equities. Furthermore, even if the assets are used on a volatility-adjusted basis, we find in unreported results that the strategy remains profitable.[12] These results are robust to restrictive assumptions on transaction costs employed as standard data mining tests by Romano and Wolf (2005).[13]

In another stability test we run the momentum strategies without the volatility normalization in Eq. (5). The results remain essentially unchanged as we continue to obtain high Sharpe ratios of 0.818, 0.798, and 1.008 for the 1-month, 12−1-month, and combined macro momentum strategy, respectively. The other statistics also remain fairly robust. Furthermore, correlations of the momentum strategies without the volatility scaling with their standard specification counterparts are 0.937 and 0.982, indicating that the strategies behave very similarly. Thus, we conclude that our results are not sensitive to the volatility scaling in Eq. (5).

11 Our results are not sensitive to longer average block length.

12 Sharpe ratios for the 1-month, 12-month, and 12−1-month macro momentum with volatility-adjusted returns are 0.928, 0.770, and 1.021, respectively.

13 Supporting material is available from the authors.

3 The alternative: a conditional macro model

In Sect. 2, we show that macro momentum creates investment opportunities that earn significant abnormal returns. Now we explore the possibility of generating excess returns from predictive regressions. In other words, we create the theorist's alternative to a momentum strategy.

This section has a dual purpose. First, it contributes to the predictability debate. Just as in Fama and French (1989), we use variables associated with states of the economy to forecast returns on asset classes. These economic state variables are either highly correlated with the business cycle or can even forecast it. An example of the latter is the term spread (yield spread between long and short maturity bonds), which also predicts future returns, as described in Campbell (1987) and Fama and French (1989). To illustrate this, imagine that the economy is in the middle of a recession. In this environment, risk aversion increases due to depressed levels of wealth. To induce investors to hold equities, risk premia need to be large. Hence, variables that reflect the economic state will signal future equity returns (high in a recession, which will be true on average). Lettau and Ludvigson (2001), Brandt and Wang (2003), and Maio (2013, 2012b) are good examples of analyses that discuss the predictability of equity returns as a result of time-varying risk aversion. In this worldview, macroeconomic predictability arises from rational decision makers hedging their consumption risk and not from violations of market efficiency. This follows an early observation by Merton (1971): rational investors hedge against predictable changes in investment opportunities.

In the literature, there is disagreement over the degree to which asset returns are predictable. Campbell and Cochrane (1999) and Campbell (1987, 1988) find predictability in asset class returns whereas Goyal and Welch (2008) do not. The present analysis is also related to Avramov et al. (2011) who find that macroeconomic variables have predictive power for hedge fund returns. In accordance with the literature, we use a common set of predictor variables to build long/short portfolios of major asset classes from predictive regressions using lagged economic state variables. What makes our work different is that we build an investment strategy that invests *across* asset classes, rather than testing predictability *within* an asset class.

The second purpose of this section is to use its results to explore the link (similarity) between long/short strategies based on macro momentum and long/short strategies based on predictive regressions. Is macro momentum a poor man's version of more sophisticated predictive regressions?

We adopt the methodology established by Chordia and Shivakumar (2002) in the context of equity returns. The authors apply four macroeconomic factors: equity market dividend yields, default spread, term spread, and 3-month Treasury bills. This approach is clearly motivated by Fama and French (1989), who, in earlier studies, use dividend yields, default spread, and term spread and find them to be significant predictors of future equity and bond returns. The Treasury bill rate is added as explanatory factor as it is another important indicator of future economic development and financial market returns.[14]

[14] Compare, e.g., Fama (1981) and Fama and Schwert (1977).

The choice of regression variables is difficult as there is a large range of alternative factors shown in other studies to have forecasting power for future asset returns. We use the factors from Chordia and Shivakumar (2002) as a starting point for our analysis since we construct our research on their methodology and, moreover, this factor set has been used often in other research. However, to test for the effect of other factors on our results, we use factors such as the yield gap applied by Maio (2012b), the change in the Fed funds rate applied by Maio (2012a), and the realized stock market variance applied in Guo (2006); however, the success of the forecasting strategy was not improved by any of these factors.

Our macroeconomic data are obtained from the U.S. Federal Reserve (credit spread, term spread, 3-month T-Bill rate, dividend yields). We start by taking the first difference of the monthly factors used by Chordia and Shivakumar (2002) to avoid spurious regressions by including non-stationary explanatory variables in a return forecasting model.[15] All these factors are easily obtainable from financial markets and do not have a publication lag. This results in the following predictive regression model:

$$R_{t,i} = c_i + \sum_{k=1}^{K} \beta_{i,k} m_{t-1,k} + \varepsilon_{t,i} \tag{8}$$

where $m_{t-1,k}$ is the value of the macroeconomic factor k at time $t-1$. We estimate Eq. (8) using OLS with a rolling window of 60 months to generate real-time forecasts (forecasts evolve over time using only historically available information at the time of forecast). A rolling window of 60 months is chosen to remain consistent with Chordia and Shivakumar (2002). The results are robust when using different lengths of regression windows (including, e.g., 84 and 120 months) or when using a growing regression window. When using a rolling window of 120 months, for example, mean returns are at 0.82 % with a Sharpe ratio of 0.74. Using a growing window, the mean returns are 0.45 % with a Sharpe ratio of 0.41.

The estimated factor sensitivities (parameters) $\hat{\beta}_{i,k}$ and the macroeconomic factors at time t generate forecasts for the next period asset returns:

$$\hat{R}^{\text{Predict}}_{t+1,i} = \hat{c}_i + \sum_{k=1}^{K} \hat{\beta}_{i,k} m_{t,k} \tag{9}$$

Because $\hat{c}_i$ captures a drift in the equity returns, it is linked to momentum. To be conservative and eliminate all possible links to momentum from the return forecasts for the economic regression strategy, we estimate the parameters in a regression with intercept but forecast excess returns without the regression intercept.[16] We use

[15] See Ferson et al. (2003).

[16] Keeping the regression intercept in the estimation of the regression parameters as well as the forecasts leads to a stronger risk-adjusted performance of the economic forecasting strategy. Applying an approach where the forecasting regression in Eq. (8) does not include an intercept leads to a better risk-adjusted return of the economic forecasting strategy as well. However, when testing for a link between the economic forecasting strategy and macro momentum, which is the centerpiece of this article, the results remain essentially unchanged when using the two modifications. Thus, we prefer to estimate the regression parameters

these forecasts to construct self-financing portfolios with portfolio weights $w_{t,i}^{\text{Predict}}$ equal to:[17]

$$w_{t,i}^{\text{Predict},+} = \frac{v_{t,i}^{\text{Predict},+}}{\sum v_{t,i}^{\text{Predict},+}}, \quad w_{t,i}^{\text{Predict},-} = -\frac{v_{t,i}^{\text{Predict},-}}{\sum v_{t,i}^{\text{Predict},-}} \tag{10}$$

where

$$v_{t,i}^{\text{Predict},\mp} = \begin{cases} -1 & \hat{R}_{t+1,i} - \underset{i}{\text{median}}(\hat{R}_{t+1,i}) < 0 \\ +1 & \hat{R}_{t+1,i} - \underset{i}{\text{median}}(\hat{R}_{t+1,i}) \geq 0. \end{cases} \tag{11}$$

Finally, we apply the normalization and the rescaling factor γ (to rescale the portfolio to an ex ante annualized target volatility of 1 %) used in Eq. (5). This strategy is referred to as MRS4.

How does this strategy perform? Panel A in Table 2 summarizes the performance of our macroeconomic regression strategy with four factors (MRS4). Its Sharpe ratio (0.42) over the full sample period is considerably lower than the Sharpe ratio of macro momentum. This difference (0.98 for momentum vs. 0.42 for economic forecasting) for the period 1988/1 to 2010/4 is statistically significant with a p value of 0.02 using the Ledoit and Wolf (2008) testing procedure. Regression-based forecasts appear particularly weak from 1988/1 until 1994/12, with a Sharpe ratio of only 0.13 and a t-statistic for average returns larger than zero of 0.34. Thus, during that period, markets do not appear to be driven by macroeconomic developments. From 2003/1 until 2010/4, the strategy's performance improved to a respectable Sharpe ratio of 0.62 and a t-statistic of 1.68. For the entire time period, the t-statistic for average returns larger than zero is significant at the 10 % level (with a t-value of 1.71). While volatile in the short run, it is important that a strategy building on macroeconomic variables can achieve significantly positive excess returns in the long run.

To this point, the predictive variables have been macroeconomic in nature, but derived from financial markets, which has the advantage of being forward looking with zero measurement error and no publication lag. Now we extend the variable set used by Chordia and Shivakumar (2002) by adding two purely macroeconomic

Footnote 16 continued
with an intercept but construct the return forecast used for the investment portfolio of the strategy without the intercept to eliminate all momentum-like aspects out of the economic regression strategy. Furthermore, using an intercept in the regression allows, later in the article, a cleaner decomposition into return elements associated with changes in the economic environment and idiosyncratic elements.

[17] This naïve portfolio construction framework (essentially ignoring covariance information) is employed to achieve comparability with our momentum portfolio. Doing so additionally ensures that the impact of estimation error is limited (at the expense of in sample optimality).

Table 2 Performance summary of the macroeconomic regression strategy

	1988/1–1994/12	1995/1–2002/12	2003/1–2010/4	1988/1–2010/4
Panel A: MRS4, using default spread, term spread, dividend yield, T-Bill rate				
Mean (p.a.)	0.12 %	0.42 %	0.84 %	0.46 %
Volatility (p.a.)	0.94 %	1.01 %	1.35 %	1.11 %
Min	−0.63 %	−0.64 %	−0.71 %	−0.71 %
Max	1.19 %	0.62 %	2.21 %	2.21 %
Skewness	0.79	−0.44	2.10	1.31
Excess Kurtosis	3.53	−0.40	9.97	7.91
t-stat	(0.34)	(1.13)	(1.68)*	(1.96)**
Sharpe ratio	0.13	0.42	0.62	0.42
Panel B: MRS6, Adding Unemployment Rate and Producer Confidence				
Mean (p.a.)	0.18 %	0.60 %	1.02 %	0.61 %
Volatility (p.a.)	0.98 %	1.07 %	1.36 %	1.15 %
Min	−0.73 %	−0.71 %	−0.96 %	−0.96 %
Max	1.23 %	1.04 %	2.21 %	2.21 %
Skewness	0.82	−0.02	1.85	1.21
Excess Kurtosis	3.47	0.39	9.7	7.17
t-stat	(0.49)	(1.68)*	(2.02)**	(2.45)***
Sharpe ratio	0.19	0.62	0.75	0.53

Performance and summary statistics of 60-month rolling-regression-based forecasts using Eq. (9) combined with the portfolio construction rule (Eq. 11) for alternative subperiods. We present two model specifications with $k = 4$ (Panel A) and $k = 6$ (Panel B) as the explaining variables

factors:[18] changes in U.S. producer confidence and the U.S. unemployment rate.[19] The strategy that uses this extended set of six forecasting variables is called MRS6. As these additional variables are less responsive to changes in the economic environment than the MRS4 variables, we use 12-month differences to account for their slow-moving character rather than the 1-month differences applied for the other factors.[20] To be conservative, we use a publication lag of 1 month.[21]

Panel B of Table 2 shows the impact of extending the number of forecasting variables. In short, the forecasting power of the regression approach improves. For the overall time period, the strategy now achieves positive average annual returns of 0.6 % at an annual volatility of 1.15 %. This translates into a Sharpe ratio of 0.53 and a

18 Certainly, a large range of alternative macroeconomic factors could have been applied in this analysis, but we want to limit the forecasting factors to some of the most important indicators for economic activity. For an extensive analysis of the link between a large range of macroeconomic factors and asset returns, see Ludvigson and Ng (2009) and Bai (2007).

19 Data obtained from Datastream and the U.S. Federal Reserve, respectively.

20 Results are stable when using 6-month changes or 1-month changes for unemployment and producer confidence.

21 Lagging producer confidence and unemployment by an extra month leads essentially to the same results.

significant t-statistic of 2.45. The subperiod from 1988/1 to 1994/12 continues to be the one with the weakest performance (t-statistic of 0.49), while the time period from 2003/1 until 2010/4 exhibits the strongest positive abnormal returns; it results in a t-statistic for positive abnormal mean returns of 2.03. Thus, while the results remain comparable to the forecasts with the standard set of macroeconomic factors, adding changes in unemployment and producer confidence can improve the power of the forecasting regression over the specification used by Chordia and Shivakumar (2002). We also add a January dummy to our extended model to capture a possible January effect in the returns. However, results are essentially unaffected by this dummy as the t-statistic of 2.32 for abnormal positive mean returns for the whole timeframe is only slightly lower than the 2.45 observed without the dummy. This suggests that the January effect often observed in equities (compare Dyl 1977; Grinblatt and Moskowitz 2004) is not as important in a cross-asset class context. In summary, we showed in this section that macroeconomic variables can be used to forecast asset returns and build a successful investment strategy on those forecasts.

4 Macro momentum and the business cycle

4.1 Business cycle impact on performance

Now that we have established a profitable macro momentum strategy and a successful macroeconomic regression forecasting strategy, we can analyze the link between the two. We first focus on how business cycles influence strategy performance. Table 3 provides performance figures broken down into seven separate, non-overlapping, time periods according to NBER business cycle definitions.[22] Our data cover four expansions and three contractions. While a larger number of cycles is desirable to achieve statistically stable results, our analysis is still able to shed some light on how business cycles influence strategy performance.

We test the null hypothesis that macro momentum returns are the same in expansions as they are in contractions by running an OLS regression against an expansion dummy (1 if the economy is in expansion mode; 0 otherwise) and a contraction dummy (1 minus the expansion dummy).[23] For the 1-month momentum version, the standard F-test for the equality of both regression coefficients is $F(1, 316) = 13.751$, with a significance level 0.0002. In other words, we reject the null hypothesis of equality with a p value of 0.02 % in favor of higher returns in contractions. This difference in returns between expansions and contractions is economically significant as it amounts to 228 basis points (p.a.) on a 100 basis points risk strategy. If the macro momentum strategy was run at an equity volatility of 10 %, the return difference would be 22.8 %. The 1-month macro momentum works very well in contractions; however, evidence

[22] The NBER business cycle dates can be found at http://www.nber.org/cycles/cyclesmain.html.

[23] Results are not reported in a table to conserve space, but are available from the authors upon request.

Table 3 Performance of macro momentum in economic expansions and contractions

	Expansion				
	Period	1M macro momentum	12−1M macro momentum	Comb. macro momentum	MRS6: economic regression
Mean (p.a.)	1984/1	0.52 %	0.89 %	1.02 %	−0.39 %
t-stat	to	(1.18)	(2.22)**	(2.22)**	−0.59
Sharpe ratio	1990/7	0.46	0.87	0.87	−0.37
Mean (p.a.)	1991/4	0.64 %	0.98 %	1.10 %	0.66 %
t-stat	to	(2.46)***	(3.23)***	(3.83)***	(2.33)**
Sharpe ratio	2001/3	0.78	1.02	1.21	0.74
Mean (p.a.)	2001/12	0.65 %	0.95 %	1.12 %	0.18 %
t-stat	to	(1.86)*	(2.54)***	(3.14)***	0.46
Sharpe ratio	2007/12	0.62	1.04	1.19	0.29
Mean (p.a.)	2009/7	−0.22 %	−0.37 %	−0.31 %	0.53 %
t-stat	to	−0.19	−0.30	−0.22	1.11
Sharpe ratio	2010/4	−0.21	−0.33	−0.24	1.21
Mean (p.a.)	All expansions	0.58 %	0.90 %	1.03 %	0.36 %
t-stat		(3.01)***	(4.48)***	(5.03)***	(1.74)*
Sharpe ratio		0.62	0.92	1.04	0.39
Mean (p.a.)	1990/8	3.54 %	−1.37 %	0.89 %	0.29 %
t-stat	to	(1.74)*	−0.73	0.36	0.13
Sharpe ratio	1991/3	2.13	−0.89	0.44	0.16
Mean (p.a.)	2001/4	2.43 %	1.89 %	2.35 %	1.28 %
t-stat	to	1.56	1.24	1.42	0.79
Sharpe ratio	2001/11	1.91	1.52	1.74	0.97
Mean (p.a.)	2008/1	3.06 %	1.81 %	2.30 %	3.58 %
t-stat	to	(1.86)*	1.14	1.19	(1.79)*
Sharpe ratio	2009/6	1.52	0.93	0.97	1.46
Mean (p.a.)					
t-stat					
Sharpe ratio					
Mean (p.a.)	All contractions	3.03 %	1.08 %	1.98 %	2.27 %
t-stat		(2.93)***	1.06	1.63	(1.83)*
Sharpe ratio		1.74	0.63	0.97	1.09

We split the performance series for our three momentum- and one regression-based strategies into seven subperiods ranging from 1984/1 to 2010/4. For each strategy and each subperiod, we calculate the annualized mean, its t-value, and the annualized strategy Sharpe ratio and report them in that order below

for the 12-month momentum is mixed. We cannot reject the null hypothesis of equality with $F(1, 316) = 0.791$. Twelve-month momentum reacts slowly to changing economic conditions and given that recessions have been short lived in the past, it does not appear suited to capitalize on the quickly changing economic environment in a crisis.[24]

How does this can be compared with a macroeconomic strategy based on using economic state variables? This series is our benchmark case for (rational) macroeconomic predictability. While the returns of the economic forecasting strategy MRS6 follow a similar pattern (higher returns in contractions than in expansions), individual period results are less significant. However, when looking at the full sample of expansions and contractions, our null hypothesis of equal returns across both economic regimes is rejected with $F(1, 268) = 6.982$, i.e., a p value of 0.009. Again, performance in contractions is stronger. These results suggest that payoffs from macro momentum as well as economic predictability vary across the business cycle. Thus, the returns of both strategies are countercyclical to macroeconomic developments and can serve as a good diversifiers. It is worth emphasizing that the two strategies do not capture a macroeconomic risk premia as this would result in larger returns in expansions, and not in contractions as we observe. Instead, the strategies are particularly good at reacting to adverse changes in the economic environment.

The fact that macro momentum delivers higher returns in recessions than in expansions is different from what Chordia and Shivakumar (2002) find for an equity momentum portfolio. In their analysis, where momentum portfolios are created by going long and short single shares, performance in recessions is significantly lower than in expansions. Cooper et al. (2004) find that momentum strategies applied to single equities are more profitable after periods of general market gains. Assuming that markets are falling in recessions and climbing in expansions, Cooper et al. (2004) findings are also a sign that our results for macro momentum returns across the business cycle are different from those obtained from momentum portfolios based on single equities. Liu and Zhang (2008) is another momentum study in the single equity context that finds that momentum portfolios have higher returns when economic growth, measured by growth of industrial production, is higher. One article that does find evidence for a stronger equity momentum performance in volatile down markets is Rey and Schmid (2007), which studies the Swiss market. It is not surprising, however, that cross-asset momentum differs in its reaction to changes in the macroeconomic environment compared to most findings on equity-based momentum as it has a broader investment universe. The resulting broader investment opportunity set means that in each market environment there will be opportunities to invest in assets with a positive price trend for the long positions and identify assets with a downward drift for the short positions (e.g., in market distress, bond prices often rise and equity prices fall).

Finally, we want a better understanding of the return drivers. Maybe the macro momentum strategy simply "learned" that some assets have higher (lower) average returns than others and the performance comes from structural positions (positions that do not change or benefit from differences in risk premia) and not from capturing the volatility of a return series (frequently adjusting positions to gain from short-term

[24] Providers of CTA funds are well aware of this and hence diversify across momentum strategies operating at different time scales.

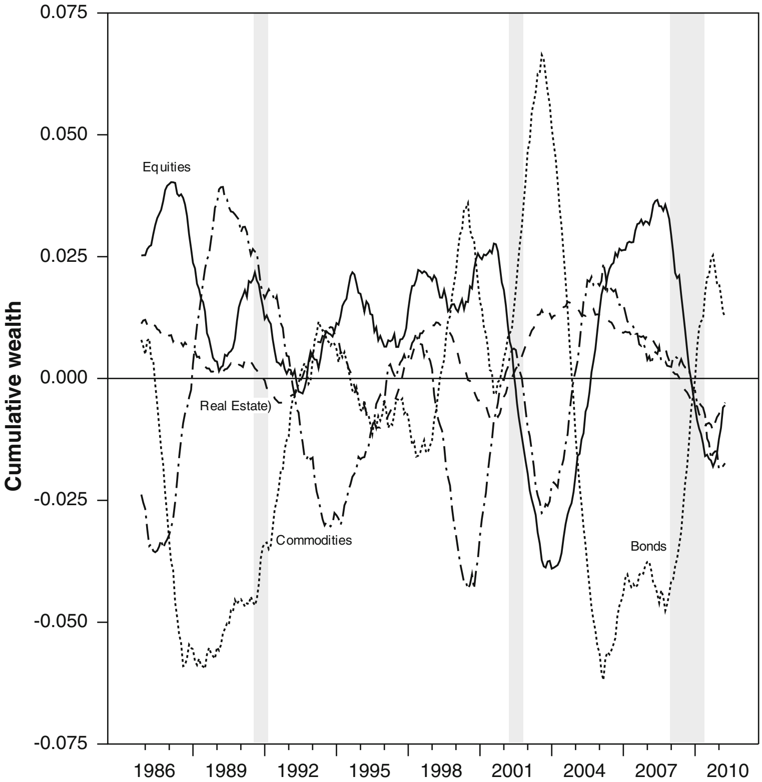

Fig. 1 Total Weights of Asset Classes Over Time We aggregate asset class positions and plot them across time as a 24-month moving average to smooth out the volatility in positions over time. NBER recessions are marked as *gray-shaded* areas.

deviations from average risk premia). To obtain more insight into the asset allocation decisions of the momentum strategies, we study the 24-month rolling average of the weights in the different asset classes (compare Fig. 1).

The striking spikes in performance discussed in the previous paragraph are accompanied by a countercyclical movement in fixed income and equity positions, as Fig. 1 illustrates. When the technology bubble burst in 2000/2001 and the subprime mortgage crisis reached its peak in 2008, the overall momentum strategy shifted to long positions in fixed income and short positions in equities. This behavior corresponds to an immunization strategy that shifts to safe harbors in times of economic distress. However, in times of macroeconomic stability and growth (non-shaded periods in Fig. 1, reflecting economic expansions as identified by NBER) the strategy appears to have a tendency to be long in equities and short in fixed income. While these positions are chosen by a statistically driven momentum strategy, they would also have been chosen by a macroeconomically driven strategy as crises often are accompanied by declining equity markets and rallying fixed income markets (the latter through a flight to safe harbors as well as falling interest rates). Commodity positions also appear to behave countercyclically with fixed income, but are not as clearly linked to business cycles. Thus, the momentum strategy, while driven by a purely statistical process, appears to invest in a way that is also economically sensible. Further analyses of this possible link between the macroeconomic environment and the profits of a cross-asset class momentum strategy are conducted in Sect. 5 of this paper. The large variation of the momentum strategy weights over time indicates that strategy returns are not simply a risk premium earned by static positions. The strong performance of the macro momentum strategy might be driven by the fact that in contractions, markets are predominantly driven by macroeconomic developments, inducing drifts in asset prices so as to adjust to the new economic environment. Macro momentum would benefit particularly from the fact that these drifts have different directions in different asset classes. For example, in a contraction, equity markets typically decline as the business outlook for companies worsens, while fixed income markets rally through central bank interest rate cuts aimed at stimulating the economy.

4.2 Return attribution: macroeconomic predictability versus asset specific information

This section decomposes macro momentum returns into two components. The first component accounts for macroeconomic predictability; the second component is idiosyncratic to our economic regression model (i.e., specific to a particular asset class). This decomposition will shed more light on the drivers behind the performance of the macro momentum strategy. Following Chordia and Shivakumar (2002), we write:

$$R_{t,i} = \hat{R}_{t,i}^{\text{Predict}} + \hat{\varepsilon}_{t,i}, \tag{12}$$

where $\hat{\varepsilon}_{t,i}$ are the empirical residuals for asset i at time t and $\hat{R}_{t+1,i}^{\text{Predict}}$ is defined by Eq. (9) from the MRS6 model. Thus, we can rewrite Eq. (12) as:

$$R_{t,i} = \hat{c}_i + \sum_{k=1}^{K} \hat{\beta}_{i,k} m_{t,k} + \hat{\varepsilon}_{t,i}. \tag{13}$$

We calculate returns for macro momentum (EM) from:

$$R_t^{\text{EM}} = \sum_{i=1}^{m} w_{t-1,i}^{n} R_{t,i}. \tag{14}$$

As previously defined, $w_{t-1,i}^{n}$ are the period $t-1$ weights from our macro momentum strategy that we evaluate with period t returns. Using Eq. (13) in Eq. (14), we can decompose $R_{t,i}$ as follows:

$$R_t^{\text{EM|Predict}} = \sum_{i=1}^{m} w_{t-1,i}^{n} \left(\sum_{k=1}^{K} \hat{\beta}_{i,k} m_{t,k} \right) \tag{15}$$

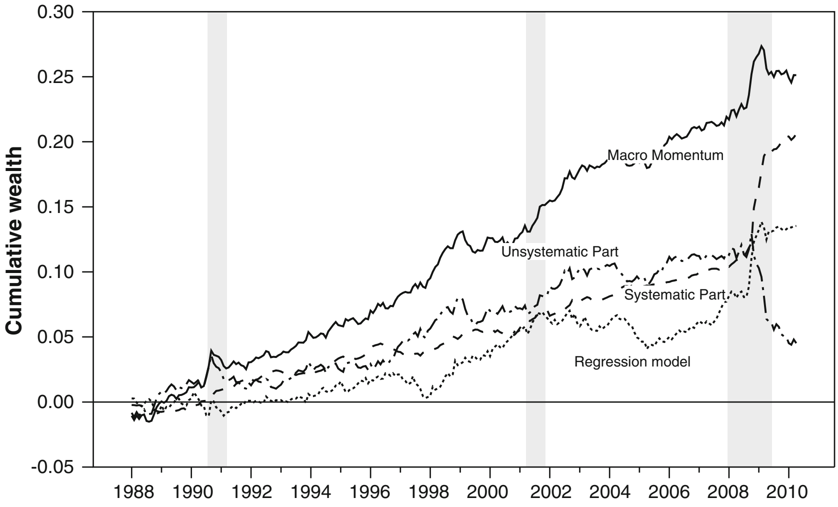

Fig. 2 Macro Momentum and its Decomposition The graph shows cumulative wealth for our combined macro momentum strategy as well as its decomposition into systematic and idiosyncratic components. It also includes the evolution of wealth for an investor following the MRS6 regression strategy.

$$R_t^{\mathrm{EM|Idiosynchratic}} = \sum_{i=1}^{m} w_{t-1,i}^{n} \left(\hat{c}_i + \hat{\varepsilon}_{t,i} \right) \tag{16}$$

This allows us to study the behavior of macro momentum return components attributable to macroeconomic factors in Eq. (15) and idiosyncratic factors in Eq. (16) separately instead of observing R_t^{EM} alone. We move the intercept from the forecasting Eq. (12) to the idiosyncratic return component in Eq. (16) as it essentially captures a momentum effect unrelated to macroeconomics.

The analysis is performed using data from 1988/1 until 2010/4. This coincides with the time period for the regression model as we need fitted returns from this model. Figure 2 shows the cumulative returns of the combined macro momentum strategy, of the decomposition into systematic and idiosyncratic components, and of the regression strategy MRS6. All four strategies appear to work consistently during the whole time period. Only the macroeconomic forecasting remains flat until the 1990s. During the subprime crisis in 2007/2008, the regression model MRS6 performs particularly well.

Table 4 provides summary statistics for different strategies and strategy components. The systematic part of the momentum strategy has a Sharpe ratio of 1.14, illustrating the importance of macroeconomic factors in the application of our macro momentum strategy. With a t-statistic of 5.39, the component has a highly significant contribution to the returns of the momentum strategy. In contractions, the systematic component of macro momentum achieves a Sharpe ratio of 2.01, outperforming the returns of the systematic component in expansions (Sharpe ratio of 1.30). We reject the null hypothesis of equal returns of the systematic component in expansions and contractions at

Table 4 Decomposition of Macro Momentum Returns

	Combined macro momentum	Macro regression (MRS6)	Systematic returns from (15)	Idiosyncratic returns from (16)
Mean (p.a.)	1.12 %	0.61 %	0.92 %	0.20 %
Volatility (p.a.)	1.15 %	1.15 %	0.81 %	1.28 %
Min	−1.41 %	−0.96 %	−0.43 %	−1.75 %
Max	1.60 %	2.21 %	2.68 %	1.23 %
Skewness	0.09	1.21	6.24	−0.92
Excess Kurtosis	3.02	7.17	61.46	3.95
t-stat	(4.61)***	(2.50)***	(5.39)***	(0.75)
Sharpe ratio (p.a.)	0.98	0.53	1.14	0.16
Sharpe ratio (p.a.) in expansions	1.04	0.39	1.30	0.48
Sharpe ratio (p.a.) in contractions	0.97	1.09	2.01	−0.73

This table gives descriptive statistics for the period 1988/1 to 2010/4 (268 data points) for our combined macro momentum strategy, its decomposition into systematic and idiosyncratic components, and the regression strategy MRS6. The beginning of the timeframe is chosen to coincide with the date from which we have returns for the MRS6 strategy. Statistics are based on monthly returns unless indicated otherwise. Min and Max give the minimum and maximum monthly returns, respectively

the 99 % confidence level.[25] For the macro momentum strategy, the idiosyncratic part of the strategy has a positive return contribution, but the returns are not significantly positive (t-statistic of 0.75). The returns in contractions are significantly worse than the returns in expansions.[26] Consistent with Fig. 2, the idiosyncratic part's contribution to overall performance of the asset momentum strategy is highly significant (t-statistic of 2.45) once the time period from 2007 and onward is removed from consideration.

The macroeconomic forecasting strategy (Sharpe ratio of 0.53) and the macroeconomic component of the momentum strategy are constructed using the same macroeconomic forecasting variables, but there is a considerable performance difference. We attribute this effect to a negative idiosyncratic return component of the economic regression forecasting strategy: since the economic forecasting strategy is per construction always long the assets with the highest return forecast and short the ones with the lowest, the pure systematic economic forecasting component of the overall returns of the economic forecasting strategy must be higher than systematic returns from the macro momentum strategy defined in Eq. (15). The only way that economic regression forecasting can result in lower overall performance than the macro momen-

[25] To perform this test, we run strategy returns against two dummies that are either 1 or 0 depending on whether the economy is in contraction or expansion. A standard F-test on the equality of both regression coefficients yields $F(1, 268) = 45.301$, with a p value of 0.000.

[26] We perform the same test as described in footnote 25 and reject the hypothesis of equal returns with a test statistic of $F(1, 268) = 7.688$ and a p value of 0.006.

tum is when the idiosyncratic proportion of the returns in the economic forecasting strategy is negative.

Macroeconomic forecasting plays a considerable role in the performance decomposition of the momentum strategy; however, correlations between the macroeconomic regression forecasting strategy MRS6 and macro momentum are moderate, having a value of 0.373. However, this value is highly significant with a t-statistic of 6.58 and indicates that there is a common element between macro momentum and returns from macroeconomic forecasting. When focusing on returns from 2000/1 to 2010/4, the correlation of macro momentum with the economic forecasting strategy increases considerable to 0.525.

Using first differences in the definition of our forecasting factor div could result in indirectly including momentum factors in the forecasting regression. Such a link might exist as the dividend yield depends on the level of the S&P 500 and, thus, the monthly dividend yield changes might pick up a 1-month S&P 500 momentum factor. Similarly, the factor $term$ might pick up a 1-month momentum effect in the fixed income space as changes in the term structure are directly linked to the price changes of bonds. To test that our results are not biased by such an indirect momentum effect, we repeat the previous analysis without div and $term$. In this modified approach, the remaining forecasting variables in our MRS6 strategy achieve an annualized Sharpe ratio of 0.400, which is slightly lower compared to that of the full factor set, but still on the same order of magnitude. In the decomposition, the systematic part of the returns corresponds to a Sharpe ratio of 1.128 and the idiosyncratic part to a Sharpe ratio of 0.274. Thus, the results of this stability test are consistent with the results in Table 4, indicating that our results are not biased by indirect momentum effects.

4.3 Controlling macro momentum performance using two-way sorts

The previous section illustrated that macroeconomic factors can explain part of the performance of macro momentum. Cooper et al. (2004) argue that the macroeconomic variables used in Chordia and Shivakumar (2002) are dominated by the 6-month market return in terms of their forecasting ability for momentum returns. Thus, we need to address this issue in our analysis. In contrast to Cooper et al. (2004), who sort equities by macroeconomic forecasting and 6-month market returns before applying momentum sorts, we need to take a different route as there is no benchmark readily available for our cross-asset class momentum context.

We apply a similar analysis by first sorting our asset universe by the forecasts from the economic regression model and then by their combined 1-month and $12-1$-month momentum score. Having a rather restricted breadth of assets in our universe, the analysis is confined to 3×3 sorts. The results of this analysis are summarized in Table 5.

For each of the three economic regression forecast bands there is a monotonic increase in returns when moving from the low to the high macro momentum return portfolio. The difference of average annual returns between the high and the low momentum portfolio is between 7.85 % (for the medium economic regression forecast bucket) and 10.13 % (for the low economic regression forecast bucket). The high–low

Table 5 Two-way sort on economic regression forecasts and macro momentum

	Macro momentum			
	Low	Medium	High	High–low
Economic regression forecast				
Low				
Mean (p.a.)	−5.97 %	−0.47 %	4.16 %	10.13 %
Volatility (p.a.)	16.83 %	11.15 %	16.47 %	19.19 %
t-stat	−1.68	−0.20	1.19	2.49
Medium				
Mean (p.a.)	−3.85 %	−0.95 %	4.00 %	7.85 %
Volatility (p.a.)	9.06 %	7.57 %	8.80 %	12.83 %
t-stat	−2.01	−0.59	2.15	2.89
High				
Mean (p.a.)	2.17 %	3.42 %	11.35 %	9.18 %
Volatility (p.a.)	12.36 %	8.03 %	10.85 %	15.20 %
t-stat	0.83	2.01	4.94	2.85

This table sets out portfolio returns based on 3×3 sorts of our assets. The analysis sorts first on the economic regression forecasts and then on the combined 1-month and $12-1$-month momentum score. The return of a portfolio long in the high momentum assets and short in the low momentum assets is given for each economic regression forecast band. Performance is summarized by annualized mean returns, volatilities, and t-statistics

difference in each bucket is significant with a t-statistic of at least 2.49. The Sharpe ratios for the high-minus-low momentum portfolios are 0.528, 0.612, and 0.604 for the low, medium, and high economic regression first-stage sorting, respectively.

Application of the first-stage sort means that we control for economic factors in the momentum portfolio construction. The resulting Sharpe ratios in each of the buckets are much lower than the Sharpe ratio of 1.056 that we would achieve for the high-minus-low momentum portfolio without any first-stage sort. The fact that the Sharpe ratios of the momentum portfolios are much lower when controlling for economic factors is another indication that macro momentum and economic forecasting are linked. While the Sharpe ratios of the momentum portfolios decay quite substantially when applying the first-stage sort compared to an unconditional strategy, we do not know if these differences are significant. Thus, we construct and apply a two-stage sorting approach in the remainder of this section to help us judge whether macro momentum and economic forecasting are linked.

Using this two-way sort framework, we base our approach for testing the significance of a link between regression forecasting and macro momentum on the following rational. If the regression forecasting model would lead to an asset selection completely orthogonal to the momentum approach (i.e., both approaches are independent), then the high-minus-low momentum portfolios within each regression forecasting band should not be significantly different from a case in which the first-stage sort is done using a randomized selection. Thus, we run 10,000 bootstrapped 3×3 sorts in which the first-stage sort is purely random and the second-stage sort is conducted on the momentum score.

When running our 10,000 bootstrap sorts with a random first-stage asset selection, we obtain an average high-minus-low return of 11.7 %, which is higher than any of the average returns in our three economic regression forecast buckets. In addition, only seven (i.e., 0.07 %) of the resulting bootstrapped random sorts have a lower t-statistic of high-minus-low returns jointly for all three economic regression forecast buckets. Thus, the first sort on the economic regression forecast captures some of the return forecasts implicit in the momentum approach. From these results we can deduct that the economic forecasting approach and the macro momentum approach have a significant link and are not capturing orthogonal effects. This is further evidence for the hypothesis that macro momentum captures effects that are related to the business cycle.

5 Analyzing macro momentum returns using a factor model conditioned on macroeconomic information

Ferson and Schadt (1996) modify a standard factor model to allow for the possibility of predictable factor variation timing. Their approach can be adapted to our context by regressing the performance of macro momentum on the main Fung and Hsieh (2001, 2004) variables and by making the exposure depend on our four main economic variables (credit spread, term spread, 3-month T-Bill rate, dividend yields). Thus, we arrive at the following factor model:

$$\begin{aligned} R_t^{\text{EM}} &= \beta_t^T f_t^{\text{FH}} + \upsilon_t \\ \beta_t &= b_0 + BZ_{t-1} \end{aligned} \tag{17}$$

where f_t^{FH} is a vector of the $j = 1, 2, \ldots, m = 8$ Fung and Hsieh (2001, 2004) factor returns and an intercept. All used factors reflect self-financing portfolios of traded factors and, thus, the intercept of this factor regression can be interpreted as alpha. We drop the credit and the term spread from the Fung and Hsieh (2001, 2004) factor universe as we use these two factors as instruments to condition factor exposures on the economic environment. In turn, $\beta_{i,t}^T$ represents a 1×9 vector of (potentially) time-varying factor betas. Factor variability for each of the m factors is described by a 9×4 matrix B that contains 10 4×1 vectors of factor sensitivities b_j. Our vector Z_{t-1} is of dimension 4×1 and contains our four macroeconomic variables, which are thought to possess predictability for time-varying exposures of the momentum strategy to the Fung and Hsieh (2001, 2004) factors. In the analysis we use the lagged and centered first differences of the macroeconomic variables. The results of this analysis are summarized in Table 6. The explanatory power of this model with time-varying factor exposures for macro momentum returns increases to an $\bar{R}^2$ of 0.408 compared to 0.295 for the standard Fung and Hsieh (2001, 2004) model in Appendix B. Since the explanatory power increases substantially, changes in the economic environment appear to have a strong impact on the factor exposures of macro momentum. Another interesting observation is that, in contrast to the findings for the

Table 6 Time varying betas in the FUNG/HSIEH model

	β_0	β_{Term}	β_{Credit}	β_{Bond}	β_{Dividend}
Intercept (p.a.)	0.001	0.000	0.000	0.000	0.000
	(0.945)	(0.573)	(0.265)	(0.209)	(−0.759)
MKT	0.019	−0.013	−0.037	−0.005	0.040
	(0.800)	(−1.337)	(−1.961)**	(−0.739)	(2.610)**
HML	−0.076	−0.008	−0.027	−0.011	−0.019
	(−2.843)***	(−0.749)	(−1.754)*	(−1.200)	(−1.261)
SMB	−0.057	−0.021	0.018	−0.022	−0.021
	(−1.667)*	(−1.529)	(0.776)	(−2.198)**	(−1.412)
Bond-LBS	0.007	0.003	0.002	0.002	0.003
	(2.683)***	(1.457)	(0.724)	(1.520)	(1.194)
FX-LBS	0.004	−0.002	0.004	−0.001	0.005
	(1.385)	(−2.240)**	(0.998)	(−1.166)	(1.814)*
COM-LBS	0.006	−0.002	−0.008	−0.001	0.006
	(1.241)	(−0.943)	(−1.124)	(−0.792)	(1.285)
FI-LBS	−0.006	0.001	0.005	0.000	−0.007
	(−2.136)**	(0.559)	(0.999)	(0.042)	(−2.248)**
EQ-LBS	0.008	0.000	0.003	−0.001	0.003
	(1.419)	(0.014)	(0.700)	(−0.378)	(0.719)
Adjusted R^2	0.408				

This table provides estimates for a Ferson and Schadt (1996) version of the Fung and Hsieh (2001, 2004) model of macro momentum strategy returns, R_t. The $j = 1, 2, \ldots, m = 8$ Fung and Hsieh (2001, 2004) factors and the intercept are described by the 8×1 vector f_t^{FH} of previously described factor returns. In turn β_t^T represents a 1×9 vector of (potentially) time-varying factor betas. Factor variability for each of the m factors is described by a 9×4 matrix B that contains 10 4×1 vectors of factor sensitivities b_j. Our vector Z_{t-1} is of dimension 4×1 and contains the lagged first differences of (centered) realizations of variables thought to exhibit predictability. $\begin{array}{l} R_t = \beta_t^T f_t^{\text{FH}} + \upsilon_t \\ \beta_t = b_0 + BZ_{t-1} \end{array}$ We give the estimated parameters and the t-statistics. Credit stands for credit spread, Term for term spread, Bond for the T-Bill rate, and Dividend for the dividend yields

standard Fung and Hsieh (2001, 2004) approach, the regression intercept is no longer significantly different from zero (value of 0.001 and t-statistic of 0.945). Thus, the macro momentum strategy does not generate any significant alpha once we control for a changing economic environment in the factor exposure. This is more strong support for our hypothesis that macro momentum is partially driven by economic factors. In the Ferson and Schadt (1996) framework, the factor b_0 is significantly negative for *HML* and *SMB* (t-statistics of −2.843 and −1.667, respectively). An increase in the credit spread is significantly associated (t-statistic of −1.754) with an even more negative factor exposure. Similarly, the negative exposure to the *SMB* factors becomes more negative when the T-Bill rate rises (parameter of −0.022 and t-statistic of −2.198). While the *market* factor is not significant (t-statistic of 0.800) in general, a higher dividend yield, as well as a lower credit spread, lead to a significant (t-statistics of 2.610

and -1.961, respectively) increase in the market exposure. Since both changes to the economic environment are associated with an expansion, macro momentum increases market exposure when economic conditions improve. The macro momentum strategy has a significantly positive exposure to the look-back straddle bond strategy (parameter of 0.007). Additionally, a significantly negative exposure to the look-back straddle interest rate strategy is found and this exposure is even more negative in times of high dividend yields.

In summary, this section found that macro momentum shows significantly higher exposures to systematic market factors once we control for the economic environment. In fact, the intercept of the regression model is no longer significantly different from zero.

6 Conclusion

We find substantial evidence for the profitability of momentum investing across asset classes. The strategy performs very well during the studied time period from 1984 to 2010. The strategy performs particularly well during times of economic distress, such as recessions, as markets adapt asset class valuations to the changing environment. In recessions, the statistically driven momentum strategy shifts assets into fixed income securities and out of equities, which is consistent with the safe haven trade that fundamental investors will often make in such a market environment. This link between momentum investing across asset classes and economic development prompts us to call this strategy "macro momentum."

Decomposing the returns of the macro momentum strategy into a part driven by macroeconomic predictability and an idiosyncratic part illustrates that a large part of the profitability of macro momentum can be linked to changes in the macroeconomic environment. However, in times of stable economic growth, an increasing part of momentum returns can be attributed to factors unrelated to the macroeconomic environment. Once we allow for predictable time variation in returns, the risk-adjusted outperformance of cross-asset class momentum disappears.

Our results indicate that the macro momentum strategy derives part of its performance from a response to changes in the economic environment. This is remarkable because macro momentum is driven exclusively by statistical filters and not by macroeconomic rationale.

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Appendix A: Data characteristics

Table 7 Summary Statistics of Investment Instruments

	Mean excess returns (p.a.) (%)	Volatility (p.a.) (%)	Min (%)	Max (%)	t-stat	Sharpe ratio
Fixed Income						
German 2Y	0.97	1.49	−1.23	1.56	3.367	0.655
German 10Y	2.54	4.67	−5.45	4.27	2.791	0.543
USA 2Y	1.32	1.78	−1.43	1.71	3.798	0.739
USA 10Y	3.41	6.81	−6.42	7.51	2.573	0.501
Japan 2Y	0.67	1.46	−1.70	1.83	2.357	0.459
Japan 10Y	3.12	5.44	−6.65	4.70	2.949	0.574
UK 2Y	0.55	2.36	−3.21	3.02	1.201	0.234
UK 10Y	1.65	6.52	−8.59	6.74	1.304	0.254
FX						
EUR	0.94	10.65	−10.58	9.26	0.454	0.088
JPY	0.67	11.63	−11.07	15.11	0.295	0.057
GBP	2.15	10.57	−12.72	13.99	1.048	0.204
Equities						
S&P 500	5.95	15.80	−24.12	12.40	1.934	0.376
FTSE 100	3.64	16.35	−30.84	12.55	1.144	0.223
TOPIX	−0.01	19.82	−23.23	16.02	−0.003	−0.001
MSCI Emerging Markets	9.86	24.11	−34.59	16.58	2.102	0.409
DJ Eurostoxx 50	4.48	19.31	−24.51	14.64	1.192	0.232
Commodities						
S&P GSCI Light Energy	0.80	13.80	−27.80	13.15	0.298	0.058
S&P GSCI Agriculture	−4.90	16.92	−19.11	15.86	−1.488	−0.289
S&P GSCI Energy	4.15	32.01	−37.47	31.42	0.666	0.130
S&P GSCI Industrial Metals	6.24	23.24	−31.08	32.03	1.381	0.269
S&P GSCI Livestock	−0.78	14.50	−17.23	15.31	−0.275	−0.054
Real Estate						
REITs	8.79	21.65	−45.73	32.22	2.087	0.406

This table provides summary statistics for the investment instruments used in the momentum and economic forecasting strategies studied in this article. All statistics are based on excess returns. In the columns Min and Max we give the smallest and largest monthly excess returns, respectively. The data cover the timeframe 1983/12–2010/4

Appendix B: Momentum and economic risk factors

Does macro momentum have systematic risk exposure? In other words, is macro momentum spanned by systematic risk premia and are the returns, thus, just a reward for risk taking? To answer this second question, we regress the macro momentum returns against the Fama and French (1992, 1993) factors: market excess return (MKT),

Table 8 Macro momentum strategy versus Fung and Hsieh (2001, 2004) factors

Parameters	1M macro momentum	12−1M macro momentum	Comb. macro momentum
α	1.23 %	1.34 %	1.57 %
(p.a. in %)	(4.494)***	(6.019)***	(7.372)***
β_{MKT}	−0.007	−0.016	−0.014
	(−1.354)	(−1.962)**	(−2.082)**
β_{HML}	−0.002	−0.032	−0.025
	(−0.403)	(−5.486)***	(−2.942)***
β_{SMB}	0.008	−0.001	0.003
	(1.806)*	(−0.075)	(0.279)
$\beta_{Bond-LBS}$	−0.000	−0.002	−0.001
	(−0.090)	(−1.269)	(−0.645)
β_{FX-LBS}	0.002	−0.000	0.001
	(1.901)*	(−0.399)	(1.139)
$\beta_{COM-LBS}$	0.004	0.003	0.004
	(2.422)***	(1.681)*	(2.405)***
β_{FI-LBS}	0.001	−0.000	0.000
	(0.608)	(−0.622)	(0.107)
β_{EQ-LBS}	0.005	0.003	0.004
	(2.486)***	(1.943)*	(2.122)**
$\beta_{\Delta 10y}$	0.001	−0.001	0.000
	(1.613)	(−0.958)	(0.154)
$\beta_{\Delta spread}$	0.001	0.002	0.002
	(0.517)	(1.441)	(1.902)*
$\bar{R}^2$	0.148	0.319	0.295

Each column represents a linear regression of standardized (to 100bps of annual risk) macro momentum strategies against the Fung and Hsieh factor model. The data period covered is from 1994/1 to 2009/12 (192 observations) due to the availability of the Fung and Hsieh factors. We separately test 1 month and 12 minus 1 month strategies as well as the combined strategy. The explanatory factors are market excess return (*MKT*), value factor (*HML*), size factor (*SMB*), payoffs from look-back straddles on bond (*Bond-LBS*), currency (*FX-LBS*), commodity (*COM-LBS*), fixed income (*FI-LBS*), and equities (*EQ-LBS*), as well as changes in constant maturity 10-year Treasury yields ($\Delta 10y$) and credit spread (Moody BAA yield minus constant maturity treasuries) changes ($\Delta spread$). All t-values (in parentheses) are HAC adjusted (using a Newey–West adjustment with 3 lags). Significance at the 1 %, 5 %, and 10 % level is indicated by ***, **,*

the high-minus-low book-to-market value factor (HML), and the small-minus-big market capitalization factor (SMB). We complement the Fama and French (1992, 1993) factors with the Fung and Hsieh (2001, 2004) factors as they are designed to capture risk factors in such absolute return strategies such as macro momentum. These factors include trend following like payoffs from look-back straddles on bonds (Bond-LBS), currencies (FX-LBS), commodities (COM-LBS), fixed income (FI-LBS), and equities (EQ-LBS). Theses payoffs replicate the success of a perfect trader that buys at the period low and sells at the period high. We also add changes in constant maturity

10-year treasury yields ($\Delta 10y$) and credit spread (Moody BAA corporate yield minus constant maturity treasuries) changes (Δspread).[27] Using a total of 10 risk factors allow us to control for the systematic risk factors to which hedge-fund-type strategies like momentum (e.g., CTA) might be exposed. In our choice of risk factors we follow the standard literature on the analysis of hedge fund returns (compare, e.g., Fung and Hsieh 2001, 2004; Avramov et al. 2011) as momentum is one concept frequently used by hedge funds. The results are displayed in Table 8. The combined momentum strategy has a significant exposure to market risk (t-statistic of -2.08) and the HML factor (t-statistic of -2.94). Both exposures have a negative sign and, therefore, a negative exposure to the respective risk premia. A negative loading on the value premium, however, is further evidence that the strategy pays off in bad times. The intercept for the strategy is positive and highly significant (t-statistic of 7.37), indicating that the strategy produces significant alpha of 1.57 % per annum (at the 1 % risk level, i.e., 31.4 % at the 20 % risk level).[28]

All regressions show moderate $\bar{R}^2$ between 15 and 30 %, suggesting that our momentum strategy is not explained by well-known risk factors. We also observe that short-term momentum exhibits a more significant exposure to the Fung and Hsieh (2001, 2004) factors, whereas long-term momentum shows more exposure to Fama and French (1992, 1993) factors. This is not surprising given that monthly momentum trading (trend following) is likely to be correlated with payoffs from monthly look-back straddles. The positive loadings on commodity and equity market trend-following factors also suggest that our strategy pays off well if these markets exhibit large moves (in either direction).

References

Andreu, L., Swinkels, L., Tjong-A-Tjoe, L.: Can exchange traded funds be used to exploit industry and country momentum? Financ. Markets Portf. Manage. **27**(2), 127–148 (2013)

Asness, C., Moskowitz, T., Pedersen, L.H.: Value and momentum everywhere. J. Financ. 929–985 (2013, forthcoming)

Avramov, D., Kosowski, R., Naik, N., Teo, M.: Hedge funds, managerial skill, and macroeconomic variables. J. Financ. Econ. **99**(3), 672–692 (2011)

Bai, J.: Predictive Macro Indices as Asset Pricing Risk Factors, Working Paper, pp. 1–45 (2007)

Barroso, P., Santa-Clara, P.: Managing the Risk of Momentum, pp. 1–26. Working Paper, NOVA School of Business and, Economics (2012)

Blitz, D.C., Van Vliet, P.: Global tactical cross-asset allocation: applying value and momentum across asset classes. J. Portf. Manage. Fall 23–28 (2008)

Brandt, M., Wang, K.: Time-varying risk aversion and unexpected inflation. J. Monet. Econ. **50**, 1457–1498 (2003)

Campbell, J.: Stock returns and the term structure. J. Financ. Econ. **18**, 373–399 (1987)

Campbell, J., Cochrane, J.: By force of habit: a consumption-based explanation of aggregate stock market behavior. J. Polit. Econ. **107**, 205–251 (1999)

Campbell, J., Shiller, R.: Stock prices. earnings, and expected dividends. J. Financ. **43**(3), 661–676 (1988)

[27] The data for the Fung and Hsieh (2001, 2004) factors can be downloaded from the webpage of David Hsieh at http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm. The only exception is the data for the Bond Market and Credit Spread factors, which are available at http://www.federalreserve.gov/releases/h15/.

[28] Given that all right-hand side variables are the payoffs from long short strategies, i.e., excess returns, the intercept of this regression also has an alpha interpretation.

Chordia, T., Shivakumar, L.: Momentum, business cycle, and time-varying expected returns. J. Financ. **57**(2), 985–1019 (2002)
Cooper, M., Gutierrez, R.C., Hameed, A.: Market states and momentum. J. Financ. **59**(3), 1345–1365 (2004)
Danial, K., Moskowitz, T.: Momentum Crashes, pp. 793–805. Columbia University, Working Paper (2011)
DeBondt, W., Thaler, R.: Does the stock market overreact? J. Financ. **42**(3), 793–805 (1985)
DeBondt, W., Thaler, R.: Further evidence of overreaction and stock market seasonality. J. Financ. **42**, 557–581 (1987)
Diamond, D., Verrecchia, R.: Constraints on short-selling and asset price adjustment to private information. J. Financ. Econ. **18**(2), 277–311 (1987)
Dyl, E.: Capital gains taxation and year-end stock market behavior. J. Financ. **32**, 165–175 (1977)
Fama, E.: Stock returns, real activity, inflation, and money. Am. Econ. Rev. **71**(4), 545–565 (1981)
Fama, E., French, K.: Business conditions and expected returns on stocks and bonds. J. Financ. Econ. **25**, 23–49 (1989)
Fama, E., French, K.: The cross-section of expected stock returns. J. Financ. **47**(2), 427–465 (1992)
Fama, E., French, K.: Common risk factors in the returns on stocks and bonds. J. Financ. Econ. **33**(1), 3–56 (1993)
Fama, E., Schwert, W.: Asset returns and inflation. J. Financ. Econ. **5**(2), 115–146 (1977)
Ferreira, M., Santa-Clara, P.: Forecasting stock market returns: the sum of the parts is more than the whole. J. Financ. Econ. **100**, 514–537 (2011)
Ferson, W., Sarkissian, S., Simin, T.: Spurious regressions in financial economics? J. Financ. **58**, 1393–1414 (2003)
Ferson, W., Schadt, R.: Measuring fund strategy and performance in changing economic conditions. J. Financ. **51**(2), 425–461 (1996)
Frazzini, A.: The disposition effect and underreaction to news. J. Financ. **61**(4), 2017–2046 (2006)
Fung, W., Hsieh, D.A.: The risk in hedge fund strategies, theory and evidence from trend followers. Rev. Financ. Stud. **14**, 313–341 (2001)
Fung, W., Hsieh, D.A.: Hedge fund benchmarks: a risk-based approach. Financ. Anal. J. **60**, 65–80 (2004)
Goyal, A., Welch, I.: A comprehensive look at the empirical performance of equity premium prediction. Rev. Financ. Stud. **21**(4), 1455–1508 (2008)
Griffin, J., Ji, S., Martin, J.S.: Momentum investing and business cycle risk: evidence from pole to pole. J. Financ. **58**(6), 2515–2547 (2003)
Grinblatt, M., Han, B.: Prospect theory, mental accounting, and momentum. J. Financ. Econ. **78**, 311–339 (2005)
Grinblatt, M., Moskowitz, T.J.: Predicting stock price movements from past returns: the role of consistency and tax-loss selling. J. Financ. Econ. **71**, 541–579 (2004)
Guo, H.: On the out-of-sample predictability of stock returns. J. Bus. **79**, 645–670 (2006)
Hong, H., Lim, T., Stein, J.C.: Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. J. Financ. **55**, 265–295 (2000)
Hong, H., Stein, J.: A unified theory of underreaction, momentum and overreaction in asset markets. J. Financ. **54**, 2143–2184 (1999)
Jegadeesh, N.: Evidence of predictable behavior of security returns. J. Financ. **45**, 881–898 (1990)
Jegadeesh, N., Titman, S.: Returns to buying winners and selling losers: implications for stock market efficiency. J. Financ. **48**(1), 65–91 (1993)
Jobson, J.D., Korkie, B.M.: Performance hypothesis testing with the sharpe and treynor measures. J. Financ. **36**, 889–908 (1981)
Judice, D., Kessler, S., Scherer, B.: Price reversals in global equity markets. J. Asset Manage. **11**, 332–345 (2010)
Lamont, O.A., Stein, J.C.: Aggregate short interest and market valuations. Am. Econ. Rev. **94**(2), 29–32 (2004)
Ledoit, O., Wolf, M.: Robust performance hypothesis testing with the sharpe ratio. J. Empir. Financ. **15**(5), 850–859 (2008)
Lettau, M., Ludvigson, S.: Resurrecting the (C)CAPM: a cross-sectional test when risk premia are time-varying. J. Polit. Econ. **109**, 1238–1287 (2001)
Liu, L., Zhang, L.: Momentum profits, factor pricing, and macroeconomic risk. Rev. Financ. Stud. **21**(6), 2417–2448 (2008)
Lo, A., Mackinlay, C.: When are contrarian profits due to stock market overreaction? Rev. Financ. Stud. **3**, 175–205 (1990)

Ludvigson, S., Ng, S.: Macro factors in bond risk premia. Rev. Financ. Stud. **22**, 5027–5067 (2009)
Maio, P.: Intertemporal CAPM with conditioning variables. Management Science 1–20 (2013, forthcoming)
Maio, P.: Don't fight the fed! Rev. Financ. (2012a, forthcoming)
Maio, P.: The "Fed Model" and the predictability of stock returns. Rev. Financ. (2012b, forthcoming)
Memmel, C.: Performance hypothesis testing with the sharpe ratio. Financ. Lett. **1**, 21–23 (2003)
Merton, R.: Optimum consumption and portfolio rules in a continuous-time model. J. Econ. Theory **3**, 373–413 (1971)
Moskowitz, T., Grinblatt, M.: Does industry explain momentum? J. Financ. **54**, 1249–1290 (1999)
Moskowitz, T., Ooi, Y.H., Pedersen, L.H.: Time series momentum. J. Financ. Econ. **104**(2), 228–250 (2012)
Newey, W., West, K.: A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica **55**(3), 703–708 (1987)
Pastor, L., Stambaugh, R.: Liquidity risk and expected stock returns. J. Polit. Econ. **111**, 642–685 (2003)
Qin, Y.: Foreign Ownership Restriction and Momentum-Evidence from Emerging Markets, Working Paper, pp. 1–48 (2009)
Rapach, D., Strauss, J., Tu, J., Zhou, G.: Out-of-Sample Industry Return Predictability: Evidence from a Large Number of Predictors. Working Paper. Washington University in St. Louis (2011)
Rey, D., Schmid, M.: Feasible momentum strategies: evidence from the swiss stock market. Financ. Markets Portf. Manage. **21**(3), 325–352 (2007)
Ribeiro, C., Loeys, J.: Exploiting Cross-Market Momentum. JPMorgan Investment, Strategy (2006)
Romano, J.P., Wolf, M.: Stepwise multiple testing as formalized data snooping. Econometrica **73**, 1237–1282 (2005)

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