# Cross-Asset Signals and Time Series Momentum[☆]

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**Abstract**

We document a new phenomenon in bond and equity markets that we call cross-asset time series momentum. Using data from 20 countries, we show that past bond market returns are positive predictors of future equity market returns, and past equity market returns are negative predictors of future bond market returns. We use this predictability to construct a diversified cross-asset time series momentum portfolio that yields a Sharpe ratio 45% higher than a standard time series momentum portfolio. We present evidence that time series momentum and cross-asset time series momentum are driven by slow-moving capital in bond and equity markets.

*JEL classification*: G12, G15, F37

*Keywords*: asset pricing, time series momentum, cross-asset predictability, slow-moving capital, international financial markets

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## 1. Introduction

Moskowitz, Ooi, and Pedersen (2012) show for a wide range of assets that assets' past one- to 12-month returns are positive predictors of their future returns. They refer to this phenomenon as time series momentum. In this paper, we build on this work by documenting a related cross-asset phenomenon in bond and equity markets that we refer to as cross-asset time series momentum. Specifically, using a sample of bond and equity market index returns from 20 leading developed countries, we show that past bond market returns are positive predictors of future equity market returns, while past equity market returns are negative predictors of future bond market returns.

We further show that these patterns of cross-asset predictability can be used to construct cross-asset time series momentum strategies that generate significant, positive monthly alphas even after controlling for time series momentum strategies with the same lookback and holding periods, passive exposures to bond and equity markets, and standard asset pricing factors. A diversified portfolio of the cross-asset time series momentum strategies yields a Sharpe ratio 45% higher than a similarly diversified time series momentum portfolio, and almost 70% higher than a similarly diversified buy-and-hold portfolio.[1] Moreover, controlling for the returns of the cross-asset time series momentum portfolio, the alpha of the time series momentum portfolio is insignificant in our sample.

As a motivating example, in Figs. 1 and 2 we illustrate the time series momentum and cross-asset time series momentum phenomena in the U.S. equity market. Specifically, in Fig. 1 we plot the cumulative excess returns of a portfolio that is long the CRSP value-weighted

[1] From January 1980 to December 2016, the annualised gross Sharpe ratio of a diversified cross-asset time series momentum portfolio was 0.89, while the Sharpe ratios of diversified time series momentum and buy-and-hold portfolios were 0.61 and 0.52, respectively.

index only in positive (negative) equity momentum regimes, which we define as months for which the previous 12-month equity return was positive (negative). In Fig. 2, we do the same for positive (negative) bond momentum regimes; that is, months for which the previous 12-month change in the long-term Treasury yield was negative (positive).

FIGURES 1 AND 2 HERE

From Fig. 1 we can see that the strategy that holds the equity index only in positive equity momentum regimes dramatically outperforms the strategy that holds the index only in negative equity momentum regimes. Reflecting the importance of time series momentum, the positive equity regime strategy would actually have captured all of the excess return of the CRSP value-weighted index over this 90-year period. From Fig. 2 we can see that a similar pattern in excess returns exists when conditioning equity holdings on positive and negative *bond* momentum regimes. Reflecting the importance of cross-asset time series momentum, positive bond regimes outperform the negative ones, with a Sharpe ratio over three times higher than that of the negative regime strategy.

To understand the economics behind this time series predictability of bond and equity market returns, we study the relations between past bond and equity returns, future bond and equity demand, and monetary policy. In particular, we use data on bond and equity mutual fund flows, margin debt, and stock repurchases to show that past 12-month bond and equity returns predict future changes in bond and equity demand in a manner that is consistent with both the time series momentum and the cross-asset time series momentum phenomena. The changes in demand following 12-month bond or equity market returns take place slowly over the course of several months, presumably because impediments to the frictionless movement of capital, such as time-consuming organisational decision-making and frictions in funding capital markets, are resolved only gradually, as argued in Duffie (2010). We find that capital moves particularly slowly across asset classes, creating long-term predictability in securities market flows and returns.

We also relate time series momentum and cross-asset time series momentum to real economic activity, by linking different bond and equity momentum regimes with future changes in key economic indicators. For example, we show that simultaneously positive momentum regimes in bond and equity markets predict better outcomes for the economy, with high industrial production growth, high investment, and decreasing unemployment over the next 12 months. In contrast, simultaneously negative momentum regimes predict negative industrial production growth, low investment, and increasing unemployment. We thus show that time series momentum and cross-asset time series momentum are not just financial market phenomena; they also contain information about fundamental changes in economy activity.

Our results extend and help explain the time series momentum effect first documented by Moskowitz, Ooi, and Pedersen (2012), and later examined by several other researchers.[2] Our paper is also related to the literature on cross-asset momentum spillovers at the individual asset level. In contrast to us, the momentum in these studies refers to cross-sectional return rankings, rather than time series momentum. For example, Gebhardt, Hvidkjaer, and Swaminathan (2005) show that the investment grade corporate bonds of past six-month equity

[2] Hurst, Ooi, and Pedersen (2013) and Baltas and Kosowski (2013) use time series momentum strategies to explain the performance of Managed Futures funds and commodity trading advisors, and find that a large part of their performance can be explained by these strategies. Hurst, Ooi, and Pedersen (2017) simulate the performance of a diversified portfolio of time series momentum strategies from 1880 to 2016, and show that the Sharpe ratio of the portfolio is positive in each decade even after estimated fees and transaction costs. Szakmary and Lancaster (2015), D'Souza, Srichanachaichok, Wang, and Yao (2016), and Goyal and Jegadeesh (2018) show that individual stocks also exhibit time series momentum.

momentum winners outperform the bonds of past six-month equity momentum losers over the next one to six months. Jostova, Nikolova, Philipov, and Stahel (2013) present evidence of a similar effect in non-investment grade bonds, while Lee, Naranjo, and Sirmans (2016) show that a momentum spillover exists between credit default swaps and individual stocks. Geczy and Samonov (2017), in turn, study cross-sectional momentum in a sample of country-level bond and equity indexes from 1846 to 2014, and show that sorting equity indexes into winner and loser portfolios based on past bond index returns yields a significant winner minus loser spread of 0.59% per month. To the best of our knowledge, we are the first to study cross-asset effects in a time series momentum context.

The theoretical literature on financial market frictions and slow-moving capital, as discussed in Duffie (2010), provides a context through which our results can be viewed. In particular, our empirical findings parallel the predictions in Greenwood, Hanson, and Liao (2018), who study asset price dynamics in partially segmented markets. Their model examines how supply (and demand) shocks in one market spill over gradually to other markets with partially different end investors. They show that while asset prices in the directly affected market initially overreact to supply shocks, prices in the unaffected market underreact, as arbitrageurs only slowly reallocate their capital, thus generating momentum. The idea that investors' gradual portfolio reallocation generates momentum is present also in Vayanos and Woolley (2013), but in the Greenwood, Hanson, and Liao (2018) model the shocks originate from other asset classes, very much as we find empirically to be the case.

Within the context of Greenwood, Hanson, and Liao (2018), we can view the positive predictability from bonds to equities as originating from slow portfolio rebalancing of cross-market investors (or "generalists", to use their terminology) following shocks in the bond market. We can also view the negative predictability from equities to bonds in the slow-moving capital context. First, equity shocks are transmitted gradually to the money market via monetary policy—which from our results and from independent work by Cieslak and Vissing-Jorgensen (2017) we know reacts slowly to past equity returns—and then from the money market to bonds via portfolio rebalancing by fixed income investors. To the extent that the money and bond markets are partially segmented, this latter transmission may also happen slowly through the rebalancing of "generalists" operating in both markets. Finally, our paper is related to the literature on forecasting macroeconomic variables with asset prices, as surveyed in Stock and Watson (2003).

The rest of the paper is structured as follows. Section 2 describes the data. Section 3 documents our findings on single- and cross-asset time series predictability, and Section 4 applies these findings to the construction and analysis of cross-asset time series momentum trading strategies. Section 5 offers a partial explanation for time series momentum by relating it to the presence of slow-moving capital in bond and equity markets, while Section 6 does the same for cross-asset time series momentum. Section 7 relates time series momentum and cross-asset time series momentum to changes in economic activity. Section 8 concludes. We collect additional robustness tests in the Internet Appendix, including tests not referenced in the text.

## 2. Data and preliminaries

### *2.1. International data*

Most of the research on time series momentum has used futures and forwards returns. We instead use index returns, for two reasons. First, using index returns allows us to avoid issues specific to futures trading, such as choosing when to roll one contract over to another, that potentially affect time series momentum performance without necessarily being directly related to the time series momentum effect. Second, to study the cross-asset effects that are the focus of our paper, we need a large set of countries with both bond and equity market returns available. The futures data sources used in previous papers would limit us to only five or seven countries. In contrast, by using index returns we can collect matching bond and equity returns from 20 countries, thus allowing us to perform our main analyses on a significantly larger and geographically more diverse sample.[3]

We begin by collecting MSCI equity total return index returns for each country classified as a developed market by MSCI. We then match these equity returns with Datastream Benchmark Government Bond total return index returns at the five-year maturity for those countries for which data are available. We use five-year maturity bond index returns because this maturity has the most data available. This leaves us a final sample of monthly bond and equity index returns for 20 developed countries, with the earliest return series starting in January 1980 and all return series ending in December 2016. All returns are from Thomson Reuters Datastream.

When constructing time series momentum portfolios, we convert all local currency indexes into U.S. dollar indexes using exchange rates from Datastream and the Deutsche Bundesbank. When calculating country-level excess returns we proxy for national risk-free returns with JPMorgan 1-Month Cash total return indexes, national interbank offer rates, or government bond yields at the one-month maturity; see Appendix A for more details. When

[3] Moskowitz, Ooi, and Pedersen (2012) include 13 bond futures and nine equity futures in their data set, and Baltas and Kosowski (2015) include 19 bond futures and 23 equity futures. However, because they include multiple bond futures with different maturities from the same country, and futures that are not country-specific, the number of countries with both bond and equity returns in their data sets is only five or seven, respectively. In the Internet Appendix, we also implement the time series momentum and cross-asset time series momentum strategies on a smaller sample of futures data from the same five countries as in Moskowitz, Ooi, and Pedersen (2012). We find that the results are qualitatively similar to our main results.

calculating excess returns for dollar-denominated portfolios we use the one-month Treasury bill return. The national risk-free returns are from Datastream and the Treasury bill returns are from Ibbotson Associates via Kenneth French's data library.

### *2.2. Benchmark data*

We evaluate the performance of our time series momentum strategies by comparing their returns to the returns from buy-and-hold exposures to global bond and equity markets, as well as to standard asset pricing factors. As the benchmark bond index we use the Barclays Capital Aggregate Bond Index, and as the benchmark equity index we use the MSCI World equity index. As the asset pricing factors we use the Fama-French-Carhart size, value, and momentum factors, and the Asness, Moskowitz, and Pedersen (2013) value and momentum "everywhere" factors. The index returns are from Datastream, the Fama-French-Carhart factors from Kenneth French's data library, and the "everywhere" factors from the AQR data library.

### *2.3. U.S. data*

In Sections 5, 6, and 7 we relate time series momentum to slow-moving capital in bond and equity markets, and to real economic activity. Due to superior data availability, in these sections we use a longer sample of U.S. data on equity market returns, government bond yields, margin debt balances, mutual fund flows, stock repurchases, SEOs, risk-free yields, and different economic indicators.

We begin by collecting data on the use of NYSE margin debt. Before 1959, the data are from Table 143 of Federal Reserve Board (1976a) and Table 12.23 of Federal Reserve Board

(1976b). From 1959 onwards, the data are from the NYSE. We confirm that the data are reported consistently over time by comparing data from periods in which the sources overlap.

We then calculate monthly aggregate bond and equity mutual fund flow and assets under management (AUM) series from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database. For consistency with the government bond total return indexes in our international data set, our bond fund series include only those funds with CRSP Style Codes beginning with "IG", to limit our series to funds that focus on government bonds. Our equity fund series include all funds with CRSP Style Codes beginning with "ED", and thus include all domestic equity funds. For each fund-month pair, we confirm the validity of these classifications by consulting the most recent quarterly holdings data and removing any observations with negative or missing allocations to government bonds or equities, respectively. Each series starts in December 1990, which is when monthly data become available.

Next, we collect stock repurchase and SEO data from SDC Platinum. We include all buybacks on U.S. targets and all issues of U.S. common stock, excluding IPOs. For both variables, we sum the firm-level observations into aggregate monthly series from September 1980. We also collect Commodity Futures Trading Commission (CFTC) data on speculators' net positions and open interest on the five-year Treasury and S&P 500 futures contracts from April 1987. Finally, we collect data on the effective federal funds rate, industrial production, gross private domestic investment, and the inflation and unemployment rates from the Federal Reserve Bank of St. Louis.

We combine these data with CRSP value-weighted index returns from January 1926 and Datastream U.S. Five-Year Benchmark Government Bond total return index returns from January 1980. Because the availability of the bond market returns limits how far back in time we can perform our analyses, where possible we also use data on five-year constant maturity Treasury yields to extend some of our analyses back to April 1953.

### *2.4. Volatility scaling*

The convention in the time series momentum literature has been to divide assets' returns by their ex ante volatilities when performing regressions and constructing time series momentum portfolios (e.g. Moskowitz, Ooi, and Pedersen, 2012; Baltas and Kosowski, 2015). This has had two important effects. First, it has had a large impact on time series momentum performance. For example, Kim, Tse, and Wald (2016) show that a volatility-scaled time series momentum portfolio generates an alpha of 1.08% per month, whereas a similar unscaled time series momentum portfolio generates a monthly alpha of only 0.39%.

Second, it has made it challenging to disentangle time series momentum from risk parity investing and other volatility-related effects. While Moskowitz, Ooi, and Pedersen (2012) show that a diversified time series momentum portfolio outperforms a similarly diversified risk parity portfolio over their sample, and volatility scaling therefore cannot explain all of their results, it does make the interpretation of their results somewhat more complicated. To avoid this complication and focus solely on time series momentum, in this paper we do not apply any volatility scaling when performing regressions and constructing portfolios. To ensure that this decision does not drive our main results, in the Internet Appendix we implement the time series momentum and cross-asset time series momentum strategies using volatility-scaled returns as a robustness test, and find that the results are qualitatively similar to our main results.

## 3. Time series predictability

### *3.1. Single-asset time series predictability*

We begin our analysis of time series predictability by examining whether the signs of assets' lagged returns are predictive of their future returns in our international data set. Following Moskowitz, Ooi, and Pedersen (2012) and Baltas and Kosowski (2015), we focus our attention on the predictive power of the signs of assets' lagged returns because these are most closely related to the time series momentum strategies we study in later sections.

For bonds and equities separately, we perform a pooled panel regression where we pool all assets and dates, and regress the excess return $r_t^s$ of asset *s* in month *t* on the sign of its own excess return lagged $h = 1, 2, \ldots, 60$ months:

$$r_t^s = \alpha + \beta_h \mathrm{sign}(r_{t-h}^s) + \varepsilon_t^s. \tag{1}$$

The *t*-statistics of the signs of the lagged returns for each lag are plotted in Fig. 3. Following Moskowitz, Ooi, and Pedersen (2012), the *t*-statistics are clustered by month.

FIGURE 3 HERE

In both panels of Fig. 3, we can see a general pattern of mostly positive *t*-statistics for the first 12 months, indicating return continuations over the first year, and mostly negative *t*-statistics thereafter, indicating return reversals at longer time horizons. This pattern is clearest for the equity indexes, where each of the first 12 lags is positive, while for the bond indexes the positive return continuations are concentrated at the first four lags. This is consistent with the bond and equity results in Moskowitz, Ooi, and Pedersen (2012).

*3.2. Cross-asset time series predictability*

We now extend our analysis of time series predictability by examining whether the signs of a given country's lagged bond returns are predictive of the same country's future equity returns, and vice versa. To start, we perform a pooled panel regression where we pool all equity indexes and dates, and regress the excess return $r_t^e$ of equity index *e* in month *t* on the sign of its own excess return lagged $h = 1, 2, \dots, 60$ months, as well as the sign of the similarly lagged excess return of the corresponding bond index:

$$r_t^e = \alpha + \beta_h^e \operatorname{sign}(r_{t-h}^e) + \beta_h^b \operatorname{sign}\left(r_{t-h}^b\right) + \varepsilon_t^e. \tag{2}$$

We then do the same for all the bond indexes:

$$r_t^b = \alpha + \beta_h^b \operatorname{sign}\left(r_{t-h}^b\right) + \beta_h^e \operatorname{sign}(r_{t-h}^e) + \varepsilon_t^b. \tag{3}$$

The *t*-statistics of the signs of the lagged returns for each lag are plotted in Fig. 4. As in the previous section, the *t*-statistics are clustered by month.

FIGURE 4 HERE

From Panel A we can see that the *t*-statistics of the signs of the lagged bond returns in Regression (2) are mostly positive for the first 40 months, with several lags being statistically significant. Conversely, from Panel B we can see that the *t*-statistics of the signs of the lagged equity returns from Regression (3) are negative for all but one of the first 20 months, with several lags again being statistically significant. We thus find evidence of a country's past bond returns being positive predictors of the country's future equity returns, and of a country's past equity returns being negative predictors of the country's future bond returns.[4]

*3.3. Returns by momentum regime*

To demonstrate the value of these patterns of cross-asset predictability in a time series momentum context, in Table 1 we report the average monthly excess returns and annualised gross Sharpe ratios of the bond and equity indexes in our international data set during different bond and equity momentum regimes. An asset belongs to a positive (negative) momentum regime in month $t$ if the $t$ - 12 to $t$ - 1 cumulative excess return of the asset was positive (negative).

TABLE 1 HERE

From Panel A of Table 1, we can see that the equity return is highest during positive bond and equity momentum regimes, while the bond return is highest during positive bond and negative equity momentum regimes. This is consistent with past bond returns being positive predictors of future bond and equity returns, and with past equity returns being positive predictors of future equity returns and negative predictors of future bond returns.

[4] In unreported tests, we confirm that these patterns of cross-asset predictability are robust to using ten-year rather than five-year bond indexes, signs of actual rather than excess returns, and lagged returns rather than signs of lagged returns. In the Internet Appendix, we report the results from cross-asset predictability regressions that include currency and commodity returns, and cross-country cross-asset predictability regressions with U.S. and global returns. We confirm the robustness of our main cross-asset results and find evidence of additional cross-asset and cross-country predictive relations that can be linked to slow-moving capital.

In Panel B, we repeat the same analysis using combined bond and equity momentum regimes. This allows us to see how the bond and equity returns during different bond and equity momentum regimes depend on the prevailing regime in the other market. For example, while the equity return is 0.81% during positive equity momentum regimes, when the bond regime is also positive the return increases to 1.04%. Using the combined regimes thus allows us to identify in finer detail those periods when the return is maximized.

In particular, we can make three observations based on the results of Panel B. First, the equity returns during periods of simultaneously positive (negative) bond and equity momentum regimes are higher (lower) than the returns during any of the other regimes. This is consistent with past bond returns having positive marginal predictive power over future equity returns. Second, the lowest bond return occurs during periods where the bond momentum regime is negative and the equity momentum regime is positive, which is consistent with past equity returns being a negative predictor of future bond returns. Finally, the highest bond returns occur in those regimes where the past equity returns are negative. The fact that negative past equity returns seem to be a stronger positive predictor of future bond returns than past bond returns, as the results in Panel B suggest, highlights the importance of considering cross-asset predictors in a time series momentum context.

## 4. Cross-asset time series momentum

We now turn to the construction of cross-asset time series momentum strategies. We first review how we construct the single-asset strategies, and then describe how we modify them to construct the cross-asset strategies.

### *4.1. Single-asset strategies*

We start by taking the perspective of a U.S.-based investor holding their investable capital in a dollar-denominated margin account. For each asset in our data set we take a long (short) position in a given month if the past *k*-month excess return of the asset is positive (negative). We finance long positions by borrowing at the local risk-free rate, while investing proceeds from short positions at the local risk-free rate. We then hold the position for *h* months. Regardless of the holding period *h*, we take a new position every month based on the asset's past *k*-month excess return. For holding periods longer than one month, we thus have multiple active positions in the asset each month. To obtain a single time series of monthly time series momentum returns for the asset, we combine each of the active positions by calculating an equal-weighted average of the returns of the active positions.

Once we have generated single-asset time series momentum return series for each combination of lookback period *k* and holding period *h* for each asset, we form diversified time series momentum portfolios, which we denote $TSMOM^{(k,h)}$, by taking equal-weighted averages of the individual assets' time series momentum returns for the given lookback and holding periods. Our procedure is comparable to the futures-based implementation used by Moskowitz, Ooi, and Pedersen (2012), except for the volatility scaling of position sizes that we leave out for reasons explained in Section 2.4.

### *4.2. Cross-asset strategies*

The cross-asset time series momentum strategies build on the single-asset strategies by adding a cross-asset predictor to the strategy's trading rule. For cross-asset strategies that trade a given country's bond index, the cross-asset predictor is the same country's equity index, and for cross-asset strategies that trade a given country's equity index, the cross-asset predictor is the same country's bond index.

Concretely, the cross-asset strategies are just like the single-asset strategies, except we take a long (short) position in an asset only when both the past *k*-month excess return of the asset itself, and the past *k*-month excess return of the cross-asset predictor, indicate that a long (short) position should be taken. For a strategy trading an equity index we thus require positive (negative) excess returns from both markets, while for a strategy trading a bond index we require a positive excess return from the bond market and a negative excess return from the equity market. If the excess returns of the asset and the cross-asset predictor disagree, we hold the risk-free asset. We thus require consistent signals from both the bond and equity markets before taking an active position.

Once we have generated cross-asset time series momentum return series for each combination of lookback period *k* and holding period *h* for each asset, we again form diversified portfolios, which we denote $XTSMOM^{(k,h)}$, by taking equal-weighted averages of the individual assets' cross-asset time series momentum returns. Because the cross-asset strategy sometimes holds the risk-free asset, the amount of capital allocated to active positions is smaller on average than the amount allocated by the single-asset strategy. To account for this, we scale up all of the portfolio weights of the cross-asset strategy so that each month the amount of capital allocated to active positions is the same for both strategies.

### *4.3. Lookback and holding period analysis*

We begin our analysis of the cross-asset strategies by calculating their alphas from the following regression:

$$XTSMOM_t^{(k,h)} = \alpha + \beta_1 TSMOM_t^{(k,h)} + \beta_2 MKT_t + \beta_3 BOND_t + \beta_4 SMB_t + \beta_5 HML_t + \beta_6 UMD_t + \varepsilon_t. \quad (4)$$

Here $XTSMOM_t^{(k,h)}$ denotes the excess return in month $t$ of the diversified $XTSMOM^{(k,h)}$ portfolio with lookback period $k$ and holding period $h$, and $TSMOM_t^{(k,h)}$ denotes the excess return of the diversified $TSMOM^{(k,h)}$ portfolio with the same lookback and holding periods. $MKT_t$ denotes the excess return of the MSCI World total return index and $BOND_t$ denotes the excess return of the Barclays Capital Aggregate Bond Index. $SMB_t$, $HML_t$, and $UMD_t$ denote the Fama-French-Carhart size, value, and momentum factors. We are thus interested in seeing whether diversified cross-asset time series momentum portfolios generate abnormal performance relative to corresponding time series momentum portfolios, while also controlling for bond and equity market benchmarks and standard asset pricing factors. We repeat the regression for different combinations of lookback period $k$ and holding period $h$. The $t$-statistics of the alphas from the regressions can be seen in Table 2.

TABLE 2 HERE

From Table 2 we can see that the $t$-statistics of the alphas of the cross-asset time series momentum portfolios are positive and statistically significant across all lookback and holding periods. Based on these results it is clear that the cross-asset time series momentum portfolios outperform time series momentum portfolios across a wide range of time horizons.

*4.4. Risk-adjusted performance*

For consistency with the prior time series momentum literature, we now limit our focus to 12-month lookback periods and one-month holding periods. For brevity, we drop the $(k, h)$ superscript and refer to $TSMOM^{(12,1)}$ and $XTSMOM^{(12,1)}$ as TSMOM and XTSMOM.

As a first indicator of the risk-adjusted performance of the XTSMOM portfolio, in Fig. 5 we plot the cumulative excess returns of buy-and-hold, TSMOM, and XTSMOM portfolios diversified across each bond and equity index in our data set. To allow for a fair comparison, we scale the returns of each portfolio so that their realised annualised volatilities are 10%. As we can see, the cross-asset time series momentum portfolio delivers consistently higher returns than the time series momentum and buy-and-hold portfolios.

FIGURE 5 HERE

In the Internet Appendix, we plot similar figures for bond-only and equity-only versions of the portfolios. In both asset classes the cross-asset time series momentum portfolio outperforms the other two portfolios.

The outperformance of cross-asset time series momentum is remarkably consistent across countries. In Fig. 6, we plot the annualised gross Sharpe ratios of cross-asset time series momentum portfolios diversified across a country's bond and equity indexes for each country in our data set. For comparison, we also plot the Sharpe ratios of similarly diversified time series momentum portfolios. As we can see, the cross-asset time series momentum portfolio outperforms the time series momentum portfolio in all but one of the 20 countries.

FIGURE 6 HERE

The outperformance of cross-asset time series momentum is also consistent across time. For example, the XTSMOM portfolio has a higher Sharpe ratio than the TSMOM portfolio in each individual decade.

We next evaluate the risk-adjusted performance of the XTSMOM portfolio by regressing its excess returns on the excess returns of a similarly diversified TSMOM portfolio, the MSCI World index, and either the Fama-French-Carhart size, value, and momentum factors, or the Asness, Moskowitz, and Pedersen (2013) value and momentum "everywhere" factors. In the latter specifications, we also consider controlling for a cross-country momentum factor (XSMOM) constructed from the bond and equity indexes in our sample using the Asness, Moskowitz, and Pedersen (2013) methodology. The results can be seen in Table 3.

TABLE 3 HERE

From Panel A we can see that the XTSMOM portfolio generates a highly significant alpha of 0.54% per month while also loading significantly and positively on the global equity market and cross-sectional momentum factor. When controlling for the TSMOM portfolio in the second regression specification, we see that the TSMOM portfolio is able to explain a large portion of the returns, but the XTSMOM portfolio still generates a significant and positive alpha of 0.25% per month that is not captured by the TSMOM portfolio.

From Panel B we can see that the results are very similar with the value and momentum "everywhere" factors. The XTSMOM portfolio generates a statistically significant monthly alpha of 0.35% or 0.29% depending on whether we control for the TSMOM portfolio return. The results when controlling for the cross-country XSMOM factor are similar.

From the regression results and the country-level Sharpe ratios, we can see that cross-asset time series momentum is not just a way to repackage the familiar time series momentum effect. Instead, cross-asset time series momentum yields significant improvements in risk-adjusted performance that are not captured by time series momentum.

In the Internet Appendix, we also consider return- and rank-weighted versions of the single- and cross-asset strategies, and show that the risk-adjusted performance is very similar across the different strategy versions. Our strategy performance results are thus robust to reasonable changes in the way we define the strategies.

### *4.5. Spanning tests*

In Table 4, we report the results from spanning tests of the diversified XTSMOM, TSMOM, and XSMOM portfolio returns. As before, the XSMOM portfolio is constructed using the methodology of Asness, Moskowitz, and Pedersen (2013).

TABLE 4 HERE

From the first three rows of Table 4, we can see that the returns of the diversified XTSMOM portfolio are not spanned by the TSMOM and XSMOM returns. Instead, the XTSMOM portfolio generates a highly significant monthly alpha between 0.33% and 0.50% (*t*-statistic between 3.82 and 4.39) depending on the specification. XTSMOM thus seems to be capturing something novel that TSMOM and XSMOM do not capture.

While the XTSMOM returns are not spanned by TSMOM and XSMOM, in the opposite direction we find that the TSMOM returns are spanned by XTSMOM. Specifically, from the fourth row of Table 4 we can see that XTSMOM explains away the returns of TSMOM (alpha: -0.02%; *t*-statistic: -0.38). From the seventh row of Table 4 we can see that XTSMOM is also significant in explaining the returns of XSMOM in our sample of country-level indexes, leaving XSMOM a positive but statistically insignificant alpha of 0.16% (*t*-statistic: 0.83).

In the Internet Appendix, we perform similar spanning tests for bond-only and equity-only versions of the portfolios. The results for the individual asset classes are similar to the main results.

### *4.6. The XTSMOM smile*

Moskowitz, Ooi, and Pedersen (2012) show that the quarterly returns to time series momentum exhibit a "smile" when plotted against the quarterly returns of the equity market index, meaning time series momentum performs well in both up and down markets. In this section, we show that cross-asset time series momentum exhibits a similar smile.

Concretely, in Fig. 7 we plot the non-overlapping quarterly returns of diversified TSMOM and XTSMOM portfolios against the corresponding non-overlapping quarterly returns of the CRSP value-weighted index. To allow for a fair comparison, the returns of the portfolios are scaled so that their ex post volatilities are the same.

FIGURE 7 HERE

From Fig. 7 we can see that both TSMOM and XTSMOM exhibit smiles, though the smiles are not perfectly symmetric: the TSMOM smile is more pronounced in the negative return domain, while the XTSMOM smile is more pronounced in the positive return domain. Based on visual inspection, the magnitudes of the differences between the smiles are roughly similar in the negative and positive domains.

These results suggest that from a portfolio diversification perspective the TSMOM portfolio is valuable because of the slightly higher returns it offers during periods when the market return is negative. However, the XTSMOM portfolio compensates for this by offering higher returns during periods when the market return is near zero or positive. Because the XTSMOM portfolio outperforms the TSMOM portfolio in terms of risk-adjusted performance, both on average and in individual countries, this seems to be a trade-off worth making.[5]

### *4.7. Net speculator position differences by regime*

Moskowitz, Ooi, and Pedersen (2012) use CFTC data on the trading activity of speculators and hedgers to show that speculators profit from time series momentum at the expense of hedgers. Specifically, they plot average net speculator positions during positive and negative TSMOM regimes, and find that speculators are more long than average during positive regimes and more short than average during negative regimes. This pattern holds for every contract they study except the S&P 500, which is surprising since it suggests that S&P 500 speculators are acting as contrarians in their trading.

We begin by replicating their analysis using the five-year Treasury and S&P 500 futures, since these are closest to the bond and equity indexes we study. Consistent with their results, the difference in average net speculator positions between positive and negative TSMOM regimes is positive (3.10%) for the five-year Treasury futures and negative (-1.92%) for the S&P 500 futures. We then repeat the same analysis using XTSMOM regimes. We find that the differences in the average net speculator positions between positive and negative XTSMOM regimes are larger than the differences between positive and negative TSMOM

[5] It is conceivable that investors demand a higher premium for XTSMOM compared to TSMOM precisely because TSMOM is a better hedge for poor market returns.

regimes: 6.50% for the Treasury futures and 3.11% for the S&P 500 futures. Notably, the net speculator position difference for the S&P 500 futures is positive for the XTSMOM regimes, which suggests that speculators use cross-asset time series momentum signals in their equity futures trading.

## 5. What drives time series momentum?

Moskowitz, Ooi, and Pedersen (2012) show that time series momentum does not seem to be explained by market volatility, liquidity, or investor sentiment, nor does it seem to be compensation for crash risk. Hutchinson and O'Brien (2015) show that the returns to time series momentum depend on the macroeconomic cycle, being larger in economic expansions, and argue that the returns are therefore compensation for business cycle risk. Andrei and Cujean (2017), in turn, propose a model where time series momentum arises due to information flows in the economy.

In this section, we add to the literature on the drivers of time series momentum by relating it to the presence of slow-moving capital in bond and equity markets. We provide evidence of several channels through which past bond and equity market returns affect future changes in bond and equity demand. Furthermore, we show that these changes in demand occur gradually over the course of several months, thus helping to prolong trends.

### *5.1. Returns and mutual fund flows*

We begin by illustrating the close relation between returns and flows at the aggregate level. Specifically, in Fig. 8 we plot the 12-month cumulative returns of the CRSP value-weighted equity index against detrended 12-month cumulative equity mutual fund flows. In

Fig. 9, we do the same for the Datastream U.S. Five-Year Benchmark Government Bond total return index and bond mutual fund flows.

FIGURES 8 AND 9 HERE

From both figures, we can see that returns and flows are closely related, with high contemporaneous correlations of 0.44 between the equity returns and equity fund flows, and 0.39 between the bond returns and bond fund flows. Moreover, as the size and significance of the mutual fund industry grows over the sample period, the comovement of returns and flows becomes increasingly pronounced over time, as evidenced by the correlations increasing to 0.45 and 0.49 for the most recent 15 years, and to 0.82 and 0.70 for the most recent five years. Although not proof of a causal relation between returns and flows, these results are consistent with the idea that equity market returns might be partially caused by aggregate fund flows, as recently argued by Ben-Rephael, Kandel, and Wohl (2011, 2012), among others.

Relating this to time series momentum, we next present evidence that mutual fund flows chase performance at the aggregate level. Specifically, in Fig. 10 we plot the correlations between CRSP value-weighted index 12-month cumulative returns and equity mutual fund flows, and between Datastream U.S. Five-Year Benchmark Government Bond total return index 12-month cumulative returns and bond mutual fund flows, one to 24 months in the future.

FIGURE 10 HERE

From Fig. 10 we can see that past returns are positively correlated with future fund flows in both asset classes. The correlations are initially significant and peak at one to three months, and then persist for about a year before partially reversing at longer lags. This evidence is consistent with the "feedback trading" hypothesis discussed in e.g. Edelen and Warner (2001). If flows affect contemporaneous returns and they chase performance, this provides one channel through which past bond and equity market performance can lead to return continuations and time series momentum. These results mirror at the market level earlier findings that flows chase performance at the individual fund level (Sirri and Tufano, 1998) and that stocks' cross-sectional momentum can be related to persistence in fund flows (Lou, 2012). Further evidence that mutual fund flows cause large price effects in the cross-section of stocks is presented in Coval and Stafford (2007) and Hau and Lai (2013).

### *5.2. Other proxies for demand*

Other proxies for demand yield similar results. For example, in Fig. 11 we plot the correlations between CRSP value-weighted index 12-month cumulative returns and monthly percentage changes in NYSE margin debt, and between the same returns and total stock repurchases net of SEOs, one to 24 months in the future.[6] We also construct an equal-weighted aggregate demand index from the equity mutual fund flows, margin debt changes, and net repurchases, and plot the same correlations for this index. The results are qualitatively similar if we adjust for scale and standardise the variables in the aggregate demand index to zero mean and unit variance before averaging, or use the first principal component from the correlation matrix as the aggregate demand index. For all measures of demand, we see a clear pattern of significant positive correlations that peak at one to four months and then persist for at least a year, before then converging to zero.

[6] For consistency with the mutual fund flow results in Fig. 10, we plot the correlations from December 1990 onwards. The results are very similar if we use the full sample periods.

FIGURE 11 HERE

Across all of the proxies for demand, we thus find a consistent pattern of past bond and equity market returns predicting future changes in bond and equity demand, in ways that support return continuations and thus help to explain the returns of trend-following time series momentum strategies.

## 6. What drives cross-asset time series momentum?

We now extend the results of the previous section by showing that slow-moving capital in bond and equity markets also helps explain cross-asset time series momentum. In particular, we provide evidence of three channels through which past bond market returns can positively affect future equity market returns, and past equity market returns can negatively affect future bond market returns.

### *6.1. The fund flow channel*

The first channel through which bond market returns can affect future equity market returns is the mutual fund flow channel. To illustrate this, in Fig. 12 we plot the correlations between Datastream U.S. Five-Year Benchmark Government Bond total return index 12-month cumulative returns and equity mutual fund flows one to 24 months in the future.

FIGURE 12 HERE

From Fig. 12 we can see that past bond market returns are positively correlated with future equity mutual fund flows, and that this effect is highly persistent. The correlations remain significantly different from zero for 21 months, before eventually converging to zero after 50 months. This highly persistent effect is consistent with the international results on bond-to-equity cross-asset predictability in Fig. 4, and provides a channel through which past bond market returns positively affect future equity market returns.

Mutual fund flows also provide a channel through which past equity market returns affect future bond market returns. In particular, in Fig. 12 we also plot the correlations between CRSP value-weighted index 12-month cumulative returns and bond mutual fund flows one to 24 months in the future. From the figure we can see that past equity market returns are negatively correlated with future bond mutual fund flows. The negative correlations are significant up to five months and are persistent, converging to zero only after 17 months. This persistent effect is again consistent with the results in Fig. 4.

Comparing Fig. 12 with Fig. 10, we see that the cross-asset return-flow effects are far more persistent than the single-asset return-flow effects. It is even conceivable that price patterns that look like time series momentum within one asset class are upon closer inspection driven by investors' slow and persistent reactions to return shocks in another asset class.

The return-flow effects within and across markets are not just slow and statistically significant, their magnitudes are also economically meaningful. For example, following a positive one standard deviation shock to past 12-month bond returns, the predicted flow to bond funds in the next month equals 1.05% of total bond mutual fund AUM, while the flow to equity funds equals 0.49% of total equity mutual fund AUM. For comparison, the average monthly AUM-adjusted flow in our sample is 0.26% for bond funds and 0.24% for equity funds.

Finally, we examine the predictable relations between bond and equity market returns and fund flows in a vector autoregression with six lags of returns and flows. In Table 5, we report the coefficient sums of the lagged variables and *p*-values from tests of the hypothesis that the coefficients of each lag of a given variable are zero.

TABLE 5 HERE

From Table 5 we can see that the signs of the past return coefficients are all consistent with time series momentum and cross-asset time series momentum, but controlling for flows leaves only the negative cross-asset return effect from equity to bonds significant.[7] It is thus clear that capital flows influence return predictability in these markets. In particular, we find that the only significant predictor of equity returns is past equity flows. This is consistent with the Ben-Rephael, Kandel, and Wohl (2011, 2012) hypothesis that fund flows drive return predictability in the equity market.

Consistent with the important role of flows, we find that both bond and equity flows are significantly positively autocorrelated, which is in line with single-asset time series momentum. In addition, we find highly significant cross-asset effects in flows, with equity flows negatively predicting bond flows and bond flows positively predicting equity flows, which is in line with cross-asset time series momentum. The evidence that returns would affect flows is weak however: the signs of past returns are as expected, but they are insignificant.

For an alternative view of the dynamic relations between returns and flows, in Figs. 13 and 14 we plot cumulative impulse responses from the vector autoregression in Table 5. In

[7] The reason why this effect survives can be related to monetary policy, and in particular to the positive correlation between equity returns and future changes in the federal funds rate that we document in Section 6.3.

particular, we are interested in seeing how shocks to equity and bond returns reverberate through the system over time.

FIGURES 13 AND 14 HERE

Consistent with our earlier results, from the figures we can see that both equity and bond market shocks lead to return spillovers in both asset classes. In line with cross-asset time series momentum, bond returns are significantly negative for six months following an equity return shock, while equity returns are persistently positive following a bond return shock. In this dynamic setting, we can also see that a bond return shock causes a significant and persistent positive effect on equity fund flows. Allowing for dynamic feedback effects, we thus find evidence of returns affecting flows that was not apparent in the regression results of Table 5.

### *6.2. The credit channel*

Another channel through which bond market returns can affect equity market returns is the credit channel. One reason why credit conditions matter is provided in Constantinides, Donaldson, and Mehra (2002), who explain the equity premium puzzle with an overlapping-generations model in which young investors are subject to a borrowing constraint. In their model, young investors would like to smooth their lifetime consumption by borrowing against future wage income and investing in equity, but cannot do so because they lack the collateral required for loans.

Positive bond market returns address the credit-constrained investors' problem in two ways. First, positive bond market returns (if associated with declines in yields more generally) lower investors' borrowing costs and improve their ability to obtain loans due to better interest coverage from wage income. Second, if investors also hold bonds in their portfolios, positive bond market returns will increase the value of their portfolios, thus giving them more collateral to bid for new loans.[8] As a result, when bond market returns are positive, investors become less constrained in their borrowing, and can thus take on more leverage and increase their equity investments. This leads to an increase in equity demand and boosts equity returns.

Empirically, we try to identify these effects by looking at changes in the use of margin debt. Here margin debt should be thought of as a proxy for investors' more general willingness to take on debt to invest in equity. Consistent with the idea of slow-moving capital in bond and equity markets, we find that past bond market returns gradually affect future changes in margin debt, and that this effect is highly persistent. Specifically, in Fig. 15 we plot the average abnormal monthly percentage change in margin debt during, and one to 24 months after, months belonging to positive and negative bond momentum regimes.

FIGURE 15 HERE

As we can see, positive bond market returns predict positive abnormal changes in margin debt and negative bond market returns predict negative abnormal changes in margin debt. In both cases, the effect is most pronounced in the first months, remains strong for the first year, and then slowly converges to zero over the next year. As a result, this persistent effect influences future equity market returns over a long period, which helps explain the persistent effect from bond returns to equity returns in Fig. 4, and the returns of the cross-asset time series momentum strategy in the equity market.

[8] While credit-constrained individuals may own bonds only marginally, the same logic also applies to constrained institutional investors whose equity positions can be constrained e.g. by solvency requirements.

We also examine the effects from margin debt in a vector autoregression setting, which we report in the Internet Appendix. We find that the effect of bond returns on margin debt is highly significant, which is consistent with the intuition provided above, and with the results of Zhang, Seyedian, and Li (2005) and Domian and Racine (2006). In those regressions, both the past equity return and yield change coefficients are consistent with our findings of the time series and cross-asset time series momentum effects shown e.g. in Figs. 3 and 4.

### *6.3. The monetary policy channel*

A second channel through which equity market returns can affect future bond market returns is the monetary policy channel, for instance if equity returns affect changes in the Federal Reserve's central monetary policy tool, the federal funds rate. In Fig. 16 we plot the correlations between CRSP value-weighted index 12-month cumulative returns and monthly percentage changes in the federal funds rate one to 24 months in the future.

FIGURE 16 HERE

From Fig. 16 we can see that equity market returns are positively correlated with future changes in the federal funds rate, and this effect persists for over 12 months before converging to zero. It thus appears that the Federal Reserve conditions its monetary policy on past stock market returns. Since increases in the federal funds rate will typically increase yields across the entire yield curve, through this channel positive equity market returns can have a broad, negative impact on future bond market returns.

## 7. Time series momentum and the economy

We now relate time series momentum to the real economy, by showing how future changes in industrial production, investment, inflation, and unemployment depend on bond and equity momentum regimes. In the Internet Appendix, we also link momentum regimes more closely to the economic cycle by showing how the likelihood of being in a given regime varies in and around recessions. We thus show that time series momentum and cross-asset time series momentum contain information about real economic activity, in addition to the information they contain about risk premiums in bond and equity markets.

To start, in Table 6 we report the average next 12-month percentage changes in industrial production and gross private domestic investment, and the average next 12-month changes in the inflation and unemployment rates, for different bond and equity momentum regimes. Then, to complement this regime-based analysis, in Fig. 17 we plot the same next 12-month changes for 5x5 double sorts of past 12-month CRSP value-weighted index returns and five-year constant maturity Treasury yield changes.

TABLE 6 AND FIGURE 17 HERE

From Panel A of Table 6, we can see that positive bond and equity momentum regimes are associated with better outcomes for the economy, with high industrial production growth, high investment growth, and decreasing unemployment over the next 12 months, while negative regimes are associated with low industrial production growth, low investment growth, and increasing unemployment. The simple time series momentum regimes thus seem to be able to partition future changes in these variables into good and bad outcomes.

From Panel B of Table 6, we can see that the combined bond and equity momentum regimes also contain information about the future prospects of the real economy. For example, while the negative bond and equity momentum regimes in Panel A are both associated with poor outcomes for industrial production growth, it is only the combination of simultaneously negative bond and equity momentum regimes that allows us to identify the periods when industrial production growth is actually negative over the next 12 months. Similarly, the simultaneously negative regimes also identify the worst outcomes for investment growth and the change in unemployment. In contrast, the best outcomes for industrial production and investment growth, and the change in unemployment, all occur in periods with simultaneously positive bond and equity momentum regimes. The combined regimes also identify the best and worst outcomes for changes in inflation. Conditioning on both bond and equity momentum regimes thus provides additional information that is not captured by either regime alone.[9]

To understand why momentum regimes, and in particular the combined regimes, contain information about future economic activity, we follow Fama (1990) and Schwert (1990), among others, and highlight two channels. First, positive past bond and equity returns are associated with lower costs of debt and equity, and thus higher net present values for firms' investment projects, which, at the margin, should increase investment (and, as a consequence, production and employment as well). However, because investments take time to plan and execute, the economic indicators react with a lag, thus creating predictability from past returns to future economic activity. Second, positive past returns increase investors' wealth, which

[9] Viewed in this macroeconomic context, another reason why cross-asset time series momentum outperforms time series momentum is that it relies on regimes that more accurately reflect future economic conditions. Specifically, cross-asset time series momentum is long (short) an equity index when industrial production and investment growth, and the change in unemployment, have their best (worst) outcomes, and is long (short) a bond index when the change in inflation has its best (worst) outcome.

leads to increases in real activity as firms react to investors' increased capacity to consume. Because this reaction also takes time, the result is a predictable relation between bond and equity returns and real activity. Finally, since these two channels through which security market returns can affect the real economy apply to both bond and equity returns, it is understandable that conditioning on both bond and equity momentum regimes gives the best indication of future economic activity.

## 8. Conclusion

In this paper, we document a cross-asset phenomenon in bond and equity markets that we refer to as cross-asset time series momentum. Using an international data set of bond and equity market returns from 20 developed countries, we show that past bond market returns are positive predictors of future equity market returns, and that past equity market returns are negative predictors of future bond market returns. Motivated by these findings, we construct cross-asset time series momentum strategies that consistently outperform traditional time series momentum and country-level cross-sectional momentum strategies.

By examining the relations between past bond and equity market returns and future changes in bond and equity demand, we show that both time series momentum and cross-asset time series momentum can be partially explained by the presence of slow-moving capital in bond and equity markets. In particular, we find that positive past returns in bond and equity markets attract fund flows to equity funds for a prolonged period of time, thus supporting cross-asset time series momentum. Similarly, positive bond returns and negative equity returns predict fund flows to bond funds for several months ahead. Past bond and equity returns also affect other proxies of demand gradually, which provides further evidence that slow-moving capital contributes to the cross-asset time series momentum effect. Our results show that the cross-asset effects are particularly persistent and visible, making a cross-asset setup such as ours ideal for studying the effects of slow-moving capital on asset prices.

We also show that past bond and equity market returns predict future changes in several key economic indicators. For instance, high past 12-month bond and equity returns predict gradual increases in investments and economic growth, and gradual decreases in unemployment. The increased flows to equity funds during these positive regimes thus seem to be justified by changes in the economic environment that support higher future equity valuations. Similarly, high past 12-month bond returns and low past 12-month equity returns predict gradual decreases in inflation, so the increased flows to bond funds during these regimes also seem to be justified by changes in the economic environment that support higher future bond valuations. Put together, our results thus show that time series momentum and cross-asset time series momentum are not just financial market phenomena; they also contain information about future changes in asset demand and economy activity.

## Appendix A: Data

The countries included in our international data set are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the UK, and the U.S. The Datastream codes and data start dates for each data series are listed below. Unless otherwise specified, the data end date is Dec-2016 for each series.

**Bond Returns**: BMAU05Y (Mar-1987), BMOE05Y (Jan-1985), BMBG05Y (Jan-1985), BMCN05Y (Jan-1985), BMDK05Y (Jan-1985), BMFN05Y (May-1991), BMFR05Y (Jan-1985), BMBD05Y (Jan-1980), BMIR05Y (Jan-1985), BMIT05Y (Feb-1991), BMJP05Y (Jan-1982), BMNL05Y (Jan-1980), BMNZ05Y (Jan-1989), BMNW05Y (Jan-1989), BMPT05Y (Feb-1993), BMES05Y (Jul-1989), BMSD05Y (Feb-1985), BMSW05Y (Jan-1981), BMUK05Y (Jan-1980), BMUS05Y (Jan-1980).

**Equity Returns**: MSAUSTL (Jan-1980), MSASTRL (Jan-1980), MSBELGL (Jan-1980), MSCNDAL (Jan-1980), MSDNMKL (Jan-1980), MSFINDL (Jan-1988), MSFRNCL (Jan-1980), MSGERML (Jan-1980), MSEIREL (Jan-1988), MSITALL (Jan-1980), MSJPANL (Jan-1980), MSNETHL (Jan-1980), MSNZEAL (Jan-1988), MSNWAYL (Jan-1980), MSPORDL (Jan-1988), MSSPANL (Jan-1980), MSSWDNL (Jan-1980), MSSWITL (Jan-1980), MSUTDKL (Jan-1980), MSUSAML (Jan-1980).

**Local Risk-Free Rates**: JPAU1ML (Jan-1986); ASVIB1M (Jul-1991); JPBG1ML (Jan-1986); JPCN1ML (Jan-1986); JPDK1ML (Jan-1986); FNIBF1M (Feb-1987–Jan-1990), JPFN1ML (Feb-1990); JPFR1ML (Jan-1986); JPBD1ML (Jan-1986); EIRED1M (Feb-1984–Dec-1987), JPIR1ML (Jan-1988); JPIT1ML (Jan-1986); JPJP1ML (Jan-1986); JPNL1ML (Jan-1986); JPNZ1ML (Jan-1988); NWIBN1M (Feb-1986); LISBO1M (Feb-1999); JPES1ML (Jan-1986); JPSD1ML (Jan-1986); SWIBK1M (Jan-1980–Dec-1985), JPSW1ML (Jan-1986); BOELI1M (Jan-1980–Dec-1985), JPUK1ML (Jan-1986); U.S. 1-Month Treasury Bill (Jan-1980–Dec-1985), JPUS1ML (Jan-1986).

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**Figure 1: Cumulative Excess Equity Returns by Equity Momentum Regime**

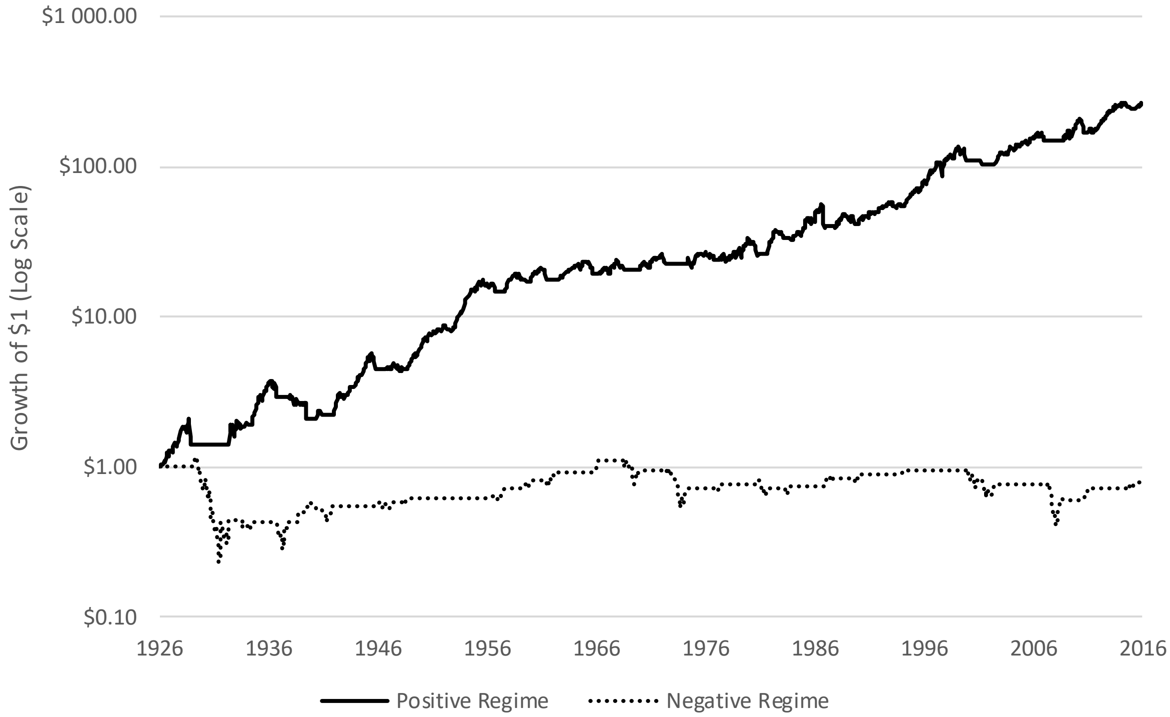


**Figure 1: Cumulative Excess Equity Returns by Equity Momentum Regime**

Plotted are the cumulative excess returns from holding the CRSP value-weighted index during positive or negative equity momentum regimes, and otherwise holding the risk-free asset. Month $t$ belongs to a positive (negative) regime if the $t$ - 12 to $t$ - 1 cumulative CRSP value-weighted index return was positive (negative). The sample period is Dec-1926 to Dec-2016.

**Figure 2: Cumulative Excess Equity Returns by Bond Momentum Regime**

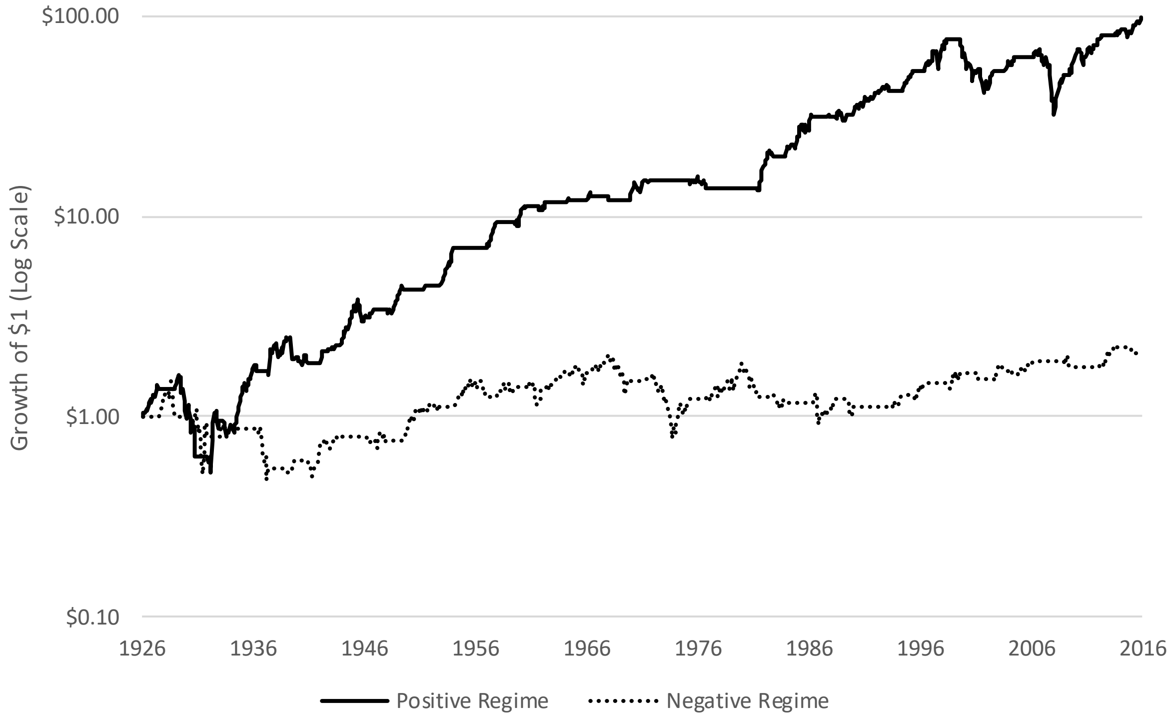


**Figure 2: Cumulative Excess Equity Returns by Bond Momentum Regime**

Plotted are the cumulative excess returns from holding the CRSP value-weighted index during positive or negative bond momentum regimes, and otherwise holding the risk-free asset. Month *t* belongs to a positive (negative) regime if the *t* - 12 to *t* - 1 cumulative change in the long-term Treasury yield was negative (positive). The sample period is Dec-1926 to Dec-2016. Before Apr-1953 the long-term Treasury yield is from Federal Reserve Board (1976a, 1976b). From Apr-1953 it is the ten-year constant maturity Treasury yield.

**Figure 3: Single-Asset Time Series Predictability**

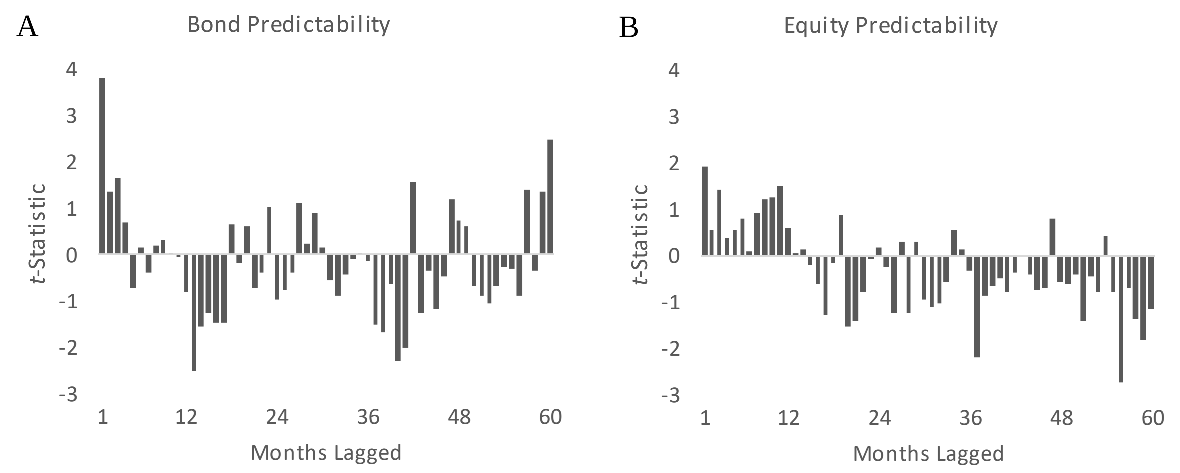


**Figure 3: Single-Asset Time Series Predictability**

Plotted are the *t*-statistics clustered by month from pooled panel regressions where we regress the monthly excess return of each bond (equity) index in our data set on the sign of its own excess return lagged one to sixty months. The sample period is Jan-1980 to Dec-2016. (A) Panel A: Bond *t*-statistics; (B) Panel B: Equity *t*-statistics.

## Figure 4: Cross-Asset Time Series Predictability

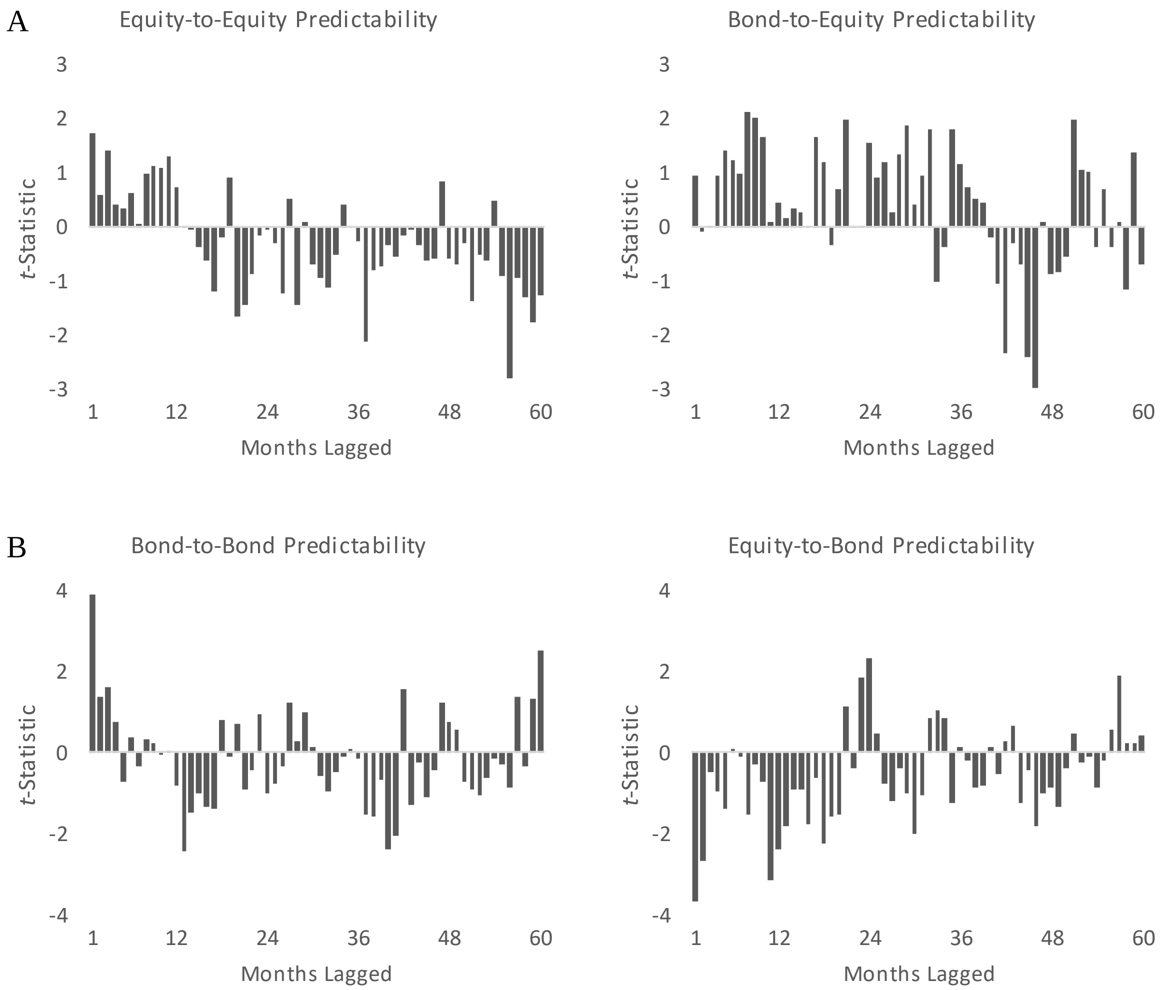


**Figure 4: Cross-Asset Time Series Predictability**

Plotted are the *t*-statistics clustered by month from pooled panel regressions where we regress the monthly excess return of each bond (equity) index in our data set on the sign of its own excess return lagged one to sixty months, and the sign of the similarly lagged excess return of the corresponding equity (bond) index. The sample period is Jan-1980 to Dec-2016. (A) Panel A: Equity regression *t*-statistics; (B) Panel B: Bond regression *t*-statistics.

**Figure 5: Cumulative Excess Returns of Diversified Portfolios**

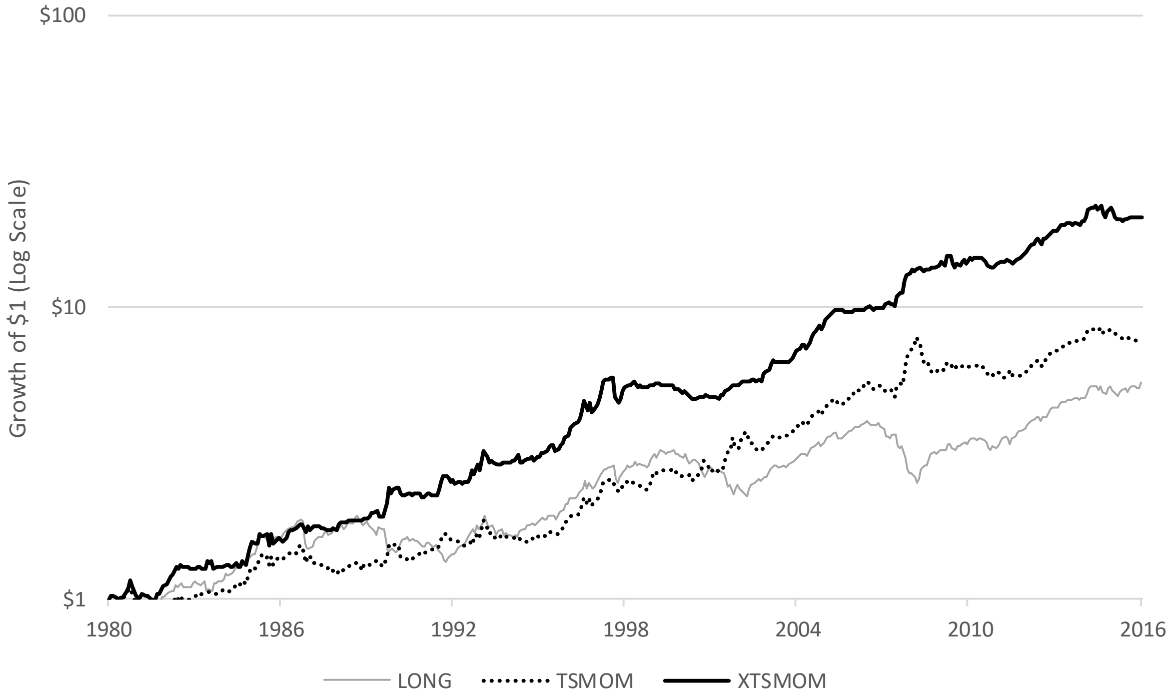


**Figure 5: Cumulative Excess Returns of Diversified Portfolios**

Plotted are the cumulative excess returns of buy-and-hold (LONG), time series momentum (TSMOM), and cross-asset time series momentum (XTSMOM) portfolios diversified across each bond and equity index in our data set. Each strategy uses a lookback period of 12 months and a holding period of one month. The returns of each portfolio are scaled so that their ex post annualised volatilities are 10%. The sample period is Jan-1980 to Dec-2016.

## Figure 6: Sharpe Ratios of Time Series Momentum Portfolios

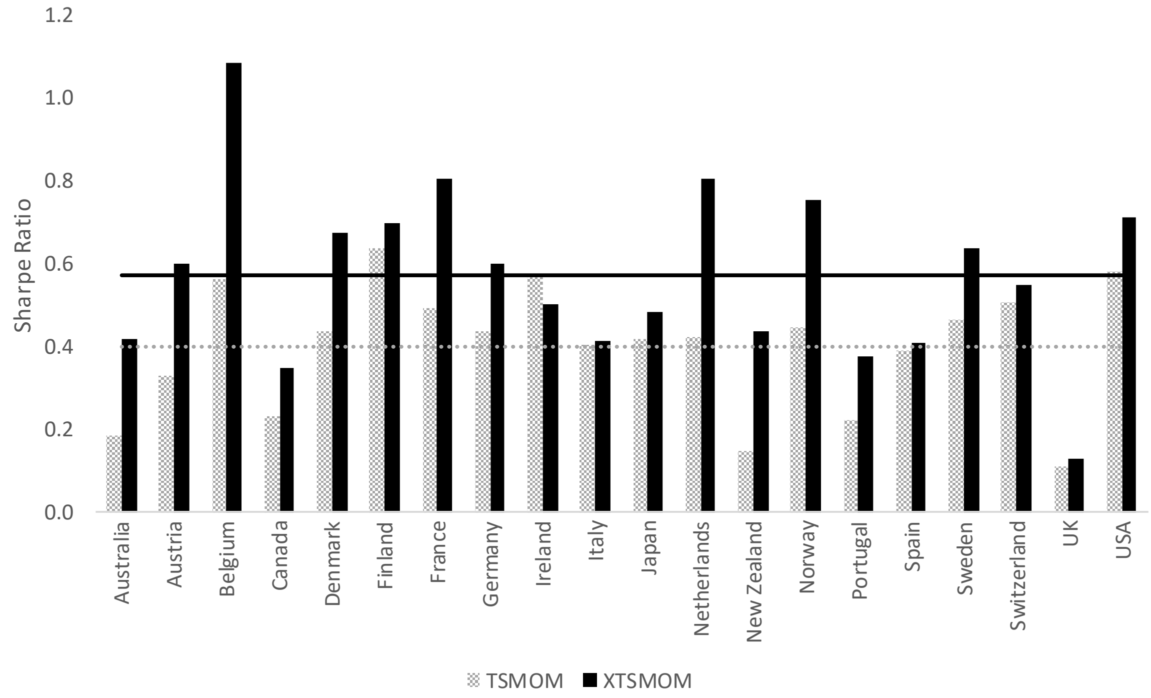


**Figure 6: Sharpe Ratios of Time Series Momentum Portfolios**

Plotted are the annualised gross Sharpe ratios of time series momentum (TSMOM) and cross-asset time series momentum (XTSMOM) portfolios diversified across a country's bond and equity indexes for each country in our data set. Each strategy uses a lookback period of 12 months and a holding period of one month. Horizontal lines indicate the average Sharpe ratios of the portfolios. The sample period is Jan-1980 to Dec-2016.

## Figure 7: The XTSMOM Smile

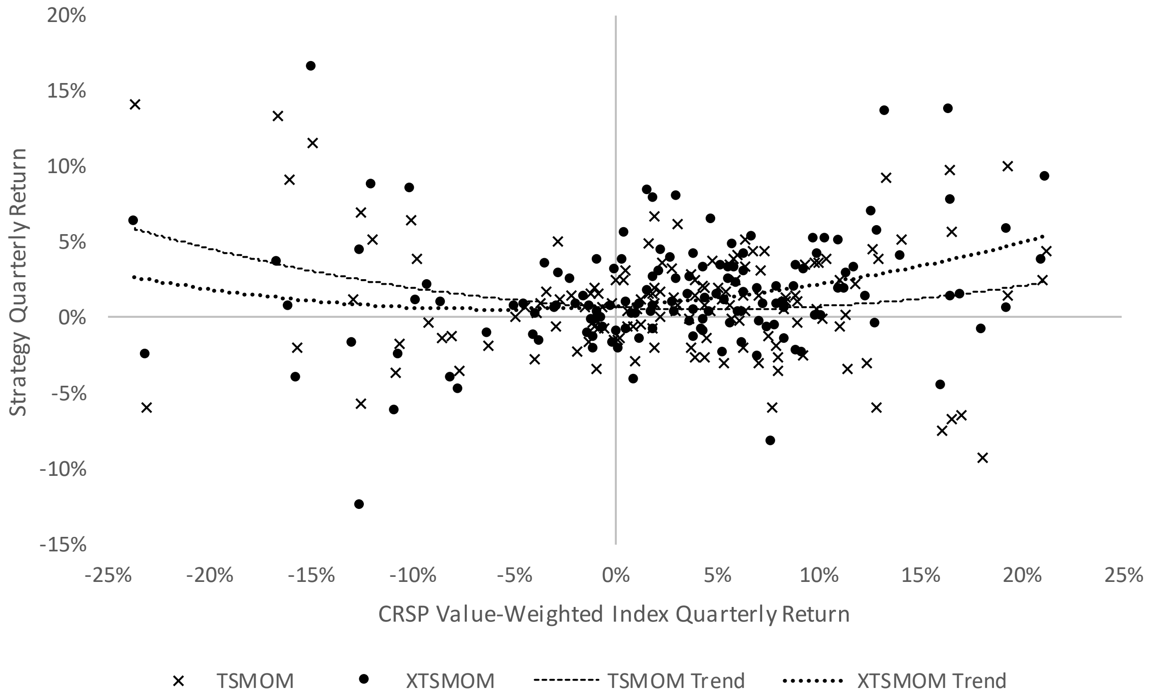


**Figure 7: The XTSMOM Smile**

Plotted are the non-overlapping quarterly returns of diversified time series momentum (TSMOM) and cross-asset time series momentum (XTSMOM) portfolios against the corresponding non-overlapping quarterly returns of the CRSP value-weighted index. Also plotted are the second-order polynomial trendlines for both the TSMOM and XTSMOM returns. The returns of the portfolios are scaled so that their ex post volatilies are the same. The sample period is Jan-1980 to Dec-2016.

**Figure 8: Comovement of Equity Returns and Equity Fund Flows**

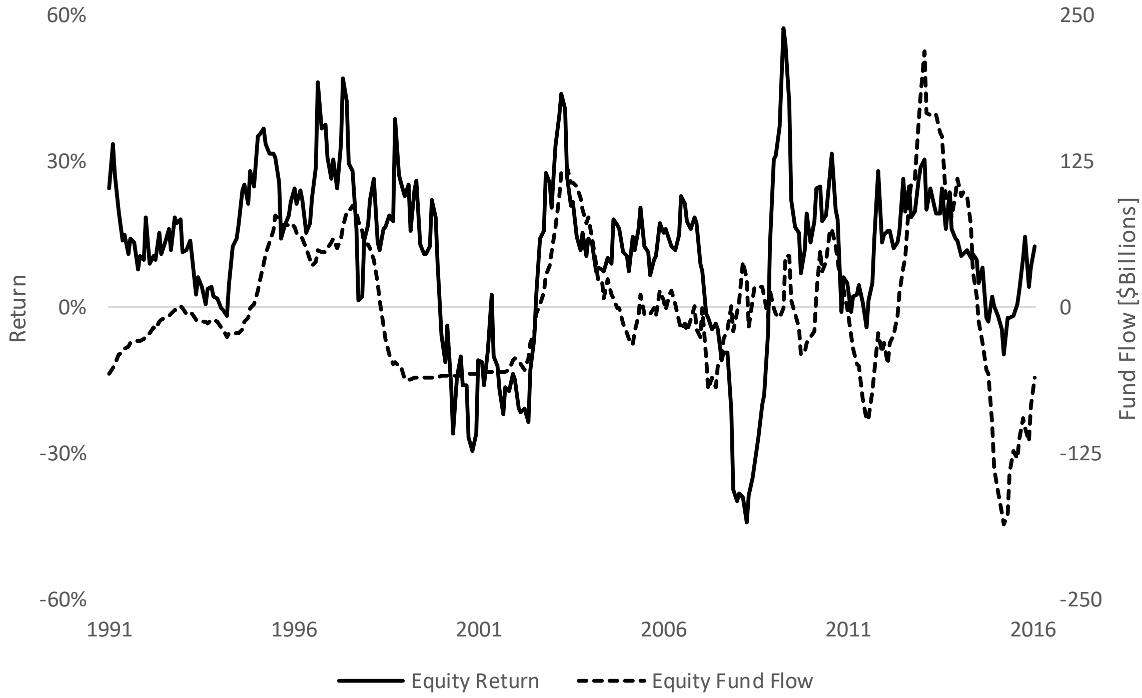


**Figure 8: Comovement of Equity Returns and Equity Fund Flows**

Plotted are the 12-month cumulative returns of the CRSP value-weighted index (left axis) and detrended 12-month cumulative equity mutual fund flows (right axis). The correlation between the series is 0.44. The sample period is Nov-1991 to Dec-2016.

**Figure 9: Comovement of Bond Returns and Bond Fund Flows**

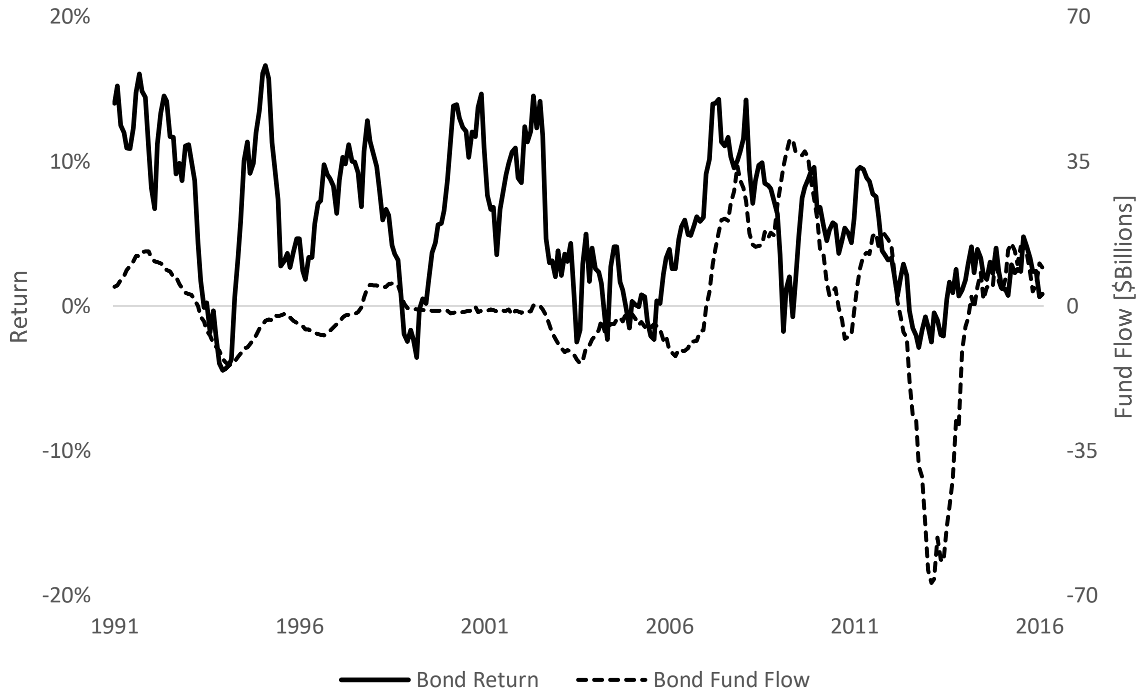


**Figure 9: Comovement of Bond Returns and Bond Fund Flows**

Plotted are the 12-month cumulative returns of the Datastream U.S. Five-Year Benchmark Government Bond total return index (left axis) and detrended 12-month cumulative bond mutual fund flows (right axis). The correlation between the series is 0.39. The sample period is Nov-1991 to Dec-2016.

**Figure 10: Single-Asset Correlations Between Returns and Future Fund Flows**

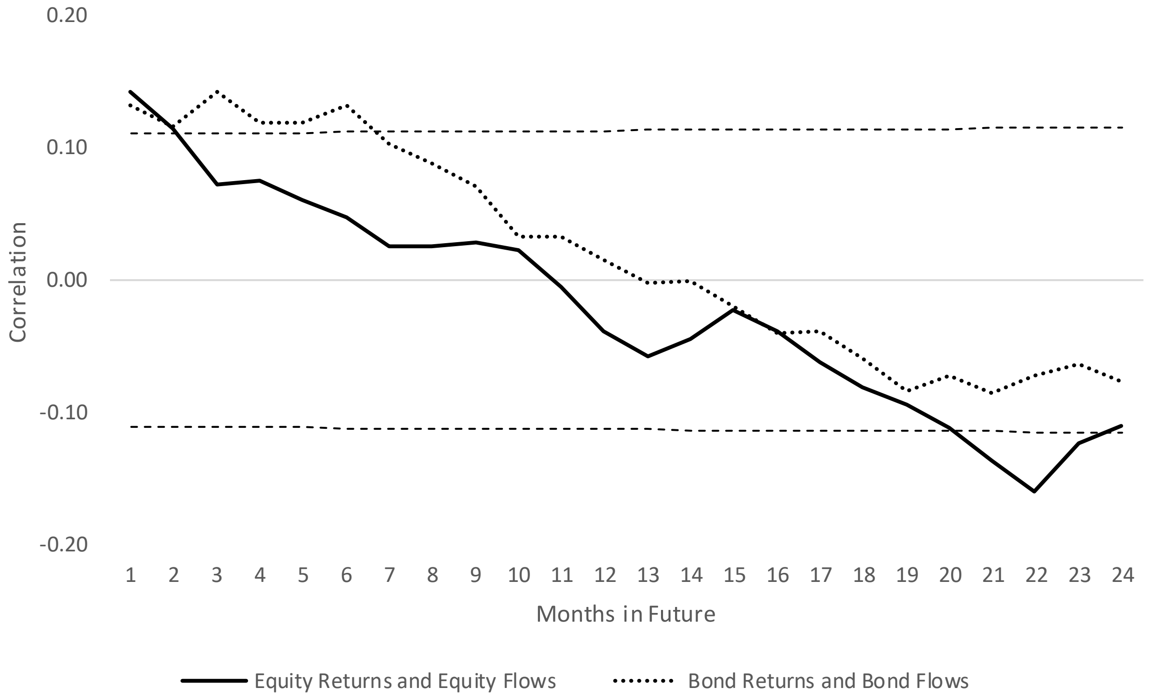


**Figure 10: Single-Asset Correlations Between Returns and Future Fund Flows**

Plotted are the correlations between CRSP value-weighted index 12-month cumulative returns and equity mutual fund flows, and between Datastream US Five-Year Benchmark Government Bond total return index 12-month cumulative returns and bond mutual fund flows, one to 24 months in the future. The equity (bond) fund flows are normalised by equity (bond) mutual fund assets under management. Horizontal lines indicate approximate 5% critical values. The sample period is Dec-1990 to Dec-2016.

## Figure 11: Correlations Between Equity Returns and Future Changes in Equity Demand

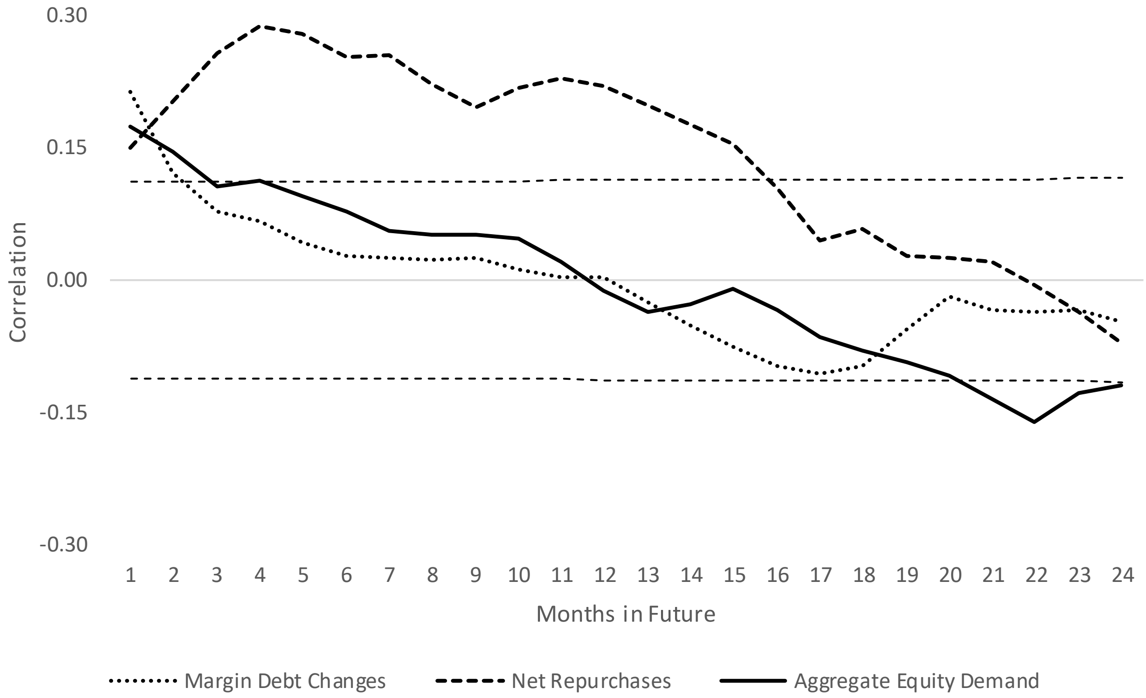


**Figure 11: Correlations Between Equity Returns and Future Changes in Equity Demand**

Plotted are the correlations between CRSP value-weighted index 12-month cumulative returns and monthly changes in NYSE margin debt (dotted line); total stock repurchases net of SEOs (dashed line); and changes in an equal-weighted index of equity mutual fund flows, margin debt changes, and net repurchases (solid line); one to 24 months in the future. The fund flows are normalised by equity mutual fund assets under management. The margin debt changes and repurchases are normalised by U.S. equity market capitalisation. Horizontal lines indicate approximate 5% critical values. The sample period is Dec-1990 to Dec-2016.

**Figure 12: Cross-Asset Correlations Between Returns and Future Fund Flows**

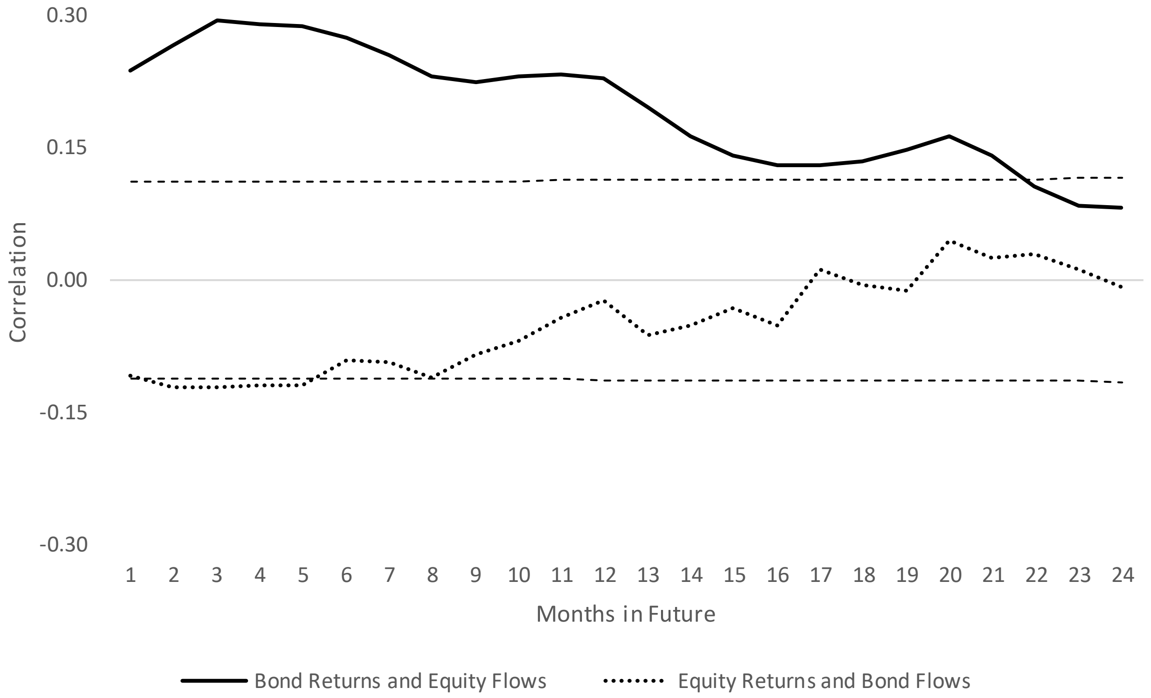


**Figure 12: Cross-Asset Correlations Between Returns and Future Fund Flows**

Plotted are the correlations between Datastream U.S. Five-Year Benchmark Government Bond total return index 12-month cumulative returns and equity mutual fund flows, and between CRSP value-weighted index 12-month cumulative returns and bond mutual fund flows, one to 24 months in the future. The equity (bond) fund flows are normalised by equity (bond) mutual fund assets under management. Horizontal lines indicate approximate 5% critical values. The sample period is Dec-1990 to Dec-2016.

## Figure 13: Cumulative Impulse Response from a Shock to Equity Returns

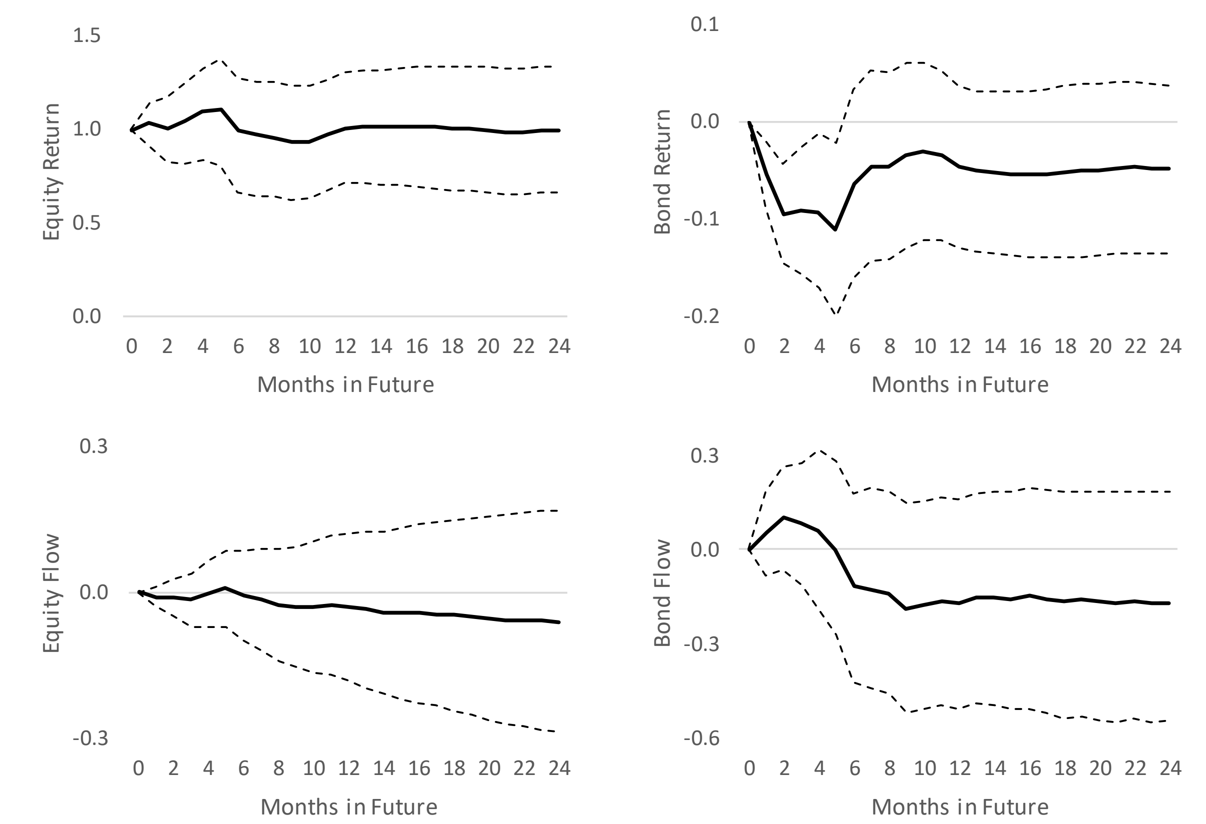


**Figure 13: Cumulative Impulse Response from a Shock to Equity Returns**

Plotted are the cumulative impulse responses from a unit shock to equity returns in the mutual fund flow vector autoregression in Table 5. Dashed lines indicate 95% confidence intervals from 10,000 bootstrap simulations.

**Figure 14: Cumulative Impulse Response from a Shock to Bond Returns**

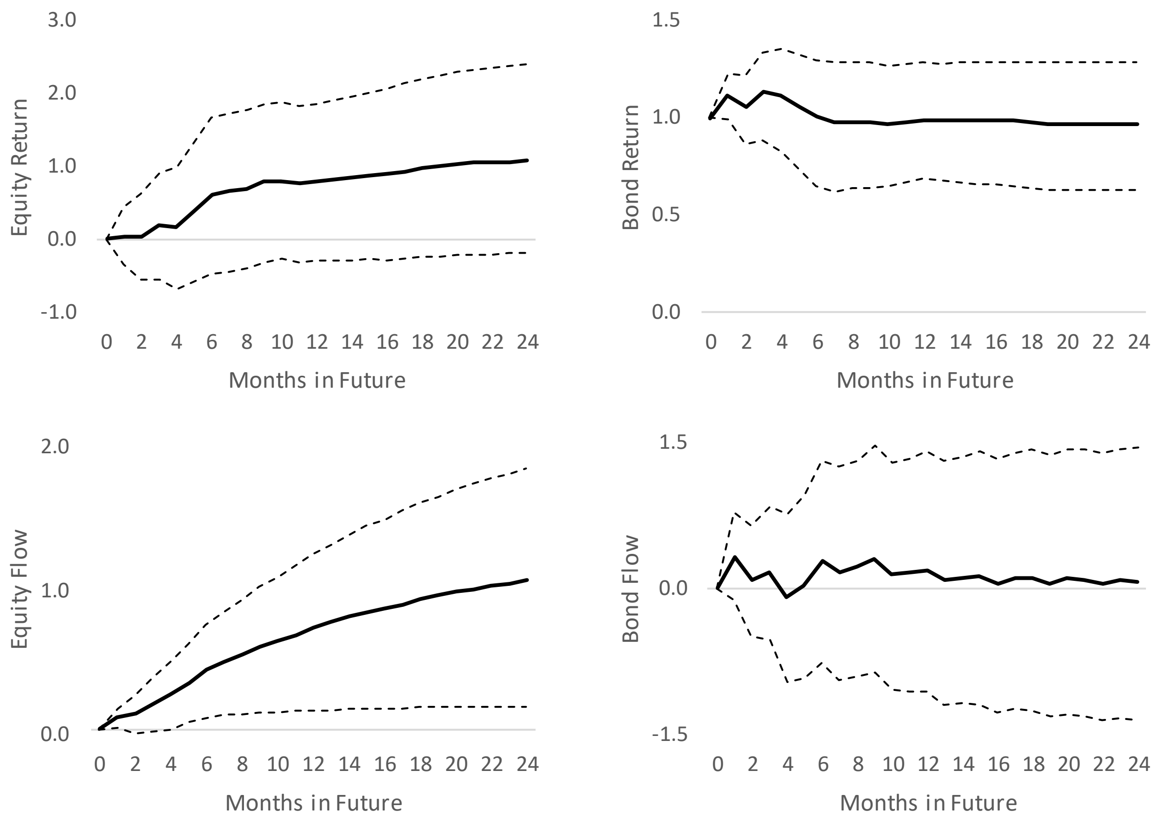


**Figure 14: Cumulative Impulse Response from a Shock to Bond Returns**

Plotted are the cumulative impulse responses from a unit shock to bond returns in the mutual fund flow vector autoregression in Table 5. Dashed lines indicate 95% confidence intervals from 10,000 bootstrap simulations.

**Figure 15: Abnormal Changes in Margin Debt by Bond Momentum Regime**

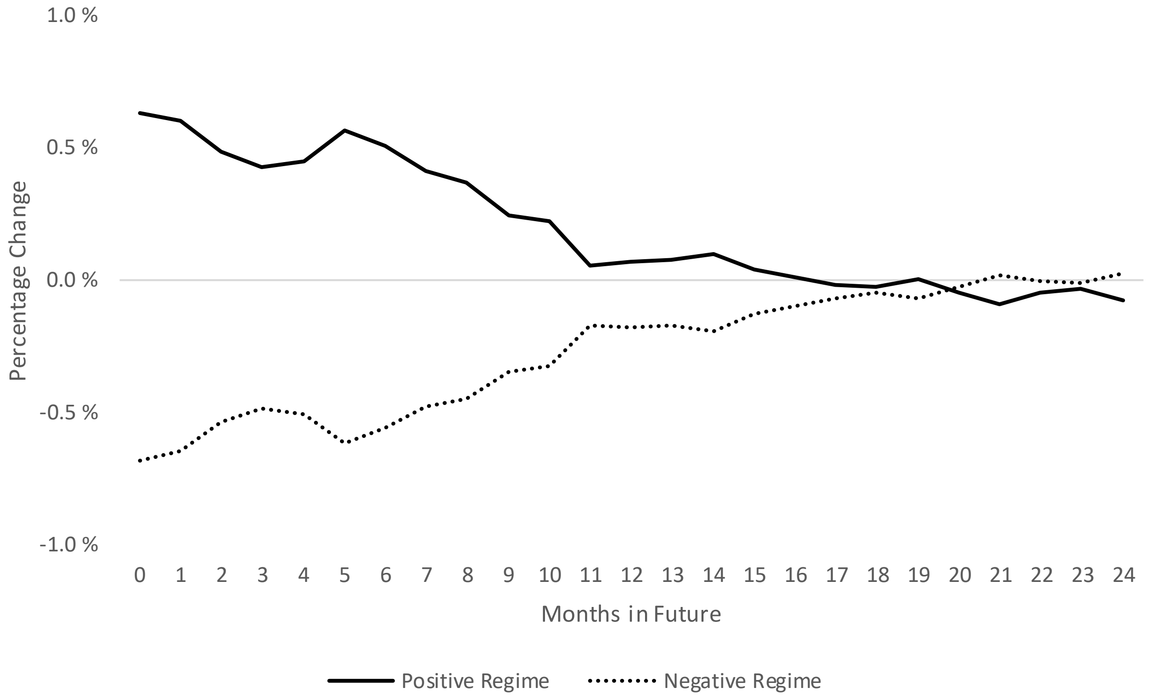


**Figure 15: Abnormal Changes in Margin Debt by Bond Momentum Regime**

Plotted are the average abnormal monthly percentage changes in NYSE margin debt during, and one to 24 months after, positive and negative bond momentum regimes. The abnormal change is defined as the monthly percentage change minus the average monthly percentage change from the beginning of the sample to month *t* - 1. Month *t* belongs to a positive (negative) regime if the *t* - 12 to *t* - 1 cumulative change in the five-year constant maturity Treasury yield was negative (positive). The sample period is Apr-1954 to Dec-2016.

**Figure 16: Correlations Between Equity Returns and Future Federal Funds Rate Changes**

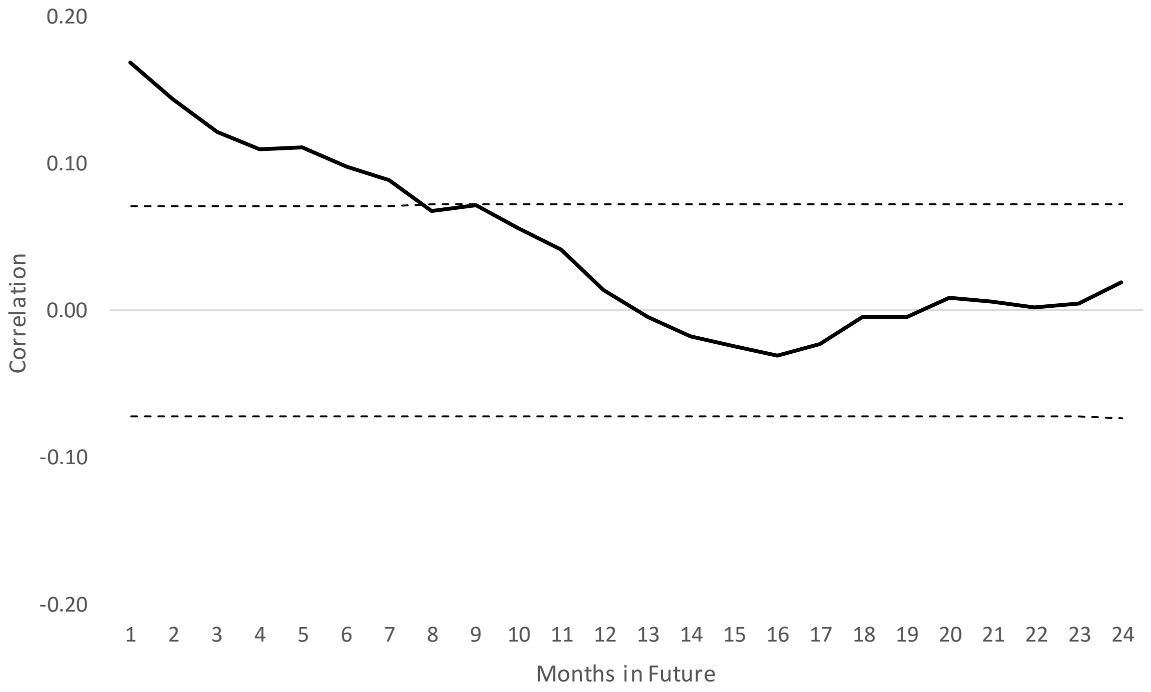


**Figure 16: Correlations Between Equity Returns and Future Federal Funds Rate Changes**

Plotted are the correlations between CRSP value-weighted index 12-month cumulative returns and monthly percentage changes in the federal funds rate one to 24 months in the future. Horizontal lines indicate approximate 5% critical values. The sample period is Jul-1954 to Dec-2016.

## Figure 17: Economic Indicators by Past Return Quintiles

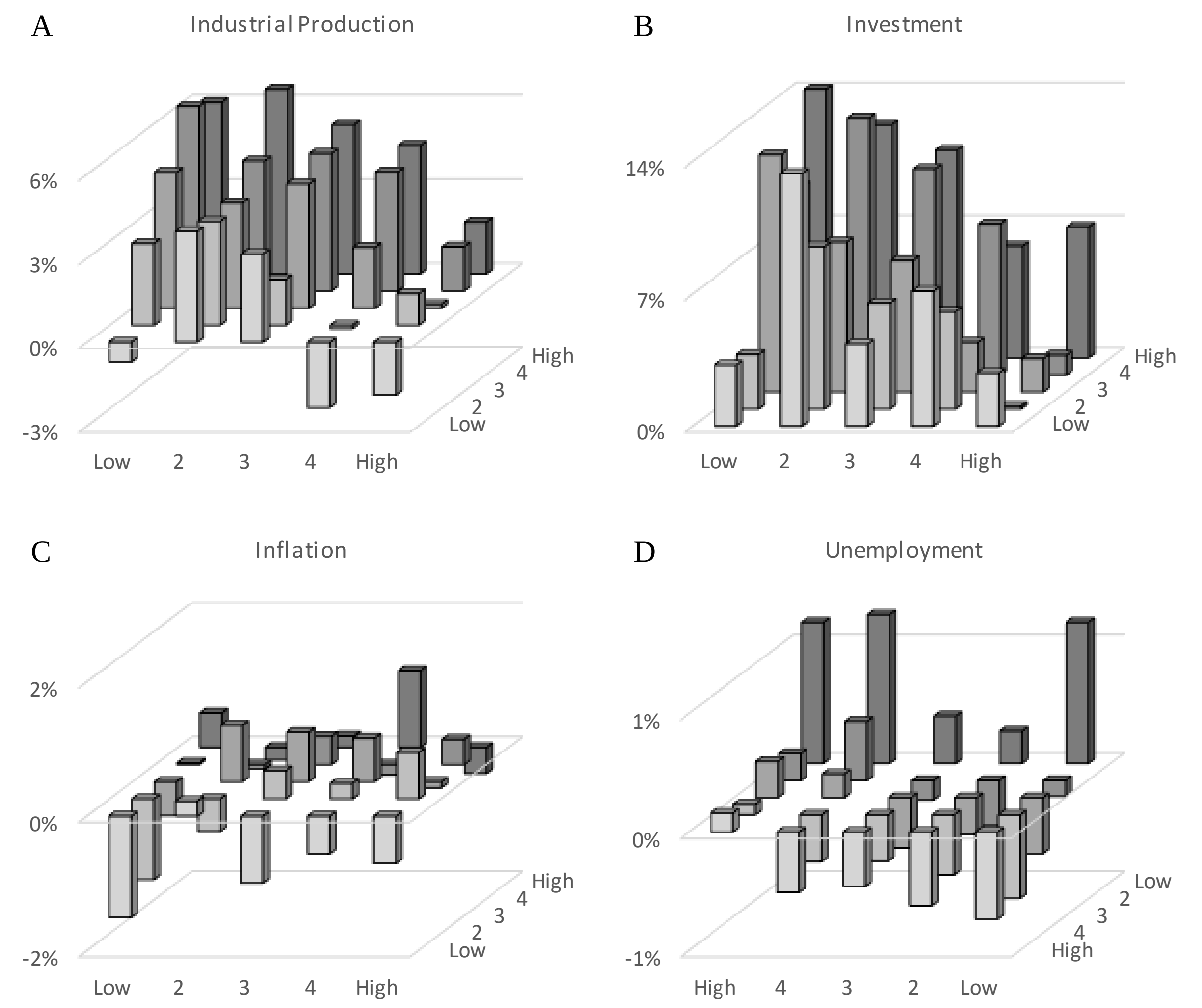


**Figure 17: Economic Indicators by Past Return Quintiles**

Plotted are the average next 12-month (A) percentage change in industrial production, (B) percentage change in gross private domestic investment, (C) change in the inflation (consumer price index) rate, and (D) change in the unemployment rate for 5x5 sorts of past 12-month CRSP value-weighted index returns and five-year constant maturity Treasury yield changes. In each panel, the bond yield change quintiles are on the horizontal axis and the equity return quintiles are on the depth axis. In Panels A and B the vertical axis is the percentage change, and in Panels C and D it is the percentage point change. Note the reversed axes in Panel D. The sample period is Apr-1954 to Dec-2016. (A) Panel A: Industrial production; (B) Panel B: Investment; (C) Panel C: Inflation; (D) Panel D: Unemployment.

## Table 1: Returns by Momentum Regime

**Table 1: Returns by Momentum Regime**

Reported are the number of index-month combinations, the annualised gross Sharpe ratios, and the average monthly excess returns of the bond and equity indexes in our international data set during different bond and equity momentum regimes. An asset belongs to a positive (negative) regime in month $t$ if the $t$ - 12 to $t$ - 1 cumulative excess return of the asset was positive (negative). The sample period is Jan-1980 to Dec-2016. (A) Panel A: TSMOM regimes; (B) Panel B: XTSMOM regimes.

*Panel A:* TSMOM regimes

| | Positive Bond | Negative Bond | Positive Equity | Negative Equity |
|---|---|---|---|---|
| N | 4858 | 2082 | 4420 | 2700 |
| Equity Return | 0.73 % | -0.15 % | 0.81 % | -0.20 % |
| Equity Sharpe Ratio | 0.40 | -0.09 | 0.52 | -0.09 |
| Bond Return | 0.24 % | 0.07 % | 0.11 % | 0.32 % |
| Bond Sharpe Ratio | 0.26 | 0.08 | 0.14 | 0.29 |

*Panel B:* XTSMOM regimes

| | Positive Bond & Negative Equity | Negative Bond & Positive Equity | Positive Equity & Positive Bond | Negative Equity & Negative Bond |
|---|---|---|---|---|
| N | 1856 | 1357 | 2980 | 711 |
| Equity Return | 0.23 % | 0.38 % | 1.04 % | -1.18 % |
| Equity Sharpe Ratio | 0.11 | 0.25 | 0.66 | -0.53 |
| Bond Return | 0.31 % | -0.07 % | 0.20 % | 0.36 % |
| Bond Sharpe Ratio | 0.29 | -0.09 | 0.24 | 0.32 |

## Table 2: Cross-Asset Time Series Momentum Alpha *t*-Statistics

**Table 2: Cross-Asset Time Series Momentum Alpha *t*-Statistics**

Reported are the *t*-statistics of the alphas from regressing the monthly excess returns of diversified cross-asset time series momentum (XTSMOM) portfolios with different lookback and holding periods on passive exposures to bond and equity markets, the excess returns of a corresponding diversified single-asset time series momentum (TSMOM) portfolio, as well as the Fama-French-Carhart size, value, and momentum factors. The sample period is Jan-1980 to Dec-2016.

| | | Holding Period (Months) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 24 | 36 | 48 |
| Lookback Period (Months) | 1 | 2.07 | 3.04 | 4.09 | 4.66 | 4.57 | 4.32 | 4.63 | 4.24 |
| | 3 | 2.84 | 3.58 | 4.09 | 4.55 | 4.19 | 4.10 | 4.41 | 3.82 |
| | 6 | 3.58 | 3.94 | 4.55 | 4.29 | 4.26 | 4.18 | 5.04 | 4.64 |
| | 9 | 3.10 | 3.76 | 3.86 | 3.98 | 3.82 | 4.18 | 4.76 | 4.62 |
| | 12 | 3.27 | 4.01 | 4.24 | 3.86 | 3.86 | 4.34 | 4.84 | 4.97 |
| | 24 | 3.41 | 3.57 | 3.42 | 3.25 | 3.26 | 3.70 | 3.59 | 3.69 |
| | 36 | 3.85 | 4.36 | 4.70 | 4.68 | 4.57 | 3.86 | 3.65 | 3.53 |
| | 48 | 4.24 | 3.88 | 3.89 | 3.55 | 3.22 | 3.19 | 2.96 | 2.66 |

## Table 3: Cross-Asset Time Series Momentum Risk-Adjusted Performance

**Table 3: Cross-Asset Time Series Momentum Risk-Adjusted Performance**

Reported are the results from regressing the monthly excess returns of the diversified cross-asset time series momentum portfolio (XTSMOM) on the excess returns of the diversified single-asset time series momentum portfolio (TSMOM), the excess returns of the MSCI World total return index, and standard asset pricing factors. The sample period is Jan-1980 to Dec-2016. Controls in Panel A: Fama-French-Carhart size, value, and momentum factors; and in Panel B: Asness, Moskowitz, and Pedersen (2013) value and momentum "everywhere" factors, and a momentum (XSMOM) factor constructed using their methodology from the bond and equity indexes in our data set. Following Asness, Moskowitz, and Pedersen (2013) our XSMOM factor is based on the relative ranking of each asset's past 12-month returns, and is long or short the assets in proportion to their ranks relative to the median rank. As in Asness, Moskowitz, and Pedersen (2013), we skip the most recent month when computing 12-month cross-sectional momentum.

*Panel A:* Fama-French-Carhart factors

| | Alpha | TSMOM | MSCI World | SMB | HML | UMD | Adj. $R^2$ |
|---|---|---|---|---|---|---|---|
| Coefficient | 0.54 % | | 0.14 | 0.01 | 0.01 | 0.08 | 0.051 |
| (*t*-Stat) | (4.32) | | (4.65) | (0.21) | (0.23) | (2.98) | |
| Coefficient | 0.25 % | 1.13 | 0.13 | 0.03 | 0.06 | -0.11 | 0.636 |
| (*t*-Stat) | (3.16) | (26.23) | (6.88) | (1.29) | (2.09) | (-5.88) | |

*Panel B:* Asness, Moskowitz, and Pedersen (2013) factors

| | Alpha | TSMOM | MSCI World | VAL Everywhere | MOM Everywhere | XSMOM | Adj. $R^2$ |
|---|---|---|---|---|---|---|---|
| Coefficient | 0.35 % | | 0.15 | 0.27 | 0.44 | | 0.104 |
| (*t*-Stat) | (2.69) | | (5.39) | (2.88) | (5.74) | | |
| Coefficient | 0.29 % | 1.15 | 0.13 | 0.03 | -0.25 | | 0.633 |
| (*t*-Stat) | (3.43) | (24.84) | (7.23) | (0.55) | (-4.53) | | |
| Coefficient | 0.36 % | | 0.14 | 0.16 | | 0.29 | 0.242 |
| (*t*-Stat) | (3.15) | | (5.66) | (2.35) | | (10.82) | |
| Coefficient | 0.21 % | 1.32 | 0.14 | 0.14 | | -0.17 | 0.645 |
| (*t*-Stat) | (2.65) | (22.08) | (8.01) | (2.91) | | (-6.05) | |

## Table 4: Spanning Tests with Diversified Portfolios

**Table 4: Spanning Tests with Diversified Portfolios**

Reported are the results from regressing the monthly returns of cross-asset time series momentum (XTSMOM), time series momentum (TSMOM), and cross-sectional momentum (XSMOM) portfolios on each other. The portfolios are diversified across each bond and equity index in our data set, and use lookback periods of 12 months and holding periods of one month. The XSMOM portfolios are constructed using the methodology from Asness, Moskowitz, and Pedersen (2013). The sample period is Jan-1980 to Dec-2016.

| Dependent Variable | XTSMOM | TSMOM | XSMOM | Alpha | Adj. $R^2$ |
|---|---|---|---|---|---|
| XTSMOM | | 0.99<br>(22.80) | | 0.33 %<br>(3.82) | 0.546 |
| XTSMOM | | | 0.26<br>(9.86) | 0.50 %<br>(4.39) | 0.183 |
| XTSMOM | | 1.33<br>(20.67) | -0.20<br>(-6.80) | 0.34 %<br>(4.14) | 0.589 |
| TSMOM | 0.55<br>(22.80) | | | -0.02 %<br>(-0.38) | 0.546 |
| TSMOM | | | 0.35<br>(24.54) | 0.12 %<br>(2.04) | 0.582 |
| TSMOM | 0.38<br>(20.67) | | 0.25<br>(22.39) | -0.06 %<br>(-1.46) | 0.790 |
| XSMOM | 0.70<br>(9.86) | | | 0.16 %<br>(0.83) | 0.183 |
| XSMOM | | 1.67<br>(24.54) | | 0.05 %<br>(0.39) | 0.582 |
| XSMOM | -0.49<br>(-6.80) | 2.16<br>(22.39) | | 0.21 %<br>(1.64) | 0.622 |

## Table 5: Mutual Fund Flow Vector Autoregression

**Table 5: Mutual Fund Flow Vector Autoregression**

Reported are the results from a multivariate vector autoregression on monthly CRSP value-weighted index returns, Datastream U.S. Five-Year Benchmark Government Bond total return index returns, AUM-adjusted equity mutual fund flows, and AUM-adjusted bond mutual fund flows. Six lags of each variable are used. The coefficient sums are the sums of the coefficients of the lags of the respective variable. The *p*-values are from tests of the hypothesis that the coefficients of each lag of a given variable are zero. The sample period is Dec-1990 to Dec-2016. ***: Significant at 0.1%. **: Significant at 1%. *: Significant at 5%.

| Dependent Variable | Equity Return | | Bond Return | | Equity Flow | | Bond Flow | | Adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| | Coef. Sum | *p*-Val. | Coef. Sum | *p*-Val. | Coef. Sum | *p*-Val. | Coef. Sum | *p*-Val. | |
| Equity Return | 0.00 | (0.467) | 0.57 | (0.749) | 0.59* | (0.012) | -0.30 | (0.051) | 0.045 |
| Bond Return | -0.04** | (0.001) | 0.02 | (0.280) | -0.01 | (0.355) | 0.04 | (0.581) | 0.085 |
| Equity Flow | 0.00 | (0.506) | 0.21 | (0.134) | 0.85*** | (0.000) | 0.03*** | (0.000) | 0.561 |
| Bond Flow | -0.14 | (0.277) | 0.26 | (0.180) | -0.06** | (0.004) | 0.08*** | (0.000) | 0.408 |

## Table 6: Economic Indicators by Momentum Regime

**Table 6: Economic Indicators by Momentum Regime**

Reported are the average next 12-month percentage change in industrial production, percentage change in gross private domestic investment, change in the inflation rate, and change in the unemployment rate during positive and negative bond and equity momentum regimes. Month *t* belongs to a positive (negative) bond regime if the *t* - 12 to *t* - 1 cumulative change in the five-year constant maturity Treasury yield was negative (positive), and to a positive (negative) equity regime if the *t* - 12 to *t* - 1 cumulative CRSP value-weighted index return was positive (negative). The sample period is Apr-1954 to Dec-2016. (A) Panel A: TSMOM regimes; (B) Panel B: XTSMOM regimes.

*Panel A:* TSMOM regimes

| | Positive Bond | Negative Bond | Positive Equity | Negative Equity |
|---|---|---|---|---|
| Industrial Production | 3.96 % | 1.96 % | 3.68 % | 0.29 % |
| Investment | 9.42 % | 4.98 % | 7.62 % | 5.07 % |
| Inflation Rate | -0.14 % | 0.17 % | 0.24 % | -0.69 % |
| Unemployment Rate | -0.21 % | 0.17 % | -0.27 % | 0.86 % |

*Panel B:* XTSMOM regimes

| | Positive Bond & Negative Equity | Negative Bond & Positive Equity | Positive Bond & Positive Equity | Negative Bond & Negative Equity |
|---|---|---|---|---|
| Industrial Production | 1.86 % | 2.86 % | 4.69 % | -1.37 % |
| Investment | 5.49 % | 5.06 % | 10.61 % | 4.65 % |
| Inflation Rate | -0.88 % | 0.34 % | 0.11 % | -0.48 % |
| Unemployment Rate | 0.65 % | -0.08 % | -0.51 % | 1.08 % |

# Cross-Asset Signals and Time Series Momentum: Internet Appendix

Aleksi Pitkäjärvi
Matti Suominen
Lauri Vaittinen

This version: January 2019
First version: December 2016

## Contents

## A. Cross-Asset Time Series Momentum with Futures Data

In this section, we implement the time series momentum and cross-asset time series momentum strategies using a smaller sample of futures data that we collect from Datastream. Specifically, we collect the bond and equity futures used by Moskowitz, Ooi, and Pedersen (2012) for those countries with both bond and equity futures available. Since the start dates of the futures returns vary from 1982 to 2005, we follow Moskowitz, Ooi, and Pedersen (2012) and use MSCI country-level equity index returns and Datastream Benchmark Government Bond index returns to fill out the series prior to the availability of futures returns. This leaves a final sample of five countries (Australia, Germany, Japan, the UK, and the U.S.), five equity futures, and twelve bond futures from January 1980 to December 2016, which matches the sample period we use in our main analyses.

Implementing the strategies with this data set, we can see from Figure A1 that the outperformance of cross-asset time series momentum is robust to using this smaller sample of futures returns. Our choice to use index returns thus does not drive our main results.

FIGURE A1 HERE

## B. Cross-Asset Time Series Momentum with Volatility Scaling

In this section, we implement the time series momentum and cross-asset time series momentum strategies using returns that are scaled by their ex ante volatilities, estimated using the same exponentially-weighted moving average method as in Moskowitz, Ooi, and Pedersen (2012). Consistent with Kim, Tse, and Wald (2016), volatility scaling improves the absolute performance of all strategies, but the relative performance of the strategies is unchanged, so the fact that cross-asset time series momentum outperforms time series momentum in our main results is not driven by the fact that we do not use volatility scaling.

FIGURE B1 HERE

## C. Alternative Regression Specifications

In this section, we report the results from alternative time series predictability regression specifications. In addition to the single-asset and cross-asset predictability regressions from Figures 3 and 4 of the main text, we consider cross-asset predictability with FX returns, cross-asset predictability with oil returns, and cross-country cross-asset predictability with U.S. returns. Concretely, for the FX returns we use the Bank of England's effective exchange rate indices for each of the countries in our data set. For the oil returns, we use the IMF's oil price index.[10] For the cross-country predictability regressions, we take the nineteen non-U.S. countries in our data set, and perform the cross-asset predictability regressions with the signs of lagged U.S. bond and equity returns included as additional predictors. The results are summarised in Table C1. For the sake of brevity, instead of plotting the *t*-statistics for sixty lags of each variable in each regression specification, we report the average *t*-statistics of the first twelve lags of each variable.

TABLE C1 HERE

The most important result from Table C1 is that our four main effects (bond-to-bond, bond-to-equity, equity-to-bond, equity-to-equity) are very stable across each of the first four specifications, thus demonstrating the robustness of our main results. The only anomaly is the cross-country specification in the fifth column, where the average *t*-statistics of the single-asset effects decrease from 0.56 and 0.88 to 0.18 and 0.24, respectively, while the average *t*-statistics of the cross-asset effects increase (in absolute value) from 1.00 and -1.44 to 1.38 and -1.61, respectively. The inclusion of the lagged U.S. returns as controls thus weakens the single-asset predictability effects but strengthens the cross-asset predictability effects, thus highlighting the value and importance of the cross-asset effects.

From the third regression specification in Table C1, we can see that the average effect of FX returns on equity returns is negative, while the average effect of FX returns on bond returns is positive. One explanation for these effects could be that a weaker currency increases the competitiveness of a country's exports, thus supporting export-driven economic growth and triggering reallocations from bonds to equities, which would put downward pressure on bond

[10] The results are similar if we use the IMF's aggregate commodity price index.

prices and upward pressure on equity prices. Conversely, a stronger currency decreases competitiveness, hindering growth and triggering reallocations in the opposite direction.

From the fourth regression specification in Table C1, we can see that the average effect of oil returns on equity returns is negative. This makes sense considering that all but three of the countries in our data set are oil importers, and their growth prospects and thus equity returns are likely to be negatively affected by rising oil prices. When we perform the regression separately for the three oil exporters in our data set (Canada, Denmark, Norway), the negative effect is not present.

## D. Alternative Strategy Specifications

In this section, we define return- and rank-weighted versions of the TSMOM and XTSMOM strategies, which we denote WTSMOM, RTSMOM, WXTSMOM, and RXTSMOM. The performance of diversified portfolios of each strategy is summarised in Table D1.

TABLE D1 HERE

As we can see, the Sharpe ratios of TSMOM, WTSMOM, and RTSMOM are very similar, ranging from 0.56 to 0.63. The Sharpe ratios of XTSMOM, WXTSMOM, and RXTSMOM are also very similar, ranging from 0.80 to 0.90. Overall, these results show that our strategy performance results are robust to reasonable changes in the way we define the strategies, with the rank-weighted versions even offering a tiny improvement in performance.

To see how we define the return- and rank-weighted strategies, note first that in any given month *t*, the portfolio weight of country *c*'s bond index *b* in the regular TSMOM portfolio is

$$w_{b,c}^{TSMOM} = \frac{1}{N} \cdot \operatorname{sign}\{R_{b,c} - R_{f,c}\},$$

and the portfolio weight of country *c*'s equity index *e* is

$$w_{e,c}^{TSMOM} = \frac{1}{N} \cdot \operatorname{sign}\{R_{e,c} - R_{f,c}\},$$

where $N$ is the total number of assets with data available in month $t$, $R_{b,c}$ is the past twelve-month return of country $c$'s bond index, $R_{e,c}$ is the past twelve-month return of country $c$'s equity index, and $R_{f,c}$ is country $c$'s past twelve-month risk-free return. Similarly, in the regular XTSMOM portfolio the weights of country $c$'s bond and equity indices are

$$w_{b,c}^{XTSMOM} = \frac{w_{b,c}^{TSMOM} - w_{e,c}^{TSMOM}}{2} \qquad \text{and} \qquad w_{e,c}^{XTSMOM} = \frac{w_{e,c}^{TSMOM} + w_{b,c}^{TSMOM}}{2},$$

respectively.[11]

For the return-weighted WTSMOM and WXTSMOM portfolios, we simply drop the sign functions and let the magnitudes of the signals determine the portfolio weights. We thus have

$$w_{b,c}^{WTSMOM} = \frac{1}{N} \cdot \left(R_{b,c} - R_{f,c}\right) \qquad \text{and} \qquad w_{e,c}^{WTSMOM} = \frac{1}{N} \cdot \left(R_{e,c} - R_{f,c}\right)$$

for WTSMOM, and

$$w_{b,c}^{WXTSMOM} = \frac{w_{b,c}^{WTSMOM} - w_{e,c}^{WTSMOM}}{2} \qquad \text{and} \qquad w_{e,c}^{WXTSMOM} = \frac{w_{e,c}^{WTSMOM} + w_{b,c}^{WTSMOM}}{2}$$

for WXTSMOM.

Since the magnitude of the signal is between -1 and 1 in all cases in our data set, the return-weighted portfolios will by construction have portfolio weights that are smaller in absolute value than the weights of the regular TSMOM and XTSMOM portfolios. To account for this, we scale up the return-weighted portfolio weights so that each month the amount of capital invested in the return-weighted portfolios matches the amount invested in the regular portfolios.

In constructing the rank-weighted RTSMOM portfolio we resist the temptation of simply ranking assets by their past twelve-month returns and going long the high ranks and short the

[11] The first equation uses the difference of the weights and the second equation uses the sum because equity returns are negative predictors of bond returns while bond returns are positive predictors of equity returns.

low ranks, as one might do in a cross-sectional momentum context. We avoid this approach because it can lead to situations such as shorting an asset with a positive return signal just because it has a low cross-sectional rank, which runs counter to time series momentum's focus on assets' own past performance as the primary predictor of future performance. Instead, we define our rank-weighted strategy in such a way that an asset's past return determines the sign of its portfolio weight, while the asset's rank only affects the magnitude of the weight.

Concretely, to construct the rank-weighted RTSMOM portfolio we start with $N$ total assets of which $N_b$ are bond indices. Of the $N_b$ bond indices $L_b$ have a positive past twelve-month return and $N_b - L_b$ have a negative past twelve-month return. We rank the $L_b$ bond indices from one to $L_b$, with rank $L_b$ going to the bond index with the most positive past twelve-month return. We then rank the remaining bond indices in reverse order from minus one to $-(N_b - L_b)$, with rank $-(N_b - L_b)$ going to the bond index with the most negative past twelve-month return. The rank-weighted RTSMOM portfolio weight of bond index *i* of country *c* is then given by

$$w_{i,c}^{RTSMOM} = \frac{L_b}{N} \cdot \frac{\text{Rank}_i}{1 + 2 + \cdots + L_b}$$

if the index has a positive past twelve-month return, and by

$$w_{i,c}^{RTSMOM} = \frac{N_b - L_b}{N} \cdot \frac{\text{Rank}_i}{1 + 2 + \cdots + (N_b - L_b)}$$

if it has a negative past twelve-month return. The rank-weighted RTSMOM portfolio weights for the equity indices are calculated in exactly the same way. Note that defining the weights in this way accomplishes our goal of giving positive weights to all assets that have positive past returns, and negative weights to all assets that have negative past returns.

The portfolio weights for the rank-weighted RXTSMOM portfolio follow the same logic as the XTSMOM and WXTSMOM portfolios, so we have

$$w_{b,c}^{RXTSMOM} = \frac{w_{b,c}^{RTSMOM} - w_{e,c}^{RTSMOM}}{2} \quad \text{and} \quad w_{e,c}^{RXTSMOM} = \frac{w_{e,c}^{RTSMOM} + w_{b,c}^{RTSMOM}}{2}.$$

Because the RXTSMOM portfolio weights do not necessarily sum to one, we again scale the weights so that each month the amount of capital invested matches the XTSMOM portfolio.[12]

### E. Strategy Performance by Asset Class

In this section, we plot the strategy returns separately for bond-only and equity-only TSMOM and XTSMOM portfolios. From Figure E1 we can see that the bond-only XTSMOM portfolio outperforms the bond-only TSMOM portfolio, and the equity-only XTSMOM portfolio outperforms the equity-only TSMOM portfolio, so cross-asset time series momentum outperforms time series momentum in both asset classes.

FIGURE E1 HERE

### F. Spanning Tests in Individual Asset Classes

In this section, we report the results of spanning tests of XTSMOM, TSMOM, and XSMOM portfolio returns separately for bond-only (Table F1) and equity-only (Table F2) versions of the portfolios. From the first three rows of both tables, we can see that the TSMOM and XSMOM returns do not span the XTSMOM returns, either alone or in combination. In contrast, from the fourth and seventh rows of both tables we can see that the TSMOM and XSMOM returns are spanned by the XTSMOM returns. The spanning test results of Table 4 from the main text thus hold in both asset classes.

TABLES F1 AND F2 HERE

### G. Margin Debt Vector Autoregression

In this section, we report the results from a vector autoregression with six lags of monthly CRSP value-weighted index returns, percentage changes in the five-year constant maturity Treasury yield, and percentage changes in NYSE margin debt. The sample period is May-1953 to Dec-2016.

[12] The RTSMOM portfolio weights sum to one by construction, so they require no scaling.

TABLE G1 HERE

## H. Cross-Asset Time Series Momentum and Recessions

In this section, we link momentum regimes more closely to the economic cycle by documenting how the likelihood of being in a given regime varies in and around recessions. Specifically, in Figure H1 we plot the frequencies with which individual months occurring 24 months before and 24 months after the starts of NBER recessions belong to the different cross-asset time series momentum regimes. The sample period is Apr-1954 to Dec-2016, and contains nine separate recessions.

FIGURE H1 HERE

From Panel A of Figure H1, we can see that in the 24 months before a recession begins the economy is typically in a negative bond and positive equity regime.[13] From Panels B and C, we can see that in the first six months of a recession the equity regime typically turns negative, followed in the next six months by the bond regime turning positive. Finally, from Panel D we can see that twelve to 24 months after a recession starts, the equity regime again typically turns positive as the recovery begins. Bond and equity returns thus exhibit a cyclicality in and around recessions, and this cyclicality is neatly captured by the combined bond and equity momentum regimes that are used by cross-asset time series momentum.

[13] This combination of regimes would seem likely when inflation or inflation expectations are high.

**Figure A1: Cumulative Excess Returns of Diversified Portfolios with Futures Data**

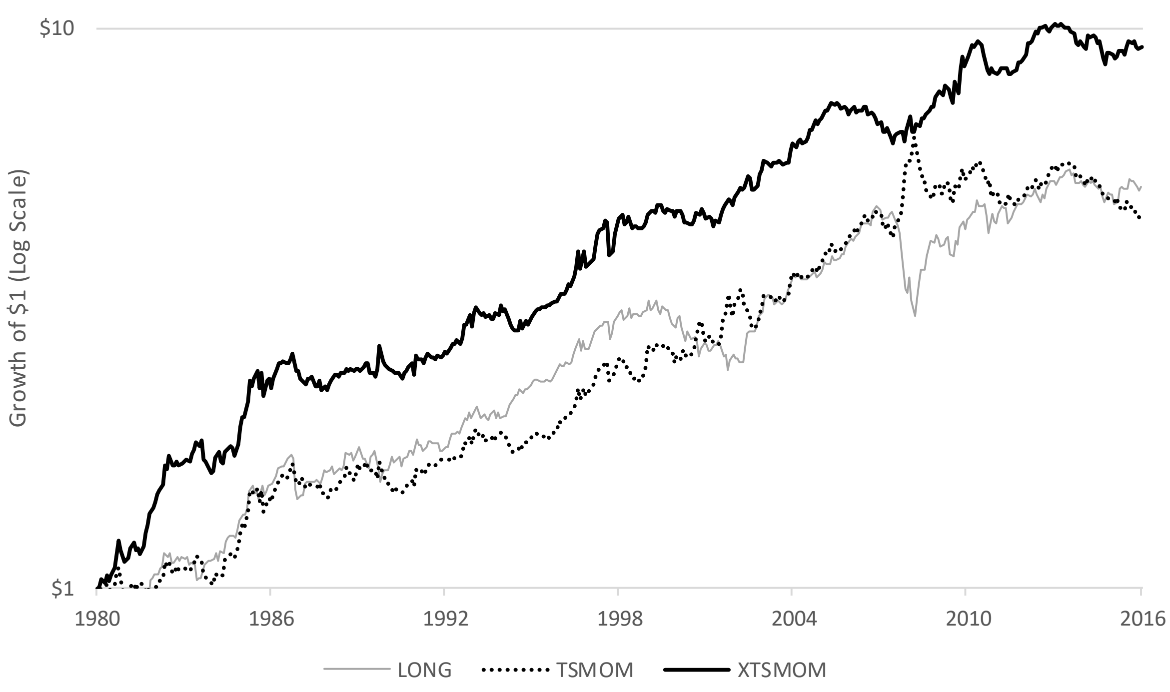


**Figure A1: Cumulative Excess Returns of Diversified Portfolios with Futures Data**

Plotted are the cumulative excess returns of buy-and-hold (LONG), time series momentum (TSMOM), and cross-asset time series momentum (XTSMOM) portfolios diversified across each bond and equity index future in our data set. Each strategy uses a lookback period of twelve months and a holding period of one month. The returns of each portfolio are scaled so that their ex post annualised volatilities are 10%. The sample period is Jan-1980 to Dec-2016.

**Figure B1: Cumulative Excess Returns of Diversified Portfolios with Volatility Scaling**

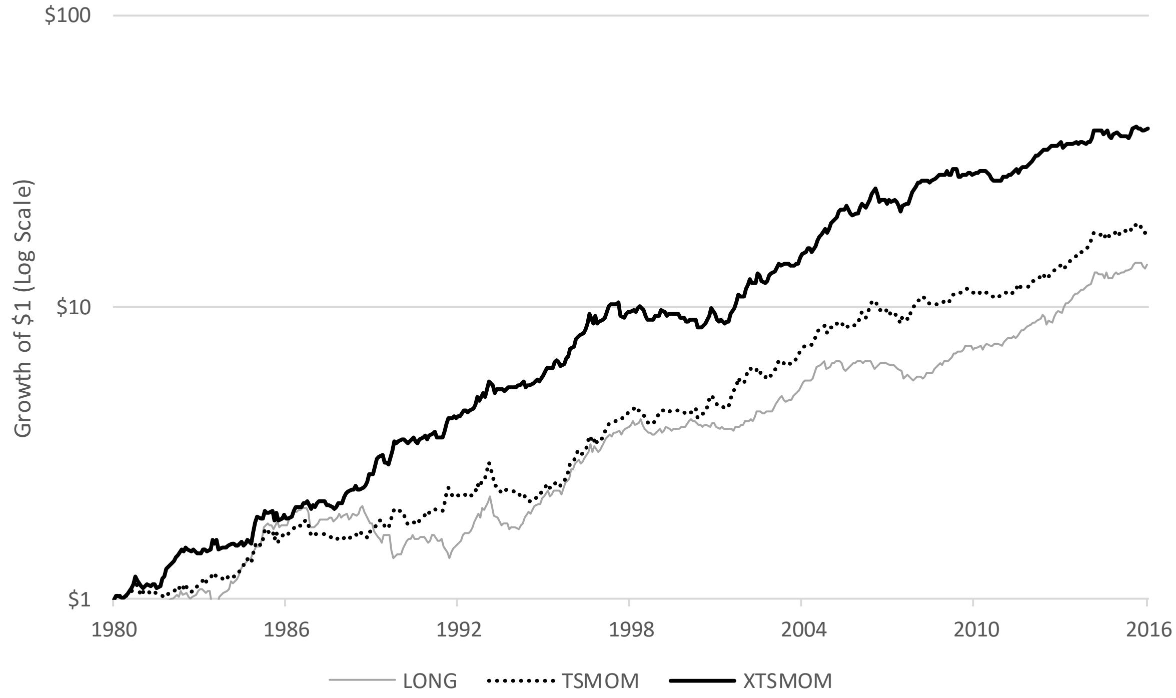


**Figure B1: Cumulative Excess Returns of Diversified Portfolios with Volatility Scaling**

Plotted are the cumulative excess returns of buy-and-hold (LONG), time series momentum (TSMOM), and cross-asset time series momentum (XTSMOM) portfolios diversified across each bond and equity index in our data set. The proportion of a portfolio allocated to a given asset is inversely related to the asset's ex ante volatility, so assets with a lower volatility are given a relatively higher weight, and vice versa. Each strategy uses a lookback period of twelve months and a holding period of one month. The returns of each portfolio are scaled so that their ex post annualised volatilities are 10%. The sample period is Jan-1980 to Dec-2016.

## Table C1: Robustness of Time Series Predictability Results

**Table C1: Robustness of Time Series Predictability Results**

Reported are the average *t*-statistics of the first twelve lags of each predictor in five regression specifications: (1) single-asset time series predictability, (2) cross-asset time series predictability, (3) cross-asset time series predictability with FX returns, (4) cross-asset time series predictability with oil returns, and (5) cross-country cross-asset time series predictability. The sample period is Jan-1980 to Dec-2016.

| Effect | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Bond to Bond | 0.54 | 0.56 | 0.61 | 0.57 | 0.18 |
| Bond to Equity | | 1.00 | 0.98 | 0.94 | 1.38 |
| Bond to FX | | | -0.51 | | |
| Bond to Oil | | | | -0.87 | |
| Equity to Bond | | -1.44 | -1.44 | -1.44 | -1.61 |
| Equity to Equity | 0.94 | 0.88 | 0.88 | 0.89 | 0.24 |
| Equity to FX | | | -0.06 | | |
| Equity to Oil | | | | 0.35 | |
| FX to Bond | | | 1.07 | | |
| FX to Equity | | | -0.53 | | |
| FX to FX | | | 0.28 | | |
| Oil to Bond | | | | 0.18 | |
| Oil to Equity | | | | -0.93 | |
| Oil to Oil | | | | 0.28 | |
| U.S. Bond to Local Bond | | | | | 0.66 |
| U.S. Bond to Local Equity | | | | | -0.75 |
| U.S. Equity to Local Bond | | | | | 0.53 |
| U.S. Equity to Local Equity | | | | | 0.77 |

## Table D1: Performance of Alternative Strategy Specifications

**Table D1: Performance of Alternative Strategy Specifications**

Reported are the annualised gross Sharpe ratios, mean returns, and volatilities of regular, return-weighted, and rank-weighted time series momentum (TSMOM, WTSMOM, RTSMOM) and cross-asset time series momentum (XTSMOM, WXTSMOM, RXTSMOM) portfolios diversified across each bond and equity index in our data set. Each strategy uses a lookback period of twelve months and a holding period of one month. The sample period is Jan-1980 to Dec-2016.

| | Sharpe Ratio | Mean | Volatility |
|---|---|---|---|
| TSMOM | 0.61 | 4.09 % | 6.68 % |
| WTSMOM | 0.56 | 7.22 % | 12.93 % |
| RTSMOM | 0.63 | 4.71 % | 7.44 % |
| XTSMOM | 0.89 | 7.97 % | 8.97 % |
| WXTSMOM | 0.80 | 6.30 % | 7.89 % |
| RXTSMOM | 0.90 | 6.97 % | 7.73 % |

**Figure E1: Cumulative Excess Returns of Bond and Equity Portfolios**

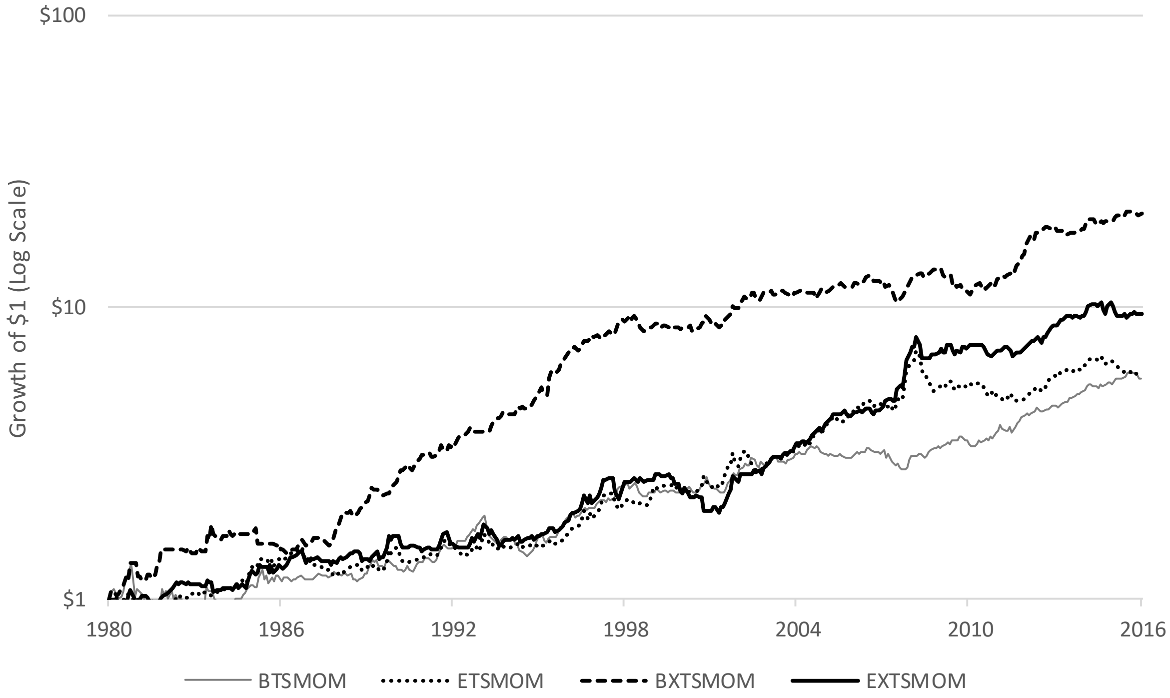


**Figure E1: Cumulative Excess Returns of Bond and Equity Portfolios**

Plotted are the cumulative excess returns of time series momentum (BTSMOM, ETSMOM), and cross-asset time series momentum (BXTSMOM, EXTSMOM) portfolios diversified separately across each bond index or each equity index in our data set. Each strategy uses a lookback period of twelve months and a holding period of one month. The returns of each portfolio are scaled so that their ex post annualised volatilities are 10%. The sample period is Jan-1980 to Dec-2016.

## Table F1: Spanning Tests with Bond Portfolios

**Table F1: Spanning Tests with Bond Portfolios**

Reported are the results from regressing the monthly returns of cross-asset time series momentum (XTSMOM), time series momentum (TSMOM), and cross-sectional momentum (XSMOM) portfolios on each other. The portfolios are diversified across each bond index in our data set, and use lookback periods of twelve months and holding periods of one month. The XSMOM portfolios are constructed using the methodology from Asness, Moskowitz, and Pedersen (2013). The sample period is Jan-1980 to Dec-2016.

| Dependent Variable | XTSMOM | TSMOM | XSMOM | Alpha | Adj. $R^2$ |
|---|---|---|---|---|---|
| XTSMOM | | 0.54<br>(11.20) | | 0.18 %<br>(4.32) | 0.224 |
| XTSMOM | | | 0.04<br>(1.82) | 0.24 %<br>(5.26) | 0.005 |
| XTSMOM | | 0.54<br>(11.01) | 0.01<br>(0.36) | 0.18 %<br>(4.30) | 0.223 |
| TSMOM | 0.42<br>(11.20) | | | 0.03 %<br>(0.72) | 0.224 |
| TSMOM | | | 0.06<br>(3.19) | 0.12 %<br>(3.03) | 0.021 |
| TSMOM | 0.41<br>(11.01) | | 0.04<br>(2.63) | 0.02 %<br>(0.61) | 0.235 |
| XSMOM | 0.21<br>(1.82) | | | 0.10 %<br>(0.87) | 0.005 |
| XSMOM | | 0.41<br>(3.19) | | 0.10 %<br>(0.88) | 0.021 |
| XSMOM | 0.05<br>(0.36) | 0.38<br>(2.63) | | 0.09 %<br>(0.79) | 0.019 |

## Table F2: Spanning Tests with Equity Portfolios

**Table F2: Spanning Tests with Equity Portfolios**

Reported are the results from regressing the monthly returns of cross-asset time series momentum (XTSMOM), time series momentum (TSMOM), and cross-sectional momentum (XSMOM) portfolios on each other. The portfolios are diversified across each equity index in our data set, and use lookback periods of twelve months and holding periods of one month. The XSMOM portfolios are constructed using the methodology from Asness, Moskowitz, and Pedersen (2013). The sample period is Jan-1980 to Dec-2016.

| Dependent Variable | XTSMOM | TSMOM | XSMOM | Alpha | Adj. $R^2$ |
|---|---|---|---|---|---|
| XTSMOM | | 0.80<br>(22.02) | | 0.32 %<br>(2.45) | 0.529 |
| XTSMOM | | | 0.27<br>(5.22) | 0.63 %<br>(3.43) | 0.057 |
| XTSMOM | | 0.82<br>(20.82) | -0.06<br>(-1.43) | 0.33 %<br>(2.56) | 0.530 |
| TSMOM | 0.67<br>(22.02) | | | 0.05 %<br>(0.41) | 0.529 |
| TSMOM | | | 0.40<br>(8.91) | 0.36 %<br>(2.27) | 0.154 |
| TSMOM | 0.61<br>(20.82) | | 0.23<br>(7.16) | -0.03 %<br>(-0.22) | 0.578 |
| XSMOM | 0.22<br>(5.22) | | | 0.32 %<br>(1.91) | 0.057 |
| XSMOM | | 0.39<br>(8.91) | | 0.27 %<br>(1.72) | 0.154 |
| XSMOM | -0.08<br>(-1.43) | 0.45<br>(7.16) | | 0.30 %<br>(1.88) | 0.156 |

## Table G1: Margin Debt Vector Autoregression

**Table G1: Margin Debt Vector Autoregression**

Reported are the results from a multivariate vector autoregression on monthly CRSP value-weighted index returns, percentage changes in the five-year constant maturity Treasury yield, and percentage changes in NYSE margin debt. Six lags of each variable are used. The coefficient sums are the sums of the coefficients of the lags of the respective variable. The *p*-values are from tests of the hypothesis that the coefficients of each lag of a given variable are zero. The sample period is May-1953 to Dec-2016. ***: Significant at 0.1%. **: Significant at 1%. *: Significant at 5%.

| Dependent | Equity Return | | Yield Change | | Margin Debt Change | | Adj. $R^2$ |
|---|---|---|---|---|---|---|---|
| Variable | Coef. Sum | *p*-Val. | Coef. Sum | *p*-Val. | Coef. Sum | *p*-Val. | |
| Equity Return | 0.19* | (0.038) | -0.14 | (0.084) | -0.02 | (0.416) | 0.013 |
| Yield Change | 0.26* | (0.036) | 0.08*** | (0.000) | 0.18 | (0.139) | 0.125 |
| Margin Debt Change | 0.57*** | (0.000) | -0.15** | (0.002) | 0.29*** | (0.000) | 0.254 |

**Figure H1: Momentum Regimes around the Starts of Recessions**

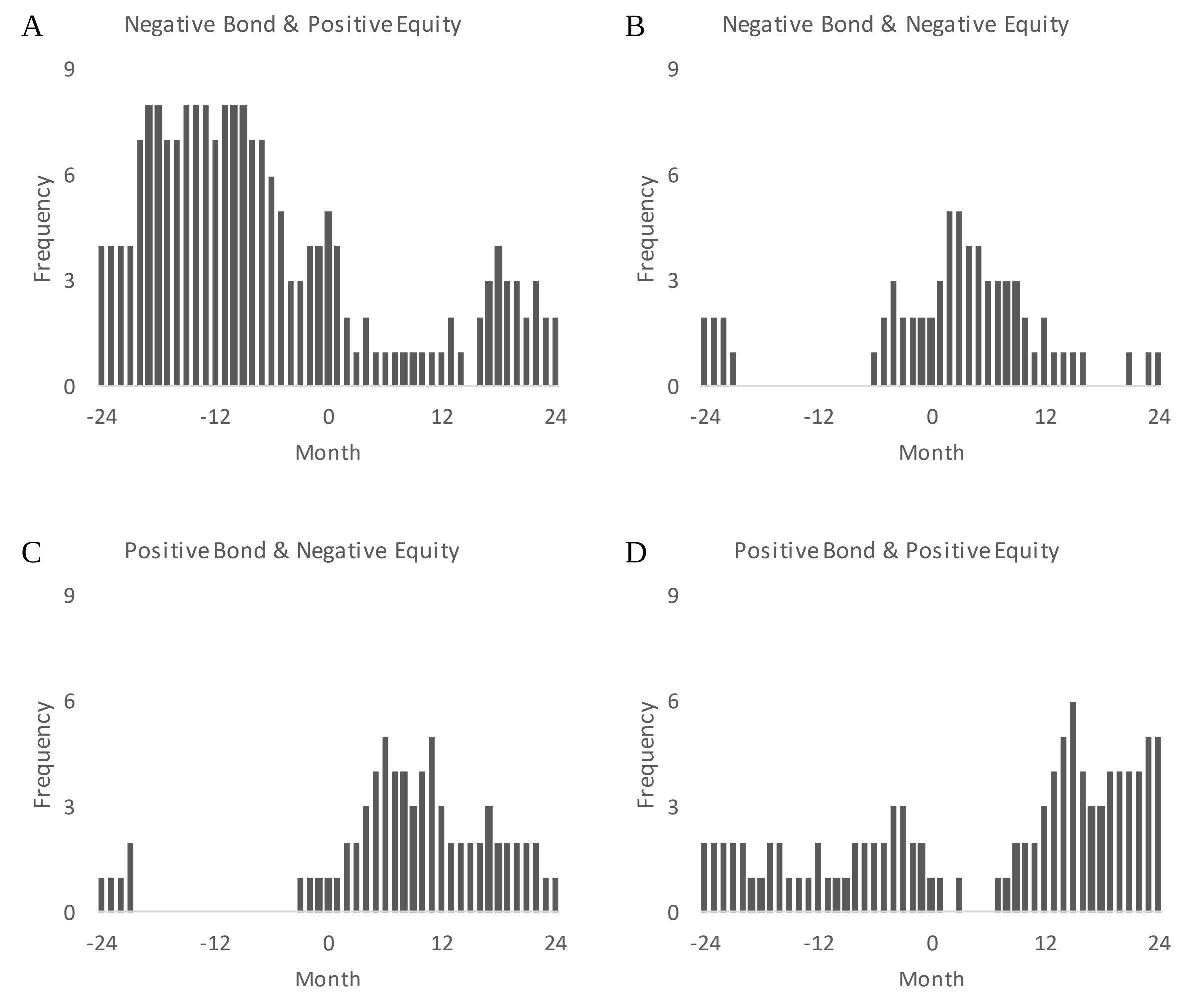


**Figure H1: Momentum Regimes around the Starts of Recessions**

Plotted are the frequencies with which the individual months occurring 24 months before and 24 months after the starts of NBER recessions belong to the different cross-asset time series momentum regimes. Month 0 denotes the start of a recession as defined by NBER. The sample period is Apr-1954 to Dec-2016, and contains nine separate recessions. (A) Panel A: Negative bond and positive equity regimes; (B) Panel B: Negative bond and negative equity regimes; (C) Panel C: Positive bond and negative equity regimes; (D) Panel D: Positive bond and positive equity regimes.