Decomposing Cross-Asset Time Series Momentum*

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Abstract

I decompose the expected return difference between cross-asset time series momentum and time series momentum into market timing and risk premium components, and show that market timing accounts for 71–79% of the difference. I thus show that two recent critiques of time series momentum do not apply to cross-asset time series momentum. Instead, the outperformance of cross-asset time series momentum is driven specifically by the strategy's ability to exploit cross-asset time series predictability in global bond and equity markets.

Keywords: asset pricing, cross-asset time series momentum, time series momentum, momentum decomposition

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1 Introduction

Using a sample of bond and equity market returns from twenty developed countries, Pitkäjärvi, Suominen, and Vaittinen (2020) show that the past excess returns of a country's equity index predict the future excess returns of the same country's bond index, while the past excess returns of a country's bond index predict the future excess returns of the same country's equity index. Motivated by this cross-asset time series predictability in global bond and equity markets, the authors introduce a strategy that they refer to as cross-asset time series momentum, which significantly outperforms the traditional time series momentum strategy of Moskowitz, Ooi, and Pedersen (2012).

In this paper, I extend the work of Pitkäjärvi, Suominen, and Vaittinen (2020) by identifying precisely why cross-asset time series momentum outperforms time series momentum. I derive a decomposition of the expected return difference between the two strategies which shows that 71–79% of the return difference is explained by two market timing components that are directly related to the cross-asset time series predictability results of Pitkäjärvi, Suominen, and Vaittinen (2020). I thus show that the outperformance of cross-asset time series momentum is driven specifically by the strategy's ability to exploit cross-asset time series predictability in global bond and equity markets.

This paper is motivated by two recent critiques of time series momentum. In the first critique, Goyal and Jegadeesh (2018) compare the returns of time series momentum and cross-sectional momentum, and show that the return difference between the two strategies is explained by the fact that, unlike cross-sectional momentum, time series momentum is not a zero net investment strategy. Instead, time series momentum typically has a net long exposure to risky assets, thus earning an additional risk premium. After taking this risk premium into account, Goyal and Jegadeesh (2018) find no evidence that time series momentum significantly outperforms cross-sectional momentum.

In the second critique, Huang, Li, Wang, and Zhou (2020) revisit the time series predictability regressions of Moskowitz, Ooi, and Pedersen (2012), and argue that the evidence for time series predictability at the individual asset level is much weaker than the evidence from the pooled regressions presented by Moskowitz, Ooi, and Pedersen (2012). Partly motivated by this, the authors also show that average time series momentum returns are not significantly different from the returns of a simple "time series history" strategy that does not rely on time series predictability. Huang, Li, Wang, and Zhou (2020) thus raise the question of whether the time series momentum profitability documented by Moskowitz, Ooi, and Pedersen (2012), Georgopoulou and Wang (2017), and others is actually driven by the strategy's ability to exploit time series predictability in the underlying assets, or by some other factors.[1]

Applying these critiques of time series momentum to cross-asset time series momentum suggests two hypotheses about the outperformance of the latter strategy. The first hypothesis is that cross-asset time series momentum outperforms time series momentum because it has a larger net long exposure to risky assets, and thus earns an additional risk premium that accounts for the return difference. The second hypothesis is that the returns of cross-asset time series momentum can also be replicated by a "cross-asset time series history" strategy that does not rely on cross-asset time series predictability, and thus the outperformance of cross-asset time series momentum is not related to the strategy's ability to exploit cross-asset time series predictability in the underlying assets, but is instead driven by some other factors.

The results in this paper allow us to reject both hypotheses. I start by using the Pitkäjärvi, Suominen, and Vaittinen (2020) data set to show that cross-asset time series momentum and time series momentum have very similar average exposures to risky assets, so the return difference is not explained by an additional risk premium. Instead, the decomposition I derive shows that 71–79% of the return difference is explained by market timing—that is, by the fact that cross-asset time series momentum successfully increases its exposure to risky assets during times of high expected returns, and

[1] A third critique of time series momentum, by Kim, Tse, and Wald (2016), shows that time series momentum profitability is strongly influenced by the volatility scaling scheme used by Moskowitz, Ooi, and Pedersen (2012). Because of this, Pitkäjärvi, Suominen, and Vaittinen (2020) do not include volatility scaling in their definition of cross-asset time series momentum. In this paper, I follow the same approach, and do not consider the effects of volatility scaling.

decreases its exposure to risky assets during times of low expected returns.

I then continue by extending the time series predictability regressions of Huang, Li, Wang, and Zhou (2020) to the cross-asset setting, to show that while the tests find little evidence of time series predictability at the individual asset level, the evidence for cross-asset time series predictability at the individual asset level is much stronger. Moreover, I show that the returns of cross-asset time series momentum cannot be replicated by a cross-asset extension of the Huang, Li, Wang, and Zhou (2020) time series history strategy. I thus show that neither the risk premium critique of Goyal and Jegadeesh (2018) nor the time series predictability critique of Huang, Li, Wang, and Zhou (2020) applies to cross-asset time series momentum.

Related Literature. This paper contributes to the literature on time series momentum and cross-asset time series momentum profitability. Since it was first introduced by Moskowitz, Ooi, and Pedersen (2012), time series momentum has been documented in individual stocks (Szakmary and Lancaster, 2015; Lim, Wang, and Yao, 2018), emerging markets (Georgopoulou and Wang, 2017), numerous assets and asset classes (Babu, Levine, Ooi, Pedersen, and Stamelos, 2020), and in global futures data stretching all the way back to the year 1880 (Hurst, Ooi, and Pedersen, 2017). Formal theories of time series momentum have focused on how time series momentum can arise from the interplay between fundamental, momentum, and contrarian traders in financial markets (He and Li, 2015; Andrei and Cujean, 2017; Wang, Liu, Yang, and Wu, 2020), and on the role of limited investor attention in generating time series and cross-asset time series predictability (Pitkäjärvi, 2021). Empirical studies of time series momentum and cross-asset time series momentum have also linked their profitability to slow-moving capital in global financial markets (Pitkäjärvi, Suominen, and Vaittinen, 2020), and to macroeconomic risk (Hutchinson and O'Brien, 2020).

The rest of the paper is structured as follows. Section 2 describes the data. Section 3 addresses the risk premium critique and derives the return decomposition. Section 4 addresses the time series predictability critique and presents the cross-asset time series predictability results. Section 5 concludes.

2 Data

I implement all of the empirical analyses in this paper on the Pitkäjärvi, Suominen, and Vaittinen (2020) data set, which consists of bond and equity index returns from twenty countries and covers the period from January 1980 to December 2016. The bond indices are five-year maturity Datastream Benchmark Government Bond total return indices and the equity indices are MSCI equity total return indices. For more information on the data set, see Pitkäjärvi, Suominen, and Vaittinen (2020).

3 The Risk Premium Critique

Goyal and Jegadeesh (2018) define the net long position of a trading strategy in month t as

$$\text{NetLong}_t := \sum_i w_i, \tag{1}$$

where w_i is the portfolio weight the strategy allocates to asset i in month t. For cross-sectional momentum and other zero net investment strategies, NetLong_t is always zero by construction. By contrast, for time series momentum NetLong_t is typically positive, because the time series momentum portfolio weight of an asset is determined by the sign of the asset's past return, and past returns are positive on average. Goyal and Jegadeesh (2018) show that the return difference between time series momentum and cross-sectional momentum is explained by this net long position of time series momentum.

Applying this same logic to cross-asset time series momentum suggests the hypothesis that the return difference between cross-asset time series momentum and time series momentum is explained by cross-asset time series momentum having a larger net long position, and thus earning an additional risk premium that accounts for the return difference. Table 1 shows that this hypothesis is false: regardless of the lookback period used, the average NetLong_t values of time series momentum and cross-asset time series momentum are very similar, and the difference in their NetLong_t values is not significantly different from zero for any of the lookback periods.

For an indirect test of the same hypothesis, I compare the performance of the long and short legs of both strategies. In particular, if cross-asset time series momentum outperformance was explained by a larger net long position, then we could expect the fraction of profits stemming from the long leg of the strategy to be larger than the corresponding fraction for time series momentum. However, using a twelve-month lookback period and a one-month holding period, from January 1980 to December 2016 one dollar invested in time series momentum would have grown to 3.76 dollars, with 104.36% of the profit coming from the long leg, while one dollar invested in cross-asset time series momentum would have grown to 15.12 dollars, with only 83.97% of the profit coming from the long leg. Cross-asset time series momentum is thus less dependent on the long leg than time series momentum.[2]

These tests show that a larger net long position does not explain the return difference between cross-asset time series momentum and time series momentum. In order to explain the return difference, in this section I derive a decomposition of the expected return difference between the two strategies. In contrast with other momentum decompositions (e.g., Lewellen, 2002; Moskowitz, Ooi, and Pedersen, 2012) that rely on assumptions about the underlying return process, the decomposition I derive does not require any such assumptions.

3.1 Return Decomposition

To economize on notation, consider first the case of one country with two assets: a bond index denoted by b, and an equity index denoted by e. Let $r_{b,t-12} - r_{f,t-12}$ denote the excess cumulative return of the bond index over the past twelve months, and let $r_{e,t-12} - r_{f,t-12}$ denote the corresponding excess cumulative return of the equity index. Assuming a holding period of one month, the time series momentum portfolio weights

[2] The same is true for one-, three-, and six-month lookback periods.

in month t are

$$w_b := \frac{1}{N} \operatorname{sgn}\{r_{b,t-12} - r_{f,t-12}\} \tag{2}$$

for the bond index and

$$w_e := \frac{1}{N} \operatorname{sgn}\{r_{e,t-12} - r_{f,t-12}\} \tag{3}$$

for the equity index. In the current case $N = 2$.

Following Pitkäjärvi, Suominen, and Vaittinen (2020), the corresponding cross-asset time series momentum portfolio weights can be written in terms of the time series momentum weights. Specifically, the cross-asset time series momentum portfolio weight for the bond index is

$$w_b^X := w_b - w_e \tag{4}$$

and the cross-asset time series momentum portfolio weight for the equity index is

$$w_e^X := w_e + w_b, \tag{5}$$

where the minus sign in Equation 4 derives from the fact that past equity returns are negative predictors of future bond returns, while the plus sign in Equation 5 derives from the fact that past bond returns are positive predictors of future equity returns.

Using these portfolio weights, the realized return of time series momentum in month t is

$$r^T := w_b r_b + w_e r_e \tag{6}$$

and the realized return of cross-asset time series momentum in month t is

$$r^X := w_b^X r_b + w_e^X r_e, \tag{7}$$

where r_b and r_e are the returns of the bond and equity indices in month t. Substituting

Equations 4 and 5 into Equation 7,

$$\begin{aligned} r^X &= (w_b - w_e)r_b + (w_e + w_b)r_e \\ &= r^T + w_b r_e - w_e r_b, \end{aligned} \tag{8}$$

so the realized return difference $r^X - r^T$ in month t equals $w_b r_e - w_e r_b$. Finally, by taking expectations,

$$\begin{aligned} \mathrm{E}[r^X - r^T] &= \mathrm{E}[w_b r_e] - \mathrm{E}[w_e r_b] \\ &= \mathrm{Cov}(w_b, r_e) + \mathrm{E}[w_b]\,\mathrm{E}[r_e] - \mathrm{Cov}(w_e, r_b) - \mathrm{E}[w_e]\,\mathrm{E}[r_b]. \end{aligned} \tag{9}$$

Generalizing Equation 9 to $K > 1$ countries is straightforward, and yields an expected return difference $\mathrm{E}[r^X - r^T]$ equal to

$$\sum_{k=1}^{K} \Big(\underbrace{\mathrm{Cov}(w_{bk}, r_{ek})}_{\substack{\text{Equity} \\ \text{Market Timing}}} + \underbrace{\mathrm{E}[w_{bk}]\,\mathrm{E}[r_{ek}]}_{\substack{\text{Equity} \\ \text{Risk Premium}}} - \underbrace{\mathrm{Cov}(w_{ek}, r_{bk})}_{\substack{\text{Bond} \\ \text{Market Timing}}} - \underbrace{\mathrm{E}[w_{ek}]\,\mathrm{E}[r_{bk}]}_{\substack{\text{Bond} \\ \text{Risk Premium}}} \Big), \tag{10}$$

where subscripts *bk* and *ek* refer to the bond and equity indices of country k.[3]

Equation 10 shows that the expected return difference between cross-asset time series momentum and time series momentum in month t is a sum of covariances between weights and returns, and of products of expected weights and expected returns. Following Goyal and Jegadeesh (2018), I refer to the covariances as the equity and bond market timing components, and to the products as the equity and bond risk premium components.

The effect the risk premium components have on the expected return difference is clear: since returns are positive on average, and since weights are determined by past returns, the equity component will add to the expected return difference while

[3]Equation 10 assumes that each country has data available in each month. In practice, data from different countries may cover different time periods, in which case the decomposition can be applied piecewise in the following way. First, partition the sample period in such a way that the number of countries with data available is constant within a subperiod. Next, perform the decomposition separately for each subperiod. Finally, combine the decompositions by taking their weighted sum, with the weight on a subperiod being the proportion of the total sample period covered by that subperiod.

the bond component will subtract from it. The effect of the market timing components, on the other hand, depends on how past returns covary with subsequent returns. In particular, if past bond returns did not predict future equity returns, and if past equity returns did not predict future bond returns—that is, if there was no cross-asset time series predictability in bond and equity markets—then both market timing components would be equal to zero. In reality, Pitkäjärvi, Suominen, and Vaittinen (2020) show that past bond returns are positive predictors of future equity returns, while past equity returns are negative predictors of future bond returns, so bond weights will covary positively with equity returns, while equity weights will covary negatively with bond returns. As a result, both market timing components will contribute positively to the expected return difference.

3.2 Empirical Results

The results of the decomposition for different lookback periods are presented in Table 2. With a lookback period of twelve months and a holding period of one month, the expected return difference between cross-asset time series momentum and time series momentum in the Pitkäjärvi, Suominen, and Vaittinen (2020) data set is 0.339% per month. Using Equation 10, this difference can be decomposed as

$$\underbrace{0.175\%}_{\substack{\text{Equity}\\\text{Market Timing}}} + \underbrace{0.115\%}_{\substack{\text{Equity}\\\text{Risk Premium}}} + \underbrace{0.067\%}_{\substack{\text{Bond}\\\text{Market Timing}}} - \underbrace{0.018\%}_{\substack{\text{Bond}\\\text{Risk Premium}}} = 0.339\%. \tag{11}$$

As expected, the equity market timing, equity risk premium, and bond market timing components are positive, while the bond risk premium component is negative. The main contributor to the expected return difference is the equity market timing component, which accounts for 52% of the difference. In total, the market timing components account for 71% of the difference.

For shorter lookback periods the importance of the market timing components is similar or even larger. For example, with a one-month lookback period the market timing components account for 79% of the expected return difference. Across all of the lookback periods, the market timing components account for 71–79% of the difference.

In summary, the risk premium components explain only a small minority of the expected return difference between cross-asset time series momentum and time series momentum. The time series momentum critique of Goyal and Jegadeesh (2018) is thus not applicable to cross-asset time series momentum.

4 The Time Series Predictability Critique

The results of the return decomposition may seem surprising in light of Huang, Li, Wang, and Zhou (2020), since their time series predictability regressions show little evidence of time series predictability at the individual asset level.[4] Partly motivated by this result, the authors also show that the average returns of time series momentum can be replicated with a "time series history" strategy that buys assets with positive historical mean returns and sells assets with negative historical mean returns. Since this strategy requires no conditional time series predictability, the fact that the difference in average returns between the two strategies is not significantly different from zero casts doubt on the view that time series momentum profitability is driven by the strategy's ability to exploit time series predictability in the returns of the underlying assets.[5]

If time series momentum profitability is not driven by time series predictability, then applying the same logic to cross-asset time series momentum would suggest the hypothesis that cross-asset time series momentum profitability is not driven by cross-asset time series predictability. In this section, I show that this hypothesis is false, because the evidence for cross-asset time series predictability is much stronger than the evidence for time series predictability, and because cross-asset time series momentum does in fact exploit this predictability.

[4] In their data set—which is comparable to the one used by Moskowitz, Ooi, and Pedersen (2012)—only three of the 55 assets generate coefficients significant at the 5% level when regressing an asset's future one-month return on its past twelve-month return.

[5] The idea that momentum strategies can be profitable even in the absence of time series predictability is, of course, not new—see, for example, Jegadeesh and Titman (1993, p. 72) and Lewellen (2002, p. 543).

4.1 Cross-Asset Time Series Predictability

To start, I extend the asset-level time series predictability regressions of Huang, Li, Wang, and Zhou (2020) to the cross-asset setting by adding a cross-asset predictor to the regressions. Specifically, in Tables 3 and 4 I report the results from the regressions

$$r_{b,t} = \alpha + \beta_e r_{e,t-12} + \beta_b r_{b,t-12} + \varepsilon_t \tag{12}$$

and

$$r_{e,t} = \alpha + \beta_e r_{e,t-12} + \beta_b r_{b,t-12} + \varepsilon_t, \tag{13}$$

where $r_{b,t}$ and $r_{e,t}$ are the excess returns of a given country's bond and equity indices in month t, and $r_{b,t-12}$ and $r_{e,t-12}$ are the excess cumulative returns of the same indices over the past twelve months. The regressions are performed separately for each country in the Pitkäjärvi, Suominen, and Vaittinen (2020) data set using local currency returns.[6] All t-statistics are based on Newey and West (1987) standard errors with VAR(1) prewhitening (Andrews and Monahan, 1992) and automatic lag selection (Newey and West, 1994).

From Table 3, we can see that the evidence for past bond returns predicting future bond returns at the individual asset level is indeed very weak, with only two of the twenty indices generating coefficients significant at the 5% level when controlling for the past equity returns of the same country. Similarly, from Table 4 we can see that none of the twenty equity indices generate significant coefficients when controlling for the past bond returns of the same country. The Huang, Li, Wang, and Zhou (2020) findings for time series predictability at the individual asset level are thus confirmed in the Pitkäjärvi, Suominen, and Vaittinen (2020) data set.

By contrast, from Table 3 we can see that past equity returns are negative predictors of future bond returns in all countries, with thirteen of the twenty coefficients significant at the 5% level. Similarly, from Table 4 we can see that past bond returns are positive predictors of future equity returns in all countries, with significant coefficients in

[6] The results are very similar if all of the returns are first converted into US dollars.

twelve of the twenty countries. The evidence for cross-asset time series predictability at the individual asset level is thus much stronger than the evidence for time series predictability.

4.2 Cross-Asset Time Series History

Of course, the mere existence of cross-asset time series predictability does not necessarily mean that cross-asset time series momentum profitability is driven by the strategy's ability to exploit the predictability. As with other momentum strategies, it could instead be the case that the cross-asset time series momentum trading rule causes the strategy to buy assets with high unconditional expected returns and sell assets with low unconditional expected returns, and thus generate a profit independent of any conditional predictability in lookback period returns. To rule out this possibility, I next extend the time series history strategy of Huang, Li, Wang, and Zhou (2020) to the cross-asset setting by defining a "cross-asset time series history" strategy.

As mentioned above, Huang, Li, Wang, and Zhou (2020) show that the average returns of time series momentum can be replicated with a time series history strategy that buys assets with positive historical mean returns and sells assets with negative historical mean returns. Specifically, whereas the return of time series momentum in month t is

$$r^{TSM} := \frac{1}{N} \sum_{i=1}^{N} \text{sgn}\{r_{i,t-12} - r_{f,t-12}\} r_i, \tag{14}$$

where $r_{i,t-12} - r_{f,t-12}$ denotes the excess cumulative return of asset i over the past twelve months, and r_i is the return of asset i in month t, the corresponding return of the time series history strategy is

$$r^{TSH} := \frac{1}{N} \sum_{i=1}^{N} \text{sgn}\{r_{i,1} - r_{f,1}\} r_i, \tag{15}$$

where $r_{i,1} - r_{f,1}$ denotes the excess cumulative return of asset i from the earliest month for which data is available to the beginning of month t. In other words, the only difference between the time series history and time series momentum strategies is the lookback period. In particular, the time series history strategy can be viewed as a time series momentum strategy with an expanding lookback period that starts from the beginning of the data set. In line with this view, I thus define the cross-asset time series history strategy in the same way—that is, as cross-asset time series momentum, but with an expanding lookback period that starts from the earliest month for which data is available.

In the Pitkäjärvi, Suominen, and Vaittinen (2020) data set, the average return difference between time series momentum and time series history is 0.094% per month (p-value: 0.466) and the difference in annualized Sharpe ratios is 0.16 (p-value: 0.549), which again confirms the Huang, Li, Wang, and Zhou (2020) finding that the average returns of time series momentum and time series history are not significantly different from each other. By contrast, the average return difference between cross-asset time series momentum and cross-asset time series history is 0.359% per month (p-value: 0.059) and the difference in annualized Sharpe ratios is 0.54 (p-value: 0.025), which is both economically and statistically significant.[7] The cross-asset time series history strategy, which does not exploit cross-asset time series predictability, is thus not able to replicate the performance of cross-asset time series momentum, which does.

In summary, both the cross-asset time series predictability regressions and the cross-asset time series history strategy support the return decomposition results, and show that the time series momentum critique of Huang, Li, Wang, and Zhou (2020) does not apply to cross-asset time series momentum.

5 Conclusion

In this paper, I decompose the expected return difference between cross-asset time series momentum and time series momentum into market timing and risk premium components, and show that market timing accounts for 71–79% of the return difference. I thus show that the time series momentum critiques of Goyal and Jegadeesh (2018) and

[7] The p-values for the Sharpe ratio differences are from the heteroskedasticity and autocorrelation consistent tests discussed in Ledoit and Wolf (2008).

Huang, Li, Wang, and Zhou (2020) do not apply to cross-asset time series momentum. Instead, the outperformance of cross-asset time series momentum is driven specifically by the strategy's ability to exploit cross-asset time series predictability in global bond and equity markets.

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Table 1: NetLong_t by Lookback Period.

Reported are the average NetLong_t of time series momentum and cross-asset time series momentum for one-, three-, six-, and twelve-month lookback periods. In each case the holding period is one month. NetLong_t is defined in Equation 1. The p-values are from Welch (1947) t-tests of the hypothesis that the difference in NetLong_t between cross-asset time series momentum and time series momentum equals zero. The data set consists of bond and equity index returns from twenty countries and covers the period from January 1980 to December 2016.

Lookback Period	TSMOM NetLong_t	XTSMOM NetLong_t	NetLong_t Difference	p-value
1	0.152	0.163	0.011	0.788
3	0.210	0.213	0.003	0.942
6	0.256	0.257	0.001	0.979
12	0.305	0.328	0.023	0.587

Table 2: Return Decomposition by Lookback Period.

Panel A reports the return decomposition results for one-, three-, six-, and twelve-month lookback periods. In each case the holding period is one month. The return difference is the average difference in monthly returns between cross-asset time series momentum and time series momentum. The return decomposition components are defined in Equation 10. Panel B reports the percentage of the return difference for a given lookback period contributed by each return decomposition component. The data set consists of bond and equity index returns from twenty countries and covers the period from January 1980 to December 2016.

Panel A: Return Decomposition Components

Lookback Period	Return Difference (%)	Equity Market Timing (%)	Equity Risk Premium (%)	Bond Market Timing (%)	Bond Risk Premium (%)
1	0.217	0.087	0.056	0.085	-0.010
3	0.196	0.077	0.073	0.062	-0.016
6	0.291	0.166	0.076	0.059	-0.010
12	0.339	0.175	0.115	0.067	-0.018

Panel B: Percentage of Return Difference

Lookback Period	Equity Market Timing (%)	Equity Risk Premium (%)	Bond Market Timing (%)	Bond Risk Premium (%)
1	39.79	25.94	39.08	-4.81
3	39.14	37.16	31.65	-7.96
6	57.06	26.22	20.26	-3.54
12	51.68	34.03	19.71	-5.43

Table 3: Bond Cross-Asset Time Series Predictability.

Reported are the results from the regression $r_{b,t} = \alpha + \beta_e r_{e,t-12} + \beta_b r_{b,t-12} + \varepsilon_t$, where $r_{b,t}$ is the excess return of a given country's bond index in month t, $r_{b,t-12}$ is the excess cumulative return of the same index over the past twelve months, and $r_{e,t-12}$ is the excess cumulative return of the same country's equity index over the past twelve months. The regression is performed separately for each country in the Pitkäjärvi, Suominen, and Vaittinen (2020) data set. All t-statistics are based on Newey and West (1987) standard errors with VAR(1) prewhitening (Andrews and Monahan, 1992) and automatic lag selection (Newey and West, 1994). The sample period is Jan-1980 to Dec-2016.

	Equity Index		Bond Index		
	β_e	t-stat	β_b	t-stat	Adj. R^2 (%)
Australia	-0.0130	-2.03	0.0074	0.56	2.10
Austria	-0.0048	-2.05	0.0062	0.50	1.39
Belgium	-0.0059	-2.98	0.0221	1.76	1.85
Canada	-0.0069	-1.78	-0.0099	-0.53	0.42
Denmark	-0.0063	-2.81	0.0052	0.46	1.72
Finland	-0.0032	-2.07	0.0104	0.62	1.48
France	-0.0072	-2.96	0.0145	1.24	2.77
Germany	-0.0051	-1.98	0.0074	0.55	1.47
Ireland	-0.0010	-0.28	0.0243	0.87	0.77
Italy	-0.0041	-1.25	0.0133	1.11	-0.12
Japan	-0.0030	-1.14	0.0206	0.92	1.02
Netherlands	-0.0052	-2.09	0.0199	1.60	2.00
New Zealand	-0.0138	-3.12	0.0163	1.31	4.79
Norway	-0.0037	-1.37	0.0103	0.77	0.42
Portugal	-0.0214	-2.14	0.0189	1.07	3.04
Spain	-0.0044	-1.49	0.0243	2.00	0.44
Sweden	-0.0030	-1.19	0.0086	0.74	0.17
Switzerland	-0.0058	-2.83	0.0215	2.32	2.87
UK	-0.0132	-2.57	0.0010	0.08	1.22
US	-0.0115	-2.52	0.0190	1.36	1.99
#(5% significant)	13		2		

Table 4: Equity Cross-Asset Time Series Predictability.

Reported are the results from the regression $r_{e,t} = \alpha + \beta_e r_{e,t-12} + \beta_b r_{b,t-12} + \varepsilon_t$, where $r_{e,t}$ is the excess return of a given country's equity index in month t, $r_{e,t-12}$ is the excess cumulative return of the same index over the past twelve months, and $r_{b,t-12}$ is the excess cumulative return of the same country's bond index over the past twelve months. The regression is performed separately for each country in the Pitkäjärvi, Suominen, and Vaittinen (2020) data set. All t-statistics are based on Newey and West (1987) standard errors with VAR(1) prewhitening (Andrews and Monahan, 1992) and automatic lag selection (Newey and West, 1994). The sample period is Jan-1980 to Dec-2016.

	Equity Index		Bond Index		
	β_e	t-stat	β_b	t-stat	Adj. R^2 (%)
Australia	-0.0031	-0.15	0.0471	1.34	-0.05
Austria	0.0185	0.72	0.2619	3.07	2.19
Belgium	0.0143	0.71	0.2447	4.24	4.25
Canada	0.0031	0.18	0.0370	0.64	-0.41
Denmark	0.0165	1.30	0.1804	3.77	2.77
Finland	0.0269	1.46	0.0908	0.82	1.83
France	0.0131	0.86	0.2359	3.26	3.45
Germany	0.0192	1.17	0.2081	2.47	1.40
Ireland	0.0347	1.46	0.0384	1.34	2.44
Italy	0.0088	0.49	0.0632	1.27	-0.01
Japan	0.0202	1.55	0.1897	2.66	1.67
Netherlands	0.0210	1.30	0.2287	4.21	3.39
New Zealand	0.0086	0.46	0.1160	2.47	1.09
Norway	0.0098	0.64	0.2018	3.28	1.98
Portugal	0.0096	0.51	0.0261	1.33	-0.26
Spain	-0.0015	-0.08	0.1248	2.23	0.95
Sweden	0.0116	0.76	0.0843	1.16	0.30
Switzerland	0.0194	1.74	0.1360	2.91	1.63
UK	-0.0158	-0.81	0.0306	0.99	-0.04
US	0.0059	0.32	0.0837	2.35	0.98
#(5% significant)	0		12		