Monetary Policy and Factor Premia: A Potential Feedback Loop

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Abstract

Existing literature studies the impact of monetary policy on factor premia; however, the potential bidirectional relationship between factor premia across asset classes and monetary policy stance is unstudied. This potential relationship can help better understand the feedback effects, especially within the financial system. Currently, no dataset has the necessary granularity and comprehensiveness to study such feedback effects, especially from the perspective of factor premia. To satisfy this gap, this study constructs a novel dataset and conducts preliminary statistical analysis, creating the foundation for future, more rigorous investigation of the potential relationship of factor premia on monetary policy. The findings of this study hint at the potential correlation between the factors and monetary policy stance, encouraging further investigation regarding the causal relationship between these two variables. This study is novel since it sets the robust empirical framework necessary to understand the complex feedback mechanisms in the financial market.

[1] https://github.com/mbek-128/Monetary-Policy-and-Factor-Premia-A-Potential-Feedback-Loop.git

Literature commonly studies the effect of monetary policy on factor premia. This effect occurs through different transmission mechanisms. Through the Liquidity Channel, expansion monetary policy increases liquidity, which decreases risk premium and increases asset prices across different asset classes with a greater effect on riskier assets and assets with longer maturities) (Rudebusch & Swanson, 2021). Another channel is the Investment Channel where expansionary monetary policy helps increase investment through lower interest rates, especially in the capital-intensive industries (Gali & Rabanal, 2005). The Risk-Shifting Channel is an alternative transmission channel. It captures the wealth distribution among households with high risk tolerance under expansionary monetary policy. As a result of such a redistribution, risk premia across factors decreases (Asavov, 2010). Another possible channel is the Expectations Channel: expected future interest rates and inflation impact discount rates and risk assessment, which, by extension, impacts premia across factors (Bernanke, 1999; Cochrane, 2004; Mishkin, 2007).

Little to no literature, however, considers the potential bidirectional relationship between monetary policy and factor premia. This study will attempt to test such a potential because the quantitative effect of factor premia across asset classes on the stance of monetary policy is unclear. Specifically, this study will test the possibility of feedback loop where the effect of factor premia is so strong that it impacts the degree of monetary policy.

One of the potential feedback loops is market expectations. Investor expectations regarding future monetary policy can help shape factor premia behavior. For example, if investors have expansionary monetary policy expectations, risk-taking behavior may increase, and momentum stocks increase. This dynamic can then affect economic activity and inflation, helping shape monetary policy.

Another possible feedback loop can be financial stability. Large variability in factor premia can increase financial stability risks. An example includes increase in margin calls and liquidity issues when an economic downturn impacts carry-related asset. In response, if such a financial stability risk is systematic, the Fed can adjust their monetary policy.

Policy adjustments can be another feedback loop. If the Fed witnesses persistent weakness in specific factors, the Fed can implement monetary policy easing to boost economic growth. This concern is especially relevant because the financial market has grown in complexity recently. This growth can have a more pronounced impact on the economy, including inflation and unemployment. In other words, the financial market may be increasingly affecting the Fed's commitment to its dual mandate.

This study investigates the potential for feedback loops between factor premia (value, momentum, carry, and defensive) and monetary policy stance, first testing their individual existence. The key contribution is a novel monthly dataset merging Ilmanen (2021)'s factor premia data with Cooper (2020)'s monetary policy measure across a century and six asset classes (US stock, international stocks, commodities, equity indices, fixed income, and currencies). Initial evidence from preliminary analyses suggests promise in further exploration of this relationship.

Data

1. Factor Premia
    a. Data Description

Factor premia is obtained from the dataset provided by Ilmanen (2023). They provide monthly data on factor premia – value, momentum, carry, and defensive – over a century from six asset classes – US stock, international stocks, commodities, equity indices, fixed income, and currencies – from 1926-07-03 until 2023-10-31 on a monthly and quarterly basis. The dataset included the following columns: 'US Stock Selection Value', 'US Stock Selection Momentum', 'US Stock Selection Defensive', 'US Stock Selection Multi-style', 'Intl Stock Selection

Value', 'Intl Stock Selection Momentum', 'Intl Stock Selection Defensive', 'Intl Stock Selection Multi-style', 'Equity indices Value', 'Equity indices Momentum', 'Equity indices Carry', 'Equity indices Defensive', 'Equity indices Multi-style', 'Fixed income Value', 'Fixed income Momentum', 'Fixed income Carry', 'Fixed income Defensive', 'Fixed income Multi-style', 'Currencies Value', 'Currencies Momentum', 'Currencies Carry', 'Currencies Multi-style', 'Commodities Value', 'Commodities Momentum', 'Commodities Carry', 'Commodities Multi-style', 'All Stock Selection Value', 'All Stock Selection Momentum', 'All Stock Selection Defensive', 'All Stock Selection Multi-style', 'All Macro Value', 'All Macro Momentum', 'All Macro Carry', 'All Macro Defensive', 'All Macro Multi-style', 'All asset classes Value', 'All asset classes Momentum', 'All asset classes Carry', 'All asset classes Defensive', 'All asset classes Multi-style', 'Equity indices Market', 'Fixed income Market', 'Commodities Market', and 'All Macro Market.' This dataset is suitable for the current research goal because it is a comprehensive, novel dataset that captures factor premia across different asset classes. With the dimension of asset class, the potential feedback loop of factor premia on monetary policy stance can be better understood since factor premia differ based on asset class. Also, the asset class component provides dimensionality to the study of the current research question. Most importantly, this dataset from Ilmanen (2023) helps provide the necessary and timely independent variables, which without them, the current research question would be unanswerable.

b. Factor Definitions

As defined by Ilmanen (2023), the four factors have the following definitions:

- **Value:** the value of securities in comparison to the fundamentals of the respective asset class. This factor usually has descriptors such as "cheap" or "expensive," depending on factors such as risk or mispricing.
- **Momentum:** the "past 12-month cumulative excess-of-cash return on an asset, following Jegadeesh and Titman (1993)."
- **Carry:** the expected return of securities under the assumption that market conditions are constant, and that security is held over that time.
- **Defensive:** factor determined by the beta of the security relative to its local market index.

c. Data Cleaning

Originally, the dataset was not suitable for the goal of analyzing and merging it. Firstly, the dataset had description in the first few rows, no values. As a result, the original dataset had to be filtered such that only the values of the variables – rather than the details of the source. Secondly, the data type of the values of the variables was "object." So, numerical operations – especially regression analysis – cannot be conducted. Also, when merging, the dates in "datetime" format could process seamlessly in contrast if the dates had a data type of "object." Due to these inconsistencies, data cleaning steps included the following: deleting irrelevant rows to have a dataset of the relevant columns and their values only and converting the "object" data type to "float" data type for numerical values and "datetime" for dates. To make the data understandable, the column with dates was renamed from NaN to "Date." These data cleaning steps are necessary for merging because without filtering information, merging will produce a useless dataset with noisy and irrelevant information. Moreover, without contextually correct data types, merging may not happen or may result in data that cannot be used (regression analysis – thus, the potential relationship between monetary policy stance and factor premia across asset classes – cannot be made on "object" data type, for example).

2. Monetary Policy Stance

Cooper (2020) from the Federal Reserve Bank of Boston measure monetary policy stance using the following formula:

$$MP_t = FF_t - FF_t^* = FF_t - (RFF_t^* + 10YIE)$$

where MP_t is the stance of monetary policy, FF_t is the federal funds rate obtained from the Federal Reserve of St. Louis (2023), and FF_t^* is the estimate of the (nominal) neutral rate. Cooper (2020) set FF_t^* as the sum of RFF_t^* or neutral real interest rate from the Federal Reserve of New York (2023) (the Laubach and Williams neutral real rate of interest) and $10YIE$ (the Hoey-Philadelphia Fed Survey of Professional Forecasters (SPF) 10-year inflation expectations, as reported in the FRB/US data set) from the Federal Reserve Board (2023). Each of these datasets are necessary for the goal of studying the potential feedback loop of factor premia on monetary policy because the datasets in Section (2) of Data are all of the components of the best estimate of the monetary policy stance of the Federal Reserve. Without these datasets, no dependent variable would exist.

a. The Federal Funds Rate dataset from Federal Reserve of St. Louis (2023)

This dataset had monthly data from 1954-07-01 until 2023-11-01 in percent. It had the correct data type of "float." This choice ensures flexibility for representing all variables in the dataset, capturing the decimal precision for accurate statistical analysis and showing the possible nuanced relationships between variables.

b. The Neutral Real Interest Rate dataset from the Federal Reserve of New York (2023)

The Neutral Real Interest Rate dataset from the Federal Reserve of New York (2023) has a quarterly frequency from 1961-01-01 until 2023-07-01. This quarterly frequency challenges the monthly frequency provided by Ilmanen (2020) and the Federal Funds Rate dataset from Federal Reserve of St. Louis (2023). Since a monthly frequency can provide greater granularity in the potential feedback loop from factor premia on monetary policy stance, monthly frequency is the standard timing frequency. As a result, I converted quarterly data to monthly data when merging this dataset with the Federal Funds Rate dataset from Federal Reserve of St. Louis (2023). I merged the two datasets using only keys from the left frame (the Federal Funds Rate dataset) and then used forward fill, assuming that the neutral real interest rate is constant for each quarter. This assumption is fair since the neutral real interest rate is not a volatile metric. Standardizing timing and dates through this data cleaning step helps ensure seamless merging – especially since the datasets area merged on the columns for dates – and enhances the validity of subsequent analyses.

The data type of this dataset was "float," preserving the assigned data type for numerical values. That way, this study and future research can leverage the flexibility of this data type and conduct statistical analysis to reveal the relationship between the variables in the dataset introduced by this study. Although the dataset had a quarterly frequency originally, the dates were in year-month-day format. Thus, the format of the date did not have to change.

c. The Hoey-Philadelphia Fed Survey of Professional Forecasters (SPF) 10-year inflation expectations, as reported in the FRB/US data set) from the Federal Reserve Board (2023)

The Hoey-Philadelphia Fed Survey of Professional Forecasters (SPF) 10-year inflation expectations, as reported in the FRB/US data set) from the Federal Reserve Board (2023) has quarterly frequency from Q1 of 1994 until Q4 of 2023. In addition, this dataset had two columns – "YEAR" and "QUARTER" – to represent dates. For this reason, data cleaning consisted of creating one column "Date" to capture both of the "YEAR" and "QUARTER" columns. Also, unlike the Neutral Real Interest Rate dataset, the Hoey-Philadelphia Fed Survey of Professional Forecasters (SPF) 10-year inflation expectations had dates in year-quarter format. Thus, one of the data cleaning steps included transforming the quarter element into month-date format. That way, the dataset would have a consistent date format, helping ensure a seamless merging process. Similarly, to the Neutral Real Interest Rate dataset, forward fill helped repeat the 10-year inflation expectations over the respective quarters. The assumption that 10-year inflation expectations are constant for each quarter is again reasonable since 10-year inflation expectations are not as volatile as the shorter-term inflation expectations.

At the same time, when converting quarterly to monthly frequency, the dates assumed a "datetime" format. The values of the variables already were "float." With such consistent data types, merging can happen.

d. Computing Monetary Policy Stance

When merging, the time frame was set from Q4 of 1991 because that was the earliest date for the Hoey-Philadelphia Fed Survey of Professional Forecasters (SPF) 10-year inflation expectations, as reported in the FRB/US data set) from the Federal Reserve Board (2023). Merging datasets helped standardize the frequency of the dates from quarterly to monthly frequency, as described in Sections 2 (b) and (c). Overall, merging helped calculate the monetary policy stance, according to the methodology set by Cooper (2020).

To verify the accuracy of the merging and computation, Figure 1 shows the monetary policy stance from years October of 1991 until November 2023. Figure 1 is very similar to Figure 2, which is the monetary policy stance published by Cooper (2020), proving that the data is in a suitable state, given its accuracy.

3. Merging Independent and Dependent Variables

After the data cleaning steps, both datasets of the independent and dependent variables have monthly frequency. However, both datasets have different days: independent variables dataset takes the last day of each month, while dependent variable dataset takes the first day of each month. Given this inconsistency, I converted the dates of both datasets to have a month-year format. Also, I ensure that the dates have both "datetime" format to ensure that their merging is seamless. After such a data cleaning step, the dataset was ready for regression analysis because all of the quantitative variables had a "float" datatype. To further ensure that the merged dataset was ready for regression analysis, I captured the descriptive data of the novel dataset, which can be seen in Table 1. It has no empty values. Instead, each variable has values for each summary statistic and are economically reasonable. With the necessary variables to study the relationship between factor premia and the monetary policy stance and having these variables fit for regression analysis to study such a relationship, the merged dataset was successfully employed for the subsequent analysis.

Analysis

To test the usefulness of such a dataset, preliminary statistical analysis was conducted. To leverage the asset class dimensionality in terms of factor premia, this research study decided to explore the potential feedback loop of factor premia across different asset classes on monetary policy. Meaning, 'US Stock Selection Value', 'US Stock Selection Momentum', 'US Stock Selection Defensive', 'US Stock Selection Multi-style', 'Intl Stock Selection Value', 'Intl Stock Selection Momentum', 'Intl Stock Selection Defensive', 'Intl Stock Selection Multi-style', 'Equity indices Value', 'Equity indices Momentum', 'Equity indices Carry', 'Equity indices Defensive', 'Equity indices Multi-style', 'Fixed income Value', 'Fixed income Momentum', 'Fixed income Carry', 'Fixed income Defensive', 'Fixed income Multi-style', 'Currencies Value', 'Currencies Momentum', 'Currencies Carry', 'Currencies Multi-style', 'Commodities Value', 'Commodities Momentum', 'Commodities Carry', and 'Commodities Multi-style' were included. At the same time, the variables – 'All Stock Selection Value', 'All Stock Selection Momentum', 'All Stock Selection Defensive', 'All Stock Selection Multi-style', 'All Macro Value', 'All Macro Momentum', 'All Macro Carry', 'All Macro Defensive', 'All Macro Multi-style', 'All asset classes Value', 'All asset classes Momentum', 'All asset classes Carry', 'All asset classes Defensive', 'All asset classes Multi-style', 'Equity indices Market', 'Fixed income Market', 'Commodities Market', and 'All Macro Market' – were excluded. The reason is that the inclusion of the excluded variables must have high multicollinearity with the ones included in the current model using economic reasoning. For example, "Currencies Value" as an independent variable must have high multicollinearity with "All Macro Value" since "Currencies Value" should be a subcomponent of "All Macro Value." The provided dataset from this research project will include all of the variables; however, to test the utility of the current dataset, a question in terms of factor premia across different asset classes was posed: a subtopic under the overall goal of the dataset, which is to study the potential feedback loop of factor premia on monetary policy stance. As a result, to test the usefulness of the dataset, this study tackles a subcomponent of the overarching goal of this study, filtering the dataset to the most relevant variables.

OLS regression set R^2 of 7.8% and adjusted R^2 of 0.11% (Table 2). These values did not change with stepwise regression (Table 3). Meaning, OLS regression explains a relatively small proportion of the variance in the dependent variable. Also, the inclusion or exclusion of features through stepwise regression does not help improve the explanatory power. As a result, these models may not help capture the potential feedback loop of factor premia on monetary policy.

Given such results, perhaps, factor premia as lagged variables specific to the asset classes may help explain monetary policy stance. This logic has economic reasoning because factor premia effects may not immediately result in policy adjustments. Also, due to the nature of forward guidance, gradual policy shifts are necessary to avoid market shocks. Most importantly, to answer the research question, a dataset with the independent variables at their most best lags can help disentangle the complex relationship between factor premia and monetary policy stance, addressing endogeneity concerns.

To find the best lag number for each independent variable, I conducted the Granger causality test for each independent variable in terms of the dependent variable as a single variable regression model. Then, the lag number that yielded the lowest p-value was determined as the "Best Lag" (Table 4). With such an approach, another novel dataset was formed.

With this dataset of lagged independent variables, R^2 improved from 7.8% to 9.5% and adjusted R^2 increased from 0.11% to 0.27% in an OLS regression. Despite the improvements, they are marginal. Stepwise regression proved to benefit the most from the lagged features. R^2 increased from 7.8% to 26.6% and adjusted R^2 increased from 0.11% to 21.1% (Table 6). These large improvements suggest that the lagged features most likely have valuable information, reflecting the potential delayed impact of factor premia on monetary policy stance. However, the large increase of R^2 through stepwise regression needed greater scrutiny.

I studied some of the potential reasons for such a large improvement. One of the reasons being the multicollinearity among the lagged independent variables. As a result, as seen in Table 7, I examined the Variance Inflation Factor (VIF) for each independent variable, finding that all of them had a value less than 5. Most had a range from 1 to 2.5, proving little to no multicollinearity. Based on these results, I considered overfitting by increasing the number of folds in stepwise regression. After increasing from 0 (Table 6) to 5 folds, R^2 decreased from its vast improvement of 26.6% to 19.5% and adjusted R^2, from 21.1% to 15.4% (Table 7). Although the values decreased, they remain significantly higher relative to the models considering non-lagged independent variables. For this reason, lagged independent variables may be helpful in understanding the dynamic relationship between factor premia and monetary policy decisions since when controlling for multicollinearity and overfitting, lagged independent variables helped explain moentary policy stance to a greater degree.

Limitations and Future Research

To provide flexibility for future research, this study included variables important to conduct regression analysis to examine the potential feedback loop of factor premia on monetary policy stance. The current statistical analysis was preliminary. It did not study the causal relationship of both of the variables, nor did the study robustly examine the potential of OLS regression to capture such an effect. Nonlinear relationships may exist between the variables. Additionally, the effect may vary across time and across asset classes, calling for the potential use of the novel dataset as panel data and using panel data methodologies. Although with the novel dataset lagged variables seem important, a more robust statistical and economic analysis is necessary to fully understand their role in the potential bidirectional between factor premia and monetary policy stance. For this reason, this study will not provide the independent variables at their "Best Lag" in the novel dataset.

Conclusion

The current preliminary analysis suggests a potentially novel bidirectional relationship between monetary policy and lagged factor premia – value, momentum, carry, and defensive –from six asset classes – US stock, international stocks, commodities, equity indices, fixed income, and currencies – from 1991 until 2023. Introducing lagged effects of factor premia on monetary policy led to a significant 11% increase in R-squared, hinting at potential significant relationship of factor premia on monetary policy. While further investigation is needed, this initial finding underscores the potential benefits of employing our novel dataset to shed new light on this intricate relationship.

References

Asavov, A. (2010). “A Model of Monetary Policy and Risk Premia.” *The American Economic Review*, 100(4), 1106-1149.

Bernanke, Ben S. "Asset prices and monetary policy." *The Federal Reserve Bank of St. Louis Review*, 81.11 (1999): 1-45.

Cochrane, John H. "Discount rates and asset prices." *The Review of Financial Studies*, 17.4 (2004): 1079-1129.

Cooper, Daniel H., et al. (2020). “Predicting Recessions Using the Yield Curve: The Role of the Stance of Monetary Policy.” *Federal Reserve Bank of Boston*, https://www.bostonfed.org/publications/current-policy-perspectives/2020/predicting-recessions-using-the-yield-curve.aspx#ftn8.

Gali, J., & Rabanal, P. (2005). “How Do Monetary Policy Rules Affect Term Premia?” *Journal of Monetary Economics*, 52(4), 619-655.

Ilmanen, Antti, et al. (2019). “How Do Factor Premia Vary Over Time? A Century of Evidence.” *Journal of Investment Management*, 19(4), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3400998.

Jegadeesh, N. and Titman, S. (1993). “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency,” *Journal of Finance* 48, 65–91.

Mishkin, Frederic S. The economics of money and banking. *Pearson Addison Wesley*, 2007.

Rudebusch, G. D., & Swanson, E. T. (2021). “Monetary Policy, Bond Risk Premia, and the Economy.” *Journal of Economic Perspectives*, 35(3), 83-114.

Federal Reserve Bank of Philadelphia. (2023). “Survey of Professional Forecasters.” https://www.philadelphiafed.org/surveys-and-data/real-time-data-research.

Federal Reserve Bank of St. Louis. (2023). Federal Funds Rate [FEDFUNDS]. FRED, *Federal Reserve Bank of St. Louis*. https://fred.stlouisfed.org/series/FEDFUNDS.

Federal Reserve Bank of New York. (2023). “Measuring the Natural Rate of Interest.” https://www.newyorkfed.org/markets/data-hub.

Appendix

Figure 1. The Stance of Monetary Policy Computed Using Methodology from Cooper (2020) Using Data Collected from Federal Reserve of St. Louis (2023), Federal Reserve of New York (2023), and Federal Reserve Board (2023)

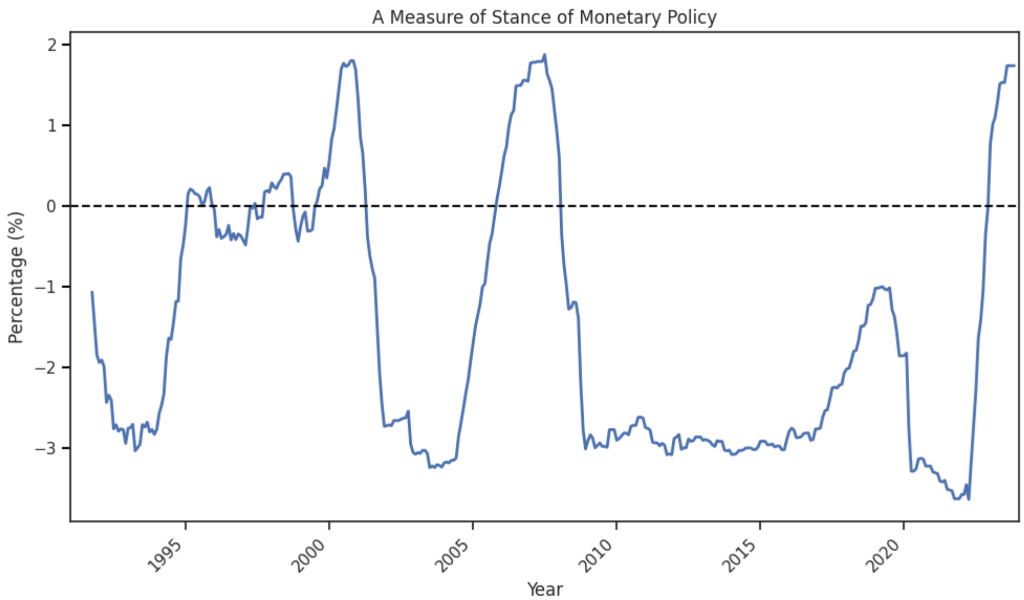

Figure 2. The Term Spread and the Stance of Monetary Policy from 1965m1 to 2020m1 Presented by Cooper (2020).

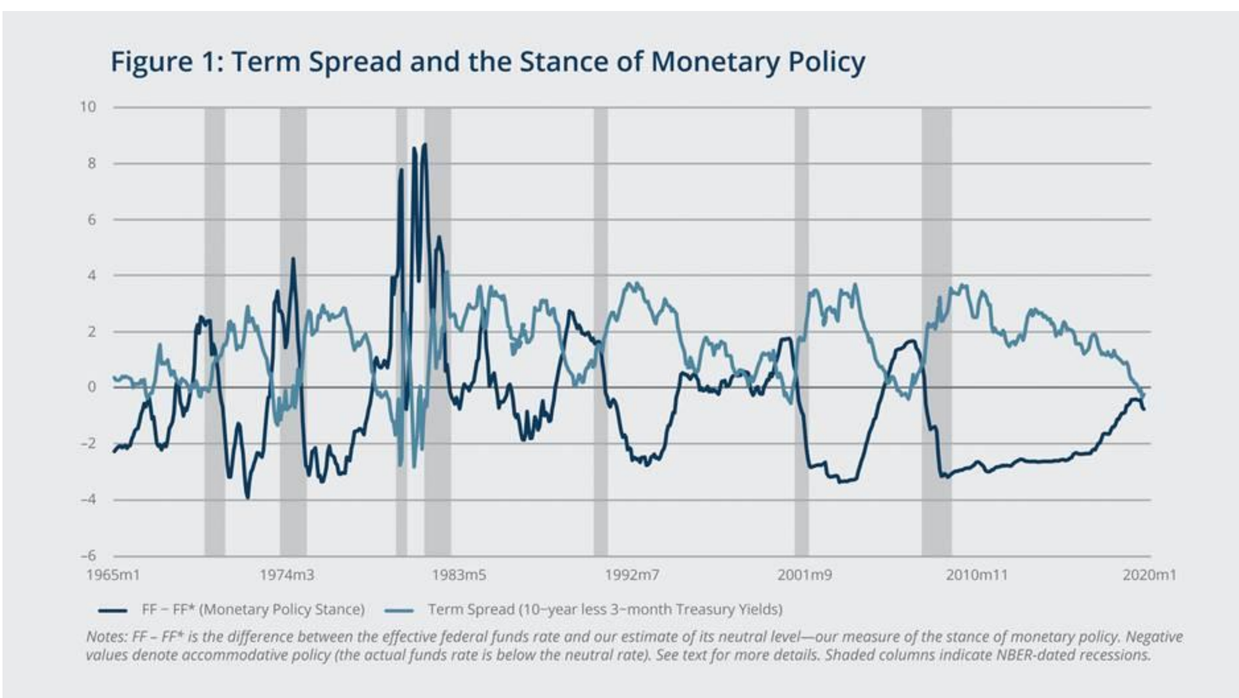

Table 1. Descriptive Statistics of the Novel Dataset with Monetary Policy Stancy Calculated Using Methodology from Cooper (2020) as the Dependent Variable and Factor Premia – Value, Momentum, Carry, And Defensive – Over A Century from Six Asset Classes – US Stock, International Stocks, Commodities, Equity Indices, Fixed Income, And Currencies – from Ilmanen (2023) as the Independent Variables.

	count	mean	std	min	25%	50%	75%	max
MPSTANCE	385.0	-1.575847	1.609479	-3.632442	-2.913888	-2.317276	-0.251730	1.879327
US Stock Selection Value	385.0	0.001869	0.039640	-0.179909	-0.018197	-0.000963	0.018828	0.268644
US Stock Selection Momentum	385.0	0.004968	0.047369	-0.345550	-0.012514	0.007462	0.027808	0.170105
US Stock Selection Defensive	385.0	0.007767	0.038074	-0.156752	-0.007443	0.009025	0.024081	0.153617
US Stock Selection Multi-style	385.0	0.004868	0.021195	-0.093900	-0.004280	0.004318	0.013947	0.129638
Intl Stock Selection Value	385.0	0.004368	0.026673	-0.153945	-0.008786	0.003903	0.016051	0.150568
Intl Stock Selection Momentum	385.0	0.007834	0.034701	-0.235631	-0.007102	0.011658	0.023497	0.110266
Intl Stock Selection Defensive	385.0	0.008581	0.026150	-0.077346	-0.006726	0.007949	0.023646	0.116790
Intl Stock Selection Multi-style	385.0	0.006928	0.014497	-0.051151	-0.000142	0.007141	0.013814	0.079515
Equity indices Value	385.0	0.000693	0.024067	-0.077782	-0.014109	0.000638	0.014426	0.115582
Equity indices Momentum	385.0	0.003358	0.029498	-0.104106	-0.013823	0.002883	0.019123	0.093560
Equity indices Carry	385.0	0.000986	0.027347	-0.111908	-0.014183	0.000304	0.015608	0.108947
Equity indices Defensive	385.0	0.000942	0.023137	-0.075392	-0.012116	0.001208	0.016537	0.064739
Equity indices Multi-style	385.0	0.001495	0.012651	-0.051622	-0.005211	0.001333	0.008088	0.041562
Fixed income Value	385.0	0.000889	0.010636	-0.058048	-0.003806	0.000497	0.005518	0.054971
Fixed income Momentum	385.0	0.000451	0.011579	-0.037861	-0.005742	0.000729	0.006778	0.061359
Fixed income Carry	385.0	0.001067	0.011342	-0.072643	-0.004240	0.001513	0.006902	0.049742
Fixed income Defensive	385.0	0.000055	0.009046	-0.038571	-0.004520	0.000233	0.005408	0.040497
Fixed income Multi-style	385.0	0.000616	0.004784	-0.023786	-0.001438	0.000561	0.002980	0.020605
Currencies Value	385.0	0.002645	0.016655	-0.052978	-0.007505	0.002455	0.012753	0.058280
Currencies Momentum	385.0	0.000544	0.019433	-0.072587	-0.011533	0.002590	0.013477	0.046543
Currencies Carry	385.0	0.002412	0.021488	-0.105273	-0.008250	0.003632	0.016653	0.091580
Currencies Multi-style	385.0	0.001867	0.011997	-0.043489	-0.004529	0.002413	0.008708	0.033029
Commodities Value	385.0	0.005986	0.057086	-0.184889	-0.030503	0.005875	0.046623	0.239637
Commodities Momentum	385.0	0.003090	0.055873	-0.232763	-0.030457	0.007145	0.035488	0.195606
Commodities Carry	385.0	0.007711	0.045573	-0.171286	-0.016506	0.007756	0.033609	0.173386
Commodities Multi-style	385.0	0.005596	0.025587	-0.115345	-0.008203	0.005113	0.020475	0.088961
All Stock Selection Value	385.0	0.003333	0.029352	-0.166350	-0.012287	0.002044	0.016062	0.180447
All Stock Selection Momentum	385.0	0.006779	0.037970	-0.279422	-0.008268	0.009618	0.024399	0.139087
All Stock Selection Defensive	385.0	0.008294	0.026183	-0.076559	-0.003801	0.009166	0.020698	0.118442
All Stock Selection Multi-style	385.0	0.006153	0.015460	-0.051469	-0.000914	0.005994	0.013183	0.095662
All Macro Value	385.0	0.001557	0.009272	-0.026298	-0.004373	0.001470	0.007738	0.030325
All Macro Momentum	385.0	0.001255	0.012169	-0.034831	-0.005971	0.001696	0.008793	0.036735
All Macro Carry	385.0	0.001911	0.010220	-0.036677	-0.003601	0.002361	0.008116	0.034910
All Macro Defensive	385.0	0.000262	0.008301	-0.033972	-0.004494	0.000227	0.005449	0.038059
All Macro Multi-style	385.0	0.001380	0.004842	-0.014812	-0.001441	0.001557	0.004447	0.019146
All asset classes Value	385.0	0.001511	0.010596	-0.039657	-0.004750	0.001630	0.008264	0.068825
All asset classes Momentum	385.0	0.002612	0.014692	-0.079745	-0.004883	0.003314	0.011623	0.048754
All asset classes Carry	385.0	0.001911	0.010220	-0.036677	-0.003601	0.002361	0.008116	0.034910
All asset classes Defensive	385.0	0.002816	0.010148	-0.039723	-0.002604	0.003305	0.008999	0.031458
All asset classes Multi-style	385.0	0.002364	0.004948	-0.013400	-0.000471	0.002580	0.005420	0.020796
Equity indices Market	385.0	0.005483	0.041825	-0.172081	-0.019026	0.010869	0.031828	0.138181
Fixed income Market	385.0	0.002306	0.013788	-0.044218	-0.005989	0.003312	0.010752	0.047022
Commodities Market	385.0	0.002825	0.038678	-0.209366	-0.017449	0.004715	0.025008	0.134221
All Macro Market	385.0	0.002239	0.013660	-0.063719	-0.006018	0.003560	0.011151	0.036209

Table 2. OLS Regression

OLS Regression Results

Dep. Variable:	MPSTANCE	R-squared:	0.078
Model:	OLS	Adj. R-squared:	0.011
Method:	Least Squares	F-statistic:	1.158
Date:	Thu, 21 Dec 2023	Prob (F-statistic):	0.273
Time:	03:55:26	Log-Likelihood:	-713.47
No. Observations:	385	AIC:	1481.
Df Residuals:	358	BIC:	1588.
Df Model:	26		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.5038	0.100	-15.025	0.000	-1.701	-1.307
US Stock Selection Value	-6.752e+11	6.73e+11	-1.004	0.316	-2e+12	6.48e+11
US Stock Selection Momentum	-6.752e+11	6.73e+11	-1.004	0.316	-2e+12	6.48e+11
US Stock Selection Defensive	-6.752e+11	6.73e+11	-1.004	0.316	-2e+12	6.48e+11
US Stock Selection Multi-style	2.026e+12	2.02e+12	1.004	0.316	-1.94e+12	5.99e+12
Intl Stock Selection Value	4.84e+11	9.35e+11	0.518	0.605	-1.35e+12	2.32e+12
Intl Stock Selection Momentum	4.84e+11	9.35e+11	0.518	0.605	-1.35e+12	2.32e+12
Intl Stock Selection Defensive	4.84e+11	9.35e+11	0.518	0.605	-1.35e+12	2.32e+12
Intl Stock Selection Multi-style	-1.452e+12	2.8e+12	-0.518	0.605	-6.97e+12	4.06e+12
Equity indices Value	-1.946e+12	1.02e+12	-1.917	0.056	-3.94e+12	5.04e+10
Equity indices Momentum	-1.946e+12	1.02e+12	-1.917	0.056	-3.94e+12	5.04e+10
Equity indices Carry	-1.946e+12	1.02e+12	-1.917	0.056	-3.94e+12	5.04e+10
Equity indices Defensive	-1.946e+12	1.02e+12	-1.917	0.056	-3.94e+12	5.04e+10
Equity indices Multi-style	7.783e+12	4.06e+12	1.917	0.056	-2.01e+11	1.58e+13
Fixed income Value	-3.068e+12	2.38e+12	-1.287	0.199	-7.76e+12	1.62e+12
Fixed income Momentum	-3.068e+12	2.38e+12	-1.287	0.199	-7.76e+12	1.62e+12
Fixed income Carry	-3.068e+12	2.38e+12	-1.287	0.199	-7.76e+12	1.62e+12
Fixed income Defensive	-3.068e+12	2.38e+12	-1.287	0.199	-7.76e+12	1.62e+12
Fixed income Multi-style	1.227e+13	9.54e+12	1.287	0.199	-6.48e+12	3.1e+13
Currencies Value	9.493e+11	1.19e+12	0.800	0.424	-1.38e+12	3.28e+12
Currencies Momentum	9.493e+11	1.19e+12	0.800	0.424	-1.38e+12	3.28e+12
Currencies Carry	9.493e+11	1.19e+12	0.800	0.424	-1.38e+12	3.28e+12
Currencies Multi-style	-2.848e+12	3.56e+12	-0.800	0.424	-9.84e+12	4.15e+12
Commodities Value	-7.946e+11	5.12e+11	-1.551	0.122	-1.8e+12	2.13e+11
Commodities Momentum	-7.946e+11	5.12e+11	-1.551	0.122	-1.8e+12	2.13e+11
Commodities Carry	-7.946e+11	5.12e+11	-1.551	0.122	-1.8e+12	2.13e+11
Commodities Multi-style	2.384e+12	1.54e+12	1.551	0.122	-6.4e+11	5.41e+12

Omnibus:	36.770	Durbin-Watson:	0.166
Prob(Omnibus):	0.000	Jarque-Bera (JB):	37.085
Skew:	0.705	Prob(JB):	8.85e-09
Kurtosis:	2.433	Cond. No.	1.31e+14

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.25e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Table 3. Stepwise Regression

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               MPSTANCE   R-squared:                       0.078
Model:                            OLS   Adj. R-squared:                  0.011
Method:                 Least Squares   F-statistic:                     1.158
Date:                Thu, 21 Dec 2023   Prob (F-statistic):              0.273
Time:                        03:55:27   Log-Likelihood:                -713.47
No. Observations:                 385   AIC:                             1481.
Df Residuals:                     358   BIC:                             1588.
Df Model:                          26
Covariance Type:            nonrobust
======================================================================================================
                                      coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------------
const                              -1.5038      0.100    -15.025      0.000      -1.701      -1.307
US Stock Selection Value        -6.752e+11   6.73e+11     -1.004      0.316       -2e+12    6.48e+11
US Stock Selection Momentum     -6.752e+11   6.73e+11     -1.004      0.316       -2e+12    6.48e+11
US Stock Selection Defensive    -6.752e+11   6.73e+11     -1.004      0.316       -2e+12    6.48e+11
US Stock Selection Multi-style   2.026e+12   2.02e+12      1.004      0.316   -1.94e+12    5.99e+12
Intl Stock Selection Value        4.84e+11   9.35e+11      0.518      0.605   -1.35e+12    2.32e+12
Intl Stock Selection Momentum     4.84e+11   9.35e+11      0.518      0.605   -1.35e+12    2.32e+12
Intl Stock Selection Defensive    4.84e+11   9.35e+11      0.518      0.605   -1.35e+12    2.32e+12
Intl Stock Selection Multi-style -1.452e+12    2.8e+12     -0.518      0.605   -6.97e+12    4.06e+12
Equity indices Value            -1.946e+12   1.02e+12     -1.917      0.056   -3.94e+12    5.04e+10
Equity indices Momentum         -1.946e+12   1.02e+12     -1.917      0.056   -3.94e+12    5.04e+10
Equity indices Carry            -1.946e+12   1.02e+12     -1.917      0.056   -3.94e+12    5.04e+10
Equity indices Defensive        -1.946e+12   1.02e+12     -1.917      0.056   -3.94e+12    5.04e+10
Equity indices Multi-style       7.783e+12   4.06e+12      1.917      0.056   -2.01e+11    1.58e+13
Fixed income Value              -3.068e+12   2.38e+12     -1.287      0.199   -7.76e+12    1.62e+12
Fixed income Momentum           -3.068e+12   2.38e+12     -1.287      0.199   -7.76e+12    1.62e+12
Fixed income Carry              -3.068e+12   2.38e+12     -1.287      0.199   -7.76e+12    1.62e+12
Fixed income Defensive          -3.068e+12   2.38e+12     -1.287      0.199   -7.76e+12    1.62e+12
Fixed income Multi-style         1.227e+13   9.54e+12      1.287      0.199   -6.48e+12     3.1e+13
Currencies Value                 9.493e+11   1.19e+12      0.800      0.424   -1.38e+12    3.28e+12
Currencies Momentum              9.493e+11   1.19e+12      0.800      0.424   -1.38e+12    3.28e+12
Currencies Carry                 9.493e+11   1.19e+12      0.800      0.424   -1.38e+12    3.28e+12
Currencies Multi-style          -2.848e+12   3.56e+12     -0.800      0.424   -9.84e+12    4.15e+12
Commodities Value               -7.946e+11   5.12e+11     -1.551      0.122    -1.8e+12    2.13e+11
Commodities Momentum            -7.946e+11   5.12e+11     -1.551      0.122    -1.8e+12    2.13e+11
Commodities Carry               -7.946e+11   5.12e+11     -1.551      0.122    -1.8e+12    2.13e+11
Commodities Multi-style          2.384e+12   1.54e+12      1.551      0.122    -6.4e+11    5.41e+12
==============================================================================
Omnibus:                       36.770   Durbin-Watson:                   0.166
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               37.085
Skew:                           0.705   Prob(JB):                     8.85e-09
Kurtosis:                       2.433   Cond. No.                     1.31e+14
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.25e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Table 4. Best Lag Number for Each Independent Variable

	Column	Best Lag
0	US Stock Selection Value	6
1	US Stock Selection Momentum	6
2	US Stock Selection Defensive	6
3	US Stock Selection Multi-style	1
4	Intl Stock Selection Value	3
5	Intl Stock Selection Momentum	6
6	Intl Stock Selection Defensive	1
7	Intl Stock Selection Multi-style	6
8	Equity indices Value	12
9	Equity indices Momentum	7
10	Equity indices Carry	12
11	Equity indices Defensive	2
12	Equity indices Multi-style	2
13	Fixed income Value	9
14	Fixed income Momentum	5
15	Fixed income Carry	12
16	Fixed income Defensive	7
17	Fixed income Multi-style	1
18	Currencies Value	10
19	Currencies Momentum	6
20	Currencies Carry	9
21	Currencies Multi-style	10
22	Commodities Value	4
23	Commodities Momentum	10
24	Commodities Carry	9
25	Commodities Multi-style	9

Table 5. OLS Regression with Independent Variables at their Best Lag

OLS Regression Results

Dep. Variable:	MPSTANCE	R-squared:	0.095
Model:	OLS	Adj. R-squared:	0.027
Method:	Least Squares	F-statistic:	1.400
Date:	Thu, 21 Dec 2023	Prob (F-statistic):	0.0953
Time:	03:55:37	Log-Likelihood:	-692.22
No. Observations:	373	AIC:	1438.
Df Residuals:	346	BIC:	1544.
Df Model:	26		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.4795	0.107	-13.863	0.000	-1.689	-1.270
US Stock Selection Value_lag6	-2.6510	3.482	-0.761	0.447	-9.500	4.198
US Stock Selection Momentum_lag6	5.9411	3.545	1.676	0.095	-1.031	12.913
US Stock Selection Defensive_lag6	-3.4136	2.877	-1.187	0.236	-9.072	2.245
US Stock Selection Multi-style_lag1	-1.2000	4.599	-0.261	0.794	-10.245	7.845
Intl Stock Selection Value_lag3	-0.5324	3.251	-0.164	0.870	-6.927	5.862
Intl Stock Selection Momentum_lag6	-6.5985	4.839	-1.364	0.174	-16.116	2.920
Intl Stock Selection Defensive_lag1	-4.4178	3.786	-1.167	0.244	-11.865	3.029
Intl Stock Selection Multi-style_lag6	-4.9760	9.368	-0.531	0.596	-23.402	13.450
Equity indices Value_lag12	0.4942	3.631	0.136	0.892	-6.647	7.635
Equity indices Momentum_lag7	2.6204	3.026	0.866	0.387	-3.331	8.572
Equity indices Carry_lag12	0.4367	3.140	0.139	0.889	-5.739	6.613
Equity indices Defensive_lag2	-6.0454	4.600	-1.314	0.190	-15.093	3.003
Equity indices Multi-style_lag2	10.9670	8.448	1.298	0.195	-5.650	27.584
Fixed income Value_lag9	0.3604	8.125	0.044	0.965	-15.621	16.342
Fixed income Momentum_lag5	-7.4620	7.592	-0.983	0.326	-22.395	7.471
Fixed income Carry_lag12	-7.2867	7.630	-0.955	0.340	-22.293	7.720
Fixed income Defensive_lag7	6.9191	9.670	0.716	0.475	-12.100	25.939
Fixed income Multi-style_lag1	-0.8271	18.375	-0.045	0.964	-36.967	35.313
Currencies Value_lag10	-3.4532	6.067	-0.569	0.570	-15.385	8.479
Currencies Momentum_lag6	4.4949	4.553	0.987	0.324	-4.461	13.451
Currencies Carry_lag9	3.1764	3.969	0.800	0.424	-4.631	10.983
Currencies Multi-style_lag10	5.7866	8.278	0.699	0.485	-10.494	22.067
Commodities Value_lag4	-2.7479	1.484	-1.852	0.065	-5.667	0.171
Commodities Momentum_lag10	3.6725	1.543	2.380	0.018	0.638	6.707
Commodities Carry_lag9	4.5699	2.725	1.677	0.094	-0.790	9.930
Commodities Multi-style_lag9	1.5253	4.884	0.312	0.755	-8.082	11.132

Omnibus:	34.843	Durbin-Watson:	0.183
Prob(Omnibus):	0.000	Jarque-Bera (JB):	29.404
Skew:	0.603	Prob(JB):	4.12e-07
Kurtosis:	2.340	Cond. No.	222.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Table 6. Stepwise Regression with Independent Variables at their Best Lag with No Folds

OLS Regression Results

Dep. Variable:	MPSTANCE	R-squared (uncentered):	0.266
Model:	OLS	Adj. R-squared (uncentered):	0.211
Method:	Least Squares	F-statistic:	4.828
Date:	Thu, 21 Dec 2023	Prob (F-statistic):	1.98e-12
Time:	03:55:38	Log-Likelihood:	-774.61
No. Observations:	373	AIC:	1601.
Df Residuals:	347	BIC:	1703.
Df Model:	26		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
US Stock Selection Value_lag6	-0.3204	4.332	-0.074	0.941	-8.840	8.199
US Stock Selection Momentum_lag6	11.5994	4.385	2.645	0.009	2.974	20.225
US Stock Selection Defensive_lag6	1.7069	3.553	0.480	0.631	-5.282	8.695
US Stock Selection Multi-style_lag1	-2.8387	5.725	-0.496	0.620	-14.100	8.422
Intl Stock Selection Value_lag3	-3.7892	4.038	-0.938	0.349	-11.731	4.153
Intl Stock Selection Momentum_lag6	-8.1513	6.025	-1.353	0.177	-20.002	3.699
Intl Stock Selection Defensive_lag1	-18.4710	4.543	-4.066	0.000	-27.407	-9.535
Intl Stock Selection Multi-style_lag6	-51.4806	10.894	-4.726	0.000	-72.907	-30.054
Equity indices Value_lag12	2.9139	4.516	0.645	0.519	-5.969	11.797
Equity indices Momentum_lag7	-3.1113	3.733	-0.833	0.405	-10.454	4.231
Equity indices Carry_lag12	-0.8718	3.909	-0.223	0.824	-8.560	6.816
Equity indices Defensive_lag2	-5.3546	5.729	-0.935	0.351	-16.622	5.913
Equity indices Multi-style_lag2	-0.5744	10.470	-0.055	0.956	-21.168	20.019
Fixed income Value_lag9	-5.0408	10.108	-0.499	0.618	-24.921	14.839
Fixed income Momentum_lag5	-6.8331	9.455	-0.723	0.470	-25.430	11.764
Fixed income Carry_lag12	-15.2096	9.475	-1.605	0.109	-33.846	3.427
Fixed income Defensive_lag7	7.0374	12.043	0.584	0.559	-16.649	30.724
Fixed income Multi-style_lag1	-28.0650	22.752	-1.233	0.218	-72.815	16.685
Currencies Value_lag10	-10.1753	7.531	-1.351	0.178	-24.987	4.637
Currencies Momentum_lag6	5.1712	5.670	0.912	0.362	-5.982	16.324
Currencies Carry_lag9	-1.7834	4.923	-0.362	0.717	-11.466	7.900
Currencies Multi-style_lag10	0.4700	10.298	0.046	0.964	-19.784	20.724
Commodities Value_lag4	-4.7638	1.839	-2.590	0.010	-8.381	-1.146
Commodities Momentum_lag10	2.7291	1.920	1.422	0.156	-1.047	6.505
Commodities Carry_lag9	4.9504	3.394	1.459	0.146	-1.724	11.625
Commodities Multi-style_lag9	-8.0368	6.022	-1.335	0.183	-19.881	3.808

Omnibus:	9.789	Durbin-Watson:	0.390
Prob(Omnibus):	0.007	Jarque-Bera (JB):	10.081
Skew:	0.384	Prob(JB):	0.00647
Kurtosis:	2.757	Cond. No.	14.7

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Table 7. Testing for Collinearity After Stepwise Regression

Feature	VIF Factor
US Stock Selection Value_lag6	2.760328
US Stock Selection Momentum_lag6	4.114655
US Stock Selection Defensive_lag6	1.790010
US Stock Selection Multi-style_lag1	1.464652
Intl Stock Selection Value_lag3	1.116226
Intl Stock Selection Momentum_lag6	4.368596
Intl Stock Selection Defensive_lag1	1.459311
Intl Stock Selection Multi-style_lag6	2.914620
Equity indices Value_lag12	1.097838
Equity indices Momentum_lag7	1.164022
Equity indices Carry_lag12	1.083239
Equity indices Defensive_lag2	1.636143
Equity indices Multi-style_lag2	1.561823
Fixed income Value_lag9	1.094976
Fixed income Momentum_lag5	1.130025
Fixed income Carry_lag12	1.078979
Fixed income Defensive_lag7	1.117884
Fixed income Multi-style_lag1	1.094701
Currencies Value_lag10	1.518580
Currencies Momentum_lag6	1.128337
Currencies Carry_lag9	1.058096
Currencies Multi-style_lag10	1.485572
Commodities Value_lag4	1.056474
Commodities Momentum_lag10	1.089720
Commodities Carry_lag9	2.338233
Commodities Multi-style_lag9	2.346706

Table 8. Stepwise Regression with Independent Variables at their Best Lags with 5 Folds

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:               MPSTANCE   R-squared (uncentered):                   0.195
Model:                            OLS   Adj. R-squared (uncentered):              0.154
Method:                 Least Squares   F-statistic:                              4.769
Date:                Thu, 21 Dec 2023   Prob (F-statistic):                    1.52e-09
Time:                        03:55:42   Log-Likelihood:                         -791.81
No. Observations:                 373   AIC:                                      1620.
Df Residuals:                     355   BIC:                                      1690.
Df Model:                          18
Covariance Type:            nonrobust
=========================================================================================================
                                         coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------------
US Stock Selection Momentum_lag6      14.8325      3.848      3.855      0.000       7.265      22.400
US Stock Selection Defensive_lag6     -8.5474      3.025     -2.825      0.005     -14.498      -2.597
US Stock Selection Multi-style_lag1   -2.3255      5.821     -0.400      0.690     -13.773       9.122
Intl Stock Selection Momentum_lag6   -22.7721      5.105     -4.461      0.000     -32.812     -12.732
Intl Stock Selection Defensive_lag1  -20.7884      4.593     -4.526      0.000     -29.821     -11.756
Equity indices Momentum_lag7          -2.4342      3.765     -0.647      0.518      -9.838       4.970
Equity indices Carry_lag12            -1.4451      3.974     -0.364      0.716      -9.262       6.371
Equity indices Defensive_lag2         -5.5025      5.844     -0.942      0.347     -16.995       5.990
Equity indices Multi-style_lag2        2.9111     10.772      0.270      0.787     -18.273      24.095
Fixed income Value_lag9               -9.9476     10.272     -0.968      0.333     -30.148      10.253
Fixed income Momentum_lag5            -6.0311      9.695     -0.622      0.534     -25.099      13.037
Fixed income Carry_lag12             -18.3909      9.674     -1.901      0.058     -37.417       0.636
Currencies Momentum_lag6               5.0276      5.721      0.879      0.380      -6.224      16.279
Currencies Carry_lag9                 -1.9610      5.051     -0.388      0.698     -11.894       7.972
Currencies Multi-style_lag10         -10.8316      9.023     -1.201      0.231     -28.576       6.913
Commodities Value_lag4                -4.4708      1.894     -2.360      0.019      -8.196      -0.746
Commodities Carry_lag9                 3.4467      3.460      0.996      0.320      -3.358      10.252
Commodities Multi-style_lag9          -6.7452      6.149     -1.097      0.273     -18.838       5.347
==============================================================================
Omnibus:                       12.665   Durbin-Watson:                   0.320
Prob(Omnibus):                  0.002   Jarque-Bera (JB):               13.020
Skew:                           0.432   Prob(JB):                      0.00149
Kurtosis:                       2.700   Cond. No.                         6.63
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```