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Seeking the cues in macro markets

THORFINN

Political market making

Trading financial markets using Thorfinn political indices

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It is challenging to understand how to model external shocks when trading financial markets. However, in recent years, it has become particularly notable that these risks, such as Brexit, the election of Trump, or coronavirus can greatly impact markets. Hence, we need to have a way to model them. In this paper we investigate the Thorfinn Sensitivity Index (TSI) which quantifies event risks related to geopolitics and related areas. We find that, historically when the index flags increases in risk this tends to be accompanied by an underperformance of risky assets and outperformance of safe haven assets. We use the TSI index to create systematic trading strategies for macro-based assets. Our macro trading basket strategy which uses signals based on TSI has annualized returns of 14.8% and risk adjusted returns of 1.32 over the past 2 years, outperforming a passive strategy.

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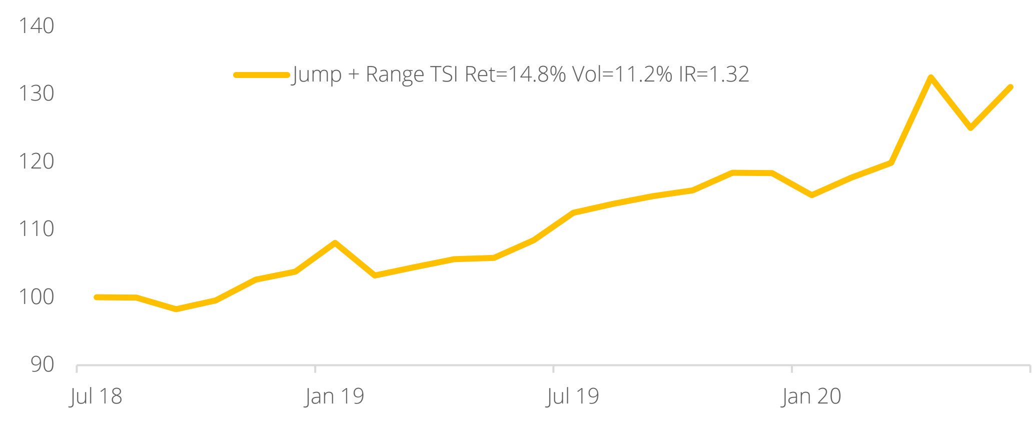
Introduction

Traditionally, price data has been the most important data sources for traders. Alongside that, we have had other common factors followed by traders, such as economic data and also company specific data. However, very often such datasets may miss event risks emanating from the political arena or broader external shocks. To quantify such risks, we need an index which is designed specifically to monitor political developments and external shocks.

Figure 1: Macro trading basket using Thorfinn Sensitivity Index



Source: Thorfinn AI, Cuemacro, Bloomberg

In this paper we investigate the Thorfinn Sensitivity Index (TSI), which quantifies political risks, and we talk about how it is constructed. We also seek to quantify the relationship between TSI and macro assets. Later, we discuss a trading strategy for macro assets, which uses the TSI as an input (see Figure 1).

What is the Thorfinn Sensitivity Index (TSI)?

The TSI flags event risks related to geopolitics and associated areas. The aim is to provide a quantifiable output for these risks. Such an output can be easier to interpret for market participants, whether they are discretionary or systematic traders.

The TSI uses machine learning and natural language processing to parse through text-based sources which are in the political and geo-economic arena, in particular, it parses through think thanks, research centres, and certain social media activity. Experts are also involved at various stages in the process to score the various inputs once they have been aggregated into a more digestible form.

Think tanks are specifically tasked with providing an independent view of major themes and topics. The rationale behind looking at think tanks is that they will often be earlier to track shifts compared to the mainstream media, which often amplifies narratives only once they have already begun to develop. In total, over 30,000 daily feeds are parsed when constructing the index, including 1800 US think tanks, 6000 international peers for event risk, and thousands of academic & governmental publications. Clearly, with this number of inputs, automated techniques such as natural language processing need to be used and can't be done purely in a manual method by people.

The shift in narratives from these sources – budgetary, political, military and economic – and how they could impact sentiment is captured daily. In particular, the shifts in language and themes are reflected in changes in the various output scores. These various developments are categorised in 72 geopolitical drivers. These are then aggregated into 12 broader categories.

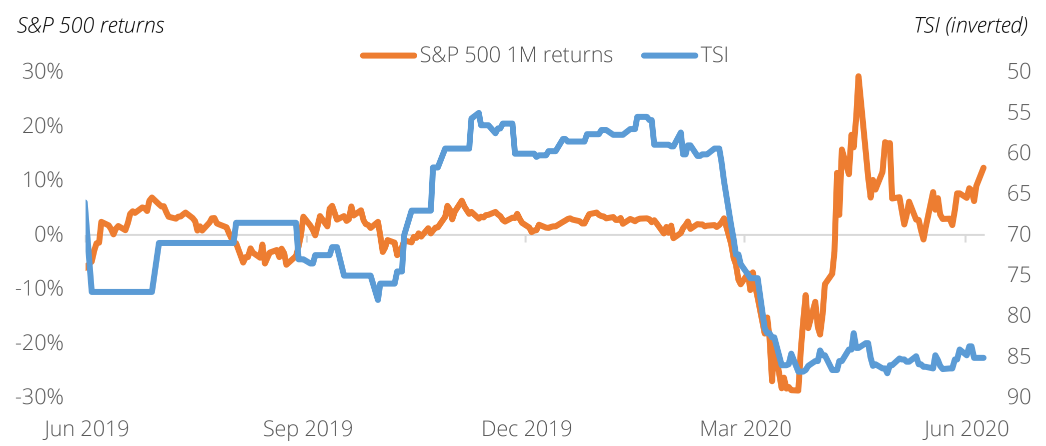
Finally, a team of experts, with experience in both markets and policy decision making, assigns a daily risk score for each of these 12 categories based on the AI inputs. The TSI is an equally weighted average of these 12 categories. Thus, we note that final output is a hybrid of both machine learning based methods and also expert human analysis.

This idea of combining human expertise with quantitative methods can also be seen in other areas of trading. One such example is alpha capture. In this case, large numbers of broker recommendations which have been generated by analysts are collected by quantitative hedge funds. These expert recommendations are aggregated into a quantitative model which is traded in a systematic manner.

The relationship between TSI and macro markets

If we want to use TSI to trade macro markets, we first need to understand the relationship between them. As a first step we plot 1M rolling returns for S&P 500 against an inverse of TSI over the past year. In this stylized example, we note that in the earlier part of the history the TSI data was published monthly, although this frequency has been increased to daily in recent months. Perhaps the most obvious observation from Figure 1 is a steep rise in TSI flagging increased risk during February 2020 as the coronavirus took hold globally. We also note that when there are smaller moves in the index we see some elements of mean reversion.

Figure 2: S&P 500 futures 1M returns vs. TSI (inverted)



Source: Thorfinn AI, Cuemacro, Bloomberg

The next step is to understand the relationship between TSI and many different macro assets over a longer history. To do this, we'll calculate long term contemporaneous correlations between the changes on TSI and the returns of a number of a macro assets. We want to see how consistent the relationship is across multiple asset classes.

Our data sample is between June 2018 and June 2020. We use monthly data because, prior to August 2019, TSI was generated on a monthly basis and we would like to have as large a sample as possible. Whilst the sample is not huge and it is likely that we would extend the analysis as more data becomes available over time, we note that our sample period does contain several different market regimes. In particular, over the past two years that have been both periods of high and low volatility in equity markets more broadly. Furthermore, the equities market has been punctuated both by rallies and pullbacks.

We shall look at a number of asset classes, which we list below:

- Equity futures: FTSE 100, S&P 500, MSCI EM, CSI 300 and MSCI World 1st dated futures
- Bonds futures and ETF: UST 10Y 1st dated futures, US HY ETF and US IG ETF
- Volatility futures: VIX 1st dated futures
- Commodity futures: Gold and bitcoin 1st dated futures
- FX: USD vs. EUR, JPY, AUD, CNY, RUB and ZAR
- Volatility: VIX index, EURUSD 1Y implied vol and USDJPY 1Y implied vol

Our futures time series have been back-adjusted for each contract roll and for FX we have used total returns indices. In Figure 3, we present these correlations. We see that assets which are traditionally considered to be risky the correlation is broadly negative, as we might expect. For example, for nearly all the equity futures, the correlation is strongly negative between -40% and -50%. In other words, heightened risks flagged by TSI are accompanied by falls in equities. The main exception is CSI 300, where the correlation, whilst negative, is close to zero.

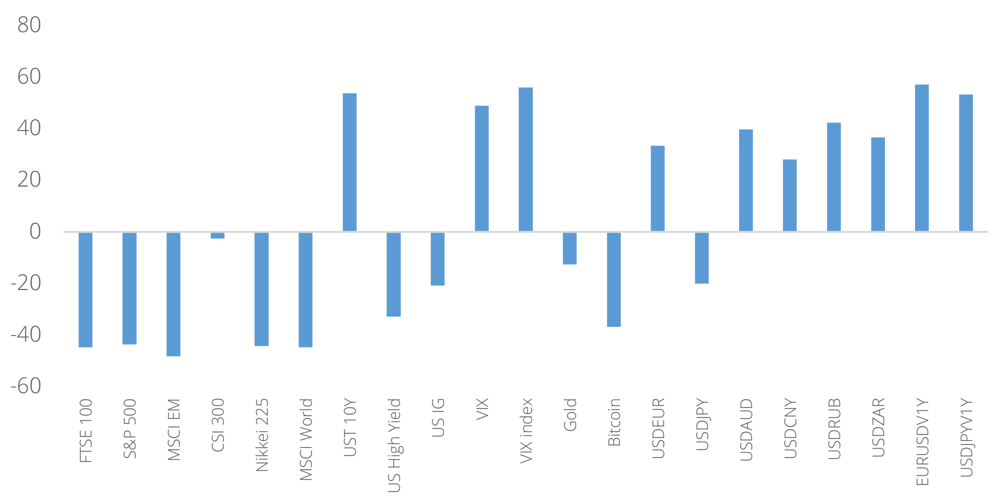
High yield and investment grade bonds display a negative correlation. UST bond futures, meanwhile, have a strong positive correlation, which fits in with the general market wisdom that these instruments are safe havens. Measures of market volatility have a strong positive correlation both in equity markets (VIX futures and VIX index) as well as 1Y implied vols in EURUSD and USDJPY. During periods of risk aversion, we would expect implied volatility to rise as market participants scramble to buy options to hedge exposure.

In FX space, for consistency, we've always quoted USD as a base currency rather than using the market convention quotation style. We see in most cases USD vs. EM has a positive correlation with TSI. This fits in with market intuition, namely that at times of risk aversion USD is seen as safe haven (in particular when compared with EM), given the importance of the US economy and given that USD is the most important reserve currency. This is also true of commodity currencies in G10 such as AUD. The main exception is USDJPY. The main explanation is that JPY has consistently been used as a funding currency, hence, USDJPY tends to be unwound during risk aversion, as carry trades are liquidated.

Gold also has a relatively small negative correlation with TSI, which suggests it behaves more like a risky asset. Whilst gold is sometimes considered as a safe haven asset, we would note that often it can display the characteristics of a risk asset. However, we note that in any case the magnitude of the correlation is small compared to most of the other assets, which makes the classification less strong. We also see that bitcoin has a strong negative correlation with TSI, which fits in with the notion of bitcoin largely trading like a risky asset.

In Figure A, in the Appendix, we also present correlations between all the components of TSI and also assets, flagging where the correlations are greater than +25% and more negative than -25%.

Figure 3: Correlation between markets and TSI



Source: Thorfinn AI, Cuemacro, Bloomberg

Developing a macro trading strategy using TSI

The next step is to create a trading rule. We'll use the TSI as the basis of our systematic trading rule, as opposed to the individual components of TSI. In nearly all the cases for TSI, the correlations fit in with our prior intuition.

Furthermore, using an equally weighted index such as TSI means that we will hopefully pick up risks wherever they might come from. We could also create our own weighted version of TSI, but we must be careful not to overfit it. The origins of crises and risk events are not always the same as the past, hence, it is often better to cast our net wide. For example, the 2008 crisis emanated from the US subprime market. If we were to use the years leading up to that as a template, it is likely we'd have overweighted any risk indicator or similar early warning model on emerging markets, owing to various EM crises in the early 2000s.

We noted that, in general, the relationship between TSI and most macro markets fit in with intuition, and often the magnitudes of the correlations are fairly large. Hence, heightened TSI is accompanied by falls in equity, rises in safe haven assets like UST futures, USD, VIX futures and so on. This suggests that when interpreting TSI, we need to flip the sign depending on whether the asset being traded is a safe haven or a risk asset.

One easy way to do this, is by looking at the sign of the correlation between TSI and the asset:

- If the correlation between TSI and the asset is positive, the asset is a safe haven
- If the correlation between TSI and the asset is negative, the asset is a risky asset

We should, however, note that with those assets where the correlation magnitude is relatively small, this classification could be less clear. Based on this metric we can define safe haven (ie. rise when there's risk aversion/TSI rises) and risky assets (ie. fall when there's risk aversion/TSI rises) as follows:

- safe havens: UST 10Y, VIX, VIX index, USDEUR, USDAUD, USDCNY, USDRUB, USDZAR, EURUSDV1Y and USDJPYV1Y
- risky assets: FTSE 100, S&P 500, MSCI EM, CSI 300, Nikkei 225, MSCI World, US High Yield, US IG, Gold, Bitcoin and USDJPY

How should interpret moves in TSI if we are constructing a trading rule, given that we are trading we cannot trade a contemporaneous relationship? Our observations from Figure 2 suggest that we should treat moves in TSI differently depending on their magnitude. For large jumps in TSI, they are signals of major risks and potential market unwinds, hence, we should be willing to sell risky assets and buy safe haven assets during this period. However, for smaller moves in TSI, it is likely that the market will quickly price in such risks and begin to fade them, giving rise to mean reverting price moves.

We can see a parallel with how traders react to changes in market volatility. Typically, market volatility tends to be relatively mean reverting. Hence, traders can attempt to trade the range in vol. However, when there are large spikes in volatility, this can be indicative of deeper market dislocations and attempting to fade such large moves can be very painful. Thus, we need to treat the two regimes differently, fading small moves in risk measured by TSI, but going with large moves in TSI.

We shall create two trading rules, which we label “range” and “jump” along these lines. For the range trading rule:

- when there are small increases in TSI, we “fade” the move by buying risky assets and selling safe haven assets
- when there are small decreases in TSI, we “fade” the move by selling risky assets and buying safe haven assets
- when there are any large jumps to the upside or downside in TSI, we have flat exposure

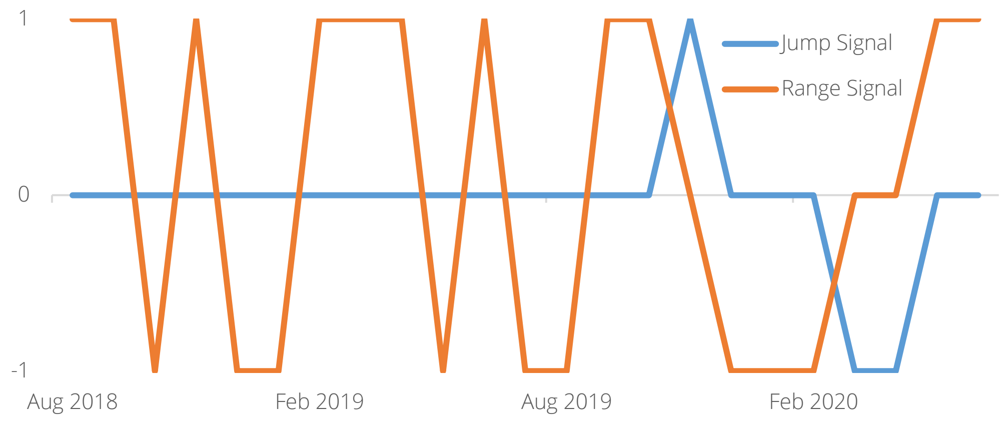
For the jump trading rule:

- when there are large jumps in TSI, we go with the big jump by selling risky assets and buying safe haven assets
- when there are large falls in TSI, we go with the large falls by buying risky assets and selling safe haven assets
- when there are any small changes in TSI, we have flat exposure

We quantify a large jump as being greater than +10 change in TSI and a large fall as being in excess of -10 change in TSI. To help illustrate these trading rules, we plot the long/short/flat positions that would be generated from them from the perspective of a risky asset (eg. S&P 500) in Figure 4. We can see that the jump signal was mostly flat during our sample, given for the most part TSI was range bound in the historical sample.

The jump signal was, however, short risky assets during March 2020, when TSI jumped higher. Conversely, it was long risky assets in November 2019. The range based TSI signal flipped between long and short exposure throughout the sample.

Figure 4: Jump and Range based TSI trading rule signals



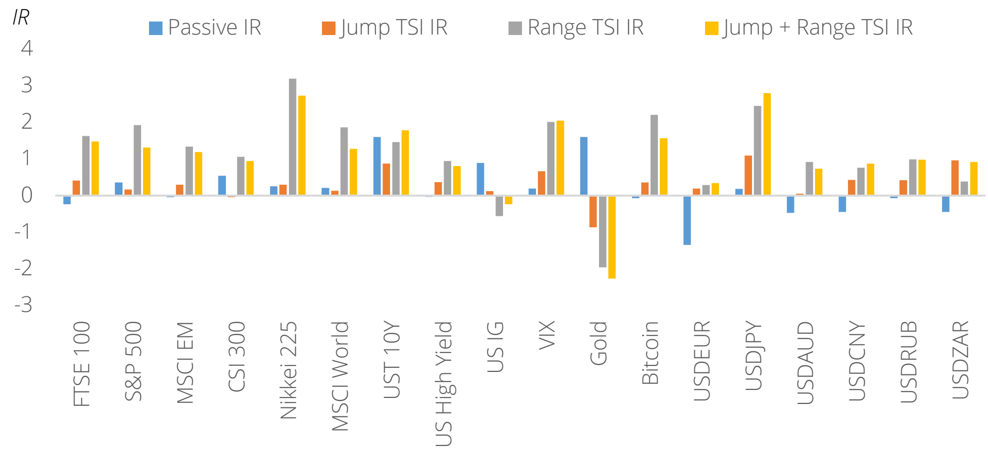
Source: Thorfinn AI, Cuemacro, Bloomberg

We shall also look at a combined jump + range trading rule. Lastly, we also have a "passive" rule, which is the typical static position of most investors, i.e. long equities, long bonds, short vol and long higher beta currencies.

We shall backtest all of these trading rules for the tradable assets listed from Figure 3 (ie. all the futures contracts, ETFs and FX crosses) using a sample of monthly data between June 2018-June 2020. We trade on the first business day of each month.

We present the risk adjusted returns (information ratios) in Figure 5 for each of these trading rules. In Figure B, in the Appendix, we present a full table showing the returns and volatilities as well. Note that we have not taken into account funding costs or dividends for the ETFs. These are already implicitly included in the futures contracts and FX total return indices, and these represent the vast majority of our portfolio. We have assumed transaction costs of 5bp bid/ask in all cases.

Figure 5: Risk adjusted returns for a passive position and TSI based trading rules



Source: Thorfinn AI, Cuemacro, Bloomberg

We see that that, in general, either the range based TSI trading rule or the combined jump + range TSI trading rule have the highest risk adjusted returns, outperforming passive exposures in nearly every case. There are, however, some exceptions, like gold futures and US IG ETFs, where passive exposure heavily outperformed our trading rules. For UST10Y the passive (long) exposure yielded similar risk adjusted returns.

Developing a trading basket using TSI

We have seen that our trading rules are profitable in nearly every case during our sample. Our next step is to combine all the individual assets into a trading basket. We shall omit both VIX futures and bitcoin from our basket given that they are more "exotic" instruments and are less likely to be in trading mandates.

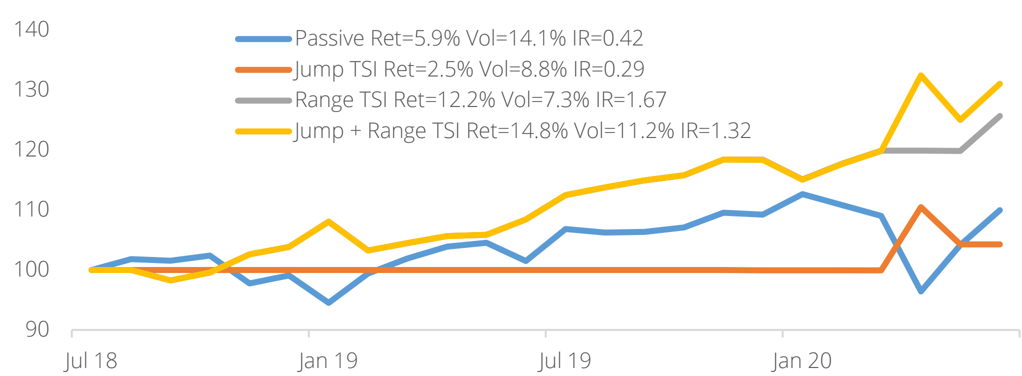
We shall create a basket where all the assets are equally weighted by notional for simplicity. In practice, it is likely that traders would adopt some sort of volatility weighting. Hence, lower volatility assets like UST 10Y futures would be overleveraged, whilst high volatility assets like equities would have reduced leverage.

In Figure 6, we present the returns for trading baskets based on the passive jump TSI, range TSI and jump + range TSI trading rules. Our sample is between summer 2018 to the present. We have again used monthly data, rather than the daily or weekly data for TSI, to construct our trading rule so that we can maximise the historical sample as much as possible.

The trading rule with the highest risk adjusted returns is the range TSI trading rule with an IR of 1.67, closest followed by the jump + range TSI trading rule which has risk adjusted returns of 1.32. By contrast, the passive based strategy has risk adjusted returns of 0.42.

The jump based trading strategy has risk adjusted returns of 0.29. However, we should note that the jump based strategy would have hedged the passive exposure during the recent crisis. We note that in live trading (which would be out-of-sample) the risk adjusted returns would likely be somewhat smaller for a number of reasons, including transaction costs, changes in the market regime and so on. However, even if we took half the risk adjusted returns, which is a common rule of thumb in the market when trying to adjust historical in-sample risk adjusted returns for understand live performance, the results for the range model and range + jump models, would still be well in excess of the passive risk adjusted returns.

Figure 6: Return statistics for TSI based trading rules



Source: Thorfinn AI, Cuemacro, Bloomberg

Conclusion

In recent years, it has become very clear that political factors and external shocks are moving markets, whether it's Brexit, the election of Trump or, more recently, coronavirus. However, it can often be difficult to gauge political risks in a concise and quantitative way, which can be inputted easily into a trading strategy.

In this paper, we introduced Thorfinn's political indices which quantify political risk, making it easy to include political risk as a factor in your trading decisions. We discussed how these indices are constructed. In particular, we noted how the initial source data comes from think tanks and other sources which are likely to flag risks quicker than mainstream media.

The construction of the indices uses both techniques such as NLP to classify a large amount of text data from these sources, and also experts during the process. We showed how the correlation between TSI and various macro assets is intuitive, namely that when TSI increases indicated heightened risks, this tends to be accompanied by falls in risky assets such as stocks. We showed how to create trading rules based on mean-reversion and jumps in TSI, to trade risky assets and safe haven assets.

Our basket of macro assets which uses TSI jump + range based trading rules has a risk adjusted return of 1.32 and annualised returns of 14.8% for the past 2 years. This outperformed a passive strategy which had risk adjusted returns of 0.42 over the same sample period.

Appendix

In Figure A, we present the long-term correlations between major financial markets and the components of TSI. Our sample is monthly data between June 2018 and June 2020. We have highlighted those entries where the magnitude of the correlations are greater than 25%. We see that the narrower the categories of the components, generally the smaller the size of the correlations.

Figure A: Long term correlations between markets and TSI components

	US Domestic	US Foreign	SoKo Japan	NoKo	Taiwan	India Pakistan	Hong Kong	EU	Gulf	China Tariffs	EM	Russia	TSI
FTSE 100	-14	-30	-2	14	-9	4	6	-52	-33	-29	-60	-69	-45
S&P 500	-25	-46	7	5	-5	3	12	-55	-44	-14	-52	-57	-44
MSCI EM	-30	-54	-2	12	-2	13	-5	-59	-36	-34	-50	-50	-48
CSI 300	-13	-40	9	18	16	50	26	-40	-10	-34	-23	0	-3
Nikkei 225	-6	-39	-9	-1	-22	-4	13	-55	-44	-15	-41	-49	-44
MSCI World	-24	-42	1	10	-9	-2	9	-54	-41	-17	-50	-57	-45
UST 10Y	-2	21	28	6	44	14	0	34	37	38	49	52	54
US High Yield	-21	-44	20	11	3	25	12	-55	-33	-16	-64	-55	-33
US IG	-28	-35	28	15	19	19	17	-54	-22	-1	-55	-41	-21
VIX	10	49	-4	-6	29	3	9	49	40	12	54	57	49
VIX index	24	51	13	-13	15	11	5	51	49	23	48	57	56
Gold	-32	-31	0	12	38	5	-5	-22	-12	-9	-14	-3	-13
Bitcoin	-5	-44	2	4	-6	30	14	-63	-27	-31	-68	-45	-37
USDEUR	10	50	19	-15	-5	-18	15	37	20	46	34	8	33
USDJPY	11	-23	1	-18	-41	4	3	-22	-30	6	-10	-12	-20
USDAUD	30	58	-2	-22	-16	-6	-1	53	25	32	44	49	40
USDCNY	33	31	11	-21	19	-15	9	33	10	38	13	10	28
USDRUB	16	49	-9	-20	14	-12	1	60	28	28	60	52	42
USDZAR	23	41	-17	-22	16	-2	10	45	25	22	40	49	37
EURUSDV1Y	25	34	0	-14	34	18	8	58	44	-5	64	71	57
USDJPYV1Y	15	31	8	-1	27	13	1	47	45	12	51	69	53

Source: Thorfinn AI, Cuemacro, Bloomberg

In Figure B, we present the full return statistics for the various TSI based trading rules discussed in the paper alongside a passive strategy which can be used as a benchmark.

Figure B: Return statistics for TSI based macro trading rules

	Passive			*Jump TSI*			*Range TSI*			*Jump + Range TSI*		
Asset	**Ret**	**Vol**	**IR**	**Ret**	**Vol**	**IR**	**Ret**	**Vol**	**IR**	**Ret**	**Vol**	**IR**
FTSE 100	-4.2%	17.3%	-0.24	4.8%	11.7%	0.41	18.7%	11.5%	1.63	23.5%	15.9%	1.48
S&P 500	8.8%	24.4%	0.36	3.1%	18.4%	0.17	26.9%	14.0%	1.93	30.0%	22.8%	1.32
MSCI EM	-1.0%	22.3%	-0.05	4.5%	14.8%	0.30	20.5%	15.3%	1.34	25.0%	20.9%	1.20
CSI 300	13.5%	25.0%	0.54	-0.4%	9.8%	-0.04	23.5%	22.2%	1.06	23.1%	24.3%	0.95
Nikkei 225	6.6%	25.5%	0.26	4.0%	13.4%	0.30	49.7%	15.5%	3.20	53.7%	19.7%	2.73
MSCI World	4.9%	23.1%	0.21	2.2%	17.0%	0.13	25.4%	13.6%	1.87	27.6%	21.5%	1.28
UST 10Y	6.9%	4.3%	1.60	1.7%	1.9%	0.88	5.7%	3.9%	1.46	7.4%	4.2%	1.79
US High Yield	-0.5%	12.7%	-0.04	4.0%	10.8%	0.37	6.0%	6.3%	0.94	10.0%	12.3%	0.81
US IG	7.8%	8.7%	0.89	0.9%	7.2%	0.12	-3.0%	5.4%	-0.56	-2.1%	9.0%	-0.24
VIX	21.1%	111.6%	0.19	46.1%	69.0%	0.67	148.0%	73.5%	2.01	194.1%	94.7%	2.05
Gold	16.4%	10.3%	1.60	-4.9%	5.6%	-0.87	-16.5%	8.4%	-1.96	-21.3%	9.4%	-2.27
Bitcoin	-4.6%	66.0%	-0.07	18.8%	51.7%	0.36	75.3%	34.1%	2.21	94.1%	59.9%	1.57
USDEUR	-4.9%	3.6%	-1.35	0.3%	1.4%	0.20	1.0%	3.6%	0.29	1.3%	3.9%	0.34
USDJPY	0.9%	4.8%	0.18	1.0%	0.9%	1.10	9.0%	3.7%	2.45	10.0%	3.6%	2.81
USDAUD	-5.2%	10.9%	-0.48	0.4%	7.0%	0.05	7.6%	8.2%	0.92	7.9%	10.8%	0.74
USDCNY	-2.1%	4.7%	-0.45	0.6%	1.5%	0.43	3.1%	4.1%	0.77	3.8%	4.3%	0.88
USDRUB	-1.3%	18.8%	-0.07	5.9%	13.9%	0.42	11.9%	12.0%	0.99	17.7%	18.0%	0.98
USDZAR	-9.5%	21.3%	-0.45	12.7%	13.2%	0.96	6.2%	16.1%	0.39	18.9%	20.4%	0.92

Source: Thorfinn AI, Cuemacro, Bloomberg

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