How to build portfolios with macro-conditional market regimes

Insights on forecasting from Fathom Consulting's exploration of LSEG Datastream data

Summary

In their popular book Superforecasting: The art and science of prediction, Philip Tetlock and Dan Gardner argue that good forecasts are born out of good practices, such as frequent updating, working in teams, formulating base rates, striving for objectivity by seeking different views, and establishing a track record.

At Fathom Consulting, to gain insights about the value of forecasting and forecasts of macroeconomic variables, we are analysing data sourced from LSEG Datastream, which enables detailed exploration of relationships between data series. In this paper, we will:

- Explore how economic forecasts and market data can be used to build portfolios that incorporate information embedded in forecasts and remain true to some of Professor Tetlock's best practices
- Demonstrate how to construct portfolios that are conditional on LSEG's polling data of key macroeconomic variables
- Shed light on the information embedded in macroeconomic forecasts and give some ideas about how to exploit the spread of opinions among the polled forecasters
- Explore the idea that extra rewards are potentially available to investors who formulate joint forecasts of market and macro conditions rather than treating them as separate
- Provide an example of how to express such forecasts and incorporate them into a portfolio

Overall, we find that it is both possible and desirable to create relatively simple and efficient portfolios that incorporate macroeconomic and market forecasts in a systematic fashion.

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LSEG DATA & ANALYTICS

Dabbling with macroeconomic forecasts

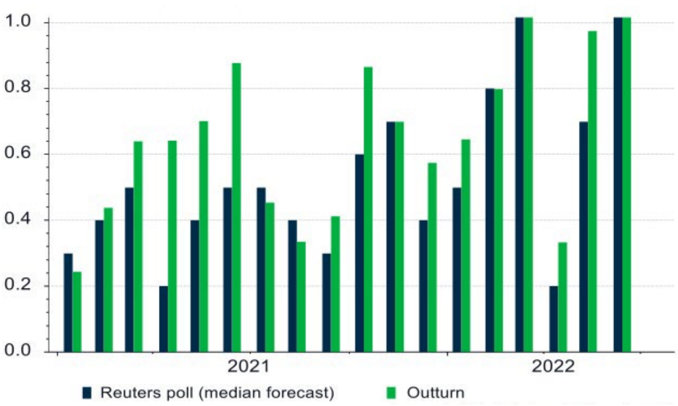
Investment strategies centred on macroeconomic fundamentals are often given a wide berth thanks to the belief that it is futile to try to beat the market or that returns are unpredictable, and that macro offers, at best, a nice narrative with the benefit of hindsight.

This stance partly derives from a simplistic interpretation of market efficiency, as if this had been set in stone back in the 1960s. In truth, market efficiency remains a very complex concept to define, let alone prove conclusively.

In this paper, we build on the idea that the market may be efficient precisely because investors are constantly trying to beat it. This does not mean that all should try, but neither does it mean that none should. The decision to do so should come down to an investor's perceived edge relative to their opportunity costs.

Some of the scepticism around forecasters and their investment recommendations is also born out of the presence of clear biases. For example, many macroeconomic forecasters (including the Fed) were slow to catch on to 2021's inflationary impulse, despite clear signs of building price pressures by spring. As you can see in Figure 1, the median forecast for monthly US Consumer Price Index (CPI), as submitted to Reuters, has often been well below actual outturns throughout 2021 and some of 2022.

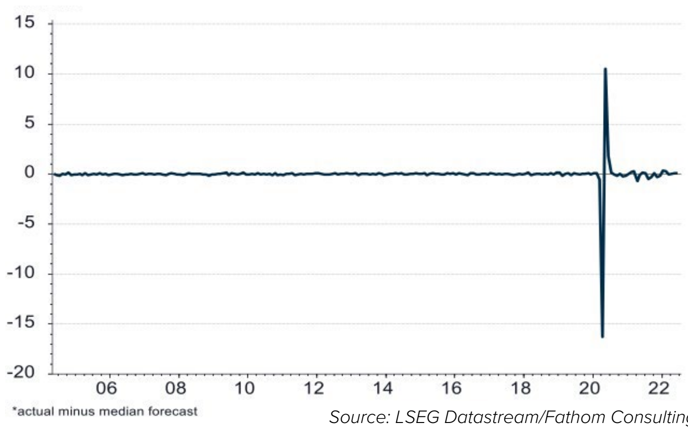
Figure 1: US CPI-median forecasts vs outturns 2021-2022
Monthly percentage changes



Source: LSEG Datastream/Fathom Consulting

Forecasters, in general, are poor at picking up big outliers in the data. In April 2020 (see Figure 2), forecasters had little to go on when thinking about the impact of 'stay at home' orders on US employment. As a group, economists were far too optimistic about the number of jobs that would be lost that month. Likewise, they were far too pessimistic about the number of jobs that would be created in May and June 2021, when hiring reached levels previously unseen.

Figure 2: Reuters poll surprise* for US nonfarm payrolls
Millions

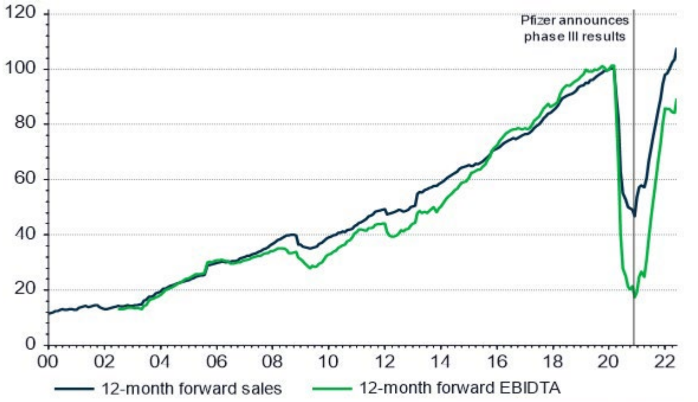


Source: LSEG Datastream/Fathom Consulting

Being human, forecasters are prone to emotion. This means they can 'overshoot' by being too optimistic when times are good, and too pessimistic when things are going badly. Equity strategists were far too pessimistic about the pandemic's impact on the financial performance of US travel and tourism companies (see Figure 3) until vaccines were announced.

Figure 3: US Datastream travel and tourism equity index

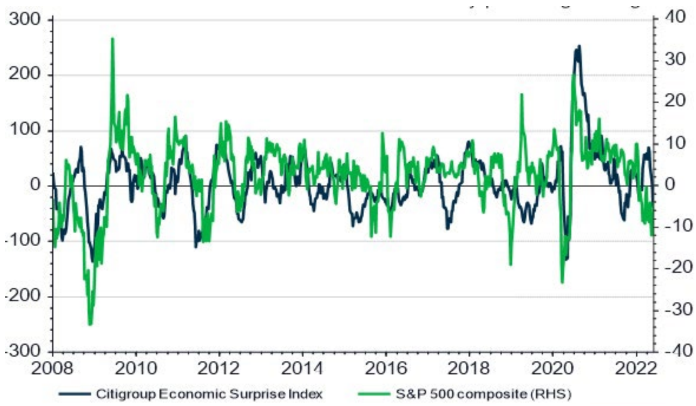
Indices, 31/12/2019 = 100



Source: LSEG Datastream/Fathom Consulting

Figure 4: US equities and Economic Surprise Index

Index Quarterly percentage change



Source: LSEG Datastream/Fathom Consulting

Despite these biases,[1] forecasts, just like asset prices, still offer important clues about consensus and what might surprise investors. For example, macroeconomic surprises are clearly linked to equity returns as you can see in Figure 4.

Just like any tool, the challenge is to put it to good use. This note aims to provide a flavour of how you would set up a process that integrates uncertainty about the macroeconomy into market strategies.

1 See Box 1 for how we think StarMine's smart estimates lower the occurrence of these biases and increase the accuracy of available forecasts.

Disagreement-based portfolios

A sensible starting point is the Reuters Poll database, which can be accessed through the LSEG Datastream Data Loader and Datastream Web Service. This database includes quarterly, monthly, and even weekly macroeconomic forecasts for over 900 indicators. To narrow down the field of exploration, we focus here on six US indicators that the National Bureau of Economic Research (NBER) closely monitors to date economic expansions and contractions. These are:

- Nonfarm payrolls
- Industrial production
- Unemployment
- Personal income
- Personal consumption
- Retail sales

For each of these six indicators, the focus of the exploration will be a measure of disagreement between forecasters, defined as the difference in the max-min forecast relative to its 12-month trailing average. A dispersion metric can be thought of as the ex-ante level of uncertainty prior to an economic release.[2]

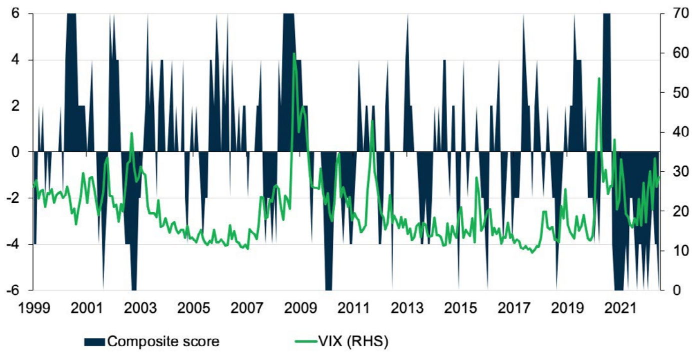
A seventh measure, which combines the six dispersion metrics above, is also constructed. This is calculated using a simple score card approach. Whenever one of the six macro variables is in a high (low) disagreement regime,[3] a score of +1 (-1) is assigned. So, the maximum (minimum) score for this composite indicator is +6 (-6) whenever all six macro variables are in a high (low) dispersion regime.

Focusing on disagreements among forecasters has been motivated by a prolific academic literature relating analysts' disagreements to asset returns. In a seminal paper, Edward Miller found that stocks with higher levels of disagreement among investors about their fundamentals were also the most likely to be overvalued and exhibit lower subsequent returns due to shortsale constraints.[4] The evidence is more mixed when forecasters disagree about macroeconomic variables. For example, one paper[5] finds that, just like stocks, a high dispersion in macro forecasts is associated with lower asset returns.

The intuition for this negative relationship stems from the idea that periods of economic uncertainty generally correlate with periods of lower returns. The chart in Figure 5 lends support to that idea by showing the composite metric of disagreements among forecasters being able to capture periods of extreme volatility in markets, as measured by the VIX. However, the chart also makes clear that not all periods of extreme disagreement coincide with extreme market volatility, opening the door for a more nuanced relationship between the dispersion of macroeconomic forecasts and market returns. Indeed, recently, Gao et al. (2019)[6] showed that when controlling for the level of systemic risk, a high level of disagreement implies better, not worse, return opportunities across assets.

Figure 5: Composite ranking of NBER indicators* and VIX

Score Volatility level



*The score takes values between -6 and 6, with lower (<=-3) indicating risk-on and higher (>3) indicating risk-off periods

Source: LSEG Datastream/Fathom Consulting

To investigate the investment value of disagreements among forecasters, we integrate each of the six dispersion metrics and the scorecard combination in seven different multi-asset portfolios. These portfolios are constructed to maximise the Sharpe ratio using all the periods that share the same market regime of either high or low disagreement.

2 Statistics for the higher, lower, and median forecast as well as the surprise (actual minus median forecast) and the forecast dispersion measure for these six indicators are available in Appendix 1.

3 The construction of a high or low regime for each macro variable is explained further down the paragraph.

4 Miller, Edward M. (1977), 'Risk, uncertainty, and divergence of opinion', The Journal of Finance, 32/4, pp.1151-1168.

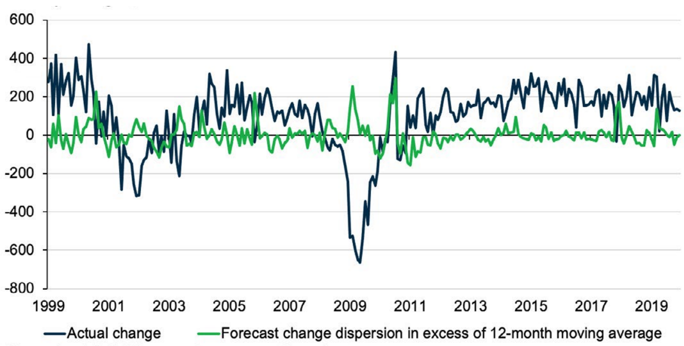
5 Li, Frank Weikai (2016), 'Macro Disagreement and the Cross-Section of Stock Returns', Review of Asset Pricing Studies, 6, issue 1, pp. 1-45.

6 Gao, George P., Lu, Xiaomeng, Song, Zhaogang, Yan, Hongjun (2019), 'Disagreement beta', Journal of Monetary Economics, Volume 107, pp. 96-113.

For example, assume that at time of the disagreement among forecasters about US nonfarm payrolls was in the top 35% of its distribution, the high disagreement regime. That period would probably coincide, as Figure 6 shows, with volatile and mostly negative actual payroll changes, which in turn leads to a very uncertain period for risky assets. The weights for period t+1 would then be given by an optimisation routine using the returns across all the periods that share this high dispersion regime in US nonfarm payrolls forecasts.[7]

Figure 6: Actual change and dispersion in forecast change for nonfarm payrolls*

Monthly changes, thousands



*The sample ends in 2019 for presentation purposes and due to the extreme 2020/2021 figures

Source: LSEG Datastream/Fathom Consulting

The same procedure is repeated separately for any period t that falls in the low disagreement regime, the bottom 35%. For the scorecard dispersion metric (referred to as the combo), the high and low disagreement regimes are defined as a score of above +3 and below -3, respectively.

7 A symmetric 35% threshold is used for all optimisations in this section. The weights for the middle 30% of the distribution are held at the same level as the most recent optimisation. Each portfolio is optimally rebalanced on a quarterly basis to keep transaction costs down.

Portfolio definitions

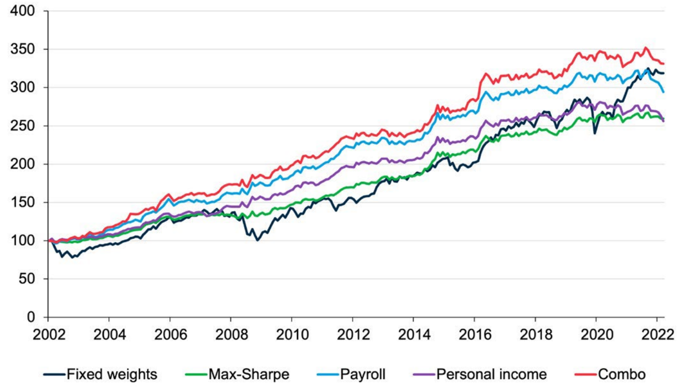
The investable universe across all seven portfolios introduced in the previous section is comprised of ten different asset classes.[8]

The performance of each portfolio is also compared to two separate benchmark strategies. The first benchmark is a fixed-weight portfolio (see Appendix 2 for details) and the second (referred to as the max-Sharpe benchmark) uses the weights derived from a full-sample maximum Sharpe ratio portfolio that is rebalanced every quarter.[9] Both benchmark strategies are macroeconomically agnostic as opposed to the seven macro dispersion strategies whose performance is conditional on the level of disagreement on each macroeconomic variable.

In Figure 7, you can see the summary statistics for each of the seven macro-based strategies and the two benchmarks. Figure 8 focuses on the performance of the best three strategies and the two benchmarks.

Figure 8: Asset allocation performance

Indices, 01/04/2002 = 100



Source: LSEG Datastream/Fathom Consulting

Figure 7: Summary statistics for macro-disagreement-based portfolios and benchmarks

	Fixed weights	Max-Sharpe	Payroll	"Industrial production"	Unemployment	Personal income	Personal consumption	Retail sales	Combo
Annualised return (no txn costs)	6.15%	4.87%	5.54%	4.61%	4.54%	4.76%	4.89%	4.61%	6.17%
Annualised return (txn costs)	6.12%	4.84%	5.37%	4.44%	4.33%	4.64%	4.72%	4.48%	5.95%
Annualised standard deviation (no txn costs)	10.16%	4.47%	5.34%	4.95%	5.24%	4.90%	5.00%	4.82%	5.77%
Annualised standard deviation (txn costs)	10.16%	4.47%	5.34%	4.96%	5.26%	4.91%	5.01%	4.83%	5.78%
Annualised Sharpe (risk-free=0%; no txn costs)	0.61	1.09	1.04	0.93	0.87	0.97	0.98	0.96	1.07
Annualised Sharpe (risk-free=0%; txn costs)	0.60	1.08	1.01	0.90	0.82	0.95	0.94	0.93	1.03
Alpha relative to Max-Sharpe (monthly; no txn costs)	-	-	0.06%	-0.02%	-0.03%	-0.01%	0.00%	-0.02%	0.10%
Alpha relative to Max-Sharpe (monthly; txn costs)	-	-	0.04%	-0.03%	-0.04%	-0.02%	-0.01%	-0.03%	0.08%
T-stat for alpha (no txn costs)	-	-	1.78	-0.52	-0.57	-0.20	0.04	-0.62	1.99
T-stat for alpha (txn costs)	-	-	1.70	-0.81	-0.88	-0.38	-0.22	-0.84	1.84
Average turnover	0.02	0.02	0.14	0.14	0.17	0.10	0.14	0.10	0.15

**txt=transaction costs assumed to be 10bp per round trip transaction*
Source: Datastream/Fathom Consulting

8 The assets picked (except for cash) are all included in the Personal Investment Management and Financial Advice Association (PIMFA) asset allocation, but this is also broadened to include high-yield credit, and both non-precious and precious commodities.

9 No further constraints are imposed other than the usual long-only and full-investment constraints.

You'll notice that the strategy based on the composite forecasters' disagreements is the best performing. Average correlations among the seven dispersion strategies and the max-Sharpe benchmark are very high (88%), suggesting that a large share of the performance is driven by the optimisation objective. However, the combo and the payroll dispersion strategy do provide 10bps and 6bps, respectively, of monthly alpha (about 1.2% and 0.7%, respectively, annualised) relative to the max-Sharpe benchmark and those are significant at the 10% level. Relative to the simple fixed weight benchmark, all strategies of Figure 8 provide significant improvements in efficiency without being eroded by the additional turnover costs.

Overall, this section has provided evidence that some disagreements on macroeconomic variables matter more than others. Tracking the dispersion of forecasts for payroll data appears particularly valuable and combining disagreements over different variables in a simple score card strengthens the signal and boosts returns.

BOX 1: How smart are Smart forecasts?

In this paper, we are primarily focusing on the dispersion in the range of contributor-level responses to the Reuters Poll and have demonstrated that rebalancing portfolios based upon this can generate additional returns for investors. However, the primary focus of the polls is to determine consensus estimates of the most-likely outturns for economic indicators. To the extent that the consensus numbers published by Reuters are what is then priced in by investors, any way of improving upon the accuracy of the polls could potentially be valuable information.

The consensus estimates published by Reuters, which are available on both the Datastream Data Loader and Datastream Web Service, reflect the median respondent's forecast for any given indicator. However, StarMine also calculate 'SmartEstimates' from the contributor-level data. These forecasts are available from 2013 and are calculated by looking at the historical performances of the analysts included in the poll, up-weighting those with a proven track record.

Figure 9 compares the forecasting accuracy of StarMine's estimates to those of the Reuters Poll and also to those of simple AR(1) processes.[10] As you can see, the StarMine SmartEstimates outperform the regular Reuters Poll estimates for most indicators and across most measures of forecasting accuracy.[11] This result does not materially change if observations taken during the recent pandemic are excluded from the sample. Interestingly, there are occasions where averaging across estimates provides a better forecast than simply picking one of the three point estimates. This appears to be the case for the unemployment rate and, dependent on the preferred metric of forecasting accuracy, personal income.

Figure 9: Comparison of forecast accuracy

	August 2013 – latest				August 2013 – December 2019			
	RMSE	MAE	SMAPE	Theil U1	RMSE	MAE	SMAPE	Theil U1
Personal income	Simple median	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Simple median	Smart estimate
Retail sales	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate
Unemployment rate	Simple mean	Simple mean	Simple mean	Simple mean	Reuters poll	Reuters poll	Reuters poll	Reuters poll
Personal consumption expenditure	Reuters poll	Reuters poll	Reuters poll	Reuters poll	Smart estimate	Reuters poll	Reuters poll	Smart estimate
Industrial produciton	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate
Nonfarm payrolls	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate	Smart estimate

Source: Datastream/Fathom Consulting

10 The AR(1) estimate is constructed as E_t (Outturn_(t+1))=Outturn_t. In other words, this is testing whether the current outturn is the best predictor of the next outturn. By construction, this is a very simplistic forecast, designed to test whether a series can be described purely as 'noise'.

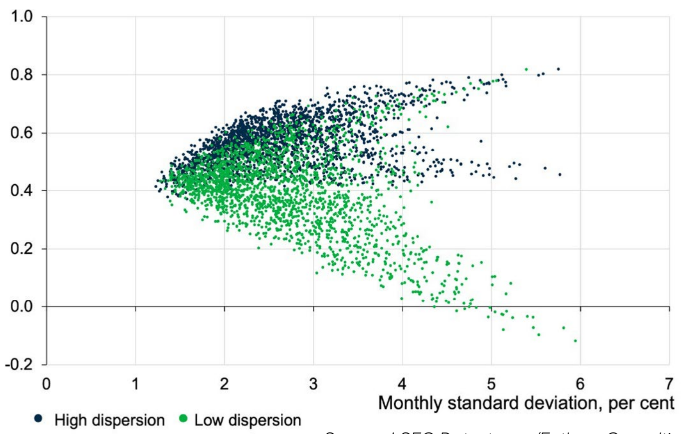
11 The four measures used to evaluate forecasting accuracy are the root mean squared error (RMSE), the mean absolute error (MAE), the symmetric mean absolute percentage error (SMAPE) and the Theil inequality coefficient (Theil U1).

From absolute to conditional forecasts

The previous analysis has showcased the potential of building portfolios using regimes of high and low dispersion in macro forecasts. However, the exercise remained silent about the sign of the relationship between asset returns and dispersion regimes. For example, does the US nonfarm payrolls strategy work because periods of high forecast dispersion are followed by high or lower portfolio returns? Looking at the risk and return distribution of 2000 random portfolios (e.g., the feasibility space) for the payroll strategy can help answer this question.

Figure 10: Payroll-regime-based efficient spaces

Monthly mean return, per cent



Source: LSEG Datastream/Fathom Consulting

Even with a substantial overlap between the two regimes, forecasters' disagreements about US payrolls can help disentangle the return/risk characteristics. Optimising portfolios using macro regimes is equivalent to generating a market forecast conditional on a macro indicator. In general, the more informative the macro indicator, the better the market forecast, the smaller the overlap between the risk and returns of the two regimes and the higher the risk-adjusted return of the overall strategy.

In the case of the nonfarm payroll strategy, periods of high dispersion in forecasts are associated with portfolio returns that are higher than during periods of low dispersion (e.g., a large share of blue dots are above the green ones). This finding is present in all six NBER-indicator strategies considered.[12, 13] In this respect, this paper lends support to Gao et al. (2019) who relate high dispersions of macro forecasts to periods with better market opportunities once the level of risk has been accounted for.[14]

The latter disclaimer is important as it implies that the dispersion in macroeconomic forecasts can be thought of as a risk and signal with separate properties from the overall level of market risk. To see this, another strategy can be constructed, this time using regimes on the VIX index. A level of the VIX above 20 is taken as a high-risk regime and below as a low-risk regime. The resulting feasibility space of this strategy is portrayed in Figure 11.

Figure 11: VIX-regime-based efficient spaces

Monthly mean return, per cent

Source: LSEG Datastream/Fathom Consulting

12 The positive relationship between dispersion and portfolio returns is also robust to the definition of dispersion. For example, defining dispersion as the simple 12-month rolling average in the difference between the max and min forecast does not alter the finding.

13 The combo strategy can be also thought of as a joint probability of witnessing extreme disagreements among a broader set of macroeconomic indicators. This joint probability aligns the risk signals of the macroeconomic forecasts with market-based risk signals, such as those coming from VIX. Unlike for the single macroeconomic indicators, the combo strategy unsurprisingly shares some fundamental similarities with the VIX strategy, such as the negative relationship between regime and returns whereby higher (lower) combo dispersion is associated with lower (higher) returns.

14 In our set-up, the level of risk is controlled for by the optimisation routine. By maximising the portfolio Sharpe ratio in each regime and quarter, we are effectively picking the combination of assets with highest return per unit of risk conditional on the level of dispersion in macro forecasts.

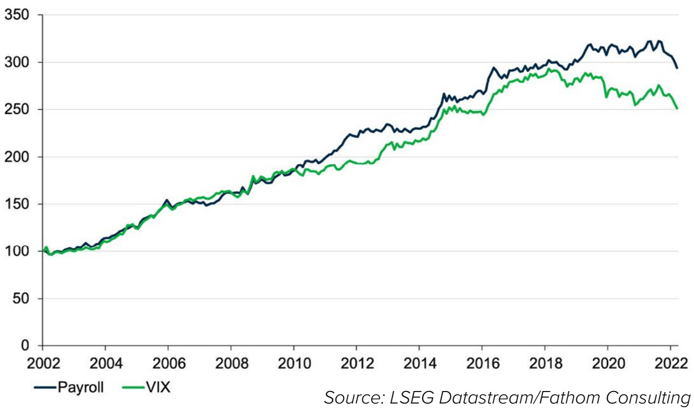
A few points stand out:

- The relationship between regime and returns is negative; the high VIX regime is the one consistent with lower portfolio returns and higher risk
- The separation between the two regimes appears more net than with the payroll regimes
- The portfolio relationship between risk and return is broadly upward sloping in the low VIX regime and downward sloping in the high VIX regime

Figure 12, which compares the performance of the payroll and the VIX strategies, shows a similar level of performance up to 2010 followed by two clear periods of underperformance between 2010 and 2013 and since 2018. As observed before, periods of high levels of disagreement among forecasters nest periods of high VIX. Controlling for the level of market risk (through the optimisation routine) allows the fainter, but more frequent, signal from forecast disagreements to reveal itself.

The relationship between the VIX and forecast dispersion can also be seen as the result of the conceptual difference between risk, such as market risk, and Knightian uncertainty, a truer expression of a fundamental disagreement among informed agents. The first is the realisation of fears in markets. Market risk can generally be hedged, and its effect tends to be more persistent over time (e.g., during recessions). Knightian uncertainty, however, occurs perhaps much more frequently than large market sell-offs, but it is not hedgeable since it does not directly relate to market prices.

Figure 12: Asset allocation performance
Indices, 01/04/2002 = 100



Source: LSEG Datastream/Fathom Consulting

The Holy Grail for a macro investor would be to combine the information held in both market prices (e.g., the VIX) and macro dispersions measures in a robust way. The first provides information about risks in markets that are only imperfectly related to the economy, while the second holds valuable information about risks in the economy but only indirectly about markets.

Ideally, an investor could observe many independent forecasts of market returns conditional on the state of the economy and then create a dispersion measure around these. This is essentially what we strive to do: relate market outcomes to macro trends in as transparent a way as possible through clear scenarios and forecast ranges. Given the scarcity of observation of such conditional forecasts, the options available to investors are:

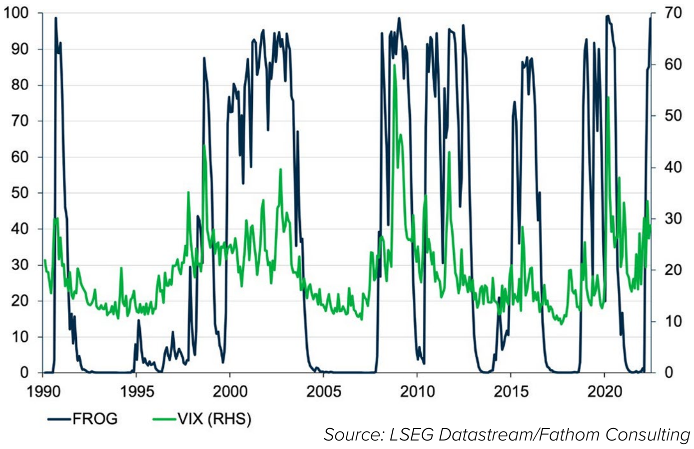
1. Leverage economists' unconditional forecasts, such as those supplied by LSEG, in a process like the one described in the previous section
2. Generate their own market forecasts conditional on macro variables

A conditional forecast application

In this last section, we briefly introduce an example of how investors could go down the second of the above routes and generate their own market forecasts conditional on macro variables using data available from LSEG. A conditional forecast could be as simple as a regression between current asset prices and lagged macroeconomic variables, or a sorting of historical returns across deciles of macroeconomic variables. The drawback with both approaches is that they either rely on univariate relationships or assume a strict causal relationship between asset prices and macroeconomic variables. In both cases, the methods generally lead to weak market signals. Another method, and one which we have had more success with, relies on forecasting market regimes where the probability of being in a certain phase depends on the evolution of macroeconomic and financial variables. We have constructed one such forecast using LSEG data, which incorporates the evolution of the macro cycle, market liquidity, and the correlation between bond and equity markets. The output is what we call FROG (Fathom Risk-Off Gauge), a probability that markets are in a risk-on or -off regime.[15] Conceptually, this type of indicator is attractive because it mimics the kind of forecaster who is continuously learning about the relationship between markets and the economy, who is never sure which market regime will prevail at any given point in time, but who is also undeterred in providing clear probability estimates. The risk-off regime is defined as whenever the risk-off probability rises above 30%. Figure 13 provides a visual comparison between the risk-off probability regime and VIX overtime.

Figure 13: FROG and VIX

Probability, per cent | Annualised standard deviation

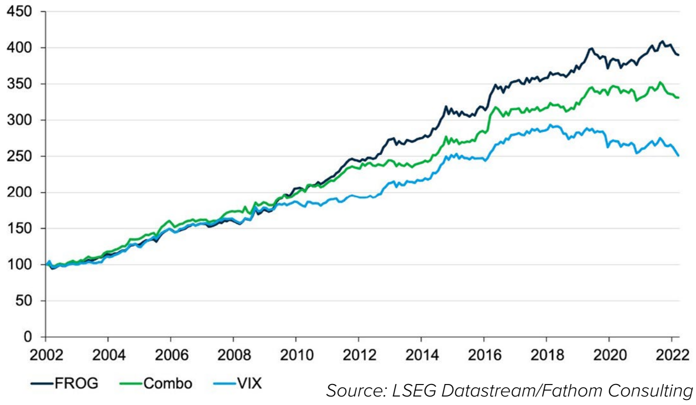


Source: LSEG Datastream/Fathom Consulting

Figure 14 compares the performance of using a probabilistic insight about market regimes relative to the VIX and the combo strategies explored earlier. The two strategies accounting for macroeconomic forecasts significantly outperform the price-based VIX strategy. Moreover, the FROG-based portfolio, by incorporating both macroeconomic and market dynamics, outperforms in absolute and relative terms by delivering an annualised 6.8% average return with a 1.22 Sharpe ratio.

Figure 14: Asset allocation performance

Indices, 01/04/2002 = 100



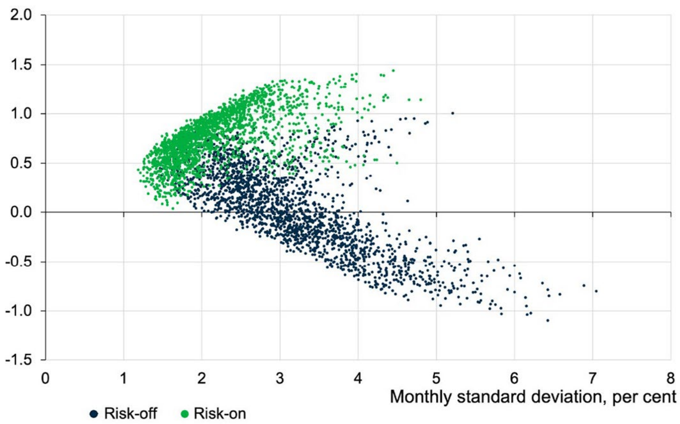
Source: LSEG Datastream/Fathom Consulting

15 In more detail, FROG models the monthly excess returns of equity over bonds as a two-regime Markov switching model with time-varying volatility and transition probabilities conditional on the level of macro variables. The model follows long established ideas from Hamilton (1989) and Filardo (1994) and integrated readily available series from LSEG. A detailed explanation of FROG is beyond the scope of this note.

Exploring the feasibility space of the FROG strategy in Figure 15 highlights some key properties that investors should look out for when creating their own conditional forecasts.

Figure 15: FROG-regime-based efficient spaces

Monthly mean return, per cent



Source: LSEG Datastream/Fathom Consulting

- Risk-on and risk-off phases should be as clearly differentiated as possible (little overlap between regimes)
- The relationship between risk and return should be broadly downward sloping in risk-off periods and upward sloping in risk-on phases

Ultimately, it is the continuous interaction between macroeconomic trends and market prices that creates better defined regimes by allowing macroeconomic uncertainty to influence the probability of being in a certain market regime.

Conclusion

In this paper, we have provided several insights about the value of forecasting and forecasts of macroeconomic variables. First, better portfolios can be constructed by leveraging the level of disagreement among macroeconomic forecasters polled by Reuters. Second, the constructed strategies provide evidence supporting the findings of Gao et al. (2019) that a higher level of disagreement among macro forecasters is associated with higher asset returns when controlling for the level of market risk. This last point further highlights a complementarity between the signals provided by macroeconomic and market risks that can be exploited by formulating well specified market forecasts conditional on macroeconomic trends. To confirm this, we showed an example of how we integrate such conditional forecast through using readily available macro and financial market data from LSEG.

Appendix 1

Appendix 1a: US nonfarm payrolls, since 1999

	Initial	High	Low	Median	Surprise	Dispersion
Mean	79.73	284.35	-83.91	110.16	-30.43	8.73
Standard deviation	1292.40	651.87	1326.05	619.08	1164.15	1222.95
Smallest value	-20537.00	-1657.00	-17000.00	-8000.00	-16287.00	-3909.75
35 percentile	98.25	195.00	40.00	120.10	-40.95	-26.41
Median	147.00	230.00	94.50	171.50	-13.50	-9.50
65 percentile	198.85	258.85	125.00	188.95	20.00	6.63
Greatest value	4800.00	9000.00	656.00	3000.00	10509.00	12530.58

Source: Datastream/Fathom Consulting

Appendix 1b: US industrial production, since 1999

	Initial	High	Low	Median	Surprise	Dispersion
Mean	0.14	0.80	-0.47	0.18	-0.04	0.01
Standard deviation	1.05	1.03	1.66	0.90	0.48	1.61
Smallest value	-11.20	-3.00	-25.10	-11.50	-2.50	-4.63
35 percentile	0.00	0.50	-0.40	0.20	-0.20	-0.21
Median	0.20	0.70	-0.20	0.20	0.00	-0.09
65 percentile	0.40	0.80	-0.10	0.30	0.10	0.03
Greatest value	5.40	12.30	1.70	4.30	1.20	18.64

Source: Datastream/Fathom Consulting

Appendix 1c: US unemployment, since 1999

	Initial	High	Low	Median	Surprise	Dispersion
Mean	5.84	6.13	5.73	5.93	-0.09	0.00
Standard deviation	1.94	2.48	1.95	2.19	0.52	0.80
Smallest value	3.50	3.60	3.10	3.50	-6.50	-2.56
35 percentile	4.70	4.90	4.60	4.70	-0.10	-0.05
Median	5.30	5.50	5.20	5.30	0.00	-0.02
65 percentile	5.90	6.00	5.80	5.90	0.00	0.02
Greatest value	14.70	27.00	16.70	19.80	0.60	8.33

Source: Datastream/Fathom Consulting

Appendix 1d: US personal consumption, since 1999

	Initial	High	Low	Median	Surprise	Dispersion
Mean	0.36	0.80	-0.09	0.35	0.01	0.02
Standard deviation	1.22	1.69	1.66	1.12	0.27	1.72
Smallest value	-13.60	-5.00	-22.00	-12.60	-2.50	-4.73
35 percentile	0.20	0.50	0.00	0.30	-0.10	-0.11
Median	0.40	0.60	0.10	0.40	0.00	-0.05
65 percentile	0.50	0.70	0.20	0.40	0.10	0.02
Greatest value	8.20	24.00	3.50	9.00	0.70	17.04

Source: Datastream/Fathom Consulting

Appendix 1e: US retail sales, since 1999

	Initial	High	Low	Median	Surprise	Dispersion
Mean	0.33	1.08	-0.51	0.28	0.05	0.03
Standard deviation	1.96	1.37	2.00	1.24	0.96	1.69
Smallest value	-16.40	-4.00	-24.00	-12.00	-4.40	-5.00
35 percentile	0.10	0.61	-0.50	0.20	-0.20	-0.27
Median	0.30	0.80	-0.20	0.30	0.00	-0.10
65 percentile	0.60	1.00	0.00	0.50	0.20	0.06
Greatest value	17.70	13.00	3.50	8.00	9.70	20.38

Source: Datastream/Fathom Consulting

Appendix 1f: US personal income, since 1999

	Initial	High	Low	Median	Surprise	Dispersion
Mean	0.35	0.76	-0.24	0.25	0.10	0.01
Standard deviation	1.86	1.81	2.32	1.78	1.06	2.09
Smallest value	-13.10	-8.00	-21.50	-14.10	-1.40	-5.74
35 percentile	0.30	0.50	0.00	0.30	-0.10	-0.13
Median	0.35	0.60	0.10	0.30	0.00	-0.05
65 percentile	0.40	0.60	0.20	0.40	0.10	0.01
Greatest value	21.10	22.50	17.20	20.30	17.00	28.55

Source: Datastream/Fathom Consulting

Appendix 2

Appendix 2: Asset definitions*

Abbreviation	Description	DS codes
eq_uk	FTSE 100	FTSE100
eq_exuk	MSCI ACWI , excl. UK	MSWFUK$
fi_corp	IBoxx UK corporates	IB£CSAL
fi_hy	Bloomberg global HY corporates	BGHYDGU
fi_gilt	IBoxx UK gilts	IB£GLAL
fi_idx_gilt	FTSE index-linked all-maturity UK govt bonds	BGILALL
comn	S&P Goldman Sachs commodity index	GSCITOT
comn_prec	S&P Goldman Sachs commodity index - precious metals	GSPMTOT
alt	MSCI ACWI diversified multifactor - 0.7*MSCI ACWI	MSAFMFL, MSACWF$
prop	LSEG Datastream UK real estate	RLESTUK

**We denominate all prices to GBP, if they are not already, using the FX rates*
Source: Datastream/Fathom Consulting

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