Caught by surprise: how markets respond to macroeconomic news

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Abstract

We propose a new method to measure the current state of economic surprises across different economic releases. Empirically, economic surprises related to macroeconomic growth consistently and robustly predict short-term returns in risky asset classes (equities, credits, commodities), while it predicts bond returns over a yearly forecast horizon. These effects are attributable to short-run momentum in economic surprises. A simple investment strategy using growth surprises outperforms equity markets, providing annualized alpha's between 2.74% and 4.22%.

1 Introduction

Participants in financial markets observe a rich stream of economic news on a daily basis. The information content in this news flow is used by these participants in order to update their perception of the state of the economy. For investors, this flow of news serves as an input for their financial decision-making process. A basic, yet important, question is whether news on fundamentals have an impact on asset prices. Understanding this pattern is an important empirical question, since it plays a central role in asset pricing and investments. In this paper, we comprehensively study this link in equity, bond, credit, and commodity markets across the world.

Theoretically, the state of economic fundamentals should alter the pricing kernel, and therefore also asset returns. For example, the Intertemporal Capital Asset Pricing Model (ICAPM) (Merton, 1973) stipulates that in a risk-averse economy any variable that affects the set of future investment or consumption opportunities earns a risk premium. Macroeconomic variables should be a main candidate since they impact the cash flows of agents in the real economy. Chen, Roll, and Ross (1986), Fama and French (1989) and Ferson and Harvey (1991) argue that expected business conditions are fundamental drivers of time-variation in expected risk premia.

The informational content of macroeconomic news can be decomposed in an unexpected part ('surprise'), relative to a market consensus, and in an anticipated component. Asset prices (should) incorporate the informational content of the surprise component of this news shortly after the news, but have no impact on markets afterwards (Fama et al., 1969). To date, studies on the link between surprises in macroeconomic news and asset returns have been ambiguous. Most studies are typically isolated to a particular market or asset class, isolated to a handful of releases or plagued by substantial measurement issues of macroeconomic

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fundamentals. Moreover, the impact of surprises has been typically studied on a short time horizon around the news release. In general, macroeconomic surprises are found to move markets the minutes around their release times (Balduzzi, Elton, & Green, 2001).

In this paper, we study the impact of surprises in macroeconomic news on asset markets along multiple dimensions. First, we examine the behaviour of macroeconomic surprises. Second, we focus on two main categories of macroeconomic fundamentals, namely economic growth and inflation. These are the major aspects in theoretical models about the impact of macroeconomic variables on markets, and generally seen as the main macroeconomic drivers of financial markets. Third, we examine the impact of macroeconomic news surprises across all major asset classes (equities, bonds, credits, and commodities) and across major economic regions (U.S., U.K., the Eurozone and Japan). All these asset classes are affected by time variations in growth and inflation conditions, admittedly to various degrees. Fourth, we examine the relevance of both surprises in global macroeconomic news and regional news. Lastly, we explore the channels that links economic surprises to asset returns.

To these ends, we construct a measure of surprises in macroeconomic news. However, three major challenges arise in constructing such a measure. The first question that arises is how to measure macroeconomic news as was historically available to investors (i.e. in real time). Macroeconomic news is released with a time delay and the contained information often suffers from restatements. Ghysels et al. (2014) finds that the use of unrevised data and properly accounting for publication delay can severely impact findings, undoing most of the previously found predictability of Ludvigson and Ng (2009) for bond returns. Secondly, macroeconomic releases are infrequent (typically monthly). As a consequence, individual series on macroeconomic fundamentals are observed at a low frequency, unlike the near-continuous flow of macroeconomic information available to investors. The third challenge is how to measure macroeconomic conditions. Almost daily, macroeconomic numbers are released, that are studied and appreciated by investors. Previous studies have typically focused on a few selected macroeconomic series over their release frequency (typically the PPI or CPI rate, non-farm payrolls or the unemployment rate at a monthly frequency, see amongst others Boyd, Hu, and Jagannathan (2005), Smirlock (1986), Urich and Wachtel (1984), and Beber and Brandt (2009)). However, each individual macroeconomic series reflects only a part of the economy, and is an incomplete measurement of the underlying macroeconomic fundamental.

To tackle these challenges, we utilize real-time information as actually released on the announcement days, capture macroeconomic information flows across all major releases classified in either a 'growth' or an 'inflation' category and combine them in a daily measure of surprises in macroeconomic news. To do so, we measure the current state of surprises across different economic releases using a methodology similar to Beber, Brandt, and Luisi (2015). A unique differentiating feature of our approach is that we account for both surprises to current numbers and revisions to past numbers, as both reflect the arrival of new information (Krueger and Fortson (2003), Faust, Rogers, Wang, and Wright (2007) and Ghysels et al. (2014)). Their proposed methodology allows to distill the news flow of all major macroeconomic releases observed at different times and frequencies into a daily measure of aggregate macroeconomic conditions. This eliminates the reliance on a small number of imperfectly measured indicators to proxy for macroeconomic conditions and thereby spanning the information in all major macroeconomic releases available to market participants.

The main benefits of this method are that it (i) allows to focus on well interpretable categories of economic information (growth and inflation), instead of purely statistical factors, (ii) it relies on real-time data and does not utilize future information, thereby not creating a confounding impact on future returns, (iii) extracts the common information within a category based on the cross-sectional variation in a category, and (iv) allows for data available at the daily frequency[1]. Beber et al. (2015) shows that their resulting real-time indices are highly correlated with other approaches, like GDP, CFNAI and ADS, but appear more timely and informative about future macroeconomic fundamentals.

We document the following results. First, surprises appear to be persistent over time, suggesting that surprises do not occur randomly (figure 2). The autocorrelation that we document in our surprise indexes stem both from autocorrelation in the underlying surprise time series and auto-covariance between surprise series (figure 3). Second, economic surprises consistently predict returns on risky assets (table 4). We sort our surprise index in increasing order for each market over the full sample and divide it in five equally-sized buckets. For each bucket we compute the subsequent monthly excess return of the asset classes and average these over all markets. In the lowest surprise quintile, the subsequent average monthly excess equity return for the U.S. is -0.42%, while it increases over the buckets to 1.11% for the highest quintile. The resulting top minus bottom quintile spread equals 1.53%. We find that higher global surprises predict higher subsequent monthly excess stock returns for our sample period which spans from January 1997 to June 2019. The latter result is in line with business cycle studies that, show that a global business cycle factor is a major source in explaining variation in macroeconomic aggregates per country, while country-specific or regional information is of smaller importance (Kose, Otrok, and Whiteman (2003) , Canova, Ciccarelli, and Ortega (2007)).

We explore this predictability more formally using in-sample regressions and out-of-sample forecasts metrics that control for information availability in real-time. In-sample, we document that both local and global growth surprises predict future monthly equity returns after controlling for multiple other predictors (table 6). Furthermore, from an out-of-sample perspective, we find that economic growth surprises generate substantial gains in utility for a mean-variance investor who divides his wealth between equities and risk-free bills. Lastly, a simple investment strategy based on global growth surprises outperforms equity markets and yields annualized alpha's between 2.74% and 4.22% (table 9).

In addition, in-sample, we find that growth surprises predict bond returns negatively, while it predicts positively predicts future excess returns in credits and commodity markets. Thus, growth surprises seem to positively predict future returns in risky asset classes. Surprises inflation do not seem to predict future excess returns in all the asset classes that we analyze. Besides, we vary the look-back period of our surprises and the forecast horizon of returns. Equity returns ranging from daily to monthly forecast horizons are predictable using past growth surprises up to the previous month. In addition, long-term bond returns are predictable using surprises in macroeconomic growth using lookback periods up to one year.

Furthermore, we document an asymmetric effect of growth surprises on financial returns across the market state. Specifically, we find that market return predictability increases during bear markets. Surprises in macroeconomic growth surprises become significantly stronger when the past 12-month market return was

[1] Other approaches that summarize the cross-section of macroeconomic series into a few common dimensions are the dynamic factor approach of Ludvigson and Ng (2009), the CFNAI index based on Stock and Watson (1989) and the nowcast approaches of Aruoba, Diebold, and Scotti (2009) or Gilbert et al. (2017) (GSSV). The dynamic factor approach extracts the main latent factors, complicating their exact interpretation as either growth or inflation factors, and is not available at the daily frequency. CFNAI is only available at monthly frequency. Aruoba et al. (2009) only considers a few indicators. The GSSV approach assigns weights to each macroeconomic release depending on the contribution to a business condition index capturing the future state of the economy. Scotti (2016) proposes a dynamic factor method to summarize macroeconomic information of five to six key indicators of real activity based on their contribution to a coincident index of economic activity (the ADS index).

negative. Previous studies also suggest that announcement effects are asymmetric over recessions and expansions. For example, Boyd et al. (2005) show that during contractions stock markets respond negatively to an announcement of rising unemployment, while during expansion both stock and bond prices respond positively to such news. Likewise, Beber and Brandt (2009) shows that macroeconomic announcements is most important when it contains bad news for bond returns in expansion and less important for good news in contractions.

What drives the predictive relationship between the macroeconomic news and asset returns? Two main explanations exists. First, the predictability may align with market efficiency and reflect rational time-varying required returns. Risk premia vary over time and a variable predicting stock returns could indicate predictable variation of risk premia across economic states of the world, or changing investment opportunities in the spirit of the ICAPM of Merton (1973). Alternatively, it may capture changes in market-wide risk aversion. Second, the documented predictability may reflect a market inefficiency, and signal market timing opportunities not properly related to increases in risk. We provide several observations that are in line with the latter explanation.

First, in efficient markets, higher expected stock returns may be the results of increases in risk and hence yield a higher risk premia. However, we document that global growth surprises negatively predicts future realized volatility in equity markets. Admittedly, we may have overlooked other explanations. However, regardless of the true explanation, a rational time-varying risk premia explanation is hard to align with negative expected returns (Baker and Wurgler (2000)). Therefore, we expect no negative expected returns when the predictability is due to market efficiency. By contrast, a market inefficiency explanation is likely to imply predictable negative returns. Secondly, we document evidence in favour of the latter explanation, yielding us to conclude that the predictability reflects a market inefficiency due to investors' expectations being sticky. We conjecture that surprises occur systematically due to an anchoring bias in forecasts. We test this hypothesis, inspired by Campbell and Sharpe (2009), and indeed find that forecasters tend to put too much weight on recent past information.

Lastly, we also consider other methodologies to extract a common factor in macroeconomic news. First, we use the Three-pass regression filter (3PRF) introduced by Kelly and Pruitt (2015). Second, we use Partial Least Squares (PLS). Lastly, we use a simple equal-weighted (EW) average of all surprises to construct an index. The former two techniques are aimed at predictability, while the latter is one of the most simplest weighting scheme. We find that 3PRF and PLS yield in-sample results that are even stronger than our previous results, but not out-of-sample. The EW surprise index is not able to predict future asset returns, indicating the added value of a sophisticated weighting scheme.

The remainder of the paper is structured as follows. In section 2, we describe the macroeconomic news data and the methodology to construct economic surprise indexes. Section 3 describes the dynamics of these indexes and documents momentum in economic surprises. Section 4 examines the predictive power of economic surprises on asset returns. Sections 5 presents various robustness tests results. Section 6 examines the channels behind the documented predictability of asset returns using economic surprises. Section 7 concludes.

2 Data and Methodology

Do fundamental macroeconomic news impact asset prices? Understanding this relationship is important, as it plays an essential role in asset pricing and investments. Several studies document an impact of economic releases on financial markets. Announcements on unemployment, balance of trade, housing variables, inflation and money growth have been documented to impact U.S. stock returns (McQueen and Roley (1993), Flannery and Protopapadakis (2002), Boyd et al. (2005), Campbell and Diebold (2009)), U.S. stock volatility (Flannery and Protopapadakis (2002), Paye (2012)), U.S. bond returns (Boyd et al. (2005), Beber and Brandt (2009)) and U.S. bond volatility (Beber and Brandt (2009)). In addition, several papers study the impact of macroeconomic surprises on asset markets.

These studies typically focus on intra-day or daily responses (Balduzzi et al. (2001), Andersen, Bollerslev, Diebold, and Vega (2007), Faust et al. (2007), Gilbert et al. (2017)) or a particular announcement relative to an econometric model of expectations (Boyd et al. (2005)). However, most of these studies focus on one to several announcement series and typically focus on U.S. stock or bond returns. Each announcement series reflects a part of the state of the economy. To provide a more comprehensive measure of the state of the economy, it is essential to study a broad range of announcements. Flannery and Protopapadakis (2002) are one of the first to study a broad range of macroeconomic releases across nominal and real variables (17 in total).

Our approach differs from most of these papers by considering a large set of macroeconomic surprises. In addition, we comprehensively study how these surprises impact several asset classes and regions on a longer time horizon. Lastly, up to our knowledge, we are first to also include surprises due to data revisions in economic releases. To provide a measure of surprises on the state of the economy, we present a methodology that allows us to construct latent surprise factors that summarize the cross-section of macroeconomic surprises. We first elaborate on the data that has been collected for this study, and afterwards explain how this data can be processed into a latent factor that represents the state of economic surprises via our methodology.

2.1 Bloomberg Economic Calendar

The use of real-time information is a crucial ingredient for studying the impact of macroeconomic information on asset prices (Ghysels et al., 2014). Therefore, we collect real-time macroeconomic announcement records for the United States, the European Union, the United Kingdom and Japan from the Bloomberg Economic Calendar (BEC). The sample period spans the period between January 1997 and June 2019. Each announcement record consists of a release time, announcement value, a consensus forecast, the standard deviation of this forecast and potentially a revision to the previous announcements[2]. Bloomberg consensus estimates are widely followed by investors, as for example witnessed by their frequent appearances in headline news and by actual numbers deviating from these numbers triggering a market reaction (Vrugt, 2009). Since 1997, BEC provides exact time-stamped real-time, non-revised and non-restated data. We select 62 distinct macroeconomic variables for the U.S., 79 for the EU, 34 for the U.K. and 31 for Japan[3]. Thus, globally, we use over 200 different macroeconomic variables. This amounts to a data set containing approximately 10.500 unique surprises for US, 3.500 for UK, 3.000 for Japan, and 8.000 for Europe. In total we have around 25.000 unique macroeconomic surprises in our data set. Our set of selected macroeconomic variables slightly differs

[2]Bloomberg surveys economists during the weeks up to three days prior to the announcement.

[3]Some specific remarks based on the regions: US: we exclude the Conference Board US Leading Index as this is a composite index which is already covered by other variables which we already include. EU: we only choose variables that are from Germany, France, Italy, Spain and the Eurozone aggregate, as these countries cover the major part of the Eurozone economy.

from Beber et al. (2015). We extend their set of macroeconomic variables by adding a number of housing related releases (such as home sales). These variables are widely tracked by investors and economists and provide additional information about the state of the economy.

In addition, we add several other macroeconomic variables according to the relevance index in Bloomberg. This index tells us how closely an announcement is followed and provides an indication of how important the variable is according to economists[4]. In appendix A, we provide further information on the exact set of macroeconomic news variable that is included in our sample. Bloomberg also contains data prior to 1997. However this information is stored in historical fields dated according to their reference period. In addition, this information may have been restated over time. Nevertheless, we collect this data between January 1990 till December 1996 to construct an estimate for a initial correlation matrix, as will be explained in section 2.2.

We follow Beber et al. (2015) and impose structure on our set of macroeconomic announcements based on economic rationale. We subset macroeconomic variables in two categories: "inflation" and "growth". This approach has two advantages over other approaches. First, the factors are easy to interpret from an economic point of view (unlike the statistical approach used in Ludvigson and Ng (2009)). Second, it combines all relevant macroeconomic announcements that are studied by investors within each category into one factor (in contrast to studies focusing on a single or few announcement time series). We subdivide the "growth" category further into three subcategories: output, employment and sentiment. The former two categories contain information on variables like GDP growth, and non-farm payroll. Sentiment contains subjective views on the current or future state of the economy, which are obtained from surveys. We ignore any financial market measure related to interest rates or central bank policy (like FOMC rate decisions) to focus on macroeconomic news announcements not driven by interest rate movements. In contrast, other studies use information like interest rates, credits spread, stock prices or the VIX index (Ludvigson and Ng (2009), Aruoba et al. (2009)). However, such information may already reflect market's opinion on the state of the economy. We construct daily latent factors that summarizes the macroeconomic series per category (inflation, employment, output and sentiment). Appendix A provides the allocation of announcements to the subsets that we use.

2.2 Expanding window principal component analysis

In order to construct our latent factors, we opt here for a principal component analysis (PCA) on an expanding window size, i.e. recursively. This allows us to handle data releases at different frequencies and missing values. In addition, this allows us to construct a real-time high-frequency latent factor of the state of the economy and surprises. Before the start of the expanding window PCA, each announcement time series is recursively standardized such that it has zero mean and unit variance for every day t. To initialize the recursive principal component analysis, we use the historical data between January 1990 and December 1996 to calculate an initial correlation matrix per category. Using this initial correlation matrix, we calculate an initial weight for each variable via computing the first principal component [5].

A recursive PCA is conducted for each class of macroeconomic surprises series by region. On each day t,

[4] Bloomberg's relevance score represents the number of alerts set on Bloomberg terminals for an economic event relative to all alerts set for a particular country or region.

[5] The historical data does not contain the announcement dates, but only the reference dates. Beber et al. (2015) suggest to correct these historical reference date by estimating the median lag length between the reference date and announcement date in the data-set after 1997. Throughout the analysis, we work with factors without this correction. However, a robustness test in section 5.2 shows that our factors are highly correlated with corresponding factors estimated after the correction.

within class i, we first compute the correlation matrix $\Omega_{t,i}$ using information up to day t for all currently active macroeconomic series. We use the correlation matrix, rather than the co-variance matrix, to correct for different scaling used for the macroeconomic variables. After calculating the correlation matrix at time t, we extract the daily factor loadings obtained from the first principal component of this correlation matrix. These loadings are assigned, as a weight, to its corresponding macroeconomic news series within class i. Other studies, like (Ludvigson & Ng, 2009), also use the second and the third principal component. However, it is difficult to assign economic meaning to the second and third principal components. Therefore, we only focus on the first principal component. Several technical issues have been taken into account when estimating this correlation matrix. First, we have an unbalanced panel data-set, since some series start after the start date of the estimation window. Not every macroeconomic series has records of real-time announcements from January 1990. Some variables have records of real-time announcements from an arbitrary date after Jan 1990. We include them into the analysis sequentially, conditional on at least 5-year data being available to calculate an initial correlation matrix. To deal with unequal sample lengths, we follow the methodology as proposed by (Stambaugh, 1997). This methodology results in a correlation matrix estimate that is constructed using adjusted first and second moments. The idea behind the methodology is to use the observed data of the longer time series with a projection of the shorter series on the longer series, when both are observed, to adjust the moments of the shorter time series.

Second, most macroeconomic announcement series have an autocorrelation structure. This is due to the natural autocorrelation of the raw data in announcement time (before forward-filling), misalignment of the news in calendar time, and forward-filling of missing values. Especially forward-filling creates local constancy and thereby a high persistency within time series. To account for the local constancy, we perform subsampling over 22 business days, as described in Beber et al. (2015). On day t we draw 22 sub-samples backwards from the forward-filled news announcement series. These sub-samples start from $t-1$, $t-2$, $t-3$, $\cdots$, $t-22$, respectively (in other words, the first sub-sample has observations on day $t-1$, $t-23$, $t-45$, $\cdots$, etc.). Subsequently, we use the Newey-West method to calculate a heteroskedasticity and autocorrelation consistent correlation matrix using four lags. For each sub-sample, we calculate this Newey-West correlation matrix, and then take the average over all the estimates of the 22 correlation matrixes[6].

2.3 Latent factors

The methodology above allows us to extract daily factor loadings from a set of economic announcement series within a category and region. We use these factor loadings to construct our latent factors. Per category within a region, we build three daily indexes; (i) the actual state of the economy (level), (ii) the ex ante uncertainty surrounding the level (uncertainty), and (iii) the current surprise in the level. We use the following formula to build the level factors ("Actuals"):

$$A^r_{c,t} = \sum_{i \in \omega_t} \lambda^r_{i,c,t} A^r_{i,c,t}$$

Superscript r denotes the regions. Subscript c denotes the category. ω_t denotes the set of currently active macroeconomic news series at day t. We sum at each day t the product of the factor loadings ($\lambda^r_{i,c,t}$) multiplied by its corresponding forward-filled real-time announcement value ($A^r_{i,c,t}$). In appendix B we plot the time-varying factor loadings for U.S. sentiment, employment, and output variables. As can be seen from these plots, the loadings are relatively stable over time, but differ across economic variables. This indicates

[6] See also (Ait-Sahalia, Mykland, & Zhang, 2005) for more specifics about this subsampling method.

that different weights are being assigned to different macroeconomic series within the same category.

Since we have four regions (U.S., U.K., EU, JP) and four categories (inflation, employment, output and sentiment), we obtain sixteen level factors. We can construct the uncertainty and surprise factors in the same fashion, where we use the standard deviation across economic forecasters, respectively the economic surprise, instead of the announcement value. The economic surprise consists of two parts. The first part is the announcement surprise, which is the difference between the latest real-time announcement value and the economists' survey consensus[7]. The second part is defined as the 'revision surprise', defined as the difference between the latest revision value and last period's announcement. This latter term is, to the best of our knowledge, not employed in earlier literature, but does reflect the arrival of new information to investors (Ghysels et al., 2014).

In addition, we build a "growth" and "inflation" level per region by taking an equal-weighted average of the employment, output and sentiment level factors. In the same manner, we also construct a "growth" and "inflation" uncertainty and surprise factor. In our analysis, we are interested in the surprise factors for both the growth and inflation category across the four regions. The level and uncertainty factor are used to control for the actual state of the economy and disagreement among economists.

2.4 Data transformations and forward-filling

Several data transformations are be required for the data analysis. First, the data series might be non-stationary. To check for stationary, we conduct an (augmented) Dickey-Fuller test for each macroeconomic variable. In addition, based on the description and definition of a variable, we determine whether a variable is stationary from an economic perspective. A growth rate, for example, would be considered as a stationary time series. Time series that are non-stationary are first-differenced before the start of the analysis. Conclusions from the two methods differ in some cases, because some data series are too short with less than 5 years of announcements, for example. In these cases, we rely mostly on the economic definition and description to determine whether the time series are stationary or not. Appendix A lists which announcement series are adjusted to deal with non-stationarity. Furthermore, a small portion of macroeconomic variables are not seasonally adjusted. These are mainly U.K. and Eurozone inflation variables. We show, in Appendix C, that inflation factors created from seasonally adjusted series are highly correlated with the initial set of data.

Second, we convert the data from announcement time format to calendar time. This, however, generates a sparse data matrix with many missing values. We solve this by forward-filling the missing value by the last observed value of each macroeconomic variable for each day in the sample. In this case, we can think of the time series in calendar time as a step function that changes in value when a new announcement is released for that variable. Other statistical models exist to impute missing values, however these models are far more complex. We favor the simplicity of filling the missing values by the last observed value. Third, some macroeconomic variables do not span the whole time period. Some time-series start later in the sample or stop to exist before the end of the sample. Imputation by forward-filling is not able to solve this problem. We take this into account in our methodology by recursively conducting PCA analysis and use the cross-section of currently active time series.

[7] We define the consensus as the median expected release value for the upcoming news announcement across economic forecasters

2.5 Financial market data and control variables

In order to study whether macroeconomic surprises affect financial markets, we obtain data for several asset classes. For the stock market, we obtain historical prices of the front-month futures contract rolled the day before expiry of the S&P 500, FTSE 100, NIKKEI 225 and EUROSTOXX 50 from DataStream. The stock market excess return is calculated as the return on the index futures contract minus the 3-month LIBOR. For the bond market, we calculate government bond excess returns from government bond trackers indexes obtained from DataStream. For commodities, excess returns from the DJ-UBS overall index and the GSCI commodity index is calculated.

We use the corresponding volatility index (VIX for the S&P 500, VFTSE for the FTSE 100, VXJ for NIKKEI 225 and VSTOXX for the EUROSTOXX 50), price earnings ratio and dividend yield of each stock market as control variables, obtained from Datastream. For bond and commodity markets, we control for the short rate, default spread and term spread. The short rate is the return on three-month treasury bills; term spread is the difference between the 10 year government bond and the three-month T-bill yields. All data are country-specific and from Datastream. Default spread is the difference between Moody's BAA and AAA corporate bond spreads for U.S. issuers. We use U.S. data as proxy for other countries due to data availability.

3 The dynamics of economic surprises

In this section we describe the behaviour and properties of our real-time indexes, with a special focus on the surprise indexes. We first show that surprises do not appear at random, but rather exhibit positive autocorrelation. We call this phenomenon "economic surprise momentum". Second, we show that local surprises are strongly correlated with global surprises, indicating a common component in the cross-section as well. Third, we show that the autocorrelation in the surprise index is due to autocorrelation in the underlying series and auto-covariance among the underlying surprises.

Figure 1 provides the time series plots for the global growth and inflation factor. The upper panel provides time series plots for the global growth level and surprise series, respectively. The lower panel of figure 1 provides the time series plots of global inflation level and surprises. Multiple observations can be drawn from the time series plots. First, the level factor growth seems to be aligned with economic events, like the Great Financial Crisis. However, the level factor in inflation seems to exhibit dynamics that are more erratic in variation and less aligned with periods of expansions and recessions.

Besides, inflation and growth seem to be weakly positively correlated. This weak link indicates that both factors factors capture different aspects of the economy. For this reason, we don't aggregate these factors together, while we do aggregate employment, output and sentiment together into growth (because these factors have a strong positive correlation among each other). Compared to the level series, the surprise series behave differently.

For the growth category, we find that surprises are typically positive during periods of economic expansion and negative during recessions. This indicates that forecasts are typically too low during periods of expansions, but too high during periods of recessions. For inflation surprises, we tend to see the reverse pattern. Surprises tend to be negative during periods of economic expansion, indicating that expectations are too high. One remarkable observation is that the surprise series seem to be positively autocorrelated. Positive surprises are typically followed-up by more positive surprises, while negative surprises are followed up by negative surprises. However, in rational markets, surprises ought to be zero on average and not exhibit any autocorrelation pattern. We explore this potential autocorrelation structure in-depth.

Figure 1: **Time series plots for global growth and inflation factors.** The first row shows the global growth actual and surprise factors, respectively. The second row shows the global inflation actual and surprise factors, respectively.

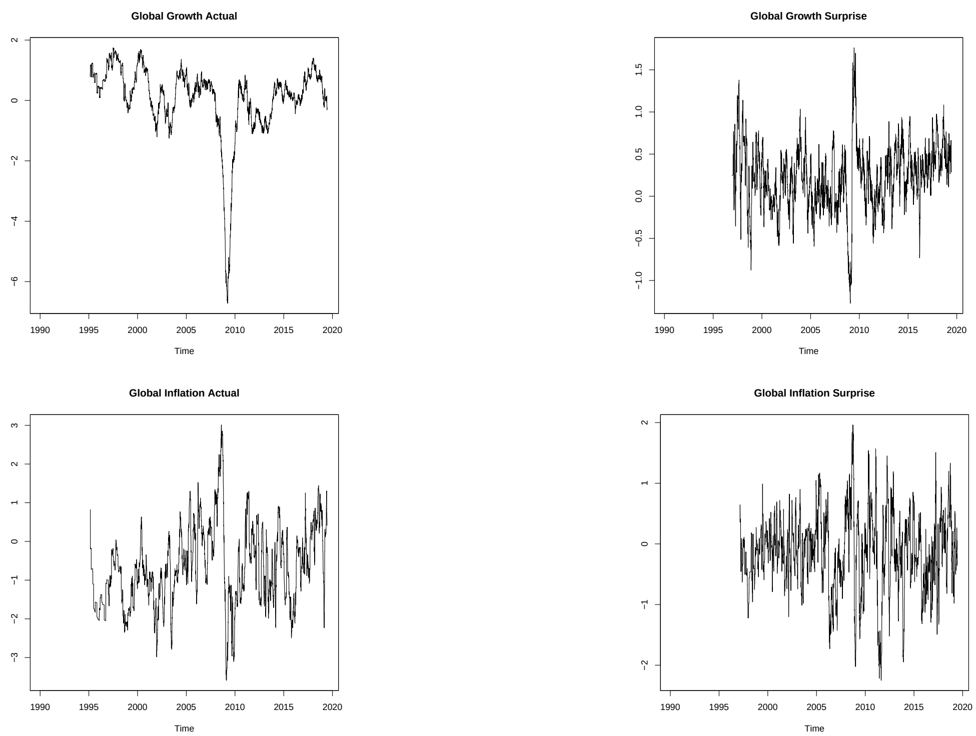


Table 1 reports the descriptive statistics for the surprise indexes. The upper (lower) panel shows the local and global growth (inflation) indexes. Growth surprises typically have a positive mean, indicating that forecasts are typically smaller than the actual announcement value. Inflation surprises, in contrast, are negative on average. This indicates that forecasted inflation is larger than the announced inflation. This is reflected back in the proportion of positive (negative) observations. For example, almost 3 out of 4 observations for the global growth surprise index are positive.

Table 1: **Descriptive statistics.** Local and global surprise indexes extracted from a large cross-section of macroeconomic surprises. Surprise series are volatility standardized on an expanding window before constructing the indexes. The indexes have a daily frequency starting from 1996-12-06 till 2019-06-13. This table reports the number of observation (N), time-series mean (mean), standard deviation (sd), median (med), minimum (min), maximum (max), skewness (skew) and kurtosis (kurt), the proportion of positive observations (pos) and negative observations (neg). $\hat{\rho}_i$ denotes the estimated autocorrelation between month t and $t-i$ using 22-day subsampling.

Var.	N	mean	sd	med	skew	kurt	pos	neg	$\hat{\rho}_1$	$\hat{\rho}_3$	$\hat{\rho}_{12}$
$S_{g,US}$	5875	-0.08	0.68	-0.03	-0.95	2.43	0.48	0.52	0.50	0.21	0.14
$S_{g,UK}$	5802	0.36	0.63	0.37	0.20	0.65	0.72	0.28	0.44	0.16	-0.01
$S_{g,EU}$	5795	0.22	0.76	0.27	-0.10	1.67	0.66	0.34	0.64	0.25	0.01
$S_{g,JP}$	5033	0.41	0.69	0.46	-0.11	-0.34	0.73	0.27	0.68	0.54	0.29
$S_{g,GL}$	5875	0.23	0.39	0.24	-0.07	1.19	0.74	0.26	0.60	0.21	0.06
$S_{i,US}$	5726	0.10	1.09	0.10	-0.14	0.31	0.53	0.47	0.25	0.03	0.04
$S_{i,UK}$	5770	-0.14	1.08	-0.13	0.03	1.86	0.40	0.60	0.45	0.15	0.10
$S_{i,EU}$	5767	-0.13	1.09	-0.17	0.09	0.43	0.44	0.56	0.42	0.04	-0.18
$S_{i,JP}$	4623	-0.41	1.59	-0.07	-1.99	5.21	0.48	0.52	0.74	0.49	-0.07
$S_{i,GL}$	5819	-0.13	0.64	-0.12	-0.28	0.62	0.42	0.58	0.49	0.09	-0.20

The last three columns of table 1 shows the estimated 1-month, 3-month and 12-month autocorrelations. We calculate these autocorrelations by using the 22-day sub-sampling method on the daily surprise indexes. Across all surprise indexes, we observe a substantial positive 1-month auto-correlation. This positive 1-month autocorrelation ranges from 0.25 to 0.75. In addition, we observe a positive, although weaker, autocorrelation between surprises at month t and month $t-3$. This autocorrelation ranges from 0.03 to 0.49. We also consider the 12-month (1 year) autocorrelation. However, this autocorrelation seem to be weak and close to zero. Based on these estimates, it seems to be the case that economic surprises are correlated over time and non-random. On the short-term time horizon, positive (negative) surprises tend to be followed-up by positive (negative) surprise afterwards. We observe this short-run "economic surprise momentum" across all regions and for both the growth and inflation factor.

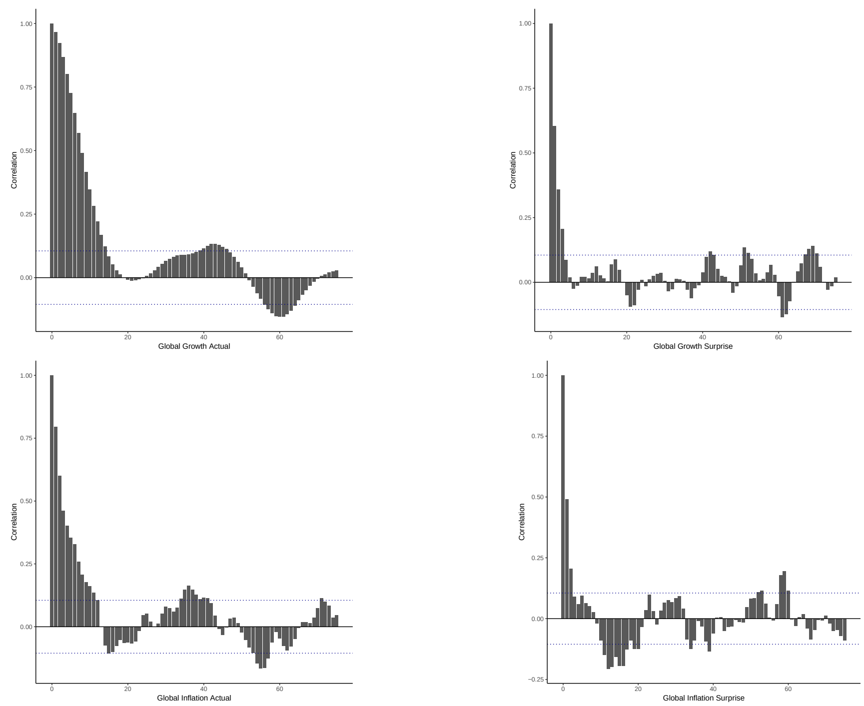
3.1 Correlation structure

To obtain a comprehensive overview of the autocorrelation structure of surprises in growth and inflation, we consider their corresponding autocorrelation function. Figure 2 provides the autocorrelation plots for levels and surprises in global growth and global inflation. To calculate the autocorrelations, we use daily data and apply our 22-day resampling procedure. Note that this resampling procedure allows us to calculate autocorrelations while controlling, to a large extent, for local persistency due forward-filling.

The top left plot provides the autocorrelation function (ACF) for the global growth actual index. First, we observe positive and significant autocorrelation up to 16 months. In addition, the autocorrelation structure tends to exhibit business-cycle-like periods of negative and positive values. Around the 5-year lag, we observe negative significant autocorrelations. The bottom left plot provides the ACF for the global inflation actual index. Likewise, we also document similar patterns as in the global growth actual index.

The upper right plot provides the ACF for surprises in global growth. Consistent with our descriptive statistics, we observe positive and significant autocorrelations up to and including the third lag. For inflation surprises, we find positive and significant autocorrelations up to the third lag. In addition, for inflation surprises, we also document significant negative autocorrelations between the 10 and 20-month lags. For both categories, we find that economic surprises exhibit a short-run momentum-like pattern. Positive (negative) surprises indeed tend to be followed-up by more positive (negative) surprises, on average.

Figure 2: **Autocorrelation function plots.** The first column shows the autocorrelation plots for the actual series. The right column shows the autocorrelation plots for the surprise factors.



In addition to the surprise and level indexes, we also constructed the disagreement (dispersion) indexes across all regions. Table 2 describes the relationship among all estimated factors within regions in terms of correlations. On average, we find that surprises are positively correlated (except for Japan) with the level indexes. This is in line with our earlier observation that surprises tend to follow the level factors. Growth surprises are high during economic expansions, when the actual growth index also tends to be high. Surprises in inflation are negative, when actual inflation is low, which coincide with periods of recession. In addition, we observe that actual inflation is weakly to uncorrelated with growth factors, with correlations ranging from -0.35 (with actual growth, in UK) to 0.25 (with actual growth, globally). Second, we observe a negative correlation between the level factors and the disagreement factors. Globally, the correlation is -0.37 within the growth category, and -0.40 within the inflation category. This observation is also documented in Beber et al. (2015). In times of economic expansion, disagreement among forecasters are low on average. Disagreement across categories tend to be positively correlation, both globally as well as local. Disagreement has a weak negative correlation with surprises, both globally and locally (with UK being the exception).

We also assess the correlation of each index across countries. Table 3 shows how local factors within categories are correlated across regions. We observe a mild positive correlation structure across regions in their actual growth (ranging from 0.32 to 0.62), indicating that a global business cycle factor is a common source in explaining variation in local macroeconomic aggregates.

Table 2: **Factor correlations over categories within regions:** the table reports the correlation matrix of the regional latent factors (U.S., U.K., Japan and the Eurozone) and global latent factors.

US	G_{act}	G_{sur}	G_{FD}	I_{act}	I_{sur}	I_{FD}
G_{act}	1					
G_{sur}	0.43	1				
G_{FD}	-0.26	-0.19	1			
I_{act}	0.01	0.08	-0.16	1		
I_{sur}	0.16	0.15	-0.06	0.51	1	
I_{FD}	0.02	-0.12	0.53	-0.13	-0.03	1
UK	G_{act}	G_{sur}	G_{FD}	I_{act}	I_{sur}	I_{FD}
G_{act}	1					
G_{sur}	0.09	1				
G_{FD}	0.07	-0.02	1			
I_{act}	-0.35	-0.01	-0.15	1		
I_{sur}	-0.33	-0.06	0.10	0.46	1	
I_{FD}	-0.46	-0.11	0.16	-0.09	0.15	1
EU	G_{act}	G_{sur}	G_{FD}	I_{act}	I_{sur}	I_{FD}
G_{act}	1					
G_{sur}	0.28	1				
G_{FD}	-0.53	-0.1	1			
I_{act}	0.36	0.14	-0.19	1		
I_{sur}	0.19	0.12	-0.12	0.56	1	
I_{FD}	-0.27	-0.02	0.42	-0.21	-0.16	1
JP	G_{act}	G_{sur}	G_{FD}	I_{act}	I_{sur}	I_{FD}
G_{act}	1					
G_{sur}	-0.08	1				
G_{FD}	-0.19	0.02	1			
I_{act}	0.05	0.17	-0.20	1		
I_{sur}	0.09	0.27	-0.15	0.12	1	
I_{FD}	-0.09	-0.27	0.18	-0.37	-0.05	1
GL	G_{act}	G_{sur}	G_{FD}	I_{act}	I_{sur}	I_{FD}
G_{act}	1					
G_{sur}	0.16	1				
G_{FD}	-0.37	-0.18	1			
I_{act}	0.25	0.05	-0.41	1		
I_{sur}	0.05	0.05	-0.04	0.29	1	
I_{FD}	-0.40	-0.12	0.62	-0.40	-0.06	1

Moreover, the local growth indexes are strongly correlated with the global growth factor (correlations ranging from 0.58 to 0.86). The correlations for the actual inflation factors are less strong, sometimes even negative, than for growth across regions. The correlations range from -0.15 to 0.49. However, the correlation with the global inflation factor is relatively substantial, ranging from 0.39 to 0.79. For both categories, a global component may explain a substantial part of the local variation in the level series. Surprises in growth tend to be weakly positively correlated across regions, but strongly correlated to the global growth surprise factor. We document the same pattern also for surprises in inflation across regions. Table 3 stresses out the importance of global common component in local macroeconomic levels and surprises.

Table 3: **Factor correlations over regions within categories:** The table reports the correlation estimates of the growth level (G_{act}), inflation level (I_{act}), growth surprise (G_{sur}) and inflation surprise (I_{sur}) across regions.

G_{act}	US	UK	EU	JP	GL
US	1				
UK	0.62	1			
EU	0.57	0.50	1		
JP	0.41	0.37	0.32	1	
GL	0.85	0.76	0.86	0.58	1
G_{sur}	US	UK	EU	JP	GL
US	1				
UK	0.15	1			
EU	0.22	0.05	1		
JP	0.13	0.00	-0.09	1	
GL	0.68	0.50	0.57	0.47	1

I_{act}	US	UK	EU	JP	GL
US	1				
UK	0.16	1			
EU	0.29	0.49	1		
JP	0.19	-0.09	-0.15	1	
GL	0.58	0.56	0.74	0.46	1
I_{sur}	US	UK	EU	JP	GL
US	1				
UK	0.06	1			
EU	0.03	0.23	1		
JP	-0.12	0.11	0.02	1	
GL	0.39	0.62	0.55	0.58	1

3.2 Autocorrelation decomposition surprise index

In Figure 2 we have shown that global growth surprise exhibit significant positive short-term autocorrelation, which we call "economic surprise momentum". In addition, we have shown, in table 1 that this also holds regionally. On top of this, we can also decompose the autocorrelation structure of the surprise factors even further.

To reiterate, the surprise index ($S^r_{c,t}$) for each region r by category c is a weighted linear combination of all currently active underlying surprise series ($S^r_{i,c,t}$), where the weights are extracted via our recursive principal component analysis:

$$S^r_{c,t} = \sum_{i \in \omega_t} \lambda^r_{i,c,t} S^r_{i,c,t}$$

Since $S^r_{c,t}$ is a linear combination of its underlying surprise series, we can express the autocorrelation of $S^r_{c,t}$ in terms of the autocorrelations of $S^r_{i,c,t}$ and cross terms. For simplicity, we focus on autocovariances, as it amount to scaling with the variance of $S^r_{c,t}$. In addition, we assume that the set of active series is constant over time, implying that we have a balanced panel data-set. The auto-covariance between $S^r_{c,t}$ and $S^r_{c,t-j}$ is equal to:

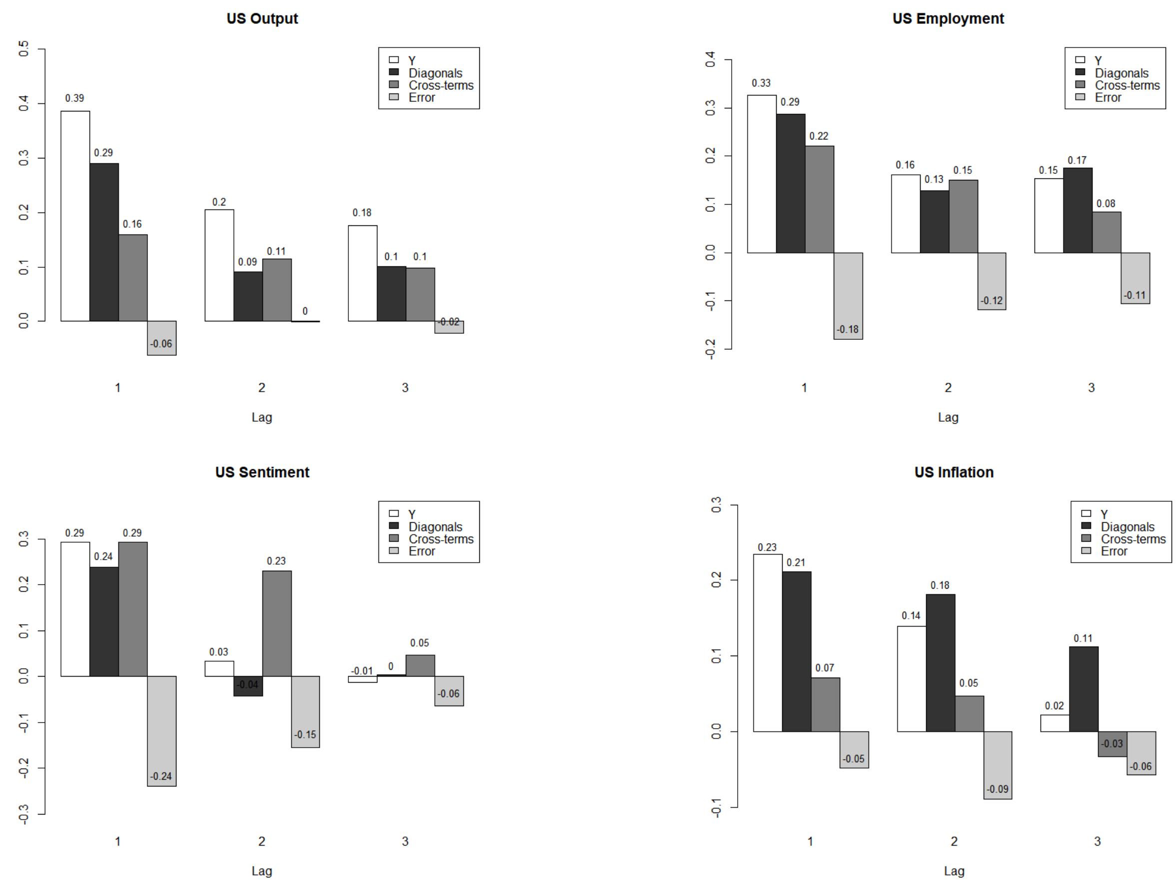
$$\begin{aligned} cov(S^r_{c,t}, S^r_{c,t-j}) &= cov(\sum_{i \in \omega_t} \lambda^r_{i,c,t} S^r_{i,c,t}, \sum_{i \in \omega_t} \lambda^r_{i,c,t-j} S^r_{i,c,t-j}) \\ &= \sum_{i \in \omega_t} cov(\lambda^r_{i,c,t} S^r_{i,c,t}, \lambda^r_{i,c,t-j} S^r_{i,c,t-j}) + \sum_{i \in \omega_t, i \neq k} \sum_{j \in \omega_t, k \neq i} cov(\lambda^r_{i,c,t} S^r_{i,c,t}, \lambda^r_{k,c,t-j} S^r_{k,c,t-j}) \end{aligned}$$

The first term of the last equation denotes the contribution to the autocorrelation in our surprise indexes due to serial correlation within the individual time-series. The second term is the contribution of cross autocovariance between individual time series. One can think of the second part as a measure of spill-overs in surprises. It indicates to what extent lagged surprises i affect future surprises j. We estimate both terms to determine the composition of index-level autocorrelation in surprises. However, in the formula above, we assumed that the active set of time-series is constant, while we have an unbalanced panel data set of surprises. By doing so, the index-level autocovariance will not exactly match the two right-hand side terms. We explicitly measure the discrepancy for our estimates of the left-hand and right-hand side. This discrepancy is expected to be smaller for more balanced sets of time-series. Even in presence of a discrepancy, calculating the two right-hand sides provides an idea of the importance of individual surprise momentum and surprise spillover momentum.

In figure 3 we provide the decomposition estimates for each category (output, employment, sentiment, and inflation) for the United States for the first three lags. We include the results for the remaining regions in appendix C. We observe positive autocorrelation on an index-level for all categories at all lags (except U.S. sentiment at lag 3). In general, decomposing the index-level autocorrelation reveals positive scaled autocovariances for individual surprise series. This implies that individual surprise series, weighted by their factor loadings, exhibit short-run autocorrelation on a stand-alone basis. We find positive scaled autocovariances across all lags for U.S. output, employment and inflation variables. Only for U.S. sentiment variables we find small autocorrelations individually at lag 2 and 3.

In addition, we also document positive spill-overs among surprise series for each category, on average. This implies that past surprises for a specific macroeconomic variable may predict future surprises for other macroeconomic variables, i.e. surprises may spill-over across macroeconomic announcements. These terms, just like the index-level autocorrelation, decrease over the lag length. Figure 3 suggests that short-run momentum in economic surprise is due to both short-run momentum in individual surprise, on a stand-alone basis, and spill-over among different surprise series.

Figure 3: **Decomposition of Surprises (United States):** shown are the autocorrelation decomposition for the Output (top left), Employment (top right), Sentiment (bottom left) and Inflation (bottom right) category. We scale all auto-variances by the full sample variance of the corresponding surprise index. The white bar indicates the autocorrelation at lag j of the surprise index for a given category. Every second bar measures the weighted average of the scaled autocovariances of all underlying surprise series. Every third bar measures the cross co-variances of all underlying surprise series. Every fourth bar measures the differences between the autocorrelation of the surprise index and our decomposition.



4 Economic surprise momentum: predictive regressions and economic significance

We have shown that surprises do not appear randomly, but exhibit short-run positive autocorrelation. In addition, we find that local surprises are strongly correlated with global surprises, indicating the importance of a global factor. In this section, we examine whether risk premia across asset classes can be predicted by real-time measured economic surprises by the constructed surprise indexes. We first start the analysis with a simple sorting procedure. Subsequently, we deploy both formal in-sample and out-of-sample regressions.

4.1 Sorting surprises and asset returns

We first assess the link between economic surprises and asset returns by a simply sorting procedure. We sort the global growth and inflation surprise index in an increasing order and divide it in five equally-sized buckets. For each bucket we compute the future average monthly asset return for each asset class. For equity markets, we provide results for each local equity market individually. For the remaining asset classes we provide equal-weighted pooled results.

Table 4 provides the results for equity markets. The future equity premium is higher, on average, if the global growth surprise at the start of the period takes a higher value. In the lowest global growth surprise quintile, the subsequent average monthly excess equity return ranges between −0.39% per month (U.K.) and −0.77% (JP), while it increases almost monotonically over the buckets to at least 0.58% (JP) and at most 1.18% per month (EU) for the highest quintile. The resulting top minus bottom quintile spread, shown in the last column, ranges from 1.09$ per month (U.K.) to 1.83% per month (EU). Thus, for equity markets, we find that higher global growth surprises predicts higher subsequent monthly excess stock returns for our sample period which spans from January 1997 to June 2019.

For global inflation surprises, as shown in panel (2), the findings are reversed. The top minus bottom spread ranges from −0.64% per month (EU) to −1.80% per month (JP). Negative global inflation surprises are associated, on average, with higher future equity returns. However, we do not find a monotonically decreasing pattern over the buckets. Thus, future equity market returns tend to increase when the announced inflation is lower than the forecasted inflation.

Panel (3) shows the average returns when we sort on local growth surprises. Similar to panel (1), with EU being an exception, we find that higher local growth surprises are associated with higher future equity returns. Panel (4) shows the average local equity returns when we quintile sorts are based on local inflation surprises. In line with panel (2), with U.S. being an exception, we find that lower local inflation surprises are associated with higher future equity returns, on average.

The pooled results for the remaining asset classes are given below, in table 5. For bonds, we find that higher global growth surprises are associated with lower future bond returns. Compared to equities, however, we find that the magnitude is substantially larger and a reverse sign. The top minus bottom spread is merely −0.05% per month for bonds. In addition, we find that lower global inflation surprises tend to be associated with higher future bond returns, providing a top minus bottom spread of −0.02% per month. For credits and commodities, we find that higher global growth surprises predicts higher future returns, yielding a spread of 0.59% per month for credits and 1.56% for commodities, similar to equities. In addition, for these two asset

Table 4: **Sorting surprises and asset returns (1):** We sort global growth surprises (1), global inflation surprises (2), local growth surprises (3) and local inflation surprises (4) in five buckets. Subsequently we calculate next day's return over a monthly forecast horizon and take the average per bucket. All returns are in reported in percentages.

(1)	Q1	Q2	Q3	Q4	Q5	Q5-Q1
US	-0.42	0.29	1.16	1.15	1.11	1.53
UK	-0.39	0.11	1.06	0.41	0.70	1.09
JP	-0.77	-0.16	0.39	1.78	0.58	1.35
EU	-0.65	0.28	0.07	0.69	1.18	1.83
(2)	Q1	Q2	Q3	Q4	Q5	Q5-Q1
US	0.94	0.77	0.64	0.98	-0.21	-1.15
UK	0.86	0.58	0.06	0.99	-0.70	-1.56
JP	0.98	0.48	1.23	0.37	-0.82	-1.80
EU	0.01	0.19	0.43	1.46	-0.62	-0.64

(3)	Q1	Q2	Q3	Q4	Q5	Q5-Q1
US	-0.27	0.17	0.77	0.50	2.11	2.38
UK	-0.58	0.81	1.06	-0.35	0.89	1.47
JP	0.03	0.88	0.09	-0.60	1.89	1.86
EU	0.54	-0.61	0.45	0.65	0.38	-0.16
(4)	Q1	Q2	Q3	Q4	Q5	Q5-Q1
US	-0.08	0.23	1.54	0.93	0.61	0.69
UK	0.66	0.84	0.32	0.44	-0.70	-1.35
JP	1.23	0.01	0.21	2.31	0.08	-1.15
EU	1.35	0.32	0.19	0.27	-0.74	-2.09

classes, lower global inflation surprises predicts higher future returns.

Table 5: **Sorting surprise and asset returns (2):** We sort global growth surprises (1) and global inflation surprises (2) in five buckets. Subsequently we calculate next day's return over a monthly forecast horizon and take the average per bucket by asset class. Pooled averages are shown for bonds, credits, and commodities. All returns are reported in percentages.

(1)	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Bonds	0.08	0.03	0.05	0.00	0.03	-0.05
Credits	-0.19	0.24	0.40	0.51	0.40	0.59
Commodities	-1.18	0.36	0.47	0.92	0.38	1.56
(2)	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Bonds	0.07	0.04	0.01	0.03	0.05	-0.02
Credits	0.14	0.22	0.75	0.50	-0.04	-0.18
Commodities	-0.41	0.12	1.73	0.31	-0.83	-0.42

4.2 In-sample regressions

To investigate the relationship between surprises and market returns, more formally, the following predictive regression model is used:

$$R_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h} \;\; \forall t = 1, \cdots, T-h$$

Where $R_{t:t+h} = (R_{t+1}+1) \times \cdots \times (R_{t+h}+1) - 1$. R_t denotes the excess return of a market index at day t. x_t, the variable of interest, denotes the surprise index at day t. We estimate this equation by OLS using a monthly forecast horizon and frequency. The last surprise value of the month is used to predict next month's return, i.e. we use non-overlapping observations. $\epsilon_{t:t+h}$ is the prediction error, which is assumed to be normally distributed with mean zero. Our null hypothesis equals $\beta = 0$, implying no predictive ability. Our alternative hypothesis is $\beta \neq 0$, implying predictive ability. The statistical inference is based on Newey-West corrected t-values in non-pooled regressions. In pooled regressions, statistical inference is based on t-value that are double cluster corrected (by time and asset).

We present the predictive pooled regression results for equity markets in table 6. Univariately, local growth surprises positively predict future equity market returns (column 1). This effect is significant at the 1% significance level. Splitting the local growth surprise up into a local minus global part and a global part indicates that the predictability predominantly stems from global growth surprises (column 2). A two standard deviation increase in growth surprises is associated with an increase of 1.56% in the monthly equity premium, on average. When announcement values regarding economic growth exceed their corresponding forecasts, expectations of the (future) state of the economy will improve. This will increase future expected risk premia in equity markets.

Local inflation surprises do not seem to exhibit predictive power for equity market as the estimate in column 3 is not significant. Local-global inflation surprises and global inflation surprises also do not predict future excess equity market returns (column 4). Using all surprise factors as regressors do not qualitatively alter the results as is shown in column 5. Including level and disagreement factors for growth and inflation do not alter the results (column 6). The estimate on the global growth surprise factor remains economically large and statistically significant at the 1% significance with a t-statistic of 2.312, while inflation surprise factors do not appear to have any predictive power. In this multivariate regression, we also find a positive and significant estimate on the global disagreement factor for inflation. Higher disagreement among inflation forecasters positively predicts future excess equity returns. Lastly, we also include financial-related control variables, such as dividend yields of the local equity markets and volatility indexes (column 7). However, this does not alter the results for global growth surprises. Thus, the predictive power of the global growth surprise factor is not subsumed by other predictors for aggregate returns. After the inclusion of financial control variables, global inflation surprises negatively and significantly predict future equity returns at the 10% significance level.

So far we document that global growth surprises consistently predict future equity premium, while global inflation surprises do not. We provide pooled predictive regression results for the bond, credits and commodity markets in appendix E[8]. For the bond market, we find that local growth surprises negatively predict future monthly bond returns. The effect is statistically significant at the 1% significance level after controlling for other surprises, the level and disagreements factors, and financial control variables. However the magnitude of the estimate seem to be rather small.

For the commodity market, we obtain similar results as in equity markets. We, again, document that global growth surprises positively predict future asset returns. This effect is both economically and statistically significant at the 1%. We find that a two standard deviation increase in the global growth surprise factor increases future monthly commodity excess return by 2.03%, after controlling for all other global latent factors. This effect becomes slightly stronger after the inclusion of financial control variables (U.S. short rate, term spread and default spread). Likewise, for the credit markets, global growth surprises again positively predict future excess returns, although the magnitude is smaller compared to commodity and equity markets.

To summarize our results, we document that global growth surprises positively predict equity, credits and commodity returns at the monthly forecast horizon. For bond markets, we find that local growth surprises negatively predicts future bond market returns.

4.3 Look-back period and forecast horizon

In the results above, we only used one forecast horizon (one month) and one look-back period (surprises lagged by one day). Estimating predictive regressions for several time horizons allows us to analyze both the short-run and long-run predictive power of surprises. Therefore, we repeat the predictive regressions, univariately. for several forecast horizons (1 business day up to 1 year) and for each asset class. In addition, we also consider a broad range of different look-back periods. Surprises have been shown to exhibit short-run momentum (up to 3 months). Based on this short-run momentum in surprises, we expect that historical surprises, beyond one business day, but in the recent past, also exhibit predictive power. Therefore, we use moving averages for look-back periods ranging from 1 day to up till 1 year, using overlapping observations to obtain sufficient observations at the quarterly and yearly forecast horizon.

In table 7 reports the estimated slope coefficients of the predictive regressions for equity markets. The estimates for all remaining asset classes are provided in appendix G. For global growth surprises, we find that returns based on a daily forecast horizon can be predicted by past surprises ranging from the previous day up to the previous month. For the weekly forecast horizon, we obtain somewhat weaker predictability, which is significant at the 10% using past day and past week surprises, but significant at the 5% level when using past month's surprises.

[8] Unpooled regional regression results for equity markets are provided in appendix F.

Table 6: **In-sample regressions (Equity):** The table shows the results of regressing the global growth and/or the global inflation surprise index on future excess equity market returns. We control for the level and dispersion factors. In addition, we use volatility indexes, dividend yields and price-earnings ratios, and 1-week reversal as financial control variables. A one day implementation lag for predicting future returns is assumed. Shown are the in-sample regression estimates, its corresponding t-values (in parentheses), and the adjusted R^2. The t-values are shown between brackets and are country-time cluster corrected. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

	Pooled Equity Returns						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$G_{sur,l}$	0.696***						
	(4.042)						
$G_{sur,l-g}$		0.218			0.261	0.255	0.401**
		(1.134)			(1.236)	(1.414)	(2.219)
$G_{sur,g}$		1.960***			1.893**	1.977***	1.830**
		(2.672)			(2.496)	(2.800)	(2.352)
$I_{sur,l}$			−0.114				
			(−0.543)				
$I_{sur,l-g}$				−0.050	−0.062	−0.062	−0.030
				(−0.209)	(−0.260)	(−0.267)	(−0.146)
$I_{sur,g}$				−0.295	−0.397	−0.129	−0.272
				(−0.553)	(−0.762)	(−0.275)	(−0.617)
MACRO.	NO	NO	NO	NO	NO	YES	YES
FIN.	NO	NO	NO	NO	NO	NO	YES
Obs.	1,017	1,017	989	989	989	989	789
Adj. R^2	0.009	0.020	−0.0002	−0.001	0.018	0.043	0.065

The strongest predictability is found for the monthly forecast horizon, where past surprises up to the previous month are able to predict future equity returns. We do not find that global growth surprises are able to predict returns on a longer forecast horizon. Including surprises beyond the past one month also do not yield predictability. For inflation surprises, we do not find any clear pattern with respect to the predictability of future equity market returns. We only observe that the past 6 months of surprises negatively predict returns ranging from the daily forecast horizon up to three months.

The effect of global growth surprises in bond markets are rather different, compared to equity markets. The previous day surprise negatively predicts returns at the daily forecast horizon, contains no predictive information between one week and 3 months, but positively predicts returns at the (semi-)annual forecast horizon. Using a weekly and monthly lookback period, we can positively predict returns at the (semi-)annual forecast horizon as well. A quarterly lookback period allows us to positively predict quarterly returns or at longer forecast horizons. Similar results are found using a semi-annual or annual lookback period. In contrast to equity markets, long-term bond returns can be predicted using past growth surprises. In addition, a wide lookback period of surprise is also able to predict future bond returns, while this does not hold in equity markets. However, in line with equity markets, global inflation surprises do not predict future bond returns.

Table 7: **Different forecast horizons and look-back periods:** The table shows the results of regressing the global growth (panel A) and/or the global inflation surprise index (panel B) on future excess equity market returns for various look back periods (L) and forecast horizons (F). A one day implementation lag for predicting future returns is assumed. Shown are the in-sample regression estimates, and its corresponding t-values (in parentheses). Overlapping observations are used to increase statistical power. T-values are Newey-West adjusted to correct for serial correlation and heteroscedasticity. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample period is January 1997 to June 2019.

	Growth Surprise (A)					
	$F = 1d$	$F = 1w$	$F = 1m$	$F = 3m$	$F = 6m$	$F = 1y$
$L = 1d$	0.066**	0.293*	1.348**	1.658	0.378	-1.519
	(2.392)	(1.889)	(2.283)	(1.277)	(0.205)	(-0.536)
$L = 1w$	0.058**	0.281*	1.395**	1.537	0.184	-1.702
	(2.074)	(1.745)	(2.136)	(0.983)	(0.075)	(-0.481)
$L = 1m$	0.067**	0.352**	1.426**	0.962	-0.710	-2.654
	(2.330)	(2.053)	(1.974)	(0.534)	(-0.237)	(-0.586)
$L = 3m$	0.035	0.168	0.376	-0.647	-3.660	-4.869
	(1.112)	(0.850)	(0.423)	(-0.289)	(-0.936)	(-0.787)
$L = 6m$	0.003	0.003	-0.331	-2.605	-6.062	-5.225
	(0.082)	(0.014)	(-0.332)	(-1.211)	(-1.296)	(-0.555)
$L = 1y$	-0.009	-0.051	-0.467	-1.963	-3.265	2.907
	(-0.215)	(-0.188)	(-0.363)	(-0.653)	(-0.489)	(0.198)
	Inflation Surprise (A)					
	$h = 1d$	$h = 1w$	$h = 1m$	$h = 3m$	$h = 6m$	$h = 1y$
$L = 1d$	-0.023	-0.114	-0.555	-0.913	-2.417	-1.525
	(-1.369)	(-1.211)	(-1.582)	(-1.071)	(-1.824)	(-0.933)
$L = 1w$	-0.022	-0.130	-0.573	-0.955	-2.507	-1.541
	(-1.267)	(-1.330)	(-1.487)	(-0.940)	(-1.475)	(-0.718)
$L = 1m$	-0.029	-0.153	-0.494	-1.087	-2.793	-1.610
	(-1.469)	(-1.378)	(-1.137)	(-1.041)	(-1.511)	(-0.617)
$L = 3m$	-0.025	-0.137	-0.610	-2.030*	-3.751*	-2.081
	(-0.987)	(-1.028)	(-1.228)	(-1.826)	(-1.888)	(-0.669)
$L = 6m$	-0.055*	-0.288*	-1.224**	-2.982**	-3.998	-2.475
	(-1.825)	(-1.894)	(-2.501)	(-2.639)	(-1.619)	(-0.693)
$L = 1y$	-0.029	-0.154	-0.636	-1.345	-1.686	0.481
	(-0.779)	(-0.816)	(-0.919)	(-0.726)	(-0.466)	(0.082)

Considering credit and commodity markets, we find that global growth surprises strongly and positively predict daily returns using past surprises up to month, similar to equity markets. Furthermore, we find weak predictability of credit and commodity returns at the weekly and monthly forecast horizon. In addition, global inflation surprises also do not predict future credits and commodity returns.

4.4 Asymmetry and market states

Some macroeconomic information may receive more weight and attention than others. There is a growing literature that suggests the existence of asymmetric market reactions to "good" and "bad" macroeconomic news (Beber & Brandt, 2009). We test this as well in our setting by distinguishing the effect of positive and negative surprises on equity market returns. Therefore, we examine whether surprise effects vary with the sign of the surprise. To this end, we estimate the following equation:

$$R_{t:t+h} = \alpha + \alpha_{\{S_t<0\}} + (\beta + \gamma I_{\{S_t<0\}})S_t + \epsilon_{t:t+h}$$

$I_{\{S_t<0\}}$ takes value one when the surprise factor is negative, else zero. γ estimates the marginal effect of negative surprises in addition to β. When γ is significantly different from zero, the effect of negative surprises is significantly different than for positive surprises. In addition, we also define a "down"-market dummy (D). This dummy takes value one when the past 12-month equity return is smaller than zero, and estimate the following equation:

$$R_{t:t+h} = \alpha + \alpha_{\{D=1\}} + \beta S_t + \gamma S_t I_{\{D=1\}} + \epsilon_{t:t+h}$$

This specification allows us to determine whether the effect of macroeconomic surprises differ by market state. γ, in this case, estimates the marginal effect of surprises on equity returns during down markets. When surprises behave differently during down-markets than up-markets, we expect γ to be significantly different from zero. Lastly, we combine both equations into the following equation.

$$R_{t:t+h} = \alpha + \alpha_{\{D=1\}*\{S_t<0\}} + \alpha_{\{S_t<0\}} + \alpha_{\{D=1\}} + (\beta + \phi I_{\{D=1\}} + \gamma I_{\{S_t<0\}} + \kappa I_{\{D=1\}} I_{\{S_t<0\}})S_t + \epsilon_{t:t+h}$$

This equation combines the first two equations and allows to consider interactions between up - and down-markets and positive and negative surprises. In all equations, we also allow the intercept to change by state. The estimates of these equations are report in table 8. The estimates of the first equation (column 1) indicates that global growth surprises predict future equity returns positively and significantly at the 1% level. The effect of negative surprises is magnitude-wise larger than the effect of positive surprises. An equal-sized decrease in the global surprise index results in a stronger decrease in future equity market returns than an equal-sized increase in the index increase future equity market returns. However, this marginal effect is not statistically significant. Thus, for growth surprises we do not document an asymmetric effect of surprises on equity returns. When we consider the effect of growth surprises on future equity returns by market state, we find that surprises are not informative about future returns during up-markets. We rather find that global growth surprises weakly predict future equity returns during down markets. Column 3 shows the estimates of the combined equation.

Allowing for interactions by market state and the sign of surprises, we find that global growth surprises positively and significantly predict future equity returns during down markets (at the 5% significance level). When the past 12-month local excess return is negative, surprises especially seem to be relevant. One hypothesis behind this is that news receive more attention and weight, to resolve uncertainty, during down markets than in up markets.

Column 4-6 show the estimates of the three equations using global inflation surprises. In table 6, we found no evidence that global inflation surprises predict future equity returns. Allowing this effect to differ by the sign of the surprise, alters these results significantly. Positive inflation surprises negatively predict future equity returns. This estimate is statistically significant at the 1% level and economically large. A two standard deviation increase in the global inflation surprise index predicts a decrease in future monthly equity returns of 5.5%. However, the marginal effect of negative surprises relative to positive surprises is 0.055 and is statistically significant at the 1% level. The total effect of negative surprises on future equity returns is 0.012 and is statistically significant (p=0.012). This implies that negative inflation surprises predict negative future equity returns. It appears that both positive and negative inflation surprises predict lower future equity returns, however the effect is stronger for positive inflation surprises.

Column 5 indicates that higher global inflation surprises predict future equity returns negatively only during down markets ($S_t \times D$). However, this estimate is only statistically significant at the 10%. When allowing for both market states and conditioning on the sign of inflation surprises (column 6), this result disappears. Qualitatively, the finding that both positive and negative inflation surprises predict decreases in future equity returns remains. One possible rationale is that inflation forecasts are linked to inflation targets (as set by centrals banks). Inflation rates that are too low might indicate deflation, which is typically perceived as a negative signal. Inflation rates that are too high, relative to the target, might indicate that economic growth will slow down in the future.

In appendix H we provide the estimates for all remaining asset classes. The results are as follows. For both bond and credit markets, similar to equity markets, we find that global growth surprises positively predict future monthly returns when the past 12-month return was negative. For commodity markets, growth surprises are asymmetric. Negative growth surprises strongly predict negative future commodity returns, while there is no significant link between positive surprises and commodity returns. Furthermore, negative global inflation surprises predict future bond returns, while positive global inflation surprises do not exhibit predictive power. Both positive and negative global inflation surprises (differentials), however, predict lower future credits and commodity returns, irrespective of the market state.

Table 8: **Asymmetry and down markets (equity markets):** The table shows the results of regressing the global growth (column 1-3) and the global inflation surprise index (column 4-6) on future excess pooled equity market returns. D takes value one when the past 12-month local excess return is negative. The t-values are shown between brackets and are country-time cluster corrected. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

	Pooled Equity Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
α	-0.465	0.504^{*}	0.209	2.039^{***}	0.737^{***}	1.801^{***}
	(-0.963)	(1.926)	(0.404)	(3.134)	(3.235)	(3.180)
$\alpha_{\{S_t<0\}}$	1.776^{**}		1.113	-0.951		-0.106
	(2.022)		(1.240)	(-1.102)		(-0.149)
$\alpha_{\{D=1\}}$		-1.163^{*}	-1.864^{**}		-1.210^{**}	0.420
		(-1.902)	(-2.191)		(-2.175)	(0.285)
$\alpha_{\{D=1\}*\{S_t<0\}}$			1.568			-2.534
			(0.851)			(-1.346)
S_t	2.438^{***}	0.685	1.209	-4.321^{***}	0.424	-2.607^{**}
	(2.829)	(1.086)	(1.100)	(-3.000)	(1.185)	(-2.179)
$I_{\{S_t<0\}}$	2.950		3.158	5.544^{***}		4.579^{***}
	(1.002)		(0.989)	(3.393)		(3.303)
$I_{\{S_t<0\}} \times D$			-2.232			0.880
			(-0.445)			(0.283)
$S_t \times D$		2.184^{*}	3.280^{**}		-2.081^{*}	-3.645
		(1.735)	(2.117)		(-1.911)	(-1.424)
Obs.	1,058	1,010	1,010	1,052	1,010	1,010
Adj. R^2	0.029	0.030	0.038	0.042	0.023	0.061

4.5 Cumulative return and Sharpe ratios

The in-sample regressions in section 4.2, for equity markets, have shown that global growth surprises positively and significantly predicts future excess returns. Furthermore, section 4.3 indicates that growth surprises are able to predict equity returns on the short-run using past surprise information up to the previous month. In this section, we consider a simple investment strategy in equity markets using past surprises and assess its cumulative return and Sharpe ratio.

We consider the following investment strategy: we take positions in the risky asset, with position size equal to the 1-day lagged value of global growth (inflation) index on the last day of the month. This position has a holding period of 1-month, which will be updated using the subsequent end-of-the-month signal. We restrict these positions between -2 and +2 to avoid unreasonable levels of leverage and shorting. For this strategy, we compute the annualized return in %, the Sharpe ratio, full sample standard deviation, the CAPM alpha and beta using the corresponding underlying market. This strategy is compared with a simple buy-and-hold strategy, where we invest in the market at the start of the period and hold onto this position until the end of the sample period.

The results for equity markets are shown in table 9. In panel A (B), we report the results for the growth (inflation) surprise strategy. The results of all other asset classes are provided in appendix I. For the U.S., we find that the average annualized return for the growth surprise strategy (4.15%) is lower than that of the buy-and-hold strategy (5.58%). However, the growth surprise strategy, on average, has a substantial lower volatility (7.48%) compared to the market (15.71%). This results into an annualized Sharpe ratio of 0.56, which is higher than that of the market (0.36). Thus, in terms of risk-adjusted returns, the growth surprise investment strategy outperforms the market substantially. The last row of table 9 considers a global strategy that equally weights the growth surprise strategies across the four regions. Globally, we also find that this strategy outperforms in terms of cumulative return, risk and risk-adjusted performance.

The first plot of figure **??** shows the cumulative return for the growth surprise strategy and the buy-and-hold strategy. We observe during the first ten years that the growth surprise strategy is relatively stable in terms of cumulative return and avoids losses made during the burst of the Dot-Com bubble, while this is observed in the buy-and-hold strategy. The strength of the growth surprise strategy is seen during the Great Financial Crisis. While the buy-and-hold strategy yields negative returns, the growth surprise strategy avoids these losses by placing short positions on the market. The reasoning behind this is that the growth surprise strategy is, in particular, able to time the market due to its short-term momentum. When negative growth surprises occur, markets will react negatively as well. As surprises are positively autocorrelated on the short-term, we are able to predict when negative surprises will occur, and time the market.

The results do not only hold for the U.S. equity market, but also for other major developed markets. In fact, the results are stronger for the U.K., Japan, and Europe. In the U.K., the average annualized monthly return for the growth surprise strategy is 2.92%, while the buy-and-hold strategy yields an annualized monthly return of 2.17%. For Europe, we find that the average annualized monthly return (3.67%) for the growth surprise strategy is even 50% larger than that of the market. Likewise, the growth surprise strategy yields lower risk across all countries compared to the market. Lastly, the growth surprise strategy yields superior Sharpe ratios across these countries. For the U.K., the growth surprise investment strategy provides a Sharpe ratio of 0.43. The buy-and-hold strategy, however, yields merely a Sharpe ratio of 0.149. So the Sharpe ratio of our global growth surprise strategy is almost three times the Sharpe ratio of the FTSE 100. Figure **??**

provides the cumulative return plots of the other developed markets. Similar to the U.S., we also observe that the growth surprise strategy is stable in the first half of the sample, and that most of the gains are made during and after the Great Financial Crisis.

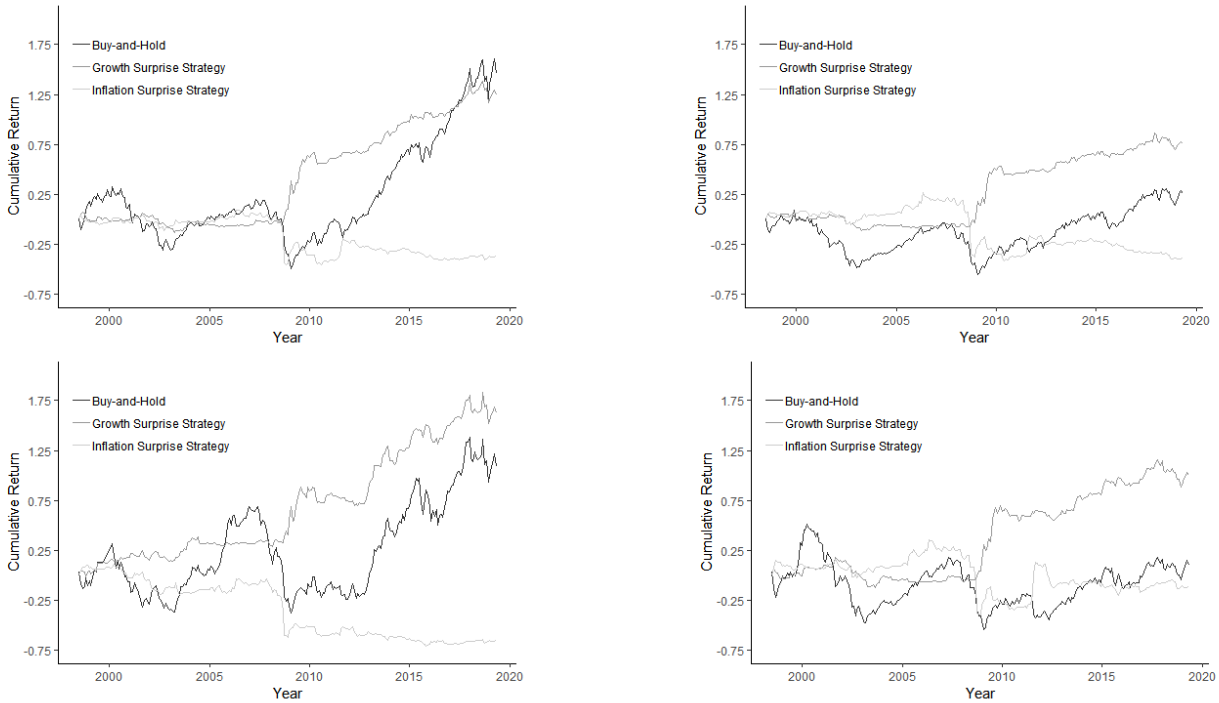
Panel B of table 9 shows that, in stark contrast to the growth surprise strategy, the inflation surprise strategy generates relatively low average annualized monthly returns across all equity markets compared to their underlying market. This result makes sense as we previously found that the predictive power of inflation surprises in equity markets is relatively weak. For the other asset classes, the results (see appendix I) are as follows. For bond markets, both surprise strategies do not outperform the buy-and-hold strategy, not in terms of average returns nor Sharpe ratios. For credit markets, only the growth surprise strategy outperforms the buy-and-hold strategy in terms of Sharpe ratios. For commodity markets, the growth investment strategy performs remarkably well by yielding Sharpe ratios of 0.452 (BCOM) and 0.640 (GSCI), while the buy-and-hold strategy provides Sharpe ratios of -0.051 (BCOM) and 0.221 (GSCI).

Table 9: **Performance global growth and inflation surprise strategy**: Panel A (B) provides the results for an investment strategy using global growth (inflation) surprises as positions. We report the annualized return in % (R), standard deviation in % (σ), and Sharpe ratio. Furthermore, we reported the annualized $\hat{\alpha}$ in %, and the market exposure ($\hat{\beta}$) of each investment strategy relative to the corresponding equity market. We regress $R_{s,t} = \alpha + \beta R_{m,t}$. The sample spans 1998-07-01 till 2019-06-03. The t-values are shown between brackets and Newey-West corrected. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

	Growth Surprise (A)					Inflation Surprise (B)				
	R	σ	Sharpe	$\hat{\alpha}$	$\hat{\beta}$	R	σ	Sharpe	$\hat{\alpha}$	$\hat{\beta}$
US	4.15	7.48	0.56	4.07	0.014	1.36	12.03	0.11	1.77	-0.072
	[5.58]	[15.71]	[0.36]	(2.021)	(0.146)	[5.58]	[15.71]	[0.36]	(0.410)	(-0.417)
UK	2.92	6.75	0.43	2.74	0.086	1.70	11.14	0.15	1.79	-0.040
	[2.17]	[14.57]	[0.15]	(1.757)	(1.005)	[2.17]	[14.57]	[0.15]	(0.486)	(-0.223)
JP	4.96	8.26	0.60	4.22	0.133	3.89	14.90	0.26	4.23	-0.062
	[5.53]	[19.99]	[0.28]	(2.395)	(2.359)	[5.53]	[19.99]	[0.28]	(0.927)	(-0.426)
EU	3.67	8.59	0.43	3.50	0.071	-0.54	14.52	-0.04	-0.61	0.030
	[2.41]	[19.49]	[0.12]	(1.722)	(1.050)	[2.41]	[19.49]	[0.124]	(-0.126)	(0.200)
G	3.93	6.94	0.57	3.73	0.051	1.60	12.29	0.13	1.93	-0.084
	[3.92]	[15.44]	[0.25]	(2.146)	(0.610)	[3.92]	[15.44]	[0.254]	(0.450)	(-0.451)

Lastly, we examine the market exposure of the global growth and inflation surprise strategy. In table 9 we also provide these estimates. Panel (A) shows the estimated α and market exposure for the global growth surprise strategy. For the U.S. and the U.K., we estimate a statistically significant (at the 5% level) and positive monthly α. For Japan and Europe, the estimated α's are positive, but only significant at the 10% level. The estimated monthly α's range between 2.74% and 4.22% on a annual basis. The growth surprise strategy therefore yields economically sizeable out-performance relative to the market. This is in line with the findings in table 9, where we also document that the global growth surprise outperforms a buy-and-hold strategy in terms of both risk and return. The growth surprise strategy has a relatively small positive market exposure. This is due to the fact that the global growth surprise is on average positive and approximately 3 out of 4 positions are positive (see table 1). The market exposure for the growth surprise strategy is not statistically significant in the U.S., U.K. and Europe. We only find a significant positive market exposure of our strategy in Japan. Panel (B) shows the estimated α and market exposure for the global inflation surprise strategy. This strategy does not yield significant out-performance, in terms of α, relative to the market. None of our estimates are positive and significant, in line with our previous findings regarding inflation surprises.

Figure 4: **Cumulative Return:** The figure plots the cumulative return for the growth/inflation investment strategy and for the buy-and-hold strategy for each equity market. The plots are provided for the U.S (top-left), UK (top-right), Japan (bot-left), and EU (bot-right).



4.6 Out-of-sample regressions

The preceding analysis employs information over the full sample period, which is not be known at time t. We check the robustness of the in-sample results by also adopting an out-of-sample (OOS) return predictability framework, following Campbell and Thompson (2007), Welch and Goyal (2007) and Rapach, Ringgenberg, and Zhou (2016). We forms forecasts of $R_{t:t+h}$, conditional on the time t information set, by using:

$$\hat{r}_{t:t+h} = \hat{\alpha} + \hat{\beta}_t x_t$$

Where $\hat{\alpha}$ is the OLS estimate of the constant and $\hat{\beta}_t$ is the OLS estimate of the slope, both based on data up through month t. Under the null hypothesis of no predictability, the benchmark is the prevailing mean forecasts. This is the average excess return from the start of the sample up till month t. The null hypothesis corresponds with $\beta = 0$ in the equation above. Our recursive regressions start with an initial sample size of 190 months (start in October 2012). If our surprise indexes contain relevant information for forecasting returns, then we expect that forecasts based on our surprise indexes outperform forecasts based on the benchmark model. To compare the performance of the forecasts, we use the out-of-sample (OOS) R^2 statistic proposed by Campbell and Thompson (2007):

$$R^2_{OOS} = 1 - \frac{\sum_t \epsilon^2_{PR,t+1}}{\sum_t \epsilon^2_{BM,t+1}} \tag{1}$$

This metric measures the reduction in the mean-squared forecast error for the forecast based on the surprise index relative to the benchmark forecasts. When the OOS R^2 is significantly higher than 0, forecasts based on the surprise index outperforms benchmark forecasts. To ensure whether our predictors provide superior forecasts relative to the benchmark model, we use the Clark and West (2007) test (CW test) to test the null hypothesis that the mean squared forecast error of the prevailing mean is less than or equal to the mean squared forecast error provided by the predictive regressions using our surprise predictors. The alternative hypothesis is that the mean squared forecast error of the prevailing mean is greater than that of the predictive regression using our surprise predictors.

We report the out-of-sample results in table 10. The second through the fifth column of the upper panel of table 10 reports the R^2_{OOS} for the predictive regression using global growth surprises. For the U.S., global growth surprises outperforms the benchmark, at the quarterly, semi-annual and annual forecast horizons, with R^2_{OOS} statistics of 6.37%, 9.89% and 12.27%, respectively, which are all statistically significant according to the CW statistic. For Japan and Europe, we find that significant out-performance of the global growth surprise at the monthly and quarterly horizon. Whereas for the U.K., we never find out-performance across any time horizon. The second through fifth columns of the lower panel of table 10 report the R^2_{OOS} for predictive regressions using local growth surprises. For the U.S., we find significant positive R^2_{OOS} at the semi-annual and annual horizon, with R^2_{OOS} being 8.83% and 10.24%, respectively. For Japan, we find significant out-performance across all time horizons, while we only find out-performance at the quarterly and semi-annual horizon for Europe. Again, we do not find any out-performance of local growth surprises for UK.

The sixth through the ninth column of the upper panel of table 10 reports the R^2_{OOS} for the predictive regression using global inflation surprises. Across all regions and time horizons we document positive OOS-R^2 statistics. For the U.S., these statistics are always significant, except at the monthly horizon. For the UK, global inflation surprises provide significant R^2_{OOS} statistics at the quarterly horizon (3.25%). For Japan, we only find significant R^2_{OOS} statistics at the annual horizon. For Europe, the OOS-R^2 statistics is significant at the semi-annual horizon. This out-of-sample finding contrasts our earlier in-sample result that inflation surprises are not able to predict future equity returns. The lower panel of these columns provide R^2_{OOS} statistics for local inflation surprises. For U.S., and Japan, we document significant R^2_{OOS} statistics at all horizons. For UK, R^2_{OOS} statistics are significant and positive at the monthly, quarterly and semi-annual horizon. For Europe, local inflation surprises never out-perform the mean-prevailing benchmark in terms of R^2_{OOS}.

All in all, these results suggest that growth and inflation surprises, both local and global, are able to deliver forecasts that can be superior to forecasts generated by a simple mean-prevailing benchmark model in equity markets. In appendix J, we provide the R^2_{OOS} statistics for the remaining asset classes. In contrast to equity markets, we do not find any consistent pattern with respect to out-of-sample predictability in the remaining asset classes.

Table 10: **Out-of-sample R^2**: The table contains the results of various trading strategies for a mean-variance investor who allocates her money between the risky equity index (for the U.S., U.K., Japan, and Europe) and the risk-free asset. We consider the strategy that uses predictive information, using growth (A) and inflation (B) surprises, versus a benchmark strategy that uses no predictive information (mean prevailing). The sample period consists of 270 monthly close observations between January 1997 and June 2019. The expanding window starts with an initial sample size of 190 months. Reported are the out-of-sample R^2 relative to the benchmark model, and its one-sided t-values (in parentheses) computed with the Clarke and West (2007) test. The t-values are computed with robust Newey-West standard errors corrected for heteroskedasticity and auto-correlation. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

Global:	Growth Surprise (A)				Inflation Surprise (B)			
	$h = 1m$	$h = 3m$	$h = 6m$	$h = 12m$	$h = 1m$	$h = 3m$	$h = 6m$	$h = 12m$
US	0.16	6.37**	9.89**	12.27***	0.27	5.47***	11.09***	9.23**
	(1.024)	(1.762)	(1.915)	(2.777)	(0.567)	(3.083)	(2.776)	(2.088)
UK	-0.88	-2.00	-1.29	3.82	1.26*	3.25**	6.26*	3.544
	(0.933)	(0.747)	(0.486)	(0.853)	(1.373)	(2.115)	(1.588)	(0.830)
JP	4.19**	4.45**	1.09	-1.86	1.07	2.14	2.09	6.41**
	(1.958)	(1.974)	(0.685)	(-0.124)	(0.924)	(1.221)	(1.021)	(1.661)
EU	2.99**	5.05*	6.32*	9.60*	1.26*	3.27*	8.02**	9.54*
	(1.814)	(1.618)	(1.354)	(1.334)	(1.472)	(1.325)	(1.679)	(1.456)
Local:	Growth Surprise (A)				Inflation Surprise (B)			
	$h = 1m$	$h = 3m$	$h = 6m$	$h = 12m$	$h = 1m$	$h = 3m$	$h = 6m$	$h = 12m$
US	-2.21	0.85	8.83**	10.24**	4.02**	2.88*	5.87**	3.47**
	(0.739)	(1.261)	(1.985)	(2.188)	(2.300)	(1.708)	(2.235)	(1.834)
UK	0.34	0.30	-4.20	-2.44	1.23**	3.20*	7.37**	4.05
	(0.952)	(0.957)	(0.471)	(0.415)	(1.676)	(1.473)	(1.706)	(0.881)
JP	2.74*	6.49**	8.53**	13.83**	4.13**	10.21**	12.87**	16.58**
	(1.631)	(1.866)	(1.902)	(1.941)	(2.134)	(2.183)	(1.859)	(1.942)
EU	0.04	4.40**	9.65***	-0.86	-0.20	-16.74	-11.49	4.77
	(0.504)	(2.171)	(2.372)	(1.534)	(0.798)	(0.106)	(0.757)	(0.945)

4.7 Economic significance of surprises

In this section, we assess the economic significance of the predictive ability from an asset allocation view. Even though, surprises exhibit predictive power for returns, both the in-sample as well out-of-sample analyses have some practical drawbacks. First of all, forecast errors are punished likewise, while in practice the sign of the error tends to be especially important and not its precise value. In addition, these analyses do not take into account the risk borne by an investor. Therefore, we next analyze a trading strategy that exploits economic surprises.

Consider a mean-variance investor who allocates between a risky asset and risk-free bills using a predictive regression forecast. At the end of period t, this investor allocates a share of $w_t = \frac{1}{\gamma}\frac{\hat{R}_{t+1}}{\hat{\sigma}^2_{t+1}}$ into the risky asset during the subsequent period $t+1$. Let γ denote the coefficient of relative risk aversion (RRA), $\hat{R}_{t+1}$ denote the predictive regression excess return forecast, and $\hat{\sigma}^2_{t+1}$ stands for the forecast of the excess return variance. The volatility forecast is computed on a ten-year moving window of past returns (Campbell & Thompson, 2007).

We report the results for a risk-averse investor ($\gamma = 3$), consistent with estimates of the RRA from the literature. To limit the effect of extreme positions, outliers, and estimation errors, portfolio weights are constrained between $w_t = -0,5$ and $w_t + 1,5$. In addition, we impose the restriction that no short selling, nor the use of leverage, is allowed ($0 \leq w_t \leq 1$). An investor who uses these weighting schemes realizes a certainty equivalent return (CER) of $CER = \bar{R}_p - 0.5\gamma\sigma^2_p$. Where $\bar{R}_p$ and σ^2_p denotes the mean and variance, respectively, of the portfolio return over the forecast evaluation period. The CER can be interpreted as the risk-free rate of return that an investor would be willing to accept in lieu of holding the risky portfolio. In addition, we compute the CER for an investor who uses a simple moving average strategy. The CER gain is defined as the difference between the CER using the surprise forecasts and the CER using the moving average strategy. The CER gain is annualized, so that it can be interpreted as the maximum portfolio management fee that an investor is willing to pay to have access to the predictive strategy. We assume that the investor re-balances at the same frequency as the forecast horizon.

We report the CER gains in table 11. Column two through five shows the CER gains accruing to predictive regression forecasts based on global growth surprises. For a very-risk averse investor, we document CER gains that are positive across all regions, time horizons and weight constraints. The only exception is Japan, with a CER loss of 138 basis points at the annual horizon using weights between -0.5 and $+1.5$. The positive CER gains estimates range between 160 basis points up to 639 basis points. As these CER gains are substantial and almost always positive, we conclude that global growth surprises provide substantial utility gains to investors vis-a-vis the benchmark model. The sixth through the ninth column of table 11 reports the economic significance of global inflation surprises in terms of CER gains. In general, we observe substantial positive CER gains, ranging from 34 up to 268 basis points. The CER gains are always positive irrespective of the holding period, regions, and weight restriction. Similar to growth surprises, inflation surprises provide superior forecasts that yield substantial economic value to investors. We also report the Sharpe ratios for the portfolios, since this allows to compare portfolio performance independently from the relative risk aversion parameter γ. The middle (lower) panel of table 11 shows the out-of-sample Sharpe ratio using portfolio weights capped between -0.5 and $+1.5$ (0 and 1). Especially at short holding periods (1m and 3m), we observe Sharpe ratios that are higher than obtained by the benchmark strategy across all regions [9].

[9] appendix K reports CER gains using local growth and inflation surprises. The results do not differ qualitatively from the

Table 11: **Out-of-sample CER gains and Sharpe ratios**: The table contains the results of various trading strategies for a mean-variance investor who allocates her money between the risky equity index (for the U.S., U.K., Japan, and Europe) and the risk-free asset. We consider the strategy that uses predictive information, using growth (A) and inflation (B) surprises, versus a benchmark strategy that uses no predictive information (mean prevailing). The sample period consists of 270 monthly close observations between January 1997 and June 2019. The expanding window starts with an initial sample size of 190 months. Shown are the CER gains for the predictive strategy over the benchmark strategy constraining portfolio weights between -0.5 and $+1.5$. Between the brackets we report the CER gains using portfolio weights capped by 0.0 and $+1.0$. We report Sharpe ratios using weights between -0.5 and $+1.5$ and 0.0 and $+1.0$ in the middle and bottom panel, respectively.

$\gamma = 3$	Growth Surprise (A)				Inflation Surprise (B)			
CER gain	$h = 1m$	$h = 3m$	$h = 6m$	$h = 12m$	$h = 1m$	$h = 3m$	$h = 6m$	$h = 12m$
US	5.274	4.493	2.842	2.454	0.899	2.684	2.087	1.043
	[4.018]	[4.486]	[2.842]	[2.454]	[1.853]	[2.293]	[2.004]	[1.043]
UK	3.530	3.651	1.477	1.078	1.938	1.651	0.537	0.439
	[3.821]	[3.997]	[1.477]	[1.078]	[1.712]	[1.651]	[0.596]	[0.439]
JP	6.390	2.476	0.230	-1.386	1.006	1.814	0.342	2.034
	[6.147]	[1.756]	[0.963]	[0.437]	[1.464]	[1.860]	[1.079]	[1.466]
EU	6.033	2.538	1.602	1.691	0.467	0.657	1.282	1.257
	[4.980]	[2.082]	[1.275]	[1.150]	[0.185]	[0.430]	[1.036]	[0.715]
$\gamma = 3$	Growth Surprise (A)				Inflation Surprise (B)			
Sharpe	$h = 1m$	$h = 3m$	$h = 6m$	$h = 12m$	$h = 1m$	$h = 3m$	$h = 6m$	$h = 12m$
US	1.013	1.195	2.04	1.449	0.856	1.269	1.844	1.280
	(0.889)	(1.240)	(2.160)	(1.505)	(0.889)	(1.240)	(2.160)	(1.505)
UK	0.600	0.723	0.721	0.584	0.670	0.841	0.546	0.483
	(0.446)	(0.686)	(0.721)	(0.502)	(0.446)	(0.686)	(0.721)	(0.502)
JP	0.591	0.578	0.045	-0.150	0.153	0.428	0.074	0.624
	(-0.402)	(-0.018)	(-0.106)	(0.025)	(-0.402)	(-0.018)	(-0.106)	(0.025)
EU	0.576	0.418	0.369	0.463	0.028	0.143	0.336	0.379
	(-1.141)	(-0.316)	(-0.398)	(-0.422)	(-1.141)	(-0.316)	(-0.398)	(-0.422)
$\gamma = 3$	Growth Surprise (A)				Inflation Surprise (B)			
Sharpe$_c$	$h = 1m$	$h = 3m$	$h = 6m$	$h = 12m$	$h = 1m$	$h = 3m$	$h = 6m$	$h = 12m$
US	1.158	1.370	2.048	1.449	1.054	1.326	1.859	1.280
	(0.913)	(1.240)	(2.160)	(1.505)	(0.913)	(1.240)	(2.160)	(1.505)
UK	0.724	0.900	0.721	0.584	0.645	0.841	0.565	0.483
	(0.446)	(0.686)	(0.721)	(0.502)	(0.446)	(0.686)	(0.721)	(0.502)
JP	0.705	0.623	0.588	0.436	0.304	0.712	0.529	0.624
	(0.070)	(0.541)	(0.519)	(0.421)	(0.070)	(0.541)	(0.519)	(0.421)
EU	0.226	0.263	0.313	0.418	0.196	0.237	0.314	0.399
	(-0.538)	(0.100)	(-0.004)	(0.155)	(-0.538)	(0.100)	(-0.004)	(0.155)

previous reported results using local surprises. In addition, we also report the CER gains and Sharpe ratios for the remaining asset classes. In line with the OOS-R^2 results, we find that global surprises do not generate substantial positive CER gains, but rather CER losses. Likewise, global surprises do not generate superior Sharpe ratios relative to the mean-prevailing benchmark model in the remaining asset classes.

5 Robustness tests

In this section we consider several robustness tests. First, we decompose our surprise index into a "revision surprise" factor and a "no revision surprise" factor. We show that a global growth revision surprise factors is able to predict future equity returns. Second, we consider the use of alternative econometric methodologies to extract a common component in macroeconomic series, and show the added value of a sophisticated weighting scheme relative to simply using equal weights to construct the surprise index.

5.1 Revision versus no revision

Economic surprises consist of two parts. The first part is the announcement surprise, defined as the difference between the latest real-time announcement value and the economists' survey consensus. The second part is the 'revision' surprise, which is the difference between the latest revision value and last period's announcement. The revision surprise is, to our knowledge, not employed in earlier literature, while revisions do reflect the arrival of new information to investors. The predictability of asset returns due to economic surprises, that we document, can thus come from either the first part, the second part or both parts. We construct surprise indexes that exclude revisions. This allows us to assess whether revisions surprises add predictive information. We run in-sample pooled regressions using these "no revision" and "revision only" surprise factors. The latter is the difference between the original surprise factors minus the "no revision" factors.

Table 12 provides the pooled regression estimates considering equity market returns. In column (1), we consider a bivariate regression of the local growth surprise with revision ($G^{r}_{sur,l}$) and without ($G^{r}_{sur,l}$) on pooled equity returns. Both local growth surprises, with and without revisions, positively predict future equity returns. However, the local growth surprise factor with revisions-only has a larger coefficient than surprises without revisions. We test for coefficient equality and find that the "revision-only" coefficient is significantly larger than the "no revision" ($p = 0.003$). This implies that a factor consisting only of local revision surprises is stronger than a surprise factor without revisions, with respect to forecasting future equity returns.

Replacing the local factors by "local-global" and "global" factors indicate that a "revision-only" global surprise factor has the largest effect on future monthly returns. A two standard deviation increase in this factor predicts a 0.98% increase in future equity returns, on average. The magnitude of the coefficient for this factor is substantially larger than the estimated coefficient on the "no revision" global surprise factor ($p = 0.013$). This documented result is, to our knowledge, novel in the literature: revision surprises in macroeconomic growth variables contain predictive power for future equity returns. Revision in macroeconomic growth variables reflect the arrival of new information that is used to update the state of the economy, thereby affecting equity prices. Local-global growth surprises without revisions also positively and significantly predict future returns. However, the magnitude of the effect is rather small. A two standard deviation increase in this factor predicts a 0.12% increase in future equity returns. The results remain qualitatively the same after controlling for the growth level and disagreement factor. The global revision surprise in growth positively predicts future equity returns and is significantly stronger than its (global) "no revision" counterpart. Earlier, we documented that surprises in inflation do not exhibit predictive power to forecast future equity returns. We find a similar result here. Irrespective of the use of "revision only" and "no revision" factors, surprises in inflation variables do not predict future equity returns.

For the remaining asset classes, we provide the estimates in appendix L. We find that a global revision growth surprise factor significantly and negatively predict future bond market returns at the monthly forecast horizon. In contrast to the bond market, for credits, we find that local growth "no revision" surprises significantly and positively predict future credits returns. In addition, both revision and no-revision global growth surprises weakly predict future credit returns. For commodities, only global growth revision surprises predict future commodity returns.

Table 12: **Revisions versus No Revisions:** The table shows the results of regressing the global growth/inflation surprise index (with and without revisions) on future excess pooled equity market returns. We control for the level and dispersion factors. In addition, we use volatility indexes, dividend yields and price earning ratios as control variables. The t-values are shown between brackets and are country-time cluster corrected. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

Equity	(1)	(2)	(3)		(4)	(5)	(6)
$G^r_{sur,l}$	0.940***			$I^r_{sur,l}$	−0.006		
	(5.409)				(−0.027)		
$G^{nr}_{sur,l}$	0.461**			$I^{nr}_{sur,l}$	−0.272		
	(2.101)				(−1.031)		
$G^r_{sur,l-g}$		0.215	0.392	$I^r_{sur,l-g}$		−0.035	−0.011
		(1.362)	(1.602)			(−0.127)	(−0.049)
$G^{nr}_{sur,l-g}$		0.215**	0.314***	$I^{nr}_{sur,l-g}$		−0.071	−0.052
		(2.047)	(6.197)			(−0.374)	(−0.289)
$G^r_{sur,g}$		3.373***	2.605***	$I^r_{sur,g}$		0.105	0.035
		(3.632)	(2.915)			(0.180)	(0.066)
$G^{nr}_{sur,g}$		0.891	1.370	$I^{nr}_{sur,g}$		−0.844	−0.489
		(1.052)	(1.403)			(−1.248)	(−0.913)
Controls	NO	NO	YES		NO	NO	YES
Obs.	1,016	1,016	802		989	989	789
Adj.R^2	0.010	0.031	0.062		0.001	0.004	0.043

5.2 Do other weighting schemes matter?

One goal of this paper is to summarize a large cross-section of economic surprises into one statistic over a wide time span using a sound and simple methodology. Here we opted for using principal component analysis using an recursive time window. However, several other methodologies exist that are also able to distill a large cross-section of daily economic surprises into one measure. In this section, we use multiple other methodologies to construct a surprise index and subsequently predict equity market returns for the U.S., U.K., Japan, and Europe.

The first, and most simple, method is to use equal weights. We construct growth and inflation surprise indexes by assigning equal weights to the corresponding individual surprise time series. Subsequently, we use a recent technique, developed by Kelly and Pruitt (2015), called the "three-pass regression filter" (3PRF). PCA achieves dimension reduction by decomposing the predictor's covariance matrix into eigenvalues, thereby extracting predictive information according to the covariance within the cross-section. However, in the 3PRF, predictive information is extracted according to the covariance with the factors driving the dependent variable. The first pass of the 3PRF consists of time series regressions where each predictor variable is the dependent variable and the proxy (the equity market return here) is the regressor. The second pass is a cross-sectional regression where the underlying surprise variables are used as predictors and the first-pass slope coefficients as regressors. The second pass slope coefficients are then used to predict market returns in a third pass predictive regression. This approach is especially advantageous when the set of predictors is large. Kelly and Pruitt (2015) apply this methodology to forecast market returns and cash flow growth and find positive in-sample and out-of-sample R^2 that outperform OLS and PCA. Lastly, we construct our surprise indexes by applying Partial Least Squares (PLS). Kelly and Pruitt (2015) note that PLS is a special case of 3PRF, where the predictors are standardized prior to the first pass and the forecasting variable is used as a regressor in the first pass.

We first run in-sample predictive regressions using the three alternative weighting scheme and compare this to our methodology. In Table 13 we report the estimated slope coefficient, its t-value (between parenthesis), and the R^2. Across all countries, we find that growth surprises strongly and positively predict future equity market returns using the 3PRF methodology. The reported R^2 range between 0.50% and 17.24%, and all in-sample slope estimates are statistically significant at the 1%. Likewise, PLS also generates a latent growth surprise factor that significantly (at the 5% level) and positively predicts future equity market returns across all regions. These in-sample results are, on average, stronger than the results obtained by using OLS with growth surprise factors as obtained by our PCA methodology. The 3PRF methodology is also able to construct a latent inflation surprise factor that significantly and positively predicts future equity market returns, with R^2 estimates ranging between 6.77% and 10.47%. For PLS we obtain qualitatively similar results, although weaker. This is in contrast with the results obtained by our methodology, as the PCA-based inflation surprise factor does not predict future equity market returns. However, this result can be rationalized by the fact that 3PRF and PLS select the surprise variables that are correlated with the market return. Considering an equal-weighted surprise index, we find that this does not predict future equity market returns. Both global growth and inflation surprises do not exhibit any predict power. This result suggests the added-value of a more sophisticated weighting scheme rather than a simply naive scheme.

Lastly, we also consider the out-of-sample performance of these methodologies. In Table 14 reports the OOS R^2, CW test (between parenthesis), CER gain and Sharpe ratios (between brackets). We consider a mean-variance investor with a relative risk aversion parameter of $\gamma = 3$, with a holding period of 1 month, and use constraint portfolio weights between -0.5 and $+1.5$. In stark contrast to the in-sample results, we find that 3PRF and PLS typically yields OOS R^2, CER gains and Sharpe ratios that are inferior than those obtained by our methodology. For example, the CER gains generated by our methodology vary between 3.53% and 6.39% for growth surprises, while the CER gain generated via 3PRF is at most 3.07%. Although 3PRF and PLS yield stronger results in-sample, this does not necessarily hold in an out-of-sample setting in our case.

Table 13: **Alternative weighting schemes: univariate in-sample regressions.** The table shows the results of regressing global growth and inflation surprises using the three-pass regression filter of (Kelly & Pruitt, 2015), Partial Least Squares, OLS with surprise factors obtained from our PCA methodology, and OLS using an equal-weighted surprise factor. Monthly observations are used for estimation. The sample period spans 1997-01-01 till 2019-05-01. Reported are the univariate coefficient estimates, its corresponding t-values (between parenthesis), and the R^2. The t-values are Newey-West adjusted for serial correlation and heteroscedasticity.

	3PRF		PLS		PCA		EW	
	$G_{sur,g}$	$I_{sur,g}$	$G_{sur,g}$	$I_{sur,g}$	$G_{sur,g}$	$I_{sur,g}$	$G_{sur,g}$	$I_{sur,g}$
US	0.085***	0.081*	0.006***	0.004*	0.015**	-0.003	0.005	-0.014
	(3.183)	(1.872)	(3.634)	(1.769)	(2.417)	(-0.418)	(0.430)	(-1.072)
	7.51%	6.99%	4.37%	1.51%	4.56%	0.13%	0.03%	0.79%
UK	0.024***	0.108***	0.006***	0.003*	0.011*	-0.004	0.006	-0.010
	(3.053)	(3.057)	(3.085)	(1.700)	(1.709)	(-0.751)	(0.572)	(-0.859)
	2.77%	10.47%	3.67%	1.35%	0.90%	0.39%	0.07%	0.48%
JP	0.005***	0.076***	0.007***	0.004*	0.017**	-0.005	0.008	-0.024
	(2.783)	(2.827)	(2.690)	(1.795)	(2.131)	(-0.671)	(0.405)	(-1.528)
	0.50%	6.77%	4.49%	2.03%	1.17%	0.27%	0.06%	1.47%
EU	0.152***	0.093***	0.006**	0.018*	0.04*	0.175	0.004	0.003
	(5.618)	(3.136)	(2.433)	(1.826)	(1.726)	(0.184)	(0.186)	(0.183)
	17.24%	8.19%	3.23%	1.53%	1.64%	0.04%	0.01%	0.02%

Table 14: **Alternative weighting schemes: Out-of-sample performance.** The table contains the results of various trading strategies for a mean-variance investor who allocates her money between the risky equity index and the risk-free asset. We consider the strategy that uses predictive information, using 3PRF, PLS, OLS with PCA Surprises and OLS with EW Surprises versus a benchmark strategy that uses no predictive information (mean prevailing). The sample period consists of 270 monthly close observations between January 1997 and June 2019. The expanding window starts with an initial sample size of 190 months. Reported are the out-of-sample R^2, its one-sided t-values (in parentheses) computed with the Clarke and West (2007) test. The t-values are computed with robust Newey-West standard errors corrected for heteroskedasticity and auto-correlation. Asterisks are used to indicate significance at a 10% (*), 5% (**)or 1% (***) level. In addition, we show the Sharpe ratios and CER gains for these predictive strategies between brackets. Portfolio weights are constrained between -0.5 and $+1.5$. We report the results for a very risk averse investor ($\gamma = 3$).

	3PRF		PLS		PCA		EW	
	$G_{sur,g}$	$I_{sur,g}$	$G_{sur,g}$	$I_{sur,g}$	$G_{sur,g}$	$I_{sur,g}$	$G_{sur,g}$	$I_{sur,g}$
US	-1.04	-2.19	0.20	-0.69	0.16	0.27	0.16	0.86
	(0.984)	(0.903)	(1.213)	(0.392)	(1.024)	(0.567)	(1.583)	(-0.112)
	[1.754]	[1.264]	[2.674]	[2.749]	[5.274]	[0.899]	[0.000]	[-0.003]
	[0.599]	[0.567]	[0.568]	[0.668]	[1.013]	[0.856]	[1.191]	[1.176]
UK	-2.17	-11.92	-4.05	0.209	-0.88	1.26*	0.58	0.79
	(0.601)	(-1.088)	(0.179)	(0.588)	(0.933)	(1.373)	(0.679)	(1.135)
	[0.595]	[-4.280]	[0.352]	[1.329]	[3.530]	[1.938]	[-0.004]	[-0.006]
	[0.350]	[-0.081]	[0.198]	[0.338]	[0.600]	[0.670]	[0.639]	[0.627]
JP	3.44*	1.69**	3.83**	2.639*	4.19**	1.07	2.13**	0.67
	(1.550)	(1.985)	(1.653)	(1.435)	(1.958)	(0.924)	(2.253)	(0.707)
	[3.006]	[3.425]	[4.746]	[8.199]	[6.390]	[1.006]	[0.004]	[-0.053]
	[0.553]	[0.573]	[0.514]	[0.780]	[0.591]	[0.153]	[0.670]	[0.531]
EU	0.983	-18.69	-5.71	-5.764	2.99**	1.26*	1.36	1.45**
	(1.278)	(-0.947)	(0.112)	(-0.701)	(1.814)	(1.472)	(1.215)	(1.672)
	[1.277]	[-8.775]	[-1.002]	[-1.615]	[6.033]	[0.467]	[-0.082]	[-0.002]
	[0.464]	[-0.243]	[0.152]	[0.070]	[0.576]	[0.028]	[-0.083]	[0.266]

6 Explaining the predictability

Our results suggest that global growth surprises predict higher future equity return premia. In this section, we explore the potential sources of this predictability. First, we examine whether surprises are related to increases in risk and skewness. Second, we test if surprises predict negative expected returns. Subsequently, we conduct an anchoring test, following Campbell and Sharpe (2009), to examine whether forecasts depend on past actuals.

6.1 Predicting volatility and skewness

First, we study whether surprises forecast higher level of risk and skewness. In efficient markets, higher expected stock returns may be the result of increases in risk and hence higher risk premia demanded by investors. To test this predictive link, we test whether economic surprises predicts realized volatility (defined as the sum of next month's daily squared returns) and realized skewness.

Table 15 provides the corresponding estimates. We find that higher global growth surprises results into lower future realized volatilities, in univariate regressions. After controlling for the growth level and disagreement, the results remain qualitatively similar. The estimates are both economically and statistically significant. A two standard deviation change in global growth surprises results in an approximate -0.234% lower monthly realized volatility. Moreover, global growth surprises do not predict future realized skewness. The estimate is negative, but statistically not significant. Based on Table 15, a premium based on global growth surprises is not justified on future volatility nor future skewness. In addition, we find that global inflation surprises do not predict future realized volatility. On the other hand, we find that an increase global inflation surprises results higher future skewness in equity market returns. This effect becomes stronger after including the inflation level and disagreement factor. Nevertheless, we have seen that global inflation surprises do not predict future equity market returns. Therefore, market inefficiency is more likely to be the driving force behind the predictability of asset returns due to economic surprises.

In appendix M we provide the results for the remaining asset classes. For bonds, we find that higher global growth surprises predict lower future realized variance. In addition, higher global inflation surprises predict lower future skewness. However, appendix M indicates that both global inflation and growth surprises do not predict future bond returns. For the other three asset classes, we also find that global growth surprises negatively predict future realized volatility. Yet, global growth surprises positively and significantly predict future credit and commodity returns. We would expect, given market efficiency, that global growth surprises positively predict future realized volatility, given the positive predictive power of global growth surprises in credit and commodity markets. In addition, inflation surprises do not predict future realized volatility. For commodity and credit markets, only inflation surprises predict future skewness significantly. However inflation surprises do not have predictive power when it comes to commodity and credits returns. None of the results favour market efficiency.

6.2 Negative Expected Returns

Next, we test if economic surprises predict negative expected excess equity returns. A rational time-varying risk premia explanation is hard to align with negative expected equity premia. Rational finance models require that the aggregate stock market is a hedge against aggregate consumption risk in order to yield negative expected returns (Baker & Wurgler, 2000). Yet, expected equity premia can be negative if the

Table 15: **Predicting volatility and skewness (equity):** Panel (A) shows the results of regressing the global growth or inflation surprise index on the future realized variances of equity markets. Panel (B) shows the results of regressing the global growth or inflation surprise index on the future realized skewness of equity markets. We control for the level and dispersion factors (Macro Controls). In addition, we use the volatility index, price-earning ratio, dividend yields and 1-week reversal of the underlying market as Financial Controls. The t-values are shown between brackets and are country-time cluster corrected. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

Panel A (RV)	(1)	(2)	(3)		(4)	(5)	(6)
G_{sur}	-0.408^{***}	-0.318^{***}	-0.157^{**}	I_{sur}	0.155	0.144	0.143
	(−3.693)	(−3.811)	(−2.369)		(1.216)	(1.489)	(1.425)
Macro Controls	NO	YES	YES		NO	YES	YES
Fin. Controls	NO	NO	YES		NO	NO	YES
Obs.	1,058	1,055	802		1,052	1,052	801
Adj. R^2	0.051	0.144	0.320		0.019	0.130	0.329
Panel. B (RS)	**(1)**	**(2)**	**(3)**		**(4)**	**(5)**	**(6)**
G_{sur}	−1.342	−1.451	−0.875	I_{sur}	5.916^{**}	7.380^{***}	8.488^{***}
	(−0.334)	(−0.334)	(−0.157)		(2.377)	(3.226)	(3.091)
Macro Controls	NO	YES	YES		NO	YES	YES
Fin. Controls	NO	NO	YES		NO	NO	YES
Obs.	1,058	1,055	802		1,052	1,052	801
Adj. R^2	−0.001	0.010	0.028		0.004	0.016	0.039

predictability reflects a market inefficiency. The sorting results obtained from table 4 provide an indication of predictable negative equity premia. We found that the equity premium is negative across all regions in the lowest (highest) global growth (inflation) surprise quantile. In addition, a pooled univariate regression of equity returns on global growth surprise yields a coefficient estimate of −0.03 and growth surprise coefficient of 1.83, while the mean and standard deviation of the global growth surprise equal 0.23 and 0.39. Hence, we observe negative forecasts for next month's equity premium for values of the global growth surprise of roughly half a standard deviation below its average. This implies that the expected equity premium is forecasted to be negative in 28.9% (306 out of 1058) of all cases.

To take forecast uncertainty into account, we calculate the 90% confidence interval estimate around these predicted values. We predict negative expected excess returns in 10.1% of all observations (Panel A, table 16). These results might be due to an omitted non-linearity in the relationship between the global growth surprise and the equity premium. Potentially, predictability is only derived from medium to high values of the global growth surprise, while there might be no relationship between low values of the growth surprise and equity premia. This would imply that the results may still be aligned with a time-varying risk premium explanation.

Subsequently, we calculate the cumulative prediction error of the above analysis over all negative predicted equity premia months. The presence of convexity between global growth surprises and future equity premia would result in a positive cumulative prediction error. We find a positive cumulative prediction error equal to 0.544%. However, when we only focus on the 10.1% of predictions that are significantly negative, we find a cumulative prediction error of −0.927%. To formally test for convexity, following Driespong, Jacobsen and Maat (2008), we estimate:

$$r_{t+1} = \alpha + \beta_1 S_t + \beta_2 D_{t+1} S_t + \epsilon_{t+1}$$

D_{t+1} takes a value of one when predicted returns are negative (based on the estimates of the regression $R_{t+1} = \alpha + \beta S_t$), and zero otherwise. β_1 measures the predictive relationship between the global growth surprise and the monthly equity premium for positive predicted returns. β_2 measures whether the relationship is different for negative expected return predictions. $\beta_1 + \beta_2$ measures the total predictive effect for negative expected return predictions.

To test whether $\beta_1 + \beta_2$ is significantly different from zero, we use a Wald test. The results (panel B of table 16) show that the predictive effect is not different for negative or positive expected returns. The estimate of β_1 is equal to 1.357. If convexity is present, we expect β_2 to be equal to roughly $-\beta_1$. However, we find an estimate of β_2 equal to 1.596. We do not reject the hypothesis that the slope for the negative expected return domain is different from the positive expected return domain (p-value=0.570). In addition, we reject the hypothesis that $\beta_1 + \beta_2$ equals zero (p-value=0.000), implying a significant predictive relationship for the negative return domain.

The above two procedures depend on a relatively little number of observations in the negative expected return domain, assume normality of the error term, and may lack power. As a final check, we implement the minimum expected return test of Eleswarapu and Thompson (2007). They propose to test the distance between the parameter estimates and the closest point in parameter space consistent with non-negativity, while employing a bootstrap procedure to deal with sample issues and violations of normality. The results, reported in Panel C of table 16, show that the minimum expected return of -1.06% is significantly smaller than zero (p-value =0.002). These tests all indicate evidence of predictable negative returns, contradicting a market efficiency-based explanation.

In table 16 we also report the results for the remaining asset classes. We draw similar conclusions for the credits and commodity market. For the bond market, however, we find zero predictions that are significantly negative and we reject the null hypothesis of no predictability of negative returns using the minimum expected return test.

6.3 Anchoring and Overreaction

Empirically, many studies documents systematic departures from the rational expectations hypothesis using data of professional forecasters, for example, in the context of inflation variables (Coibion & Gorodnichenko, 2012). Let A_t denote the actual value of a data release, and let F_t be the available corresponding forecasts. The surprise is defined as $S_t = A_t - F_t$. A basic rationality test (Campbell & Sharpe, 2009) can be conducted by regressing the actual value on the forecast: $A_t = \beta F_t + \epsilon_t$ (1). Under the null hypothesis of rationality, β will be equal to 0. In addition, we test the null hypothesis that $\beta = 1$ against the alternative hypothesis that $\beta < 1$. Rejection of the null hypothesis implies that forecasts are systematically larger than the announcement value, i.e. forecasters are overreacting and upward biased. When the null hypothesis of rationality is rejected, under the alternative, forecasters could potentially suffer from an anchoring heuristic. Campbell and Sharpe (2009) therefore estimate the following model of forecast anchoring: $F_t = \lambda E(A_t) + (1 - \lambda)\bar{A}_h$ (2). Where $\bar{A}_h$ is a lagged moving average of the past h announcement values. When $\lambda < 1$, consensus forecasts are biased to lagged values of actual data releases, indicating that forecasts are anchored towards actual data releases in the recent past. We follow this approach and estimate both equation (1) and (2) to test for rationality, overreaction, and anchoring. Rather than using the surprise factors, we use the raw

Table 16: **Negative expected return tests:** Panel A reports the number (#) and fraction (%) of expected return forecasts for which the 90% confidence interval lies below zero. Panel B reports the estimate of the non-linearity regression using global growth surprises. D_{t+1} takes value one if expected excess returns are negative, and zero otherwise. The last row report the Wald test on being statistically significantly different from zero ($\chi^2(1)$). The p-values are computed with double-clustered (by time and asset) standard errors. Panel C reports the minimum expected return and its p-value based on the minimum expected return test of Eleswarapu and Thompson (2007) using 10.000 bootstraps. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

Panel A	Equity	Credits	Comm.	Bonds
$E(r) < 0$	107 of 1058	22 of 792	116 of 542	0 of 1076
	(10.1%)	(2.78%)	(21.40%)	(0%)
Panel B				
α	0.165	0.235	0174	0.047***
	(0.436)	(0.137)	(0.642)	(3.213)
$G_{sur,t}$	1.357*	0.406	1.079	-0.049
	(0.069)	(0.162)	(1.228)	(-1.263)
$D_{t+1} \times G_{sur,t}$	1.596	1.089	4.738**	0.110*
	(0.570)	(0.140)	(0.017)	(1.805)
$G_{sur,t} + D_{t+1} \times G_{sur,t}$	2.953***	1.495***	5.817***	0.060***
Wald Test	10.733	11.846	10.047	4.793
Panel C				
Min. $E(r)(\%)$	-2.00**	-0.70***	-3.00***	-0.00
	(0.002)	(0.012)	(0.002)	(0.4249)

individual time series to test for anchoring on a disaggregated level.

Table 17 reports the amount of times (and proportion) that we reject the null hypothesis of rationality, no overreaction and no anchoring. We compute these rejection rates for each region by growth and inflation category. We estimate the model of forecast anchoring using four different values of $h : (1m, 3m, 6m, 1y)$. Panel A provides the rejection rates for the rationality model. The estimates indicate that the rationality hypothesis is widely rejected. For the growth series, the rejection rate varies between 66.7% and 84.6%. For inflation series the rejection rate varies from 50% to 100%. Pooling the amount of rejections across the regions and categories results in a rejection rate of 77.2%. Thus, in more than 3 out of 4 time series we are reject the rationality hypothesis.

Panel B reports how many times we favour the alternative hypothesis of $\beta < 1$ given the rejection of the rationality hypothesis. For growth series, we document a strong presence of overreaction. Between 77.8% and 100% of the cases exhibit overreaction by forecaster's. Likewise, we document this for inflation series, with EU being an exception. Pooled, we find that for 87% of the cases exhibit overreacting forecasts.

Panel C-F provides the results for the forecast anchoring model for different values of h. Let the previous announcement be the anchor ($h = 1$), we find that λ is significantly lower than 1 in 63.6% up to 85.7% of the cases. Pooled, this equals 75.9%. So in more than 3 out of 4 series, we find that forecaster's put some weight to the previous announcement value. Increasing h and thereby including older past announcement values in the anchor slightly decreases this rate. For $h = 3$, we find that 69% of the series exhibit λ significantly lower than 1. Using a 6-month anchor and 1-year anchor, we find that 65.6% and 55.2% of the cases have a λ significantly lower than 1. Forecasters are anchored towards past recent data, this anchoring bias is a cause for autocorrelation in surprises. Because forecaster's do not exhibit rational expectations and put (too much) weight in past realizations, forecasts will deviate from the current realizations. As this occurs systematically, autocorrelations in surprises will occur.

To summarize, in this section, we explored the source of predictability via three routes. In efficient markets, higher expected stock returns may be the result of increases in risk. First, we find that the predictability of future asset returns is not aligned with the predictability of future higher moments (volatility and skewness). We find that global growth surprises predict future realized volatility negatively, while it predicts future equity market returns positively. Second, rational finance models require that the aggregate stock market is a hedge against aggregate consumption risk in order to yield negative expected returns (Baker & Wurgler, 2000). We do not support this requirement using negative expected returns tests. We conjecture that the impact of surprises is caused by anchoring. Our results indicate that forecasts are anchored toward past recent data. This anchoring bias creates persistency in surprises.

Table 17: **Rationality, Overreaction and Anchoring.**

Panel A (Rationality)	#	%	**Panel B (Overreaction)**	#	%
Growth US	42 of 52	80.8%	Growth US	38 of 42	90.5%
Growth UK	22 of 26	84.6%	Growth UK	22 of 22	100%
Growth JP	18 of 22	81.8%	Growth JP	14 of 18	77.8%
Growth EU	44 of 66	66.7%	Growth EU	40 of 44	90.9%
Inflation US	6 of 7	85.7%	Inflation US	6 of 6	100%
Inflation UK	6 of 6	100%	Inflation UK	6 of 6	100%
Inflation JP	9 of 9	100%	Inflation JP	7 of 9	77.8%
Inflation EU	7 of 14	50.0%	Inflation EU	1 of 7	14.3%
Panel C (Anchoring,1m)	#	%	**Panel D (Anchoring,3m)**	#	%
Growth US	29 of 42	69.0%	Growth US	26 of 42	61.9%
Growth UK	14 of 22	63.6%	Growth UK	15 of 23	65.2%
Growth JP	12 of 18	66.7%	Growth JP	11 of 18	61.1%
Growth EU	33 of 44	75.0%	Growth EU	34 of 44	77.3%
Inflation US	4 of 6	85.7%	Inflation US	5 of 6	83.3%
Inflation UK	5 of 6	83.3%	Inflation UK	3 of 6	50.0%
Inflation JP	8 of 9	88.9%	Inflation JP	7 of 9	77.8%
Inflation EU	6 of 7	85.7%	Inflation EU	6 of 7	85.7%
Panel E (Anchoring,6m)	#	%	**Panel F (Anchoring,1y)**	#	%
Growth US	27 of 42	64.3%	Growth US	28 of 42	66.7%
Growth UK	15 of 22	68.2%	Growth UK	10 of 22	45.4%
Growth JP	11 of 18	61.1%	Growth JP	7 of 18	38.9%
Growth EU	30 of 44	68.2%	Growth EU	26 of 44	59.1%
Inflation US	3 of 6	50.0%	Inflation US	3 of 6	50.0%
Inflation UK	4 of 6	66.7%	Inflation UK	4 of 6	66.7%
Inflation JP	5 of 9	55.6%	Inflation JP	1 of 9	11.1%
Inflation EU	6 of 7	85.7%	Inflation EU	6 of 7	85.7%

7 Conclusion

Almost daily, macroeconomic numbers are released that are studied and appreciated by investors. The informational content of macroeconomic news consists of two parts, an anticipated component and a surprise component. In this paper, we focus on the latter part and measure macroeconomic surprises using real-time information as released on the announcement days (rather than restated data). To this end, we use a simple methodology inspired by Beber et al. (2015). We examine the behaviour of these macroeconomic surprises, and find that macroeconomic surprises do not appear at random. Surprises rather exhibit a short-term positive autocorrelation structure, which we call "economic surprise momentum". We find that this economic surprise momentum stems both from autocorrelation in individual surprise series as well as cross autocovariance between surprise series. The latter resembles a spillover effect among surprises. In addition, we examine whether macroeconomic surprises are able to predict risk premia across regions and asset classes. Both in-sample as well as out-of-sample results indicate that global surprises in macroeconomic growth variables are able to forecast future equity market returns across major developed regions. These findings survive, in-sample, after the inclusion of several control variables. Furthermore, we find that the growth surprises also positively predict future risk premia in other asset classes (commodities and credits using short-term forecast horizons, and bonds using long-term forecast horizons). However, the ability to predict future asset returns using surprises in inflation seems to be limited. Novel to the literature, we also incorporate surprises due to revisions in macroeconomic data. We show that this revision component plays a substantial role in predicting future returns in multiple asset classes.

We conjecture that predictability of economic surprises is a reflection of an anchoring bias in macroeconomic expectations. Multiple tests confirm this. In efficient markets, we would expect that higher expected stock returns may be the result of increases in risk, resulting higher demanded risk premia. We, however, find that surprises in growth predict lower future realized volatility rather than higher. Furthermore, a rational time-varying risk premia explanation is hard to align with negative expected equity premia. We find that surprises in macroeconomic growth are able to predict negative equity premia. Lastly, we directly provide evidence that forecasts are anchored towards recent historical announcement values of macroeconomic variables. These findings have important implications for economic theory and investors. For theory, our results stress out the importance of surprises and news shocks for asset pricing. For investors, risk premia is predictable by surprises in macroeconomic growth variables. In fact, a simple real-life trading strategy based on economic growth surprises is able to consistently outperform the market, yielding annualized alpha's ranging between 2.74% and 4.07%.

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