Master Thesis

MSc. Economics & Business Economics

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Macroeconomic surprises and stock returns

A study on the U.S. market

Author: **Francesco Ancona (578649)**

Thesis supervisor: PhD Candidate. Amar Soebhag, EUR
Second assessor: Prof. Dr. (Jan) JJG Lemmen, EUR

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Abstract

We investigate the role of macroeconomic surprises in the U.S., defined as the difference between the realized value of macro releases and the average (consensus) of the forecasts. Empirically, macroeconomic growth surprises significantly explain short-run market returns, differently from macroeconomic inflation surprises. We estimate stock exposure to a growth surprise factor and inflation surprise factor and show that stocks in the highest surprise beta quintile perform significantly better than stocks in the lowest surprise beta quintile by building simple long-short investment strategies. The surprise premium is primarily driven by the outperformance of stocks with high surprise betas. Nevertheless, the presence of small-cap stocks is proved to be relevant to achieve the extra-return when building the long-short portfolios.

1 Introduction

The question of what drives asset prices has been at the core of the financial literature for the past four decades. A branch of it has focused on understanding to what extent macroeconomics announcements impact and move asset prices. The rationale behind these studies is that relevant macroeconomic news may spark asset prices reactions since they are great candidates as additional risk factors beyond the market one, given the effect of those on listed companies' cash flows and/or discount rates which are very important when assessing the intrinsic value of the stock.

Starting with Chen et al. (1986), many other papers tried to show a significant correlation between asset returns and macroeconomic variables. Nevertheless, whereas for inflation and money growth the literature has found a negative correlation with stock returns (see Bodie (1976), Geske and Richard (1983), and Pearce (1985)), it has been more difficult to assess the impact of news on real sector macro-variables. A broad stream of literature shows the weak empirical evidence on the effect of the real aggregate activity on stock returns. CRR found certain associations between security returns and macro variables. These findings, however, have been revisited by Shanken and Weinstein (2006). They show that the statistical significance found by CRR is reduced when making some corrections in the standard error estimates. Pearce and Roley (1983) found no significant effect of industrial production and unemployment on daily stock return. Similarly, Hardouvelis (1987) found a very weak stock response on real sector and non-monetary news. Flannery and Protopapadakis (2002) found seventeen macroeconomic news factors which significantly affect stock returns and their volatility. However, relevant real aggregate activity measures, such as GNP or industrial production are not included. Moreover, even if McQueen and Roley (1993) found a strong correlation between fundamental macro news and stock returns after controlling for different stages within a business cycle, Flannery and Protopapadakis (2002) found that their results are quite different according to the alternative definitions of the economy's status.

The reasons for this poor showing and contrasts within the literature when it comes to assessing the impact of the real aggregate activities might be several. For instance, it can be possible that even if those real activities significantly affect stock returns, these effects may not appear when certain macroeconomic variables are used as proxies in the analyses.

It is because of this uncertainty around the topic that, in this paper, we want to answer the question whether macroeconomic news affect stock returns by studying the impact of macroeconomic surprises as market movers, instead of focusing on the released news themselves. The reason is as simple as follows: it is easy for investors to see macroeconomic news and try to understand how those will impact on stock returns. However, the stock market is not the economy, and the economy is not the stock market. The stock market is forward-looking. It incorporates expectations about the future in today's stock prices. Macroeconomic news, on the other hand, are backward-looking. The release of those tells us what has already happened, and most of the times way after it has happened. Indeed, several times in the recent financial history, terrible macroeconomic daily data announcements have been paired with historically high daily stock market returns. If anticipated macroeconomic news are already incorporated into market prices, we would not expect markets to change when that news is released as anticipated. What really matters and might drive stock prices is whether those news are better or worse than expected.

For instance, the U.S. stock market started to decline in October 2007, two months before the U.S. National Bureau of Economic Research (NBER) defined the economic recession as "started". Looking at the FRED website, U.S. unemployment rate has been above 9% since May 2009 and reached a peak of 10% in October 2009. Real GDP reached its lowest point in the recession in the second quarter of 2009. The committee decision declaring the end of the recession in June 2009 did not come out until September 2010, more than a year after. Based on this macroeconomic data continuing to look worse through 2009, we would have expected the stock market to keep going down. This was not the case. The stock market bottomed out in February 2009 and then started on a strong rebound. For months after the stock market bottom the macroeconomic data were only getting worse. The reason is simply that the market had expected the economic data to be even worse. The coming bad news were better than those previously priced in. Fama and French (2019) suggest that there is strong empirical evidence about inverted yield curves which tend to forecast economic activities, but they may not tell us much about what is going to happen in the stock market. They found no evidence that yield curve inversion can help investors avoid poor stock returns. The ability to forecast the economic activity does not translate to the ability to make stock market timing decisions. The relationship between the stock market and the economy has little to do with what is happening in the economy and a lot to do with what it is happening in the economy relative to what it is expected to be happening. Jay (2012) examined the relationship between GDP growth and stock returns. On both theoretical and empirical grounds, economic growth does not benefit stockholders. For 19 mostly developed market countries from 1900 through 2011, Ritter (2005) showed that the cross-sectional correlation between the compounded real return on stocks and the compounded real growth rate of per capita GDP was -0.39. He also looked at a sample of 15 emerging market countries for the 24-years period from 1988 through 2011 (including Brazil, Russia, India, and China) and he found a similar negative correlation of -0.41. This shows how countries with stronger economic growth have historically had lower stock market returns. The explanation for this negative correlation is that in an efficient market, investors tend to build expectation into prices. Paying high prices for expected growth should only lead to high stock returns if realized growth ends up being higher than expected. If economic growth happens in line with prior expectations, there would not be a boost to stock returns.

It is for the aforementioned reasons that, in this paper, we study the impact of surprises in macroeconomic news on asset returns, by dealing with the U.S. equity market. Other papers (Flannery and Protopapadakis (2002), Anderson et al. (2007), Gilbert et al. (2017), etc.), analysed the impact of macro-surprises on different assets. However, the vast majority of these studies focus on just one or few announcement series. The main issue that arises is the low-frequency of observations relative to certain economic aggregates and the time delay in their release. For instance, GDP estimates are released quarterly and approximately one month later the end of the quarter. This is in contrast with the large amount of daily macroeconomic news available to market participants which influence investment decisions. Moreover, focusing just on specific macro indicators, such as CPI rates, unemployment rates, PPI rates, etc. (see Adams et al. (2004) and Boyd et al. (2005)), which are released on a monthly basis, is not sufficient to approximate the large spectrum of macroeconomic fundamentals that reflect the economy and can have a significant real-time effect on financial markets (e.g., Andersen et al. (2003)).

Thus, similarly to Beber et al. (2015), we analyse surprises across a large number of macroeconomic releases by grouping those into smaller sub-sets to use as representative of four relevant aspects of the economic environment: aggregate output, employment, macroeconomic sentiment, and inflation. Each macroeconomic variable associated with a particular market information is characterized by its own news releases (and surprises) at different point in times and frequencies. This reflects more what happens in reality when investors deal with a great number of different announcements which track the evolution of the economic environment on a daily basis and, therefore, it allows to overcome the limitation of relying on just few measures as proxies of the macroeconomic environment.

By using a similar approach developed by McCoy et al. (2020), we create macroeconomic surprise indexes to assess the impact of news releases on stock market returns. In particular, out of the four categories, we create two indexes: a "growth" and "inflation" index. the first one is obtained as combination of relevant macroeconomic surprises relative to output, employment, and macroeconomic sentiment. In this way, we dispose of two surprise factors which comprehend the different driving forces of the economy.

We document the following results. First, we find that surprises show a certain persistence (autocorrelation) in the short-term, suggesting that these might not occur randomly (figure 2). Second, macroeconomic surprises significantly predict U.S. market returns. In particular, we find that expected future returns in the U.S. equity market positively and significantly depend on macroeconomic growth surprises, whilst the link with inflation surprises is more limited (table 1). Moreover, we divide the surprise indexes into five equally-sized buckets after having sorted the values in an increasing order. For each bucket we compute the average return by using the market returns on the days associated to the relative surprises. In the lowest growth surprise quintile the subsequent average daily market equity return for the U.S. is -0.019%, while it increases over the buckets to 0.045% for the highest quintile. The resulting top-minus-bottom quintile (Q5-Q1) spread equals 0.064%. Thus, we find that higher growth surprises predict higher subsequent daily market returns for our sample period that spans from January 1997 to December 2020. The same procedure is followed considering inflation surprises. We find a positive difference between the top and the bottom quintile but lower than then the spread obtained when sorting for growth surprises (0.012%), which is in line with the weaker relation previously mentioned (table 2). Third, we estimate the surprise beta for each stock trading in the American (Amex), New York Stock Exchange (NYSE), and Nasdaq, and examine the performance of the monthly surprise beta in predicting future stock returns. Specifically, we sort single stocks into quintile portfolios by their surprise beta during the previous month and find the monthly average returns for the sample period. We find that stocks in the highest growth surprise beta quintile generate about 6% more annual returns than stocks in the lowest growth surprise beta quintile. Similar results are found when sorting for inflation surprise betas (almost 4% annual spread). Nevertheless, we find that small-cap stocks are the main drivers for these performances and that these are not constant over time. In certain periods high surprise beta stocks perform significantly better than stocks with low/negative surprise beta, while in other periods they perform better, but not in a meaningful way. These findings are confirmed by robustness tests.

The remainder of the paper is structured as follows. In section 2, we describe the macroeconomic surprise data and the methodology used to construct surprise factors and long-short investment strategies based on stock surprise betas. Section 3 describes the characteristics of our macroeconomic surprise factors. Section 4 focuses on the long-short investment strategies. Sections 5 concludes.

2 Data

We use macroeconomic announcements for the United States collected by the Bloomberg Economic Calendar (BEC). For each considered macroeconomic variable, surprises are defined as the difference between the realized value of the macro release and the average (consensus) of the forecasts made by a certain number of analysts. The sample period which spans from January 1997 to December 2020. A total of 63 macroeconomic variables have been selected. In particular, 35 are output macroeconomic variables, 9 are employment macroeconomic variables, 7 are sentiment macroeconomic variables, and 12 are inflation macroeconomic variables. A more detailed list of all macroeconomic variables for each category can be found at the end of the Appendix. These several macroeconomic variables have been chosen according to the most recent relevance index. The relevance index represents the percentage of users who set, in Bloomberg, an automatic alert which notifies them when an announcement on a given macro-variable has been released. the number of alerts is a proxy for how much that announcement is followed. A higher number is an indication of higher importance, and vice versa.

Based on economic rationale, we combine the entire sample of macroeconomic announcements into two main variable subsets: "growth" and "inflation". In this way, all macroeconomic variables analysed in previous studies can be grouped into one single factor from which analyses can be conducted and interpreted through reasonable economic points of view. The growth factor, in its turn, subdivides into three subcategories: employment aggregate factor, output aggregate factor, and sentiment aggregate factor. Macroeconomic variables, such as GDP growth, Home sales, Unemployment rate, etc., are included in the former two. The sentiment category, instead, refers to macroeconomic variables as results from reliable surveys on the current/future state of the economy. These three subcategories are aggregate into a main one given the demonstrated positive relationship among each other (see Wilson (1960) and Kappler and Van Aarle (2012)). The positive correlation between them is quite straightforward to interpret at an intuitive level. For instance, in presence of negative economic sentiment, producers and consumers are reluctant to hire, spend, invest, etc. Vice versa, a reduction in economic sentiment can be induced by an economic slowdown. Causalities can indeed appear in both directions. Nevertheless, these relations will not be so evident when dealing with macroeconomic surprises. Differently, inflation is not included and kept separated given the large literature around the absence of empirical evidence towards a positive correlation between inflation and the other macro variables (see Bullard and Keating (1995) and Ericsson et al. (2001)). These two aggregate factors will capture, then, different economic aspects.

Previous studies used other macro variables that we do not consider such as credit spreads, yields curves, or volatility indexes. For instance, Ang and Piazzesi (2003) found empirical support for the empirical linkage between bond prices and macroeconomic variables in a (no-arbitrage) factor model of interest rates and their term structure. Ang and Piazzesi, on the basis of Dai and Singleton (2002) and Duffee (2002) earlier works, defined a multi-factor bond pricing model that, by allowing both unobserved yield factors and observed macroeconomic variables to drive the pricing kernel, allowed for time-varying risk premium. Nevertheless, all financial market variables related to central bank policies or (in general) interest rates are not included because those might already incorporate the market participants' opinion around the state of the economy. Therefore, we only focus on macro announcements that are not influenced by any of these variables.

After having categorized every macroeconomic variable, each level surprise factor (output, employment, sentiment, and inflation) is calculated as following:

$$SUR_t = \frac{\sum_{i=1}^{N_{a,t}} Z_{i,t}}{N_{a,t}} = \frac{\sum_{i=1}^{N_{a,t}} \dfrac{(S_{i,t} - Ai)}{std(S_i - A_i)}}{N_{a,t}} \tag{1}$$

where $N_{a,t}$ is the number of macroeconomic variables available at time t for the specific level surprise factor and $Z_{i,t}$ is the z-score at time t, for the macro variable i, calculated as the difference between the surprise value at time t, $S_{i,t}$ (which is, in its turn, the difference between the actual announcement value and the average of the previous analysts' expectation), and the mean of surprise values of the entire time series A_i, divided by its standard deviation. We took, for simplicity, the equal-weighted average to avoid to under/over-weight a macroeconomic variable than another, since it is difficult to assess which one (in its surprises) has the higher impact on the market in a certain period t. Moreover, considering the z-scores for each variable is necessary since all of them have different scales. Therefore, it is essential, so to consistently aggregate them into one single surprise factor. Finally, we combine through an equal-weighted average the output, employment, and sentiment level factors to build the growth surprise factor. In this way we can rely on both inflation and growth categories to conduct our analyses.

Data transformations are also required: data time series have been converted from announcement time format to calendar time in terms of trading days. Nevertheless, this generates time series for each macroeconomic variables with many missing values since almost all of them have a monthly release frequency. This problem is solved by using a forward-filling method: missing values are forward-filled by the last observed value for each day in the sample series, until a new observation occurs, and so on until reaching the last available observed value which stops the forward-filling process.

After the creations of the two factors, we want to study if macroeconomic surprises affect financial markets and if we can profit by exploiting this relationship.

At first, we obtain historical daily returns of the S&P 500 from the Center for Research in Security Prices (CRSP) database. To assess if the macroeconomic surprise factors affect stock returns, we estimate the surprise beta by regressing the S&P 500 daily returns on the surprise factor while controlling for the Fama-French 5 factors and momentum (see Eugene (2015) and Jegadeesh and Titman (1993)). We exclude the market factor (MKT), given by the return spread between the capitalization-weighted stock market and cash, since it strongly co-moves with the S&P500 which is usually used as market portfolio itself in several analyses. Therefore, we consider the size (SMB), given by the return spread of small minus large stocks, book-to-market (HML), given by the return spread of cheap minus expensive stocks, profitability (RMW), given by the return spread of the most profitable firms minus the least profitable, investment (CMA), given by the return spread of firms that invest conservatively minus aggressively, and momentum (Mom), given by the difference between the value-weighted average of the lowest performing firms and the value-weighted average of the highest performing firms.

$$
\begin{aligned}
R_t = \alpha + \beta_{SUR} \cdot SUR_t + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{RMW} \cdot RMW_t \\
+ \beta_{CMA} \cdot CMA_t + \beta_{Mom} \cdot Mom_t + \varepsilon_t
\end{aligned}
\tag{2}
$$

To avoid the influence of outliers in our results, we remove the extreme daily returns recorded by S&P 500 index during the considered time span, by cutting the 2% extreme values (1% on each end). The 5 factors from Fama-French and the momentum factor are from Kenneth French's data library. Results from different estimates of β_{SUR} from different combinations of the aforementioned risk factors are reported in the next section, where the β_{SUR} may contain either or both the growth surprise factor and the inflation surprise factor.

Afterwards, long-short investment strategies are performed to assess the predictive power of the surprise beta over future stock returns and if extra returns can be obtained by exploiting the exposure of single stocks to the growth and inflation surprise factors. At first, a univariate portfolio-level analysis is conducted. Then, a bivariate portfolio-level analysis is conducted to examine the predictive power of the surprise beta after controlling for well-known risk factors.

We used The Center for Research in Security Prices (CRSP) database to obtain all the information related to the stocks used for the growth surprise and inflation surprise strategies. We selected all stocks available from the stock universe of the American (Amex), New York (NYSE), and Nasdaq stock over the period which runs from 1998 to 2020. In our sample, common stocks only are considered (CRSP share code 10 and 11). As pointed out by Fama and French (1992), financial stocks, such as banks and insurance companies, have been removed for multiple reasons: Non-financial companies' (debt-like) liabilities cannot be compared with financial ones; the capital structure is directly affected by the regulations on minimum capital requirement; leverage strongly influences investor insurance schemes, such as deposit insurance.

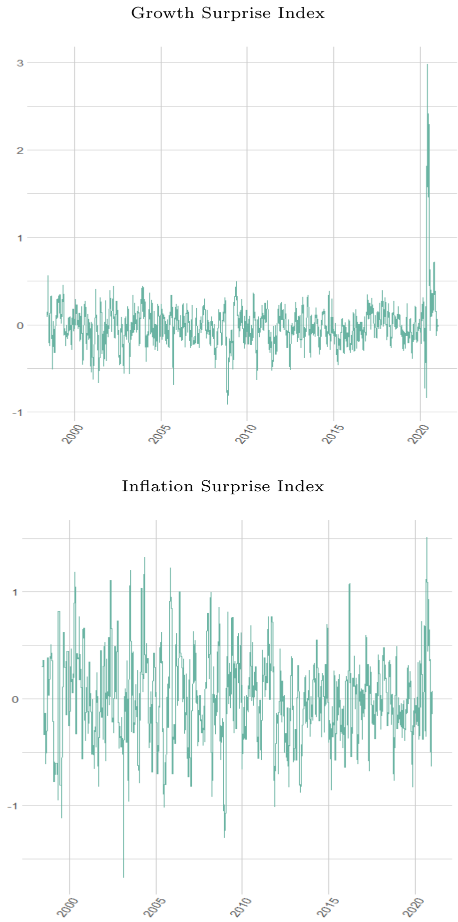
Exposures of single stocks to the surprise factors are given by monthly rolling regressions of stock returns on the one-month-ahead surprise index using a 5 years (of trading days) fixed window estimation. The first surprise beta (β_{SUR}) is obtained using the sample from June 1998 to June 2003, for both the growth surprise factor and the inflation surprise factor. Then, these monthly surprise betas, after the first one is computed, are used to predict the cross-sectional stock returns in the following months. This rolling regression approach on a monthly basis is run until the sample ends in December 2020. According to the previous month exposure (factor loadings) of each stock, quintiles are created with a monthly rebalancing, starting in July 2003.

Nevertheless, similarly to Liu (2018), since surprise betas are of main interest for this analysis, we do not want extreme beta estimates to influence results. Therefore, each month the 2% of stocks with extreme factor loadings (1% on each end) are excluded from the sample to reduce the impact of outliers. Monthly extra-returns of the long-short portfolios are then regressed on the 5 factors from Fama-French and the momentum factor, plus the liquidity factor (LIQ) taken from Lubos Pastor's data library.

3 The characteristics of macroeconomic surprises

In this section characteristics of our macroeconomic surprise factors are described. Figure 1 shows the time series plots of the growth surprise factor (upper panel) and the inflation surprise factor (lower panel). At first, it can be noticed, for both factors, how surprises tend to move around zero. Indeed, the average value for the entire period is -0.009932 for the growth surprise factor and -0.005274 for the inflation surprise factor, which are very near to 0, by being in line with what we would expect in rational markets (surprises equal to zero on average). Moreover, for the growth category, we notice a development which seems to be aligned with major economic events, such as the 2007-2009 Financial Crisis and the Covid-19 Crisis at the beginning of 2020. In particular, surprises tend to be negative during recession times (see the drops registered in 2008 and in March/April 2020) and positive during expansion/recovery times (see the pikes showed in 2009 and from May 2020, right after the previous drops). As it concerns the inflation surprises, a similar path is showed. However, it has a much more erratic evolution dynamic.

Figure (1) **Time series plots for growth surprise and inflation surprise factors.**

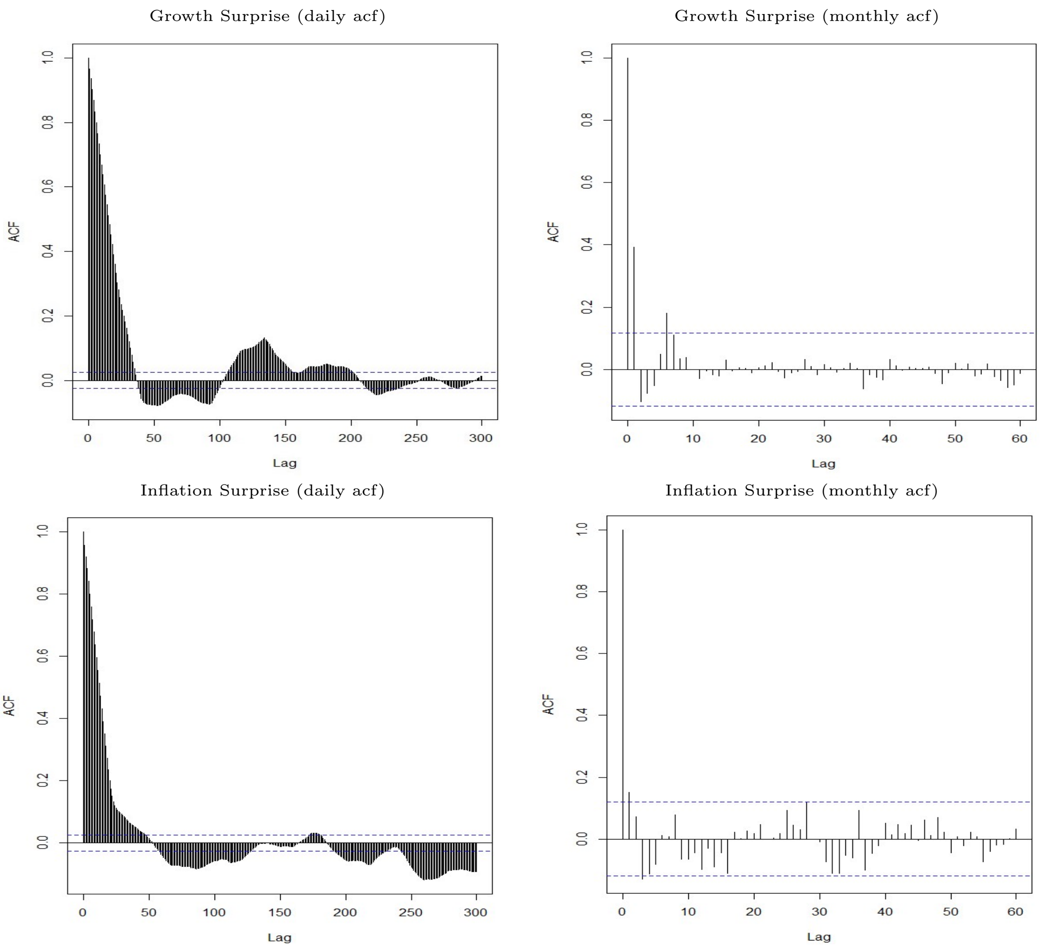


Even if surprises are roughly zero on average (for the considered time period), it seems that a positive autocorrelation path appears. Positive surprises tend to be followed by other positive surprises, and vice versa with negative surprises. In the next subsection the potential presence of autocorrelation is explored more in-depth and the correlation between level surprise factors is also showed.

3.1 Correlation analysis

The autocorrelation function (ACF) is used to provide a better overview of the potential presence of autocorrelation between surprises. Figure 2 displays autocorrelation plots for both growth and inflation surprise factor. ACF with both daily and monthly lags are showed. The latter is also plotted since the former is very likely to show an autocorrelation path due to the forward-filling procedure used to create the surprise factors. For the monthly lags, a 22-day resembling procedure is used. In this way, we can approximately control for local persistence.

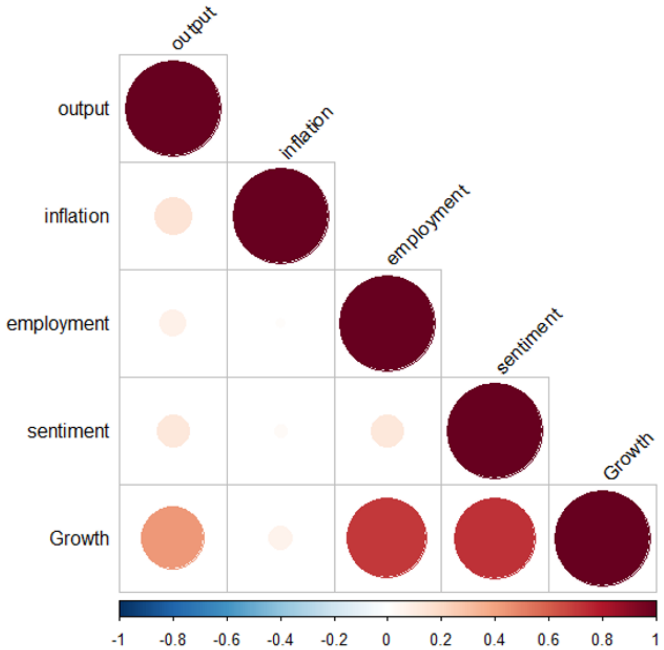
Figure (2) **Autocorrelation function plots**. The first column shows the autocorrelation function for both growth and inflation surprise factors with daily lags. The second column shows the autocorrelation function for both growth and inflation surprise factors with monthly lags.



In efficient markets, macroeconomic surprises should not present an autocorrelation path. However, it can be observed a statistically significant and positive autocorrelation at the first month lag. This autocorrelation, nevertheless, is more evident for the growth surprise factor compared to the inflation surprise factor. This is consistent with the more erratic evolution previously showed for the latter. Therefore, a short-term autocorrelation is present (for more than 30 trading days in both factors). In addition, it can be noticed how the growth surprise factor shows a significant negative autocorrelation at the sixth month lag, whereas the inflation surprise factor at the third month lag.

We also show the correlation between level surprise factors. Figure 3 shows how poorly correlated surprise factors are among them.

Figure (3) **Correlation Matrix.** This figure shows the correlation between output, employment, sentiment, inflation surprise indexes (level surprise factors), and the growth surprise factor, given by the equal-weighted combination of the first three.



All level surprise factors are positively correlated but at very low values. This can be expected since surprises are just deviation from expectations, therefore, they tend to be more random compared to the development of actual values in macroeconomic variables. Moreover, it must be considered that the forward-filling procedure influences these results. Within each level factor there is a certain degree of local persistence due to that procedure. However, macroeconomic announcements for different variables are not released at the same time. Therefore, the local persistence, in different level surprise factors, appears and evolves in different point in time during the entire time series, by leading to a low correlation among surprise factors. Nevertheless, it can be noticed that the inflation surprise factor is the one that has the lowest correlation with the other factors (with the exception of output) and that the growth surprise factor which embeds output, employment, and sentiment, is consistently highly and positively correlated with them.

3.2 Macroeconomic surprises and stock market returns

After the positive short-term autocorrelation exhibited by our surprise factors, we want to assess if there is a relationship between asset returns and macroeconomic surprises. Therefore, we examine whether market risk premium can be partially explained, and so whether it is driven by those surprises embedded into the two constructed surprise factors (growth and inflation).

To investigate the potential link between market returns and surprises we regress S&P 500 returns (as proxy for the U.S. equity market) over the surprise factors, while also controlling for other risk factors to better capture the significance of the relationship. Table 1 shows the results of these regressions.

Table (1) **Regression results for the U.S. equity market.** This table shows the coefficient results of regressing the S&P 500 historical daily returns over the growth surprise factor and/or the inflation surprise factor. Fama-French 5 factors (with the exclusion of the market factor), plus the momentum factor are used as control variables. Coefficients' corresponding t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

	Regression Coefficient						
	G_{SUR}	I_{SUR}	SMB	HML	RMW	CMA	Mom
(1)	0.155***						
	(2.851)						
(2)		0.012					
		(0.357)					
(3)	0.154***	0.006					
	(2.835)	(0.190)					
(4)	0.108**		-0.032	0.104***	-0.515***	-0.543***	-0.160***
	(2.165)		(-1.490)	(4.262	(-19.27)	(-15.01)	(-10.92)
(5)		0.005	-0.031	0.105***	-0.515***	-0.544***	-0-161***
		(0.165)	(-1.465)	(4.283)	(-19.27)	(-15.01)	(-10.99)
(6)	0.108**	0.001	-0.032	0.104***	-0.515***	-0.543***	-1-160***
	(2.159)	(0.038)	(-1.490)	(4.262)	(-19.27)	(-15.00)	(-10.91)

By looking at the direct relationship between the growth surprise factor and the S&P 500, it can be seen how growth macro surprises positively predict U.S. equity market returns. The predictive power is statistically significant at the significance level of 1%. One standard deviation change in the growth surprise factor is associated with a 0.155% increase in the daily market return, on average. Moreover, the significance is not lost when controlling for all other risk factors. Indeed, the coefficient remains positive and statistically significant at the significance level of 5%. This result is, thus, consistent with what we would expect on a theoretical basis. Expected future returns in the U.S. equity market will increase when macroeconomic announcements related to the economic growth are greater than their corresponding forecasts, and vice versa in case of lower announcement values. Inflation surprise, instead, do not show a statistically significant predictive power for market returns. Even when controlling for other risk factors, the coefficient remains positive, meaning that in the considered sample a positive inflation surprise is associated with a positive change in daily returns, and vice versa in case of negative inflation surprise. Nevertheless, this is not sufficient to expect the same relationship to happen in the future, given the non-significance of this link. This result can be somehow expected. If, from one side, an unexpected increase in inflation should rise prices by positively affecting companies' revenues and, most likely, cash flows, in a more than expected way, on the other side it also increases the nominal discount rate used when performing discount cash flow analyses to assess the companies' intrinsic value in a more than expected way. Therefore, these two effects, at a certain degree, should offset each other. This might explain the non-significant correlation and, so, the reason why the inflation surprise factor does not have predictive power.

Following these results, we want to see the difference in market returns during periods of positive surprises and period of negative surprises. A simple sorting procedure is used. Both growth and inflation surprise factors are sorted into five quintiles. The top quintile (the fifth) contains all the highest positive surprises recorded within the considered time span. The bottom quintile, vice versa, contains all the greatest negative surprises. The average returns for each quintile are then calculated by using the market returns on the days associated to the relative surprises. Table 2 shows the results.

Table (2) **Market returns by sorting surprises**. We sort growth surprises and inflation surprises into quintiles. Subsequently, we take the average of S&P 500 daily returns linked to the relative surprises by date for each quintile. Returns are expressed in percentages.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
G_{SUR}	-0.019	0.049	0.025	0.056	0.045	0.064
I_{SUR}	0.02	0.001	0.067	0.036	0.032	0.012

Consistently with the regression analysis, the average daily return of the S&P 500 during period of positive growth surprises is way higher than the average return during period of negative growth surprise (Q5-Q1). A positive difference between the top and the bottom quintile also appears when sorting for inflation surprises. However, in line with the positive but not significant beta, it can be noticed how the spread (0.012) is much lower than the spread obtained when sorting for growth surprises (0.064).

To estimate the predictive power of surprises, we run the same previous regressions by lagging macroeconomic surprises for several look-back periods (from 1 trading day up to 1 year). Table 3 shows the regression coefficients for both growth and inflation surprise factors, for each considered lagging period.

Table (3) **Regression coefficients with lagged surprises**. This table shows the coefficients of regressing the S&P 500 daily returns on both growth and inflation surprise factors where surprises are lagged for different periods. t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

	Growth Surprise	Inflation Surprise
L=1d	0.112**	0.028
	(2.059)	(0.86)
L=1w	0.129**	0.012
	(2.376)	(0.356)
L=1m	0.098*	0.015
	(1.813)	(0.468)
L=3m	0.041	-0.006
	(0.739)	(-0.191)
L=1y	0.009	-0.017
	(0.124)	(-0.499)

It is interesting to notice how 1-day lagged surprises significant explain market returns (at the 95% significance level). However, the coefficient loses some significance compared to the one found in the previous analysis with no lags taken into account (significant at the 99% level). A possible explanation for this might be related to the macroeconomic announcements average time release. While the S&P 500 daily returns are returns at the end of each trading day, macroeconomic announcements (and, therefore, the related macro surprises), are most of the time released in the morning between 8.30am and 12.30pm. Thus, on average, the market already incorporates the surprises the same day in which they are released by influencing the end-of-day return. For this reason, the day-ahead surprise might already be "old" since each morning, before the opening of the U.S. market, new macro announcements can be released. Overall, the table shows results consistent with the expectations. After the one-month lag, indeed, the regression coefficient associated to the growth surprise factor loses its statistical significance. This is coherent with the autocorrelation up to the first month lag showed by the growth surprise factor. Nevertheless, it can be stated that the growth surprises do not have long-run predictive power. As it regards the inflation surprises, these do not show any significant predictive power even when considering lagged surprises. Coefficients remain positive up to one month lag.

Considered the relationship discovered between market returns and both growth and inflation surprises, in the next section we want to dive deeper into the predictive power of the surprise betas over future equity returns. For this reason, we will build an investment strategy based on the exposure (beta) of individual stock towards the surprise factor.

4 Surprise factor investment strategies

On the basis of results found in the previous section, we construct long-short investment strategies to understand if this relationship between macroeconomic surprises and stock returns can be exploited to achieve an extra premium by investing in certain stocks and by selling others. The strategy is employed with respect to both growth and inflation surprises. At first, we build a univariate portfolio-level strategy with a single sorting procedure. Secondly, we conduct a bivariate portfolio-level strategy with a double sorting procedure. These strategies are built by using the information on stocks selected from the CRSP database as mentioned in the data section, for a total of 11173 stocks. Table 4 reports some descriptive statistics on the portfolio obtained as an equal-weighted combination of all selected stocks.

Table (4) **Descriptive statistics.** This table shows descriptive statistics on the portfolio obtained as an equal-weighted combination of all selected stocks in the CRSP database. The sample period is 1998-2020. The time-series daily average return (mean), standard deviation (sd), skewness (skew), and kurtosis (kurt) are reported. The second (third) row reports results by considering the periods in which the growth surprises are above (below) the median growth surprise value. The fourth (fifth) row reports results by considering the periods in which the inflation surprises are above (below) the median inflation surprise value.

Sample	mean	sd	skew	kurt
Entire sample	0.077	1.29	-0.52	8.33
Above median growth surprise	0.095	1.21	-1.07	11.3
Below median growth surprise	0.057	1.37	-0.12	6.31
Above median inflation surprise	0.084	1.25	-0.19	4.06
Below median inflation surprise	0.069	1.33	-0.79	11.7

Consistently with the previous findings, it can be noticed how the average daily return of the portfolio is higher during period of high positive surprises and lower during period of low/negative surprises. The spread between average returns is bigger when considering growth surprises (0.038%) compared to the spread when considering inflation surprises (0.015%).

4.1 Single-Sorting Investment strategy

Once obtained the exposures (betas) of each stock to the surprise factor for each month, quintile portfolios are formed by sorting for the surprise beta (β_{SUR}), where quintile 5 is the top quintile which contains the highest (β_{SUR}), whereas quintile 1 is the bottom quintile which contains the lowest (β_{SUR}). The investment strategy consists in buying all stocks in the top quintile, and so those that are highly sensible (in direct proportion) to macroeconomic surprises, and selling those in the bottom quintile that, vice versa, are not sensible at all to macro surprises or co-move in opposite direction (highest negative β_{SUR}). Table 5 presents the results associated to each equal-weighted quintile sorted by growth surprise betas and the top-minus-bottom (Q5-Q1) portfolio, which represents the long-short investment strategy.

Table (5) **Univariate equal-weighted portfolios of stocks sorted by growth surprise betas.** Quintile portfolios are formed by sorting single stocks according to their growth surprise beta (β_{SUR}). Quintile 5 (top quintile) contains stocks with the highest β_{SUR} in the previous month, whereas quintile 1 (bottom quintile) contains stocks with the lowest β_{SUR} in the previous month. The first column presents the equal-weighted quintiles' average return, whereas the following columns present the regression coefficients as results of regressing equal-weighted quintiles' monthly returns over Fama-French 5 factors, plus the momentum and liquidity factor, which are used as control variables. The last two rows show results relative to the portfolio (investment strategy) defined as the difference between the top (Q5) and the bottom (Q1) quintile. The Sharpe-Ratio is defined as the yearly one by multiplying the monthly Sharpe-Ratio by the root square of twelve. Coefficients' corresponding Newey-West adjusted t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

		Coefficients (Equal-weighted portfolios)							
Quintile	Avg. Return	a	MKF-RF	SMB	HML	RMW	CMA	Mom	LIQ
Low	1.077***	0.065	0.980***	0.719***	-0.269	-0.129	0.237**	-0.156***	0.106
	(2.706)	(0.556)	(20.117)	(11.838)	(-4.162)	(-1.151)	(2.220)	(-5.822)	(1.707)
2	1.148***	0.214***	0.951***	0.607***	-0.047	-0.035	0.106	-0.064***	0.062**
	(3.219)	(2.855)	(44.974)	(17.837)	(-1.233)	(-0.606)	(1.429)	(-4.417)	(2.010)
3	1.237***	0.284***	0.974***	0.648***	0.015	-0.012	0.03	-0.101***	0.061**
	(3.1394	(3.885)	(38.902)	(19.508)	(0.316)	(-0.2)	(0.542)	(-3.844)	(2.362)
4	1.420***	0.428***	1.013***	0.773***	0.014	-0.047	-0.03	-0.167***	0.039
	(3.213)	(4.234)	(34.088)	(14.911)	(0.238)	(-0.733)	(-0.459)	(-3.426)	(1.403)
High	1.611***	0.462**	1.151***	0.958***	-0.098	-0.196*	0.151	-0.355***	0.124**
	(3.062)	(2.36)	(23.165)	(11.902)	(-0.903)	(-1.742)	(1.205)	(-3.299)	(2.057)
High-Low	0.534***	0.397**	0.171***	0.238***	0.171	-0.067	-0.085	-0.199*	0.018
	(2.632)	(2.067)	(3.277)	(2.677)	(1.505)	(-0.456)	(-0.582)	(-1.695)	(0.312)
Sharpe Ratio	0.619								

The first column of Table 5 shows interesting results. Moving from quintile 1 (lowest β_{SUR} quintile) to quintile 5 (highest β_{SUR} quintile), the average next-month return increases monotonically from 1.08% to 1.61% per month. Therefore, the average return difference between the top and the bottom quintile (Q5-Q1) is 0.53% per month with a Newey-West adj. t-statistic of 2.632 (where adj. standard errors are calculated using 3 lags), meaning a statistical significance at the 99% level (see Newey and West (1987)). This result shows that stocks in the highest β_{SUR} quintile generate 6.36% higher (average) annual returns compared to stocks in the lowest β_{SUR} quintile. The Sharpe-Ratio is equal to 0.62. In additional to average returns, the level and statistical significance of the alphas, as a representation of risk adjusted returns, are shown in Table 5. The alpha (a) is the intercept obtained as result from the regression of the single quintile portfolio returns and the Fama-French 5 risk factors, plus the momentum and liquidity factor (MKF-RF, SMB, HML, RMW, CMA, Mom, LIQ). The second column shows that a increases monotonically from 0.065% to 0.462%, when moving from the lowest to the highest β_{SUR} quintile. Therefore, the difference in alphas between the high β_{SUR} portfolio and the low β_{SUR} portfolio is 0.397% (4.76% per annum) statistically significant at the 95% level (Newey-West adj. t -statistic of 2.067). We want to investigate the nature of this 4.76% annualized risk-adjusted return of the long-short portfolio. The explanation behind this can be the underperformance of the low β_{SUR} portfolio, the outperformance of the high β_{SUR} portfolio, or both of them. For this reason, we focus on the statistical and economic significance of the risk-adjusted returns of quintile 5 (high β_{SUR} stocks) and quintile 1 (low β_{SUR} stocks). a of quintile 1 is positive but not statistically significant, whereas a of quintile 5 is significantly positive. Thus, given the non-significance of the positive value of the bottom quintile's a that comes from this specific sample we considered in our analysis, we can conclude that the significant spread showed by the long-short portfolio is due to the significant outperformance of the high β_{SUR} stocks. These results are coherent with a well-known literature regarding the relationship risk(aversion)-return. The monotonically path showed by both average returns and alphas moving from quintile 1 to quintile 5 demonstrate what we would expect assuming that investors are risk-adverse individuals. High β_{SUR} stocks are stocks that perform well (higher returns) when the economy is already doing better than expected (positive surprise) and bad (lower returns) when the economy is already doing worse than expected (negative surprise). Therefore, these stocks do not represent a hedge against the economic surprise fluctuations, vice versa, they expose investors even more to those by leading to additional risk. Risk-adverse investor, thus, would require extra compensation in terms of higher expected returns to detain these stocks with high β_{SUR}. Low β_{SUR} stocks, instead, are stocks that perform bad (lower returns) when the economy is doing better than expected (positive surprise) and well (higher returns) when the economy is doing worse than expected (negative surprise). Therefore, these stocks represent a hedge against economic surprise fluctuation, since lower returns are positively compensated by the overall economic growth when higher than expected and, vice versa, higher returns are negatively compensated by the overall economic growth when lower than expected. Risk-adverse investors are willing, thus, to accept a lower compensation to hold these low β_{SUR} stocks and pay higher price since they are seen as relatively safer assets. The remaining columns show the strong explanatory power of the market factor (Newey-West adj. t-values ranging from 20.117 to 44.974) and the small-minus-big factor (Newey-West adj. t-values ranging from 11.838 to 19.508) relatively to each quintile: a great part of the positive returns achieved by each portfolio represents the compensation for bearing market risk and the risk associated with holding small stocks in the portfolio. These risk factors remain significant even in explaining the long-short portfolio returns. The momentum factor has also high explanatory power for each quintile, but it loses some significance in explaining the long-short portfolio return (significant at the 90% level).

The same investment strategy is performed by using value-weighted portfolios. Table A1 in the appendix shows the results. Similar results, in terms of quintiles' average return, are found. The average next-month return increases monotonically from 0.83% to 1.60% per month. Therefore, the difference between the top and the bottom quintile (Q5-Q1) is 0.77% per month, statistically significant at the 95% level. It is higher than the difference found for the equal-weighted strategy, however, the Sharpe Ratio is a bit lower, equal to 0.53. The strategy, then, seems to work even with value-weighted portfolios. Nevertheless, by looking at the alpha column, multiple aspects should be pointed out. First, the a monotonical increase stops at the 4^{th} quintile. The top quintile's a is, indeed, slightly lower than the 4^{th} one. Second, each value-weighted quintile a is lower than the corresponding equal-weighted quintile alpha. Third, and most importantly, the top-minus-bottom portfolio a is positive, but not statistically significant. Higher alphas for each quintile in the equal-weighted portfolios might be justified by the over-weighting of small stocks as a consequence of the equal-weighted strategy, which is not entirely captured by the SMB factor. Small stocks tend, on average, to perform better than big stocks. As it regards the non-significance of the long-short portfolio alpha, this means that the average (statistically significant) 0.77% return per month represent the compensation for other well-known risk factors. This result can be expected given the nature beyond the value-weighted portfolio composition. A value-weighted portfolio gives more weight to large market cap stocks which are more exposed to the market risk (note how the market beta for the value-weighted top-minus-bottom portfolio is higher in value and in Newey-West adj. t-statistic compared to the equal-weighted top-minus-bottom portfolio). Moreover, it is very likely that large cap U.S. stocks, by operating in most of the cases within an international economic environment and not only within the U.S. economy, are not that susceptible to local (growth) macroeconomic surprises. They rather are more sensible to global macroeconomic surprises. Vice versa, The equal-weighted strategy puts more weight into small cap U.S. stocks. These mainly rely on local revenue. They might be more affected by economic forces within the U.S. country and, therefore, by local (growth) macroeconomic surprises. In conclusion, the (over-)presence of small caps within the quintile portfolios and the long-short portfolio makes a bit of difference from an economic and statistical significance.

The same investment strategy is performed considering the inflation surprise factor. Table 6 presents the results associated to each equal-weighted quintile sorted by inflation surprise betas and the top-minus-bottom (Q5-Q1) portfolio (long-short investment strategy).

Table (6) **Univariate equal-weighted portfolios of stocks sorted by inflation surprise betas.** Quintile portfolios are formed by sorting single stocks according to their inflation surprise beta (β_{SUR}). Quintile 5 (top quintile) contains stocks with the highest β_{SUR} in the previous month, whereas quintile 1 (bottom quintile) contains stocks with the lowest β_{SUR} in the previous month. The first column presents the equal-weighted quintiles' average return, whereas the following columns present the regression coefficients as results of regressing equal-weighted quintiles' monthly returns over Fama-French 5 factors, plus the momentum and liquidity factor, which are used as control variables. The last two rows show results relative to the portfolio (investment strategy) defined as the difference between the top (Q5) and the bottom (Q1) quintile. The Sharpe-Ratio is defined as the yearly one by multiplying the monthly Sharpe-Ratio by the root square of twelve. Coefficients' corresponding Newey-West adjusted t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

		Coefficients (Equal-weighted portfolios)							
Quintile	Avg. Return	a	MKF-RF	SMB	HML	RMW	CMA	Mom	LIQ
Low	1.151**	0.134	1.080***	0.819***	-0.224***	-0.386***	0.087	-0.278***	0.146***
	(2.406)	(0.855)	(27.418)	(10.645)	(-2.733)	(-3.778)	(0.855)	(-5.798)	(2.682)
2	1.160***	0.213**	1.008***	0.686***	-0.027	-0.119*	-0.010	-0.170***	0.092**
	(2.838)	(2.127)	(38.397)	(15.255)	(-0.633)	(-1.955)	(-0.190)	(-4.715)	(2.514)
3	1.1566***	0.222***	0.983***	0.614***	-0.048	-0.007	0.132**	-0.142***	0.063***
	(3.050)	(2.705)	(47.669)	(17.123)	(-1.067)	(-0.154)	(2.594)	(-2.927)	(2.794)
4	1.329***	0.400***	0.966***	0.637***	-0.057	0.029	0.126*	-0.137***	0.052
	(3.552)	(5.473)	(33.076)	(17.005)	(-1.442)	(0.434)	(1.931)	(-5.313)	(1.513)
High	1.461***	0.443***	1.063***	0.842***	-0.089	-0.099	0.246*	-0.193***	0.073
	(3.229)	(3.239)	(16.736)	(13.975)	(-1.007)	(-0.757)	(2.267)	(-3.888)	(1.137)
High-Low	0.310**	0.309**	-0.017	0.023	0.135**	0.286**	0.158	0.085**	-0.072
	(2.169)	(2.323)	(-0.350)	(0.271)	(2.312)	(2.390)	(1.398)	(2.128)	(-1.167)
Sharpe Ratio	0.518								

Similarly to the previous strategy, the first column of Table 6 shows that the average next-month return increases, from 1.15% to 1.46% per month, moving from quintile 1 (lowest β_{SUR} quintile) to quintile 5 (highest β_{SUR} quintile). The average return difference between the top and the bottom quintile (Q5-Q1) is 0.31% per month with a Newey-West adj. t-statistic of 2.169 (statistically significant at the 95% level). Stocks in the highest β_{SUR} quintile generate 3.72% higher (average) annual returns compared to stocks in the lowest β_{SUR} quintile. The Sharpe-Ratio is equal to 0.518, which is a bit lower than the investment strategy performed using the exposure towards the growth surprise factor. After controlling for the additional risk-factors, the second column shows that a increases monotonically from 0.134% to 0.443%, when moving from the lowest to the highest β_{SUR} quintile. The difference in alphas between the high β_{SUR} portfolio and the low β_{SUR} portfolio is 0.309% (about 3.71% per annum) statistically significant at the 95% level (Newey-West adj. t -statistic of 2.323). Again, given the non significance of the positive value of the bottom quintile's a, we can conclude that the significant spread showed by the long-short portfolio is due to the significant outperformance of the high β_{SUR} stocks.

To understand if these results found for the inflation surprises strategy are already captured by the growth surprises strategy, and so, if the significant a of 0.309% is explained by the premium found for the long-short portfolio previously built upon growth surprises, we add amongst the other control variables the top-minus-bottom portfolio of stocks sorted by growth surprise betas. We did not find any significant relationship between the two. The a becomes equal to 0.328% and remains statistically significant at the 95% level. The growth surprises strategy beta is equal to -0.048% with a Newey-West adj. t-statistic of -0.584.

These results are very interesting since we would expect the opposite from an economic point of view. These findings tell us that stocks with high positive β_{SUR} which are positively correlated with inflation surprises, perform (on average) better than stocks with high negative β_{SUR} which are negatively correlated with inflation surprises. Stocks with high positive β_{SUR} represent a hedge against inflation because the loss of purchasing power after an unexpected inflation growth is compensated (ceteris paribus) by a higher return by those stocks. Vice versa in case of an unexpected inflation decrease. Stocks with high negative β_{SUR}, on the contrary, expose investors even more to the inflation risk. Risk-adverse investors, therefore, should require higher return to detain stocks with very low/negative β_{SUR}, and be willing to accept a lower compensation to hold high β_{SUR} stocks. However, this is not the case. It seems that stocks with the ability to hedge inflation lead, on average, to higher returns than stocks with low inflation-hedging abilities. In a different analysis, similar conclusions have been drawn by Ang et al. (2011). Beyond these results there might be a market inefficiency explanation. These findings outline how the hypothesis of efficient markets and rational economic individuals works only in theory.

Nevertheless, these findings are strongly driven by the over-weighting of small caps due to the equal-weighted composition of each quintile. Indeed, the same strategy is performed with value-weighted portfolios and the β_{SUR} relationships previously found disappear. Table A2 in the appendix shows the results. Reducing the weight of small caps within each portfolio makes the investment strategy totally inefficient. The long-short portfolio average return is negative (-0.018%) and not statistically significant (Newey-West adj. t-statistic of -0.073). The top-minus-bottom portfolio a is positive but very low (0.048%), and not statistically significant (Newey-West adj. t-statistic of 0.182). Consistently with the investment strategy built upon the exposure of each stock towards the growth surprise factor, the (over)presence of small cap stocks seems to be relevant when building a long-short portfolio based on local macroeconomic surprises (apparently, even more with inflation surprises). Therefore, the same conclusions previously drawn may be applied in this case too.

It is important to underline how each quintile portfolio (and their average returns) documented in Table 5 and Table 6 derives from a monthly rebalancing based on the prior month surprise β_{SUR} of each stock. Therefore, consistently with our findings, Investors may pay lower prices (in concordance with future higher returns) for stocks that have exhibited high β_{SUR} in the past and higher prices (in concordance with future lower returns) for stocks that have exhibited low/negative β_{SUR} in the past, by having the expectation that this behaviour in terms of β_{SUR} value for each stock is persistent in the future. Thus, it is natural to question whether or not those are rational expectations. The persistence of β_{SUR} is tested to address this question.

Company-level cross-sectional regressions of β_{SUR} on lagged β_{SUR} are run. In particular, a regression across companies of 1-to-5-years-ahead β_{SUR} ($\beta_{SUR,i,t}$) on the lagged β_{SUR} ($\beta_{SUR,i,t}$) is run for each month. Table 7 shows the average regression slope of both growth and inflation β_{SUR} from the Fama-MacBeth regressions.

Table (7) **Persistence of surprise beta.** This table shows the persistence of β_{SUR} on lagged β_{SUR}. The first column examines the average regression coefficients on growth β_{SUR} from the Fama-MacBeth regressions of 1-year to 5-years ahead growth β_{SUR} on lagged growth β_{SUR}. The second column examines the average regression coefficients on inflation β_{SUR} from the Fama-MacBeth regressions of 1-year to 5-years ahead inflation β_{SUR} on lagged inflation β_{SUR}. Newey-West adjusted t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

n-years-ahead β_{SUR}	Univariate predictive regression (growth β_{SUR})	Univariate predictive regression (inflation β_{SUR})
n=1	0.758***	0.807***
	(52.036)	(107.36)
n=2	0.558***	0.627***
	(33.749)	(63.531)
n=3	0.374***	0.443***
	(23.158)	(40.918)
n=4	0.216***	0.249***
	(15.538)	(26.437)
n=5	0.053***	0.059***
	(13.981)	(12.678)

It can be noticed how, for both growth β_{SUR} and inflation β_{SUR}, the regression of 1-year-ahead β_{SUR} on lagged β_{SUR} the slope coefficient is quite large and positive, and highly statistically significant. The persistence of β_{SUR} for 2, 3, 4, and 5 years ahead is also positive and highly statistically significant. In other words, stocks with high β_{SUR} tend to exhibit similar features in the following 1-to-5 years, and so, these findings shows that the estimated historical surprise betas successfully and significantly predict future surprise betas.

4.2 Double-Sorting Investment strategy

In this section we examine the relation between future stock returns and surprise betas after controlling for well-known risk factors. Bivariate portfolio sorts are performed on surprise betas β_{SUR}, in combination with market betas β_{MKT}, or SMB betas β_{SMB}. We sort stocks into quintiles according to their β_{MKT} or β_{SMB}. Afterwards, within each β_{MKT} or β_{SMB}, we sort stocks into quintile portfolios ranked based on the growth/inflation β_{SUR} so that quintile 5 (quintile 1) contains stocks with the highest (lowest) β_{SMB} values. This procedure creates a set of β_{SMB} long-short portfolios (Q5 - Q1) based on stocks with very similar levels of β_{MKT} or β_{SMB}. Table 8 shows the results long-short portfolios of stocks sorted by Market/SMB betas and growth surprise betas.

Table (8) **Bivariate equal-weighted long-short portfolios of stocks sorted by Market or SMB betas and growth surprise betas.** Stocks are firstly sorted into quintiles according to their Market or SMB beta. Secondly, in each quintile (rows from Low to High quintile), long-short portfolios are built as the difference between quintile 5 (top quintile), containing stocks with the highest growth β_{SUR} and quintile 1 (bottom quintile), containing stocks with the lowest growth β_{SUR}. For both strategies (double sorting on market betas and double sorting on SMB betas), the first column presents the equal-weighted long-short portfolio's average return. The second column presents the relative Sharpe Ratio. The third column presents the alphas as result of regressing long-short portfolios' monthly returns over Fama-French 5 factors, plus the momentum and liquidity factor, which are used as control variables. The Sharpe-Ratio is defined as the yearly one by multiplying the monthly Sharpe-Ratio by the root square of twelve. Coefficients' corresponding Newey-West adjusted t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

	Long-short portfolios (double sorting = Mkt beta + growth beta)			Long-short portfolios (double sorting = SMB beta + growth beta)		
1st sorting quintiles (Mkt/SMB)	Avg. Return	Sharpe Ratio	a	Avg. Return	Sharpe Ratio	a
Low	0.211	0.229	0.326	-0.1244	-0.114	-0.091
	(0.975)		(1.445)	(-0.485)		(-0.331)
2	0.426***	0.679	0.452***	0.271*	0.388	0.257
	(2.892)		(3.089)	(1.653)		(1.632)
3	0.222	0.355	0.293*	0.469***	0.622	0.527***
	(1.512)		(1.839)	(2.647)		(2.815)
4	0.660***	0.681	0.600***	0.459**	0.506	0.371
	(2.899)		(2.848)	(2.155)		(1.623)
High	0.295	0.171	0.480	0.489	0.303	0.390
	(0.731)		(1.383)	(1.290)		(1.072)

It can be noticed how when controlling for market beta or SMB beta levels, the long-short investment strategy not always performs significantly. When controlling for the β_{MKT}, the alpha difference between the high-β_{SUR} and low-β_{SUR} equal-weighted portfolios is statistically significant only for the second, third, and fourth β_{MKT} quintile, ranging from 0.29% to 0.60%, whilst the alpha difference between the high-β_{SUR} and low-β_{SUR} equal-weighted portfolios in the first β_{MKT} quintile (which contains stocks with the lowest β_{MKT}), and fifth β_{MKT} quintile (which contains stocks with the highest β_{MKT}) are still positive, but not statistically significant. These findings show that when considering only stocks with extreme market betas (in both direction) the long-short investment strategy does not lead to significant extra premium. Thus, for those, the market risk-premium contributes in explaining the significant macroeconomic surprise premium. The explanatory power of the SMB risk factor is even more evident as expected. Indeed, when controlling for β_{SMB} the alpha difference between the high-β_{SUR} and low-β_{SUR} equal-weighted portfolios is statistically significant only for the third β_{SMB} quintile. The same analysis is carried out considering inflation surprise betas. Table A6 in the appendix shows the results. Differently from the previous strategy, only the alpha difference between the high-β_{SUR} and low-β_{SUR} equal-weighted portfolios in the first β_{MKT} quintile and fifth β_{MKT} quintile are positive and statistically significant (0.449% and 0.753%). Therefore, after controlling for β_{MKT}), the long-short investment strategy lead to significant extra premium only when considering stocks with extreme market betas. Again, when controlling, for β_{SMB} the alpha difference is positive and significant only for one β_{SMB} quintile. In this case, the first one with an alpha of 0.612%. Similar conclusions, thus, can be drawn for this strategy too.

4.3 Robustness check

In this section we provide a series of robustness checks. First, as consequence of the difference in results previously found between equal-weighted and value-weighted strategies, we investigate if the significant difference in alphas between the top and the bottom quintile and the significant average long-short portfolio returns for both strategies based on growth and inflation surprises are driven by illiquid, small, and low-priced stocks. Similarly to Fang and Peress (2009), stocks with price below 5$ are excluded from the computation of the long-short portfolio monthly returns to ensure that illiquid and small stocks are not taken into account. More precisely, in case a stock shows a price below 5$ in a certain month, we just drop that observation for that month, so that the stock is not excluded from the sample, thus avoiding potential selection bias, but it is not taken into account in the various calculation just in that period. Table A3 in the appendix shows the results. Consistently with the expectations, the average return remains statically significant only for the long-short portfolio based on the growth surprise strategy, passing from a 99% of statistical significance to a 90% significance and a lower Sharpe Ratio (0.416), whereas for the long-short portfolio based on the inflation surprise strategy the average return remains positive but very low and not significant. Moreover, for both strategies the a remains positive (respectively 0.221% and 0.058%) but loses its significance. Again, these results show the relevance of small stocks when building the investment strategy and how those, in all probability, are more sensible to local macroeconomic surprises. Second, given the significant persistence of β_{SUR}, we want to examine how our findings are sensible to different rebalancing period. Instead of a monthly rebalancing, we test the performance of our long-short portfolios when considering a quarterly or half-yearly rebalancing. Results for both investment strategies and different rebalancing periods are shown in Table A4 in the appendix. It can be noticed how in both strategies, different rebalancing periods always lead to positive and statistically significant average returns. For the long-short portfolios where stocks are sorted by growth beta, the monthly average returns are 0.534%, 0.430%, and 0.401% respectively for a monthly, quarterly, and half-yearly rebalancing. A similar decreasing path is showed by the Sharpe Ratio. Nevertheless, only the a when considering a monthly rebalancing is statistically significant. For the long-short portfolios where stocks are sorted by inflation beta, the monthly average returns are 0.31%, 0.266%, and 0.291% respectively for a monthly, quarterly, and half-yearly rebalancing. Again, a similar path is showed by the Sharpe Ratio. For this strategy, however, the a remains statistically significant for every rebalancing period. Overall, given the persistence in surprise betas previously found, these results are in line with expectations. Nevertheless, for both strategies a monthly rebalancing remains the best one by leading to better performance in terms of average return, Sharpe Ratio, and a. Third, we want to split the considered time span in four to examine the performance of the long-short portfolios at different points in time. Results for both investment strategies at different points in time are shown in Table A5 in the appendix. It can be noticed how both strategies do not always significantly perform at each point in time. The long-short portfolio based on stocks sorted by surprise growth beta has performed quite well in the past between 2002 and 2011 with a Sharpe Ratio of 1.228 (2002-2006) and 0.933 (2007-2011), whereas between 2012 and 2016 the average return was much lower and not significant with a Sharpe Ratio of 0.067. In the last period (2017-2020) the strategy seems to recover with a Sharpe ratio of 0.395 but without regaining its significance. It is interesting to see, instead, how the long-short portfolio based on stocks sorted by surprise inflation beta has performed very well right between 2012-2016 (Sharpe Ratio of 1.204) when the other strategy has performed poorly. In the last years, instead, it seemed to perform not that well with a low positive Sharpe Ratio (0.005 between 2017-2020). Thus, from these findings, it can be concluded that the strategies' performances are not constant over time. There might be periods in which they perform significantly better and other periods in which they perform poorly.

5 Conclusions

In this paper we measure U.S. growth and inflation macroeconomic surprises using releases on the announcement days to extrapolate real-time information. After the examination of these macroeconomic surprises, we observe a significant positive autocorrelation in the short-term, confirming that surprises do not appear randomly. Moreover, we examine whether both growth and inflation surprises are able to explain market risk-premium. We find that growth macro surprises positively and significantly predict future U.S. equity market returns, whilst the ability to predict future U.S. equity market returns using inflation surprises seems to be limited.

Following these results, we also investigate the role of macroeconomic surprises in the cross-sectional pricing of individual U.S. equities. We analyse the predictive power of surprise betas over future stock returns and if extra return can be achieved by exploiting the exposure of single stocks to the growth and inflation surprise factors. After calculating the (β_{SUR}) for each stock, long-short investment strategies are built. Univariate portfolio-level analyses show that equal-weighted quintile portfolios that are long in stocks with the highest growth surprise beta and short in stocks with the lowest growth surprise beta yield a significant annualized average return of 6.36%. We find that this surprise premium is driven by the outperformance by stocks with high surprise beta. Consistently with a theoretical prediction, these results suggest that surprise-averse investors require extra compensation to hold stocks with high growth surprise beta and, vice versa, they are willing to pay high prices for stocks with negative growth surprise beta. Similar results have been found for univariate portfolio-level analyses when considering inflation surprises. Equal-weighted quintile portfolios that are long in stocks with the highest inflation surprise beta perform significantly better than equal-weighted quintile portfolios that are short in stocks with the lowest inflation surprise beta. Again, this surprise premium is driven by the outperformance by stocks with high surprise beta. Against a theoretical point of view on the risk-return trade-off, these findings show in an interesting way that stocks with the ability to hedge inflation lead, on average, to higher returns than stocks with low inflation-hedging abilities. Nevertheless, we show how small-cap stocks represent the main driver for these performances. Indeed, when moving from an equal-weighted to a value-weighted strategy, the long-short portfolios' alpha decrease and loose statistical significance, particularly for the strategy based on inflation surprises. Similar results are found when excluding illiquid, small, and low-priced stocks. Bivariate portfolio-level analyses show that when controlling for well-known risk factors, these have an impact in explaining the extra-premium in the long-short portfolios. When controlling for market beta, the alpha difference between the high-β_{SUR} low-β_{SUR} equal-weighted portfolios is not significant for all market beta level. When controlling for SMB beta, the alpha difference is significant only for one SMB beta level when using both growth and inflation surprises. Finally, we show how long-short investment strategies based on macro surprises are not constant over time. In certain periods they perform significantly better and vice versa.

Our results demonstrate the importance of macro surprises for asset prices in the U.S. market. Market risk premia is, indeed, predictable by growth surprises. Moreover, under certain conditions, long-short investment strategies based on macro surprises might lead to significant extra premia.

Appendix

Table (A1) **Univariate value-weighted portfolios of stocks sorted by growth surprise betas.** Quintile portfolios are formed by sorting single stocks according to their growth surprise beta (β_{SUR}). Quintile 5 (top quintile) contains stocks with the highest β_{SUR} in the previous month, whereas quintile 1 (bottom quintile) contains stocks with the lowest β_{SUR} in the previous month. The first column presents the value-weighted quintiles' average return, whereas the following columns present the regression coefficients as results of regressing value-weighted quintiles' monthtly returns over Fama-French 5 factors, plus the momentum and liquidity factor, which are used as control variables. The last two rows show results relative to the portfolio (investment strategy) defined as the difference between the top (Q5) and the bottom (Q1) quintile. The Sharpe-Ratio is defined as the yearly one by multiplying the monthly Sharpe-Ratio by the root square of twelve. Coefficients' corresponding Newey-West adjusted t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

		Coefficients (Value-weighted portfolios)							
Quintile	Avg. Return	a	MKF-RF	SMB	HML	RMW	CMA	Mom	LIQ
Low	0.830***	-0.007	0.937***	-0.056	-0.120	0.056	0.034	0.012	0.028
	(2.896)	(-0.063)	(23.299)	(-0.823)	(-1.58)	(0.501)	(0.330)	(0.194)	(0.540)
2	0.909***	0.070	0.935***	-0.079**	-0.190***	0.126**	0.212***	0.005	-0.027
	(3.483)	(1.197)	(53.673)	(-2.452)	(-6.855)	(2.457)	(3.482)	(0.220)	(-1.170)
3	1.0139***	0.105	0.993***	0.019	-0.088**	0.109	0.129**	-0.002	0.055**
	(3.399)	(1.288)	(31.362)	(0.501)	(-2.314)	(1.571)	(2.201)	(-0.046)	(2.090)
4	1.294***	0.290***	1.105***	0.144**	-0.051	0.063	0.007	0.011	0.029
	(3.729)	(2.657)	(24.502)	(2.423)	(-0.811)	(0.741)	(0.095)	(0.185)	(0.688)
High	1.5981***	0.263	1.362***	0.562***	-0.229*	0.071	0.106	-0.155	0.070
	(3.182)	(1.259)	(15.616)	(5.268)	(-1.725)	(0.322)	(0.637)	(-1.279)	(0.895)
High-Low	0.767**	0.270	0.425***	0.619***	-0.108	0.014	0.072	-0.168	0.042
	(2.239)	(0.953)	(3.774)	(4.296)	(-0.567)	(0.047)	(0.305)	(-0.930)	(0.355)
Sharpe Ratio	0.526								

Table (A2) **Univariate value-weighted portfolios of stocks sorted by inflation surprise betas.** Quintile portfolios are formed by sorting single stocks according to their inflation surprise beta (β_{SUR}). Quintile 5 (top quintile) contains stocks with the highest β_{SUR} in the previous month, whereas quintile 1 (bottom quintile) contains stocks with the lowest β_{SUR} in the previous month. The first column presents the value-weighted quintiles' average return, whereas the following columns present the regression coefficients as results of regressing value-weighted quintiles' monthtly returns over Fama-French 5 factors, plus the momentum and liquidity factor, which are used as control variables. The last two rows show results relative to the portfolio (investment strategy) defined as the difference between the top (Q5) and the bottom (Q1) quintile. The Sharpe-Ratio is defined as the yearly one by multiplying the monthly Sharpe-Ratio by the root square of twelve. Coefficients' corresponding Newey-West adjusted t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

		Coefficients (Value-weighted portfolios)							
Quintile	Avg. Return	a	MKF-RF	SMB	HML	RMW	CMA	Mom	LIQ
Low	1.025**	0.0138	1.090***	0.242***	-0.187**	-0.293***	-0.229**	-0.090**	0.230***
	(2.512)	(0.081)	(22.367)	(3.078)	(-2.188)	(-2.945)	(-2.153)	(-1.977)	(2.946)
2	0.998***	-0.006	1.040***	-0.015	-0.199**	0.106	0.029	0.011	0.169***
	(3.017)	(-0.054)	(24.286)	(-0.247)	(-2.331)	(1.260)	(0.250)	(0.326)	(3.247)
3	0.986***	0.125*	0.987***	-0.060**	-0.038	0.086*	0.070	0.043**	-0.005
	(3.458)	(1.943)	(49.037)	(-2.259)	(-0.895)	(1.874)	(1.293)	(2.470)	(-0.258)
4	1.000***	0.147**	0.942***	-0.006	-0.165***	0.153***	0.257***	0.028	-0.044*
	(3.552)	(2.170)	(45.091)	(-0.179)	(-5.311)	(2.833)	(4.213)	(1.397)	(-1.794)
High	1.007***	0.062	1.027***	0.141*	-0.043	0.180	0.029	0.001	0.009
	(3.037)	(0.460)	(20.844)	(1.953)	(-0.418)	(1.589)	(0.233)	(0.046)	(0.128)
High-Low	-0.018	0.048	-0.062	-0.101	0.143	0.473**	0.258	0.092	-0.221
	(-0.073)	(0.182)	(-0.757)	(-0.776)	(0.896)	(2.509)	(1.364)	(1.333)	(-1.593)
Sharpe Ratio	-0.017								

Table (A3) **Univariate equal-weighted portfolios of stocks sorted by surprise betas without illiquid, small stocks.** Quintile portfolios are formed by sorting single stocks according to their surprise beta (β_{SUR}). Quintile 5 (top quintile) contains stocks with the highest β_{SUR} in the previous month, whereas quintile 1 (bottom quintile) contains stocks with the lowest β_{SUR} in the previous month. Each quintile is formed by excluding stocks with price below 5$ at each rebalancing period. For both strategies (quintiles based on growth surprises and quintiles based on inflation surprises), the first column presents the equal-weighted quintiles' average return. The second column presents the alpha as result of regressing equal-weighted quintiles' monthtly returns over Fama-French 5 factors, plus the momentum and liquidity factor, which are used as control variables. The last two rows show results relative to the portfolio (investment strategy) defined as the difference between the top (Q5) and the bottom (Q1) quintile. The Sharpe-Ratio is defined as the yearly one by multiplying the monthly Sharpe-Ratio by the root square of twelve. Coefficients' corresponding Newey-West adjusted t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

	Stocks sorted by growth beta		Stocks sorted by inflation beta	
Quintile	Average Return	a	Average Return	a
Low	0.891**	-0.0617	1.133**	0.187
	(2.323)	(-0.442)	(2.553)	(1.324)
2	1.023***	0.133	0.978**	-0.001
	(3.077)	(1.575)	(2.430)	(-0.015)
3	1.159***	0.228**	1.047***	0.070
	(3.178)	(2.500)	(2.695)	(0.614)
4	1.358***	0.351***	1.161***	0.290***
	(3.347)	(2.893)	(3.209)	(3.123)
High	1.296**	0.159	1.223***	0.245*
	(2.591)	(0.965)	(2.974)	(1.832)
High-Low	0.405*	0.221	0.090	0.058
	(1.771)	(1.047)	(0.521)	(0.317)
Sharpe Ratio (H-L)	0.416		0.124	

Table (A4) **Univariate equal-weighted long-short portfolios of stocks sorted by surprise betas with different rebalancing periods.** Long-short portfolios are built as the difference between quintile 5 (top quintile), containing stocks with the highest β_{SUR} and quintile 1 (bottom quintile), containing stocks with the lowest β_{SUR}. Different rebalancing period in each quintile are considered: 1-month, 3-months, and 6-months. For both strategies (long-short strategies based on growth surprises and long-short strategies based on inflation surprises), the first column presents the equal-weighted long-short portfolio's average return. The second column presents the relative Sharpe Ratio. The third column presents the alpha as result of regressing long-short portfolios' monthly returns over Fama-French 5 factors, plus the momentum and liquidity factor, which are used as control variables. The Sharpe-Ratio is defined as the yearly one by multiplying the monthly Sharpe-Ratio by the root square of twelve. Coefficients' corresponding Newey-West adjusted t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

	Long-short portfolios (sorting by growth beta)			Long-short portfolios (sorting by inflation beta)		
Rebalancing period	Avg. Return	Sharpe Ratio	a	Avg. Return	Sharpe Ratio	a
1-month	0.534***	0.619	0.397**	0.310**	0.518	0.309**
	(2.632)		(2.067)	(2.169)		(2.323)
3-months	0.430**	0.517	0.239	0.266*	0.457	0.261**
	(2.202)		(1.322)	(1.915)		(2.098)
6-months	0.401**	0.474	0.212	0.291**	0.515	0.267**
	(2.019)		(1.1759)	(2.157)		(2.109)

Table (A5) **Univariate equal-weighted long-short portfolios of stocks sorted by surprise betas at different points in time.** Long-short portfolios are built as the difference between quintile 5 (top quintile), containing stocks with the highest β_{SUR} and quintile 1 (bottom quintile), containing stocks with the lowest β_{SUR}. Different time frames are considered: 2002-2006, 2007-2011, 2012-2016, and 2017-2020. For both strategies (long-short strategies based on growth surprises and long-short strategies based on inflation surprises), the first column presents the equal-weighted long-short portfolio's average return. The second column presents the relative Sharpe Ratio. The Sharpe-Ratio is defined as the yearly one by multiplying the monthly Sharpe-Ratio by the root square of twelve. Coefficients' corresponding Newey-West adjusted t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

	Long-short portfolios (sorting by growth beta)		Long-short portfolios (sorting by inflation beta)	
Time period	Average Return	Sharpe Ratio	Average Return	Sharpe Ratio
2002 - 2006	0.581**	1.228	0.144	0.251
	(2.482)		(0.470)	
2007 - 2011	1.346*	0.933	0.304	0.479
	(1.866)		(1.072)	
2012 - 2016	0.049	0.067	0.677***	1.205
	(0.151)		(2.696)	
2017 - 2020	0.221	0.395	0.003	0.005
	(0.790)		(0.010)	

Table (A6) **Bivariate equal-weighted long-short portfolios of stocks sorted by Market or SMB betas and inflation surprise betas.** Stocks are firstly sorted into quintiles according to their Market or SMB beta. Secondly, in each quintile (rows from Low to High quintile), long-short portfolios are built as the difference between quintile 5 (top quintile), containing stocks with the highest inflation β_{SUR} and quintile 1 (bottom quintile), containing stocks with the lowest inflation β_{SUR}. For both strategies (double sorting on market betas and double sorting on SMB betas), the first column presents the equal-weighted long-short portfolio's average return. The second column presents the relative Sharpe Ratio. The third column presents the alphas as result of regressing long-short portfolios' monthly returns over Fama-French 5 factors, plus the momentum and liquidity factor, which are used as control variables. The Sharpe-Ratio is defined as the yearly one by multiplying the monthly Sharpe-Ratio by the root square of twelve. Coefficients' corresponding Newey-West adjusted t-values are shown in parentheses. Asterisks indicate the significance level at 1% (***), 5% (**), or 10% (*).

	Long-short portfolios (double sorting = Mkt beta + inflation beta)			Long-short portfolios (double sorting = SMB beta + inflation beta)		
1st sorting quintiles (Mkt/SMB)	Avg. Return	Sharpe Ratio	a	Avg. Return	Sharpe Ratio	a
Low	0.459**	0.513	0.449**	0.624**	0.578	0.612**
	(2.148)		(2.243)	(2.420)		(2.358)
2	0.025	0.041	0.092	0.094	0.146	0.099
	(0.172)		(0.732)	(0.614)		(0.649)
3	0.188	0.295	0.217	0.188	0.259	0.182
	(1.429)		(1.542)	(1.086)		(1.229)
4	0.118	0.138	0.056	0.101	0.133	0.111
	(0.581)		(0.331)	(0.557)		(0.653)
High	0.870**	0.553	0.753**	0.754**	0.513	0.507
	(2.315)		(2.351)	(2.150)		(1.546)

Table (A7) **Output level Index Components**

Variable	First Observation	# Observations
Industrial Production MoM	16/12/1998	262
Trade Balance	17/12/1998	270
Capacity Utilization	16/12/1998	269
GDP Annualized QoQ	23/12/1997	274
ISM Manufacturing	01/12/1998	272
Durable Goods Orders	28/12/2001	318
New Home Sales	27/12/2002	271
Retail Sales Advance MoM	13/12/2004	236
Housing Starts	16/12/1998	272
Existing Home Sales	29/12/2005	191
Factory Orders	04/12/1998	271
Personal Income	24/12/1998	272
Personal Spending	24/12/1998	271
Construction Spending MoM	01/12/2003	210
Pending Home Sales MoM	06/12/2005	188
Monthly Budget Statement	21/12/1998	269
ISM Non-Manufacturing Index	03/12/2008	146
ISM Services Index	03/04/2020	256
Durables Ex Transportation	23/12/2004	10
Current Account Balance	16/12/2009	90
Personal Consumption	21/12/2005	214
FHFA House Price Index MoM	23/12/2008	153
Building Permits	17/02/2002	222
Cap Goods Orders Nondef Ex Air	23/12/2010	136
S&P CoreLogic CS 20-City YoY NSA	27/12/2011	164
NAHB Housing Market Index	15/12/2003	214
Wards Total Vehicle Sales	02/12/2003	216
Consumer Credit	07/12/1998	272
Business Inventories	15/12/1998	271
Wards Domestic Vehicle Sales	03/12/2002	226
Pending Home Sales NSA YoY	02/06/2010	99
Housing Starts MoM	16/12/2015	129
S&P CoreLogic CS 20-City MoM SA	31/03/2020	133
Retail Sales Ex Auto MoM	13/12/2001	236
FOMC Rate Decision (Upper Bound)	22/12/1998	178

Table (A8) **Employment level Index Components**

Variable	First Observation	Observations
Unemployment Rate	04/12/1998	272
Change in Nonfarm Payrolls	04/12/1998	273
Initial Jobless Claims	30/12/1999	1177
ADP Employment Change	06/12/2006	173
Change in Manufact. Payrolls	05/12/2003	264
Continuing Claims	18/12/2003	922
Average Hourly Earnings MoM	07/12/2012	131
Average Hourly Earnings YoY	06/12/2013	131
Average Weekly Hours All Employees	05/12/2014	131

Table (A9) **Sentiment level Index Components**

Variable	First Observation	Observations
NFIB Small Business Optimism	09/12/2014	130
Richmond Fed Manufact. Index	22/12/2009	183
Conf. Board Consumer Confidence	29/12/1998	272
U. of Mich. Sentiment	22/12/1999	517
Empire Manufacturing	15/12/2003	219
MNI Chicago PMI	31/12/1998	272
Philadelphia Fed Business Outlook	17/12/1998	272

Table (A10) **Inflation level Index Components**

Variable	First Observation	Observations
CPI MoM	15/12/1998	272
PPI Final Demand MoM	12/12/2014	73
GDP Price Index	21/12/2005	188
Import Price Index MoM	16/12/1998	266
CPI Ex Food and Energy MoM	15/12/1998	270
Employment Cost Index	28/01/1999	89
ISM Prices Paid	03/12/2001	241
PPI Ex Food and Energy MoM	12/12/2014	84
PCE Core Deflator MoM	22/12/2005	188
CPI Ex Food and Energy YoY	16/12/2003	207
Nonfarm Productivity	07/12/1999	179
PCE Core Deflator YoY	23/12/2004	196

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