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The Google Trends Uncertainty (GTU) Index: A Measure of Economic Policy Uncertainty in the EU Using Google Trends

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Abstract

The objective of this research is to use Google search data to build the Google Trends Uncertainty (GTU) index, a weekly measure of uncertainty surrounding economic policy in the four largest economies in the European Union: Germany, France, Italy, and Spain. By obtaining the relative popularity of Google searches with economic policy uncertainty connotations given a specific timeframe and geographical area, the frequency with which people search for terms related to economic policy effectively serves as a proxy for actual economic policy uncertainty. In its entirety, the various elements of this research allow to accurately and unbiasedly measure economic policy uncertainty on a higher frequency than existing indices, gauge the extent to which Germany, France, Italy, and Spain influence each other with regards to uncertainty surrounding economic policy, produce a one-step out-of-sample forecast, and estimate the magnitude with which uncertainty impacts the rate of unemployment and industrial production.

Keywords

Google Trends, Economic Policy Uncertainty, Leading Indicator, Bayesian Inference Covid-19, European Union, Vector Autoregression, Machine Learning, ARIMA modeling, Structural Shocks.

Cover Page Footnote

I am grateful for the valuable insights from Prof. Timothy Cogley at New York University.

(1) Introduction

Uncertainty in economics is defined as a state of imperfect foresight that diminishes as information is obtained. When rational individuals face decision-making processes, minimizing imperfect foresight is key for optimal behavior; therefore, assuming that the cost of information is negligible, rational individuals will engage in information gathering activities until uncertainty is minimized. This research focuses on economic policy uncertainty, which refers to imperfect foresight with regards to courses of action that are intended to influence or control the behavior of the economy.

In the absence of uncertainty, information gathering is unnecessary for achieving optimal behavior; but, when uncertainty is high, optimal behavior requires an increase in information gathering efforts. The intensity of information gathering activities is essentially a function of the level of uncertainty, but, while the former can be monitored and therefore measured, quantifying uncertainty is not as straightforward. Uncertainty regarding economic policy affects, among others, the rate of unemployment and industrial production, so it is extremely valuable to quantify uncertainty in tangible terms: however, given the difficulty of measuring uncertainty directly, the intensity of information gathering activities can serve as a proxy for quantifying uncertainty.

For most people living in the 21st century, information gathering is the “googling” of things, which is validated by the fact that “google” is a transitive verb that has entered most spoken languages around the world. Google has become the number one search engine worldwide with trillions of searches every year and a 92.51% online search market share as of January 2020.[1] Since Google search data captures the majority of information gathering activities, it qualifies as an accurate proxy for quantifying uncertainty.

The objective of this research is to use Google search data to build an index that quantifies uncertainty surrounding economic policy in the four largest economies in the European Union: Germany, France, Italy, and Spain. The way that this research intends to assign a tangible numeric value to economic policy uncertainty is by obtaining the relative popularity of Google searches with economic policy uncertainty connotations given a specific timeframe and geographical area. By doing so, the frequency with which people search for terms related to economic policy would effectively serve as a proxy for actual economic policy uncertainty. The end product of this exercise is a weekly index, namely, the Google Trends Uncertainty (GTU) index.

In addition to developing the GTU index, this research will leverage the granularity and geographical focus of the GTU to observe patterns by which economies in the EU bloc are subject to economic policy uncertainty pressure coming from their neighbors by obtaining impulse response functions representing forecast revisions of future GTU values given a shock to the German GTU in a Bayesian vector autoregressive (BVAR) framework; produce a one-step out-of-sample forecast for the German GTU using machine learning and autoregressive integrated moving average (ARIMA) modeling techniques; and simulate a shock to the German GTU index to obtain impulse response functions for the rate of unemployment and industrial production in a structural autoregressive (SVAR) model with sign restrictions. In its entirety, this

[1] GlobalStats. Search Engine Market Share Worldwide. 2019. https://gs.statcounter.com/search-engine-market-share

research introduces an innovative approach to quantifying and forecasting economic policy uncertainty and its effect on macroeconomic variables among economically interdependent countries.

The remainder of this paper is organized as follows: section (2) presents the literature pertaining to this research area, section (3) explains the methodology behind the construction of the GTU index, section (4) introduces the BVAR framework, section (5) explains the application of ARIMA and machine learning techniques, section (6) tackles the SVAR analysis with sign restrictions and section (7) concludes.

(2) Literature

This research relates to three strands of literature. The first is work on the impact of monetary, fiscal, and regulatory policy uncertainty on economic activity, which informs the very reason why an index for economic policy uncertainty is valuable. Bernanke (1983) proposes a theoretical rationale for how temporary uncertainty might lead to a persistent downturn trend in investment. Assuming risk neutrality, Bernanke (1983) asserts that when agents make investment-timing decisions they face a tradeoff between the abnormal returns from early commitment and the benefits of increased information gained by waiting. It also proves that agent willingness to forego short run returns arises when facing imperfect foresight, suggesting that investment-timing is inversely related to uncertainty regardless of future conditions improving or deteriorating. Similarly, Bloom (2009) finds that a large temporary uncertainty shock causes a rapid drop, rebound, and overshoot in employment and industrial production. The rationale in Bloom (2009) follows a similar line of reasoning to that presented in Bernanke (1983), where immediately after a shock, higher uncertainty increases the value of waiting for information, firms scale back their plans and investment rates fall dramatically.

The second strand of literature focuses on developing proxies of economic policy uncertainty. Baker et al. (2016) estimates the Economic Policy Uncertainty (EPU) index on a monthly basis as the volume of articles from 10 major newspapers discussing economic policy uncertainty across eight different policy categories, namely, Monetary, Fiscal, Political, Geopolitical, Manufacturing/Trade, European regulation, Domestic regulation, and Energy. Baker et al. (2016) finds that economic policy uncertainty, as captured by the EPU index, delays investment, hiring, and growth and moves closely with uncertainty surrounding financial markets. Currently, the EPU index is the most widespread measure of economic policy uncertainty across Europe; however, it has two major limitations. First, relying on the content of newspaper articles to predict people's sentiment implies that journalists are the *vox populi*, thus incurring into the issue of non-representativeness and potential bias. Second, the EPU index cannot distinguish between local and international policy uncertainty, in the sense that a German newspaper discussing fiscal uncertainty in France will be counted towards an increase in EPU in Germany.

Bontempi et al. (2018) was the first attempt to use online search engines to measure economic policy uncertainty. More specifically, Bontempi et al. (2018) focuses on Italy and the United States to construct the Economic Uncertainty Related Queries (EURQ) index, which measures the volume of Google searches of uncertainty-related topics within country borders. The EURQ index advocates a fundamental change in how uncertainty is measured by replacing passive consumption of media articles with the intensity of information gathering efforts. At

present, the EURQ index has been developed to fit only a narrow geographical scope, and this research intends to expand the work of Bontempi et al. (2018) to include the four major EU economies: Germany, France, Italy and Spain. Conceptually, the GTU index builds on the EURQ index; however, the two indices have some fundamental differences. First, while the EURQ index is on a monthly basis, the GTU is a weekly index. Second, the list of keywords used to construct the GTU index is significantly different from that used to estimate the EURQ index. Lastly, focusing on the four largest economies in the EU allows for the GTU index to become a valuable resource to analyze uncertainty propagation mechanisms in the context of economically interdependent countries.

The third branch of literature pertains to using Google Trends as a forecasting tool. More specifically, there are several examples in the literature showcasing how Google Trends data is able to enhance, and sometimes even outperform, traditional economic forecasts. Hyunyoung and Hal (2009) shows that autoregressive and fixed-effects models that include relevant Google Trends variables tend to outperform models that exclude those predictors in observing directional changes and turning points such as sharp increasing or decreasing patterns. Moreover, Wu (2009) uses Google Trends data to develop an index that accurately predicts future housing market sales. Furthermore, D'Amuri and Marcucci (2010) uses Google Trends data to build an index that forecasts activity in the job-search market, finding that it dramatically increases the precision of leading indicators of unemployment dynamics in the United States. Lastly, Perlin et al. (2017) looks into the interaction of Google search queries and several aspects of international equity markets. Perlin et al. (2017) uses a vector autoregressive modeling approach to investigate the impact of search queries of finance-related words on returns, volatility of returns, and traded volume, finding that financial agents resort to Google when gathering information that influences their investment decisions.

(3) Methodology

This section illustrates the methodology behind the construction of the GTU index and of its country level specifications: $\mathrm{GTU}_{\mathrm{DE}}$ (for Germany), $\mathrm{GTU}_{\mathrm{FRA}}$ (for France), $\mathrm{GTU}_{\mathrm{ITA}}$[2] (for Italy), and $\mathrm{GTU}_{\mathrm{ESP}}$ (for Spain). The central assumption behind the GTU index is that agents, represented by Google users, look for online information when they are uncertain. Therefore, constructing the GTU requires specifying the means by which search frequency is measured, and defining the terms associated with economic policy uncertainty.

For what concerns measuring search frequency, Google Trends publishes two types of data, one containing the raw number of total search queries for a given word (or group of words) in a specific geographical location and timeframe, and the other is sampled data scaled to compute the relative popularity of a search query (or a group of queries) also conditional on time and space. For the purpose of this research I will use the latter as it controls for rising internet

[2] The $\mathrm{GTU}_{\mathrm{ITA}}$ index is based on a different list of keywords from that used in Bontempi et al. (2018) to construct the EURQ_ITA index. Therefore, although similar, the $\mathrm{GTU}_{\mathrm{ITA}}$ and the EURQ_ITA are two distinct indices.

penetration over time and ensures that the time series are stationary. Google calculates the relative popularity of a query (or group of queries) *s,* in region *r,* at time *t* as:

$$\text{Relative Popularity}_{\text{srt}} = \frac{\text{SV}_{\text{srt}}}{(\text{SV}_{\text{Grt}})\times\text{MaxSV}_{[0,\text{T}]}} \times 100\,, \quad \text{MaxSV}_{[0,\text{T}]} = \frac{\text{SV}_{\text{srt}}}{\text{SV}_{\text{Grt}}} \tag{1}$$

where the SV_{srt} is the search volume of the query (or group of queries) *s,* in region *r,* at time *t* divided by the product of (1) SV_{GRT} , which is the search volume of all possible Google queries, *G*, in region *r* at time *t*, and (2) $MaxSV_{[0,T]}$, which is the ratio of SV_{srt} and SV_{GRT}, in the selected timeframe [0 ,T]. qw

To effectively define terms associated with economic policy uncertainty, it is important to take into account the different facets of economic policy. In the news based EPU index, the authors classify uncertainty according to eight policy categories: Monetary, Fiscal, Political, Geopolitical, Manufacturing/Trade, European regulation, Domestic regulation, and Energy. The GTU index follows the same structure, where each country has a detailed breakdown of uncertainty related to these eight policy categories, and the sum of all categories results in the overall GTU index. Each policy category contains a maximum of ten keywords that were arbitrarily selected (Appendix A) with the intent to focus on terminology that is relevant to economic policy affairs over time. With the exception of certain keywords referring to political party names, the list of keywords for all four countries is the same. However, assuming that the majority of Google searches within country borders are carried out in the local language, the keywords match the official language of each country of interest.

The GTU does not capture the relative popularity of the individual terms but uses a common-term aggregation approach[3] to capture the relative popularity of the group of terms that define each policy category, the resulting value being a number in the (0,100) range for each policy category. The overall GTU index is computed as the sum of the relative popularities of each policy category, so it is a value between (0,800). For the purpose of this research, data was obtained on a weekly basis over a five-year period (03/2015 –02/2020) for Germany, France, Italy and Spain. In addition, by weighting the individual GTUs for Germany, France, Italy, and Spain by their respective shares of EU GDP (w_i)[4] and then summing them up, it is possible to

[3] Using the Boolean operator "compare" to merge up to 10 search terms ensures that their relative popularity will be calculated using the same value for "*MaxSV[0,T]",* thus ensuring that the search terms will have the same scaling factor. Assuming that *j* and *n* are single search terms:

$$Relative\ Popularity_{j,nrt} = \left(\frac{SV_{jrt}}{SV_{Grt} \times MaxSV_{[0,T]}}\right) + \left(\frac{SV_{nrt}}{SV_{Grt} \times MaxSV_{[0,T]}}\right) \times 100 = \frac{100}{MaxSV_{[0,T]}} \times \left(\frac{SV_{jrt} + SV_{nrt}}{SV_{Grt}}\right)$$

[4] According to Eurostat, Germany is the leading economy, accounting for over a fifth (21.3%) of EU GDP, France follows (14.9%), then Italy (11.2%), and Spain (7.6%). Together, they contribute to 55% of EU GDP. The weights were computed as $w_{DE} = 0.213/0.55$, $w_{FRA} = 0.149/0.55$, $w_{ITA} = 0.112/0.55$, $w_{ESP} = 0.076/0.55$. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/DDN-20180511-1?inheritRedirect=true

recover the GTU_4, an overall measure of uncertainty for the four largest economies in the European Union.

$$GTU_4 = w_{DE}GTU_{DE} + w_{FRA}GTU_{FRA} + w_{ITA}GTU_{ITA} + w_{ESP}GTU_{ESP} \quad (2)$$

In an attempt to validate the performance of the GTU index, it is valuable to see how it performs compared to the VSTOXX (Appendix B), the most watched index of volatility of European financial markets.

Although the two indices measure different types of uncertainty, one being financial and the other being related to economic policy, during the weeks between March 2015 and February 2020, the normalized values of GTU_4 and VSTOXX were positively correlated with a coefficient of 0.398. Both the VSTOXX and the GTU_4 spike as a result of the Greek default in June 2015, the United Kingdom European Union membership referendum in June 2016, President Trump's announcing tariffs on steel and aluminum in March 2018, the US increasing tariffs on $200 billion worth of Chinese goods amidst the trade war in May 2019, and COVID-19 spreading to Europe in February 2020 as marked by the green dashed lines on Figure 1.

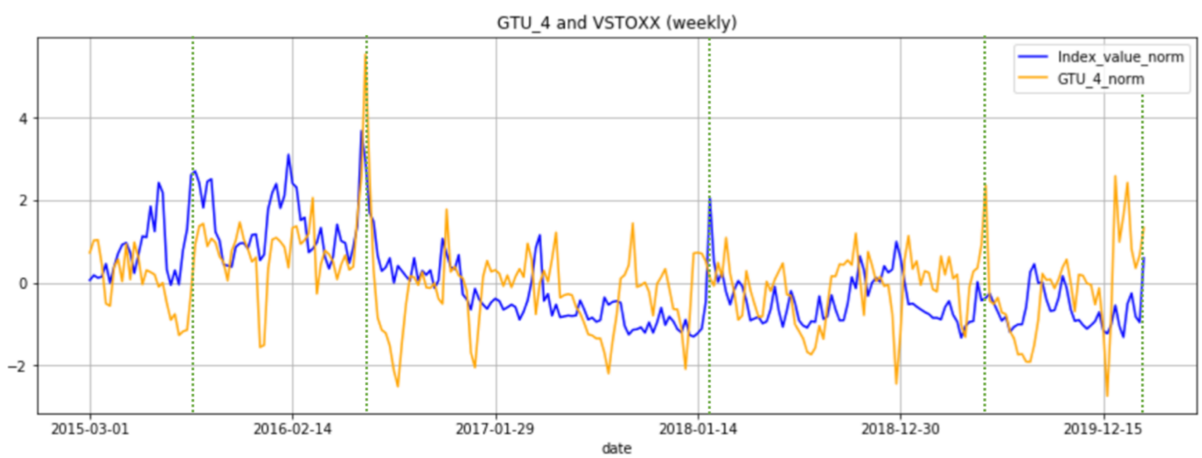

Figure 1. Compare GTU_4 and VSTOXX's performance between March 2015 and February 2020

It is interesting to notice that, throughout the five-year window, the two indices followed similar patterns, but their relationship is most informative during periods of extreme uncertainty. As a corollary, it may be the case that the prognostic qualities of the GTU are maximized during periods of above-average uncertainty surrounding economic policy.

When looking at the relationship between VSTOXX and the unweighted GTU_{DE}, the coefficient increases to 0.525, suggesting that Germany alone moves more tightly with financial

markets as compared to the weighted sum containing also France, Italy, and Spain. Similar to the GTU_4 , the $\mathrm{GTU}_{\mathrm{DE}}$ spikes for all major events marked with the green dashed lines. The $\mathrm{GTU}_{\mathrm{DE}}$ and VSTOXX move tightly together during the selected timeframe with the exception of a spike in the the $\mathrm{GTU}_{\mathrm{DE}}$ in September 2017 during the German federal elections marked with the black dashed line on Figure 2.

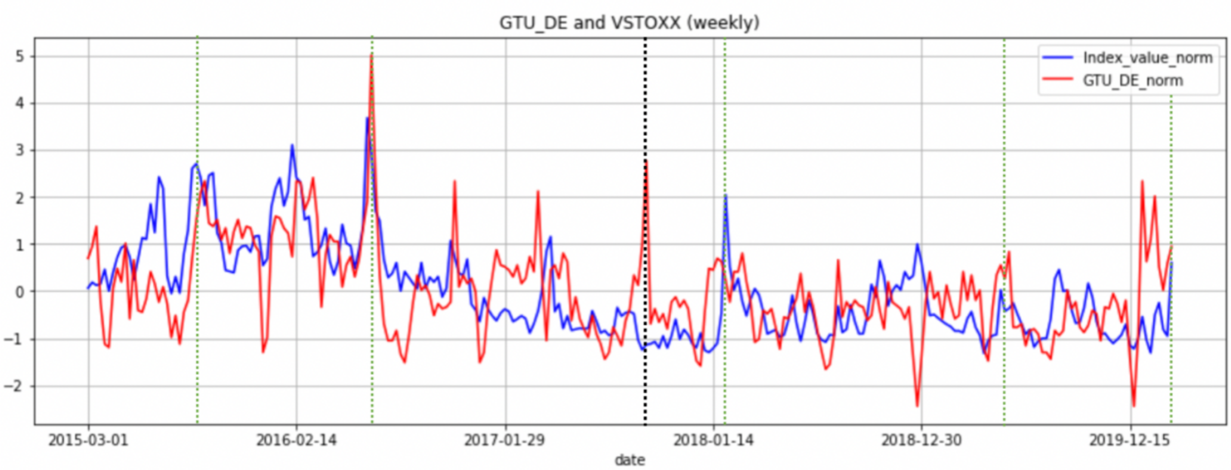

Figure 2. Compare GTU_DE and VSTOXX's performance between March 2015 and February 2020

In the context of economic interdependence among countries, these results show that the $\mathrm{GTU}_{\mathrm{DE}}$ is superior to the GTU_4 at approximating financial volatility in overall European markets; with the same logic, it might be the case that the overall level of uncertainty in the EU bloc is better approximated by the level of uncertainty in the leading economy rather than by a combination of weighted country specific indices. Compared to the GTU_4, the superiority of the $\mathrm{GTU}_{\mathrm{DE}}$ might be explained by the fact that rising uncertainty in the leading economy could induce an increase in uncertainty in the neighboring countries. The next section provides an in-depth analysis aimed at finding evidence of an uncertainty contagion mechanism running from Germany to France, Italy and Spain.

(4) Bayesian VAR for Lagged Contagion

This section focuses on testing the hypothesis that European economies might be susceptible to a lagged hierarchical uncertainty contagion pattern by which uncertainty shocks are transmitted from the leading economy to the smaller ones, with the severity of the response increasing as the size of the economy decreases. More specifically, this analysis intends to show how an increase in the German GTU might trigger revisions of forecasted GTUs for France, Italy, and Spain. The smallest economy in the sample, Spain, would be expected to suffer the most significant revision as depicted by the increasing size of the arrow in Figure 3.

$$GTU_{DE} \rightarrow GTU_{FRA} \rightarrow GTU_{ITA} \rightarrow GTU_{ESP}$$

Figure 3. Order of Uncertainty Propagation and Magnitude of Forecast Revision

Bayesian Vector autoregressive (BVAR) models are very useful for revealing something about the joint dynamics of time series; in these frameworks, each variable is a linear function of past lags of itself and past lags of the other variables, and inference is achieved by implementing Bayes' rule to update prior beliefs regarding the VAR coefficients.

For the purpose of this analysis, identification was achieved using a flat normal inverted-Wishart prior, and a Cholesky factorization with the order specified in Figure 3. The ordering of the Cholesky factorization dictates how the shock propagates across the variables in the system; therefore, to test the hypothesis of a hierarchical contagion pattern, $\mathrm{GTU}_{\mathrm{DE}}$ is ordered first and the other countries follow based on their respective shares of European GDP. By using a Cholesky factorization, it is possible to interpret impulse response functions as forecast revisions, therefore providing insights regarding the underlying degree of lagged economic policy uncertainty contagion affecting the economies in the EU bloc.

Impulse response functions (Figure 4) for a simulated one standard deviation shock to $\mathrm{GTU}_{\mathrm{DE}}$ were obtained using the *rfbvar* package in R, by specifying a two-week lag, 1000 Markov Chain Monte Carlo sampling replications, and a twelve-week horizon as in Danne (2019).

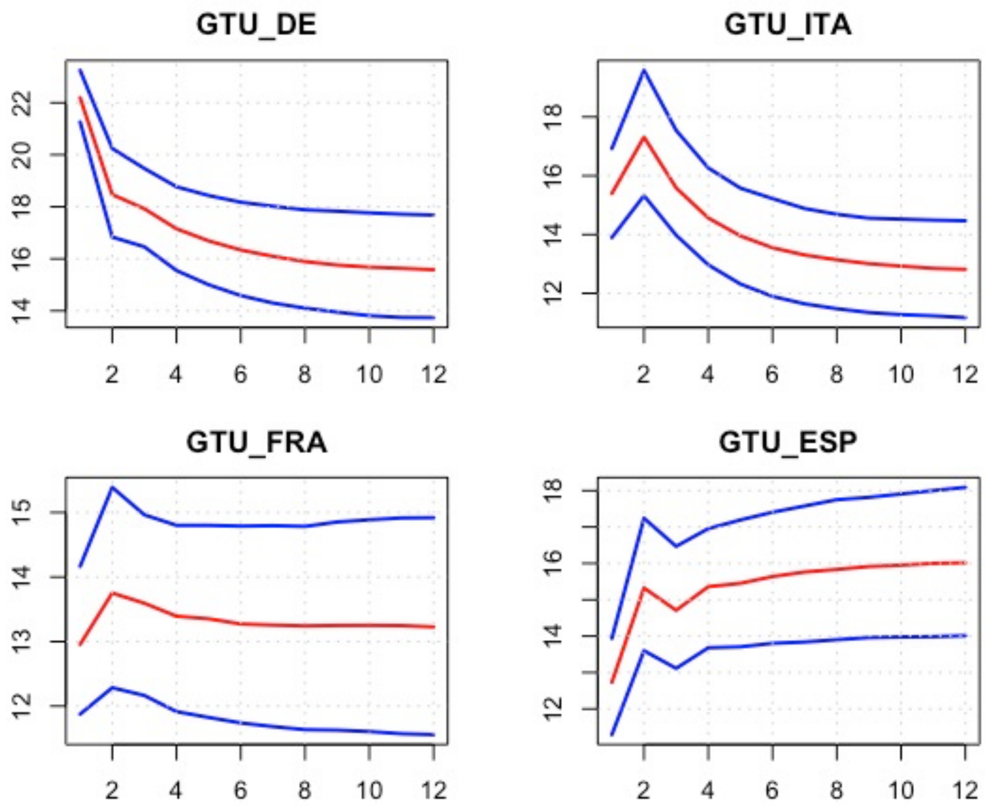

Figure 4. Impulse Response Functions with 68% confidence bands

The output from Figure 4 suggests that a higher $\mathrm{GTU_{DE}}$ today leads to upward revisions of forecasted values of $\mathrm{GTU_{FRA}}$ (~1 point), $\mathrm{GTU_{ITA}}$ (~2 points), and $\mathrm{GTU_{ESP}}$ (~2.5 points) two weeks after the shock. The results are in line with the hypothesis that it exists a pattern of uncertainty contagion propagating from the leading economy to the smaller ones and causing forecast revisions to be more substantial as the size of an economy decreases.

(5) ARIMA

Autoregressive integrated moving average (ARIMA) models are widely used in time series forecasting and are especially useful at capturing different temporal structures in data. As the name suggests, ARIMA models leverage the relationship between current and lagged observations in stationary time series data, and the dependency between the residuals and lagged observations in a moving average model to make forecasts. ARIMA models can be tuned according to three different parameters, namely, the lag order (p), the degree of differencing (d), and the order of the moving average (q). By tuning these three parameters it is possible to reduce the RMSE, thus increasing the forecasting accuracy of a model. This section illustrates how to

apply machine learning and ARIMA modeling techniques to obtain forecasts of $\mathrm{GTU_{DE}}$ one week into the future.

Before delving into the sophisticated techniques of ARIMA modeling, it is crucial to establish a baseline level of performance for a given time series forecasting problem. The naïve model in time series analysis is the persistence forecast, where we assume that prediction in the current time period is equivalent to that in the previous time period. Since values of the $\mathrm{GTU_{DE}}$ were collected on a weekly basis between March 2015 and February 2020, there is a total of 260 observations available for analysis. The first step is to divide the dataset evenly into train and test sets, such that the model can learn the behavior of the time series on a portion of the data and then test its performance on a segment to which it hadn't been exposed before. The persistence forecast model attains a RMSE of 21.153, which will be the baseline performance level for the $\mathrm{GTU_{DE}}$ time series.

In order to successfully build an ARIMA model, the residuals should be independent, homoscedastic, and normally distributed. The residuals in the $\mathrm{GTU_{DE}}$ time series satisfy all three conditions. The autocorrelation plot (Figure 5) shows that residuals are independent between the fourth and twenty-fifth lags, except for lags eighteenth to twentieth. In addition, residuals capture most trend information as shown in the line plot (Figure 6), with errors exhibiting constant variance. Lastly, the density plot (Figure 7) suggests that errors are Gaussian and centered on zero. At this point it is possible to proceed with ARIMA modeling, starting with evaluating values for parameters p, d and q and identifying the combination that minimizes RMSE.

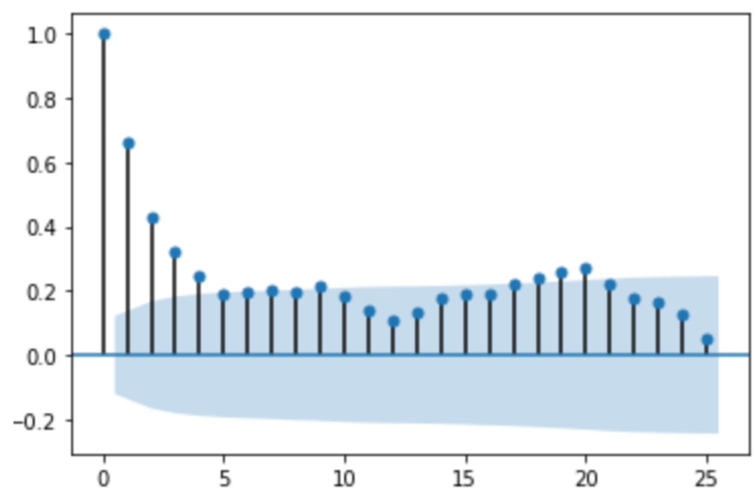

Figure 5. Residuals Autocorrelation Plot $\mathrm{GTU_{DE}}$

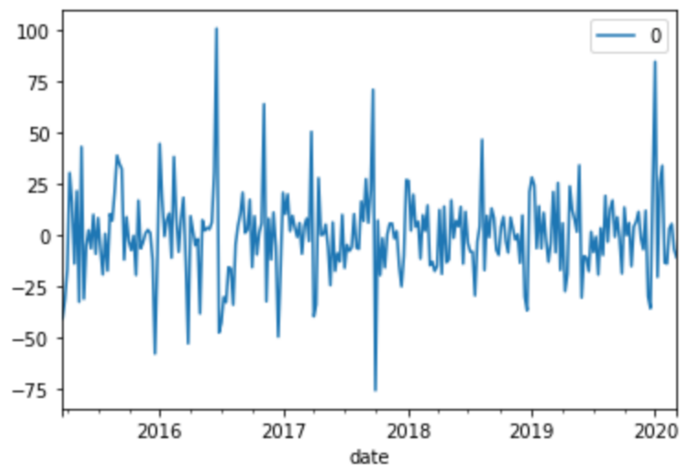

Figure 6. Residuals Line Plot GTU_{DE}

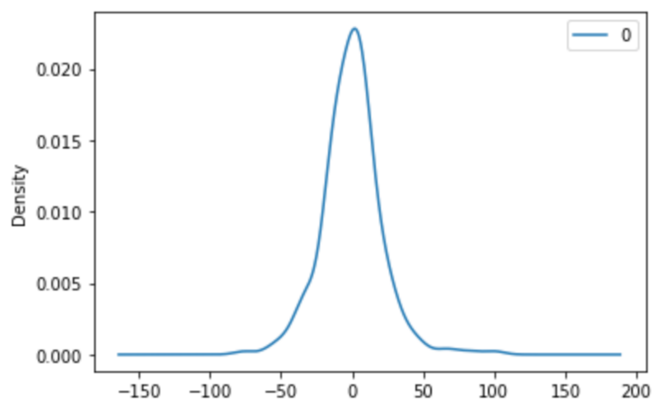

Figure 7. Residuals Density Plot GTU_{DE}

The ARIMA model with untuned parameters results in a RMSE of 18.980 (Figure 8 (a)). As the GTU_{DE} time series is stationary, the optimal degree of differencing (d) is zero, whereas the optimal lag order (p) and moving average order (q) were estimated to be two and two respectively, resulting in an ARIMA (2,0,2) model with RMSE of 18.395 (Figure 8 (b)).

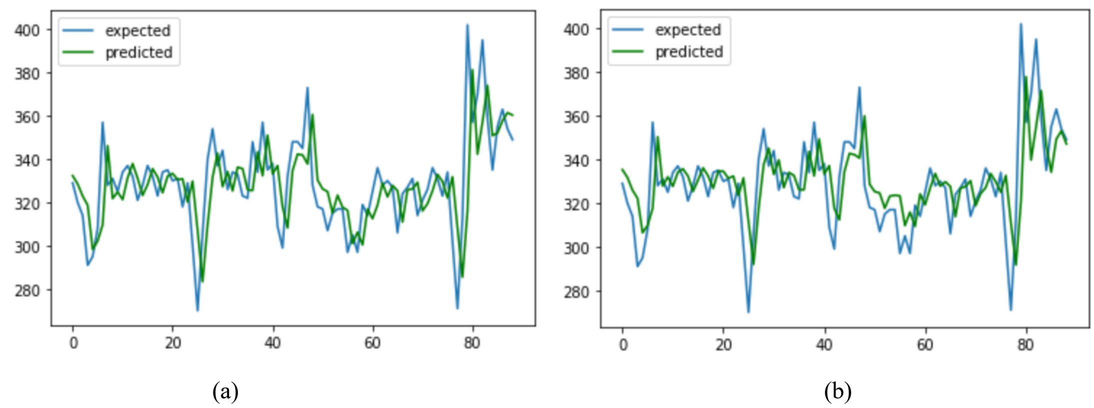

Figure 8. Untuned ARIMA, RMSE = 18.980 & Optimized ARIMA (2,0,2), RMSE = 18.395

Overall, tuning the ARIMA parameters significantly increased forecasting precision as the optimized ARIMA model reduced RMSE by 3.08% as compared to the untuned model, and outperformed the naïve persistence forecast model by 13.04%. Now that the model has been trained and its parameters tuned to minimize RMSE, it is possible to obtain a one-step out-of-sample forecast for $\mathrm{GTU_{DE}}$. In other words, it is possible to foresee the intensity of information gathering activities of terms associated with economic policy uncertainty in Germany for next week (which at the time of this analysis corresponds to the last week of February 2020). The ARIMA (2,0,2) model forecasts economic policy uncertainty increasing by 3 points (+0.82%) to a value of 369 during the last week of February 2020.

As discussed in the previous section, forecasting an increase in $\mathrm{GTU_{DE}}$ allows to have a sense of future German economic policy uncertainty, but also signals impending forecast revisions regarding economic policy uncertainty in France, Italy, and Spain. Combining the results from the impulse response functions in the previous section (Figure 4) and the forecast obtained with the ARIMA (2,0,2) model, one can speculate that forecasts for $\mathrm{GTU_{FRA}}$ should be revised upward by 0.75 points (+0.2%). Similarly forecasts for $\mathrm{GTU_{ITA}}$ and $\mathrm{GTU_{ESP}}$ should be adjusted upwards by 1.5 (+0.4%) and 1.875 points (+0.5%) respectively.

(6) Structural VAR with Sign Restrictions

Previous sections have focused on motivating and building the GTU index, implementing the index to observe uncertainty contagion patterns in the context of economically integrated countries, and then challenging the index to produce out-of-sample forecasts. This segment focuses on observing how economic policy uncertainty as captured by the GTU index affects the performance of two key macroeconomic indicators: industrial production and the rate of unemployment in Germany. This section illustrates how to implement a structural vector autoregressive (SVAR) model with sign restrictions to recover impulse response functions from a one standard deviation shock to the $\mathrm{GTU_{DE}}$ conditional on a pre-imposed order based on theoretical insights regarding the exogeneity of the variables as follows: $\mathrm{GTU_{DE}}$, Euro Stoxx 50,

10-Year German Bunds yield and, finally, the industrial production and the rate of unemployment.

In order to recover the structural shocks, the above-mentioned variables will enter the reduced form VAR model as following

$$y_t = Ay_{t-1} + B\varepsilon_t \quad \text{, for t = 1, 2, …, T} \tag{3}$$

where, y_t is the vector of endogenous variables, A is the matrix of coefficients, and $B\varepsilon_t$ is the vector of structural disturbances. The standard approach to uniquely identifying the elements of B is by using Cholesky decomposition, but for the purpose of this analysis the elements of B will be identified using sign restrictions.

The ordering of the variables is in line with the hypothesis that individuals use Google as their main information platform. The information obtained via Google is then rapidly embedded in equity markets, fixed income markets, and then reflected onto the performance of macroeconomic variables. The sign restrictions (Figure 9) arise from *a priori* theorizing that a relief from uncertainty will drive consumer confidence and encourage more spending, which will have a positive impact on company earnings and drive up share prices.

GTU_DE	Euro Stoxx 50	10-Y German Bunds	Industrial Production	Unemployment Rate
-	+	-	?	?

Figure 9. Sign Restrictions with Agnostic Assignment for Industrial Production and Unemployment Rate

The negative sign on 10-Year German Bunds is a combination of two phenomena. First, investors seeking to minimize risk via diversification will buy safe assets such as the 10-Year German Bunds, thus driving yields down to an extent. Second, and most importantly, the timeframe of the dataset used for this analysis coincides with the launch of the European Central Bank's 2015 massive bond-buying program aimed at driving European bond yields down, thus reinforcing the need for a negative sign restriction. Finally, there are no restrictions on the response of industrial production and unemployment rate such that, by design of the identification scheme, the two macroeconomic variables of interest will be completely determined by the data.

Impulse response functions were obtained using Uhlig's (2005) penalty function method, which finds the impulse vector that minimizes the total penalty incurred for violating the pre-specified sign restrictions throughout a given time horizon. More specifically, letting K be the total number of sign restrictions (in this case 3), and N be the time periods for which the restrictions apply (in this case 5), then the optimal impulse vector is the vector γ which

minimizes the total penalty $\Omega(\gamma)$ for all constrained responses $\kappa \in K$ during the constrained horizon $n \in N$. To make sure that violations are treated symmetrically across impulse responses, $\Omega(\gamma)$ was adjusted for the sign of the restrictions by assigning $\tau_\kappa = 1$ if a restriction is negative, and $\tau_\kappa = -1$ if a restriction is positive. In addition, to adjust for scale, the variables were divided by the standard error of the first differences σ_κ as in Uhlig (2005). Letting $r_{\kappa,\gamma}(n)$ be the response of k at step n to the impulse vector γ, the optimal impulse vector is the argument that minimizes

$$\underset{\gamma}{\operatorname{argmin}}\, \Omega(\gamma) = \sum_{\kappa \in K} \sum_{n \in N} \pi f(\tau_\kappa \frac{r_{\kappa,\gamma}(n)}{\sigma_\kappa}) \tag{4}$$

where π is an arbitrarily chosen scalar value for the penalty amount depending on $f(.)$ such that

$$\pi = \begin{cases} 1 & if\ f\left(\tau_\kappa \frac{r_{\kappa,\gamma}(n)}{\sigma_\kappa}\right) \leq 0 \\ penalty & if\ \ f\left(\tau_\kappa \frac{r_{\kappa,\gamma}(n)}{\sigma_\kappa}\right) > 0 \end{cases} \tag{5}$$

To summarize, one can think of this procedure as identifying the vector of impulse responses that best satisfies the assumptions motivating the sign restrictions over a specified time frame.

The output of this analysis (Figure 10) shows that low values of $\mathrm{GTU_{DE}}$ coincide with a higher level of industrial production and that a one standard deviation increase in $\mathrm{GTU_{DE}}$, that is an increase of magnitude 4 in the relative popularity of searches with economic policy uncertainty connotations in Germany, leads to a 0.3% decrease in industrial production (measured as the change in the volume of production output). Industrial production then slowly rebounds to the initial level by the 20th month after the shock, which is in line with the results in Bloom (2009), where a large temporary uncertainty shock caused a rapid drop and rebound in industrial production. However, within the 20-month horizon, the impulse response function doesn’t capture the overshoot in industrial production predicted by Bloom (2009).

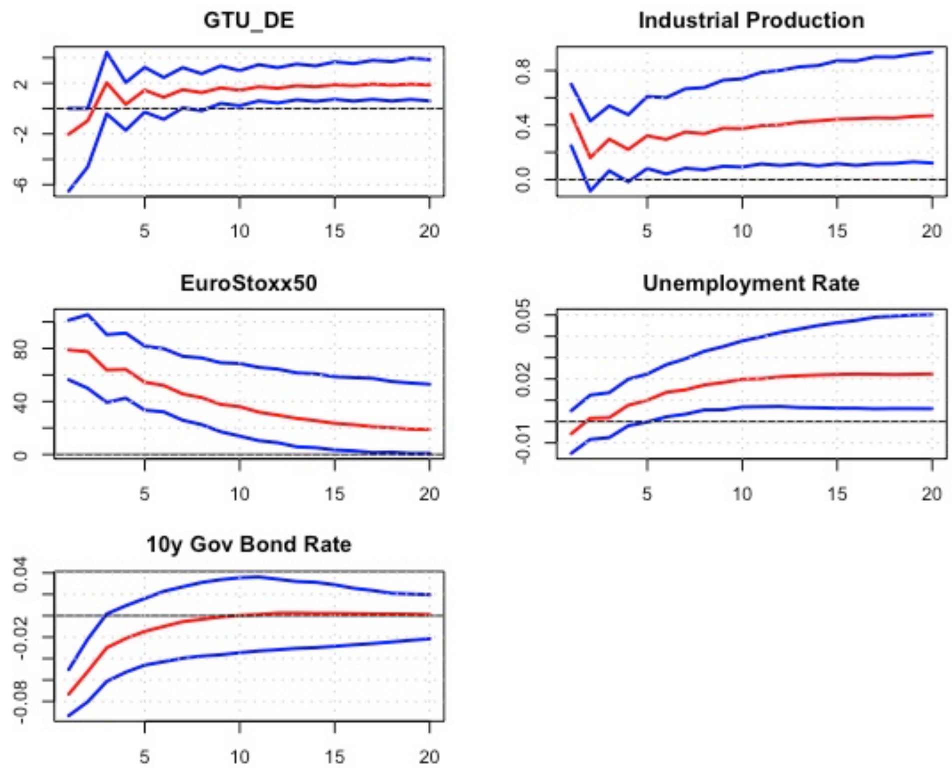

Figure 10. Impulse Response Functions on Monthly data with 68% confidence bands

For what concerns the response of the unemployment rate, a low value on $\mathrm{GTU}_{\mathrm{DE}}$ coincides with lower unemployment. Following the one standard deviation shock to the $\mathrm{GTU}_{\mathrm{DE}}$, unemployment gradually increases by 0.03% during the 10 months following the shock. Put into perspective, an increase in unemployment of this magnitude amounts to the loss of roughly 13,000 jobs.[5] Moreover, it is interesting to note that, whereas industrial production rebounded to its initial level by the twentieth month, throughout the same timeframe unemployment doesn't rebound but instead settles at a permanently higher level.

Overall, results from the structural VAR with sign restrictions yielded impulse response functions that were in line with the expected behavior of both industrial production and the rate of unemployment in times of heightened uncertainty about the economy. Therefore, the granularity of the GTU index can be leveraged to grasp a sense of the overall sentiment of the economy, and thus be used as a leading indicator for variables informing macroeconomic performance.

[5] According to the OECD, the German labor force between 2015 and 2020 amounted to an average of 43,127.72 people (in thousands). The average number of jobs lost was computed as 43,127.72 (in thousands) x 0.03% = 12,938.4. OECD (2020), Labor force (indicator). doi: 10.1787/ef2e7159-en (Accessed on 27 April 2020)

(7) Conclusion

Building on the EPU index introduced in Baker et al. (2016) and on the EURQ index from Bontempi et al. (2018), the GTU index puts forward an innovative method for quantifying the level of uncertainty regarding economic policy using Google Trends for the four largest economies in the EU bloc. The index was validated by testing its correlation with the VSTOXX, finding that the GTU moves tightly with official measures of financial volatility and especially so during periods of heightened uncertainty. In its entirety, the various elements of this research allow to accurately and unbiasedly measure economic policy uncertainty on a weekly basis, gauge the extent to which Germany, France, Italy, and Spain influence each other with regards to uncertainty surrounding economic policy, produce a one-step out-of-sample forecast, and estimate the magnitude to which uncertainty impacts the rate of unemployment and industrial production. Future directions of this research will focus on developing GTU indices for the United States, Japan, and Brazil, where Google is by far the most widely used search engine.

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Appendix A

Policy Area	**France**	**Italy**	**Spain**	**Germany**
Monetary	Euro	Euro	Euro	Euro
	taux	tasso	tasa	bewertung
	inflation	inflazione	inflación	inflation
	croissance	crescita	crecimiento	wachstum
	stagnation	stagnazione	estancamiento	stagnation
	BCE	BCE	BCE	EZB
	intérêt	interesse	interés	interesse
	monétaire	monetaria	monetario	geld
	dette	debito	deuda	schuld
	spread	spread	spread	spread
Fiscal	fiscal	fiscale	fiscal	steuerlich
	taxe	tasse	impuesto	steuern
	balance	bilancio	finanzas públicas	balance
	frais	spesa	gasto	ausgaben
	déficit	deficit	déficit	defizit
	budget	budget	presupuesto	budget
	réforme	riforma	reforma	reform
	austérité	austerità	austeridad	strenge
	fraude	frode	fraude	betrug
	récession	recessione	recesión	rezession
Political	gouvernement	governo	gobierno	regierung
	premier ministre	primo ministro	primer ministro	premierminister
	Socialiste	pd	PSOE	SPD
	Républicains	lega	Partido popular	AfD
	parlement	parlamento	parlamento	bundestag
	élections	elezioni	elecciones	wahlen
	vote	voto	voto	abstimmung
	PM	PM	PM	PM
	référendum	referendum	referéndum	referendum
	parti	partito	partido	partei
Geopolitical	militaire	militari	militar	militär
	terrorisme	terrorismo	terrorismo	terrorismus
	guerre	guerra	guerra	krieg
	armée	esercito	ejército	heer
	réfugiés	rifugiati	refugiados	flüchtlinge
	Davos	Davos	Davos	Davos
	Chine	Cina	China	China
	États-Unis	Stati Uniti	Estados Unidos	U.S
	Iran	Iran	Irán	Iran
	Syrie	Siria	Sirya	Sirya
Manufacturing/Trade	commerce	commercio	comercio	handel
	exportation	esportazione	exportación	export
	importation	importazione	importación	importe
	production	produzione	producción	produktion
	automobile	automobilistico	automotor	automobil
	tarifs	tariffe	tarifas	tarife
	quotas	quota	cuota	quoten
	fabrication	manifattura	fabricación	herstellung
	produit	prodotto	producto	freihandel
	productivité	produttività	productividad	produktivität

EU Regulation	Europe	Europa	Europa	Europa
	UE	UE	UE	EU
	Bruxelles	Bruxelles	Bruselas	Brüssel
	sanctions	sanzioni	sanciones	sanktionen
	no-deal	no-deal	no-deal	no-deal
	brexit	brexit	brexit	brexit
	BCE	BCE	BCE	EZB
	Tusk	Tusk	Tusk	Tusk
	immigration	immigrazione	inmigración	einwanderung
	intégration	integrazione	integración	integration
Domestic Regulation	union	sindacato	unión	gewerkschaften
	privatisation	privatizzazione	privatización	privatisierung
	vaccins	vaccini	vacunas	impfstoffe
	pensions	pensioni	pensiones	wohlergehen
	chômage	disoccupazione	desempleo	arbeitslosigkeit
	école	scuola	escuela	bildung
	santé	sanità	salud	gesundheit
	crime	crimine	crimen	verbrechen
	sécurité	sicurezza	seguridad	sicherheit
	allocation universelle	reddito di cittadinanza	salarios mínimos	sozialhilfe
Energy	gaz	gas	gas	gas
	combustibles fossiles	combustibili fossili	combustibles fósiles	fossiler Brennstoff
	OPEP	OPEC	OPEP	OPEC
	AIE	AIE	AIE	IEA
	échange de droits d'émission	emission trading	comercio de emisiones	emissionshandel
	CO2	CO2	CO2	kohlenstoff
	électricité	elettricità	electricidad	elektrizität
	pollution	inquinamento	polución	verschmutzung
	énergie verte	sostenibile	sostenible	nachhaltigkeit
	climat	clima	clima	klima

Appendix B

date	GTU_FRA	GTU_ESP	GTU_ITA	GTU_DE	GTU_4	VSTOXX
2015-03-01	299	368	315	359	334.6611	18.775525
2015-03-08	305	376	325	366	342.1295	19.43205
2015-03-15	305	358	316	378	342.4625	19.0831
2015-03-22	323	361	300	333	327.0897	19.237625
2015-03-29	310	318	279	308	303.696	20.929933
2015-04-05	283	365	280	306	302.2967	18.417767
2015-04-12	288	383	311	341	325.9732	20.557225
2015-04-19	287	374	319	353	330.7283	22.304675
2015-04-26	281	356	288	345	317.2299	23.459633
2015-05-03	290	388	322	368	339.887	23.707275
2015-05-10	292	371	311	323	318.4348	22.384625

2015-05-17	308	376	331	358	341.0642	19.696025
2015-05-24	287	454	317	328	331.6873	22.125
2015-05-31	283	370	301	327	315.3767	24.5715
2015-06-07	289	383	312	335	324.1251	24.427275
2015-06-14	276	360	308	351	322.8094	28.51595
2015-06-21	280	354	313	344	321.371	25.2033
2015-06-28	272	367	299	333	313.8988	31.6373
2015-07-05	275	348	303	342	316.3845	30.316125
2015-07-12	255	349	287	332	303.9865	20.15725
2015-07-19	254	349	276	312	293.7426	18.136725
2015-07-26	254	336	278	325	297.3856	20.09135
2015-08-02	247	311	273	308	284.4453	18.192175
2015-08-09	255	315	235	327	286.8035	22.7372
2015-08-16	250	310	236	334	287.671	25.4792
2015-08-23	268	326	269	359	311.1292	32.633
2015-08-30	294	360	307	382	339.4796	33.16465
2015-09-06	306	355	320	398	350.8714	31.58265
2015-09-13	302	357	318	405	352.3668	28.332975
2015-09-20	296	354	308	380	338.6224	31.7982
2015-09-27	304	375	310	378	343.3196	32.10985
2015-10-04	305	362	298	382	340.9085	25.14745
2015-10-11	297	345	302	370	332.5633	24.01435
2015-10-18	278	352	291	377	328.8582	20.8296
2015-10-25	273	342	278	362	317.6797	20.699975
2015-11-01	299	357	298	375	335.8841	20.5455
2015-11-08	306	364	301	382	342.0644	23.15805
2015-11-15	334	384	326	371	353.2276	23.61575
2015-11-22	317	354	304	378	342.7253	23.676925
2015-11-29	311	347	290	377	336.9049	22.939225
2015-12-06	322	340	261	367	329.1618	24.744725
2015-12-13	308	362	286	363	331.9322	24.842575
2015-12-20	249	339	225	303	277.1721	21.39325
2015-12-27	264	298	222	312	278.4516	22.15845
2016-01-03	326	302	251	372	324.9064	28.177025
2016-01-10	317	350	295	384	342.6683	30.29955
2016-01-17	317	354	300	383	343.8483	31.49885
2016-01-24	317	349	303	377	341.4453	28.2806
2016-01-31	322	346	288	374	338.1798	29.896575
2016-02-07	306	343	276	360	325.5774	35.352225

2016-02-14	305	352	305	405	349.8505	31.5506
2016-02-21	306	355	308	404	350.7574	30.990125
2016-02-28	308	344	290	388	339.9352	26.674225
2016-03-06	307	351	287	394	342.3433	27.04925
2016-03-13	310	347	281	407	346.417	22.43805
2016-03-20	379	367	328	383	368.1221	22.920767
2016-03-27	299	339	267	330	309.6921	23.733933
2016-04-03	292	363	289	361	327.5708	25.688525
2016-04-10	291	366	307	373	336.0119	21.89205
2016-04-17	299	348	305	369	333.7411	20.2896
2016-04-24	306	349	273	369	329.2794	21.863175
2016-05-01	286	352	296	342	318.4954	26.12615
2016-05-08	310	346	287	355	327.373	23.948325
2016-05-15	302	373	298	360	333.0998	23.689175
2016-05-22	297	351	299	348	324.2683	21.032
2016-05-29	302	358	278	358	326.1958	23.176875
2016-06-05	336	381	333	377	357.0984	25.93315
2016-06-12	375	403	353	393	380.9515	38.4868
2016-06-19	432	476	429	480	455.5638	34.497325
2016-06-26	365	429	330	406	382.1925	27.66595
2016-07-03	312	351	277	349	324.2528	26.530875
2016-07-10	268	340	255	320	295.1262	22.036425
2016-07-17	263	330	251	310	287.7097	19.980725
2016-07-24	259	312	259	310	285.7661	20.476725
2016-07-31	248	292	238	316	278.0852	21.697375
2016-08-07	234	281	216	302	262.8906	18.434225
2016-08-14	230	264	195	297	253.263	20.677325
2016-08-21	261	286	241	313	280.2269	19.988275
2016-08-28	290	308	264	333	303.528	19.2872
2016-09-04	300	313	300	349	320.427	18.69325
2016-09-11	292	321	319	340	319.7378	21.712875
2016-09-18	298	325	279	343	314.9562	18.72275
2016-09-25	305	345	307	337	322.9745	20.02015
2016-10-02	306	339	286	325	313.5104	19.466175
2016-10-09	303	317	290	332	313.1827	20.099925
2016-10-16	302	334	300	329	316.1268	17.73925
2016-10-23	283	325	283	330	306.6737	18.72515
2016-10-30	285	324	260	333	303.5695	24.251475
2016-11-06	314	404	313	405	361.0886	22.2724

2016-11-13	312	341	291	342	323.0058	20.51765
2016-11-20	314	328	300	349	326.2896	20.21935
2016-11-27	301	337	294	344	320.8569	22.1133
2016-12-04	301	306	301	347	319.1609	16.889325
2016-12-11	296	325	271	339	311.2424	16.2366
2016-12-18	257	296	239	297	273.9253	14.89575
2016-12-25	243	288	207	303	264.8547	17.652933
2017-01-01	295	296	218	331	293.1145	16.28455
2017-01-08	300	354	272	348	320.014	15.552775
2017-01-15	302	357	285	364	329.8008	14.990375
2017-01-22	301	349	276	355	323.1159	15.864075
2017-01-29	297	354	285	354	324.1623	16.3345
2017-02-05	297	366	270	352	321.9993	16.038875
2017-02-12	278	356	272	348	314.3302	14.8903
2017-02-19	289	354	278	355	320.9611	15.185325
2017-02-26	292	345	265	344	313.6358	15.5554
2017-03-05	293	370	273	347	320.1417	15.225825
2017-03-12	295	358	277	360	324.8705	13.5637
2017-03-19	296	348	275	351	319.8724	14.64625
2017-03-26	296	360	276	399	340.3074	16.105025
2017-04-02	309	355	311	347	330.1201	18.733275
2017-04-09	291	320	267	310	297.1629	23.018533
2017-04-16	290	349	263	352	316.336	24.731367
2017-04-23	325	339	254	355	323.7715	16.040025
2017-04-30	302	343	264	347	317.0268	16.9656
2017-05-07	324	343	274	362	330.8216	14.092575
2017-05-14	394	347	267	357	346.9806	15.558575
2017-05-21	275	362	287	322	307.3285	13.883275
2017-05-28	284	360	257	336	308.8186	13.995625
2017-06-04	287	356	284	323	309.5293	14.1165
2017-06-11	290	343	297	317	308.865	14.04845
2017-06-18	285	337	282	312	301.7025	14.115525
2017-06-25	276	329	256	325	297.9134	16.120825
2017-07-02	273	330	251	314	291.9667	14.93715
2017-07-09	265	324	243	308	285.0255	13.573725
2017-07-16	264	333	252	299	284.3406	13.841675
2017-07-23	255	329	250	303	282.4925	13.2839
2017-07-30	248	317	239	318	282.5122	13.505275
2017-08-06	244	307	218	313	273.8506	16.506675

2017-08-13	235	285	194	307	261.1825	15.52185
2017-08-20	252	292	233	322	280.4758	15.90805
2017-08-27	274	312	256	329	296.5736	16.033325
2017-09-03	288	335	294	349	318.9942	15.80265
2017-09-10	302	336	297	343	321.2118	12.73995
2017-09-17	294	354	279	367	327.1626	11.603775
2017-09-24	311	349	290	417	352.6609	12.228875
2017-10-01	301	372	281	320	313.7599	12.30105
2017-10-08	304	338	288	329	314.7846	12.5586
2017-10-15	311	347	297	321	316.6539	11.835375
2017-10-22	291	338	292	326	310.9139	13.222075
2017-10-29	275	335	261	317	296.3895	11.84105
2017-11-05	307	349	274	333	315.8213	13.22735
2017-11-12	308	379	267	336	319.9722	15.146125
2017-11-19	330	375	276	330	324.885	12.84875
2017-11-26	299	351	267	334	312.8961	13.976025
2017-12-03	287	326	248	329	300.4033	13.342275
2017-12-10	292	343	263	311	300.1828	12.315825
2017-12-17	281	332	252	298	288.4209	11.86265
2017-12-24	255	293	198	295	263.8725	13.56715
2017-12-31	291	305	230	327	294.1609	11.557233
2018-01-07	330	347	298	353	334.388	11.320725
2018-01-14	322	359	304	352	334.7078	11.783875
2018-01-21	317	356	297	359	334.2273	12.378025
2018-01-28	312	349	289	357	329.5088	15.91855
2018-02-04	298	351	277	346	319.2992	29.579975
2018-02-11	294	359	278	333	314.4916	21.23295
2018-02-18	293	366	310	351	328.6487	18.538625
2018-02-25	284	356	286	351	319.9586	19.886975
2018-03-04	299	360	360	362	343.8531	17.212925
2018-03-11	301	360	282	345	321.9819	15.535925
2018-03-18	299	342	265	333	310.8611	17.465875
2018-03-25	304	304	246	309	293.8266	18.6994
2018-04-01	282	356	249	311	296.4258	17.971867
2018-04-08	312	364	305	328	323.6038	16.102075
2018-04-15	293	359	280	326	311.9177	13.45595
2018-04-22	294	344	242	329	303.5656	13.71905
2018-04-29	288	335	238	318	295.6292	13.9387
2018-05-06	279	350	266	305	295.9141	13.08175

2018-05-13	300	370	293	324	317.197	13.325275
2018-05-20	293	354	286	323	311.2847	14.939775
2018-05-27	298	356	301	329	318.2822	17.94335
2018-06-03	295	363	314	335	323.3965	14.744925
2018-06-10	305	353	303	350	328.2975	12.6145
2018-06-17	288	335	288	327	309.2622	14.787125
2018-06-24	279	324	281	339	308.5291	17.368425
2018-07-01	247	327	253	330	291.1073	15.7715
2018-07-08	252	326	253	316	286.9058	13.463175
2018-07-15	248	347	245	304	282.4522	12.785
2018-07-22	249	333	234	293	274.3011	12.506075
2018-07-29	250	314	232	296	272.705	13.3725
2018-08-05	256	301	221	313	276.8824	13.27285
2018-08-12	249	339	184	358	290.1341	16.6745
2018-08-19	258	315	214	324	282.1922	13.6395
2018-08-26	277	333	260	333	302.6443	13.984775
2018-09-02	300	366	302	329	320.407	16.80745
2018-09-09	300	334	314	334	320.362	14.89985
2018-09-16	310	367	320	331	327.682	13.47125
2018-09-23	312	341	335	330	327.2938	13.487525
2018-09-30	318	346	353	322	330.1672	15.6976
2018-10-07	335	327	323	325	327.2215	19.187675
2018-10-14	328	359	373	342	346.4702	17.70135
2018-10-21	291	356	317	328	319.2469	21.958475
2018-10-28	281	316	267	317	296.6109	20.092925
2018-11-04	324	376	306	345	335.2926	16.69845
2018-11-11	331	348	298	333	327.0569	18.428075
2018-11-18	319	321	288	331	317.2761	19.11595
2018-11-25	315	345	295	329	320.1515	18.544425
2018-12-02	309	342	288	323	314.3691	20.6458
2018-12-09	297	338	297	330	315.1023	19.789875
2018-12-16	286	316	297	300	297.4764	20.1926
2018-12-23	242	287	221	271	254.9038	23.8643
2018-12-30	275	311	258	300	285.8895	21.74025
2019-01-06	316	340	338	333	330.0094	18.64585
2019-01-13	321	360	357	351	344.9469	15.584375
2019-01-20	304	351	317	335	324.7876	15.704725
2019-01-27	305	358	327	339	329.6025	15.290375
2019-02-03	304	352	291	323	315.0036	14.92015

2019-02-10	294	364	300	343	323.5176	14.575575
2019-02-17	292	374	312	332	322.5348	14.3024
2019-02-24	295	345	295	323	312.4115	13.8006
2019-03-03	294	353	280	325	310.9736	13.806625
2019-03-10	307	379	302	351	332.6113	13.589475
2019-03-17	313	355	287	334	321.3007	15.21115
2019-03-24	314	381	293	349	332.1826	16.031425
2019-03-31	304	379	271	334	318.9266	14.193975
2019-04-07	299	374	282	340	321.4371	13.317925
2019-04-14	286	310	258	305	290.6664	11.191667
2019-04-21	282	361	206	298	283.3558	12.701767
2019-04-28	288	417	252	328	313.6572	13.2624
2019-05-05	298	376	274	349	323.3012	13.3808
2019-05-12	312	362	264	355	325.4538	18.5577
2019-05-19	333	404	292	347	339.5267	16.08625
2019-05-26	352	490	356	363	375.7258	16.4078
2019-06-02	289	356	271	318	305.4971	17.032225
2019-06-09	288	354	263	318	303.3262	15.76545
2019-06-16	294	357	269	320	307.3576	14.617375
2019-06-23	283	337	278	307	298.4137	13.416675
2019-06-30	281	345	252	316	297.1809	13.974125
2019-07-07	263	327	236	317	286.9597	11.9313
2019-07-14	258	327	227	314	282.6172	12.60825
2019-07-21	246	317	222	303	272.7144	12.947975
2019-07-28	250	313	221	303	273.043	12.943
2019-08-04	243	307	219	299	268.3647	15.235
2019-08-11	245	302	187	316	268.2995	19.843575
2019-08-18	258	310	220	313	278.4632	20.9025
2019-08-25	275	326	257	316	293.9485	18.395375
2019-09-01	307	350	290	340	321.9163	18.508925
2019-09-08	306	333	305	329	318.0874	16.23905
2019-09-15	299	347	299	333	318.4531	14.71075
2019-09-22	307	351	287	318	312.9313	14.808825
2019-09-29	315	369	297	315	318.4515	16.4183
2019-10-06	341	368	292	319	325.8899	19.323175
2019-10-13	334	354	317	328	330.6196	17.732575
2019-10-20	300	352	297	326	316.299	14.88345
2019-10-27	292	337	263	310	298.9678	13.38565
2019-11-03	316	365	284	330	321.3364	13.5397

2019-11-10	303	407	272	329	320.7877	12.865425
2019-11-17	306	341	272	338	315.9754	12.35995
2019-11-24	308	335	281	332	315.1942	12.83
2019-12-01	294	322	270	321	303.1176	13.36
2019-12-08	298	330	284	334	313.1782	14.56
2019-12-15	282	314	264	300	289.4178	12.14
2019-12-22	242	279	190	271	247.5068	11.74
2019-12-29	301	325	246	314	297.8469	12.92
2020-01-05	374	364	360	405	381.3636	15.45
2020-01-12	324	375	313	357	341.2196	12.73
2020-01-19	355	376	325	370	357.2225	11.26
2020-01-26	355	409	352	396	377.3195	15.68
2020-02-02	328	386	285	354	336.9762	17.06
2020-02-09	313	367	287	340	325.2787	13.97
2020-02-16	300	381	303	356	333.129	13.22
2020-02-23	323	397	325	366	349.9037	21.71