Nowcasting Latin America
Measuring consumer confidence using Google Trends

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Abstract

In a fast-paced world, the macroeconomic reporting gap limits the effectiveness of policy interventions. Research on developed economies has shown that internet browsing habits can provide an indication of the current state of consumer behavior. To extend this observation to emerging markets, this study explores whether incorporating Google search data improves the predictive accuracy of the near-term forecasts (*nowcasts*) of consumer confidence in the five biggest Latin American economies. Using Bayesian Structural Time Series as the method of choice, I find that, for most countries, models with Google regressors outperform the benchmark specification in both the in-sample and out-of-sample nowcasts. The results also indicate that incorporating such regressors may be particularly suitable to detect shocks to consumer confidence in real time.

Keywords: Consumer confidence, nowcasting, Bayesian Structural Times Series, Latin America

List of Abbreviations

API – Application Programming Interface

BMA – Bayesian Model Averaging

BSTS – Bayesian Structural Times Series

COVID-19 – Coronavirus

CSI – Consumer Sentiment Index

GDP – Gross Domestic Product

MCMC– Markov Chain Monte Carlo

SVI – Search Volume Index

1 Introduction

Delays in data releases of macroeconomic indicators limit the effectiveness of economic policies by failing to provide an accurate picture of current conditions. This is particularly the case in emerging market economies, where the lag in data releases reduces business opportunities and gives rise to inefficiencies in public service interventions (World Bank 2016; Liu, Matheson, and Romeu 2012). An increasingly promising solution to this issue is nowcasting or 'contemporaneous forecasting', which consists of predicting the current or the very near future state of an economic indicator (Hueng 2020). In essence, an efficient nowcasting model will account for the past behaviour of the series of interest, as well as the values of readily available signals (Scott and Varian 2013b). In the past decade, an influential body of research has emerged suggesting the use of Google's Search Volume Index (SVI), better known as Google Trends, as the signal of choice for macroeconomic nowcasting.

In this study, I assess the usefulness of Google Trends categories to nowcast consumer confidence in the five biggest Latin American economies. I chose consumer confidence because it has proved to be a good predictor of economic wellbeing in the region (Julio and Grajales 2011; Vega 2015). Consumer confidence is also the most frequently released indicator across countries in Latin America. Despite the availability of data and the surge in new methodologies, no paper to my knowledge has nowcasted consumer confidence in any Latin American economy.

To answer this question in uncharted territory, I choose to employ Bayesian Structural Time Series (BSTS), a method pioneered by Scott and Varian (2013b) to nowcast economic series using Google Trends specifically. BSTS offers the possibility to combine time series with a Bayesian shrinkage prior to capture movements that could be explained by a regression component. A clear advantage of this Bayesian analysis is that it returns a marginal posterior probability of inclusion for each Google predictor as well as a graphical breakdown of how each component of the model, trend, seasonality, and regression; has contributed to the state of the series.

The main finding of this study is that incorporating Google Trend categories as regressors in the BSTS model improves the accuracy in both the in-sample and out-of-sample nowcasts for most countries. The usefulness of the regression component varied widely across countries as reductions in the test error ranged from 1% to 203%. However, across geographies, the regression component was particularly good at capturing abrupt shocks to consumer confidence, such as the COVID-19 pandemic. Another interesting result is that when economic shocks occur too often (i.e., more than

once in a two-year period), incorporating Google Trends categories as regressors does not improve the predictive accuracy of the nowcast. Instead, in such cases, it is more useful to simply rely on the underlying trend of the series to nowcast consumer confidence.

The remainder of paper proceeds as follows. Section 2 offers a literature review on consumer confidence and nowcasting. Section 3 outlines the research question and main objectives of the study. Section 4 describes Google Trends and the different conceptualizations of consumer confidence across the sample countries. Section 5 describes the methodology of choice, Bayesian Structural Time Series, and each of its elements. Section 6 provides an exposition of all the results and Section 7 offers their interpretation. Section 8 offers some concluding remarks.

2 Literature Review

2.1 Consumer Confidence

To provide a more frequent and accurate measure of consumer confidence, we first need to understand its origin and meaning. The concept of consumer confidence goes back to the 1940s, when George Katona developed the Michigan Consumer Sentiment Index (CSI) (Curtin 2002). The index is based on the adaptive theory of consumer behavior, in which consumers' spending depends on their "willingness and ability to buy" (Katona 1951). In this context, spending only entails discretionary purchases[1]. In terms of *ability to buy,* Katona not only refers to income but also credit access and wealth, and in terms of *willingness* he means consumers' assessment of future economic prospects (Katona 1968).

Moreover, Katona originally conceptualized consumer spending to be a broad measure of expected changes in income. According to Curtin (2002), "it was not simply the expected size of a consumers' future income, but the certainty or uncertainty that was attached to those expectations". Thus, a key feature to understand consumer confidence surveys is they do not only seek measure expected levels of income, but also its variation.

The core questions used to gauge consumer sentiment are based on Katona's foundational work. The surveys vary slightly by country, but typically one can expect to find both retrospective and prospective questions on the surveys. Retrospective questions compare consumers' current

[1] Consumers can make either necessary or discretionary purchases. Necessary purchases occur routinely and not much thought goes into them. On the other hand, discretionary purchases are rather infrequent. This might entail, for instance, the purchase of a home, a vehicle, or household durables. Discretionary purchases are typically planned, and so they are "the type of purchases that would reflect both current economic conditions as well as expected future changes" (Curtin 2002).

financial situation to the past whereas prospective questions look to assess their expectations for future income based on current economic conditions (Acuña 2021). In general, one can expect any index to be based on the responses to five questions: two questions of personal finances, two on the outlook of the economy, and one question on buying conditions for durable goods (Curtin 2002). These questions are not intended to establish the absolute level of consumer confidence at any given point in time, instead they intend to measure the degree to which such confidence has changed (Curtin 1982).

In Latin America, a region where, on average, a country's consumption accounts for more than two thirds of gross domestic product (GDP) (World Bank 2019), it is of pivotal importance to have robust and frequent measures of consumer confidence. In the region, most consumer confidence questionnaires are built upon the University of Michigan's CSI (Zerda, 2019; Suarez *et al.*, 2016). Moreover, across time and geography, the indices developed form these surveys have proved to be good predictors of GDP growth and consumption measures (Matsusaka and Sbordone, 1995; Julio and Grajales, 2011; Vega, 2015), making them even more relevant for effective policy-making in times of economic shocks.

2.2 Nowcasting and Google Trends

In the past decade, an influential body of research has emerged suggesting how to reduce the lag in macroeconomic reporting through the use of Google's Search Volume Index (SVI), better known as Google Trends. In their seminal paper, Choi and Varian (2012) make use of Google Trends to forecast the current level of economic activity in the home, automobile, travel, and retail markets across the United States. Using a simple linear autoregressive model, they show that including Google query variables increases the predictive accuracy of the model. Building upon this result, several papers have studied the link between Google Trends data and unemployment (Nagao, Takeda, and Tanaka 2019; González-Fernández and González-Velasco 2018; Askitas and Zimmermann 2009), as well as economic activity (Askitas et al. 2017; Woloszko 2020; Ferrara and Simoni 2020), consumption (Woo and Owen 2019; Vosen and Schmidt 2011; Fasulo, Guandalini, and Terribili 2017), and stock market activity (Hu et al. 2018; Tetlock 2007).

The number of that employ Google Trends to nowcast consumer confidence is, however, rather limited. Among the few available, we find the study by Della Penna and Huang (2009), in which a consumer confidence index is constructed using Google's SVI. In this paper, the authors recognize that direct correspondence between Google searches and survey questions is not

feasible, so they hypothesize the relationship between a broad set of Google Trends Categories and consumer confidence. The final index only includes the variables that match the hypothesized values across a panel of ten high income countries. Finally, Della Penna and Huang conclude that when it comes to forecasting consumer spending, the Google search-based index outperforms the commonly used Michigan Consumer Sentiment Index and Conference Board Consumer Confidence Index.

Another relevant study is the one by Zhang (2017). He employs a spike-and-slab regression, a Bayesian variable selection technique, to choose Google Categories that are relevant to measure consumer confidence in Sri Lanka[2]. Zhang finds that incorporating Google Trends data from the two categories into a simple autoregressive model improves the in-sample forecasting and out-of-sample forecasting of consumer confidence.

Finally, another important paper is the one by Scott and Varian (2013b). The authors nowcast consumer confidence, retail sales and unemployment claims in the United States. In this study, Scott and Varian focus on showing the benefits of using Bayesian Structural Time Series, an ensemble of statistical methods, and Google Trends to nowcast these series of indicators. They find that this approach to nowcasting different indicators reduces the cumulative absolute nowcast errors. They also find that the method is not perfect at choosing relevant predictors, and that some amount of subjectivity is needed to remove anomalies from the training data.

3 Research Design

The main gap in the nowcasting literature is its exclusive focus on the United States and European countries (Narita and Yin 2018). Despite the richness of data, there are almost no studies focusing on Latin America. To the best of my knowledge, only one paper nowcasts automobile sales in Chile (Carrière-Swallow and Labbé 2010) and there are no studies nowcasting consumer confidence in the region. I aim to address this gap in the literature by focusing on the five biggest Latin American economies, namely, Brazil, Mexico, Argentina, Colombia and Chile[3]. To this end, the primary aim of this study is to answer the following research question: *To what extent can Google's Search Volume Index improve the prediction accuracy of consumer confidence nowcasts in Latin America?* With this goal in mind, I focus on using Bayesian Structural Times Series, a

[2] Interestingly, the categories with the most predictive power that emerged from the Bayesian approach where Motorcycles and Birth Control.
[3] Measured in terms of Gross Domestic Product (World Bank 2019).

statistical technique developed for economic time series forecasting, as the method to help me answer this question. A secondary aim of this study is to compare the usefulness of the Google's SVI in improving the nowcast of consumer confidence before and during the COVID-19 pandemic. I hypothesize that incorporating Google's SVI into the nowcast should improve model performance in both time periods.

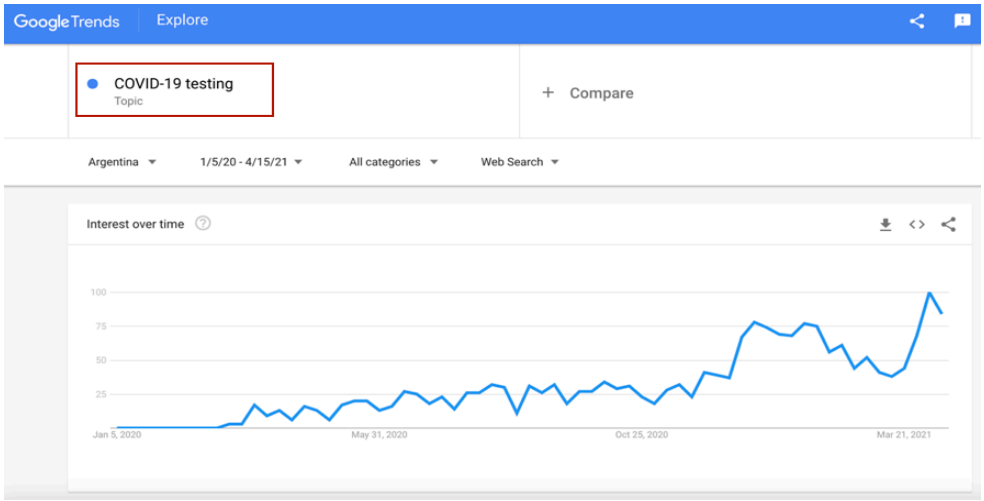
4 Data Collection

4.1 Google Trends

Google Trends is a Google-powered website that gives access to the browser's Search Volume Indices (SVI). The SVI represents the number of search queries on the Google search engine for a particular keyword. It is provided on a range that goes from 0 to 100, so that 100 represents the maximum query share in a particular time period relative to the number of all searches in a given geography (Choi and Varian, 2012; Narita and Yin, 2018; Woloszko, 2020). One important aspect of keyword searches is that they are sensible to language differences[4] and homographs[5]. To address this issue, Google uses natural language processing methods to match queries with broad topics or categories to provide a more accurate representation of users' interests (Stephens-Davidowitz and Varian 2015). Figure 1 shows a topic-based query (Panel A) and a category-based query (Panel B) in Google Trends.

Figure 1: Google Trends Interface

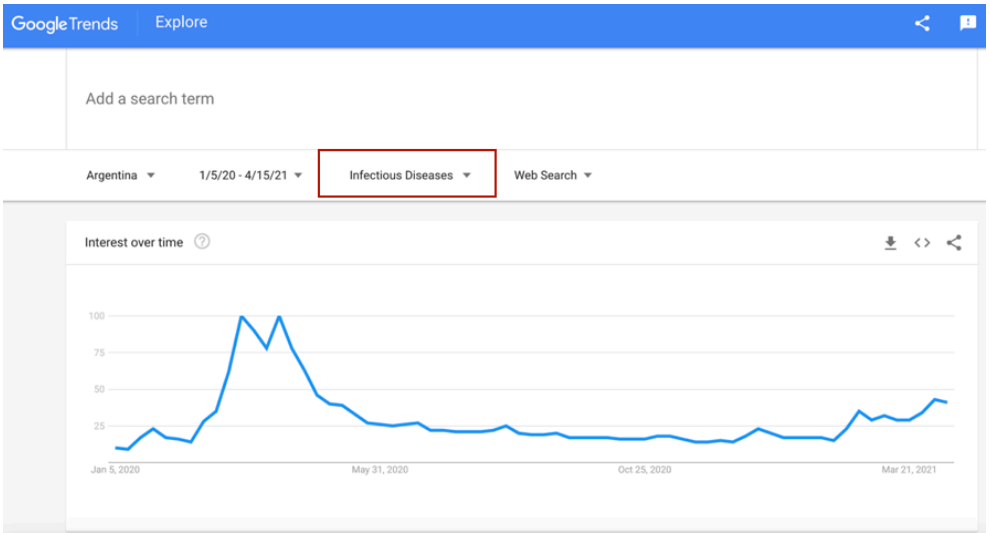
Panel A: Topic-based query in Google Trends (*COVID-19 testing in Argentina*)



[4] Looking into consumer confidence in Spanish "confianza del consumidor" and then in Portuguese "confiança do consumidor" would yield quite different results.

[5] Series for the word "apple" would mix up queries for the fruit and the company (Stephens-Davidowitz and Varian 2015).

Panel B: Category-based query in Google Trends (*interest in infectious diseases in Argentina*)

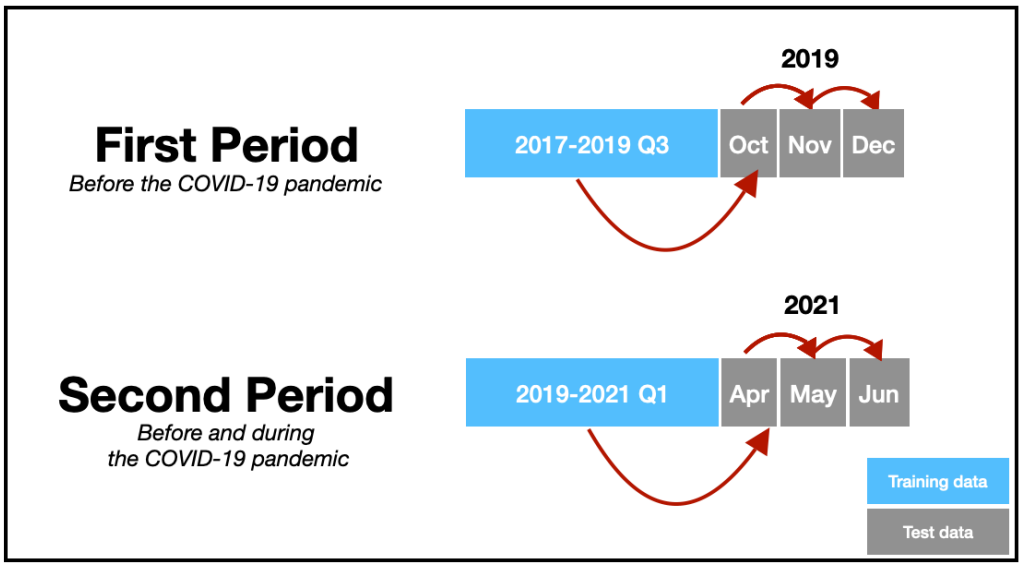


Even though categories and topics provide a solution for the keyword's limitations, there is still no consensus on how to optimally select categories or topics for parameter estimation (Kohns and Bhattacharjee 2020) or how to choose amongst them. The methods used on the studies covered in the literature section fall into: (i) use of economic intuition and backward induction to choose set of relevant keywords (Carrière-Swallow and Labbé 2010; Askitas and Zimmermann 2009), (ii) inclusion of all categories to be filtered as part of data pre-processing (Zhang 2017), and (iii) combining both categories and an arbitrary set of topics (Woloszko 2020; Narita and Yin 2018).

It has been previously shown that one cannot find one-to-one correspondence between consumer confidence surveys and Google Trends categories (Penna and Huang 2009). For this reason, I collect the weekly time series of the SVI for each country using the entire set of 1,425 categories predetermined by Google Trends. Because I have monthly values of consumer confidence, I take the average SVI of each category between the last two weeks of the previous month and the first two weeks of the current month. In other words, the SVI of each category during April 2021, would be the average SVI of each category between the last 2 weeks of March and the first two weeks of April. By adding this lag, I make sure that the SVI roughly coincides with the timing of the consumer confidence surveys' and that there is one SVI value for each value of consumer confidence.

It is also important to note that one cannot retrieve weekly data for a period longer than five years. Also, since search intensity is standardized by Google based on the maximum value during the retrieval period, it is difficult to join the search SVI retrieved over multiple five-year periods to construct a consistent weekly estimate (Nagao, Takeda, and Tanaka 2019). Given this constraint and the aim to evaluate the prediction of consumer confidence before and during the current pandemic, I opted to partition the data as shown in Figure 2.

Figure 2: Google Trends Data Partition



As shown above, 143 weeks of data are used as training data to predict consumer confidence in October 2019 and April 2021, respectively. After nowcasting each month, the actual observation is incorporated into each model to nowcast the following month (as indicated by the red arrows). By taking two different time periods, I am able to compare model performance in a pre-pandemic and pandemic world. The reasoning behind having periods no longer than two years was based on the fast-changing nature of the economy. In other words, the categories that have an impact on consumer confidence today, may not be the same as the ones that did five years ago. Finally, 2017 was taken as the starting year of the first period based on internet penetration in the countries of interest. By this year, at least 60% of all the individual in each country were active internet users (World Bank 2019).

4.2 Local Measures of Consumer Confidence

To assess the performance of a prediction of consumer confidence, we need to take the indices developed by the countries of interest as a benchmark. These indices are in fact the dependent variable of this study. Table 1 provides an overview of the topics that each country uses to measure consumer confidence. If specified, the table also shows the time at which the indicator is released.

Table 1: Consumer Confidence Survey Topics in the Five Biggest Latin American Economies

Country	Consumer Confidence Topics	Released	Source
Argentina	1) Current personal economic situation. 2) Future personal economic situation in the short term (12 months) 3) Future economic situation of the country in the short term (12 months) 4) Future economic situation of the country in the medium term (3 years) 5) Purchase of home appliances or household items.	The last week of every month (for the current month)	CIF Universidad Torcuato Di Tella
Brasil	1) Current personal economic situation. 2) Curent economic situation of the country. 3) Future personal economic situation in the short term (6 months). 4) Future economic situation of the country in the short term (6 months) 5) Purchase of home appliances or household items	The first week of every month (for the previoius month)	Fundaçao Getulio Vargas
Chile	1) Current personal economic situation. 2) Current economic situation of the country. 3) Future economic situation of the country in the short term (12 months). 4) Future economic stability of the country in the long term (5 years). 5) Purchase of home appliances or household items.	Not specified	Universidad del Desarrollo
Colombia	1) Current personal economic situation. 2) Curent economic situation of the country. 3) Future personal economic situation in the short term (12 months). 4) Future economic situation of the country in the short term (12 months) 5) Purchase of home appliances or household items	The first week of every month (for the previoius month)	Fedesarrollo
Mexico	1) Current personal economic situation. 2) Future personal economic situation in the short term (12 months). 3) Future economic situation of the country in the short term (12 months) 4) Inflation and unemployment in the country within the next year. 5) Purchase of home appliances, normal goods, and luxury goods.	The first week of every month (for the previoius month)	Instituto Nacional de Estadistica y Geografia (INEGI)

From the table above, it is worth highlighting that although all surveys consist of the five core topics used in the Michigan's CSI, the framing varies slightly across countries. For instance, Mexico's survey includes a question addressing inflation and unemployment expectations, whereas most countries simply ask about economic conditions more broadly. Moreover, some countries ask their citizens to reflect upon the economic conditions in the near future (i.e., 6 months), whereas others ask people to express their confidence on the economy in the medium term (i.e., 3-5 years).

These subtle differences on how each country defines consumer confidence implies that an overarching model of consumer confidence for the entire region might come with limitations. In Section 6, I compare the performance of models that perform variable selection of Google Trends categories for each country versus the models that take the same constraint set of categories for all countries.

5 Methodology

The main challenge that arises from using Google Trends is that it is difficult to determine exactly which categories are the most predictive to measure and predict consumer confidence. As mentioned in Section 2, Google Trends classifies queries into 1,425 categories. However, this is still a large set of possible predictors and considering all of them might lead to overfitting or spurious correlation (Varian 2014).

Inspired by the dimensionality challenge that Google Trends pose to developing estimates of macroeconomic indicators, Scott and Varian (2013b; 2013a) designed an integrated system of three statistical methods named Bayesian Structural Time Series (BSTS). The three components of BSTS are: (i) a structural time series model with Kalman Filters used for parameter estimation, (ii) a spike and slab regression for variable selection, and (iii) Bayesian model averaging. The underlying idea of this model is to combine time series, which is useful to capture trends and seasonality, with a Bayesian shrinkage prior to capture irregular movements explained by a large regression component (Kohns and Bhattacharjee 2020).

5.1 Structural Time Series and the Kalman Filter

5.1.1 Basic Structural Model

A basic structural time series model is one that consists of readily interpretable components. Typically these components consist of trend, seasonality, and an error (A. C. Harvey and Peters 1990). The trend is simply an increasing or decreasing pattern over time, seasonality consists of repeating cycles and the error captures the random variation in the series[6]. Given these components, the structural time series are simply "regression models in which the explanatory variables are functions of time and the parameters are time-varying" (A. C. Harvey and Shephard 1993). In addition, a regression component, with a non-time-varying parameter, can be added to the basic structural model to capture irregular movements (Scott and Varian 2013b). This model can be written as:

$$y_t = \mu_t + \tau_t + \beta^T \mathbf{x}_t + \varepsilon_t \,, \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \tag{1.1}$$

Where y_t is the level of consumer confidence and the independent variables μ_t, τ_t, $\beta^T \mathbf{x}_t$, ε_t are the trend, seasonal, regression, and error components at time *t*, respectively. As originally proposed by Harvey and Peters (1990), the process of generating a trend can be regarded as a "local approximation to a linear trend", which in turn can be expressed as shown in 1.2-1.3.

$$\mu_t = \mu_{t-1} + \delta_{t-1} + u_t \,, \qquad u_t \sim N(0, \sigma_u^2) \tag{1.2}$$

$$\delta_t = \delta_{t-1} + v_t \,, \qquad v_t \sim N(0, \sigma_v^2) \tag{1.3}$$

Further, the process of generating a seasonal component is described in equation (1.4).

$$\tau_t = -\sum_{s=1}^{S-1} \tau_{t-s} + w_t \,, \qquad w_t \sim N(0, \sigma_w^2) \tag{1.4}$$

The seasonal component τ_t can be thought of as a set of S dummy variables that change slowly, but that are constrained to have zero expectation over any *s* consecutive time periods (Scott and Varian 2013b; A. C. Harvey and Peters 1990).

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[6] For illustration purposes, Figure 1 in the Appendix shows the decomposition of the consumer confidence time series in Argentina between 2015-2021.

5.1.2 State-Space Representation

The state-space representation of a model consists of a set that contains all the possible states of a system. Any given observation in the system would be the addition of signal and noise. The signal is simply the linear combination of a set of variables, known as state variables, which constitute the state vector at a given point in time (Chatfield and Xing 2019).

The time series model specified in Equations 1.1-1.4 can be written in state space form (SSF) (Durbin and Koopman 2013). This abstraction of the structural time series provides powerful tool which eases the handling of the model. In particular, it will enable the computation of the optimal estimate of the unobserved state given the consumer confidence data (Chen and Brown 2013). The general SSF consists of a measurement equation and a transition equation. The measurement equation (2.1) describes the observed time series y_t and the unobserved latent state $\boldsymbol{\alpha_t}$, whereas the transition equation (2.2) describes the predicted state or, in other words, the evolution of the state variable over time (Zhang 2017; Osborn and Harvey 1991).

$$y_t = \mathbf{Z}\boldsymbol{\alpha}_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, H_t) \tag{2.1}$$

$$\boldsymbol{\alpha}_t = \mathbf{T}\boldsymbol{\alpha}_{t-1} + \boldsymbol{\eta}_t, \qquad \boldsymbol{\eta_t} \sim N(0, Q_t) \tag{2.2}$$

The state-space representation of the structural time series can be easily derived using equations 1.1-1.4 and equations 2.1-2.2. For simplicity, suppose that there are four seasons,$S = 4$, then the measurement equation can be expressed as in equation 3.1 and the transition equation is given by equation 3.2.

$$y_t = (1\ 0\ 1\ 0\ 0)\begin{pmatrix} \mu_t \\ \delta_t \\ \tau_t \\ \tau_{t-1} \\ \tau_{t-2} \end{pmatrix} + \varepsilon_t \tag{3.1}$$

$$\boldsymbol{\alpha}_t = \begin{pmatrix} \mu_t \\ \delta_t \\ \tau_t \\ \tau_{t-1} \\ \tau_{t-2} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & -1 & -1 & -1 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix}\begin{pmatrix} \mu_{t-1} \\ \delta_{t-1} \\ \tau_{t-1} \\ \tau_{t-2} \\ \tau_{t-3} \end{pmatrix} + \begin{pmatrix} u_t \\ v_t \\ w_t \\ 0 \\ 0 \end{pmatrix} \tag{3.2}$$

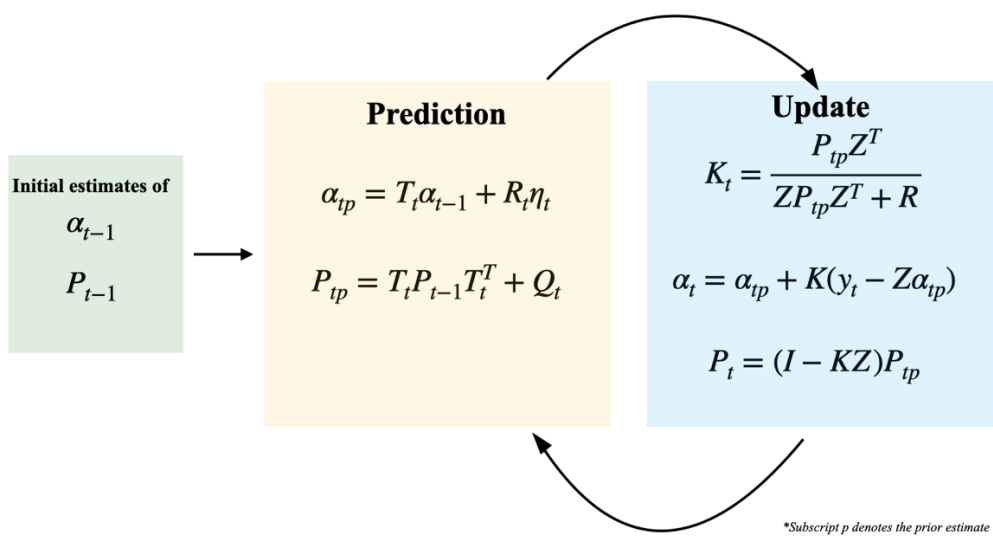
As shown in equation 3, the SSF matrices Z_t and T_t consist of known values, in practice however, it might be the case that these matrices are a mix of known values and unknown parameters. Moreover, $\eta_t^T = (u_t, v_t, w_t, 0, 0)$ contains independent components of white noise (Scott and Varian 2013b). It is also worth highlighting that the SSF is mostly composed of known values, indeed the parameters that we are trying to estimate appear in Q_t ,which is a constant diagonal matrix with diagonal elements $\{\sigma_u^2, \sigma_v^2, \sigma_w^2, 0 , 0\}$ and H_t , a constant consisting of $\{\sigma_\varepsilon^2\}$ (Perktold, Seabold, and Taylor 2021).

A missing ingredient in the state space model specified in (3.1-3.2) is the regression component. As suggested by Scott and Varian (2013b), one convenient way of adding it is by appending a constant 1 to each α_t, and append $\beta^T \mathbf{x}_t$ to Z_t in the observation equation.

5.1.3 Kalman Filter

Once a model is in its SSF, the way is open to implement a series of relevant algorithms to solve the nowcasting problem at hand. A commonly used algorithm to solve state space that requires relatively small computational power is the Kalman Filter (Chen and Brown 2013; Kim and Bang 2019). The Kalman filter is an optimal estimation algorithm that, conditional on past information, yields the minimum mean square estimator of the state vector $\boldsymbol{\alpha_t}$ along with its mean square error (MSE) matrix. Then, this outcome is used to generate the one-step-ahead predictor of y_t and its MSE matrix (Proietti 1991). An explanation of the algorithm is shown in Figure 3.

Figure



As shown in Figure 3, the Kalman filter involves a two-step iterative process. First, it generates prediction estimates of the current state variables in $\boldsymbol{\alpha_t}$ and the predicted error covariance $\boldsymbol{P_t}$,

which is simply the uncertainty associated with such estimates. In the second step, the previous estimates of $\boldsymbol{\alpha_{tp}}$ and $\boldsymbol{P_{tp}}$ from the prediction stage are used to find the posterior estimates of the state and error covariance. The Kalman gain $\boldsymbol{K_t}$ is calculated such that it minimizes the posterior error covariance $\boldsymbol{P_t}$. It does so by weighting how much the prior estimate $\boldsymbol{\alpha_{tp}}$ and the observation $\boldsymbol{y_t}$ contribute to the calculation of α_t (Zhang 2017). The Kalman filter takes care of the components of the times series state. Next, we turn our attention to the regression component and determine which predictors are the most relevant to nowcast consumer confidence.

5.2 Spike and Slab Regression for Variable Selection

Until now we have focused on how to deal with the time series aspect of nowcasting consumer confidence. We established how to write the structural time series (Equations 1.1-1.4) in its state space form (Equations 2.1-2.2) to estimate its parameters using the Kalman filter. Now, we turn our attention to the regression component $\beta^T \mathbf{x}_t$. As mentioned before, an issue that arises from incorporating Google Trends categories into our model is that the number of predictors p far exceeds the number of observations.

To address this issue, we use spike-and-slab regression. The spike-and-slab regression enables us to reduce a large set of independent variables into a parsimonious model while also incorporating prior beliefs on it. Moreover, by "using priors on the regression coefficients, the model incorporates the uncertainties of the coefficient estimates" (Larsen 2016) which yields an interval of potential values for the nowcast.

As the name suggests, the spike-and- slab regression consists of two parts. The first part is the spike, which consists of the prior probability of the regression coefficients being nonzero. To better understand it, let γ be a vector of length p (the number of predictors) having a Bernoulli distribution where $\gamma = 1$ if $\beta_k \neq 0$, and $\gamma = 0$ otherwise. At the start, we make a draw from vector γ knowing that all variables are equally likely to have non-zero coefficients. Since it is extremely complex to assign priors to each category of Google Trends, one can constraint the model to have p non-zero predictors so that the prior probability of inclusion becomes p/K, where K is the dimension of $\mathbf{x}_t$ [7](Scott and Varian 2013b).

[7] Another strategy suggested by Scott and Varian (2013b) is to set the prior of certain variables to either 0 or 1 to force certain variables to be in or out of the model. This approach is also explored in Section 6.

The second part is the slab, which consists of the prior describing the possible range of values that a coefficient can have. In other words, once we condition for a variable being included in the regression component, we draw from a normal prior to determine the probability that a variable ends up with certain coefficient (Varian 2014; Larsen 2016). The spike-and-slab prior can be written as:

$$p(\beta, \gamma, \sigma_\varepsilon^2) = p(\beta|\gamma, \sigma_\varepsilon^2)p(\sigma_\varepsilon^2|\gamma)p(\gamma) \tag{4}$$

By combining the two draws from both priors we obtain a draw from the posterior distribution on the probability of inclusion and the coefficients (Varian 2014; Scott and Varian 2013a). This process will be repeated thousands of times using a Markov Chain Monte Carlo (MCMC) algorithm. Monte Carlo sampling simply entails drawing a sample at random from a specified distribution. In contrast, in MCMC the draw of each sample is dependent on the previous one, which is known as a Markov Chain. In this way the algorithm simulates from the posterior distribution, which results in a table summarizing the probability of inclusion of each variable and the posterior distribution of their respective coefficients.

5.3 Bayesian Model Averaging

As described above, we estimate the model by sampling its parameters thousands of times from their posterior distribution. The main reason behind the iteration of the spike-and-slab regression is that we want to account for model uncertainty. Doing so, paves the way for Bayesian Model Averaging (BMA) over the space of time series regression (Scott and Varian 2013a). BMA refers to the process of estimating a model parameter under each model $\mathcal{M}_i$ and then averaging the estimates using weights determined by how likely a model is (Wasserman 2000; Hinne et al. 2020). In our case, the parameter of interest is y_{t+1}, that is, the nowcast of consumer confidence. Equations 5.1 and 5.2 show how the posterior density of y_{t+1} and the posterior expected value y_{t+1} of are obtained. The posterior density of y_{t+1} is calculated by estimating the density of y_{t+1} under model $\mathcal{M}_i$ and multiplying it by the weight, which is represents how likely it is that model $\mathcal{M}_i$ generated the data.

$$p(y_{t+1}|data) = \sum_{m}^{2^n} p(y_{t+1}|\mathcal{M}_i, data)\, p(\mathcal{M}_i\, |data) \tag{5.1}$$

$$E(y_{t+1}|data) = \sum_{m}^{2^n} E[y_{t+1}\mathcal{M}_i, data]\, p(\mathcal{M}_i\, |data) \tag{5.2}$$

An added benefit of using BMA is that the nowcast of y_{t+1} would not consist of a single value but instead a range of possible values and how likely they are. Another advantage of using BMA is that it improves the predictive performance of the out-of-sample forecast (Hoeting et al. 1999) and could therefore, lead to more accurate nowcasting predictions.

5.4 Estimating the Model

To summarize, throughout sections 5.1-5.3, I have described an integrated system of statistical methods named Bayesian Structural Time Series. This system is composed of a times series model in state space form, Kalman filters, spike-and-slab regression, and model averaging. Not only do all of these models interact well together, but they also have a natural Bayesian interpretation (Scott and Varian 2013a). To nowcast, we are interested in estimating γ, the vector indicating which Google Categories variables are relevant, β, which is a vector with the regression coefficients of those variables, the variances of the error terms $(\sigma_\varepsilon^2, \sigma_u^2, \sigma_v^2, \sigma_w^2)$, and the posterior density of y_{t+1} and its expected value.

6 Results

To simplify the presentation of results, I decided to present an in-depth account of how I obtained the results for Mexico. Then, I proceed to show concisely the results obtained for the remaining countries. Thus, the results section is divided in two parts: Section 6.1 contains Mexico's results exclusively and Section 6.2 contains the overall results.

6.1 Mexico's Results

To assess whether Google's SVI improves the accuracy of the consumer confidence nowcast, I first nowcast consumer confidence without Google's categories as regressors. In other words, I estimate consumer confidence using BSTS without the regression component $\beta^T \mathbf{x}_t$. This model is fit using 1000 MCMC iterations, then the first 100 iterations are discarded as burn in. The time series component of the model matches Equation 1.1-1.4, in that it includes both a local linear trend and an annual seasonal component with $S = 12$ months.

After producing the benchmark model, I run two other BSTS models using two different approaches to the treatment of the prior probability of inclusion of the Google's variables. First, as mentioned in Section 5.2, I constraint the model to have five non-zero predictors so that the prior inclusion probability of any variable would be the number of predictors over the number of Google Trends categories. Originally, there were 1,425 Google Trends Categories. However, after

including only the ones that had at least one non-zero value, only 915 categories remained. Thus, for Mexico, the Google Trend categories in the BSTS model had a prior probability of inclusion of 5/915 = 0.0055.

In the second approach, instead of having a uniform probability distribution for all the Google categories, I assign a prior probability of 0 to almost all categories except for five categories in the first period and seven categories in the second period. I chose these categories based on the core questions of consumer confidence but chose to add two extra categories related to COVID-19 in the second period, as the pandemic has shown to affect levels of consumer confidence (Deimante et al. 2021). Table 2 shows the mapping of the consumer confidence topics to Google Trends categories. It also shows sample queries on each category in Mexico during the sample periods.

Table 2: Consumer Confidence Survey Topics and Google Trends Categories

Consumer Confidence Topic	**Google Trends Category**	**Sample Queries in Mexico** (*translated from Spanish*)
Current Personal Economic Situation	Autos &Vehicles	"Car tax rates", "Used car sales", "Aveo 2018"
	Investing	"AFORES *(Retirement Fund Administrators)*", "Invest in Amazon", "Trust investing"
Current Economic Situation in the Country	Welfare & Unemployment	"How can I figure out my social security number", "Labor strike 2020", "Mexican Institute of Social Security"
	Finance	"Benito Juarez Scholarships", "US dolars to Mexican Peso", "Dolar price today"
Purchase of Home Appliances	Home & Garden	"IKEA Mexico", "Emma Mattress", "Vianney Catalogue"
COVID-19 concerns *(only used in the second period)*	Infectious Diseases	"Vaccine registration", "Sinovac Vaccine", "Pfizer vaccine"
	Public Health	"My vaccine", "COVID-19 prevention", "COVID-19 traffic light"

An important realization is that the value given to the prior probability of inclusion of the chosen categories can be thought of as the weight in a variable selection technique. Given that it is extremely complex to determine what is an appropriate prior for each category, in the second

approach I consider five different models[8] where each chosen variable has the same prior. Setting the prior of the chosen variables to 1 means that all the variables will be included in each iteration. On the other hand, setting it to a lower value, such as 0.1, gives the model more flexibility to update the posterior probability of inclusion.

Given that the models where we perform spike-and slab are far more complex than the one with no regressors, they are each fit using 20,000 MCMC iterations, and then discarding the first 2,000 as burn in. The output of the Bayesian model does not show a single answer but instead a distribution of different results obtained in each MCMC draw. For this reason, to measure the prediction accuracy of each variation of the BSTS, I use the Mean Absolute Percentage Error (MAPE). The MAPE (Eq. 6) measures accuracy as a percentage by subtracting each forecasted value from the corresponding actual value and dividing the result over that same actual value of consumer confidence. Then, the mean of these absolute prediction errors is calculated by adding them together and diving them by the number of times the summation iteration takes place.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|Actual_i - Forecasted_i|}{Actual_i} \tag{6}$$

Table 3 shows the performance of the different BSTS models. In the first period, the training error was roughly the same for all models. Nonetheless, the test error was reduced almost by half from 3.6% to 1.7% after introducing the regressors. Once the relevant categories were assigned a prior probability of inclusion of 0.8, the test error was further reduced to 0.9%.

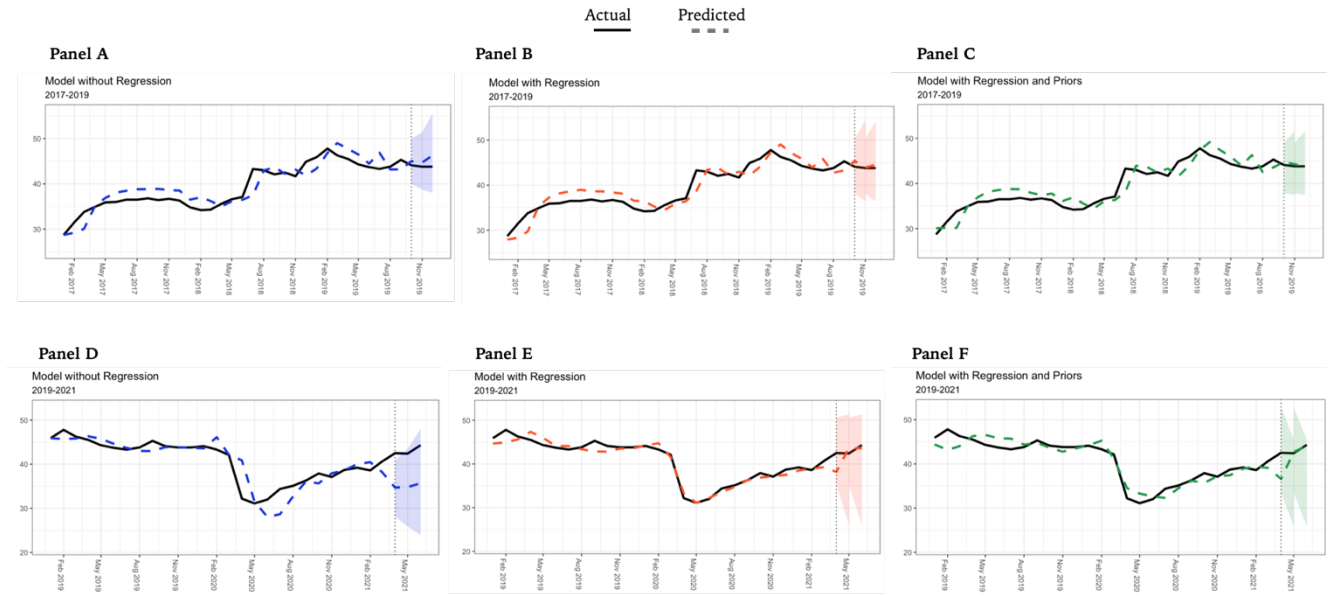
Table 3: Performance Metrics of Consumer Confidence Nowcasts in Mexico

		2017-2019		2019-2021	
		Mean Absolute Percentage Error		Mean Absolute Percentage Error	
Country	Model	Training Set	Test Set	Training Set	Test Set
Mexico	Without regressors	4.6%	3.6%	4.3%	18.6%
	With Regressors	4.5%	1.7%	2.1%	4.9%
	With Regressors and Priors*	4.3%	0.9%	3.3%	5.2%

** Using the prior probability of inclusion that yielded the lowest test error*

[8] The prior probabilities of inclusion of these five models were 0.2, 0.4, 0.6, 0.8, and 1, respectively.

Figure 4: Consumer Confidence values and nowcasts in Mexico



A more dramatic improvement from the benchmark model takes place in the second period. When regressors were not incorporated into the BSTS, the test error was 18.6%. Interestingly, once the Google Trends categories were included, the performance of the model with a uniform probability distribution for the prior performed slightly better. In this case, the test error was 4.9%, but when only the chosen variables had a prior of 0.4 and the remaining had a prior of 0 the test error increased to 5.2%.

These results can be further visualized in Figure 4. The black line in each of the panels shows the actual level of consumer confidence at a given point in time and the colored dashed lines show the fitted values. The colored shadow shows the 95% confidence interval of the prediction. We can observe that in Panels A to C the distance between the actual and the fitted values is not that wide. However, in Panel D, which shows the prediction of model without regression in the second period, we can see that the model underestimates the level of consumer confidence.

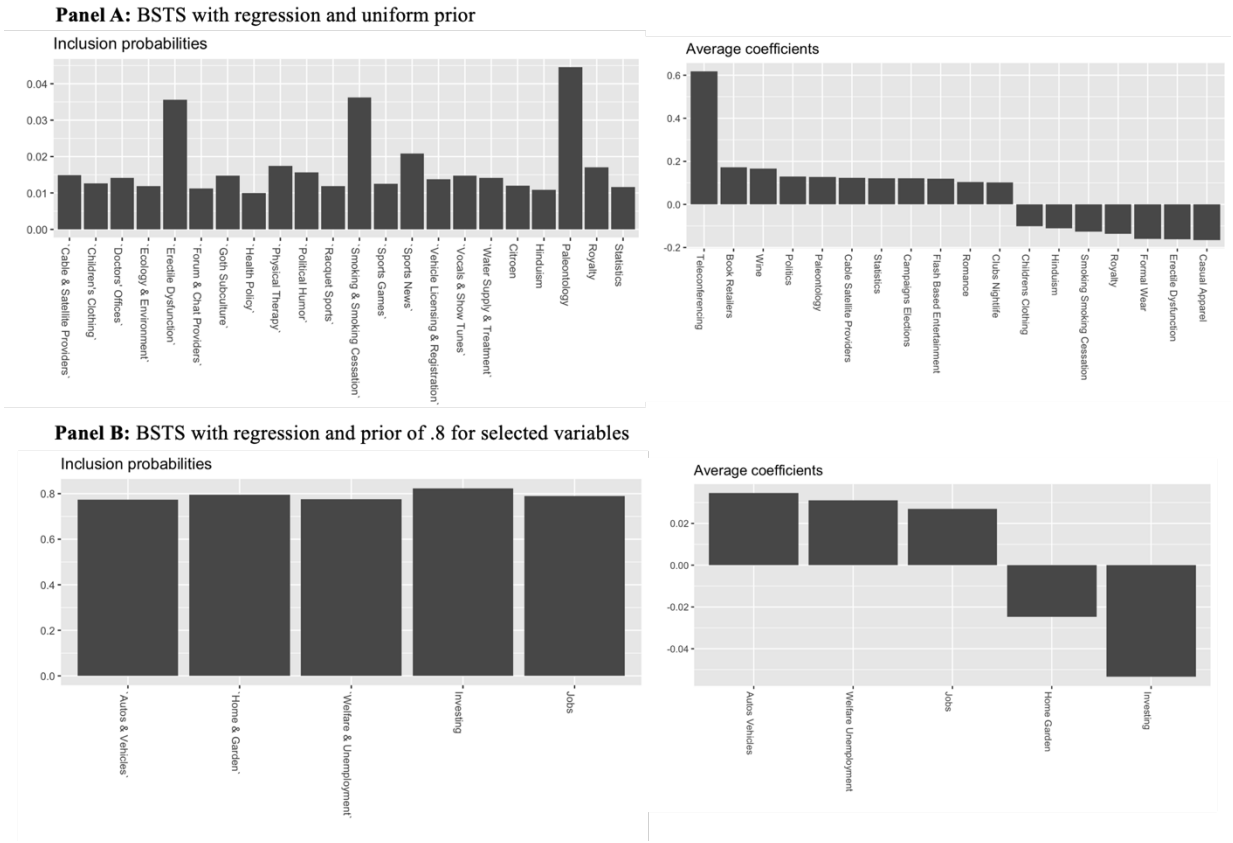
6.1.1 Decomposing Mexico's Nowcasts

One of the main advantages of BSTS is that it is a transparent model. The BSTS system can decompose the forecast into its trend, seasonal, and regression components. The trend component comes from the Kalman filter forecast, while the regression uses the Google Trends categories as predictors (Scott and Varian 2013a). Figures 5 and 6 show the predictors to which the MCMC algorithm assigned a posterior inclusion probability greater than 0.01 in the first and second time

periods respectively. In the Panel A of Figure 5, we can see that the model with uniform prior distribution struggled to find meaningful predictors. Even if there are predictors with a posterior probability of inclusion that is greater than the prior of 0.0055, no predictor has a posterior probability of inclusion greater than 0.05. Also, the three predictors with the highest posterior probability of inclusion (Paleontology, Smoking and Smoking Cessation, and Erectile Dysfunction) were not economically significant. Repeated runs with different expected model sizes and seeds showed a similar set of predictors with equally low inclusion probabilities.

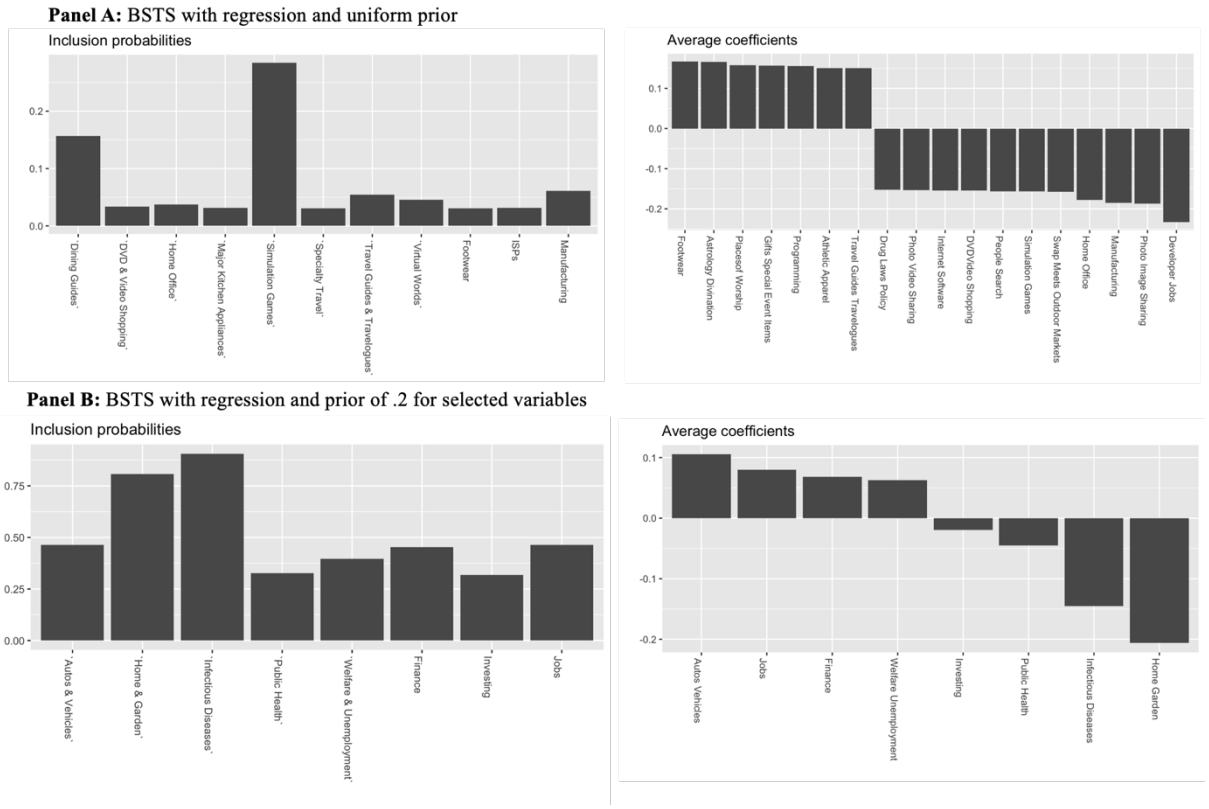
Panel B of Figure 5 shows the predictors of the model with a prior that yielded the lowest test error. In this case we can see that the posterior probability of inclusion is being forced toward 0.8 due to the strong prior belief that was imposed on this set of variables. Even though the probabilities of inclusion are high, the that the absolute value of the parameters of these predictors is very close to zero. Thus, Figure 5 reinforces what we saw in Table 3, the Google Trends variables did not seem to add much value during 2017-2019.

Figure 5: Posterior Inclusion Probability of Predictors (Mexico, 2017-2019)



In contrast, Figure 6, depicting the second period, shows that it did make sense to add Google Trend categories into the model. Panel A shows that two predictors reached a posterior probability of inclusion greater than 0.1. Most of the categories that had the highest probability of inclusion were economically relevant. Also, the absolute value of their coefficients was well above 0.1. In Panel B, we can see that because there was a weak prior belief on the set of chosen variables, the posterior probability of inclusion widely fluctuates. The two variables with the highest probability of inclusion were Infectious Diseases and Home and Garden. These variables also had average coefficients of -0.148 and -0.21 respectively.

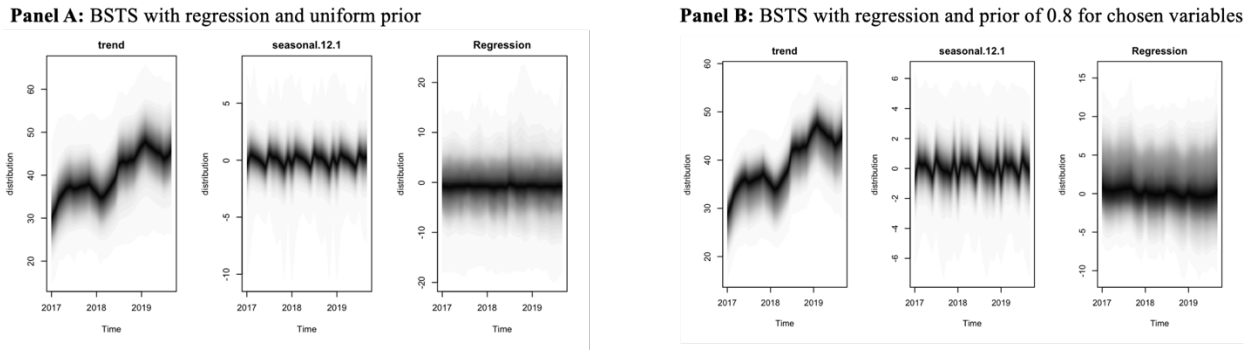
Figure 6: Posterior Inclusion Probability of Predictors (Mexico, 2019-2021)



To further explore the relevance of Google Trends categories in the two periods, Figures 7 and 8 show the contribution of each state variable to the model fit. Each plot looks blurry because it shows the marginal posterior distribution at each time point. The darker the shade, the closer it is to the median value. Both Panel A and B in Figure 7 show that the trend component exhibits

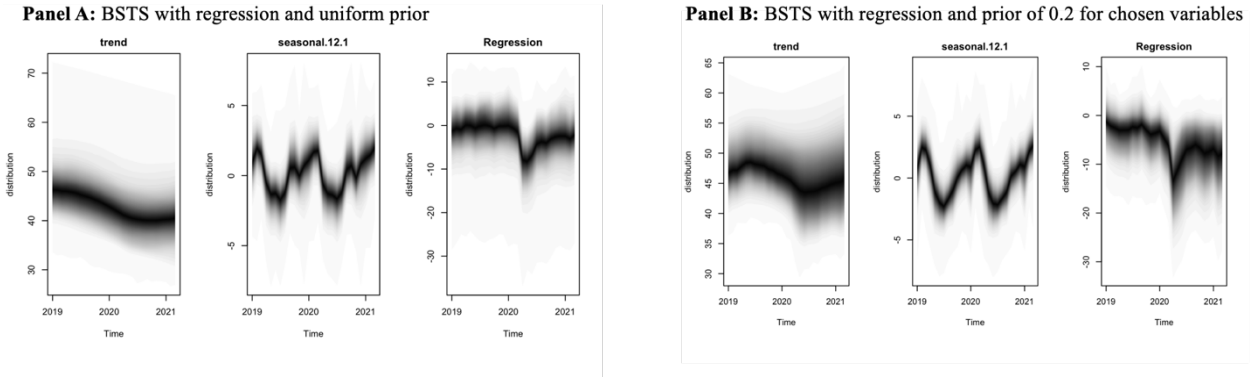
substantially more variation than the seasonal and regression components. In fact, the regression effect is somewhat flat during 2017-2019.

Figure 7: BSTS Decomposition (Mexico, 2017-2019)



The pandemic period depicted in Figure 8 highlights the relevance of the inclusion of Google Trends Categories. In both Panel A and B, the regression component was relatively flat and close to zero before the pandemic started. Around March 2020, it drops drastically, and it is followed by a relatively abrupt recovery that later stabilizes without reaching the pre-pandemic levels. Further, while regression component captures the sharp change in the value of the series, the time series remains quite smooth during the shock. The trend in both panels also shows less variation than the trend observed between 2017-2019.

Figure 8: BSTS Decomposition (Mexico, 2019-2021)



To summarize, the decomposition of the BSTS shown in Figures 7 and 8 help explain why the model performance did not increase by much after adding predictors. Figures 5 and 6 compare the predictors with the largest marginal inclusion probabilities in 2017-2019 and 2019-2021, respectively. By construction, the chosen predictors shown in Table 2 should tack the consumer

confidence series, but it turns out that, unless there is shock, the information they provide is redundant once we consider the underlying trend in consumer confidence.

6.1.2 Exploring different priors

So far, I have only shown the results of the model that yielded the lowest test error when only a set of chosen categories were given priors different from zero. In the literature, the main approach taken when not all the variables are given the same prior is to impose a prior of 1 for the relevant predictors and zero for the rest (Scott and Varian 2013a). However, an important question that remains is if there is an optimal prior value that would reduce the test error. As I have mentioned before, setting a prior of 1 for the categories related to consumer confidence (shown in Table 2) would give the model no flexibility to update this belief. On the other hand, setting a prior of 0.2 for the same set of variables would enable the model to update the posterior and determine which variables provide more relevant information about the state of consumer confidence.

To explore this issue further, I ran five different models were the prior probability of inclusion of categories related to consumer confidence took a value ranging between 0.2 and 1. The rest of the Google Trend categories were given a prior of zero, which led to the model not considering them at all. The results are shown in Table 4.

Table 4: Prior Probability of Inclusion and Model Performance

		2017-2019		2019-2021	
		Mean Absolute Percentage Error		Mean Absolute Percentage Error	
Country	Prior Probability of Inclusion	Training Set	Test Set	Training Set	Test Set
Mexico	0.2	4.7%	1.6%	3.5%	6.7%
	0.4	4.5%	1.4%	3.3%	5.2%
	0.6	4.5%	1.2%	3.1%	5.3%
	0.8	4.3%	0.9%	3.4%	7.6%
	1	4.3%	1.4%	3.1%	6.8%

As seen above, trying to tune the model by modifying the prior probability of inclusion of selected variables does not lead to a dramatic improvement in model performance. The best model in 2017-2019 had a prior of 0.8 and a test error of 0.9%, while the worst model had a prior of 0.2 and a test error of 1.6%. Thus, in the first period, imposing a stronger belief on the set of relevant variables leads to a very minor increase in accuracy.

In 2019-2021 the best model had a prior of 0.4 and a test error of 5.2%, while the worst model had a prior of 1 and a test error of 6.8%. In contrast to the previous period, the pandemic time seemed to benefit slightly from relaxing the strong assumptions imposed before. Nonetheless,

the major takeaway from this exercise was that, in either period, modifying the prior did not improve model performance drastically.

6.2 Overall Results

So far, I have given a detailed account of the results obtained for Mexico. Due to space constraints, I cannot do the same for the remaining countries, but I can provide a concise summary of the results and highlight some interesting observations along the way.

The results of all the nowcasting models are summarized in Table 5. In the table, I show the MAPE for both the training set and the test set in the first and second period. We observe that adding Google Trends categories did enhance performance in most cases. The most promising results are reported for Brazil during the second period where the test set error goes from 20.6% to 6.2% after including the regressors. Another set of interesting results are those for Colombia where we see that, in the first period, the test error for the model without regressors was 300.9% while the test error for the model with regressors and priors was 119.3%. Even though that is a dramatic improvement, we see that both the in-sample and the out-of-sample errors are remarkably high in Colombia regardless of the model specification.

Table 5: Performance Metrics of Consumer Confidence Nowcasts

		2017-2019		2019-2021	
		Mean Absolute Percentage Error		Mean Absolute Percentage Error	
Country	**Model**	**Training Set**	**Test Set**	**Training Set**	**Test Set**
Argentina	Without regressors	8.5%	2.3%	5.4%	2.8%
	With Regressors	8.0%	6.9%	4.0%	4.9%
	With Regressors and Priors*	8.1%	4.5%	5.3%	4.4%
Brasil	Without regressors	2.9%	4.6%	5.9%	20.6%
	With Regressors	2.5%	3.5%	2.1%	6.2%
	With Regressors and Priors*	2.8%	3.4%	3.1%	12.8%
Chile	Without regressors	6.2%	55.0%	13.9%	19.6%
	With Regressors	3.9%	76.5%	7.9%	35.6%
	With Regressors and Priors*	6.2%	37.2%	12.2%	35.0%
Colombia	Without regressors	122.0%	300.9%	89.8%	37.5%
	With Regressors	98.2%	358.1%	64.4%	33.1%
	With Regressors and Priors*	104.6%	119.3%	76.7%	33.0%
Mexico	Without regressors	4.6%	3.3%	4.3%	18.6%
	With Regressors	4.5%	1.7%	2.1%	4.9%
	With Regressors and Priors*	4.3%	0.9%	3.3%	5.1%

* *Using the prior probability of inclusion that yielded the lowest test error*

There were three cases, out of ten, where adding Google Trends categories to the BSTS model worsened the out-of-sample performance. This can be observed during both periods in Argentina and in Chile between 2019-2021. In the case of Argentina, the test error in 2017-2019 goes from 2.3% to 4.5% once regressors and priors are incorporated. In the following period, the difference is reduced but we still observe that the test error without regressors is 2.8% while the best alternative with regressors is 4.4%. In the case of Chile, we see that in the second period the out-of-sample error for the model without regressors was 19.6% while the same error for the model with regressors and priors was 35.0%. The model with regressors and priors did perform better in Chile during the previous period, but after the pandemic it seems that it was better to omit Google Trends categories.

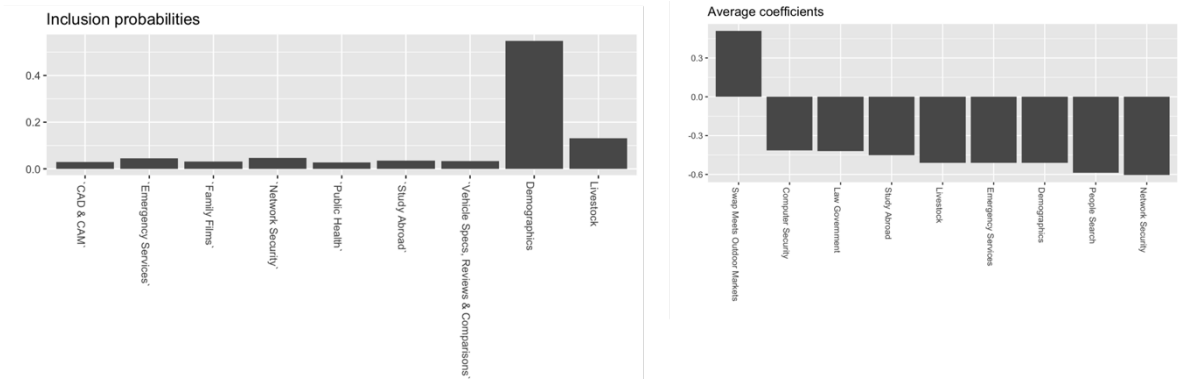
In the subsection that follows I show the BSTS decomposition of some of these models, I divide the results two categories: the models that did not benefit from regressors and the models that did. At this point it also is important to remind the reader that the focus of this exercise is prediction and not explanation. In other words, in the following subsection, I do not intend to establish a causal link between consumer confidence and the Google Trends categories that were chosen into the model. Instead, some plots showcasing such categories are presented as anecdotal evidence for the reader to better understand the mechanics behind BSTS.

6.2.1 BSTS Decomposition

We have seen that models for three out of the five countries in the sample saw an improvement in accuracy after incorporating Google Trends categories. Among these countries, we saw that Brazil's model in 2019-2021 had the most impressive improvement once the regressors were incorporated. If we look inside Brazil's BSTS during this period (Figure 9), we see that the category Demographics[9] is included in more than 45% of the models and that its average coefficient is well above -0.5.

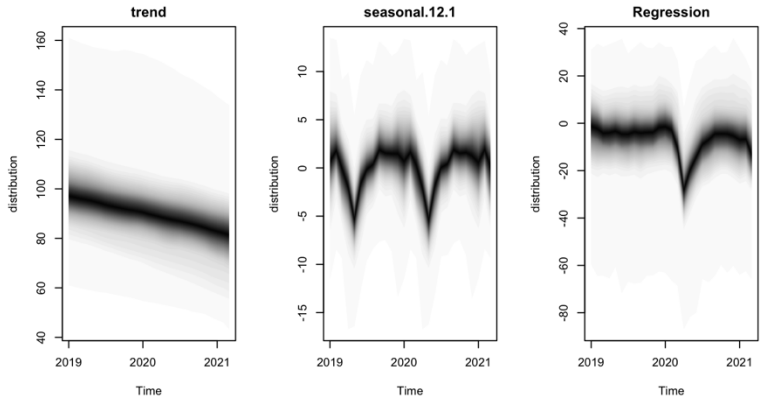
[9] The Demographics category includes queries such as "COVID deaths", "COVID in Brazil", and "Vaccinations Brazil".

Figure 9: Posterior Inclusion Probability of Predictors (Brazil, 2019-2021)



Further, just as we saw for Mexico in the same period, the BSTS decomposition for Brazil in Figure 10 shows that right before the pandemic the regression component was relatively flat and close to zero. However, just around March 2020 we see that it captures the abrupt drop in consumer confidence to later adjust to a lower mean value. Similarly, we also observe that the trend component remains quite smooth during the shock.

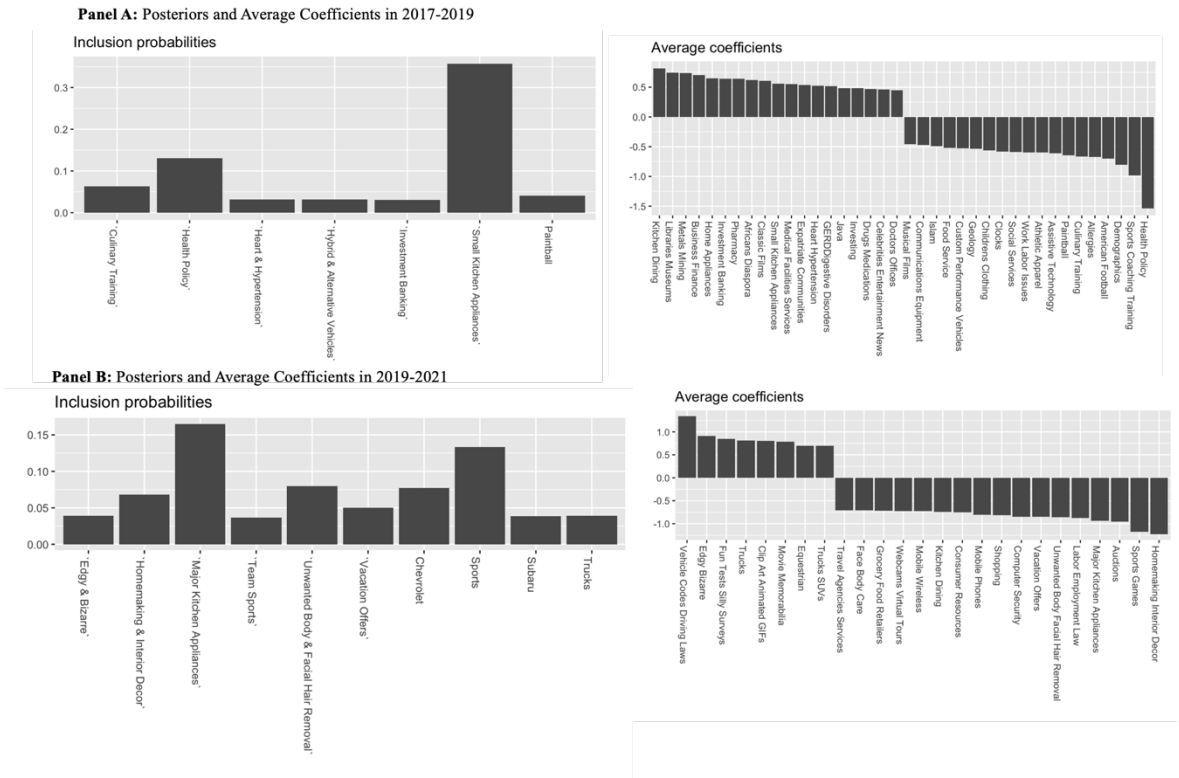
Figure 10: BSTS Decomposition (Brazil, 2019-2021)



One of the outliers that did not satisfy the hypothesis was Chile. Chile benefited from the Google Trends regressors only during the pre-pandemic period. Figure 11 shows the posterior inclusion probability and the average coefficients of predictors in both periods in Chile. In Panel A, we see that in 2017-2019 the most likely regressor to be included was Small Kitchen

Appliances[10]. This regressor had a posterior of 0.35 and an average coefficient of 0.5. We can also see that the only other predictor that reaches a posterior greater than 0.1 is Health Policy and that its average coefficient is -1.5. The rest of the predictors have very low posteriors and only the categories of Hybrid & Alternative Vehicles and Investment Banking could have some economic justification.

Figure 11: Posterior Inclusion Probability of Predictors in Chile



In Panel B of Figure 11, we see that most of the categories (such as Major Kitchen Appliances, Homemaking & Interior Décor, Vacation Offers, Chevrolet, and Subaru) with a higher posterior probability of inclusion are economically significant. For the most part, these categories also had coefficients different from zero. The category Major Kitchen Appliances was included in more than 15% of the models of the second period and had an average coefficient of -0.7.

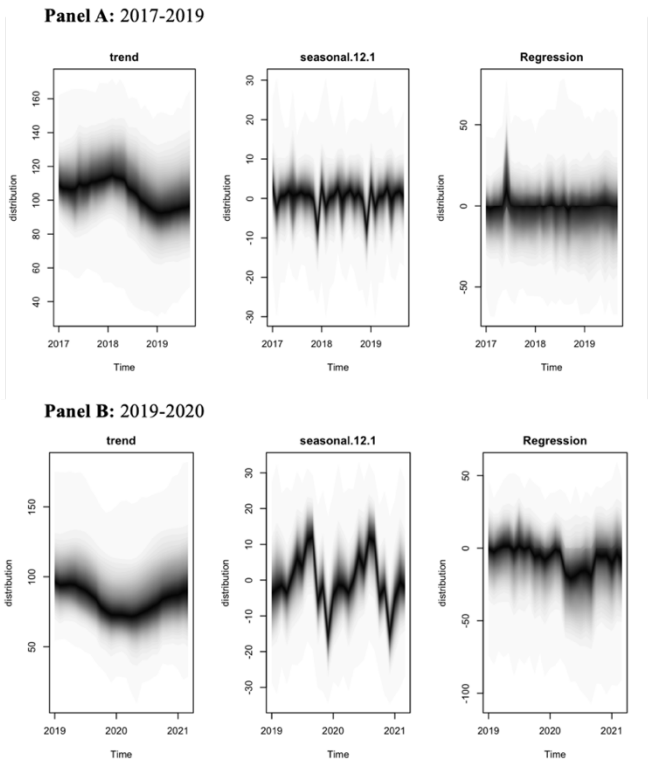
Figure G shows the BSTS decomposition in Chile during both periods. In Panel A we see that the regression component is mostly flat except for a spike in early 2017. We see that between 2017

[10] This category includes queries such as "Nespresso machine", "Bosch Kitchen robot", and "Phillips's food processor"

and 2018 there was an upward trend in consumer confidence that later became. There also seem to be strong seasonal factors toward the end of each year.

Panel B shows a U-shaped trend in consumer confidence. In contrast with Mexico (Figure 6) and Brazil (Figure 9), the pandemic shock captured in the regression component was not as steep and short lived.

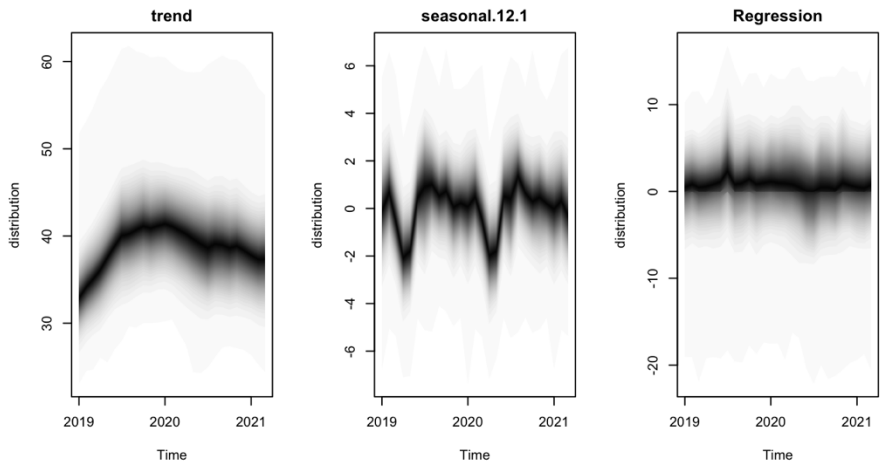
Figure 12: BSTS Decomposition in Chile



Another outlier worth exploring was Argentina. Adding Google Trends categories as predictors did not improve accuracy in either period for this country. Figure 13 shows that, in 2019-2021, the underlying trend and seasonality seem to provide all the information needed to nowcast the series. In contrast with all the other sampled countries[11], Argentina is the only one that exhibits a flat regression component during the pandemic period.

[11] Refer to the Appendix

Figure 13: BSTS Decomposition in Argentina (2019-2021)



6.2.2 Exploring Different Priors

Just as I did for Mexico in Section 6.1.2, I now show how different BSTS models with different priors perform across the sample countries. Table 6 shows the results from running five different models were the prior of the chosen categories[12] related to consumer confidence took a value ranging between 0.2 and 1. The rest of the Google Trend categories were given a prior of zero, so they were simply omitted from the model.

[12] Recall that these categories, as shown in Table 2, were Autos & Vehicles, Investing, Welfare & Unemployment, Finance, Home & Garden in both periods and that Infectious Diseases and Public Health were also included in the second period.

Table 6: Prior Probability of Inclusion and Model Performance

		2017-2019		2019-2021	
		Mean Absolute Percentage Error		Mean Absolute Percentage Error	
Country	**Prior Probability of Inclusion**	**Training Set**	**Test Set**	**Training Set**	**Test Set**
Argentina	0.2	8.6%	6.5%	5.3%	4.4%
	0.4	8.3%	5.8%	5.2%	4.5%
	0.6	8.8%	6.4%	5.0%	6.2%
	0.8	8.1%	4.5%	5.1%	7.5%
	1	8.2%	4.7%	5.1%	7.1%
Brazil	0.2	2.8%	3.4%	3.1%	12.8%
	0.4	2.8%	3.6%	2.9%	13.5%
	0.6	2.8%	3.5%	2.7%	14.8%
	0.8	2.9%	3.7%	2.6%	14.9%
	1	2.8%	3.8%	2.5%	14.3%
Chile	0.2	6.2%	37.2%	12.2%	35.0%
	0.4	6.1%	38.8%	11.1%	38.1%
	0.6	5.9%	42.9%	10.9%	39.9%
	0.8	5.8%	46.7%	10.4%	42.6%
	1	6.0%	52.7%	10.3%	42.6%
Colombia	0.2	111.6%	322.8%	76.7%	33.0%
	0.4	108.6%	318.8%	75.1%	33.9%
	0.6	106.6%	248.6%	75.9%	35.7%
	0.8	104.7%	213.3%	81.7%	39.5%
	1	104.6%	119.3%	88.8%	45.1%
Mexico	0.2	4.7%	1.6%	3.5%	6.7%
	0.4	4.5%	1.4%	3.3%	5.1%
	0.6	4.5%	1.2%	3.1%	5.3%
	0.8	4.3%	0.9%	3.4%	7.6%
	1	4.3%	1.4%	3.1%	6.8%

The first observation that one can make from Table 6 is that Brazil and Chile benefited from having low priors in both time periods. For both countries, a prior probability of inclusion of 0.2 yielded the lowest test error. For Brazil, the out of sample performance improvement between the best and the worst model was just of 0.4% in the first period and 2.1% in the second period. On the other hand, for Chile this improvement was of 15.5% in the first period and 7.6% in the second period.

For the remaining countries, we see that a lower test error was obtained in the first period when the prior was closer to 1. Indeed, the optimal prior for Argentina, Colombia, and Mexico was of 0.8, 1, and 1, respectively. On the other hand, in the second period, the optimal prior was closer to 0.2. Argentina, Colombia, and Mexico reported the lowest test errors when their priors were set to

0.2, 0.2, and 0.4, respectively. We can also see that the difference in test errors between the best and the worst model in Argentina and Mexico is negligible compared to that of Colombia. In Colombia, during the pre-COVID period, when the prior was set to 0.2, the test error was 322.8% but when it was set to 1, the test error dropped to 119.3%.

7 Discussion

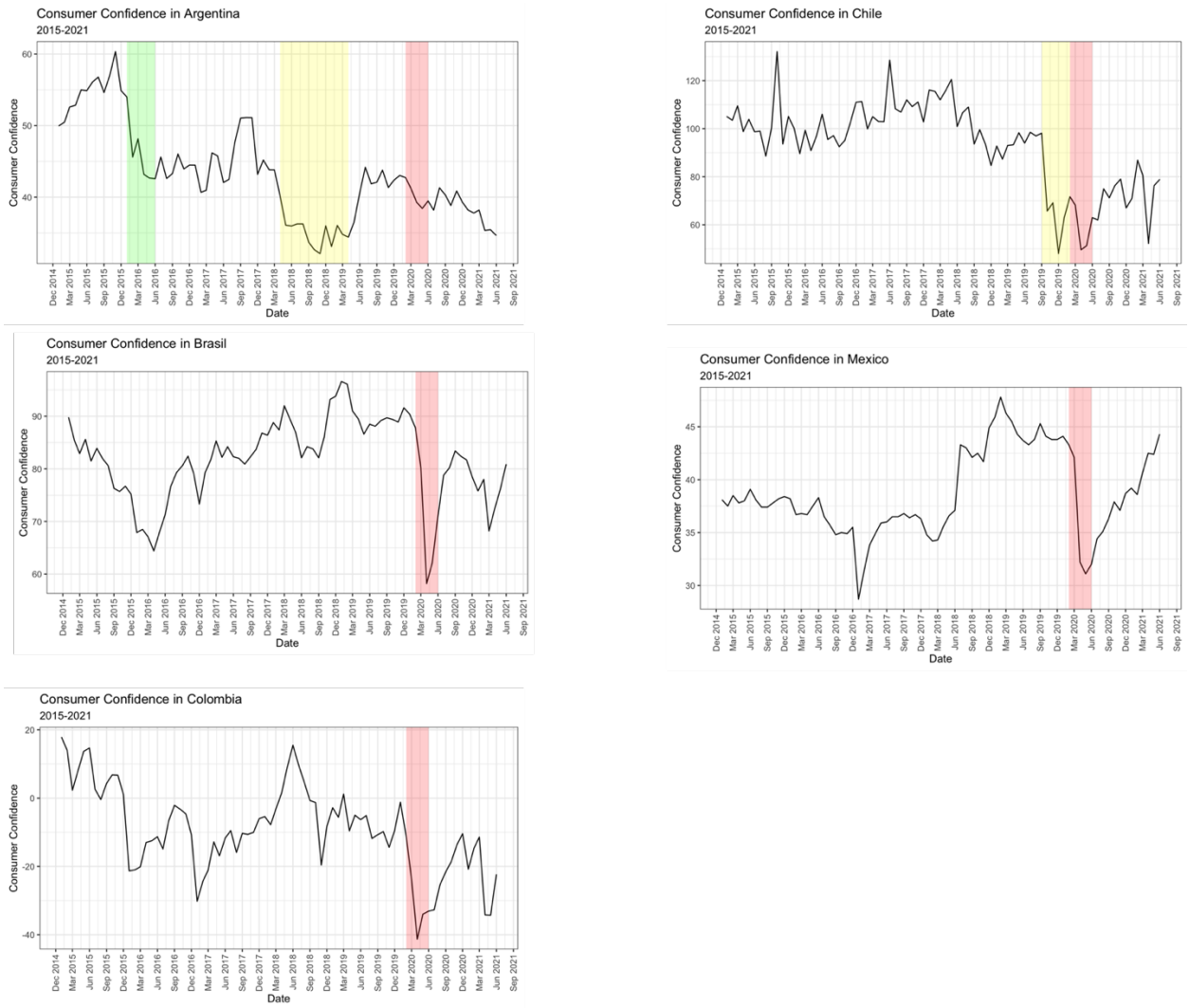
The results indicate that, for most countries, including Google Trend categories as regressors did improve the accuracy of nowcasts. For three out of the five sampled countries, namely, Brazil, Colombia, and Mexico; a lower in-sample and out-of-sample error was obtained in both periods when the Google predictors were incorporated. The main takeaway obtained from decomposing BSTS was that, in most cases, the regression component showed greater variance in the second period, especially around March 2020, when the pandemic hit the world. During the first period, the regression component remained flat and centered around zero. In other words, Google Trends categories were good at capturing a "turning point" in consumer confidence, which is consistent with the results that Scott and Varian (2013b) obtained when nowcasting consumer confidence in the US. However, it is worth noting that when there were no external shocks to the Latin American economies, the contribution of the Google predictors to nowcast performance was negligible.

To assess the usefulness of Google's SVI, I implemented BSTS model with a uniform prior probability of inclusion for all categories, and another set of BSTS models where only variables related to consumer confidence were assigned a prior different from zero. Most countries benefited, albeit slightly, from the latter approach. That is to say, excluding most categories and focusing on a set of predictors theoretically related to consumer confidence led to reductions in the test error rate. Nonetheless, the results showed that the prior given to the set of relevant predictors did not affect performance dramatically. This suggests that it is possible to reap the benefits of incorporating Google Trends predictors by relying on a limited set of categories that are subjectively relevant.

An unexpected finding in the study came from Argentina's and Chile's nowcasts. Initially, I had hypothesized that the incorporating Google's SVI as predictors would improve accuracy regardless of the period. However, Argentina's nowcasts did not perform better when the Google regressors were incorporated, and in Chile, an improvement in performance was only obtained when incorporating the predictors in the first period. Looking into the throughout the past five years sheds light as to why this was the case.

Figure E shows the actual level of consumer confidence across countries between 2015 and 2021. Highlighted in red, we can see the COVID-19 shock to consumer confidence in the five Latin American countries. It is clear to see that Argentina was the only country that did not experience an abrupt shock once the pandemic hit the world. Nonetheless, Argentina had been experiencing decaying consumer confidence since early 2016. Indeed, it is the only country among the five sampled to experience two major shocks between 2016 and 2019.

Figure 14: Consumer Confidence Across Countries (2015-Present)



One plausible explanation for Argentina's results is that, when shocks occur too frequently over a short span of time, consumers' response to shock may lead to changes in online searching behavior. The Argentinian economy experienced a recession coupled with inflation, and a

monetary crisis in 2016 and 2018 (Walker and Palumbo 2018). In both cases, consumer confidence decreased sharply, but, because of the selected time frames for this study, we do not know if Argentinians were looking for an answer to their concerns in Google or if their searching patters had changed over time. What we do know is that, when economic shocks occur too often, the underlying trend in consumer confidence provides enough information to nowcast when Google Trends categories fail to capture turning points.

In the case of Chile, we observe a similar phenomenon in the second period. Highlighted in yellow in Figure 14, we can see that Chile experienced a sharp decline in consumer confidence around September 2019. Just when consumer confidence was starting to recover from the decline in consumer confidence resulting from social uprisings (Bunyan 2019), the COVID-19 pandemic hit the economy. These two consecutive shocks might explain why Chile only benefited from the Google Trends regressors in the pre-pandemic period.

The results obtained in this study imply that making use of Google Trends categories to nowcasts consumer confidence has the potential to improve accuracy. Incorporating Google Trends regressors was particularly useful to capture turning points in the economy, especially those caused by the COVID-19 pandemic. One caveat to this finding is that, when shocks occurred too frequently, the Google predictors failed to add any additional value to the nowcasts.

7.1 Limitations

One of the main limitations in this study is its sole focus on Google Trends categories. As it has been mentioned before, Google Trends categories are useful because they encompass a broad set of keywords associated with it. Thus, using categories considerably reduces the number of predictors one can choose from, but they are far from perfect. A common shortcoming is that there are several queries that get incorporated into categories without necessarily being associated with it. This is particularly the case when a query has different meaning across different languages or when a word is a homograph[13].

Another clear shortcoming of this study was that it did not delve into the idiosyncrasies of each countries' definition of consumer confidence. Even though BSTS selects which variables are more relevant to nowcast the series, it is not a perfect method when combined with novel tools

[13] For instance, I came across mobile phone queries in the Auto and Vehicles category. In Spanish, motorcycle is spelled "moto". When users type "moto g100", it gets incorporated into the Auto and Vehicles category, but they are actually looking for a Motorola phone, not a motorcycle.

such as Google Trends. I believe that it might be more useful to set higher prior probabilities of inclusion for variables that are relevant to the social, economic, and political situation of each country.

Finally, another important consideration is that Google Trends is a relatively recent tool[14]which is constantly being optimized. In addition, we are still trying to understand how users interact with the search engine and how their queries relate to real life situations. For this reason, it is important to be cautious when extrapolating online searching behavior with actual events, as it happened with the Google Flu[15].

7.2 Future Research

The limitations in this study indicate a clear path for future research. First, future studies should focus on incorporating other elements of Google Trends, such as keywords and topics, to understand which one, if any, is more useful for nowcasting. Another avenue of research lies in the study of the relationship between Google Trends predictors and economic shocks. In particular, it is worth exploring why Google Trends has the potential to capture shocks in some countries and not others.

Finally, it is of utmost importance that future studies continue to extend the application of economic nowcasting to emerging markets. Using high frequency indicators and novel methods to monitor economies beyond the developed world has the potential to broaden our understanding of such methods while adding value in countries where governments might not be reliable data providers.

8 Conclusion

The advent of big data has led to the use of high frequency indicators, such as Google Trends, to nowcast economic series. However, whether these indicators are useful nowcasting predictors in emerging markets remains insufficiently investigated. To address this gap, I focused

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[14] It was launched in 2006 and two improvements to their data collection system have already been implemented. One took place in 2011 and a second one occurred in 2016.

[15] In 2009, Google started tracking influenza epidemics based on searches on its platform (Lazer et al. 2014). In 2013, the Google Trends algorithm overestimated the number of Americans with an influenza-like illness after widespread media coverage of the flu season prompted Google searchers to inquiry more about the virus (Butler 2013).

on nowcasting consumer confidence in the five biggest Latin American economies during a pre-pandemic (2017-2019) and a pandemic (2019-2021) period. Methodologically, I used Bayesian Structural Time Series to determine the extent to which incorporating Google Trends categories into the nowcasting model improves accuracy. Initially, I had hypothesized that including Google's SVI would improve nowcasts regardless of the period.

I found that, for most countries, incorporating Google Trend categories as predictors did increase the accuracy of nowcasts. Google Trends regressors were particularly useful to capture turning points in consumer confidence, such as the pandemic outbreak, in the Latin American economies. However, one caveat to this finding was the frequency in which shocks to consumer confidence took place. In countries where economic shocks occurred far too often, like in Argentina, models that incorporated Google Trends predictors did not perform better than the one that simply considered the time series.

Another relevant finding is that, for the sake of accuracy and interpretability, it may be more beneficial to use BSTS with a subset of relevant Google predictors. Not all the predictors chosen by spike-and-slab are economically significant and some contain spurious correlations[16]. The best approach would entail using the researcher's subjectivity to remove anomalies from the training data. To do this, it would suffice to restrict the number of predictors to a handful of variables that at least have an economic justification.

This study shows that there is great promise in the incorporation of Google Trends to nowcast macroeconomic indicators in emerging markets. Further research should exploit this tool further by incorporating keywords or topics and comparing their usefulness to nowcasting. It is my hope that this research motivates the study of novel nowcasting methods in Latin America so that their benefits of are extended beyond developed economies.

[16] For example, one of the strongest predictors of consumer confidence in Mexico during 2017-2019 was Paleontology. This variable exhibited spikes around the time Mexico's president was elected and large migrant caravans were moving towards the US, attributed to the release of a Jurassic Park video game that triggered queries related to dinosaurs.

References

Acuña, Guillermo. 2021. "Observatorio de Percepciones Económicas." Índices de Confianza Del Consumidor. 2021. https://www.percepcioneseconomicas.cl/indices/indices-de-confianza-del-consumidor/.

Askitas, Nikolaos, and Klaus F Zimmermann. 2009. "Google Econometrics and Unemployment Forecasting." *Applied Economics Quarterly*. https://doi.org/10.3790/aeq.55.2.107.

Askitas, Nikolaos, Klaus F Zimmermann, Nicolas Woloszko, Stéphanie Combes, Clément Bortoli, Hyunyoung Choi, Hal Varian, et al. 2017. "Tracking Activity in Real Time with Google Trends." *SSRN Electronic Journal* 55 (SUPPL.1): 2–9. https://doi.org/10.2139/ssrn.3037603.

Bunyan, Rachael. 2019. "18 Killed as Hundreds of Thousands of Protestors Take to the Streets in Chile. Here's What to Know." *Time*, 2019. https://time.com/5710268/chile-protests/.

Butler, Declan. 2013. "When Google Got Flu Wrong." *Nature*. https://doi.org/10.1038/494155a.

Carrière-Swallow, Yan, and Felipe Labbé. 2010. "Nowcasting with Google Trends in an Emerging Market." *Central Bank of Chile Working Papers*, no. 588.

Chatfield, Chris, and Haipeng Xing. 2019. "State-Space Models and the Kalman Filter." In *The Analysis of Time Series*, Seventh.

Chen, Zhe, and Emery N. Brown. 2013. "State Space Model." Scholarpedia, 8(3):30868. 2013.

Choi, Hyunyoung, and Hal Varian. 2012. "Predicting the Present with Google Trends." *Economic Record* 88 (SUPPL.1): 2–9. https://doi.org/10.1111/j.1475-4932.2012.00809.x.

CIF Universidad Torcuato Di Tella. 2021. "Indice de Confianza Del Consumidor."

Curtin, Richard. 1982. "Indicators of Consumer Behavior: The University of Michigan Surveys of Consumers." *Public Opinion Quarterly*. https://doi.org/10.1086/268731.

———. 2002. "Consumer Confidence in the 21 St Century : Changing Sources of Economic Uncertainty." *Journal of Economic Perspectives*, no. October.

Deimante, Teresiene, Greta Keliuotyte-Staniuleniene, Yiyi Liao, Rasa Kanapickiene, Ruihui Pu, Siyan Hu, and Xiao-Guang Yue. 2021. "The Impact of the COVID-19 Pandemic on Consumer and Business Confidence Indicators." *Journal of Risk and Financial Management* 14 (159).

Durbin, James, and Siem Jan Koopman. 2013. *Time Series Analysis by State Space Methods*. *Time Series Analysis by State Space Methods*.

https://doi.org/10.1093/acprof:oso/9780199641178.001.0001.

Fasulo, A, A Guandalini, and M D Terribili. 2017. "Google Trends For Nowcasting Quarterly Household Consumption Expenditure." *Rivista Italiana Di Economia*.

Fedesarrollo. 2021. "Encuesta de Opinion Al Consumidor."

Ferrara, Laurent, and Anna Simoni. 2020. "When Are Google Data Useful to Nowcast GDP? An Approach via Pre-Selection and Shrinkage1." *ArXiv*. https://doi.org/10.2139/ssrn.3370917.

Fundaçao Getulio Vargas. 2021. "Índice de Confiança Do Consumidor." https://portalibre.fgv.br/estudos-e-pesquisas/indices-de-precos/sondagem-do-consumidor.

González-Fernández, Marcos, and Carmen González-Velasco. 2018. "Can Google Econometrics Predict Unemployment? Evidence from Spain." *Economics Letters*. https://doi.org/10.1016/j.econlet.2018.05.031.

Harvey, A. C., and S. Peters. 1990. "Estimation Procedures for Structural Time Series Models." *Journal of Forecasting*. https://doi.org/10.1002/for.3980090203.

Harvey, Andrew C., and Neil Shephard. 1993. "Structural Time Series Models." *Handbook of Statistics* 11 (Econometrics): 261–302.

Hinne, Max, Quentin Gronau, Don van den Bergh, and Eric-Jan Wagenmakers. 2020. "A Conceptual Introduction to Bayesian Model Averaging." *Advances in Methods and Practices in Psychological Science* 3 (2): 200–215.

Hoeting, Jennifer A., David Madigan, Adrian E. Raftery, and Chris T. Volinsky. 1999. "Bayesian Model Averaging: A Tutorial." *Statistical Science*. https://doi.org/10.1214/ss/1009212519.

Hu, Hongping, Li Tang, Shuhua Zhang, and Haiyan Wang. 2018. "Predicting the Direction of Stock Markets Using Optimized Neural Networks with Google Trends." *Neurocomputing*. https://doi.org/10.1016/j.neucom.2018.01.038.

Hueng, C. James. 2020. "Alternative Economic Indicators." In *Alternative Economic Indicators*. https://doi.org/10.17848/9780880996778.ch1.

INEGI. 2021. "Confianza Del Consumidor."

Julio, Juan, and Anderson Grajales. 2011. "¿Qué Nos Dicen Los Índices de Confianza?" Bogotá.

Katona, George. 1951. *Psychological Analysis of Economic Behavior*. New York: McGraw-Hill.

———. 1968. "Consumer Behavior: Theory and Findings on Expectations and Aspirations." *American Economic Review*.

Kim, Youngjoo, and Hyochoong Bang. 2019. “Introduction to Kalman Filter and Its Applications.” In *Introduction and Implementations of the Kalman Filter*. https://doi.org/10.5772/intechopen.80600.

Kohns, David, and Arnab Bhattacharjee. 2020. “Developments on the Bayesian Structural Time Series Model: Trending Growth,” 1–34. http://arxiv.org/abs/2011.00938.

Larsen, Kim. 2016. “Sorry ARIMA, but I’m Going Bayesian.” Multithreaded. 2016. https://multithreaded.stitchfix.com/blog/2016/04/21/forget-arima/.

Lazer, David, Ryan Kennedy, Gary King, and Alessandro Vespignani. 2014. “The Parable of Google Flu: Traps in Big Data Analysis.” *Science*. https://doi.org/10.1126/science.1248506.

Liu, Philip, Troy Matheson, and Rafael Romeu. 2012. “Real-Time Forecasts of Economic Activity for Latin American Economies.” *IMF Working Paper* 29 (4): 1090–98. https://doi.org/10.1016/j.econmod.2012.03.020.

Matsusaka, JOHN G., and ARGIA M. Sbordone. 1995. “Consumer Confidence and Economic Fluctuations.” *Economic Inquiry*. https://doi.org/10.1111/j.1465-7295.1995.tb01864.x.

Nagao, Shintaro, Fumiko Takeda, and Riku Tanaka. 2019. “Nowcasting of the U.S. Unemployment Rate Using Google Trends.” *Finance Research Letters*. https://doi.org/10.1016/j.frl.2019.04.005.

Narita, Futoshi, and Rujun Yin. 2018. “In Search of Information: Use of Google Trends’ Data to Narrow Information Gaps for Low-Income Developing Countries.” *IMF Working Papers*. https://doi.org/10.5089/9781484390177.001.

Osborn, Denise R., and Andrew C. Harvey. 1991. “Forecasting, Structural Time Series Models and the Kalman Filter.” *Economica*. https://doi.org/10.2307/2554700.

Penna, Nicolás Della, and Haifang Huang. 2009. “Constructing Consumer Sentiment Index for U.S. Using Internet Search Patterns.” *Working Paper*.

Perktold, Josef, Skipper Seabold, and Jonathan Taylor. 2021. “State Space Modeling: Local Linear Trends.” Statsmodels. 2021. https://www.statsmodels.org/stable/examples/notebooks/generated/statespace_local_linear_trend.html.

Proietti, Tommaso. 1991. “Forecasting with Structural Time Series Models.” In *A Companion to Economic Forecasting*. Oxford: Blacwell Publishers.

Scott, Steven L., and Hal Varian. 2013a. “Bayesian Variable Selection for Nowcasting Economic

Time Series." *Economics of Digitization.*, no. July 2012: 1–22.

Scott, Steven L., and Hal R. Varian. 2013b. "Predicting the Present with Bayesian Structural Time Series." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2304426.

Stephens-Davidowitz, Seth, and Hal Varian. 2015. "A Hands-on Guide to Google Data." *Google, Inc.*

Suarez, Luisa, Sandra Alvarado, Rafael Zorro, and Marly Tellez. 2016. "Encuesta de Opinión Del Consumidor."

Universidad del Desarrollo. 2021. "Indice de Percepcion Del Consumidor."

Varian, Hal. 2014. "Big Data: New Tricks for Econometrics Tools to Manipulate Big Data." *Journal of Economic Perspectives*.

Vega, Matías. 2015. "Índices de Confianza Del Consumidor En Chile y Su Poder Predictivo." Universidad del Desarrollo.

Vosen, Simeon, and Torsten Schmidt. 2011. "Forecasting Private Consumption: Survey-Based Indicators vs. Google Trends." *Journal of Forecasting*. https://doi.org/10.1002/for.1213.

Walker, Andrew, and Daniele Palumbo. 2018. "Argentina - the Crisis in Six Charts." *BBC*, 2018. https://www.bbc.co.uk/news/business-45451208.

Wasserman, Larry. 2000. "Bayesian Model Selection and Model Averaging." *Journal of Mathematical Psychology*, no. 44: 91–107.

Woloszko, Nicolas. 2020. "Tracking Activity in Real Time with Google Trends." *OECD Economics Working Papers*, no. 1634.

Woo, Jaemin, and Ann L. Owen. 2019. "Forecasting Private Consumption with Google Trends Data." *Journal of Forecasting*. https://doi.org/10.1002/for.2559.

World Bank. 2016. *Digital Dividends*. *World Development Report 2016*. Washington. https://doi.org/10.1596/978-1-4648-0671-1.

———. 2019. "World Development Indicators | DataBank." DataBank. 2019.

Zhang, Haiyang. 2017. "Incorporating Google Trends Data in Predicting Consumer Confidence in Sri Lanka." *Harvard Kennedy School*. https://doi.org/10.2139/ssrn.3085010.

Appendix

Resource 1: To access the repository with the code written for this research project go to:

GitHub

github.com/ma4324/lse_capstone

Figure 1: An Example of the Decomposition of Time Series (Argentina's Consumer Confidence).

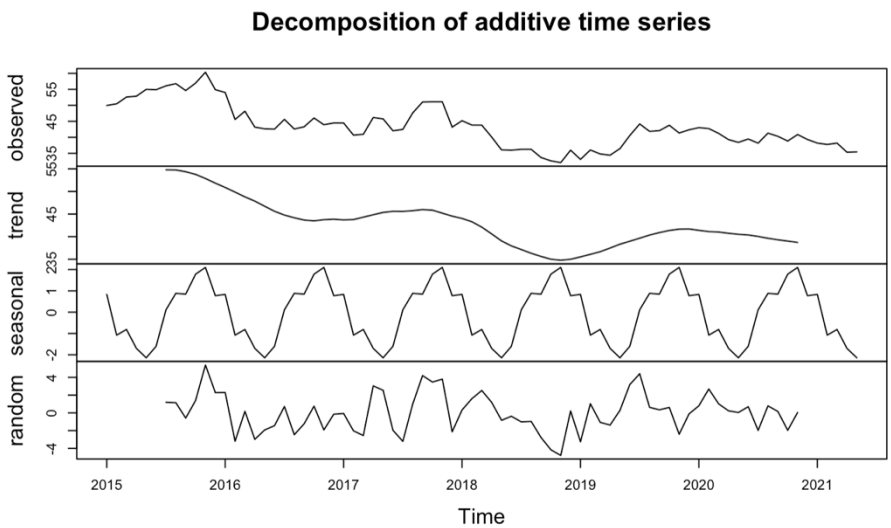


Figure 2: Consumer Confidence Values and Nowcasts in Argentina

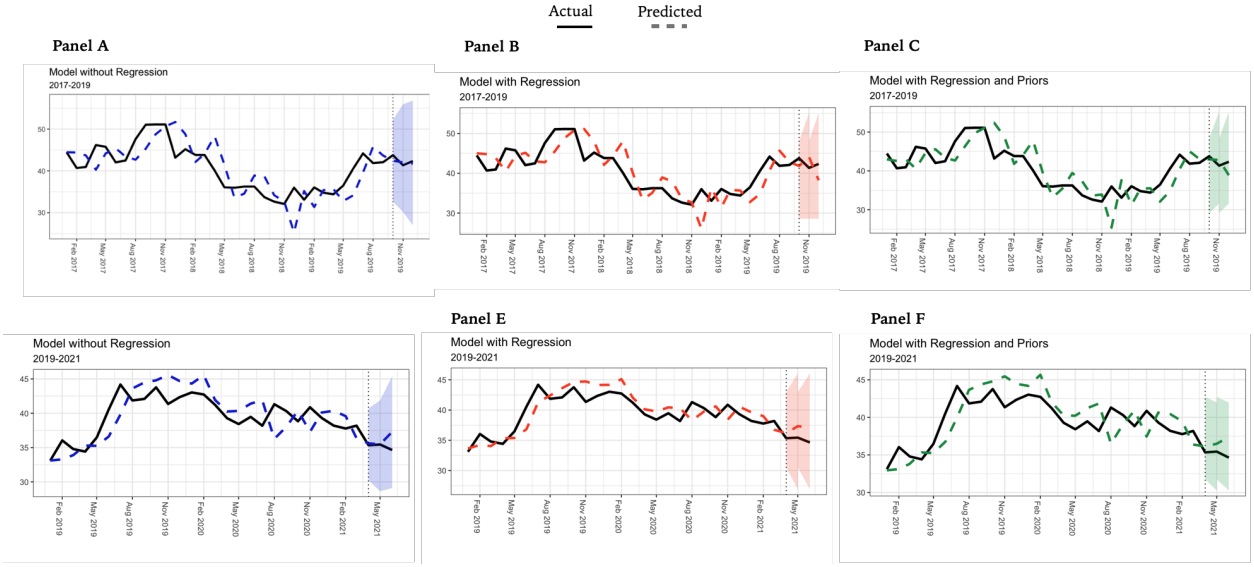


Figure 3: Posterior Probabilities of Inclusion of Predictors in Argentina (2017-2019)

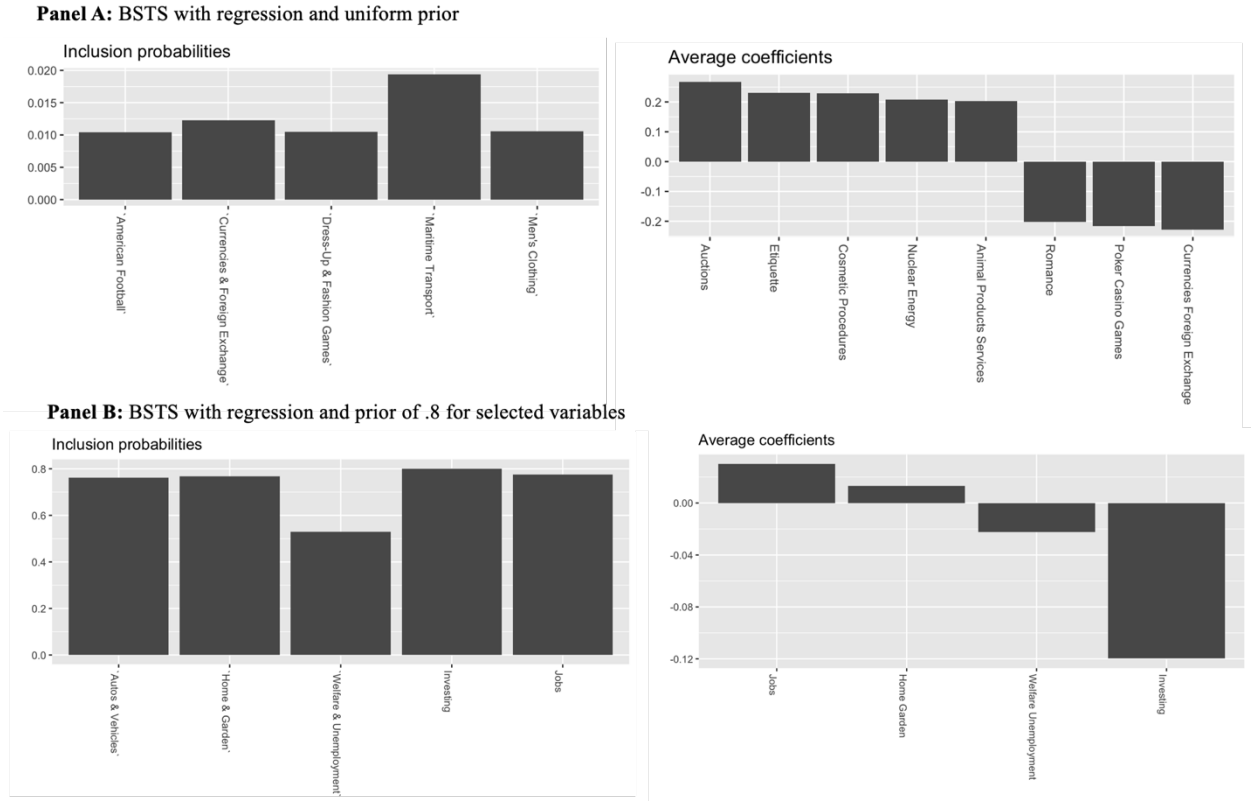


Figure 4: Posterior Probabilities of Inclusion of Predictors in Argentina (2019-2021)

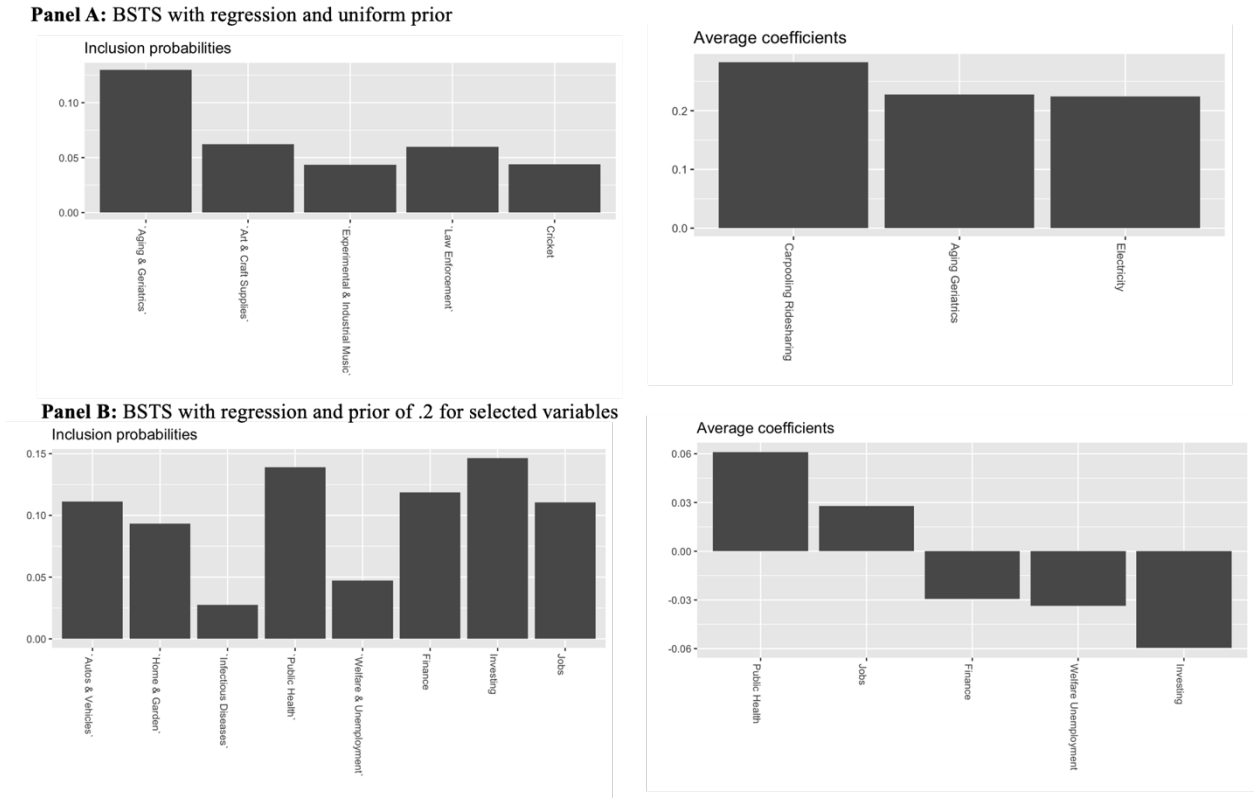


Figure 5: BSTS Decomposition in Argentina (2017-2019)

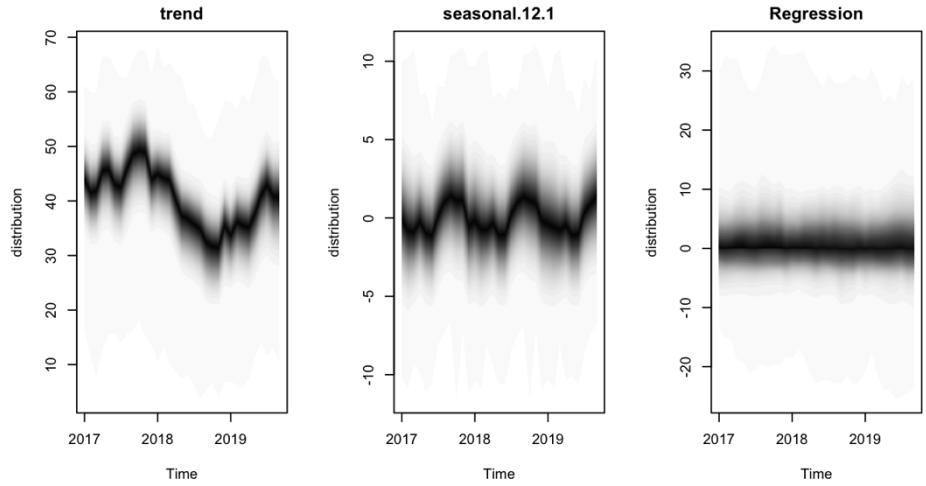


Figure 6: Consumer Confidence Values and Nowcasts in Brazil

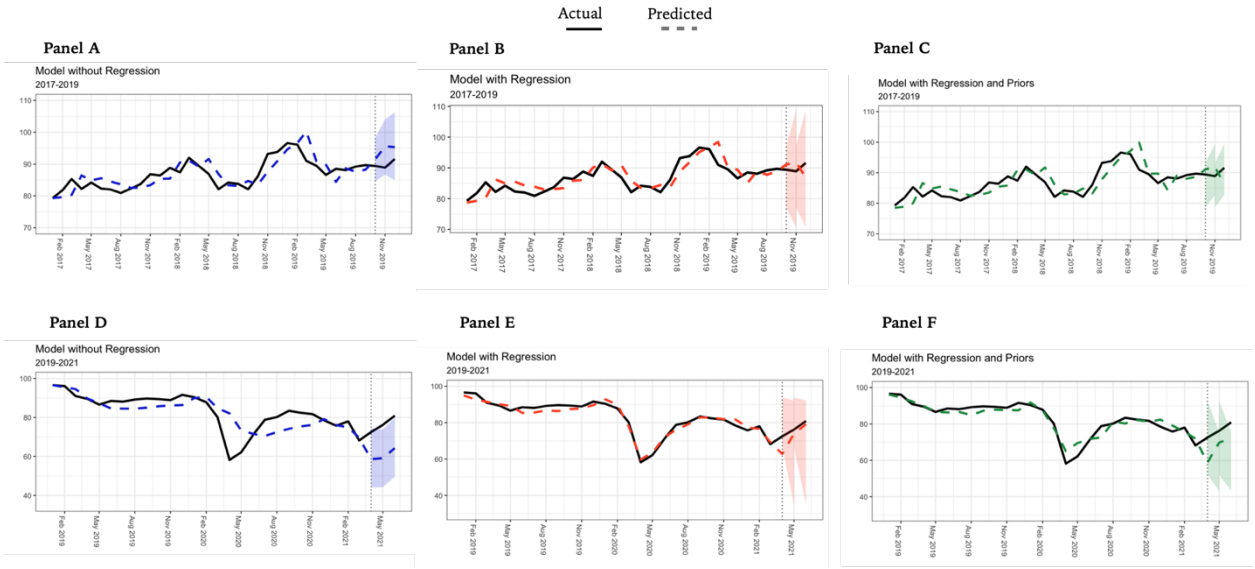


Figure 7: BSTS Decomposition in Brazil (2017-2019)

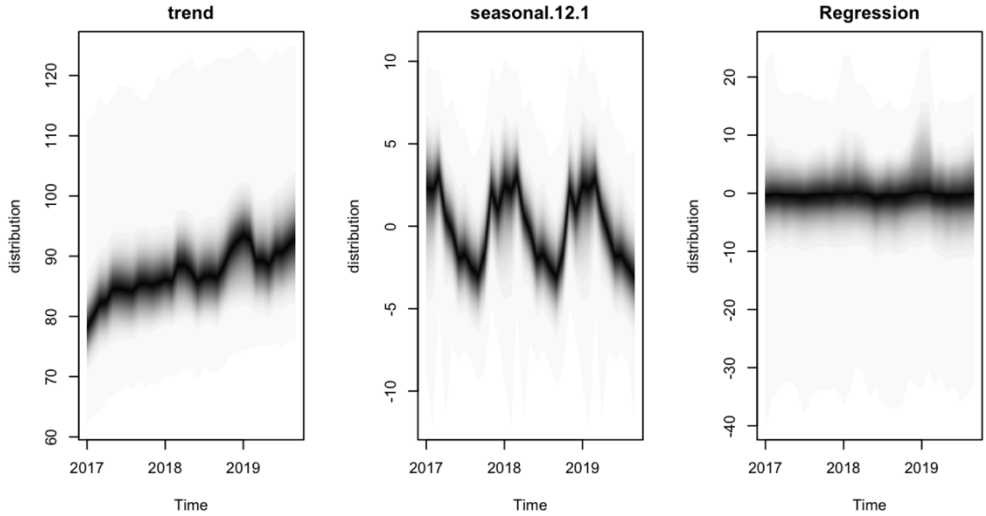
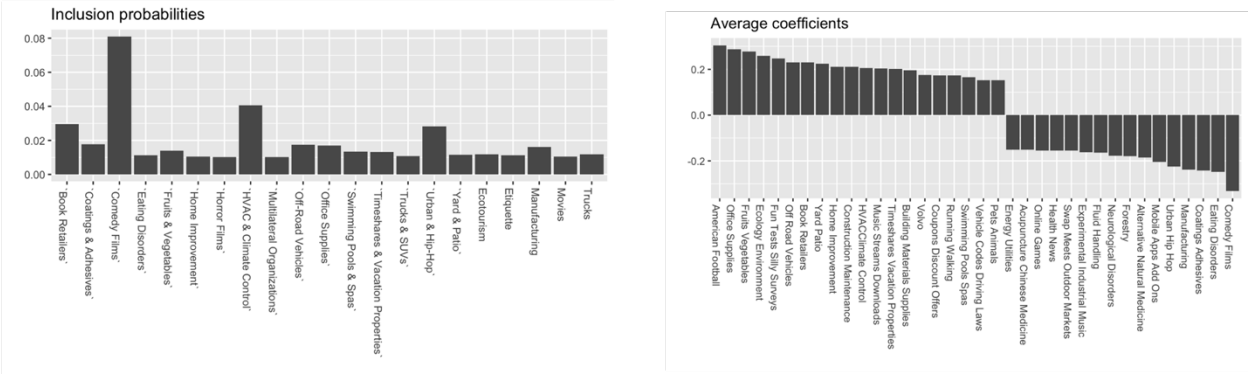


Figure 8: Posterior Probabilities of Inclusion of Predictors in Brazil (2017-2019)

Panel A: BSTS with regression and uniform prior



Panel B: BSTS with regression and prior of .2 for selected variables

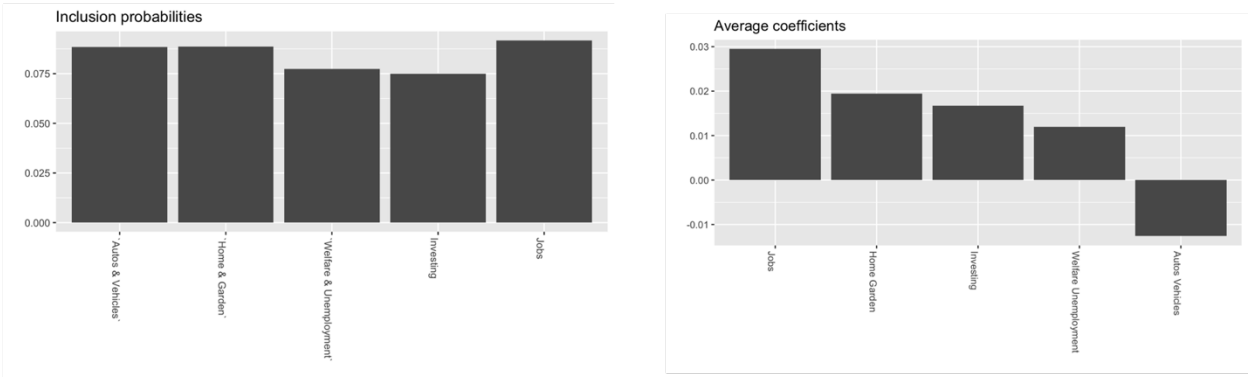


Figure 9: Consumer Confidence Values and Nowcasts in Chile

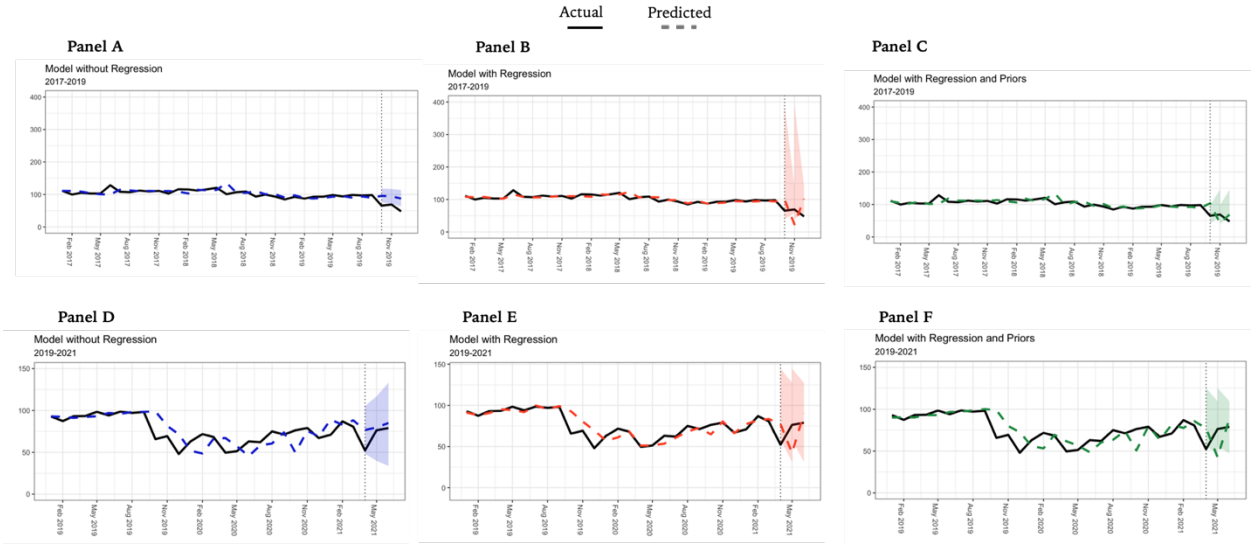


Figure 10: Consumer Confidence Values and Nowcasts in Colombia

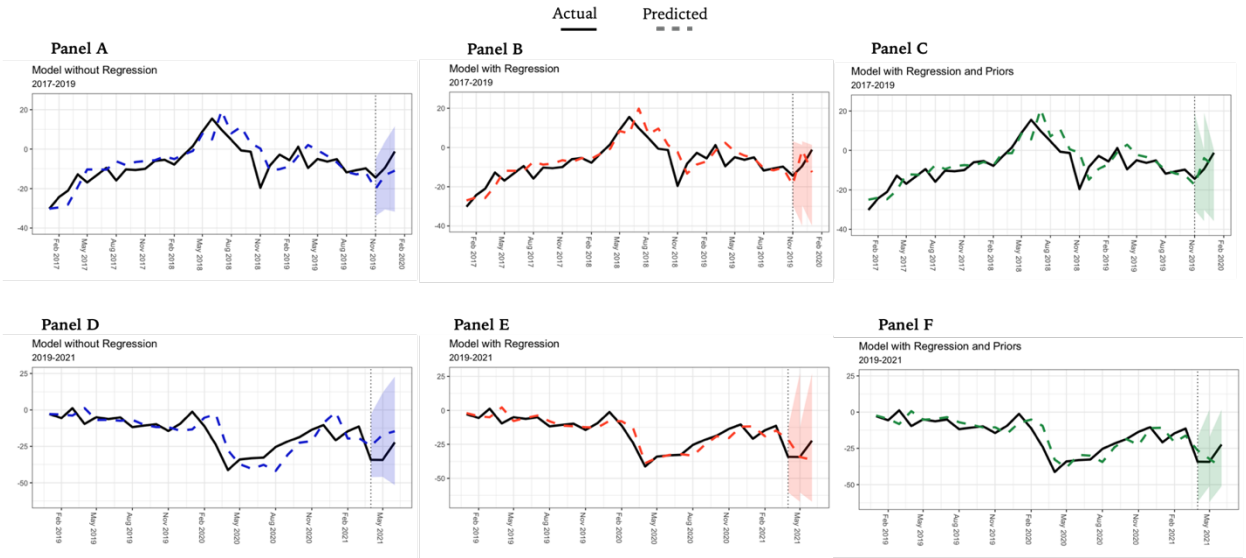


Figure 11: BSTS Decomposition in Colombia (2017-2019)

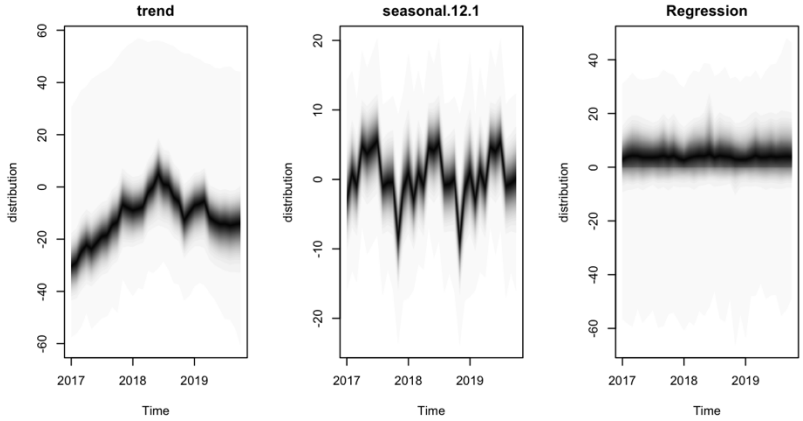
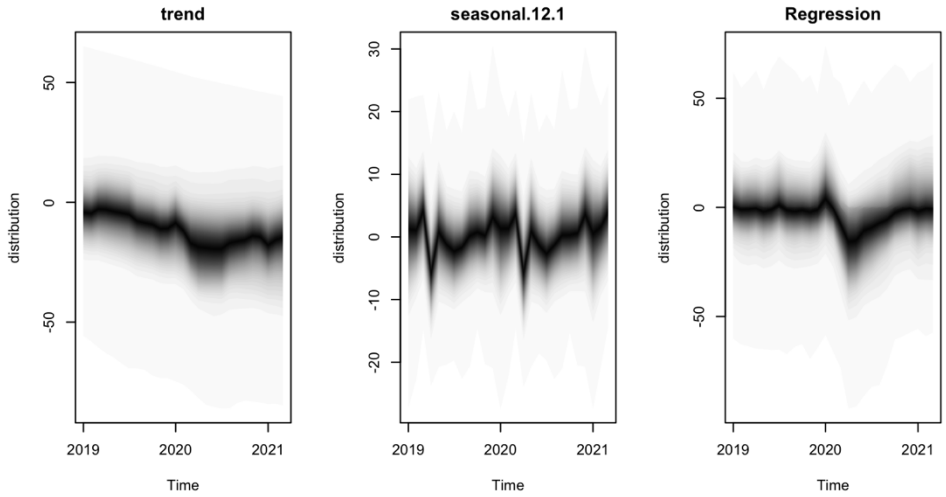



Figure 12: BSTS Decomposition in Colombia (2019-2021)