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Online Search Behavior and Consumer Intent: Implications for Nowcasting

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Abstract

This paper examines online search activity's ability to capture consumers' intentions and enhance short-term forecasting of key economic outcomes. Economic decisions such as consumption and investment are typically preceded by intentions, which, while difficult to observe directly, often manifest as online information-seeking behavior. Using a large, high-frequency dataset of search activity, we nowcast U.S. consumer confidence and private consumption, finding that legal and governmental searches are associated with shifts in consumer confidence, while real estate and news-related searches add value to forecasts of private consumption. We then extend the analysis to GDP nowcasting for selected OECD economies, assessing the predictive performance of search-based indicators across different contexts. Overall, our findings highlight the value of digital attention data as behaviorally grounded signals of consumer intentions, offering a timely complement to traditional economic indicators.

Keywords: nowcasting, online search behavior, consumer confidence, private consumption, GDP growth

JEL codes: E30, E32, E37

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1. Introduction

Timely and accurate information on economic conditions is essential for effective decision-making, especially during periods of heightened volatility. Recent global events, such as the Global Financial Crisis of 2008 (GFC) and the COVID-19 pandemic, have highlighted the limitations of traditional economic indicators, which are often released with significant delays. These lags impede policymakers and analysts who require real-time insights to respond swiftly to rapidly changing conditions.

This paper proposes a novel approach to address this challenge by leveraging online search behavior as a high-frequency, real-time proxy for consumer intentions. Economic actions such as consumption and investment are typically preceded by intentions, which, while unobservable in conventional datasets, often manifest as information-seeking behavior online. When individuals search online, they leave behavioral traces that reveal attention, sentiment, and emerging intent—often well before these translate into observable economic actions. By capturing and analyzing these digital traces, our results indicate that search-based indicators hold promise for nowcasting consumer confidence and private consumption and offer varying degrees of accuracy in GDP forecasts across selected OECD countries.

Unlike traditional forward-looking indicators, such as consumer confidence surveys—typically reported at a monthly frequency and with substantial lags—online search data is updated almost in real time and at higher frequencies (weekly or daily). This makes it a promising complement to conventional data sources for short-term forecasting and policy analysis.

Our contribution to the literature is threefold. First, we nowcast U.S. consumer confidence and private consumption using weekly search data to examine their standalone predictive performance, showing that search-based indicators capture high-frequency shifts in sentiment and spending intentions. Second, we extend the analysis to GDP nowcasting for selected OECD economies, where we benchmark search-based models against established approaches and explore additional exercises, including dynamic factor models (DFMs), the role of economic policy uncertainty, analysis of non-crisis periods, and robustness checks. Third, we identify which search categories and modeling techniques deliver the most accurate and timely forecasts, providing practical guidance for forecasters and policymakers, with evidence suggesting that law- and government-related searches may help explain movements in consumer confidence. By integrating high-frequency data with behavioral insights, this paper links consumers' information-seeking behavior to economic dynamics in real-time, offering a behaviorally grounded perspective on forecasting.

A key foundation of our approach is the behavioral link between information-seeking and intention formation. Intentions typically precede actions (Gillitzer & Prasad, 2018) and often arise when individuals recognize an information gap (Loewenstein, 1994). Searching for information signals attention, emerging intent, and sentiment—mechanisms that can be quantified and translated into predictive economic indicators.

The concept of intention has been studied extensively across disciplines. In psychology, intentions are often described as a person's commitment, plan, or decision to carry out an action or achieve a goal (Eagly & Chaiken, 1993). Ajzen (1991, p. 181) refers to intentions as an indicator of how much effort individuals are willing to invest. Lewin (1951) defines intention as a series of volitions in actions, where the consummatory intentional action is the last one, preceded by a mental act of choice, decision, or intention, terminating this struggle. Motivation precedes intention, which finally leads to action. Intentions might lead to actions immediately or after a gap of time. A common role for intentions in so-called goal-directed action is to bridge desires and their downstream effects. Bagozzi (2006) describes it as follows: goal desire leads to goal intention, leading to action desire, action intention, and finally action.

In economics, intentions have been examined as precursors to observable market actions. Symeondis, Peikos, and Arampatzis (2022) show that purchase intentions often precede actual sales. Morris et al. (2010) find that consumers frequently search online prior to purchases, while Zhao and Mei (2013) show that Google search trends effectively capture consumers' informational needs and attention. In financial markets, Da, Engelberg, and Gao (2011) demonstrate that Google search activity reflects investor attention and predicts trading behavior, particularly among less sophisticated investors. Sandoval and Walsh (2024) show that shifts in sentiment influence planned and actual spending, reinforcing the role of intentions as a precursor to economic actions.

The drivers of intentions and sentiment may originate in fundamental economic conditions or in behavioral dynamics. According to Barsky and Sims (2012) sentiments, i.e. confidence, mainly reflect the information households have about the state of the economy (news views) rather than households' beliefs that are related to non-fundamentals (animal spirits). The causal effect of confidence innovations characterizes expected productivity growth over a relatively long horizon. Building on this literature, we argue that online search behavior provides high-frequency, behaviorally grounded signals of emerging intentions, closely tied to expectations, sentiment, and confidence, and therefore to subsequent economic outcomes.

To evaluate this proposition, we analyze weekly and monthly search data across 181 subcategories spanning both the GFC and the COVID-19 pandemic. We employ advanced statistical techniques—including principal component analysis (PCA), partial least squares (PLS), and shrinkage methods such as Ridge regression, LASSO, and Elastic Net—to extract predictive signals and integrate them into pseudo–real-time nowcasting models. Our results indicate that search-based indicators capture high-frequency shifts in consumer confidence and private consumption in the United States and provide valuable predictive insights for GDP nowcasting in selected OECD economies, including Finland and Japan. For consistency and clarity, we adopt fixed model specifications in these exercises, emphasizing the behavioral signals of consumer intentions embedded in search data, rather than optimizing models purely for predictive performance.

By showcasing the practical application of search-based data in real-time forecasting, this paper highlights the utility of digital behavioral traces as complementary tools to traditional economic indicators. These insights have important implications for improving the timeliness and accuracy of economic analysis, particularly in periods of rapid change.

This paper also contributes to the growing literature on attention and its role in shaping and predicting macroeconomic outcomes. Building on studies that use online search activity to capture shifts in attention and sentiment (e.g., Da, Engelberg & Gao, 2011; Choi & Varian, 2012), we extend this framework to the domain of consumer behavior and to more recent economic shocks. By using a large, high-frequency dataset spanning a broad set of search categories and economies, we provide new evidence on how digital attention signals evolve and how they can be applied for macroeconomic forecasting.

The remainder of the paper is structured as follows. Section 2 discusses the behavioral mechanisms linking shocks, information demand, and intention formation, and reviews related literature on search data in economic nowcasting. Section 3 provides a brief overview of the nowcasting literature. Section 4 describes the data. Section 5 outlines the statistical techniques and presents specific applications for nowcasting consumer confidence and private consumption (Section 5.1) and GDP (Section 5.2). Section 6 reports the empirical results, and Section 7 concludes with key insights and implications.

2. Intentions, shock and consumption

We assume that consumer n gains utility from consumption at different periods. She maximizes her expected stream of total consumption and utility $u(x_s)$ period (t) information I_{t-1} given.

$$max_{(x_t)}\ E_t\left[\sum_{s=t}^{T}\beta^s u(x_s\ |I_{t-1})\right]$$

The maximization of expected consumption x_s takes place given the expected state of nature in the future. $\beta \in (0,1)$ is the discount factor and $u(.)$ is the utility function. Consumer's consumption x_s depends on the unexpected economic shocks which hit the economy (z_t), $z_t = \left(\mu, \sigma_{z,t}^2\right)$ and on the level of consumer sentiments, $\theta_t = (\mu, \sigma_t^2)$. Both the shocks and sentiments are unknown at $(t-1)$. As a result, the expected consumption and utility at $(t+1)$ differs from the expected consumer path at (t).

$$E_{t+1}[\textstyle\sum_{s=t}^{T}\beta^s u(x_s\ |I_t)] = E_t[\sum_{s=t}^{T}\beta^s u(x_s\ |I_{t-1})] + z_t + \theta_t$$

Consumers' intentions are constructed conditionally the state of nature, i.e. level of shocks $g(z_t)$. Consumer sentiment, $\theta_{n,t}$, is also exposed to economic shocks. A shock (z_t) changes the current state of nature and captures consumers' attention which leads to changes in intention and finally changes in aggregate consumption. Thus, whenever a new shock occurs, consumers are bound to gather new information since there is a discrepancy in what the agents know and what they want to know about the shock (Lowenstein, 1994). There is a search for new information about the current state of nature to reach the maximum utility of their expected consumption path the level of sentiments given. Consumers explore information by exploiting all possible tools with the lowest costs of information, like internet searches. The search activity originates from shock, reflects intentions and eventually alters consumption.

Thus, consumer n intentions $(y_{n,t})$ proceed (nowcasts) the consumer's consumption decision. High shock uncertainty ($\sigma^2_{z,t}$) enlarges consumer's demand for new information too. Consumer sentiments and confidence are related to the changes in the state of the economy as well. High sentiments enlarge consumer's intentions exposure to positive economic shocks, whereas low sentiments enlarge reactions to negative economic shocks. A change in the state of nature makes consumers call for new information to modify their confidence, i.e. sentiments too.

$$y_{n,t} = \ g[(z_t)]$$

$$\theta_{n,t} = f[(z_t)]$$

Thus, the change in the state of nature (z_t) leads to change in agent intentions reflected as internet searches and to changes in consumption Δx_n and aggregate GDP ($\sum_{n=1}^{N} \Delta x_n$). These intentions lead to information-seeking behavior, such as internet searches, which precede actual consumption decisions. The change in consumption Δx_n is thus a function of both intentions and sentiment:

$$\sum_{n=1}^{N} \Delta x_n = g'(f(z_t))f'(z_t)$$

Next, we will execute number of different tests stemming from our hypothesis of searching for new information leading to consumers' actions. We estimate the role of different economic shocks for internet searches. We test the relationship of sentiments and internet searches too. The focus in our analysis is to reveal to what extent the changes in state-of-the-nature lead to searches for new information proceeding the consumption which will eventually be reflected in the change of the GDP.

3. Literature of nowcasting economic actions

Nowcasting—the practice of forecasting economic indicators in near real-time—has gained prominence as a means to address the delays inherent in traditional economic data releases. Early attempts employed bridge equations to predict quarterly indicators using higher-frequency monthly data (Trehan, 1989; Rünstler & Sedillot, 2003). Over time, methods evolved to tackle the "ragged-edge" problem in time-series data, where datasets contain missing values due to staggered release schedules. Evans (2005) introduced the use of the Kalman filter to estimate missing observations, while Giannone et al. (2008) refined this approach with dynamic factor models (DFMs) that condense high-dimensional information into core components, enhancing forecasting accuracy and mitigating overfitting risks.

Traditional nowcasting integrate both "hard" and "soft" data. Hard data, such as industrial production figures, directly measure economic output. Soft data sources, like consumer confidence surveys and purchasing manager indices, offer sentiment-based insights into economic expectations and are updated more frequently (Götz & Knetsch, 2019). Soft data can significantly improve GDP growth forecasts when hard data are scarce or delayed (Bańbura and Rünstler, 2011). Nonetheless, subjective biases may bias survey-based indicators, particularly during unexpected economic shocks (Vermeulen, 2012).

An alternative soft data is online search activity, which captures real-time shifts in household interests such as attentions, intentions and economic sentiments. Since becoming publicly available, search data have become widely utilized in forecasting a range of macroeconomic indicators, including unemployment rates (Tuhkuri, 2014), private consumption (Vosen & Schmidt, 2011; Woo & Owen, 2019), consumer confidence (Della Penna & Huang, 2009), economic uncertainty (Bontempi et al., 2021), and policy-related uncertainty (Donadelli, 2015). Search-based metrics has considerable power in providing early states nowcasts for European economies (Götz and Knetsch, 2019 and Ferrara and Simoni, 2019).

Machine learning and dimension reduction techniques have expanded the use of high-dimensional data in nowcasting. Techniques like principal component analysis (PCA) and partial least squares (PLS) help distill large datasets into core components that retain predictive power while reducing complexity (James et al., 2013; Hastie et al., 2009). Additionally, shrinkage methods—such as Ridge regression, LASSO, and Elastic-net—are effective in reducing model overfitting by penalizing non-informative predictors (Zou & Hastie, 2005). It is common to apply numerous search categories and extract the most relevant signals for nowcasting.

Despite the promising results, gaps remain in the literature regarding the application of search-based data to nowcast both consumer confidence, private consumption, and GDP growth across different economic contexts. Furthermore, the effectiveness of advanced statistical techniques in processing high-dimensional search data for economic forecasting warrants further exploration.

We augment the existing literature on nowcasting proposing that internet searches reflect consumers' demand for information due to changes in mood, fears and intention and it has connection to consumer sentiments and economic actions. Our hypothesis is supported by Gillitzer and Prasad (2018) who indicate that survey-based consumer intentions are valid predictors of consumers car buying activities. Blachard and Bernanke (2023) used internet searches to capture ship shortage and car shortage due to enlarged demand and short supply. Likewise, Daas and Puts (2014), Lansdall-Welfare, Lampos and Christianini (2012) lend support that consumer sentiments and social media sentiments from Facebook were related, and sentiments can be nowcasted with Tweets and Facebook stories. We propose that the internet search data could reflect agents' intentions while they search for new information about the topic of interest. This is related to consumers' sentiments and intentions to further economic activity.

This study examines how search-based data can be used to reflect consumers intentions to nowcast consumer confidence, private consumption, and GDP growth in the United States and selected OECD countries. Our focus is on capturing the behavioral underpinnings of economic activity by using online search patterns as reflections of consumer intentions and sentiments. By integrating machine learning techniques with traditional econometric methods, we highlight the value of search-based indicators in reflecting the motivations and expectations driving economic behavior. This approach emphasizes the economic significance of consumers' information-seeking activities rather than pursuing model optimization, offering a behavioral background to real-time economic forecasting.

4. Data

Our initial analysis focuses on the United States. In part the U.S. is selected due to its status as a leading English-speaking country with a comprehensive history of internet search activity. We utilize three primary data sources: consumer confidence indices, private consumption figures, and internet searches (Google search data). In a subsequent section, we expand our analysis to include GDP data from selected OECD countries and measures of U.S. policy uncertainty of potential importance in generating consumers intentions and searches.

Consumer confidence data serves as our benchmark, acting as a proxy for traditional "soft" data sources and reflecting consumer sentiment. We use seasonally adjusted consumer confidence figures from the OECD database for the period January 2004 to October 2021.

Google measures internet searches in Search Volume Index (SVI), but not in absolute numbers. Thus, volume index measures the specific search term's relative popularity to other search terms in that specified geographical area. 100 is the maximum value in this volume index, and 0 is the minimum. We collected the search data from the Google Trends website in November 2021, aligning with the timeframe of our other data sources. Since Google Trends suffers from a significant sampling variance, we collected search data on 15 different days and averaged those different data samples; see Medeiros and Pires (2021). For Sections 4.1 and 5.2, we utilize weekly search data spanning October 16, 2016, to October 23, 2021. Conversely, for Sections 4.2 and 5.3, we apply longer-term monthly search data covering the period from January 2004 to October 2021.

Google Trends data is available for both user-specified keywords and search categories. We use Google search categories, which allow comparison between different countries. Thus, researchers are not required to translate selected keywords for different languages. We collect similar sets of search categories, henceforth subcategories, as in Götz & Knetsch (2019), Heikkinen & Heimonen (2024), see Appendix A. We reduce these subcategories to a common factor via principal component analysis (PCA) and partial least squares (PLS). From these selections, we form common factors with 16 different sets of related subcategories, and we name these common factors "broad search categories", as depicted in Table 1.

Table 1: Broad search categories via dimension reduction methods.

Autos & Vehicles	Beauty & Fitness	Business & Industrial	Computers & Electronics
Food & Drink	Health	Home & Garden	Internet
Investing	Jobs	Law	News
Real Estate	Shopping	Sports	Travel

For example, we form the Law broad category from "Government", "Legal", "Military", "Public Safety", and "Social Services" subcategories.

5. Methods

5.1. Consumer confidence and private consumption

The collected monthly internet search data is highly dimension as it has predictors *p* larger than observations *n*. This high dimensionality can cause the models to be noisy and over-fitted, generating poor-performing nowcasts. To solve this issue, we apply several different dimension reduction methods.

First, we use the *principal component analysis* (*PCA)*, which reduces the dimensional space by maximizing the variance of the underlying data and using only the first or second principal components. Assuming that the data is centered around the mean, PCA can be presented using the singular value decomposition where underlying data is multiplied by the loadings vector, and the resulting matrix contains the principal components (Jolliffe, 2002; Hastie et al., 2009; James et al., 2013).

Second, we use the *partial least squares (PLS)* dimension reduction method. It is a supervised learning method as it uses the response variable (i.e., consumer confidence) to maximize the variance between the predictors and the response. After centering the data, the PLS can be formulated as a specific algorithm to generate components. (Hastie et al., 2009; James et al., 2013.) PLS output is a similar type of score matrix as in the PCA, which can be used in OLS estimation. (Hastie et al., 2009; James et al., 2013.) We use the first components from the PCA and PLS score matrices to reduce dimensions.

For example, we apply PCA or PLS to the subcategories related to Autos & Vehicles (all 19 of them, see Appendix A, Table A1) and use the first principal component or latent variable in linear regression models. These dimension reduction techniques are re-estimated in each nowcasting period. We rescale the test sets to have the same mean and scale as the training samples to ensure consistency.

In the first step, we examine the relationship between internet searches and consumer sentiment using weekly search data to nowcast U.S. monthly consumer confidence data. Our aim is to determine whether internet searches could provide more timely information about the current state of the economy than traditional consumer sentiment surveys. Previous studies, such as Choi and Varian (2012), find that internet search models outperform baseline autoregressive models when forecasting Australian consumer confidence. Similarly, Della Penna and Huang (2009) find a strong correlation between their internet-search-based consumer confidence index and two major U.S. survey-based indexes: the Conference Board Consumer Confidence Index (CCI) and the University of Michigan Consumer Sentiment Index (MCSI).

Our nowcasting model for consumer confidence is specified as:

(1) $\text{Confidence}_t = \beta_0 + \beta_1 \text{Google}_{i,t} + \epsilon_t$

where Confidence_t is the consumer confidence at time t, $\text{Google}_{i,t}$ represents the Google search activity for category i at time t, and ϵ_t is the error term.

To align the weekly search data with the monthly consumer confidence data, we select the most recent complete week of Google data available before the official release of the MCSI each month. For example, for the October 2016 MCSI released on October 28, 2016, we use Google data from October 16 to October 22, 2016. This approach yields a monthly aggregated internet search dataset covering October 2016 to October 2021. The complete set of selected weeks is provided in Appendix B, Table B1.

Recognizing that consumer confidence often influences actual spending behavior, we extend our methodology to nowcast private consumption. Building on prior research by Vosen and Schmidt (2011) and Woo and Owen (2019), who find that internet search data can enhance nowcasting of U.S. private consumption, we examine the ability of internet searches to nowcast private consumption in the U.S. Equation 2.

(2) $\text{Consumption}_t = \beta_0 + \beta_1 \text{Google}_{i,t} + \epsilon_t$

where Consumption_t is the US private consumption expenditure at time t.

In contrast to previous studies, we use higher frequency weekly Google data collected from October 16, 2016, to October 23, 2021. To aggregate this data to monthly levels, we select the complete set of weeks preceding the official publication of private consumption data; the selected weeks are detailed in Appendix B, Table B2. This approach produces a monthly dataset spanning October 2016 to October 2021. We utilize the same set of 181 search subcategories and apply the dimension reduction methods as described earlier. Like our approach for consumer confidence, we incorporated only one search-based factor in the model, with a fixed set of subcategories. By applying these methods to private consumption, we aimed to capture real-time shifts in consumer spending behavior.

Extending our analysis further, we turn our attention to nowcasting GDP, the most comprehensive measure of economic performance. We also extend our analysis with shrinkage methods to enhance the predictive accuracy of our models. In this analysis, GDP growth is measured as quarter-over-quarter changes in volume terms, adjusted for both seasonal and working-day effects to ensure consistency and comparability.

5.2. Nowcasting GDP

For GDP nowcasting, we also employ *shrinkage methods*, which are supervised statistical learning techniques that include both the response variable and all predictors *p* from the data. These methods are similar to OLS in that they aim to create a tight fit of the data by reducing the sum of squares residuals. However, shrinkage methods include a shrinkage penalty term, which shrinks regression coefficients toward zero. In this way, shrinkage methods can reduce the variance but at the cost of an increase in bias. (James et al., 2013.)

We use three different shrinkage methods: (i) Ridge, (ii) Least absolute shrinkage and selection operator (LASSO), and (iii) Elastic-net. These methods differ in the selection of the Shrinkage penalty term or the L-norm function.

(3) $s(\boldsymbol{\beta}) = \lambda \sum_{j=1}^{p} |\beta|^{q}$

Equation 3 presents a general L_q-norm function, which affects the tuning parameter λ. When the value of λ increases, parameters are punished more heavily, and estimates shrink toward zero. We choose the optimal tuning parameter using cross-validation. (Hastie et al., 2009; James et al., 2013.) The *Ridge shrinkage method* uses L_2-norm function to punish the coefficients.

(4) $\hat{\beta}^{ridge} = \min_{\beta} \left\{ \sum_{i=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \right\}$

The Ridge regression minimization problem, as shown in Equation 4, includes a penalty term that shrinks coefficients toward zero but not exactly to zero (Hastie et al., 2009; James et al., 2013.)

(5) $\hat{\beta}^{LASSO} = \min_{\beta} \left\{ \sum_{i=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\}$

Equation 5 depicts *LASSO regression's* minimization, which now uses the L_1-norm as a penalty term function, which produces a more significant penalty than in Ridge regression. Therefore, coefficients are penalized to precisely zero. LASSO has some limitations, for example, when predictors are correlated. Elastic-net shrinkage methods have a particular penalty term that one can use to alleviate these limitations. (Hastie et al., 2009; Zou & Hastie, 2005)

(6) $\hat{\beta}^{elastic-net} = \min_{\beta} \left\{ \sum_{i=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} (\alpha \beta_j^2 + (1-\alpha)|\beta_j|) \right\}$

In Equation 6, *Elastic-net regression's* penalty term lies between the Ridge and LASSO regressions. For example, if α = 1, the Elastic-net equals ridge regression, and if α = 0, Elastic-net becomes LASSO regression. With an α = 0.5, the values of both L_1-norm and L_2-norm penalty terms are equally weighted (Zou & Hastie, 2005.)

We apply these shrinkage methods to each selection of search subcategories (16 in total) to address the high dimensionality of the data. For instance, we use the 19 subcategories related to Autos & Vehicles (see Appendix A, Table A1) in the shrinkage methods to generate nowcasts for the Autos & Vehicles broad category. The randomness in the tuning parameter λ due to cross-validation introduces variability in the results. To enhance robustness, we perform three-fold cross-validation, estimate each method five times, and average the results. This procedure is applied consistently throughout the sample periods.

We nowcast GDP with the following specifications.

Benchmark models:

(7) $\text{GDP}_{i,t} = \beta_0 + \beta_1 \text{GDP}_{i,t-1} + \epsilon_{i,t}$

Equation 7 represents the benchmark AR-1 model, which uses only the previous quarter's GDP values to nowcast county's current GDP, effectively modelling the relationship between the current and lagged GDP values.

(8) $\text{GDP}_{i,t} = \beta_0 + \beta_1 \text{Confidence}_{i,t-1} + \epsilon_{i,t}$

(9) $\text{GDP}_{i,t} = \beta_0 + \beta_1 \text{GDP}_{i,t-1} + \beta_{2,i} \text{Confidence}_{i,t} + \epsilon_{i,t}$

Equations 8 and 9 serve as additional benchmarks, incorporating consumer confidence as a predictor. Equation 8 uses only consumer confidence, while Equation 9 includes both lagged GDP and contemporaneous consumer confidence.

Search-based models:

(10) $\text{GDP}_{i,t} = \beta_0 + \beta_1 \text{Google}_{i,t} + \epsilon_t$

(11) $\text{GDP}_{i,t} = \beta_0 + \beta_1 \text{GDP}_{i,t-1} + \beta_2 \text{Google}_{i,t} + \epsilon_t$

(12) $\text{GDP}_{i,t} = \beta_0 + \beta_1 \text{GDP}_{i,t-1} + \beta_2 \text{Confidence}_{i,t} + \beta_3 \text{Google}_{i,t} + \epsilon_t$

Equations 10–12 display the search-based models. Our dimension reduction methods compress the 181 subcategories into 16 broad single factors using PCA and PLS. For example, search categories "Education" and "Jobs" are reduced to a single broad category, "Jobs & Education".

We also apply the shrinkage methods LASSO, Elastic-net, and Ridge. Thus, we input 16 broad categories subcategories into Equations 10–12 and estimate expanding rolling-window pseudo-out-of-sample forecasts with initial sample of 12 quarters. To be more specific, the selection of subcategories remained fixed throughout the nowcasting exercises, meaning that changes between subcategories were not allowed. We evaluate the model performance with Root mean squared errors (RMSE). RMSE compares forecasted GDP values to the actual realized GDP values.

While shrinkage methods provide valuable insights, we seek to further enhance our nowcasting accuracy by exploring alternative methodologies. Given the high dimensionality and potential interrelationships among the search data, we turn to Dynamic Factor Models (DFMs), which are well-suited for capturing common factors driving co-movements in large datasets.

5.2.1 Dynamic factor model

Dynamic factor models (DFM) are popular in the nowcasting literature, e.g., Banbura et al. (2010), Doz et al. (2011), Doz et al. (2012), and Giannone et al. (2008). We apply the DFM framework to construct search-based dynamic factor model to nowcast the United States GDP growth. Our approach closely aligns with the procedures outlined by Doz et al. (2012) and Giannone et al. (2008).

First, we ensure that the search data is stationary. To achieve this, we analyze the complete ex-post internet search data and use three different tests: the Ljung-Box test, the Augmented Dickey-Fuller (ADF) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. If two of the tests indicate stationarity, we regard the series as stationary. If not, we difference the series once. Second, we use PCA to extract the factor loadings and factor scores and solve the VAR equation from PCA scores (Doz et al., 2012; Giannone et al., 2008).

(13) $\mathrm{Z}_t = X\boldsymbol{C}$

(14) $\mathrm{Z}_t = A\,\mathrm{Z}_{t-1} + \epsilon_t$

The PCA score matrix Z_t in Equation 13 is a linear combination of the original variables X and the PCA loadings matrix $\boldsymbol{C}$. In Equation 14 A is the coefficient on the PCA score matrix Z_t, and ϵ_t is the VAR residual (Doz et al., 2012; Giannone et al., 2008).

In the third step, we apply the Kalman filter to estimate filtered and smoothed series.

(15) $\mathrm{x}_t = A\,\mathrm{x}_{t-1} + \epsilon_t$ where $\epsilon_t \sim (0, R)$

(16) $\mathrm{y}_t = C\,\mathrm{x}_t + \mathrm{v}_t$ where $v_t \sim (0, Q)$

The Kalman Filter in the state-space form employs the transition equation (Equation 15) and the (Equation 16) the observation equation (Durbin & Koopman, 2012). We extract the transition coefficient A from the previous VAR equation step. C is the observation coefficient extracted from the PCA loadings matrix (Doz et al., 2012; Giannone et al., 2008.) We apply Kalman filtering and smoothing using the KFAS R-package (Helske, 2017).

(17) $\mathrm{GDP}_{i,t} = \beta_0 + \beta_1 \text{Factor } 1_t + \epsilon_t$

Equation 17 depicts the dynamic factor model generated from monthly internet search data. We also estimate a one-step-ahead Kalman filter every third month to obtain the most recent information. These estimates are then applied to Equation 17, which we estimate using OLS.

Recognizing that external factors such as economic uncertainty can significantly influence both search behavior and economic activity, we examine how incorporating measures of uncertainty might enhance our nowcasting models. Previous research suggests that during periods of heightened uncertainty, individuals are more likely to engage in information-seeking behavior online.

5.2.2. Economic uncertainty

Donadelli (2015) reports that internet searches increase during periods of economic uncertainty, as individuals seek additional information related to economic conditions. Building on this insight, we investigate the impact of Economic Policy Uncertainty (EPU), as measured by Baker, Bloom, and Davis (2016), on the ability of search data to nowcast future economic activity. Specifically, we incorporate the EPU index into our models to assess whether accounting for economic uncertainty improves forecasting performance, as shown in Equation (18).

(18) $\text{GDP}_t = \beta_0 + \beta_1 \text{GDP}_{t-1} + \beta_2 \text{Google}_{i,t} + \beta_3 \text{Uncertainty}_t + \beta_4 (\text{Google}_{i,t} \times \text{Uncertainty}_t) + \epsilon_t$

6. Empirical results

In this section, we present the empirical findings of our study, focusing on the behavioral implications and effectiveness of using search activity data to nowcast consumer confidence, private consumption, and GDP growth. Online search behaviors serve as proxies for consumer intentions, reflecting how individuals actively seek information related to their concerns, needs, and anticipated economic decisions. This behavioral approach allows us to bridge the gap between immediate search interests and their economic outcomes.

6.1. Nowcasting consumer confidence

Consumer confidence reflects household sentiment and expectations, often mirrored in search activities as individuals seek information in response to real-world events. Using weekly search data, we conduct pseudo out-of-sample nowcasting exercises within an expanding rolling window framework, analyzing data from October 2016 to October 2021, with an initial training sample from October 2016 to October 2017. Importantly, the exercises rely solely on data available at the time of each nowcast to ensure a real-time perspective.

Table 2 presents the RMSE results of models augmented with search data, where we employ Principal Component Analysis (PCA) and Partial Least Squares (PLS) for dimension reduction.

Table 2: RMSE scores for nowcasting consumer confidence.[1]

Country:	**United States**	
Model specification:	**Equation (1)**	
Dimension reduction:	**PCA**	**PLS**
	RMSE	**RMSE**
Autos & Vehicles	11.630	7.456
Beauty & Fitness	11.204	9.996
Business & Industrial	8.278	7.163
Computers & Electronics	10.560	8.316
Food & Drink	10.645	10.150
Health	8.829	8.460
Home & Garden	9.954	8.994
Internet	10.072	8.084
Investing	10.904	9.010
Jobs	8.314	8.151
Law	6.148*	6.089*
News	9.018	7.309
Real Estate	11.752	10.794
Shopping	10.905	8.202
Sports	11.700	8.496
Travel	8.847	7.872

[1] *Denotes the lowest RMSE score.

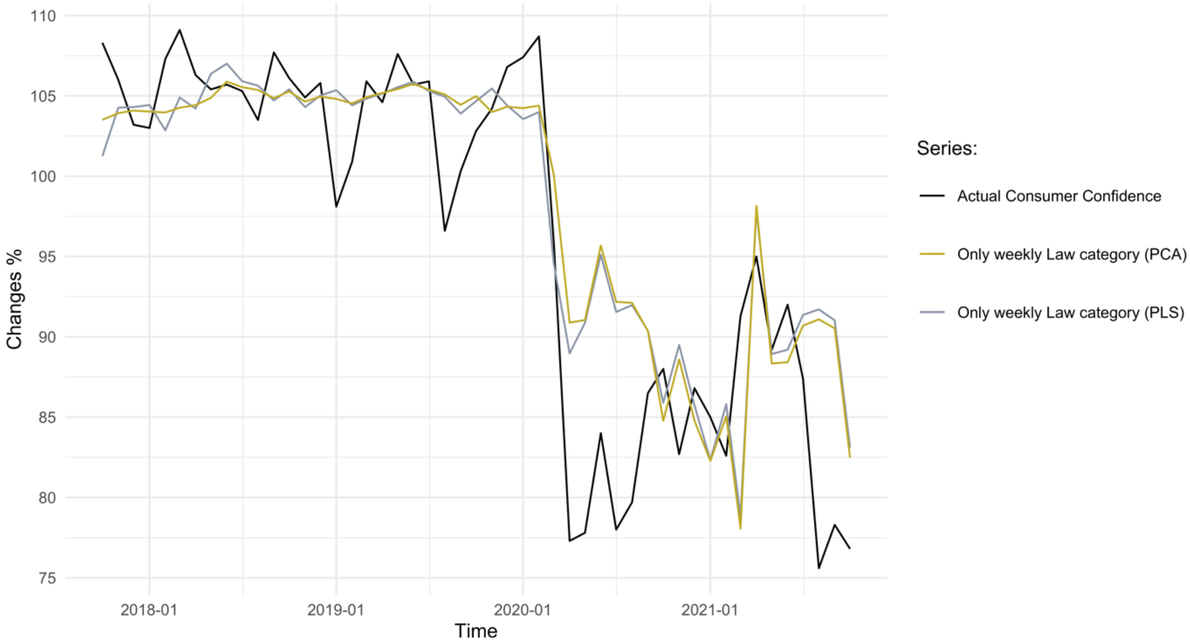

Figure 1: Nowcasts of consumer confidence from the most accurate models.

According to Table 2, the Law category provides the most accurate nowcasts for U.S. monthly consumer confidence. Figure 1 illustrates that the nowcasts from the Law category closely track actual consumer confidence, showing considerable variance that aligns with observed changes.

To understand why the Law category is particularly effective at forecasting consumer confidence, we examine the behavioral dynamics underlying searches in its subcategories: "Government," "Legal," "Military," "Public Safety," and "Social Services." These subcategories represent key areas of concern for households, particularly during periods of uncertainty. Equation (19) models the relationship between these subcategories and consumer confidence, aiming to uncover how specific search behaviors reflect broader sentiments and intentions.

$$\text{Confidence}_t = \beta_0 + \beta_1 \text{Government}_t + \beta_2 \text{Legal}_t + \beta_3 \text{Military}_t + \beta_4 \text{Public Safety}_t + \beta_5 \text{Social Services} + \epsilon_t \quad (19)$$

Table 3: Law subcategories explaining Consumer confidence

	Dependent variable:
	Consumer Confidence
Government	0.219***
	(0.080)
Legal	0.160
	(0.111)
Military	0.227*
	(0.128)
Public Safety	0.482***
	(0.169)
Social Services	-0.556***
	(0.077)
Constant	49.030***
	(8.926)
Observations	61
R^2	0.805
Adjusted R^2	0.787
Residual Std. Error	4.767 (df = 55)
F Statistic	45.453*** (df = 5; 55)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 3 presents the result of the explanatory power of Law subcategories on consumer confidence. Government (0.219***), Military (0.227*), Public Safety (0.482***), and Social Services (-0.556***) are all significantly associated with consumer confidence. The adjusted R^2 for the model is 0.787, indicating that 78.7% of the variation in consumer confidence could be explained by the Law subcategories. The F-statistic of 45.453*** indicates that the model was statistically significant. Accordingly, several Law subcategories have a significant relation to consumer confidence.

These results suggest uncertainty or economic stress launches households attention to gather particularly information about governance, security, and available social support. Positive associations for Government, Military, and Public Safety indicate that confidence rises when individuals perceive these areas as stable or improving. Conversely, the negative relationship with Social Services may reflect growing economic distress, as heightened searches in this subcategory likely correspond to increased reliance on social programs, signaling financial vulnerability among households.

Overall, the findings underscore the behavioral relevance of safety, governance, and support systems in shaping consumer sentiment during crises. This analysis demonstrates the significant role of the Law category in capturing real-time shifts in consumer confidence, reflecting household behavior and their response to evolving social and economic conditions. The observed search patterns suggest that households' intentions and concerns, as expressed through information-seeking behavior, are a precursor to broader economic actions.

6.2. Linking search activity and GDP through consumer sentiment

Building upon the behavioral insights derived from the analysis of consumer confidence, we now examine whether the Law category's relationship with consumer sentiment extends to broader economic activity, specifically GDP growth. The behavioral rationale here is that search activity in this category not only reflects immediate concerns about governance, safety, and societal support but also signals shifts in economic expectations and preparedness for financial decision-making.

We use two model specifications to assess this relationship, both leveraging Law-related search data. The first model integrates consumer sentiment alongside the Law category, as outlined in Equation (21):

$$(20)\ \mathrm{GDP}_t = \beta_0 + \beta_1 \mathrm{Law\_PLS}_t + \beta_2 \mathrm{Confidence}_t + \epsilon_t$$

where GDP_t represents quarterly GDP growth, $\mathrm{Law\_PLS}_t$ is the Law category search index processed via partial least squares (PLS) regression at time t, $\mathrm{Confidence}$ is the consumer confidence index. The second model excludes consumer confidence, focusing solely on the Law category as shown in Equation (21):

$$(21)\ \mathrm{GDP}_t = \beta_0 + \beta_2 \mathrm{Law\_PLS}_t + \epsilon_t$$

The analysis applies weekly and monthly Law-related search data aggregated to quarterly levels, selecting every third month for a sample covering six quarters. The findings demonstrate that the Law category effectively nowcasts GDP growth both independently and as a conduit for consumer sentiment. The first model, which incorporates both consumer confidence and Law search data, achieves an RMSE of 96.565. However, the second model, which relies solely on the Law category, slightly outperforms it with an RMSE of 96.178. This indicates that the Law category encapsulates consumer sentiment effectively and can serve as a direct proxy for it in GDP predictions.

Figures 3 and 4 visually reinforce these results. Figure 3 shows the combined model capturing key GDP fluctuations, reflecting the alignment between consumer sentiment (via the Law category) and GDP dynamics. Figure 4 further demonstrates that the Law category alone closely tracks actual GDP growth, substantiating its predictive strength.

Importantly, these findings underscore that search data, particularly within the Law category, transmits information about consumer sentiment that is important for real-time economic forecasting. By capturing shifts in public concerns related to legal, governmental, and societal issues, the Law category acts as a mechanism that connects consumer behavior to broader macroeconomic outcomes

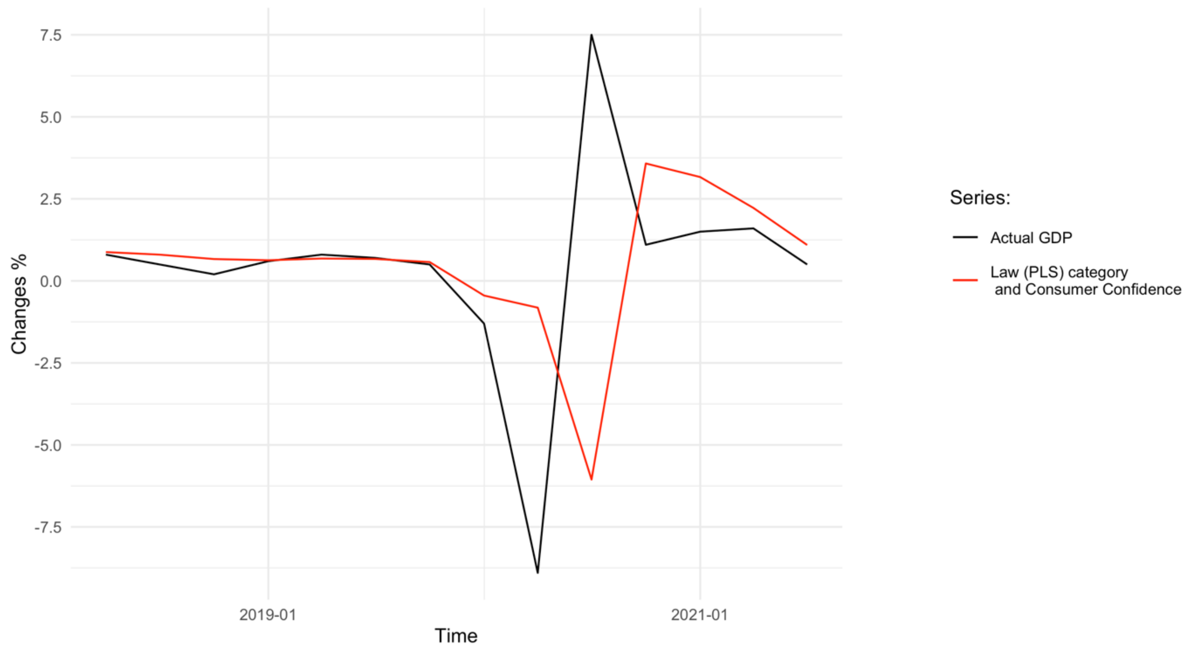

Figure 3: Nowcasts of GDP using of Law and consumer confidence.

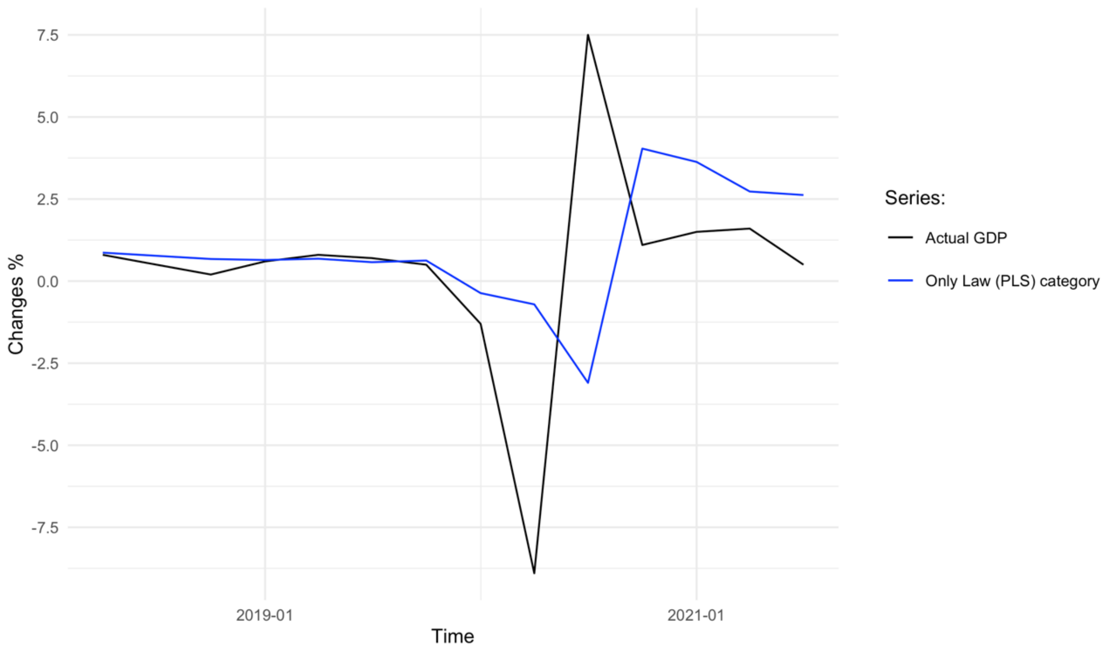

Figure 4: Nowcasts of GDP using of Law category model.

6.3. Nowcasting private consumption

Having established the efficacy of search data in nowcasting consumer confidence and GDP growth, we next examine its applicability in nowcasting private consumption. We apply similar search categories as before and use PCA and PLS dimension reduction methods.

As before, we conduct a series of pseudo out-of-sample nowcasting exercises within an expanding rolling window framework. The full observation period spans from October 2016 to October 2021, with the initial training sample consisting of the first 12 months, from October 2016 to October 2017. To maintain a real-time perspective, these exercises exclusively use data available at the time of each nowcast.

Table 4: RMSE scores for nowcasting private consumption.[2]

Country:	**United States**	
Model specification:	**Equation (2)**	
Dimension reduction:	**PCA**	**PLS**
	RMSE	**RMSE**
Autos & Vehicles	2.669	2.826
Beauty & Fitness	2.689	2.715
Business & Industrial	2.881	3.029
Computers & Electronics	2.743	2.762
Food & Drink	2.913	2.756
Health	2.953	2.812
Home & Garden	2.686	3.537
Internet	2.707	2.789
Investing	2.688	2.963
Jobs	2.862	2.920
Law	3.145	3.081
News	2.616*	2.876
Real Estate	2.633	2.600*
Shopping	2.666	3.677
Sports	2.731	3.502
Travel	2.988	2.976

[2] *Denotes the lowest RMSE score.

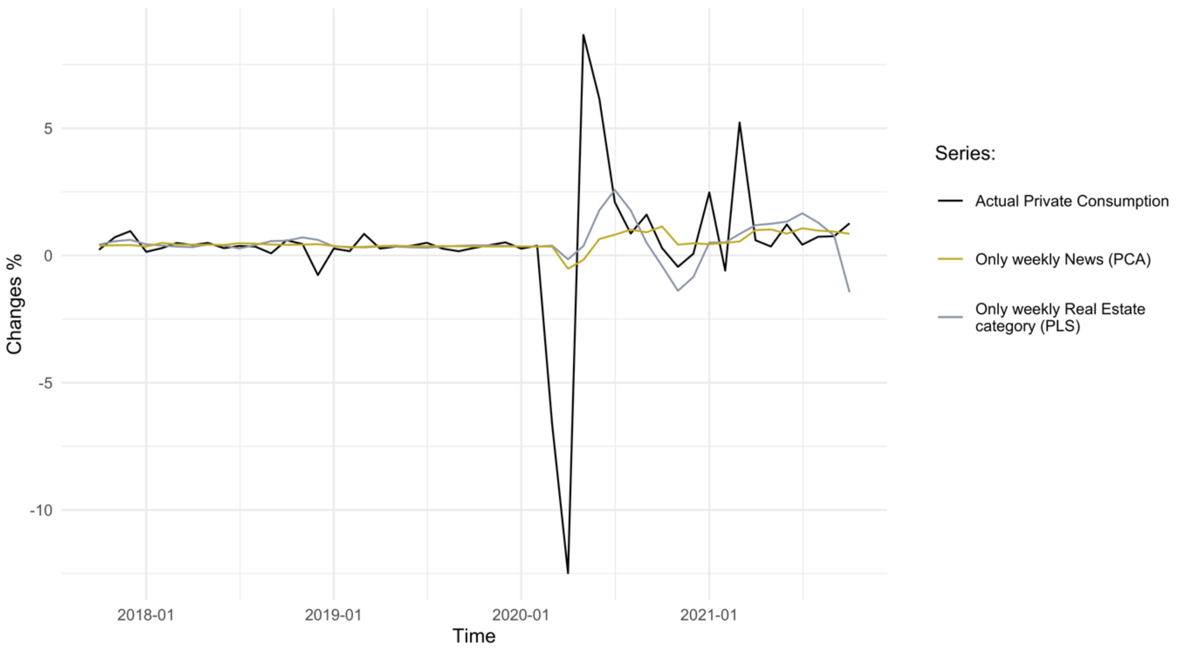

Figure 3: Nowcasts of private consumption from the most accurate models.

Estimates in Table 4 suggest that the Real Estate and News internet search models are the most accurate for nowcasting private consumption. Figure 3 indicates that even the most accurate internet search models fail to nowcast the sudden decrease in private consumption in the spring of 2020. Moreover, the Real Estate models lag behind the actual private consumption and predict a significant decrease in private consumption in the final months of the sample. The News model, on the other hand, remains more stable throughout the nowcasting exercise. These findings suggest that while the Real Estate search category may have some forecasting power, it consistently lags behind.

6.4. Nowcasting GDP

In this section, we extend our analysis by incorporating longer monthly search data obtained directly from the Google Trends platform. Unlike earlier sections, where weekly search data are aggregated to monthly levels, this approach utilizes monthly data spanning the period from January 2004 to October 2021. This methodological shift allows us to explore broader trends and long-term patterns in economic activity, offering complementary insights to the more granular observations derived from weekly data.

To evaluate the utility of this monthly data in nowcasting GDP, we conduct a series of pseudo out-of-sample nowcasting exercises within an expanding rolling window framework. The initial training sample comprises the first 12 quarters of the dataset. Importantly, these exercises adhere to a real-time perspective, relying exclusively on information available at the time each nowcast is produced.

The results are divided into two segments: (1) the "Three-month average", which aggregates data by averaging every three months, and (2) the "Every third-month" approach, which utilizes the most recent data available at the time of quarterly GDP statistics publication. References to equations from the previous section are provided in parentheses for clarity. We report only the results from the most accurate benchmark, PLS, PCA, and shrinkage models, as determined by RMSE scores. A comprehensive set of RMSE tables for each country is available in Appendix C (Tables C1, C2, C3, C4 and C5). Table 5 summarizes the RMSE results for the AR-1 and consumer confidence benchmark models, as well as the PCA and PLS-based internet search nowcasting models.

Table 5: The RMSE scores for the most accurate benchmark, PCA and PLS internet search models to nowcast GDP.[3]

Finland	RMSE	Germany	RMSE
AR-1 model (7)	1.922	AR-1 model (7)	2.786
Confidence (Three-months average) (8)	1.507*	Confidence (Three-months average) (8)	2.031*
AR-1 + Confi + Jobs category (PLS & Every third-month) (12)	1.624	Only Sports category (PCA & Every third-month) (10)	2.072
AR-1 + Confi + Jobs category (PCA & Every third-month) (12)	1.625	Only Jobs category (PLS & Every third-month) (10)	2.072

Japan	RMSE	United Kingdom	RMSE
AR-1 model (7)	2.093	AR-1 model (7)	9.169
Confidence (Every third-month) (8)	1.700	Confidence (Three-months average) (8)	3.576*
Only Investing category (PLS & Three-months average) (10)	1.653*	Only Real Estate (PLS & Three-months average) (10)	3.589
Only News category (PCA & Every third-month) (10)	1.765	Only News category (PCA & Every third month) (10)	3.594

United States	RMSE
AR-1 model (7)	2.619
Confidence (Every third-month) (8)	1.660*
Only News category (PCA & Every third month) (10)	1.677
Only Computers category (PLS & Every third month) (10)	1.686

[3] The numbers in parentheses refer to the corresponding equation numbers in the main text.

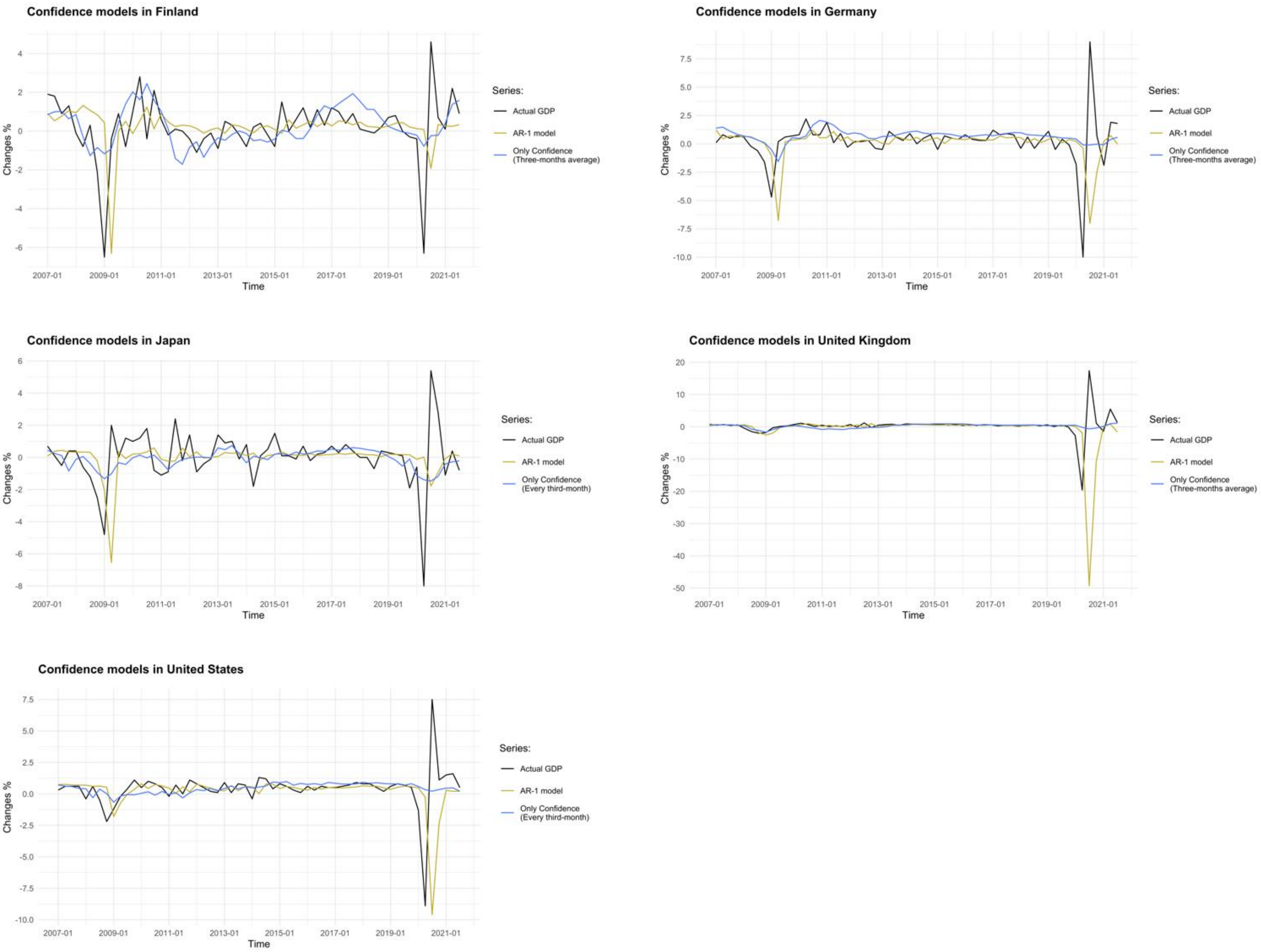

Figure 4: Nowcasts of GDP from the benchmark AR-1 and the most accurate confidence models.

Table 5 and Figure 4 suggest that consumer confidence data generates additional information about the current GDP. This is important for Finland and Japan, where the consumer confidence model's nowcasts closely track changes in each country's quarterly GDP. Next, we estimate internet search models with broad category variables generated via PCA and PLS and compare their performance with the consumer sentiment models.

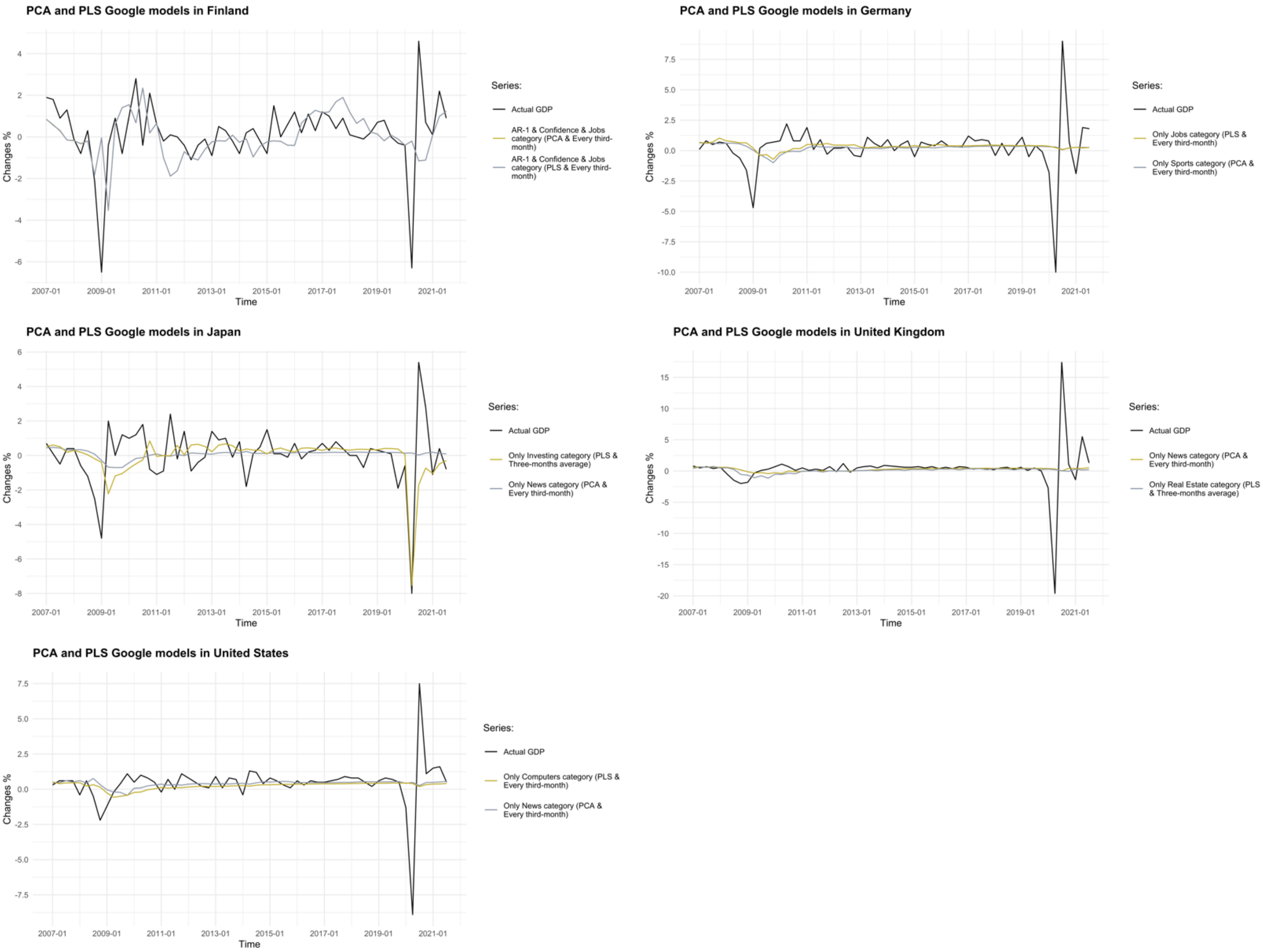

Figure 5: Nowcasts of GDP from the most accurate PLS and PCA models.

Table 5 and Figure 5 jointly display that the nowcasts of Finnish GDP vary considerably. The PCA and PLS models are the most accurate forecasters when the previous period's GDP and consumer confidence are included in the models. On the other hand, Table 4 indicates that consumer confidence is the main influence for the Finnish economy in PCA and PLS models. For other countries, the most accurate PCA and PLS models employ only a single broad category, as shown in Equation 10.

For Germany, the Jobs and Sports-related models predicted a slight decrease in GDP after the Global Financial Crisis (GFC). However, these models lack forecasting power amidst the COVID-19 pandemic. Similar results are observed for the UK and the US while the single broad category models fail to nowcast changes in the GDP growth. In contrasts, Japan's Investment category model successfully forecasts a significant decrease in Japan's GDP during the COVID-19 crisis in 2020.

Table 5 and Figure 5 highlight that PCA- and PLS-based internet search models are not superior nowcasters of GDP growth, except for Japan, where the Investing category closely relates to Japanese GDP growth. Notably, the Investing category model even outperforms the consumer confidence model in Japan. To further understand the underlying mechanism, we construct the Investing category from subcategories (see Appendix A).

$$\text{GDP}_t = \beta_0 + \beta_1 \text{Accounting \& Auditing}_t + \beta_2 \text{Banking}_t + \beta_3 \text{Credit \& Lending}_t + \beta_4 \text{Financial Planning}_t + \beta_5 \text{Grants \& Financial Assistance} + + \beta_6 \text{Insurance} + \beta_7 \text{Investing} + \epsilon_t \tag{22}$$

Ergo, we estimate Equation 22, which utilizes the Investment broad category's subcategories ("Accounting & Auditing", "Banking", "Credit & Lending", "Financial Planning", "Grants & Financial Assistance", "Insurance" and "Investing"). This regression employs complete in-sample ex-post data with a three-month average aggregation scheme.

Table 6: The regression coefficients of Investment subcategories.

	Dependent variable:
	GDP
Accounting and Auditing	-0.009
	(0.019)
Banking	0.005
	(0.032)
Credit and Lending	-0.087
	(0.058)
Financial Planning	0.105
	(0.080)
Grants and Financial Assistance	-0.105***
	(0.030)
Insurance	-0.021
	(0.044)
Investing	0.020
	(0.026)
Constant	1.751
	(1.729)
Observations	71
R^2	0.300
Adjusted R^2	0.223
Residual Std. Error	1.408 (df = 63)
F Statistic	3.862*** (df = 7; 63)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6 suggests that "Grants and Financial Assistance" is the driving factor behind Japan's Investment category, with statistically significant coefficient of -0.105. The relationship between GDP and "Grants and Financial Assistance" is more apparent in Figure 6.

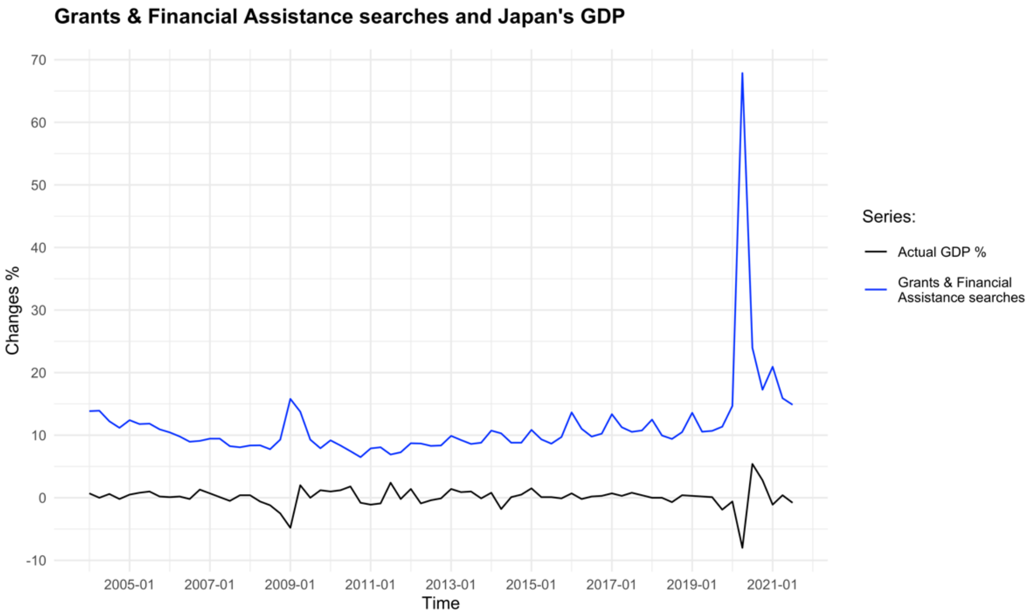

Figure 6: Japan's GDP growth and Grants & Financial Assistance.

Figure 6 depicts the three-month averaged sample of the "Grants and Financial Assistance" subcategory, i.e., just the search data without any nowcasting model, alongside Japanese GDP growth during the sample period. Furthermore, Japanese internet searches for "Grants and Financial Assistance" significantly increased during the COVID-19 crisis.

Table 7: RMSE scores of the most accurate shrinkage models to nowcast GDP.

Finland	**RMSE**	**Germany**	**RMSE**
AR-1 model (7)	1.922	AR-1 model (7)	2.786
Confidence (Three-months average) (8)	1.507	Confidence (Three-months average) (8)	2.031
AR-1 + Confi + Investing category (LASSO & Three-months average) (12)	1.484*	AR-1 + Sports category (LASSO & Three-months average) (11)	2.006*
AR-1 + Confi + Investing category (Elastic-net & Three-months average) (12)	1.551	AR + Confi + Law category (Elastic-net & Every third-month) (12)	2.006
AR-1 + Confi + Investing category (Ridge & Three-months average) (12)	1.594	Only Travel category (Ridge & Every third-month) (10)	2.011

Japan	**RMSE**	**United Kingdom**	**RMSE**
AR-1 model (7)	2.093	AR-1 model (7)	9.169
Confidence (Every third-month) (8)	1.700*	Confidence (Three-months average) (8)	3.576
AR-1 + Confi + Travel category (LASSO & Every third-month) (12)	1.706	AR-1 + Business category (Elastic-net & Three-months average) (11)	3.405*
AR-1 + Confi + Real Estate category (Elastic-net & Three-months average) (12)	1.716	AR-1 + Confi + Business (LASSO & Three-months average) (12)	3.469
AR-1 + Confi + Travel category (Ridge & Every third-month) (12)	1.737	AR-1 + Confi + Travel (Ridge & Three-months average) (12)	3.566

United States	**RMSE**
AR-1 model (7)	2.619
Confidence (Every third-month) (8)	1.660
Only News category (Elastic-net & Three-months average) (10)	1.573*
AR-1 + Confi + News category (LASSO & Three-months average) (12)	1.595
AR-1 + Confi + News category (Elastic-net & Three-months average) (12)	1.604

Figure 7: Nowcasts of GDP from the most accurate shrinkage models.

Table 7 shows that the shrinkage methods outperform PCA or PLS models in all other countries except in Japan. In Finland, Germany, and the United Kingdom, shrinkage models also require the inclusion of previous period GDP and consumer confidence in the model. The Investing category model provides the most accurate Google model for Finland, while in Germany, Lasso with Sports category-related searches outperforms other models. However, it still falls short of the previous PLS model. For Japan, the Business search category yields the best shrinkage-based model.

In the United States, the Elastic-net News category model achieves the highest accuracy for nowcasting GDP, with an RMSE score of 1.573. However, these nowcasts suffer from low variance, and shrinkage models appear to forecast only minor changes in GDP for each country (see Figure 4).

To summarize, the results suggest that each country has unique dynamics, necessitating country-specific model specifications.

6.4.1. DFM results

Our study applies internet search-based dynamic factor models (DFMs) with 16 different broad categories to nowcast U.S. GDP growth, as explained in detail in Section 4.2.1. Among the models tested, the Internet broad category model emerges as the most accurate, achieving an RMSE score of 1.643. Its corresponding forecasts are presented in Figure 8. A complete list of RMSE results for the dynamic factor models is provided in Appendix D, Table D1.

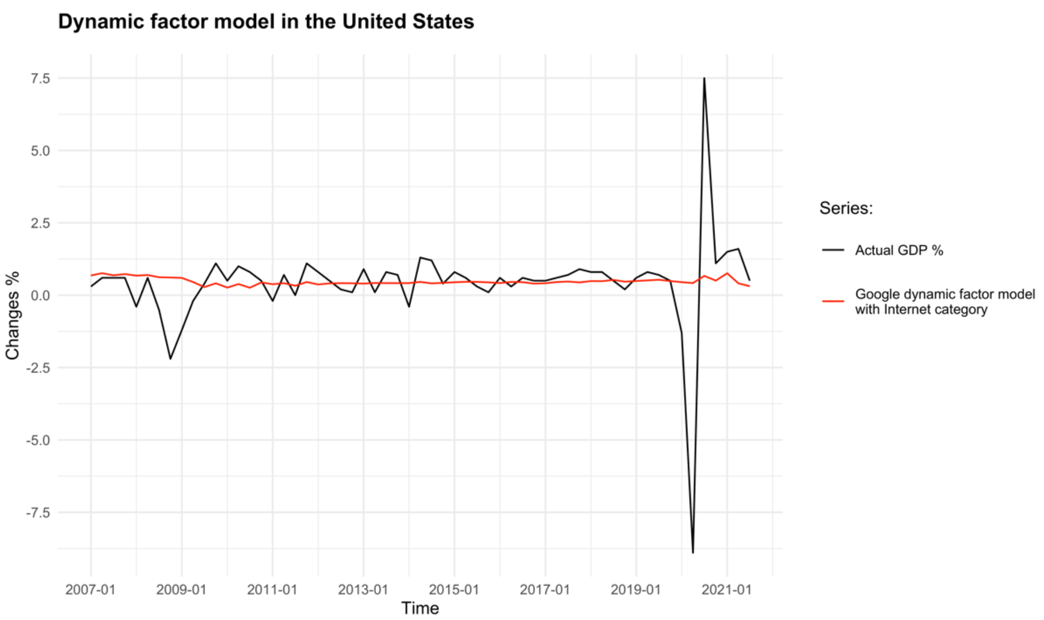

Figure 8: The most accurate DFM model with Google Trends data.

Mimicking the performance of shrinkage models in Figure 7, the Internet category nowcast model in Figure 8 exhibits only minimal variance. Furthermore, the traditional DFM specification fails to provide significant foreshadowing of either the GFC or the COVID-19 crisis. Notably, our previous Elastic-net News category model for U.S. GDP, with an RMSE of 1.573, outperforms the DFM model.

6.4.2. Economic uncertainty

Next, we present models related to U.S. policy uncertainty using only U.S. internet search data. We examine the impacts of overall economic policy uncertainty on agents' intentions and the factors underlying their sentiments. Specifically, we test the influence of U.S. policy-related uncertainty on search behavior within the U.S.

Table 8: RMSE scores of the most accurate models incorporating economic policy uncertainty for nowcasting GDP.

United States	RMSE
AR-1 + Law category + Uncertainty (PCA & Three-months average) (18)	1.929
AR-1 + Business category + Uncertainty (PCA & Three-months average) (18)	2,302

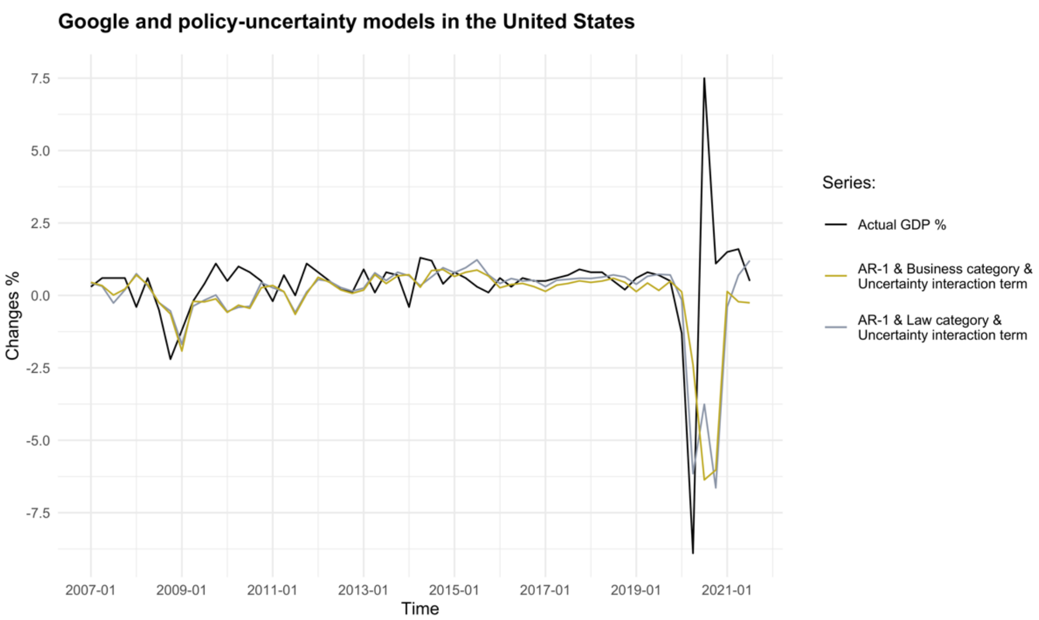

Figure 9: Nowcasts of GDP from the most accurate models incorporating economic policy uncertainty.

Table 8 and Figure 9 suggest that the most accurate internet search model incorporating uncertainty may also require categories related to Law. The "Law & Government" category includes subcategories such as "Government", "Legal", "Military", "Public Safety", and "Social Services" (see Appendix A).

These findings imply that during periods of uncertainty, individuals might seek information related to protection, safety, and economic safety nets.

The second most accurate uncertainty-augmented model incorporates the Business broad category. This category comprises multiple subcategories, including "Advertising & Marketing", "Aerospace & Defense","Agriculture & Forestry", "Automotive Industry", "Business Education", "Business Finance", "Business Operations", "Business Services", "Chemicals Industry", "Construction & Maintenance", "Energy & Utilities", "Hospitality Industry", "Industrial Materials & Equipment", and "Manufacturing."

The inclusion of the Business category might reflect increased interest in business-related information during uncertain periods, as individuals and organizations potentially seek insights on financial stability, operational risks, and industry-specific trends. Such searches could align with shifts in economic behavior, such as adjustments in investments, consumption patterns, and workforce dynamics.

6.4.3. Models in normal period (2009-2020)

The GFC and COVID-19 were sudden and unexpected events that dominate the RMSE values and might bias our assessment of the forecasting ability of the internet search models. To address this, we evaluate the performance of the internet search models during "normal" periods, excluding these abrupt changes. The "normal" period consists of GDP figures from Q3:2009 to Q1:2020. Once again, we test the performance of the most accurate search models against the restricted AR-1 models.

Table 9: The RMSE scores of the most accurate models in "normal times" for nowcasting GDP.

Finland

Model	**RMSE**	
AR-1 model (7)	5.447	
AR-1 & Confidence & Investing category (LASSO & Three-months average) (12)	5.141	*

Germany

Model	**RMSE**	
AR-1 model (7)	4.454	*
AR-1 & Confidence & Sports category (LASSO & Three-months average) (12)	4.497	

Japan

Model	**RMSE**	
AR-1 model (7)	6.246	
Only Investing category (PLS & Three-months average) (10)	5.764	*

United Kingdom

Model	**RMSE**	
AR-1 model (7)	3.759	*
AR-1 & Business category (Elastic-net & Three-months average) (11)	3.774	

United States

Model	**RMSE**	
AR-1 model (7)	5.549	
Only News category (Elastic-net & Three-months average) (10)	3.056	*

The RMSE scores in Table 9 suggest that the internet search models outperform the baseline AR-1 model in three of the five countries, regardless of an economic crisis. Specifically, search models perform better than AR-1 in Finland, Japan, and the United States, while the simple AR-1 model outperforms the search models in the UK and Germany. In summary, the results reinforce that the best forecasting models are country-dependent, highlighting the need for tailored model specifications for each country.

Figure 10: Nowcasts of GDP in the "normal times" from the most accurate models.

Figure 10 shows that internet search models exhibit significant variation during "normal" times, particularly in Finland, Japan, and the United States.

6.4.4. Robustness

Next, we assess whether the performance of the search models is influenced by a potential downward-sloping trend that might arise from an increase in the level of Google searches over time. To address this, we implement the trend extraction procedure proposed by Woloszko (2020). Our results remain robust and are unaffected by adjustments for downward-sloping trends.

Table 9: RMSE scores from the most accurate "adjusted" models for nowcasting GDP.

United States	**RMSE**
Transformed Health category (PCA & Every third-month) (10)	1.683
Transformed Health category (PCA & Every third-month) (10)	1.686

According to the RMSE scores in Table 10, the Health broad category models are the most accurate. These models include subcategories related to medicine, nutrition, mental health, pharmacy, and substance abuse. The complete set of RMSE results is provided in Appendix D, Table D3.

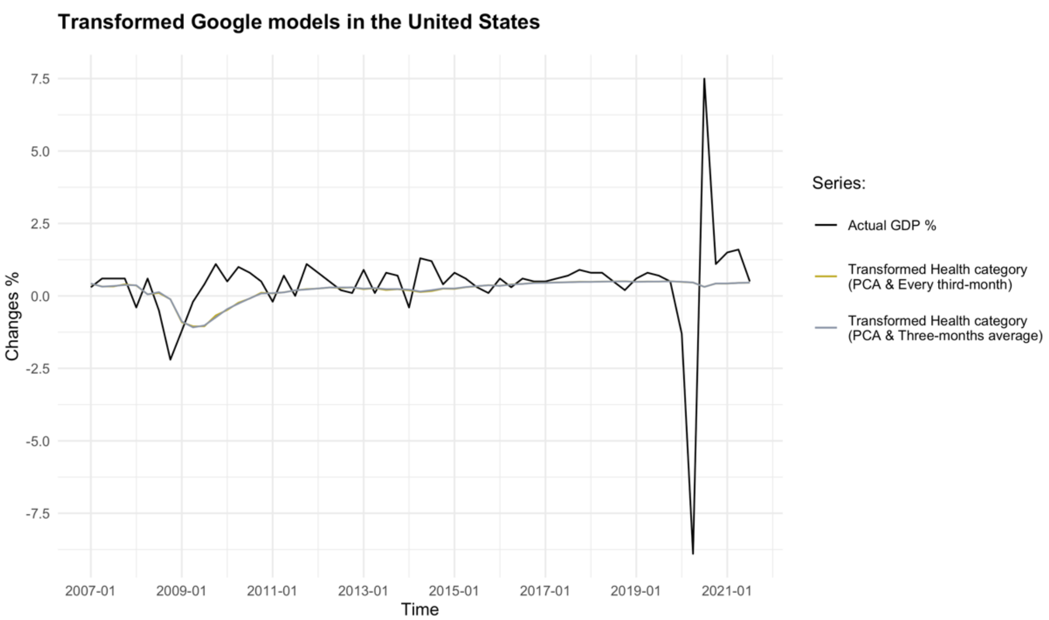

Figure 11: Nowcasts of GDP from the most accurate "adjusted" models.

Figure 11 shows that searches within the Health broad category nowcast a slight decrease in U.S. GDP following the GFC. However, a similar impact is not observed during the COVID-19 crisis. Additionally, the results in Figure

11 are not significantly different from those in Figure 5. This suggests that incorporating a downward-sloping trend is not necessary for robust and reliable inferences about the performance of search models.

7. Conclusion

The rapid and unexpected changes in global economies underscore the necessity for faster and more accurate forecasting techniques. Traditional economic indicators, while valuable, often fail to provide timely insights due to inherent delays in data collection and release. This study explores the potential of online search data as a high-frequency indicator that reflects economic agents' attention and intentions, offering a behavioral foundation for nowcasting key economic outcomes across selected OECD countries.

By employing advanced statistical techniques—such as Principal Component Analysis (PCA), Partial Least Squares (PLS), and shrinkage methods including Ridge regression, LASSO, and Elastic Net—we extract meaningful signals from complex, high-dimensional datasets to build real-time nowcasting models tailored to different economies.

Our findings indicate that search-based indicators contain meaningful high-frequency information closely aligned with shifts in consumer confidence and private consumption in the United States. In particular, the Law category appears to be a useful signal for consumer confidence, with subcategories such as "Government," "Military," "Public Safety," and "Social Services" showing consistent associations. For private consumption, the Real Estate and News categories yielded the lowest RMSE scores, indicating that these categories provided the most accurate nowcasts, although the Real Estate signal exhibited a slight lag relative to observed consumption patterns.

In the context of GDP nowcasting for selected OECD countries, search-based indicators demonstrated valuable predictive potential. In Finland, consumer confidence models augmented with search data provided the most accurate nowcasts. In Japan, the Investing category—particularly the subcategory "Grants and Financial Assistance"— was associated with GDP growth, especially during the COVID-19 crisis, suggesting that increased search activity for financial assistance reflected broader economic conditions.

However, the effectiveness of online search data varied across countries and categories, highlighting the need for country-specific model specifications. While shrinkage methods often outperformed PCA and PLS models, no single method consistently provided the best forecasts across all countries examined. Differences in economic structures and consumer search behaviors shaped the predictive power of the models.

Our exploration of economic uncertainty's impact on the predictive ability of search data yielded mixed results. In the United States, incorporating the Economic Policy Uncertainty (EPU) index did not significantly enhance the performance of forecasting models. Similarly, the Dynamic Factor Model (DFM) for U.S. search data and GDP growth produced low RMSE scores but showed limited variance in nowcasts, suggesting that alternative approaches may be more effective.

Overall, this study suggests that online search data can serve as a useful tool for capturing economic agents' information-seeking behavior, reflecting attention and emerging intentions that often precede economic actions. The real-time nature of search activity offers a valuable complement to traditional data sources, particularly when official statistics are delayed or unavailable. By integrating high-frequency, behaviorally grounded indicators into nowcasting models, policymakers and economists may gain earlier insights into economic conditions and respond more proactively to emerging trends.

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Appendix A – Search categories

Table A1: Initial subcategories 1

Broad categories	Subcategories	Broad categories	Subcategories
Autos & Vehicles		Beauty & Fitness	
	Bicycles & Accessories		*Beauty Pageants*
	Boats & Watercraft		*Body Art*
	Campers & RVs		*Cosmetology & Beauty Professionals*
	Classic Vehicles		*Cosmetic Procedures*
	Commercial Vehicles		*Face & Body Care*
	Custom & Performance Vehicles		*Fashion & Style*
	Hybrid & Alternative Vehicles		*Fitness*
	Microcars & City Cars		*Hair Care*
	Motorcycles		*Spas & Beauty Services*
	Off-Road Vehicles		*Weight Loss*
	Personal Aircraft		
	Scooters & Mopeds	Computers & Electronics	
	Trucks & SUVs		*CAD & CAM*
	Vehicle Brands		*Computer Hardware*
	Vehicle Codes & Driving Laws		*Computer Security*
	Vehicle Maintenance		*Consumer Electronics*
	Vehicle Parts & Accessories		*Electronics & Electrical*
	Vehicle Shopping		*Enterprise Technology*
	Vehicle Shows		*Networking*
			Programming
			Software

Table A2: Initial subcategories 2

Broad categories	**Subcategories**	**Broad categories**	**Subcategories**
Business & Industrial			
	Advertising & Marketing		
	Aerospace & Defense	Investing	
	Agriculture & Forestry		*Accounting & Auditing*
	Automotive Industry		*Banking*
	Business Education		*Credit & Lending*
	Business Finance		*Financial Planning*
	Business Operations		*Grants & Financial Assistance*
	Business Services		*Insurance*
	Chemicals Industry		*Investing*
	Construction & Maintenance		
	Energy & Utilities	Food & Drink	
	Hospitality Industry		*Alcoholic Beverages*
	Industrial Materials & Equipment		*Cooking & Recipes*
	Manufacturing		*Grocery & Food Retailers*
	Metals & Mining		*Non-Alcoholic Beverages*
	Pharmaceuticals & Biotech		*Restaurants*
	Printing & Publishing		
	Professional & Trade Associations	Health	
	Retail Trade		*Aging & Geriatrics*
	Small Business		*Alternative & Natural Medicine*
	Textiles & Nonwovens		*Health Conditions*
	Transportation & Logistics		*Health Education & Medical Training*
			Health Foundations & Medical Research
Home & Garden			*Medical Devices & Equipment*
	Bed & Bath		*Medical Facilities & Services*
	Domestic Services		*Medical Literature & Resources*
	Gardening & Landscaping		*Men's Health*
	Home Appliances		*Mental Health*
	Home Furnishings		*Nursing*
	Home Improvement		*Nutrition*
	Home Storage & Shelving		*Oral & Dental Care*
	Homemaking & Interior Decor		*Pediatrics*
	HVAC & Climate Control		*Pharmacy*
	Kitchen & Dining		*Public Health*
	Laundry		*Reproductive Health*
	Nursery & Playroom		*Substance Abuse*
	Pest Control		*Vision Care*
	Swimming Pools & Spas		*Women's Health*
	Yard & Patio		

Table A3: Initial subcategories 3

Broad categories	**Subcategories**	**Broad categories**	**Subcategories**
Internet & Telecom		Jobs & Education	
	Communications Equipment		*Education*
	Email & Messaging		*Jobs*
	Mobile & Wireless		
	Search Engines	News	
	Service Providers		*Broadcast & Network News*
	Teleconferencing		*Business News*
	Web Apps & Online Tools		*Gossip & Tabloid News*
	Web Portals		*Health News*
	Web Services		*Journalism & News Industry*
			Local News
Law & Government			*Newspapers*
	Government		*Politics*
	Legal		*Sports News*
	Military		*Technology News*
	Public Safety		*Weather*
	Social Services		*World News*
Shopping		Real Estate	
	Antiques & Collectibles		*Apartments & Residential Rentals*
	Apparel		*Commercial & Investment Real Estate*
	Auctions		*Property Development*
	Classifieds		*Property Inspections & Appraisals*
	Consumer Resources		*Property Management*
	Entertainment Media		*Real Estate Agencies*
	Gifts & Special Event Items		*Real Estate Listings*
	Luxury Goods		*Timeshares & Vacation Properties*
	Mass Merchants & Department Stores		
	Photo & Video Services		
	Shopping Portals & Search Engines		
	Swap Meets & Outdoor Markets		
	Tobacco Products		
	Toys		
	Wholesalers & Liquidators		

Table A4: Initial subcategories 4

Broad categories	**Subcategories**	**Broad categories**	**Subcategories**
Travel		Sports	
	Air Travel		*College Sports*
	Bus & Rail		*Combat Sports*
	Car Rental & Taxi Services		*Extreme Sports*
	Carpooling & Ridesharing		*Fantasy Sports*
	Cruises & Charters		*Individual Sports*
	Hotels & Accommodations		*Motor Sports*
	Luggage & Travel Accessories		*Sporting Goods*
	Specialty Travel		*Sports Coaching & Training*
	Tourist Destinations		*Team Sports*
	Travel Agencies & Services		*Water Sports*
	Travel Guides & Travelogues		*Winter Sports*
			World Sports Competitions

Appendix B – Selected weeks

Table B1: Selected Google data's weeks for nowcasting US consumer confidence.

Selected week	Month	Year	Selected week	Month	Year
16.10.2016 - 23.10.2016	October	2016	19.5.2019 - 26.5.2019	May	2019
13.11.2016 - 20.11.2016	November	2016	16.6.2019 - 23.6.2019	June	2019
11.12.2016 - 18.12.2016	December	2016	21.7.2019 - 28.7.2019	July	2019
15.1.2017 - 22.1.2017	January	2017	18.8.2019 - 25.8.2019	August	2019
12.2.2017 - 19.2.2017	February	2017	15.9.2019 - 22.9.2019	September	2019
19.3.2017 - 26.3.2017	March	2017	13.10.2019 - 20.10.2019	October	2019
16.4.2017 - 23.4.2017	April	2017	10.11.2019 - 17.11.2019	November	2019
14.5.2017 - 21.5.2017	May	2017	8.12.2019 - 15.12.2019	December	2019
18.6.2017 - 25.6.2017	June	2017	19.1.2020 - 26.1.2020	January	2020
16.7.2017 - 23.7.2017	July	2017	16.2.2020 - 23.2.2020	February	2020
20.8.2017 - 27.8.2017	August	2017	15.3.2020 - 22.3.2020	March	2020
17.9.2017 - 24.9.2017	September	2017	12.4.2020 - 19.4.2020	April	2020
15.10.2017 - 22.10.2017	October	2017	17.5.2020 - 24.5.2020	May	2020
12.11.2017 - 19.11.2017	November	2017	14.6.2020 - 21.6.2020	June	2020
10.12.2017 - 17.12.2017	December	2017	19.7.2020 - 26.7.2020	July	2020
21.1.2018 - 28.1.2018	January	2018	16.8.2020 - 23.8.2020	August	2020
18.2.2018 - 25.2.2018	February	2018	20.9.2020 - 27.9.2020	September	2020
18.3.2018 - 25.3.2018	March	2018	18.10.2020 - 25.10.2020	October	2020
15.4.2018 - 22.4.2018	April	2018	15.11.2020 - 22.11.2020	November	2020
13.5.2018 - 20.5.2018	May	2018	13.12.2020 - 20.12.2020	December	2020
17.6.2018 - 24.6.2018	June	2018	17.1.2021 - 24.1.2021	January	2021
15.7.2018 - 22.7.2018	July	2018	14.2.2021 - 21.2.2021	February	2021
19.8.2018 - 26.8.2018	August	2018	14.3.2021 - 21.3.2021	March	2021
16.9.2018 - 23.9.2018	September	2018	18.4.2021 - 25.4.2021	April	2021
14.10.2018 - 21.10.2018	October	2018	16.5.2021 - 23.5.2021	May	2021
11.11.2018 - 18.11.2018	November	2018	13.6.2021 - 20.6.2021	June	2021
9.12.2018 - 16.12.2018	December	2018	18.7.2021 - 25.7.2021	July	2021
20.1.2019 - 27.1.2019	January	2019	15.8.2021 - 22.8.2021	August	2021
17.2.2019 - 24.2.2019	February	2019	19.9.2021 - 26.9.2021	September	2021
17.3.2019 - 24.3.2019	March	2019	17.10.2021 - 24.10.2021	October	2021
14.4.2019 - 21.4.2019	April	2019			

Table B2: Selected Google data's weeks for nowcasting US private consumption.

Selected week	Month	Year	Selected week	Month	Year
23.10.2016 - 30.10.2016	October	2016	19.5.2019 - 26.5.2019	May	2019
20.11.2016 - 27.11.2016	November	2016	23.6.2019 - 30.6.2019	June	2019
18.12.2016 - 25.12.2016	December	2016	21.7.2019 - 28.7.2019	July	2019
22.1.2017 - 29.1.2017	January	2017	18.8.2019 - 25.8.2019	August	2019
19.2.2017 - 26.2.2017	February	2017	22.9.2019 - 29.9.2019	September	2019
19.3.2017 - 26.3.2017	March	2017	20.10.2019 - 27.10.2019	October	2019
23.4.2017 - 30.4.2017	April	2017	17.11.2019 - 24.11.2019	November	2019
21.5.2017 - 28.5.2017	May	2017	22.12.2019 - 29.12.2019	December	2019
18.6.2017 - 25.6.2017	June	2017	19.1.2020 - 26.1.2020	January	2020
23.7.2017 - 30.7.2017	July	2017	16.2.2020 - 23.2.2020	February	2020
20.8.2017 - 27.8.2017	August	2017	22.3.2020 - 29.3.2020	March	2020
17.9.2017 - 24.9.2017	September	2017	19.4.2020 - 26.4.2020	April	2020
22.10.2017 - 29.10.2017	October	2017	24.5.2020 - 31.5.2020	May	2020
19.11.2017 - 26.11.2017	November	2017	21.6.2020 - 28.6.2020	June	2020
24.12.2017 - 31.12.2017	December	2017	19.7.2020 - 26.7.2020	July	2020
21.1.2018 - 28.1.2018	January	2018	23.8.2020 - 30.8.2020	August	2020
18.2.2018 - 25.2.2018	February	2018	20.9.2020 - 27.9.2020	September	2020
18.3.2018 - 25.3.2018	March	2018	18.10.2020 - 25.10.2020	October	2020
22.4.2018 - 29.4.2018	April	2018	22.11.2020 - 29.11.2020	November	2020
20.5.2018 - 27.5.2018	May	2018	20.12.2020 - 27.12.2020	December	2020
17.6.2018 - 24.6.2018	June	2018	24.1.2021 - 31.1.2021	January	2021
22.7.2018 - 29.7.2018	July	2018	21.2.2021 - 28.2.2021	February	2021
19.8.2018 - 26.8.2018	August	2018	21.3.2021 - 28.3.2021	March	2021
23.9.2018 - 30.9.2018	September	2018	18.4.2021 - 25.4.2021	April	2021
21.10.2018 - 28.10.2018	October	2018	23.5.2021 - 30.5.2021	May	2021
18.11.2018 - 25.11.2018	November	2018	20.6.2021 - 27.6.2021	June	2021
23.12.2018 - 30.12.2018	December	2018	18.7.2021 - 25.7.2021	July	2021
20.1.2019 - 27.1.2019	January	2019	22.8.2021 - 29.8.2021	August	2021
17.2.2019 - 24.2.2019	February	2019	19.9.2021 - 26.9.2021	September	2021
24.3.2019 - 31.3.2019	March	2019	24.10.2021 - 31.10.2021	October	2021
21.4.2019 - 28.4.2019	April	2019			

Appendix C – RMSE scores for OECD countries

Table C1: RMSE scores of models for nowcasting Finland's GDP 1.

Country:	**Finland**									
Model specification:	**Only Google, Equation (10)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	1.701	1.690	1.710	1.706	1.652	1.655	1.657	1.654	1.661	1.656
Beauty & Fitness	1.708	1.712	1.708	1.715	1.637	1.645	1.648	1.645	1.645	1.652
Business & Industrial	1.695	1.693	1.709	1.693	1.654	1.658	1.654	1.661	1.657	1.655
Computers & Electronics	1.697	1.694	1.701	1.695	1.649	1.648	1.656	1.651	1.635	1.638
Food & Drink	1.698	1.695	1.716	1.702	1.654	1.654	1.654	1.655	1.657	1.655
Health	1.703	1.695	1.714	1.707	1.646	1.649	1.632	1.655	1.652	1.656
Home & Garden	1.694	1.695	1.721	1.717	1.652	1.657	1.655	1.655	1.655	1.658
Internet	1.732	1.713	1.726	1.712	1.651	1.651	1.638	1.650	1.646	1.638
Investing	1.719	1.695	1.719	1.698	1.652	1.656	1.627	1.661	1.649	1.657
Jobs	1.700	1.688	1.700	1.688	1.654	1.654	1.651	1.653	1.634	1.655
Law	1.722	1.711	1.733	1.713	1.616	1.650	1.650	1.660	1.645	1.638
News	1.702	1.703	1.733	1.742	1.653	1.653	1.649	1.656	1.654	1.656
Real Estate	1.702	1.694	1.719	1.704	1.641	1.654	1.646	1.653	1.623	1.654
Shopping	1.719	1.717	1.738	1.736	1.657	1.652	1.638	1.646	1.654	1.647
Sports	1.708	1.702	1.692	1.704	1.653	1.656	1.645	1.655	1.650	1.656
Travel	1.700	1.692	1.706	1.697	1.648	1.657	1.656	1.641	1.642	1.659

Table C2: RMSE scores of models for nowcasting Finland's GDP 2.

Country:	**Finland**									
Model specification:	**AR-1 & Google, Equation (11)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	1.903	1.924	1.904	1.921	1.653	1.654	1.657	1.655	1.663	1.655
Beauty & Fitness	1.952	1.973	1.940	1.961	1.647	1.646	1.646	1.646	1.644	1.652
Business & Industrial	1.919	1.956	1.928	1.950	1.654	1.657	1.644	1.658	1.657	1.655
Computers & Electronics	1.923	1.938	1.924	1.937	1.650	1.649	1.659	1.652	1.636	1.651
Food & Drink	1.916	1.948	1.925	1.945	1.655	1.654	1.655	1.655	1.656	1.655
Health	1.929	1.980	1.926	1.982	1.647	1.649	1.632	1.654	1.650	1.657
Home & Garden	1.924	1.943	1.935	1.944	1.652	1.655	1.655	1.655	1.654	1.657
Internet	1.957	1.963	1.937	1.960	1.652	1.651	1.631	1.651	1.652	1.640
Investing	1.941	1.958	1.936	1.965	1.651	1.654	1.631	1.664	1.648	1.657
Jobs	1.955	2.027	1.956	2.026	1.655	1.657	1.654	1.653	1.643	1.654
Law	1.938	1.984	1.944	1.985	1.623	1.653	1.648	1.655	1.646	1.645
News	1.957	1.999	1.963	1.987	1.653	1.653	1.651	1.655	1.654	1.655
Real Estate	1.937	1.972	1.947	1.966	1.651	1.656	1.649	1.655	1.629	1.653
Shopping	1.933	1.962	1.930	1.960	1.657	1.651	1.644	1.647	1.654	1.647
Sports	1.927	1.919	1.907	1.912	1.654	1.656	1.647	1.655	1.650	1.655
Travel	1.911	1.909	1.913	1.908	1.648	1.656	1.662	1.646	1.654	1.658

Table C3: RMSE scores of models for nowcasting Finland's GDP 3.

Country:	**Finland**									
Model specification:	**AR-1, Confi & Google, Equation (12)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	1.643	1.725	1.641	1.733	1.645	1.655	1.624	1.590	1.658	1.612
Beauty & Fitness	1.637	1.744	1.635	1.732	1.595	1.615	1.609	1.560	1.620	1.570
Business & Industrial	1.628	1.747	1.664	1.751	1.651	1.656	1.654	1.643	1.660	1.641
Computers & Electronics	1.625	1.723	1.629	1.728	1.642	1.630	1.551	1.564	1.557	1.553
Food & Drink	1.632	1.723	1.646	1.724	1.645	1.652	1.648	1.614	1.595	1.647
Health	1.640	1.743	1.661	1.751	1.648	1.648	1.626	1.650	1.646	1.644
Home & Garden	1.639	1.735	1.639	1.735	1.646	1.658	1.648	1.630	1.657	1.650
Internet	1.625	1.729	1.642	1.744	1.648	1.624	1.620	1.503	1.626	1.570
Investing	1.629	1.732	1.656	1.746	1.594	1.642	1.484	1.564	1.551	1.649
Jobs	1.638	1.744	1.638	1.743	1.640	1.611	1.624	1.555	1.579	1.590
Law	1.631	1.791	1.667	1.812	1.606	1.641	1.659	1.609	1.616	1.564
News	1.629	1.744	1.671	1.763	1.650	1.652	1.638	1.628	1.633	1.644
Real Estate	1.627	1.738	1.682	1.759	1.646	1.629	1.649	1.621	1.608	1.557
Shopping	1.632	1.736	1.624	1.755	1.662	1.650	1.626	1.615	1.644	1.639
Sports	1.649	1.729	1.647	1.730	1.653	1.656	1.643	1.602	1.640	1.591
Travel	1.637	1.723	1.631	1.713	1.642	1.657	1.611	1.569	1.610	1.619

Table C4: RMSE scores of models for nowcasting Germany's GDP 1.

Country:	**Germany**									
Model specification:	**Only Google, Equation (10)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	2.085	2.078	2.105	2.130	2.053	2.053	2.050	2.053	2.048	2.053
Beauty & Fitness	2.106	2.097	2.165	2.146	2.053	2.053	2.054	2.044	2.040	2.052
Business & Industrial	2.095	2.082	2.129	2.098	2.053	2.051	2.043	2.034	2.022	2.034
Computers & Electronics	2.102	2.101	2.108	2.109	2.053	2.053	2.038	2.053	2.027	2.049
Food & Drink	2.157	2.119	2.237	2.140	2.047	2.053	2.045	2.045	2.060	2.058
Health	2.091	2.076	2.198	2.173	2.053	2.052	2.055	2.054	2.044	2.053
Home & Garden	2.103	2.097	2.210	2.178	2.053	2.053	2.054	2.053	2.053	2.053
Internet	2.123	2.122	2.161	2.158	2.048	2.049	2.060	2.057	2.061	2.056
Investing	2.108	2.095	2.195	2.181	2.054	2.054	2.054	2.054	2.054	2.054
Jobs	2.097	2.079	2.085	2.072	2.053	2.053	2.053	2.052	2.053	2.053
Law	2.092	2.079	2.084	2.095	2.047	2.052	2.049	2.054	2.049	2.052
News	2.077	2.080	2.472	2.297	2.053	2.043	2.053	2.054	2.053	2.043
Real Estate	2.096	2.081	2.107	2.107	2.050	2.052	2.044	2.053	2.048	2.053
Shopping	2.109	2.092	2.177	2.143	2.053	2.053	2.058	2.060	2.051	2.056
Sports	2.088	2.072	2.103	2.101	2.025	2.045	2.006	2.036	2.020	2.035
Travel	2.105	2.107	2.112	2.110	2.048	2.011	2.056	2.031	2.055	2.023

Table C5: RMSE scores of models for nowcasting Germany's GDP 2.

Country:	**Germany**									
Model specification:	**AR-1 & Google, Equation (11)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	2.786	2.791	2.789	2.840	2.053	2.053	2.055	2.053	2.051	2.053
Beauty & Fitness	2.806	2.808	2.849	2.830	2.053	2.052	2.055	2.048	2.046	2.050
Business & Industrial	2.803	2.801	2.851	2.826	2.053	2.053	2.040	2.037	2.040	2.042
Computers & Electronics	2.825	2.820	2.830	2.827	2.054	2.053	2.048	2.054	2.054	2.046
Food & Drink	2.882	2.854	3.009	2.890	2.052	2.051	2.056	2.048	2.076	2.043
Health	2.800	2.799	2.889	2.851	2.053	2.051	2.053	2.052	2.054	2.053
Home & Garden	2.812	2.797	2.889	2.834	2.053	2.053	2.053	2.048	2.053	2.053
Internet	2.829	2.832	2.881	2.862	2.051	2.049	2.056	2.053	2.060	2.054
Investing	2.816	2.814	2.929	2.894	2.057	2.051	2.054	2.054	2.053	2.054
Jobs	2.813	2.806	2.814	2.804	2.052	2.053	2.053	2.053	2.053	2.053
Law	2.808	2.808	2.871	2.821	2.051	2.053	2.053	2.056	2.049	2.052
News	2.792	2.779	3.032	2.945	2.053	2.047	2.054	2.055	2.053	2.053
Real Estate	2.794	2.791	2.803	2.813	2.053	2.048	2.052	2.053	2.051	2.053
Shopping	2.805	2.801	2.955	2.895	2.053	2.053	2.058	2.048	2.049	2.056
Sports	2.787	2.789	2.778	2.774	2.046	2.052	2.006	2.031	2.011	2.051
Travel	2.795	2.807	2.795	2.802	2.050	2.022	2.056	2.025	2.053	2.023

Table C6: RMSE scores of models for nowcasting Germany's GDP 3.

Country:	**Germany**									
Model specification:	**AR-1, Confi & Google, Equation (12)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	2.548	2.622	2.489	2.491	2.051	2.053	2.042	2.061	2.049	2.049
Beauty & Fitness	2.617	2.643	2.420	2.408	2.052	2.051	2.054	2.046	2.047	2.050
Business & Industrial	2.567	2.591	2.327	2.350	2.053	2.053	2.038	2.032	2.038	2.046
Computers & Electronics	2.570	2.569	2.584	2.586	2.050	2.053	2.044	2.063	2.047	2.041
Food & Drink	2.797	2.778	2.917	2.809	2.047	2.041	2.017	2.046	2.043	2.031
Health	2.595	2.629	2.460	2.544	2.047	2.037	2.022	2.017	2.115	2.041
Home & Garden	2.738	2.762	2.804	2.759	2.052	2.053	2.096	2.050	2.048	2.044
Internet	2.611	2.602	2.770	2.758	2.049	2.042	2.040	2.052	2.041	2.037
Investing	2.610	2.624	2.640	2.590	2.056	2.051	2.054	2.050	2.053	2.054
Jobs	2.588	2.585	2.573	2.593	2.050	2.052	2.053	2.041	2.049	2.054
Law	2.559	2.592	2.338	2.424	2.035	2.041	2.058	2.008	2.053	2.006
News	2.506	2.575	2.841	2.698	2.052	2.028	2.054	2.061	2.052	2.028
Real Estate	2.548	2.606	2.542	2.655	2.047	2.047	2.051	2.053	2.047	2.044
Shopping	2.584	2.607	2.829	2.751	2.052	2.053	2.058	2.034	2.049	2.044
Sports	2.546	2.602	2.438	2.462	2.052	2.051	2.018	2.047	2.031	2.050
Travel	2.575	2.626	2.580	2.654	2.050	2.028	2.046	2.025	2.053	2.023

Table C7: RMSE scores of models for nowcasting Japan's GDP 1.

Country:	**Japan**									
Model specification:	**Only Google, Equation (10)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	1.770	1.771	1.797	1.805	1.749	1.747	1.741	1.740	1.744	1.746
Beauty & Fitness	1.789	1.786	1.837	1.823	1.749	1.748	1.750	1.751	1.761	1.748
Business & Industrial	1.779	1.777	1.819	1.815	1.749	1.748	1.746	1.716	1.750	1.731
Computers & Electronics	1.776	1.775	1.776	1.775	1.749	1.748	1.741	1.754	1.744	1.756
Food & Drink	1.797	1.793	1.812	1.808	1.746	1.748	1.750	1.748	1.748	1.752
Health	1.791	1.785	1.905	1.870	1.749	1.752	1.765	1.750	1.730	1.748
Home & Garden	1.821	1.808	1.852	1.838	1.748	1.749	1.753	1.747	1.748	1.748
Internet	1.770	1.768	1.794	1.783	1.748	1.746	1.718	1.751	1.747	1.747
Investing	1.794	1.810	1.653	1.763	1.769	1.791	1.894	1.833	1.857	1.828
Jobs	1.768	1.765	1.769	1.767	1.748	1.749	1.748	1.750	1.748	1.748
Law	1.770	1.767	1.777	1.775	1.748	1.748	1.750	1.748	1.748	1.748
News	1.767	1.765	1.883	1.873	1.750	1.748	1.742	1.742	1.754	1.756
Real Estate	1.783	1.779	1.807	1.788	1.746	1.749	1.739	1.751	1.734	1.748
Shopping	1.784	1.779	1.898	1.821	1.748	1.749	1.778	1.745	1.752	1.758
Sports	1.771	1.768	1.790	1.782	1.748	1.748	1.749	1.748	1.748	1.748
Travel	1.771	1.773	1.779	1.779	1.750	1.749	1.760	1.739	1.746	1.722

Table C8: RMSE scores of models for nowcasting Japan's GDP 2.

Country:	**Japan**									
Model specification:	**AR-1 & Google, Equation (11)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	2.089	2.093	2.093	2.110	1.749	1.748	1.740	1.748	1.734	1.748
Beauty & Fitness	2.110	2.109	2.184	2.160	1.749	1.749	1.749	1.750	1.750	1.749
Business & Industrial	2.093	2.095	2.135	2.137	1.751	1.748	1.751	1.727	1.752	1.725
Computers & Electronics	2.097	2.097	2.096	2.096	1.757	1.749	1.736	1.749	1.753	1.749
Food & Drink	2.113	2.107	2.135	2.126	1.754	1.755	1.750	1.750	1.750	1.752
Health	2.110	2.107	2.271	2.232	1.749	1.748	1.738	1.750	1.736	1.750
Home & Garden	2.140	2.125	2.178	2.159	1.748	1.749	1.751	1.748	1.749	1.749
Internet	2.089	2.092	2.110	2.106	1.744	1.749	1.717	1.749	1.722	1.748
Investing	2.115	2.113	1.983	2.092	1.775	1.785	1.808	1.781	1.790	1.810
Jobs	2.097	2.098	2.097	2.098	1.748	1.749	1.747	1.749	1.749	1.749
Law	2.093	2.094	2.094	2.096	1.748	1.744	1.751	1.749	1.751	1.749
News	2.095	2.096	2.190	2.196	1.756	1.750	1.747	1.749	1.754	1.749
Real Estate	2.097	2.096	2.115	2.100	1.749	1.749	1.739	1.745	1.735	1.748
Shopping	2.100	2.090	2.248	2.102	1.748	1.749	1.748	1.748	1.756	1.754
Sports	2.088	2.090	2.093	2.087	1.749	1.746	1.749	1.750	1.748	1.749
Travel	2.080	2.084	2.087	2.086	1.752	1.751	1.748	1.765	1.749	1.753

Table C8: RMSE scores of models for nowcasting Japan's GDP 3.

Country:	**Japan**									
Model specification:	**AR-1, Confi & Google, Equation (12)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	1.982	1.987	1.950	1.954	1.766	1.751	1.759	1.743	1.730	1.754
Beauty & Fitness	1.997	2.006	2.026	2.032	1.780	1.756	1.753	1.752	1.757	1.742
Business & Industrial	1.939	1.965	1.879	1.939	1.754	1.748	1.762	1.724	1.778	1.718
Computers & Electronics	1.938	1.964	1.935	1.962	1.763	1.752	1.751	1.771	1.746	1.753
Food & Drink	2.017	2.029	1.989	2.015	1.772	1.747	1.751	1.746	1.750	1.754
Health	2.017	2.022	2.052	2.050	1.750	1.748	1.753	1.751	1.741	1.746
Home & Garden	2.044	2.044	2.083	2.097	1.749	1.761	1.768	1.736	1.744	1.742
Internet	1.941	1.967	1.933	1.960	1.749	1.741	1.725	1.749	1.751	1.754
Investing	1.964	1.997	1.898	2.042	1.780	1.832	1.781	1.827	1.787	1.802
Jobs	1.968	1.980	1.960	1.980	1.746	1.743	1.748	1.747	1.757	1.733
Law	1.955	1.971	1.941	1.961	1.746	1.738	1.741	1.751	1.743	1.743
News	1.941	1.947	1.987	2.068	1.756	1.749	1.732	1.752	1.783	1.743
Real Estate	1.949	1.972	1.939	1.959	1.742	1.738	1.730	1.741	1.716	1.745
Shopping	2.008	2.022	2.060	1.970	1.784	1.760	1.830	1.746	1.757	1.757
Sports	1.973	1.984	1.947	1.967	1.751	1.757	1.743	1.764	1.751	1.761
Travel	1.973	1.979	1.967	1.974	1.744	1.737	1.745	1.706	1.759	1.733

Table C9: RMSE scores of models for nowcasting United Kingdom's GDP 1.

Country:	**United Kingdom**									
Model specification:	**Only Google, Equation (10)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	3.604	3.601	3.626	3.797	3.567	3.589	3.588	3.590	3.589	3.589
Beauty & Fitness	3.698	3.656	3.813	3.756	3.576	3.587	3.593	3.588	3.593	3.589
Business & Industrial	3.605	3.599	4.055	3.902	3.574	3.592	3.688	3.590	3.588	3.587
Computers & Electronics	3.615	3.613	3.618	3.615	3.591	3.588	3.591	3.594	3.590	3.590
Food & Drink	3.789	3.694	3.850	3.705	3.590	3.592	3.596	3.590	3.589	3.590
Health	3.599	3.601	3.964	3.801	3.592	3.586	3.592	3.585	3.592	3.586
Home & Garden	3.936	3.946	4.118	4.017	3.601	3.593	3.591	3.591	3.591	3.592
Internet	3.644	3.642	3.667	3.663	3.589	3.590	3.588	3.593	3.591	3.593
Investing	3.600	3.596	3.882	3.814	3.590	3.592	3.563	3.593	3.577	3.594
Jobs	3.662	3.625	3.668	3.622	3.592	3.592	3.593	3.593	3.592	3.592
Law	3.609	3.600	3.633	3.609	3.590	3.592	3.591	3.592	3.590	3.593
News	3.601	3.594	3.912	3.785	3.593	3.594	3.590	3.598	3.561	3.598
Real Estate	3.596	3.597	3.589	3.651	3.592	3.592	3.595	3.593	3.593	3.592
Shopping	3.597	3.606	3.898	3.854	3.592	3.592	3.692	3.592	3.591	3.592
Sports	3.640	3.623	3.696	3.656	3.591	3.593	3.597	3.593	3.592	3.591
Travel	3.652	3.645	3.756	3.696	3.590	3.591	3.592	3.590	3.589	3.591

Table C9: RMSE scores of models for nowcasting United Kingdom's GDP 2.

Country:	**United Kingdom**									
Model specification:	**AR-1 & Google, Equation (11)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	9.123	9.166	8.975	8.973	3.586	3.591	3.587	3.588	3.586	3.590
Beauty & Fitness	9.037	9.022	8.802	8.939	3.588	3.585	3.588	3.586	3.586	3.590
Business & Industrial	9.169	9.173	9.090	8.831	3.586	3.593	3.515	3.552	3.405	3.555
Computers & Electronics	9.162	9.168	9.164	9.179	3.592	3.591	3.587	3.587	3.588	3.590
Food & Drink	9.508	9.455	9.144	9.420	3.585	3.589	3.585	3.588	3.587	3.586
Health	9.182	9.176	8.679	8.972	3.590	3.585	3.586	3.585	3.587	3.583
Home & Garden	9.453	9.104	9.163	8.935	3.603	3.596	3.588	3.590	3.589	3.590
Internet	9.187	9.192	9.144	9.172	3.589	3.587	3.586	3.590	3.587	3.588
Investing	9.191	9.185	8.879	8.823	3.590	3.588	3.583	3.592	3.590	3.592
Jobs	9.177	9.187	9.172	9.186	3.592	3.592	3.591	3.592	3.591	3.595
Law	9.178	9.185	9.205	9.196	3.590	3.593	3.589	3.592	3.589	3.593
News	9.223	9.230	8.169	8.202	3.574	3.592	3.579	3.592	3.583	3.591
Real Estate	9.120	9.171	9.111	9.123	3.588	3.592	3.589	3.593	3.590	3.590
Shopping	9.179	9.182	7.966	6.941	3.593	3.613	3.632	3.590	3.590	3.589
Sports	9.107	9.139	8.756	8.926	3.594	3.593	3.590	3.592	3.590	3.588
Travel	9.040	9.082	8.850	8.991	3.569	3.584	3.592	3.590	3.589	3.588

Table C10: RMSE scores of models for nowcasting United Kingdom's GDP 3.

Country:	**United Kingdom**									
Model specification:	**AR-1, Confi & Google, Equation (12)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	9.454	9.339	9.320	9.046	3.586	3.585	3.581	3.584	3.581	3.587
Beauty & Fitness	9.242	9.169	8.738	8.880	3.576	3.575	3.581	3.585	3.514	3.584
Business & Industrial	9.493	9.350	9.066	8.657	3.591	3.594	3.469	3.546	3.507	3.546
Computers & Electronics	9.503	9.358	9.505	9.372	3.588	3.587	3.578	3.583	3.577	3.585
Food & Drink	9.439	9.386	9.112	9.380	3.579	3.586	3.578	3.586	3.583	3.580
Health	9.444	9.299	8.017	8.644	3.569	3.572	3.518	3.563	3.505	3.569
Home & Garden	8.820	8.479	8.166	8.201	3.598	3.601	3.584	3.584	3.583	3.586
Internet	9.398	9.277	9.186	9.106	3.584	3.586	3.585	3.584	3.583	3.588
Investing	9.498	9.354	8.008	8.110	3.575	3.574	3.576	3.581	3.577	3.584
Jobs	9.440	9.334	9.427	9.332	3.586	3.582	3.582	3.581	3.581	3.584
Law	9.523	9.375	9.564	9.402	3.585	3.583	3.582	3.580	3.584	3.585
News	9.559	9.415	7.848	7.956	3.573	3.590	3.579	3.584	3.563	3.585
Real Estate	9.463	9.335	9.452	9.322	3.583	3.583	3.580	3.582	3.581	3.584
Shopping	9.485	9.355	6.585	6.127	3.594	3.640	3.579	3.619	3.580	3.647
Sports	9.394	9.293	8.972	9.044	3.597	3.593	3.585	3.589	3.585	3.585
Travel	9.432	9.299	9.226	9.199	3.566	3.579	3.583	3.584	3.576	3.583

Table C11: RMSE scores of models for nowcasting United States GDP 1.

Country:	United States									
Model specification:	Only Google, Equation (10)									
Dimension reduction:	PCA		PLS		Ridge		LASSO		Elastic-net	
Aggregation scheme:	Three-months average	Every third-month	Three-months average	Every third-month	Three-months average	Every third-month	Three-months average	Every third-month	Three-months average	Every third-month
Autos & Vehicles	1.680	1.682	1.697	1.728	1.672	1.672	1.672	1.673	1.673	1.672
Beauty & Fitness	1.688	1.689	1.705	1.721	1.672	1.669	1.676	1.672	1.673	1.669
Business & Industrial	1.684	1.684	1.725	1.711	1.674	1.678	1.802	1.680	1.697	1.679
Computers & Electronics	1.686	1.685	1.688	1.686	1.672	1.670	1.666	1.671	1.673	1.673
Food & Drink	1.749	1.711	1.796	1.744	1.670	1.673	1.672	1.676	1.672	1.675
Health	1.684	1.685	1.728	1.726	1.673	1.673	1.660	1.669	1.681	1.672
Home & Garden	1.727	1.723	1.761	1.754	1.671	1.673	1.675	1.674	1.674	1.674
Internet	1.703	1.705	1.720	1.738	1.675	1.672	1.660	1.668	1.657	1.659
Investing	1.688	1.686	1.867	1.816	1.617	1.660	1.641	1.652	1.643	1.636
Jobs	1.701	1.692	1.702	1.694	1.671	1.673	1.669	1.673	1.671	1.672
Law	1.685	1.682	2.116	1.925	1.673	1.641	2.132	1.743	1.992	1.654
News	1.678	1.677	1.872	1.773	1.641	1.637	1.677	1.632	1.573	1.586
Real Estate	1.683	1.686	1.688	1.721	1.673	1.672	1.667	1.675	1.666	1.672
Shopping	1.683	1.682	1.809	1.851	1.672	1.673	1.672	1.678	1.698	1.673
Sports	1.711	1.705	1.748	1.702	1.674	1.673	1.674	1.672	1.673	1.671
Travel	1.700	1.696	1.705	1.706	1.672	1.672	1.673	1.674	1.672	1.672

Table C12: RMSE scores of models for nowcasting United States GDP 2.

Country:	**United States**									
Model specification:	**AR-1 & Google, Equation (11)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	2.617	2.624	2.603	2.632	1.672	1.673	1.672	1.668	1.673	1.671
Beauty & Fitness	2.612	2.629	2.620	2.651	1.672	1.669	1.671	1.667	1.676	1.669
Business & Industrial	2.624	2.624	2.638	2.623	1.672	1.674	1.711	1.667	1.672	1.672
Computers & Electronics	2.617	2.615	2.617	2.615	1.672	1.669	1.660	1.666	1.666	1.670
Food & Drink	2.766	2.726	2.811	2.761	1.666	1.672	1.670	1.666	1.667	1.664
Health	2.636	2.642	2.514	2.584	1.673	1.673	1.664	1.672	1.670	1.672
Home & Garden	2.731	2.719	2.744	2.714	1.670	1.673	1.671	1.669	1.670	1.672
Internet	2.645	2.642	2.662	2.655	1.664	1.673	1.670	1.668	1.658	1.665
Investing	2.625	2.625	2.572	2.630	1.648	1.651	1.642	1.645	1.654	1.647
Jobs	2.618	2.610	2.619	2.609	1.668	1.673	1.668	1.672	1.665	1.672
Law	2.623	2.624	2.714	2.652	1.671	1.668	2.102	1.669	1.945	1.639
News	2.629	2.623	2.467	2.512	1.618	1.641	1.611	1.646	1.607	1.593
Real Estate	2.622	2.632	2.610	2.627	1.668	1.668	1.660	1.671	1.661	1.666
Shopping	2.629	2.632	2.696	2.575	1.672	1.673	1.672	1.676	1.671	1.672
Sports	2.626	2.628	2.549	2.429	1.674	1.674	1.672	1.672	1.673	1.672
Travel	2.602	2.613	2.599	2.613	1.673	1.669	1.673	1.671	1.670	1.670

Table C13: RMSE scores of models for nowcasting United States GDP 3.

Country:	**United States**									
Model specification:	**AR-1, Confi & Google, Equation (12)**									
Dimension reduction:	**PCA**		**PLS**		**Ridge**		**LASSO**		**Elastic-net**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	2.617	2.624	2.603	2.632	1.672	1.673	1.672	1.668	1.673	1.671
Beauty & Fitness	2.612	2.629	2.620	2.651	1.672	1.669	1.671	1.667	1.676	1.669
Business & Industrial	2.624	2.624	2.638	2.623	1.672	1.674	1.711	1.667	1.672	1.672
Computers & Electronics	2.617	2.615	2.617	2.615	1.672	1.669	1.660	1.666	1.666	1.670
Food & Drink	2.766	2.726	2.811	2.761	1.666	1.672	1.670	1.666	1.667	1.664
Health	2.636	2.642	2.514	2.584	1.673	1.673	1.664	1.672	1.670	1.672
Home & Garden	2.731	2.719	2.744	2.714	1.670	1.673	1.671	1.669	1.670	1.672
Internet	2.645	2.642	2.662	2.655	1.664	1.673	1.670	1.668	1.658	1.665
Investing	2.625	2.625	2.572	2.630	1.648	1.651	1.642	1.645	1.654	1.647
Jobs	2.618	2.610	2.619	2.609	1.668	1.673	1.668	1.672	1.665	1.672
Law	2.623	2.624	2.714	2.652	1.671	1.668	2.102	1.669	1.945	1.639
News	2.629	2.623	2.467	2.512	1.618	1.641	1.611	1.646	1.607	1.593
Real Estate	2.622	2.632	2.610	2.627	1.668	1.668	1.660	1.671	1.661	1.666
Shopping	2.629	2.632	2.696	2.575	1.672	1.673	1.672	1.676	1.671	1.672
Sports	2.626	2.628	2.549	2.429	1.674	1.674	1.672	1.672	1.673	1.672
Travel	2.602	2.613	2.599	2.613	1.673	1.669	1.673	1.671	1.670	1.670

Appendix D – DFM, Uncertainty and robustness.

Table D1: RMSE scores of the DFM models to nowcast GDP.

Country:	**United States**
Model specification:	**Only Google, Equation (17)**
Dimension reduction:	**DFM**
Autos & Vehicles	1.703
Beauty & Fitness	1.686
Business & Industrial	1.681
Computers & Electronics	1.686
Food & Drink	1.674
Health	1.724
Home & Garden	1.674
Internet	1.643
Investing	1.701
Jobs	1.689
Law	1.703
News	1.699
Real Estate	1.690
Shopping	1.674
Sports	1.709
Travel	1.690

Table D2: RMSE scores of the models incorporating economic policy uncertainty for nowcasting GDP.

Country:	**United States**			
Model specification:	**AR-1. Google and Economic Policy Uncertainty. Equation (18)**			
Dimension reduction:	**PCA**		**PLS**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	2.670	2.520	2.680	2.791
Beauty & Fitness	2.818	2.569	2.782	2.700
Business & Industrial	2.302	2.557	2.720	2.679
Computers & Electronics	2.658	2.656	2.641	2.658
Food & Drink	2.707	2.670	2.709	2.662
Health	2.681	2.651	2.522	2.659
Home & Garden	2.821	2.709	2.594	2.497
Internet	2.761	2.715	3.000	2.909
Investing	2.556	2.648	2.569	2.648
Jobs	2.962	2.721	2.872	2.727
Law	1.929	2.389	2.749	2.780
News	2.569	2.653	2.544	2.552
Real Estate	2.698	2.561	2.644	2.680
Shopping	2.541	2.620	2.876	2.479
Sports	2.779	2.578	2.574	2.385
Travel	2.909	2.796	2.915	2.819

Table D3: RMSE scores of the "adjusted" models to nowcast GDP.

Country:	**United States**			
Model specification:	**"Adjusted" Google models, Equation (10)**			
Dimension reduction:	**PCA**		**PLS**	
Aggregation scheme:	**Three-months average**	**Every third-month**	**Three-months average**	**Every third-month**
Autos & Vehicles	1.696	1.695	1.724	1.718
Beauty & Fitness	1.695	1.694	1.716	1.710
Business & Industrial	1.691	1.690	1.705	1.705
Computers & Electronics	1.709	1.709	1.714	1.713
Food & Drink	1.725	1.725	1.738	1.739
Health	1.686	1.684	1.707	1.703
Home & Garden	1.698	1.698	1.713	1.713
Internet	1.737	1.735	1.734	1.741
Investing	1.694	1.695	1.742	1.737
Jobs	1.719	1.726	1.721	1.720
Law	1.691	1.691	1.738	1.783
News	1.729	1.723	1.823	1.829
Real Estate	1.693	1.691	1.706	1.701
Shopping	1.693	1.692	1.777	1.764
Sports	1.712	1.716	1.745	1.760
Travel	1.711	1.718	1.730	1.733

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