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Nowcasting the nowcasting - Forecasting ISM Business surveys (PMI and NSI) with weekly Google trends

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ABSTRACT
Changes in economic conditions can occur suddenly with drastic effects. However, economic statistics are published with significant lags, e.g. GDP, and more timely information about the economy is required. Nowcasting methods have become widely popular for providing up-to-date information about the current economic stance. This study adds a novel idea to the previous literature by nowcasting the nowcasting, i.e. the purchasing manager's index (PMI) and the non-manufacturing survey index (NSI) of the ISM Business survey indicators with the weekly Google Trends data. We used two-dimension reduction methods: the principal component analysis (PCA) and partial least squares (PLS) to eliminate 'the curse of dimensionality'. Pseudo-out-of-sample exercises performed with different Google Trends search categories indicated that Google Search data is able to generate useful information to nowcast the nowcasting. In particular, we contribute the existing literature that weekly Google Search data can nowcast the monthly PMI and NSI.

KEYWORDS
Nowcasting; Business survey indexes; PMI; Google Trends

JEL CLASSIFICATION
E3; E30; E37

I. Introduction

Economic statistics are published with a significant lag or delay. For example, statistical production and data availability limit the United States gross domestic product (GDP) publication speed, which is published quarterly at the latest. At a minimum, these limits in statistical production cause a two-month lag between the current and newest publications. However, changes in the underlying economic situation can occur suddenly, and more current information is desperately called-for, as policymakers and other institutions are required to make fast decisions in uncertain times. We provide a new method to speed up the evaluation of forthcoming and concurrent economic stance: Google searches.

Nowcasting attempts to produce forecasts about the current economic conditions (Choi and Varian 2012). It can provide short-term forecasts about different macroeconomic variables, sometimes months before their official publishing, e.g. Javed, Kiss and Österholm (2022) nowcasted several countries GDP growth including Australia, Canada, France, Japan, the United Kingdom, and the United States.

Nowcasting models demand high-frequency data. One highly potential timely data source is Internet search data. Google LLC's search engine is one of the most-used search engines in the world (Statista 2022). Google LLC has made its search data openly available on its Google Trends website,[1] which is one of the largest public databases available. Google Trends data has already been used to forecast consumption and unemployment (Choi and Varian 2012; Nagao, Takeda, and Tanaka 2019; Tuhkuri 2014; Vosen and Schmidt 2011), consumption and sales (Carrière-Swallow and Labbé 2013), housing and financial markets (McLaren and Shanbhogue 2011; Perlin et al. 2017), exchange rates (Bulut 2018; Ito et al. 2021) and GDP growth (Götz & Knetsch, 2019; Woloszko 2020). Previous research has also employed Google Trends data to proxy recession, interest, and sentiment. Iselin and Siliverstovs (2016) utilized Google Trends in their recession indicator, while Ma and Fang (2021) applied it to proxy regional interest and its effect on international trade. Apergis, Chatziantoniou and Gabauer (2022) proxied

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[1]https://trends.google.com/

Google Trends as their COVID-19 news sentiment to examine its relation to S&P 100, crude oil, and gold volatility indices.

To the authors' knowledge, studies using Google Trends to nowcast ISM Business surveys are scarce. ISM, which is also known a PMI, provides nowcasting information for economic outcomes while it comprises data of 400 purchasing executives survey information in manufacturing sector in 20 industries. We also examine the Google Trends nowcasting performance over non-manufacturing survey index (NSI). Cournède et al. (2020) used Google Trends data to study the purchasing manager's index (PMI) in the construction sector. This is quite an oversight as PMI indexes are typically used in economic models: see, e.g. Lahiri and Monokroussos (2013) for augmenting GDP forecasts with ISM Business survey indexes, stressing the relevance of non-manufacturing indexes.

Our research question asks: can Internet searches foreshadow a firm manager's behaviour and thus reveal their intentions? We used four different data sources to answer this question. The first two were Business Survey indexes: the Purchasing manager's index (PMI) and the non-manufacturing survey index (NSI) from the Refinitiv Marketpsych database. The third data were Google Trends, and the fourth was the US GDP. Our paper's methods greatly complement and add to the previous literature. The studies trying to nowcast ISM business Surveys are still rare. Compared to earlier studies with Google Trends, we used more timely weekly Google Trends data and simple linear nowcasting models to allow greater model transparency, i.e. to eliminate black-boxes methods. Using two transparent dimension reduction methods, we could also use a wide range of different search categories.

Our results indicate that Google Trends is able to nowcast traditional business cycles forecasting variables (i.e. nowcasting the nowcast) like PMI and NSI. The Google Trends model was even able to forecast the decrease in the PMI just before the actual decline during the spring of 2020 due to Covid-19. Accordingly, Google Trends capture firm managers' behaviour being related to the Business and Industrial category searches even before the publication of PMI information which stresses its usefulness for nowcasting purposes.

II. Research setup

Data

We used similar subcategories as Götz & Knetsch (2019). However, the subcategories of finance and food were slightly different, and we did not use Sensitive subjects' subcategories (see search categories in Appendix A Tables A1-A4). Nevertheless, selected subcategories could help us dissect the background effects in the searches. Unfortunately, the data becomes highly dimensional (i.e. we had 181 different subcategories in the dataset). We applied two dimension reduction methods to mitigate this issue: principal component analysis (PCA) and partial least squares (PLS). Moreover, we compressed these subcategories to appropriate broad categories via the first component in the PCA and PLS. These broad categories are in Table 1.

The ISM data ranged from M10:2016 – M10:2021, and the weekly Google Trends data ranged from 20 September 2016 – 20 November 2021. To alleviate any possible sampling variance (noted by Medeiros and Pires (2021)), we collected 15 samples of Google Trends data on different days, after which the data were averaged. To aggregate the weekly data, we used a single complete week of data from each month, and then the monthly Google data ranged from M10:2016 – M10:2021. For example, we used Google Trends weekly data from 16.10.2016 – 23.10.2016 to represent monthly value for October 2016. More details about selected weeks are in Appendix A Table A5. The quarterly US GDP data (in changes compared to the previous quarter) was Q4:2016 – Q3:2021. We needed to decide aggregation scheme to forecast quarterly GDP with monthly data. We found the results on aggregation methods quite sensitive and chose to aggregate the monthly data by three months averaging.

Table 1. Broad search categories.

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

Estimation method

The collected Google Trends was highly dimensional as it had p larger than n (i.e. 181 > 61). This can lead to noisy and over-fitted models with poor predictions (James et al. 2013, 266). Hence, we applied two different dimension reduction techniques. First, we used the principal component analysis (PCA).

In PCA we reduced the dimensional space by using only the first or second principal components. Moreover, PCA is trying to compute the best linear approximations of the underlying data. If we assume that the data is centered, we can present the PCA as a singular value decomposition (SVD). (Hastie et al. 2009; James et al. 2013; Jolliffe 2002)

$$\mathrm{X} = \mathrm{UDV}' \tag{1}$$

Equation (1) presents the standard decomposition, where U is an $n\ x\ p$ orthogonal matrix (U'U = Ip) with orthonormal columns, i.e. *left singular vectors* of X. V is a $p\ x\ p$ orthogonal matrix (V'V = Ip) with columns v, i.e. the *right singular vectors*. The D is the diagonal matrix with diagonal elements d, i.e. *singular values*. Using the SVD definition and multiplying the original data X with orthogonal matrix V, we can present principal components as in the Equation (2). (Jolliffe 2002.)

$$XV = UDV'V = UD = Z = (z_1, \ldots, z_n) \tag{2}$$

Equation (2) decomposes the principal components to the original data matrix X and as loadings V. By the definition of orthogonal matrix V, this can be further decomposed as principal component scores z (Jolliffe 2002.). Now, the kth number of scores can be used to reduce the data's dimension. Second, we applied the partial least squares (PLS). The PLS is a supervised statistical learning method as it uses the response variable (i.e. business survey index) to select optimal components. After centering and standardizing the data, the PLS uses a specific algorithm to formulate the components. (Hastie et al. 2009; James et al. 2013)

Algorithm 1:

$X_0 \leftarrow X$ standardize data
Form $\leftarrow$ *to p do*
$z_m \leftarrow X_{m-1}X'_{m-1}y$
$Q_m \leftarrow I_n - z_m\left(z'_n z_n\right)^{-1} z'_n$
$X_m \leftarrow Q_m X_{m-1}$
end
Output: $Z = (z_1, \ldots, z_n)$

Algorithm (1) indicates that PLS weights directions z_m by the covariance between the predictors X and response y. Highest weight is placed on the variables with the strongest relation to the response. The output is a similar type of score matrix as in PCA, which can be used in an OLS estimation (Hastie et al. 2009; James et al. 2013). We used dimension reduction methods to extract a single component, e.g. we fed subcategories related to 'Business & Industrial' the PCA (or PLS). So, we inputted the subcategories shown in Appendix A Tables A1-A4. We then used the first component in a simple linear regression estimated using OLS. Figure 2 plots the first principal component scores (Changes %) from 'Business & Industrial' broad category formed from ex-post subcategories: '*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*', '*Manufacturing*', '*Metals & Mining*', '*Pharmaceuticals & Biotech*', '*Printing & Publishing*', '*Professional & Trade Associations*', '*Retail Trade*', '*Small Business*', '*Textiles & Nonwovens*' and '*Transportation & Logistics*'. Our findings, based on ex-post Google data, indicate that on average, across broad category models, the first principal component explained approximately 49.38% of the variation. With the full dataset, the most contributing search terms in terms of PCA loadings were '*Vehicle Codes & Driving Laws*', '*Jobs*', '*Men's Health*', '*Custom & Performance Vehicles*' and '*Printing & Publishing*'. Thus, part of the searches were related to the durable goods (vehicle) and jobs (jobs).

We performed pseudo-out-of-sample nowcasting exercises in order to produce realistic forecasting conditions (i.e. restricting the moment when the data is inserted in the models). The initial training sample was 12 months (or four quarters with quarterly data), which increased every step (i.e. expanding window). The test set was always the not-yet-published business survey (or the GDP) statistic, e.g. in the first estimation step, it was the 13 months (or 5 quarters with quarterly data).

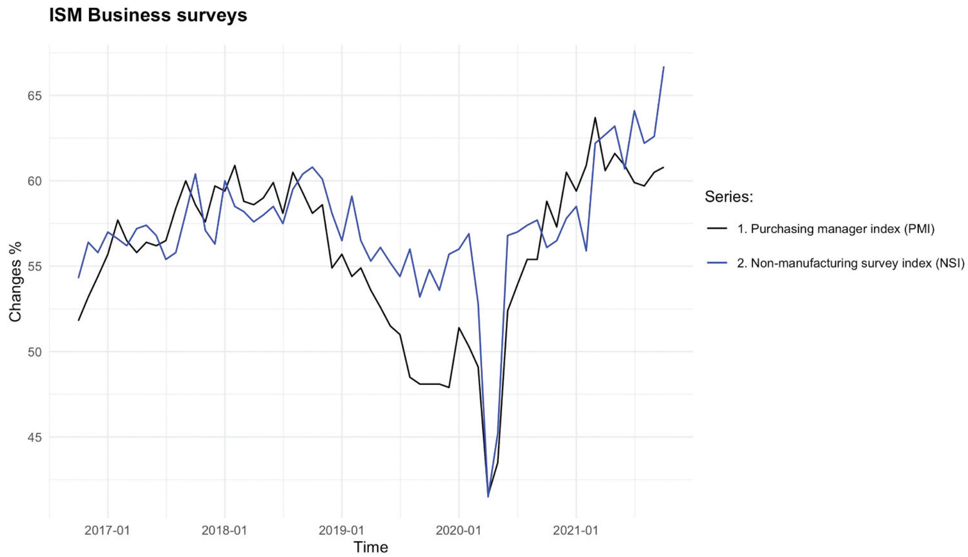

Figure 1. ISM Business surveys in the US.

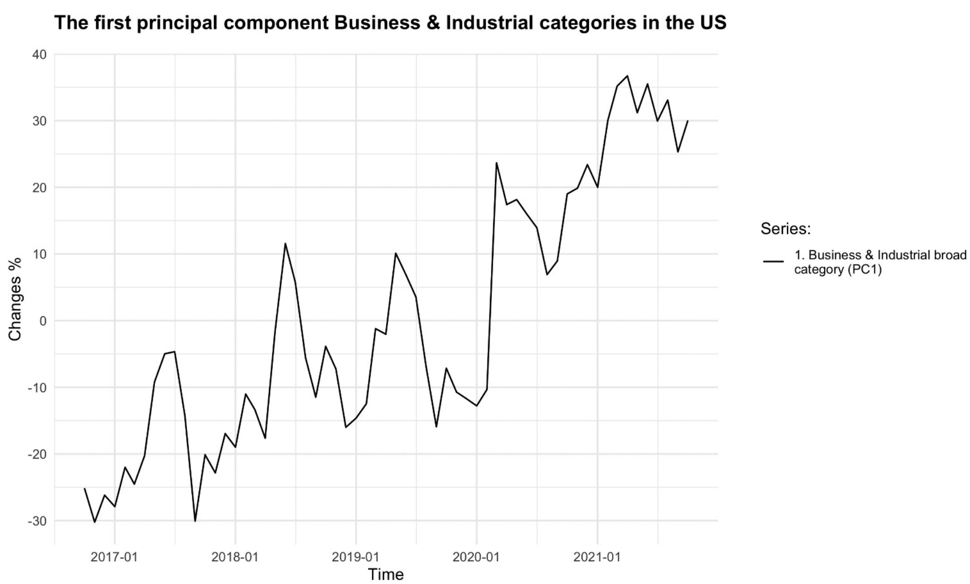

Figure 2. Business & Industrial broad category the first principal component (PC1) scores.

$$\text{Business survey}_{it} = \beta_0 + \beta_1 * \text{Google}_{it} + \epsilon_t \quad (3)$$

$$\text{Business survey}_{it} = \beta_0 + \beta_1 * \text{Business survey}_{it-1} + \epsilon_t \quad (4)$$

$$\text{Business survey}_{it} = \beta_0 + \beta_1 * \text{Business survey}_{it-1} + \beta_2 * \text{Google}_{it} + \epsilon_t \quad (5)$$

$$\text{GDP}_t = \beta_0 + \beta_1 * \text{Business survey}_{it} + \epsilon_t \quad (6)$$

$$\text{GDP}_t = \beta_0 + \beta_1 * \text{Google}_{it} + \epsilon_t \quad (7)$$

Equation (3) represents the Google Trends model with only the first component of each broad category, estimated in each forecasting step. In the first forecasting step, for example, for 'Autos & Vehicles' subcategories (i.e. 19 columns), we used data from M10:2016 – M10:2017, for which we applied dimension reduction methods to generate the single component, which we used in Equation (3). We estimated Equation (3) using OLS, from which we got the parameters β_0 and β_1. We then used these parameter estimates with the longer test sample to generate the forecast of the Business survey (i.e. PMI or NSI). In the second forecasting step, the training sample is 13 months, and the test sample is 14 months. The data included in the training and test sets continue to increase until the end of the dataset. Equation (4) serves as a benchmark AR-1 model. Equation (5) integrates both the AR-1 and Google variables, Equation (6) depicts the GDP nowcast from the Business survey indexes (i.e. PMI and NSI). In this specification, we used an initial sample of 4 quarters of the Business survey data in the training set. We estimated the parameters in Equation (6) using OLS and used them together with the more extended initial test sample of 5 quarters to generate GDP forecasts. Equation (7) denotes the GDP nowcasts from the Google category models, which we produced by a similar procedure as in Equation (3). The main difference is that data is quarterly; thus, the initial training sample was four quarters, and the initial test sample 5 quarters.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}} \tag{8}$$

To evaluate the accuracy of the nowcasting models, we used root-mean-squared errors (RMSE) as presented in Equations (8). Lower RMSE scores indicate greater accuracy of the nowcasting model. In addition, we visually assessed the overall performance of the forecasting models using figures to complement our analysis.

III. Empirical results

The most accurate model to nowcast PMI was the Google Investing category model, generated via principal component analysis (PCA), which included the AR-1 variable (Equation (5)) and achieved an RMSE score of 2.348. It was able to outperform the AR-1 model (Equation (4)), which had an RMSE score of 2.403. This suggests that Google data provides additional forecasting information. The complete set of RMSE results for the Google models is provided in Appendix B, Tables B1, B2 and B3. According to Figure 3, although the Business & Industrial (PLS) category model had a higher RMSE score of 4.398 compared to the AR-1 model, it seems to indicate a decrease in the PMI just before the actual decline during the spring of 2020. This could be attributed to firm managers' behaviour being related to the Business & Industrial category searches.

Our findings indicate that the Google model incorporating the AR-1 variable in the investing category model demonstrated superior performance, with an RMSE value of 2.874 when compared to other models nowcasting NSI. In contrast, the RMSE score of the benchmark AR-1 model was 3.172. We observed a significant decrease in Google searches related to investing, in alignment with the non-manufacturing survey index (NSI), as depicted in Figure 4. This decline in searches related to Investing category correlated with the observed drop in both PMI and NSI response variables during the spring of 2020.

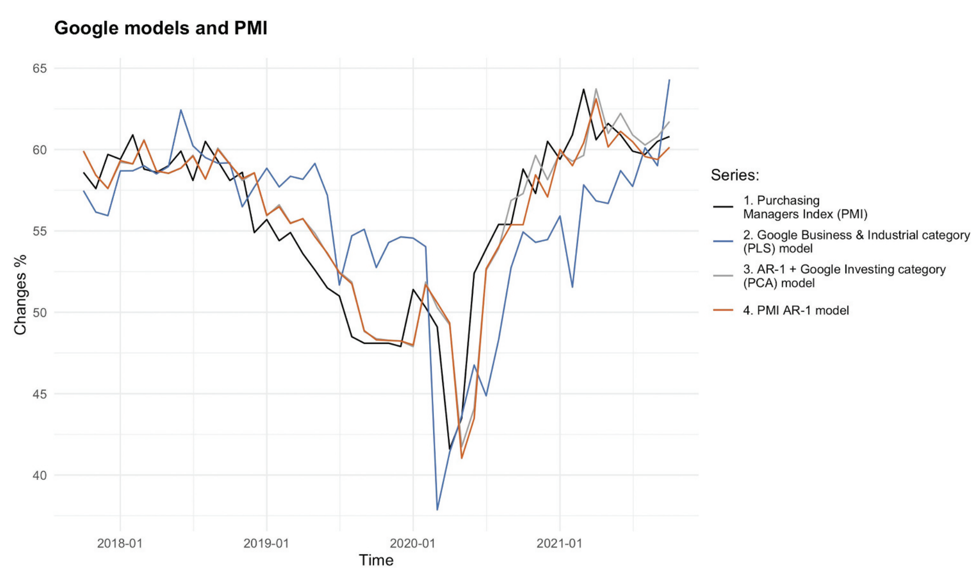

Figure 3. The most accurate Google models to nowcast PMI and AR-1 model.

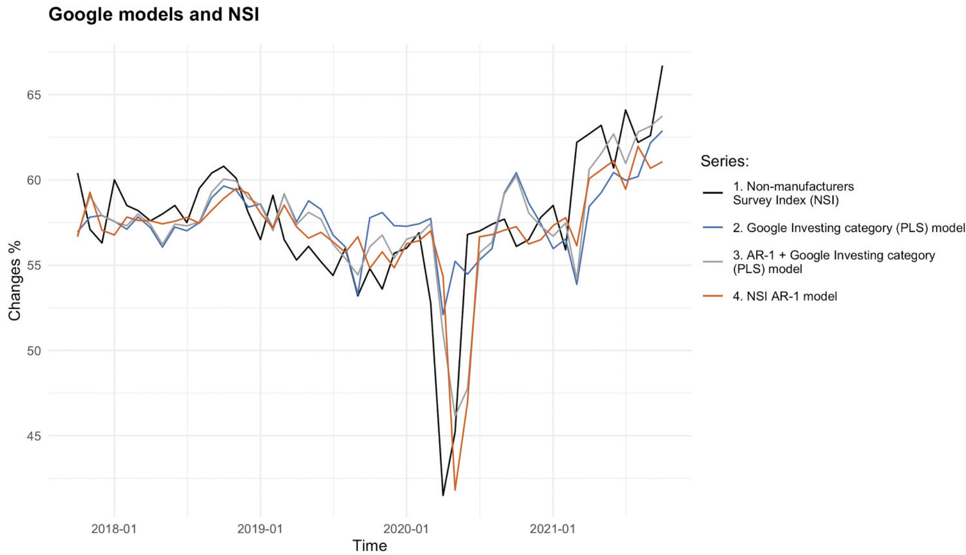

Figure 4. The most accurate Google models to nowcast NSI and AR-1 model.

Our results suggest that Google search data, particularly within the investing-related categories, can yield valuable insights for nowcasting both PMI and NSI. This underscores the potential utility of Google search data in applied economic research. This contributes novel evidence to the existing literature regarding the efficacy of Google search data as a predictive tool for forecasting the purchasing manager's index and non-manufacturing index.

Next, we evaluated the effectiveness of purchasing managers index (PMI) and non-manufacturing index (NSI) in nowcasting the GDP. Figure 5 illustrates the PMI model's (Equation (6)) nowcasts for the US GDP (RMSE = 2.995).

However, we observed that the significant decrease in the spring of 2020, which was previously displayed in Figure 1, appeared to be dampened when PMI was aggregated to quarterly levels, as shown in Figure 5. Additionally, the PMI model was unable to accurately predict the drastic GDP collapse that occurred during the spring of 2020.

A similar narrative is in Figure 6 – the NSI model nowcasts only a minor decrease in the US GDP after the spring of 2020. The NSI model's RMSE score was 3.116. Interestingly, the NSI model seems to nowcast an increase in the US GDP after the actual GDP growth.

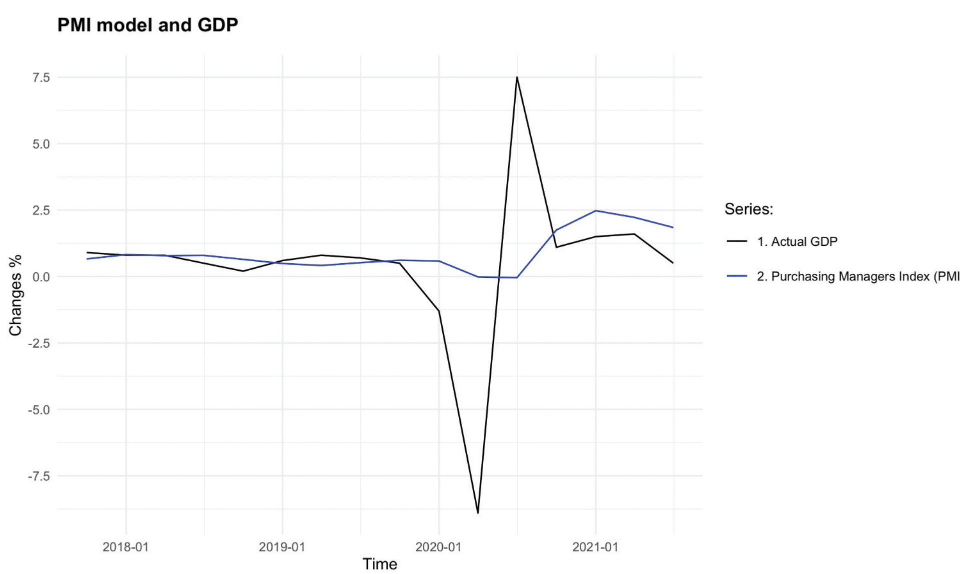

Figure 5. The PMI nowcasts of GDP.

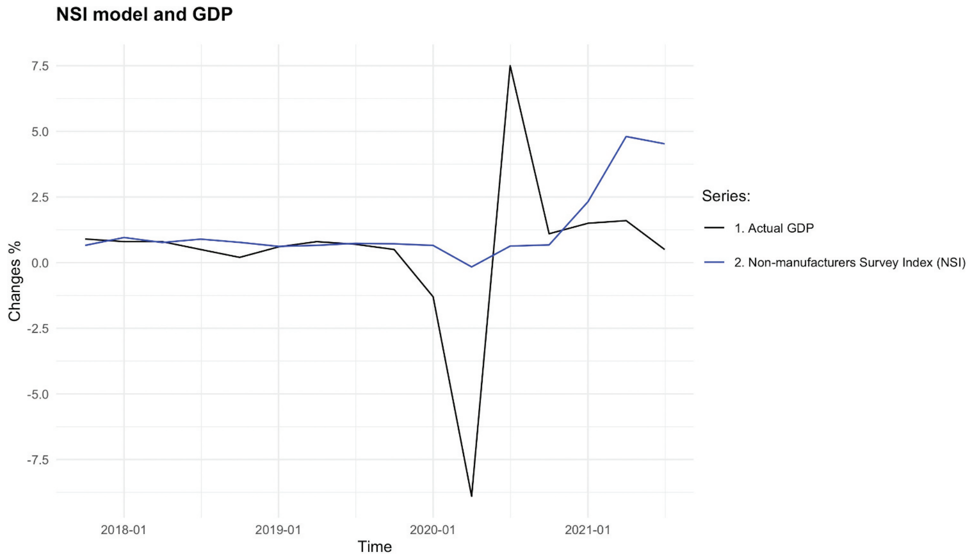

Figure 6. NSI nowcasts of GDP.

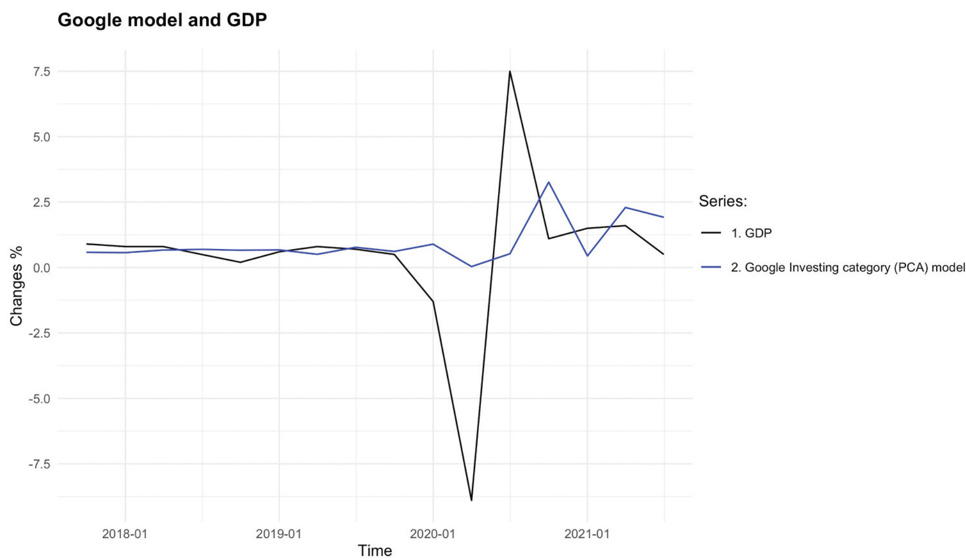

Figure 7. The most accurate Google model to nowcast US GDP.

These results indicate that while PMI and NSI data may be useful in predicting GDP under normal economic conditions, it may not be effective in predicting the impact of economic crises. Therefore, other alternative data sources should be considered for nowcasting GDP during times of significant economic downturn.

Figure 7 demonstrates the effectiveness of Google models in nowcasting the US GDP, and it reveals that investing-related searches exhibited a slight upward trend following the rise in the US GDP. Based on the findings presented in Table 2, the most accurate Google model yielded results comparable to those of the PMI and NSI models.

Specifically, the Investing category model outperformed the others, generating an RMSE of 2.981, which was marginally lower than the RMSE scores obtained by the PMI and NSI models. These results suggest that Google search data could offer valuable insights into economic trends.

Table 2. RMSE results for nowcasting GDP.

Model	RMSE
Google Investing category (PCA) (7)	2.981*
PMI model (6)	2.995
NSI model (6)	3.116

*The most accurate model

IV. Conclusions

We have discovered compelling evidence demonstrating that Google Trends can provide supplementary information for nowcasting the ISM PMI. Among the models considered, the one incorporating both AR-1 and the investing-category from Google Trends emerged as the most accurate. Interestingly, the Business & Industrial category model projected a significant decline in PMI during the spring of 2020, coinciding with the COVID-19 outbreak. Additionally, we find intriguing evidence that Google Trends data can yield valuable information when nowcasting the ISM non-manufacturing survey index (NSI). While the model featuring both the AR-1 and the investing category from Google Trends was the most accurate, the model solely utilizing the investing category accurately forecasted a sharp decrease in the NSI during the spring of 2020. Surprisingly, none of our nowcasting models was able to forecasts the sharp drop in the US GDP growth in spring 2020. Nevertheless, our results point out that weekly Google Trends data generates useful insights for nowcast the nowcasting, i.e. the purchasing manager's index (PMI). Moreover, weekly Google data's timeliness allows for an even faster estimate of the current economic conditions in the United States by helping to forecast changes in monthly economic variables and alleviating data limitations.

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Disclosure statement

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APPENDIX A

Table A1. Google Trends 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. Google Trends 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. Google Trends 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. Google Trends 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

Table A5. Selected weeks of Google Trends data.

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			

APPENDIX B

Table B1. Google Trends RMSE results for nowcasting PMI.

Response variable:	PMI	
Dimension reduction method:	PCA	**PLS**
Equation (3)		
Models:	**RMSE:**	**RMSE:**
Autos & Vehicles	5.220	5.011
Beauty & Fitness	5.249	5.150
Business & Industrial	5.591	4.398
Computers & Electronics	4.871	4.609
Food & Drink	4.457	4.921
Health	5.276	5.345
Home & Garden	5.642	5.238
Internet & Telecom	5.177	4.953
Investing	4.419	4.792
Jobs & Education	5.307	5.411
Law & Government	5.782	5.082
News	5.672	5.299
Real Estate	5.267	5.337
Shopping	5.195	4.432
Sports	5.281	5.646
Travel	5.373	5.119
Equation (5)		
Models:	**RMSE:**	**RMSE:**
Autos & Vehicles	2.446	2.527
Beauty & Fitness	2.460	2.502
Business & Industrial	2.619	2.633
Computers & Electronics	2.448	2.558
Food & Drink	2.421	2.510
Health	2.476	2.623
Home & Garden	2.488	2.700
Internet & Telecom	2.459	2.544
Investing	2.348	2.415
Jobs & Education	2.521	2.580
Law & Government	2.668	2.509
News	2.491	2.600
Real Estate	2.441	2.493
Shopping	2.433	2.468
Sports	2.480	2.753
Travel	2.530	2.518

Table B2. Google Trends RMSE results for nowcasting NSI.

Response variable:	NSI	
Dimension reduction method:	PCA	PLS
Equation (3)		
Models:	**RMSE:**	**RMSE:**
Autos & Vehicles	4.269	4.250
Beauty & Fitness	4.307	4.050
Business & Industrial	4.597	3.587
Computers & Electronics	3.640	3.462
Food & Drink	3.504	3.559
Health	4.382	4.173
Home & Garden	4.671	4.258
Internet & Telecom	3.856	3.586
Investing	3.667	3.295
Jobs & Education	4.354	4.408
Law & Government	4.584	3.976
News	4.320	3.967
Real Estate	4.273	4.250
Shopping	4.038	3.323
Sports	4.239	4.228
Travel	4.411	4.526
Equation (5)		
Models:	**RMSE:**	**RMSE:**
Autos & Vehicles	3.197	3.530
Beauty & Fitness	3.218	3.181
Business & Industrial	3.528	3.277
Computers & Electronics	3.063	2.972
Food & Drink	2.912	2.978
Health	3.296	3.319
Home & Garden	3.381	3.642
Internet & Telecom	3.127	3.056
Investing	3.038	2.874
Jobs & Education	3.432	3.523
Law & Government	3.452	3.228
News	3.156	3.439
Real Estate	3.187	3.289
Shopping	3.160	3.017
Sports	3.256	3.497
Travel	3.406	3.602

Table B3. Google Trends RMSE results for nowcasting GDP.

Response variable:	GDP	
Dimension reduction method:	PCA	PLS
Equation (7)		
Models:	**RMSE:**	**RMSE:**
Autos & Vehicles	3.140	4.141
Beauty & Fitness	3.124	3.610
Business & Industrial	4.065	3.876
Computers & Electronics	3.102	3.756
Food & Drink	3.292	3.164
Health	3.627	3.412
Home & Garden	4.194	4.260
Internet & Telecom	3.079	3.748
Investing	2.981	3.505
Jobs & Education	3.916	3.789
Law & Government	3.700	3.447
News	3.400	3.282
Real Estate	3.226	3.792
Shopping	3.091	3.071
Sports	3.257	3.817
Travel	3.704	3.814