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Monthly Assessments of Private Consumption*

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Discussion Paper No. 2010.09
August 2010

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I thank Guy Segal for his contribution and further developments, Michael Revzin for research assistance, Edward Offenbacher, Guy Navon, Ella Shachar and Tomer Kriaf for discussions and help. I am also grateful to Simcha Bar-Eliezer and Tali Shalem-Cohen for going into details concerning the CBS methodology.

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Abstract

This article sets a framework for high-frequency nowcasts of private consumption, in terms of percentage changes, which are originally observed quarterly.

The problem has been considered through two mixed-frequency models, both projecting quarterly observed percentage changes into monthly covariates: imports of consumer durables, retail trade, revenue of services, credit card and VAT payments, all adjusted for seasonal variation and available from official sources. The first model uses the MIDAS specification and produces quarterly nowcasts, updated monthly. The second model builds on state-space representation and enables monthly nowcasts.

Timeliness of monthly official information is an important parameter of mixed-frequency models, taken into account either by appropriated parameterization or by endpoint estimates which fulfill incomplete monthly data. I simulate end-of-sample estimates using consumption-related Web-query indices, available weekly from Google Insights for Search. Proceeding from a predetermined pool of 41 Google predictors, a two-step procedure for filtering series has been applied, which selects the best explanatory subset, in accordance with the AIC information criteria. As the predictive content of query indices is time-varying, the best subset is reassigned each month, based on the information known up to the previous month.

The MIDAS specification enables quarterly nowcasts for two months earlier than the bridge department equation, with almost the same RMSFE/AMFE. The monthly nowcasts of private consumption simulated from the state-space model are found (ex-post) to be consistent and highly positively correlated with quarterly realizations.

Preliminary empirical evidence was found that monthly estimated "local-demand" series are more appropriate in inflation equations than the overall index of real economic activity.

JEL Classification: C53, E27, E300, E37

Keywords: nowcasting, private consumption, mixed-frequency models, Google Insights for Search.

חיזוי חודשי של הצריכה הפרטית בזמן אמת

טניה סוחוי

תקציר

עבודה זו מציעה מסגרת לחיזוי-בזמן-אמת (nowcasts) של השינויים בצריכה הפרטית בתדירות חודשית – סדרה הנאמדת על ידי הלמ"ס בתדירות רבעונית.

מוצגים שני מודלים של תדירות מעורבת (mixed-frequency models), המקשרים ישירות בין המשתנה המוסבר (שיעורי השינוי הרבעוניים של הצריכה הפרטית) לבין המשתנים המסבירים, שתדירותם חודשית – היבוא של מוצרי צריכה בני קיימא (ללא כלי רכב), המסחר הקמעוני, פדיון ענפי השירותים, התשלומים בכרטיסי אשראי ונתוני המע"מ – כולם בנתונים מנוכי עונתיות, הזמינים מפרסומים רשמיים.

המודל הראשון הוא מודל ה-MIDAS, אשר מפיק תחזיות רבעוניות, המתעדכנות על בסיס חודשי. המודל השני הוא מודל ה-state-space, המפיק תחזיות חודשיות.

עיתוי הפרסום של הנתונים המסבירים החודשיים בזמן אמת הוא פרמטר חשוב במודלים של תדירות מעורבת, אשר מבנה הפיגורים מותאם אליו. נבדקה גם אפשרות להשלים את נתוני הקצה החסרים בָּאומדנים המבוססים על מדדי החיפוש של Google, הזמינים בזמן אמת. כך נערכו סימולציות של אומדני הקצה שמחוץ למדגם על סמך 41 קטגוריות חיפוש של Google המותאמות לקטגוריות של הוצאות משקי הבית על צריכה פרטית. מתוכן נבחר, בכל חודש מחדש, מספר קטן של קטגוריות "מובילות"; זאת על סמך מזעור של ערכי ה-AIC, המבוסס על הנתונים הידועים עד החודש הקודם.

מודל ה-MIDAS הרבעוני מאפשר תחזיות-זמן-אמת שטעויות החיזוי (RMFSE/AMFSE) בהן דומות לאלה שבמודל ה-OLS של חטיבת המחקר, אך מקדים אותן לפחות בחודשיים.

אשר למודל החודשי – ה-state-space – נמצא שתחזיות-זמן-האמת שלו מתיישבות עם הנתונים הרבעוניים הרשמיים. זאת ועוד, על פי עדויות אמפיריות ראשוניות, סדרה חודשית זו של השינויים בצריכה הפרטית מתאימה לשימוש במשוואות ה-VAR לאינפלציה יותר מאשר המדד המשולב למצב המשק, משום שהיא משקפת את הביקושים המקומיים בלבד.

1. **Introduction**

Nowcasting practice, i.e., uncovering of real-time macroeconomic data, which are subject to publication lags, has rapidly developed over the past few years. All relevant information is processed, especially that which is published more frequently than variables of interest.

This article attempts to nowcast short-term changes in private consumption, the major part of aggregate demand. Theory has distinguished between planned and cyclical fluctuations in private consumption; the former come in response to anticipated changes in macroeconomic fundamentals and forecasts of policy variables; the latter are caused by transitory shocks to the economy (Kandil and Mirzaie, 2003). Central Bank monetary monitoring, which is carried out on a monthly basis, discerns partial data of consumer demand/expenditures as main indicators of inflationary and real developments.

Official figures on private consumption—in nominal and real terms—are part of Israeli National Accounts, which are released quarterly, six weeks after the end of the quarter to which they relate.Concurrently, partial data of consumer demand are gathered by monthly statistics of consumer imports, sales value indices of large scale retail trade (marketing networks, department and chain stores), revenue indices of trade and services (accommodation, restaurants, real estate, health and welfare, personal and other), and VAT payments. Survey-based confidence indices, e.g., of Globes and Bank Hapoalim, provide early signals of consumer expectations; wealth effects may be derived from the daily performance of the Tel-Aviv Stock Exchange.

This paper looks for a way to incorporate partial high-frequency data on consumer demand in monthly nowcasting of aggregate changes in private consumption.

Recent nowcasting experiments, reviewed by Baffigi et al. (2004) have been mainly concentrated between bridge equations and dynamic factor models. The former aggregate all data at a lower frequency of the target variable, while the nowcast is recalculated each time that new explanatory data become available. Bridge equations have been widely adopted in central bank monitoring systems.[1] Nevertheless, Ghysels et al. (2004) show in their seminal paper that aggregating the data to their common lowest frequency will always be less efficient than direct projection of low-frequency target into high-frequency covariates.

Dynamic factor models directly project low-frequency (say, quarterly) observations of the target variable onto monthly/weekly/daily explanatory series (say, financial data). In this field, the MIDAS regression of Ghysels et al. (2004, 2006) is worth attention. This technique was implemented in forecasting US macro variables by daily survey expectations (Ghysels and Wright, 2006), US output growth by weekly data on asset prices and interest rates (Clements and Galvao, 2007), German quarterly GDP by 111 monthly series on prices, labor market data, interest rates and stock market indices, industry, construction and business surveys (Marcellino and Shumacher, 2008), Italian

[1] See, for example the Deutsche Bundesbank Monthly Report "Short-term forecasting methods as instruments of business cycle analysis," April 2009

GDP growth by monthly indices of business climate, industrial production, purchasing managers indices, electricity consumption, world trade, transits of trucks and M2 (Frale and Monteforte, 2009), and monthly inflation by daily expectations, extracted from market derivatives (Monteforte and Moretti,2008).

In contrast with MIDAS, which produces low-frequency forecasts, another strand of mixed-frequency models builds on interpolation of low-frequency series by a related series, available at higher frequency. Pioneered in the 1960s,[2] those models were further developed toward state-space form, as monthly GDP growth by Mitchell et al. (2005), monthly National Accounts equations by Angelini et al. (2008) and the daily Index of business conditions by Aruoba et al. (2009). The interpolation approach, enabling high-frequency representation with missing values, overcomes the high degree of uncertainty of low-frequency nowcasts, made at the beginning of the nowcast period. Moreover, it stands in greater accord with the regime of monthly monetary meetings of the central bank. Using state-space technique, this study suggests monthly estimates of changes in private consumption.

Proceeding from incompleteness of monthly official data in real time, this paper contributes to the generation of end-of-sample estimates of explanatory series. For this, consumption-related query indices from the Google Insights for Search database have been used.

Leading properties of Google-categorized web-queries (henceforth "Google predictors") have been approved for retail sales, travel and real estate (Choi and Varian, 2008), unemployment rate (Choi and Varian, 2009; Askitas and Zimmerman, 2009; D'Amuri and Marcucci, 2009) and consumers' expenditure (Kholodin et.al., 2009, Schmidt and Vosen, 2009). The latter conclude that Google predictors provide similar or even higher forecast accuracy than conventional consumer confidence indicators. A possible reason for this is that web-queries are related more closely to spending decisions than they are to intentions to purchases in the near future, collected by consumer surveys, which reflect respondents' vision of common economic conditions rather than the willingness to make a particular purchase. It is worth attention conclusion that the predictive superiority of Google indicators is more pronounced during turbulent times. A study completed on the Israeli data (Suhoy, 2009) confirmed the leading ability of Google predictors as shown by simulations of economic downturns carried out for the period 2008–2009.

In fact, Israeli consumers are still not used to daily shopping on-line via virtual retail chain stores and other stores (e.g., food, beverages, clothes and footwear), nor to vehicle shopping, but are accustomed to on-line reservations of travel, accommodation, attractions and entertainment, search for home equipment, apartment sales, and business and personal services[3]. Although the structure of the search is far from being representative of Israeli consumer spending, changes in the popularity of specific queries can be an indicator of changes in aggregate consumer demand.

[2] See Chow-Lin (1971) GLS procedure and earlier works, referenced in their article.
[3] According to the Ministry of Industry, Trade and Labor 2007 and 2010 surveys (in Hebrew).

The pool of Google predictors used for this study comprises 41 consumption-related categories, with sufficient variability of search-popularity over time. For comparison, Schmidt and Vosen (2009) used 56 similar indices, Kolodilin et.al. (2009) used 220.

It is possible to treat the problem of choosing the right predictors as the problem of reducing the dimension of mutually correlated variables. Hence, two recent studies extracted a few principal components of Google data and then applied regression analyses. Unfortunately, this did not work in our case; no information content was detected, since the factors were extracted without conditioning on the dependant variable. Another reason could be that the predictive content of web-queries is time-varying.

The two-step selection suggested here aims to account for both these circumstances. In a first step, each partial monthly indicator of consumer demand is regressed by each Google predictor, while parameters of these pair-wise regressions are time-varying.[4] Then, only predictors with positive slope in the last available month prior to the nowcast remain, while the others are filtered. The second step accounts for the mutual correlation between selected queries and tries all their possible combinations in multivariate regressions. The subset of Google predictors with the smallest value of the Akaike Information Criteria is deemed the best. In this study the code of Beal (2008), written for large datasets, has been applied. Alternatively, a Lasso shrinkage regression of Tibshirani (1996) could be used.

The rest of the paper proceeds as follow. The next section describes monthly available official indicators of consumer demand and their connection to aggregate changes in private consumption, in quarterly terms. Section 3 discusses usefulness of Google predictors, with respect to different official monthly indicators of consumer demand. Next, it describes variable selection procedure, which each month assigns a relatively small subset of Google predictors while allowing for its time-varying composition. Sections 4 and 5 suggest two mixed-frequency nowcasting specifications—the MIDAS and the state-space ones—producing, respectively, quarterly and monthly estimates of changes in private consumption. The former is compared with the department bridge equations. The latter is investigated with regard to inflation forecasts. Section 6 concludes.

2. Monthly official data on consumer demand, connected to private consumption

As in the National Accounts, private consumption expenditure has been classified by source of supply (domestic production or imports), by industry in which the different goods or services are usually produced and by type of goods/services purchased by households (food, beverages, tobacco, clothing, footwear, household equipment, healthcare, education, transportation, etc.).[5]

Household expenditure in the domestic market consists of[6] services (35%, excluding housing), housing (21.2%, excluding fuel, electricity and water), food, beverages and

[4] Meaning the TVP model of Kim and Nelson (1995).

[5] Definitions and explanations on the National Accounts methodology are given in the CBS site, URL: Cbs.gov.il

[6] 2009 annual data, at current prices.

Table 1. Monthly official indicators of consumer demand, publication lags and quarterly correlations with National Accounts data[1]

Monthly indicators / (publication lag in weeks)	Total private consumption	Thereof: households expenditure in the domestic market (98.1%)[2]				
		Services excl. housing (35.8%)	Housing (21.2%)	Food, beverages and tobacco (19.2%)	Clothing, footwear and other (9.0%)	Durable goods (8.2%)
Panel 1. Retail trade						
- Total (3 weeks)	0.37			0.15	0.31	0.25
- Durables (7 weeks)	0.56					0.48
Panel 2. Revenue of services[3] (7 weeks)						
- Total[4]	0.44	0.48	0.29			
-Trade and vehicle repairs	0.47	0.55				
-Accommodation, restaurants	0.18	0.58				
-Transport, communications	0.42	0.46				
-Banking, insurance	0.36	0.28				
- Real estate, renting[5]	0.38	0.29				
-Educ., health, social work	0.22	0.20				
Panel 3. Domestic Industrial production (7 weeks)						
- Food, beverages, tobacco	0.18			0.25		
- Textiles and footwear	0.42				0.39	
- Furniture	0.27					0.23
Panel 4. Consumer imports (2 weeks)						
- Total	0.64			0.36	0.35	0.72
- Vehicles	0.60					0.68
- Durables, excl. vehicles	0.73					0.82
- Non-durables goods	0.35			0.28	0.23	
Panel 5. Overall indicators						
Credit cards[6] (6 weeks)	0.51	0.42	0.50	0.27		0.48
VAT payments[7] (2 weeks)	0.38	0.40				0.34

[1]All series are in fixed prices and seasonally adjusted. Recorded correlations are between quarterly percentage changes.

[2] The umbers in parentheses are the weights of a given type of households expenditure in the whole of 2009 in the domestic market, at current prices.

[3]Computed based on 59.73% weight of trade services within the overall index of revenue of trade and services

[4]The correlation with expenditure on housing services peaks (0.29) at a two-month lag of monthly series; recorded coefficients for contemporaneous and one-month-lagged monthly series are 0.14 and 0.18, respectively

[5]The correlation with expenditure on housing services peaks (0.38) at a two-month lag of monthly series; recorded coefficients for contemporaneous and one-month-lagged monthly series are 0.07 and 0.19, respectively

[6]All correlations by row relate to credit card payments with a monthly lag.

[7]Net VAT, compiled as VAT paid less VAT refunded, with a two-month delay.

tobacco (19.2%), clothing, footwear and other goods (9.0%), durables (8.2%, including vehicles) and fuel, electricity and water (7.4%).

From the standpoint of nowcasting capabilities, the first thing to note is the different volatility of the components of private consumption. For instance, purchases of durable goods and business services are more volatile, in terms of real quarterly changes, than current consumption of non-durable goods or housing services, and more sensitive to business cycle fluctuations.

Until final data on private consumption have been compiled, mainly based on the Household Expenditure Surveys, the earlier Central Bureau of Statistics (CBS) estimates account explicitly for real changes in retail trade, services revenue, industrial production, imports of consumer goods and VAT payments, produced monthly by statistical systems.

Monthly indices of retail trade, revenue and industrial production are available from the CBS at constant prices and seasonally adjusted. Consumer imports are seasonal adjusted, but their real change is not available on a monthly basis. To evaluate changes in import prices, we evaluate monthly deflators, using changes in cross euro-dollar rates, scaled by quarterly observed changes in imports prices. The VAT data, provided by the Ministry of Finance, are seasonally adjusted and deflated by the CP index.

The timeliness of monthly statistics of consumer demand is presented in Table 1 in terms of publication lags, in weeks, after the end of the month. This parameter refers to the whole panel, when all related series are released at the same time or to particular series, when related series have different publication schedules.

Table 1 provides a view of connection between official monthly indicators of consumer demand and components of private consumption, as measured by National Accounts system, at constant prices, seasonally adjusted and log-differenced. For descriptive purposes of this table, all monthly series were aggregated at quarterly frequency and then log-differenced. Only correlations significant at the 99% level are displayed.

As seen from Table 1, imports of durable goods are the earliest monthly available indicator, highly correlated with the aggregate changes in private consumption. It is worth noting that vehicle imports do not improve the correlation, when percentage changes are being discussed. Next, quickly available VAT data are valuable. Variables of services, which also provide reliable information, are not available in real time and require end-of-sample estimates.

The next section focuses on end-of-sample inferences, made upon consumption-related Google queries.

3. Information and predictive content of consumption-related Google queries

Query indices, available from Google Insights for Search, represent dynamics of web-searches, produced through Google in Israel during the week and categorized according to the NAICS classification system. Appendix 1 presents consumption-related Google categories alongside the matched CBS division of trade and services, although the two classifications do not stand in one-to-one correspondence.

To exploit the leading content of Google predictors (collected from January 2004 onwards) only two first-week observations of each month are used. Due to overlaps of weeks and months, weekly data were interpolated daily with a cubic spline, in order to get equal intervals of 15 days each month; then, daily data were averaged at monthly frequency.

In general, Google predictors reveal seasonal patterns. Significant seasonal components have been removed, although calendar effects could not be detected, because of the short span. Since query indices appear mostly non-stationary (Suhoy, 2009), the series are first differenced.

Further, we distinguish two nowcast horizons, in months: $h=0$, meaning that the nowcast relates to the past month (in cases where the publication lag is three weeks or more) and $h=1$, meaning that the nowcast relates to the current month.

The information/predictive content of Google predictors was assessed relative to baseline ARIMA models, incorporating (or not) cyclical dynamics of the General Index (of shares and convertible securities) of the Tel-Aviv Stock Exchange (hereafter: the TASE Index). In parallel, the same specifications were run for Consumer Confidence indices. Then, assessed contents are compared.

3.1. Selection of Google predictors

As the predictive content of web-queries appears unstable, we have to determine which Google predictors should be used each month. To make this decision, a two-step selection is suggested.

The first steps run pair-wise regressions, each of which connects official monthly indices with Google predictors. All equations are autoregressive, with time-varying parameters, specified as follows:[7]

$$\begin{aligned} x_{t_m} &= \alpha_{t_m} + \rho_{t_m} x_{t_m-1} + \varphi_{t_m} g_{t_m} + \nu_{t_m} \qquad t_m = 1,\ldots T_m; \\ \rho_{t_m} &= \rho_{t_m-1} + \zeta_{t_m} \;,\quad \zeta \sim N(0,\sigma_\zeta^2) \\ \varphi_{t_m} &= \varphi_{t_m-1} + \eta_{t_m} \;,\quad \eta \sim N(0,\sigma_\eta^2) \end{aligned} \tag{6}$$

where t_m denotes monthly-frequency index,

x_{t_m} is a monthly official indicator,

g_{t_m} - is a Google predictor[8].

$\alpha_{t_m}, \rho_{t_m}, \varphi_{t_m}$ are time-varying parameters, estimated conditionally on information available up to $t_m - 1$,

ν, ζ, η are random disturbances.

[7] See the TVP specification of Kim and Nelson (1995). To simplify notation, two additional indexations of official monthly indicators and Google predictors are omitted.

[8] The series is taken simultaneously or lagged up to two months.

To produce the (T_m+1)-the forecast of x, we discard predictors with negative slope φ_{t_m} recorded for the month $t_m = T_m$, i.e., the last available month prior to the forecast.

Appendix 2 displays time intervals, when positive slopes ρ_{t_m} of Google predictors were recorded with respect to monthly official series of consumer demand, as revealed by pair-wise TVP regressions (4). This gives the impression that the information content of Google predictors, especially concerning consumer imports and the retail trade, is concentrated in a close range of categories, while few of them keep working over time. Examples are Home appliances (id=271) and the whole Home & Garden (id=11) category, Toys (id=432) and Vehicle Brands (id=815) which can be thought as stable predictors for consumer imports, retail trade and credit card payments.

Table 2. The probabilities of entering the monthly explanatory draw, by the most frequently selected consumption-related categories (sample: 2007:1–2010:1)

Google category/subcategory	**Probability of entering the monthly draw[1]**
Home Appliances (271)	1.0
דירה למכירה (string:"apartment for sale")[2]	1.0
Hotels & Accommodation (179)	0.9
Beauty & Personal Care (44)	0.9
Restaurants (276)	0.6
Air Travel (203),	0.5
Kids & Teens / Toys (432)	0.5
Business & Personal Listings (377)	0.2
Construction & Maintenance (48)	0.2
Luxury Goods (696)	0.2
Recruiting & Staffing (330)[3]	0.1

[1] Calculated as the maximum number of occasions that the predictor was chosen, with regard to any official monthly indicator, divided by the total number of out-of-sample simulations.
[2] Detected by the string in Hebrew; usually a two-month lag is required.
[3] As predictor for revenue of business services; with a one month lag.

Table 3. Average number of Google predictors required, by official monthly series of consumer demand (2007:1–2010:1)

Monthly official indicator	Average number of predictors required in the regression[1]
Revenue of trade and services	4.1 (1.2)
Revenue of services	3.5 (1.1)
Retail trade	2.5 (1.1)
Consumer imports - durables	1.8 (0.2)
Credit cards payments	3.2 (1.1)

[1] Not including autoregressive terms. Standard deviations are in parentheses

For services, the most apparent are searches for Apartment Sales—probably related to real estate and rent services; Vehicle Brands (815), Auto Parts (89), Luxury Goods (696) and Auctions (292)—to vehicle repair and trade services; Hotels & Accommodation (179), Food and Drink (71), Restaurants (276) and Tickets sales (614)—covering travel, food and entertainment; Beauty & Personal Care (44)—referring to personal services; Auto Financing (468)—to leasing; Business and Personal listing (377); Business Services and Consulting (329), and Human Resources (157)—to business services.

In the second step, the mutual correlation between selected positively sloped predictors is accounted for. For the pool of p predictors a sequence of $(2^p - 1)$ multivariate regressions is run. Since the number of predictors is large $(p > 10)$, we use a variable selection procedure, suggested by Beal (2008), which explicitly evaluates all possible subset models for any p, as against step-wise procedures which show results for only a small fraction of regressions.

The best subset of positively sloped predictors is reassigned every month, i.e., the one providing the smallest AIC conditioned on data up to the previous month.

Table 2 displays Google predictors which were frequently chosen by the two-step selection criteria, and provides corresponding selecting probabilities. As revealed, searches for home equipment, apartments, personal care and accommodations are the most selected Google predictors.

Table 3 provides the average number of Google predictors required for the best prediction, in terms of AIC, by different monthly reference indicators of consumer demand. These estimates are computed from simulations produced for the period between 2007:1 and 2010:1.

3.2. Information content of Google predictors

The in-sample performance of Google predictors and consumer confidence indices is assessed relative to two baseline models.

The first (baseline A) is an ARIMA model, estimated for each official monthly indicator with appropriate AR and MA orders, including up to two-month lag terms. The first lag is allowed when the nowcast horizon $h = 0$ (i.e., the month of interest is the previous one), and is not allowed for $h = 1$ (i.e., the month of interest is the current one). The order of autoregressive and moving average terms is determined according to the AIC criterion.

The second model (baseline B) is an ARIMA with introduced macroeconomic cycle, calculated from the daily TASE index, where two-first-week data are aggregated into monthly averages and then log-differenced. This indicator is proved to be positively correlated with changes in private consumption, except that there are advantages over other cyclical indicators of a publication lead and no revisions.

Appendix 3 enables a comparison to be made between the information content of Google predictors and consumer confidence indices[9] relatively to the baseline models A

[9] The estimates for the Globes and Bank Hapoalim indices are quite similar.

or B described above. It provides values of the R^2, F-statistic and $RMSE$ either for the trio A, which comprises the baseline A, A with the addition of the consumer confidence index, and A with the Google predictors, or for the trio B, which comprises the baseline B (i.e., Arima with incorporated stock-market cycle), B with the addition of the consumer confidence index, and B with the Google predictors. All models were evaluated with regard to five official monthly series of consumer demand (panels 1 to 5), with two different nowcast horizons $h = 0$ and $h = 1$.

As can be seen, Google predictors outperform consumer confidence indices in all in-sample experiments. The most notable increases in R^2 -values shared by the Google predictors are recorded for credit cards payments. Unfortunately, this fact can hardly be exploited in practice, because of the large publication lag of these series. On the contrary, the practical use of Google predictors is more justified regarding the retail trade and consumer goods imports, despite the large fluctuations and, consequently, large RMSE values of the latter, because these data are available relatively quickly.

3.3. Predictive content

To assess the out-of-sample predictive power of Google predictors and consumer confidence indices, one-step-ahead and two-step-ahead forecasts were simulated, which correspond to nowcast horizons $h = 0$ and $h = 1$, respectively. The initial data span, used for estimation, was set between 2005:1 and 2007:5. Then, out-of-sample nowcasting was conducted, while adding one month at a time and re-estimating the parameters.

Similarly to the in-sample analysis, the first two AR or/and MA terms were used for the $h = 0$ horizon, while in simulations for the $h = 1$ only second lags were allowed.

From the simulated nowcasts, corresponding values of RMSFE were calculated. Additionally, relative values of RMSFE were calculated from the models of B-trio, to compare their forecast accuracy, according to the modified Diebold-Mariano statistics[10] (see Harvey, Leybourne and Newbold, 1997).

Appendix 4 summarizes the results. First, there is no clear-cut evidence that stock data improve the predictive power of the model (trio B), as it might have seemed before. Next, Google predictors mostly outperform both autoregressive fit and consumer confidence predictors; although corresponding MDM-values point to statistically significant differences only for imports of consumer durables, credit card payments and revenue of services. Also the advantage of Google predictors appears more tangible in longer nowcast horizons ($h = 1$) than in the case of $h = 0$, which benefits from the availability of the first lags of dependant variables.

4. MIDAS-nowcasts of private consumption

The MIDAS model fits the quarterly percentage changes in private consumption by the monthly changes of explanatory series, while the parameterization depends on the availability of monthly data.

[10] This test is valid for small samples, on condition that the compared models are not nested.

A benchmark for experiments with the MIDAS-technique was provided by the Research Department's bridge equation, which has been carried out as part of National Accounts nowcasting project since 2009. Among other issues, the Department model aims to assess the quarterly change in private consumption in the current quarter. This is an autoregressive model, estimated quarterly by OLS, which includes explanatory series of consumer imports of durable goods, revenue of health, welfare and social services, VAT payments, the Globes consumer confidence Index and TASE Index. All explanatory series, originally available as daily/monthly series, are converted into quarterly averages, upon available months, and then log-differenced. Consumer imports are at current prices and seasonally adjusted; the services revenue is at fixed prices, seasonally adjusted. VAT payments are adjusted for the CPI change and for seasonality and are lagged by two months. The Globes Consumer confidence Index is given a three-quarter lag. The TASE Index is quarterly averaged and calculated relatively (in percent change) to the average of four preceding quarters.

The Department nowcasts are carried out twice a quarter: close to the publication of the National Accounts data, and a month later. To facilitate discussion, the incompleteness of the monthly series is considered below for the case of imports and revenue data. For instance, National Accounts data relating the first quarter are released on May 18. On this date, only one-month consumer imports and no revenue data concerning the second quarter are available and no nowcast is processed. At the end of June, as soon as the one-month (April) revenue and two-month imports figures become available, the bridge equation is run for the first time. A month later this is the second nowcasting, based on complete (three months') imports and two months' revenue data.

With this schedule, I distinguish three nowcast horizons, in quarters, within the MIDAS framework. The first, $H = 2/3$, is evaluated by the end of May, when only one month of imports is available. Recall, that the Department nowcasts have not been evaluated for this forecast horizon. The second, $H = 1/3$, is evaluated by the end of June, when the imports data are of two-month coverage and only one month (April) of the revenue is available. The last, $H = 0$, is evaluated by the end of July, when the imports of the second quarter are complete and the revenue has two-month coverage.

Furthermore, several MIDAS experiments were conducted with official monthly series, completed at their endpoints by inferences, from Google predictors. Section 4.2 summarizes empirical findings.

4.1. The MIDAS specification

Consider a particular case, when the dependent variable y_t is observed quarterly and is projected into the monthly observed explanatory variable $x_{t,m}$. Let $x_t^{(3)}$ denote a monthly series which takes every third observation of $x_{t,m}$ and skips the rest.

The MIDAS regression specifies the H-step-ahead forecast of the target variable y_t as follows:

$$y_t = \beta_0 + \beta_1 \quad B(L^{1/3};\theta) \quad x_{t-H}^{(3)} \quad + \quad \varepsilon_t \qquad (1)$$

where $B \quad (L^{1/3};\theta) = \sum_{k=1}^{K} b(k;\theta) L^{(k-1)/3} \qquad (2)$

and $L^{k/3}$ is a monthly lag operator which ranges from the last month in the quarter up to k months before. This means that $L^{k/3} x_t^{(3)} = x_{t-k/3}^{(3)}$ is $(3-k)-th$ monthly observation of the current quarter.

Particularly, if the first month of the current quarter is released, the model (1) becomes:

$$y_t = \beta_0 + \beta_1 \quad B(L^{1/3};\theta) \quad x_{t-2/3}^{(3)} \quad + \quad \varepsilon_t \qquad (3)$$

where the forecast horizon $H = 2/3$ means that two of the three months of the current quarter have to be predicted. Thus, the forecast horizon affects the form of the parameterization.

As the number of lags grows, the number of parameters at higher frequencies would increase rapidly with no structure imposed. To prevent this, the coefficients of lagged predictors are tightly parameterized using distributed lag functions; thus, only a small number of parameters have to be estimated. Hence, the lag coefficient $b(k;\theta)$ from (2) is assumed to follow a distributed lag function of the exponential Almon polynomial, depending on two parameters θ, as follows:

$$b(k;\theta) = \frac{\exp(\theta_1 k + \theta_2 k^2)}{\sum_{k=1}^{K} \exp(\theta_1 k + \theta_2 k^2)}$$

4.2. MIDAS-estimates for nowcasting of private consumption

The explanatory variables are monthly percentage changes (i.e., log-differences), taken at different monthly lags, while skipping two of every three observations. For the $H = 0$ horizon, the explanatory set comprises imports of consumer durable goods of five consecutive months, i.e., three months of the current quarter and the last two months of the previous one; VAT payments of the last two months of the quarter prior to the nowcast; revenue of real estate, renting and business services in the second month of the current quarter and of the previous one; revenue of accommodation services and restaurants in the first month of the current quarter and in the last month of the previous one; revenue of health, welfare and social work in the first month of the current quarter. For $H = 1/3$ and $H = 2/3$ horizons the explanatory sets shrink, thus the series relating to the third and second months of the current quarter, respectively, cannot be included.

Appendix 5 displays in-sample MIDAS parameters, obtained for different nowcast horizons. At the bottom of the table, the fit statistics are compared with those of the Department bridge equation.

At first glance, the MIDAS regressions have characteristics no worse than the benchmark, and have the advantage of earlier nowcasts, which could be produced at $H = 2/3$.

The out-of-sample simulations[11] reinforce the first impression. Table 4 provides RMSFE and AMFE[12] statistics, computed upon nowcasts simulated between 2007:I and 2010:I. This period was particularly turbulent, so the prediction errors were recorded at 15% more than ever.

Table 4. Quarterly out-of-sample forecast errors[1] of MIDAS regressions, by forecast horizon (2007:1-2010:1), compared with the Department bridge model

	Forecast horizon		
	H=0	*H=1/3*	*H=2/3*
Panel A. Department bridge equations			
RMSFE	0.821	0.824	Not
AMFE	0.621	0.628	estimated
Panel B. MIDAS equations			
RMSFE	0.688	0.744	0.833
AMFE	0.522	0.576	0.676
Panel C. MIDAS with end-point inferences[2]			
RMSFE	Not	0.693	0.825
AMFE	estimated	0.594	0.645

[1] Multiplied by 100 for easier translation from log-difference terms into quarterly percentage changes.

[2] The end-point monthly inferences were simulated for consumer imports of durables, using the Home Appliances query index and for the total revenue of services, using queries for apartment sales, hotels and accommodations, personal listings and personal care.

This table provides evidence that the MIDAS specifications outperform the benchmark both in time and in fit. In the cases of $H = 0$ and $H = 1/3$, MIDAS-estimates have the advantage, presumably because they use reliable monthly information instead of autoregressive term. In the case of $H = 2/3$, the MIDAS with end-of-sample inferences is almost equivalent to the benchmark, in terms of RMSFE or AMSFE, but has a time advantage, as it produces nowcasts for one or two months earlier.

5. Monthly changes in private consumption upon the state-space model

5.1. State-space specification with missing data

Assume that the quarterly percentage change in private consumption, denoted by y_t depends on its past rate and monthly related series $x_{t,m}$. Using this covariate, y_t could be

[11] The data span used is from 1995:II; one-step-ahead forecasts have been recorded since 2007:I till 2009:IV, while adding one quarterly observation at a time and re-estimating regressions.

[12] Meaning Root mean square forecast error and Absolute mean forecast error, respectively.

interpolated into unobservable monthly changes $y_{t,m}$ in such a way, that quarterly cumulated errors ought to be minimized. Since the dependent variable is expressed in log-difference terms, its unobservable monthly changes $y_{t,m}$ do not add up to the logarithm of the quarterly rate. Still, we can assume that the equality holds up to a constant:[13]

$$\sum_{m=1}^{3} y_{t,m} = 3\log y_t - 3\log 3 \qquad m = 1,2,3 \quad t = 1,...T$$

since monthly changes in private consumption are unlikely to exceed one percentage point.

Without loss of generality, the monthly series $y_{t,m}$—upon the available quarterly observations on $y_t \quad (t = 1,...T)$—may be considered as partially observable, where each third observation (the last month of the quarter) is available and the remainders are missing. By this, $m = 3$ may be assigned.

Assume also that $y_{t,m}$ follows $AR(1)$ with incorporated monthly covariate $x_{t,m}$. Therefore, the specification takes the form:

$$y_{t,m} = c + \rho y_{t,m-1} + \beta_0 x_{t,m} + \beta_1 x_{t,m-1} + \varepsilon_{t,m} \qquad m = 1,2,3 \quad t = 1,...T \qquad (4)$$

Regression (4) may be reformulated in terms of only the available observations. Denoting by L the first-order monthly lag operator, which yields $\rho(L) y_{t,m} = y_{t,m} - \rho y_{t,m-1}$ and using the transformation $(1 + \rho L + \rho^2 L^2)(1 - \rho L) = (1 - \rho^3 L^3)$, after the substitution we get an equivalent equation, written in terms of only third-order monthly lags of $y_{t,m}$:

$$y_{t,m} = \rho^3 y_{t-1,m} + (1 + \rho + \rho^2)c + (1 + \rho L + \rho^2 L^2)[\beta_0 x_{t,m} + \beta_1 x_{t,m-1} + \varepsilon_{t,m}]; m = 3, t = 1,..T \quad (5)$$

Equation (5) may be cast into a state-space form and estimated iteratively. By regrouping intercept and error terms, it can be shown that the dynamics of $y_{t,m}$ may be decomposed into an autoregressive component, depending on the third monthly lag $y_{t-1,m}$, an exogenous effect of the covariate $x_{t,m}$,[14] and a random walk component, denoted by $\mu_{t,m}$. The whole dynamics is captured in two equations:

$$\begin{aligned} y_{t,m} &= \hat{\rho} y_{t-1,m} + \mu_{t,m} + \beta x_{t,m} + \varepsilon_{t,m} \qquad m = 3, t = 1,..T \\ \mu_{t,m} &= \mu_{t,m-1} + \eta_{t,m} \end{aligned} \qquad (6)$$

[13] This approximation is detailed by Mitchell (2005).

[14] For simplicity, here we neglect the lags of exogenous variable, although they appear in (5), as by empirical computations, we account for more than one monthly predictor, including their lags.

Since a monthly-frequency state vector $\alpha_{t,m} = (\varepsilon_{t,m} \quad \mu_{t,m} \quad \beta_1 \quad y_{t,m} \quad y_{t-1,m})$ has been assigned, the state-space representation of (6) is straightforward:

$$
\begin{aligned}
& y_{t,m} = Z_{t,m}\alpha_{t,m} \\
& \alpha_{t,m+1} = T_{t,m}\alpha_{t,m} + \zeta_{t,m+1} \qquad \zeta_{t,m1} \sim N(0, Q_{t,m}) \qquad\qquad (7) \\
& \alpha_1 \sim N(0, P)
\end{aligned}
$$

where $\zeta_{t,m} = (\varepsilon_{t,m} \quad \eta_{t,m} \quad 0 \quad u_{t,m} \quad 0)$, $u_{t,m} = [1 \quad 1 \quad x_{t,m}]x[\varepsilon_{t,m} \quad \eta_{t,m} \quad 0]`$,

$$
Z_{t,m} = [0 \quad 0 \quad 0 \quad 1 \quad 0],\ T_{t,m} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & x_{t,m} & 0 & \rho \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix},\ Q_{t,m} = \begin{bmatrix} \sigma_\varepsilon^2 & 0 & 0 & \sigma_\varepsilon^2 & \\ 0 & \sigma_\eta^2 & 0 & \sigma_\eta^2 & \\ 0 & 0 & 0 & 0 & \\ \sigma_\varepsilon^2 & \sigma_\eta^2 & 0 & (\sigma_\varepsilon^2 + \sigma_\eta^2) & \\ 0 & 0 & 0 & 0 & \end{bmatrix}
$$

With values missing in the dependent variable, the initial state α_1 is partitioned into two parts, accordingly to Koopman's algorithm (1997): one, with properly defined probability distribution and the other, diffuse, with an infinite covariance matrix. Thus, the covariance of the initial state α_1 has the form:

$$P = P_* + kP_\infty$$

where $P_* = diag[\sigma_\varepsilon^2 \quad 0 \quad 0 \quad 0 \quad 0]$, $P_\infty = diag[0 \quad 1 \quad 1 \quad 1 \quad 1]$, and k is a large constant.

The parameters σ_ε^2 and σ_η^2 (disturbance variances) and the lag coefficient ρ are estimated by maximizing the likelihood function, while the regression coefficient β is estimated implicitly during the state estimation (smoothing).

For estimation, the UCM procedure of SAS was used. The log-likelihood function, which accounts for the diffuse part of the state vector, is computed using the one-step-ahead forecasts as follows:

$$\log L = -\frac{3T}{2}\log 2\pi - \sum_{t,m=1}^{d} w_{t,m} - \frac{1}{2}\sum_{t,m=d+1}^{T,m}(\log F_{t,m} + \frac{\nu_{t,m}^2}{F_{t,m}}) \qquad (8)$$

where $\nu_{t,m} = y_{t,m} - Z\hat{\alpha}_{t,m}$ are the one-step-ahead residuals;

$\hat{\alpha}_{t,m} = E(\alpha_{t,m} \mid \Omega_{t,m-1})$, the estimated state vector, conditional on the information set $\Omega_{t,m-1}$, which comprises observations on y and x available until a month before;

$F_{t,m} = \text{var}(y_{t,m} \mid \Omega_{t,m-1})$ and $F_{t,m} = F_{t,m}^* + kF_{\infty t,m}$;

d is the number of iterations which the initialization step takes.

$$w_{t,m} = \log(F_{\infty t,m}) \qquad if \quad F_{\infty t,m} > 0 \text{ (during the initialization step)}$$

$$= \log(F^*_{t,m} + \frac{v^2_{t,m}}{F^*_{t,m}}) \qquad if \quad F_{\infty t,m} = 0 \text{ (in the post-initialization period)}$$

The missing values of $y_{t,m}$ (where $m \neq 3$) affect (8) in such a way that the corresponding summand is deleted, and the constant term is adjusted suitably.

The non-diffuse part of the log-likelihood, which depends on the equation parameters, is given by

$$\log L = -\frac{1}{2} \sum_{t,m=d+1}^{Txm} (\log F_{t,m} + \frac{v^2_{t,m}}{F_{t,m}}) \qquad (9)$$

In the empirical results section, both diffuse and full likelihood values are presented.

Most of the model dynamics may be captured by the monthly series of consumer demand. If that is the case, $\rho = 0$. Further computed AIC values provided empirical support that the ρ-value is insignificant and thus the state vector α shrank into $\alpha_{t,m} = (\varepsilon_{t,m} \quad \mu_{t,m} \quad \beta_1)`$ and the system matrices became, respectively:

$Z_{t,m} = [1 \quad 1 \quad x_{t,m}]$, $\zeta_{t,m} = [\varepsilon_{t,m} \quad \eta_{t,m} \quad 0]$, $Q = diag[\sigma^2_\varepsilon \quad \sigma^2_\eta \quad 0]$ and

$$T = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

The parameters presented in Appendix 6 refer only to the version with no autoregressive term included. Appendix 6A displays the stochastic version of β_1-estimates.

5.2. The monthly estimates of private consumption

I replicate three types of monthly nowcasts of private consumption, produced by the state-space model (5). These estimates are feasible in the middle of each month, as soon as corresponding consumer imports became updated.

First, there are ex-post estimated percent monthly changes, based on the full information set of monthly official covariates. Those are not feasible in real-time, but of course are relevant to the past changes. Second, there are ex-ante estimates, denoted by $h = 0$, which replicate nowcasting of the previous month, when contemporaneous consumer imports are available but not services revenue, which are known only about one month before the previous one. Third, there are ex-ante estimates, denoted by $h = 1$, which replicate nowcasting of the current month, while there are no data available on contemporaneous consumer imports or on services revenue of two consecutive months.

Appendixes 6 and 6A display the estimated parameters of fixed and random versions, respectively. Figure 1 depicts all three types of monthly simulated series, alongside actually observed changes in private consumption, calculated in monthly terms.

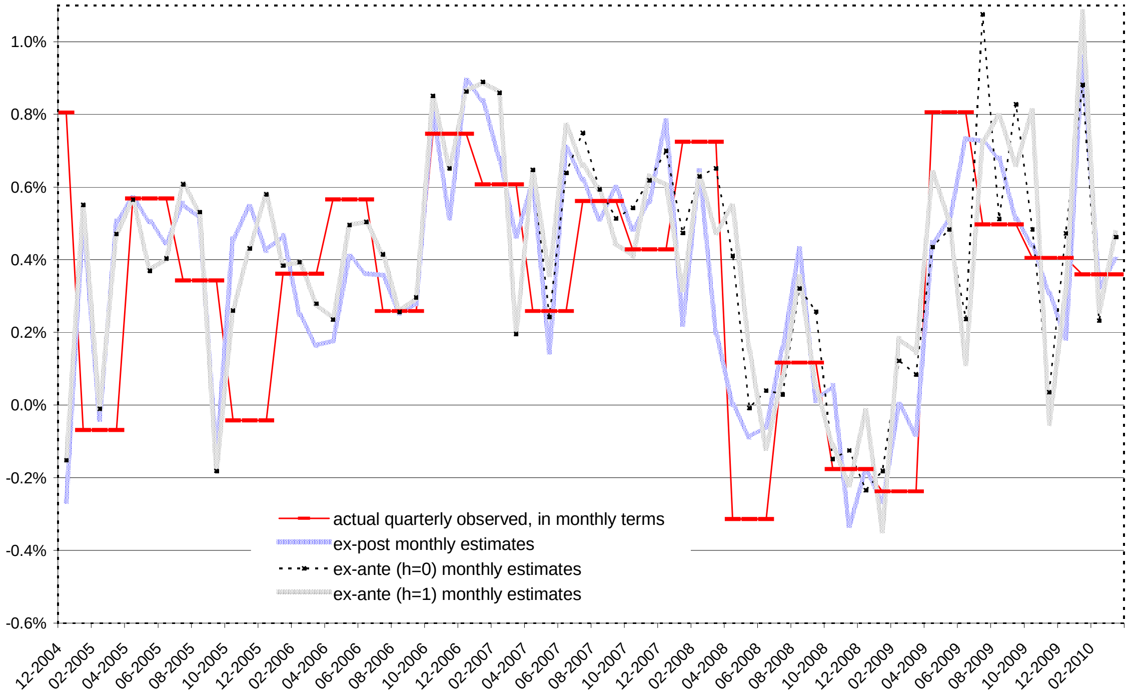


Figure 1. Monthly estimated changes in private consumption alongside actual quarterly data (red) in monthly terms (2004:12 – 2010:3); monthly simulated series are ex-post (blue), ex-ante h=0 (black, dashed) and ex-ante h=1(grey)

To enable quarterly comparisons to be made, monthly estimated changes were converted—through derived monthly indices—into quarterly ones and plotted alongside actual quarterly changes (Figure 2).

All three types of monthly estimates produce out-of-sample forecasts, assuming that the contemporaneous data from National Accounts are unknown. Thus, the forecast horizon varies, depending on what month in the quarter the data span ends. Given that the National Accounts data are released in May, August, October and February and relate to the end of the previous quarter, the forecast horizon of monthly estimates is two, three or four months for the second, third or first month of each quarter, respectively. Bearing in mind these leads, we conclude that the state-space equations exhibit high explanatory power, with R^2*-adj* decreasing from 0.64 to only 0.45, while going from ex-post to ex-ante (h=1) estimates.

The diffuse part of the log-likelihood remains small, indicating that the sample information, which contains 2/3 missing data upon monthly observations on the dependent variable, nevertheless is sufficient to create a proper prior for filtering and then computing shares of monthly covariates.

To enable quarterly comparisons to be made, monthly estimated changes were converted—through derived monthly indices—into quarterly ones and plotted alongside actual quarterly changes (Figure 2).

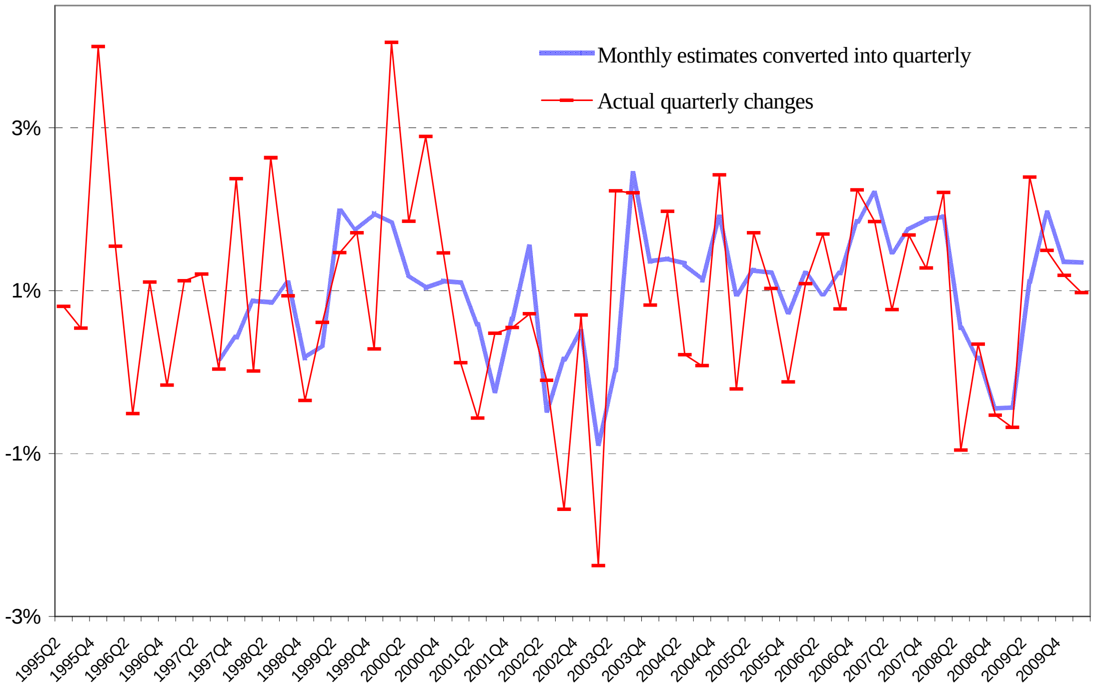


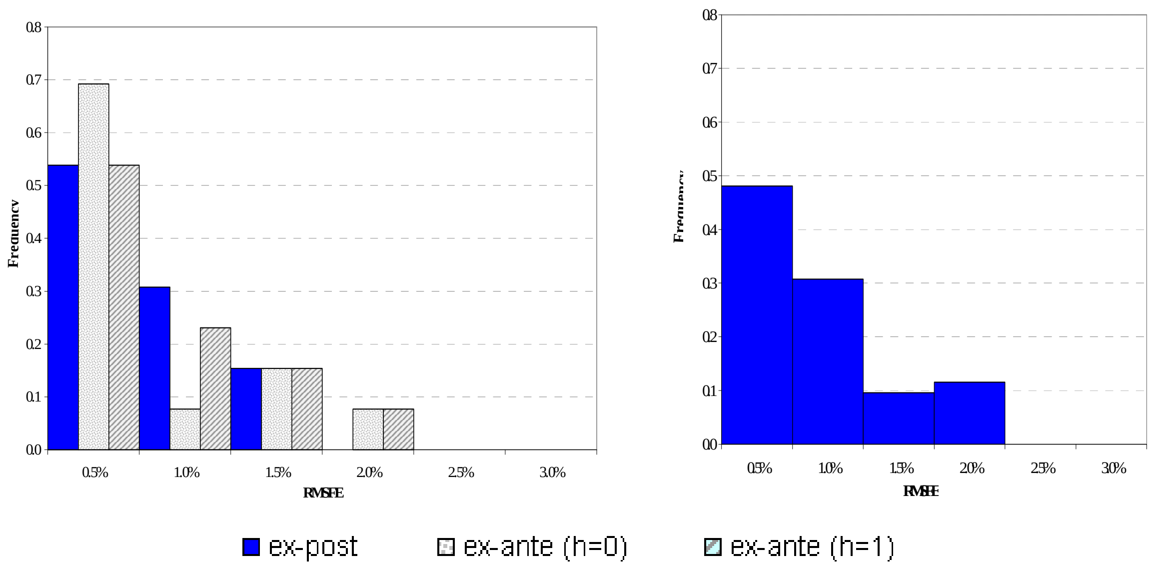
Figure 2. Monthly estimated changes in private consumption, converted into quarterly (blue line), alongside actual quarterly changes (1995Q2-2010Q1).

All three types of monthly estimates produce out-of-sample forecasts, assuming that the contemporaneous data from National Accounts are unknown. Thus, the forecast horizon varies, depending on what month in the quarter the data span ends. Given that the National Accounts data are released in May, August, October and February and relate to the end of the previous quarter, the forecast horizon of monthly estimates is two, three or four months for the second, third or first month of each quarter, respectively. Bearing in mind these leads, we conclude that the state-space equations exhibit high explanatory power, with R^2-*adj* decreasing from 0.5 to only 0.44, while going from ex-post to ex-ante (h=1) estimates.

The diffuse part of the log-likelihood remains small, indicating that the sample information, which contains 2/3 missing data upon monthly observations on the dependent variable, nevertheless is sufficient to create a proper prior for filtering and then computing shares of monthly covariates.

Note also the great similarity between monthly covariates, found significant either in the MIDAS or state-space equations. Table 5 reveals that simulated series of monthly changes in private consumption are 2.5 times less volatile than the corresponding monthly covariates (all in quarterly terms) and 1.5 times less than quarterly realized private consumption changes. A positive bias of predicted changes in private consumption, documented for the period between 2007:I – 2010:I may be due to the fact that the sharp drop in consumer demand in late 2008 and early 2009 has been underestimated, as the parameters of the covariates were specified with no variance. Among further developments of this study should be randomization of these parameters. Appendix 6A provides some evidence that random parameters may be reasonable, as by increasing $R^2 - adj$ and likelihood values, although the benefit in terms of $RMSE$ is small.

Figure 3 depicts distributions of expected root mean squared error of forecast, computed for two periods. The first is the latest "turbulent" period between 2007:I and 2010:I, for which both ex-post and ex-ante simulations were processed; the second is the longer span from 1997:1, for which only ex-post estimates are feasible, as Google predictors are not available before 2004.[15]



a) The turbulent period 2007:I-2010:I

b) The period 1997:I-2010:I

Figure 3. Distributions of the RMSFE (quarterly estimates): a) between 2007:I and 2010:I (the turbulent period); b) between 1997:1 and 2010:I (all ex-post simulations)

With regard to the ex-post estimates, the mass of the RMSFE distributions are concentrated in the lower part of the distribution, where the RMSFE does not exceed 1%, in quarterly terms; more precisely, the corresponding probabilities are 71% and 60% for the "turbulent" and the long span, respectively. No evidence was found that the model performance is worse in the turbulent period than in the whole sample. The probabilities of the ex-ante RMSFE being below 1% vary between 0.57 and 0.52, depending on the forecast horizon.

Two cyclical variables are plotted on Figure 4: one represents the overall real economic activity through the State-of-the-Economy Index, and the other, domestic consumer demand, the computed index of private consumption, smoothed by 3-term moving average. The correlation between two series is 0.45. The average periods of cycle

[15] In fact, only the spans of query indices from 2005 could be recommended for processing, as the data before are very noisy.

are 21.4 and 42.0 months, respectively.[16] Thus, the cycle in domestic consumer demand has a shorter phase and smaller amplitude of fluctuations. For instance, the troughs of the 2001–02 and 2008–early 2009 are well-pronounced in both series. However, asynchronous co-movement was documented between 2005 and 2006, while the decline in consumer demand due to political and economic uncertainty and the Second Lebanon War was not accompanied by an overall slowdown, at least not such that was recorded by the State-of-the-Economy Index.

Table 5. Volatility of monthly nowcasts, compared with standard deviations of official series and prediction errors, %, in quarterly terms (1997:1-2010:1)

Panel A. Standard deviations of percentage changes, in quarterly terms (1997:I-2010:I)		
Private consumption (actual)	1.223	
Consumer imports - durables	7.726	
Revenue of trade and services	2.058	
Revenue of services	2.527	
Retail trade	2.008	
Predicted private consumption, ex-post	0.871	
Predicted private consumption, ex-ante (*h=0*)	0.833	
Predicted private consumption, ex-ante(*h=1*)	0.832	
Panel B. Prediction errors (2007:I-2010:I)		
	Average	**RMSFE**
Predicted private consumption, ex-post	-0.264	0.669
Predicted private consumption, ex-ante (*h=0*)	-0.352	0.792
Predicted private consumption, ex-ante(*h=1*)	-0.341	0.798

The next sub-section is dedicated to the question of which cyclical variable performs better in inflation equations—the monthly estimated overall business sector growth or the monthly change in domestic consumer demand.

5.3. Connection between monthly index of private consumption and inflation

Recently estimated VARs (Azoulai and Ribon, 2010 ; Segal, 2010) encountered the phenomenon that real activity does not affect inflation while financial variables (interest and exchange rates) are controlled. In accordance with the BVAR (Segal, 2010), the parameters of the State-of-the-Economy Index, taken at its six lags, vary from insignificant to negative, and so are not intuitive. An exercise below provides some results from the likelihood ratio tests.

For simplicity, I consider a single equation as a reduced form with dropped variables, where the dependent variable is inflation, adjusted for seasonality and calendar effects and the explanatory variables are three autoregressive lags, inflationary expectations and

[16] This estimation is based on data since 1995.

real economic activity, measured either through the State-of-the-Economy Index or through the monthly index of private consumption.

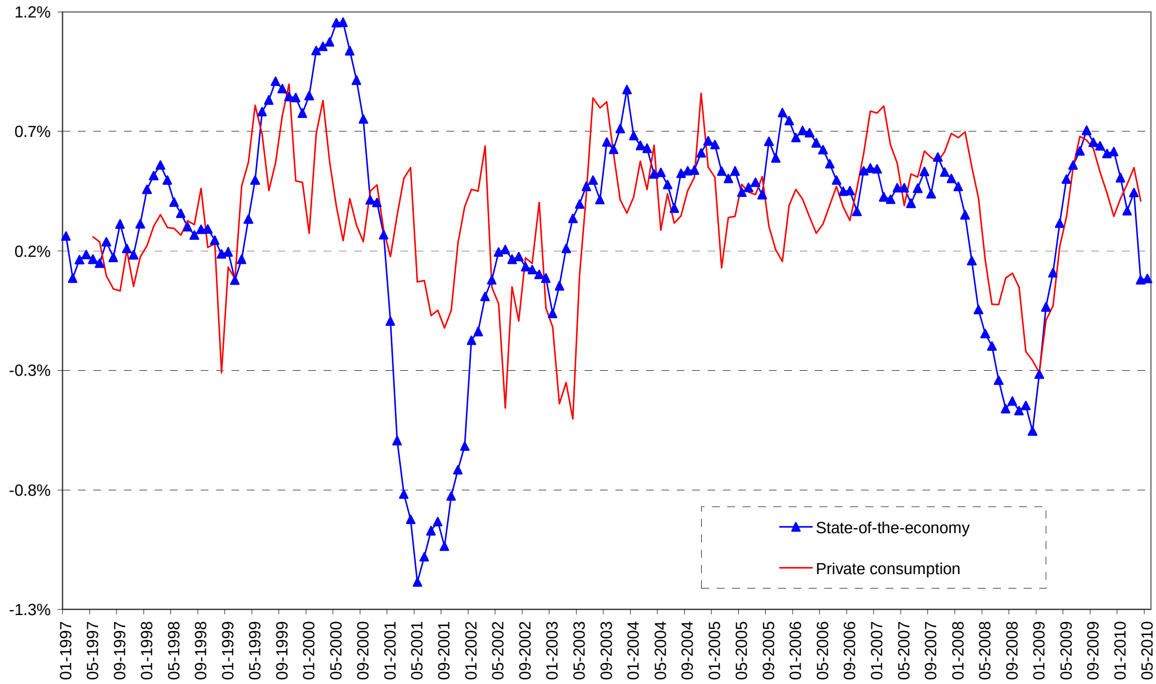


Figure 4. Index of private consumption (red line) alongside overall index of real economic activity (the State-of-the-Economy Index, blue line), monthly percent changes, 1997:1-2010:5

The restricted model (0) does not include any index of real economic activity and is specified as follows:

$$\pi_\tau = c + \sum_{p=1}^{3} \varphi_p \pi_{\tau-p} + \lambda E(\pi_{\tau+1}) + \nu_\tau \qquad (10)$$

where π_τ is the monthly change in the seasonally adjusted CPI,

$E(\pi_{\tau+1})$ denotes market-based inflation expectations,

ν_τ is a random disturbance,

$\varphi_p \ (p = 1,2,3)$ and λ are parameters,

c is an intercept and τ denotes monthly frequency.

The unrestricted models (1 and 2) include an additional exogenous variable of real economic activity. The first is fitted with the State-of-the-Economy Index $x_\tau^{(1)}$, taken at its three lags with ML-estimated coefficients $\theta_1^{(1)}, \theta_2^{(1)}, \theta_3^{(1)}$, and the second is fitted with the private consumption index $x_\tau^{(2)}$, taken at its three lags with coefficients $\theta_1^{(2)}, \theta_2^{(2)}, .\theta_3^{(2)}$.

The null is that the variable of real activity does not improve model performance. The likelihood ratio between each pair of "restricted vs. unrestricted" models is given by:

$$-2\ln\Lambda = -2(\ln L_0 - \ln L_i) \sim \chi_4^2\,(i = 1{,}2)$$

Table 7 summarizes estimated elasticities on two indices of real activity over all lags, while the indices were independently introduced into two unrestricted models. The last row displays the probability values of the likelihood ratio computed upon different samples.

Table 7. Parameters and probability values of likelihood ratio for inflation equations, fitted with or without indices of real activity, by various samples[1,2]

	Sample:1997:7-2010:5			Sample:1999:2-2010:5			Sample:2001:2-2010:5		
Parameters	(0)	(1)	(2)	(0)	(1)	(2)	(0)	(1)	(2)
λ	0.126 (***)	0.123 (***)	0.135 (***)	0.137 (***)	0.136 (***)	0.128 (***)	0.244 (***)	0.204 (***)	0.230 (***)
$\sum_{p=1}^{3}\varphi_p$	0.455 (***)	0.421 (***)	0.487 (***)	0.477 (***)	0.423 (***)	0.501 (***)	0.537 (***)	0.491 (***)	0.533 (***)
$\sum_{p=1}^{3}\theta_p^{(1)}$		-0.207			-0.166			-0.177	
$\sum_{p=1}^{3}\theta_p^{(2)}$			0.366 (**)			0.307 (**)			0.284 (**)
R^2	0.324	0.331	0.360	0.244	0.253	0.296	0.319	0.331	0.351
$p(\chi_4^2)$		0.619	0.038 (**)		0.647	0.023 (**)		0.574	0.154

Notes to the table:
[1] ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.
[2] The symbol of significance which relates to the sum of lag coefficients means at least one of them is significant.

The results suggest that the private consumption index has an expected (positive) slope and is statistically significant. The State-of-the-Economy Index, however, appears insignificant in all the experiments, supporting the VAR findings. The probabilities of likelihood ratio confirm that the State-of-the-Economy Index does not outperform the restricted model for any sample. In contrast, the null of no explanatory power is rejected for the private consumption index for the samples 1997:7–2010:5 and 1999:2–2010:5, and is accepted for the short sample 2001:2–2010:5.

6. Conclusions

Quarterly changes in private consumption may be projected into monthly covariates, computed from monthly official indicators of consumer demand. This connection, cast in a state-space form, enables early estimates of the monthly index of private consumption, which capture up to 64% of the quarterly variance (adjusted for seasonality), depending on the forecast/nowcast horizon.

Unobservable monthly changes in private consumption are restored from their decomposition into random walk, fixed effects of monthly covariates and error term. This decomposition appears to be stable; the parameters of monthly covariates are statistically significant; no evidence of need for an additional autoregressive term was found. However, the question whether the premise of fix-parameterized covariates is good enough or whether the random specification should be used in current monitoring requires further investigation.

Imports of consumer durables are the most powerful covariate. Monthly estimates of private consumption are feasible in the middle of each month, as soon as imports of consumer durables are updated. For missing official data and longer forecast/nowcast horizons, reliable monthly inferences may be drawn from Google consumption-related query indices, available weekly from Google Insights for Search. Simulated one-month-ahead forecasts reveal that Google predictors outperform consumer confidence indices.

There is some evidence that the new index, which fits domestic consumer demand, may be more appropriate in inflation models than the commonly used overall index of real economic activity.

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Appendix 1. Google consumption-related items, matched to the CBS division of trade and services

Google category/sub-category (ID)	CBS division of trade and services[1]	
	Trade:	
Automotive (47), **Vehicle Brands (815)** Motorcycles (273), Auto Parts (89), Auto insurance (467), Auto Financing (468),	Vehicles, spare parts for vehicles, other personal transport equipment	Durable goods
Home & Garden (11), Home Furnishing (270), Home Appliances (271), Homemaking & Interior (137), Home Improvement (158), Hardware (30), Auctions (292) Telecommunications/Mobile & Wireless(382)	Furniture, Household equipment and Other durable goods	
Shopping (18), Flowers Gifts & Greetings (99), Lifestyles/ Kids & Teens / Toys (432), Food & Drink (71), Cooking & Recipes (122), Cookware (120), Luxury Goods (696), Gardening (269)	Food, beverages and tobacco Clothing, footwear and personal effects	Nondurable goods
	Services:	
Industries/Retail Trade (841), Industries/Construction & Maintenance (48), Vehicle Maintenance (138), Business & Personal Listings (377)	Wholesale and Retail trade, repair of motor vehicles, motorcycles and personal and households goods (E)	
Hotels & Accommodation (179), Food & Drink (71), Restaurants (276)	Accommodation services and restaurants (F): Hotels and Accommodation services (55) Restaurants and dining services (56)	
Travel (67), Air Travel (203), Hotels & Accommodation (179), Telecommunications (528)	Transport, storage and communication (G): Air transport (62), Land transport (60), Travel and tourist agencies (633)	
Air Travel (203), Health insurance (249) Auto Financing (468), Auto insurance (467), דירה למכירה (string="apartment for sale")	Banking, Insurance and other Financial Institutions (H):	
Business services & Consulting (329) מחשוב (string="computer services")	Real Estate, Renting and Business Activities (I): Computer and related services (72), Real Estate Activities (70)	
Beauty & Personal Care (44), Lifestyles/ Kids & Teens / Toys (432), Travel/Attraction Activities (207), Business & Personal Listings (377), Tickets Sales (614)	Community, Social and Personal and other services (M)	
Domestic Services (472), Gardening (269)	Private Households with domestic personnel (N)	
Human Resources (157) Small Business (551)	No matched specifically	

Note to the table:

[1] For services, the corresponding category, two-digital division or three-digital group according with the CBS standard industrial classification of economic activities (1993) is given into parentheses.

Appendix 2. Periods of positive slopes[1,2] recorded, by Google predictor and monthly reference series

Official monthly indexes / Google category/sub-category (ID)	Retail trade	Consumer imports - durables	Revenue of services	Credit card payments
Automotive (47)	2005-2006, 2007, 2009		2005-2007, 2008, 2009	**2005-20010(*)**
Vehicle Brands (815)	2007-2010	**2005-2010(*)**	2005, 2006, **2007-2009(*)**	**2005-2010(*)**
Motorcycles (273)	2005-2008, **2009(**)**, 2010	2006, 2007	2005-2008, 2009	2005-2007, 2008, 2010
Home & Garden (11)	2006-2010	**2005-2010(*, **)**	2006-2007, 2008, 2009-2010	**2006-2010(*,**)**
Home Furnishing (270)	2007-2008	2005, 2006-2009	**2005(*)**, 2006, 2007-2010	**2006-2010(*)**
Home Appliances (271)	**2005-2010(*)**	**2005-2010(*, **)**	2007-2010	**2006-2010(*,**)**
Hardware (30)	2008	2005, 2006-2008, 2010		2005, **2006-2010(*)**
Auctions (292)	2008, 2009-2010	2005, 2006, 2009, 2010	**2005-2010(*)**	2005, 2006-**2008(*)**, 2009-2010
Shopping (18)	**2005(**)**-2010			2005-2010
Cookware (120)	2005(**), 2006, 2010	2005, 2006		2005
Cooking & Recipes (122)	**2005(**)**-2006, **2008-2009(**)**, 2010	2009, 2010		2005, 2006,2007,2008
Luxury Goods (696)	2007-2008	2005-2008	2005, 2006, **2008-2009(*)**	2007-2008, **2009-2010(*)**
Flowers Gifts & Greetings (99)	2005, 2006, 2008, 2009, 2010	2006, 2007-2010		2006-2007, 2008
Lifestyles/ Kids & Teens / Toys (432)	**2005(**)**, 2006-2010	2005, 2006, 2007, 2008, 2009-2010	2007, 2008	**2005-2010 (*,**)**
Telecommunications (528)	2006-2007, 2008	2005-2008, **2009-2010(*)**	2005-2008	2005, **2006-2007(*)**, 2008, 2009, 2010
Industries/Retail Trade (841)			2007, 2008	2006, 2007-2010
Industries/Construction & Maintenance (48)			2005-2007, 2008	2006-2010
Vehicle Maintenance (138)			2008, 2009	2008, 2009
Auto Parts (89)			2005, 2006, 2009	**2005-2010(*)**
Business & Personal Listings (377)			2005-**2009(*)**, 2010	**2006-2009(*,**)**
Food & Drink (71)	2005(**)-2007, 2008-2010		**2005(**)**-2007, **2008(**)**-2010	
Restaurants (276)			**2005-2008(*,**)**, 2009, 2010	**2006-2010(*,**)**
Travel (67)			2007, 2008, 2009, 2010	2005-2008, 2008-2010
Air Travel (203)			2005-2006, 2007, 2008-2010	2006, 2007, 2008-2010
Hotels & Accommodation (179)			2005, 2006, 2007, 2008-2010	2005, **2006-2010(*)**
Travel/Attraction Activities (207)			2005-2006, 2007-2010	2005-2006, 2007, 2009
Health insurance (249)			2006-2010	**2005-2010(*,**)**
Auto insurance (467)			2005-2010	2006-2008
Auto Financing (468)			**2005-2008(*)**	**2005-2008(*,**)**, 2009-2010
String="apartment for sale" or "דירה למכירה"			2005, 2006, **2007-2010(*,**)**	**2005-2010(*)**
Business services & Consulting (329)			2005, 2006, **2007-2010(*, **)**	**2006-2007(*)**, 2008-2010
Beauty & Personal Care (44)			**2005-2010(*,**)**	2006-2010
Business & Personal Listings (377)			**2005-2010(*)**	**2006-2007(**)**, 2008-2010
Tickets Sales (614)			**2005-2010(*)**	**2005-2008(*)**, 2009-2010
Domestic Services (472)			2005, 2007-**2009(*)**	2005, **2006(*)**, 2007-2010
Home Improvement (158)			2005, 2006, 2007, 2008-2010	2005-2008, **2009-2010(*,**)**
Homemaking & Interior (137)			2006-2010	2006-**2008(*)**, 2009-2010
Gardening (269)			2005, 2006, 2007	**2005-2010(*)**
Human Resources (157)			2005, **2006-2010(*)**	**2006(*)**-2010
Human Res./Recruitement&Staffing(330)			2005, 2006-2010	
Small Business (551)			2005, 2006, 2009, 2010	2009, 2010

Notes to the table:

[1] Estimated by pair-wise TVP regressions (from 2005:2 to 2010:2), described in section 3

[2] The hyphen denotes all months of period positive slope was recorded; comma-separated periods mean positive slope recorded for some months. Periods highlighted in bold mean statistically significant slopes: * at the 10% level and ** at the 5% level, respectively.

Appendix 3. In-sample performance of Google predictors, by reference monthly indicator[1] and forecast horizon (2005:1-2010:1)

Compared models	*h=0* R^2-adj	RMSE	F-value[2]	*h=1* R^2-adj	RMSE	F-value[2]
Panel 1. Revenue of trade and services (σ = 2.699)						
A (baseline)	0.166	2.086	13.17***	0.026	2.255	2.61
A + Consumer Confidence	0.176	2.074	13.99***	0.027	2.253	2.69*
A + Google predictors	0.272	1.949	23.83***	0.157	2.098	12.32***
B (baseline)	0.369	1.815	36.63***	0.122	2.140	9.47***
B + Consumer Confidence	0.381	1.797	38.55***	0.130	2.131	10.09***
B + Google predictors	0.418	1.743	44.75***	0.229	2.006	19.08***
Panel 2. Revenue of services ($\sigma = 3.388$)						
A (baseline)	0.273	2.919	23.88***	0.018	3.391	2.17
A + Consumer Confidence	0.275	2.914	24.16***	0.047	3.341	4.01**
A + Google predictors	0.381	2.693	38.56***	0.167	3.125	13.19***
B (baseline)	0.438	2.567	48.45***	0.101	3.245	7.86***
B + Consumer Confidence	0.480	2.468	57.31***	0.156	3.145	12.27***
B + Google predictors	0.515	2.383	65.85***	0.257	2.951	22.04***
Panel 3. Retail trade – total (σ = 2.697)						
A (baseline)	0.319	2.237	30.01***	0.015	2.690	1.94
A + Consumer Confidence	0.322	2.249	29.98***	0.032	2.689	3.01*
A + Google predictors	0.408	2.085	43.78***	0.184	2.448	14.97***
B (baseline)	0.369	2.152	37.32***	0.084	2.593	6.90**
B + Consumer Confidence	0.376	2.157	37.83***	0.087	2.610	6.84**
B + Google predictors	0.468	1.977	55.45***	0.246	2.354	21.20**
Panel 4. Consumer imports – durables ($\sigma = 9.254$)						
A (baseline)	0.236	8.176	19.13***	0.127	8.671	10.14**
A + Consumer Confidence	0.238	8.256	18.80***	0.120	8.730	9.48***
A + Google predictors	0.326	7.680	29.95***	0.224	8.172	19.23***
B (baseline)	0.271	7.987	23.03***	0.141	8.600	11.34***
B + Consumer Confidence	0.270	8.086	22.15***	0.133	8.667	10.52***
B + Google predictors	0.353	7.523	33.85***	0.233	8.125	20.16***
Panel 5. Credit card payments ($\sigma = 2.210$)						
A (baseline)	0.307	1.718	28.49***	0.067	1.994	5.44**
A + Consumer Confidence	0.330	1.692	31.07***	0.080	1.982	6.33**
A + Google predictors	0.503	1.454	63.85***	0.396	1.604	41.67***
B (baseline)	0.372	1.635	37.79***	0.110	1.947	8.64***
B + Consumer Confidence	0.389	1.615	39.92***	0.133	1.925	10.32***
B + Google predictors	0.540	1.400	73.74***	0.423	1.566	46.63***

Notes to the table:

[1] All reference monthly series are taken at their first log difference. Basic volatility of each reference series, measured by its standard deviation to be compared with the corresponding RMSE is given into parentheses at panel titles. For convenience, the standard deviations and RMSE estimates are multiplied by 100, that is are in terms of monthly percent change.

[2] *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Appendix 4. Out-of-sample forecast errors and MDM-test values, by reference monthly indicator and forecast horizon (2007:1-2010:1)

	RMSFE		MDM[1]			
			Google / B		Google / Consumer Confidence	
Compared models	*h=0*	*h=1*	*h=0*	*h=1*	*h=0*	*h=1*
Panel 1. Revenue of trade and services						
A (baseline)	2.338	2.655				
A + Consumer Confidence	2.315	2.653				
A + Google predictors	2.293	2.392				
B (baseline)	1.935	2.753				
B + Consumer Confidence	1.955	2.398				
B + Google predictors	2.052	2.315	0.68	-0.87	0.63	-0.04
Panel 2. Revenue of services						
A (baseline)	2.961	3.457				
A + Consumer Confidence	2.965	3.534				
A + Google predictors	2.683	3.125				
B (baseline)	2.688	3.585				
B + Consumer Confidence	2.657	3.245				
B + Google predictors	2.389	2.558	-0.65	-1.23*	-0.61	-0.96
Panel 3. Retail trade - total						
A (baseline)	2.438	2.901				
A + Consumer Confidence	2.541	2.874				
A + Google predictors	2.281	2.548				
B (baseline)	2.456	3.003				
B + Consumer Confidence	2.573	2.861				
B + Google predictors	2.179	2.535	-0.67	-0.79	-0.74	-0.65
Panel 4. Consumer imports – durables						
A (baseline)	9.304	9.813				
A + Consumer Confidence	9.684	10.260				
A + Google predictors	8.896	9.426				
B (baseline)	9.173	10.259				
B + Consumer Confidence	9.413	10.257				
B + Google predictors	8.789	9.121	-0.98	-1.06*	-1.29*	-1.27*
Panel 5. Credit card payments						
A (baseline)	2.009	2.967				
A + Consumer Confidence	2.192	2.966				
A + Google predictors	1.756	2.114				
B (baseline)	1.985	3.156				
B + Consumer Confidence	1.978	2.743				
B + Google predictors	1.739	1.981	-0.74	-1.37**	-0.75	-1.21*

Note to the table:

[1]The MDM-statistic enables a comparison between mean squared forecast errors of two models, calculated for small samples. The test is negative, if the first model outperforms the second one. * and ** indicate significance at the 10% and 5% levels respectively.

Appendix 5. In-sample MIDAS parameters[1] of quarterly percent changes in private consumption, by forecast horizon (sample: 1995:2 – 2009:4)

Explanatory series[2]	Quarterly lag	*H=0*	*H=1/3*	*H=2/3*
Constant term		0.0071*** (0.0009)	0.0076*** (0.0011)	0.0083*** (0.0012)
im_c_dur(3)	0	0.0521*** (0.0132)		
im_c_dur(2)	0	0.0619*** (0.0124)	0.0347** (0.0125)	
im_c_dur(1)	0	0.1107*** (0.0122)	0.0951*** (0.0134)	0.0721*** (0.0127)
im_c_dur(3)	1	0.0431*** (0.0173)	0.0247 (0.0195)	0.0136 (0.0214)
im_c_dur(2)	1	0.0386*** (0.0106)	0.0317** (0.0122)	0.0249** (0.0139)
maam(3)	1	0.0749*** (0.0252)	0.0757*** (0.0284)	0.0592* (0.0327)
maam(2)	1	0.0486*** (0.0222)	0.0495** (0.0257)	0.0783** (0.0286)
revenue_I(2)	0	0.0340 (0.0241)		
revenue_I(2)	1	0.0219 (0.0240)	0.0468* (0.0264)	0.0553* (0.0304)
revenue_F(1)	0	0.0564*** (0.0160)	0.0612*** (0.0187)	
revenue_F(3)	1	0.0704** (0.0215)	0.0760*** (0.0251)	0.0259 (0.0218)
revenue_L(1)	0	0.0795** (0.0316)	0.0627* (0.0362)	
R^2-adj		0.705	0.595	0.436
RMSE		$0.662*10^{-2}$	$0.776*10^{-2}$	$0.915*10^{-2}$
DW		1.932	2.109	2.345
Fit statistics of the bridge department equations[3]				
R^2-adj		0.652	0.607	Not estimated
RMSE		$0.700*10^{-2}$	$0.743*10^{-2}$	
DW		1.978	1.868	

Notes to the table:

[1] *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

[2] All explanatory series are in fixed prices, seasonally adjusted and log differenced at monthly frequency. Numbers (1),(2),(3) into parentheses denote monthly changes (relatively to the previous month) of the first, second and third month of the quarter, respectively. The explanatory series are: im_c_dur - consumer imports of durables; maam – total VAT payments; revenue_F - revenue of accommodations and restaurants; revenue_I - revenue of real estate, renting and business services; revenue_L - revenue of health/welfare/social services.

[3] The explanatory series are AR(1) term, consumer confidence index (Globes), quarterly averaged and 3-time lagged, in addition to the subsequent series, quarterly averaged and log differenced at quarterly frequency: consumer imports of durables, VAT payments (two-month lagged), revenue of health services and stock exchange index. Quarterly averages have been computed accordingly to the availability of monthly data.

Appendix 6. Parameters of monthly state-space models, estimated ex-post and ex-ante[1] (with forecast horizons h=0 and h=1). Sample: 1997:2 – 2009:4

Variable/ Component[2]	Description	Monthly lag	Estimate and t-value[3]		
			Ex-post	Ex-ante (*H=0*)	Ex-ante (*H=1*)
Error variance	Endogenous		$0.398*10^{-5}$ *** (*t*=4.74)	$0.490*10^{-5}$ *** (*t*=4.74)	$0.554*10^{-5}$ *** (*t*=4.74)
fore.im_c_dur	Exogenous, simulated	0		0.0198 *** (*t*=3.95)	0.0194 *** (*t*=3.60)
fore.im_c_dur	Exogenous, simulated	1			0.0195 *** (*t*=4.21)
fore.revenue_serv	Exogenous, simulated	0		0.0196 * (*t*=1.63)	0.0195 (*t*=1.42)
im_c_dur	Exogenous, raw	0	0.0215 *** (*t*=5.49)		
im_c_dur	Exogenous, raw	1	0.0185 *** (*t*=5.00)	0.0227 *** (*t*=5.09)	
im_c_dur	Exogenous, raw	2	0.0372 *** (*t*=10.61)	0.0386 *** (*t*=8.67)	0.0356 *** (*t*=8.42)
im_c_dur	Exogenous, raw	3	0.0181 *** (*t*=3.73)	0.0172 *** (*t*=2.99)	0.0141 ** (*t*=2.39)
im_c_dur	Exogenous, raw	4	0.0143 *** (*t*=4.60)	0.0144 *** (*t*=3.92)	0.0132 *** (*t*=3.55)
im_c_ndur	Exogenous, raw	1	0.0101 ** (*t*=2.46)		
maam	Exogenous, raw	3	0.0241 *** (*t*=3.27)	0.0276 *** (*t*=3.34)	0.0294 *** (*t*=3.30)
maam	Exogenous, raw	4	0.0151 ** (*t*=2.13)	0.0173 ** (*t*=2.33)	0.0189 ** (*t*=2.44)
revenue_f	Exogenous, raw	2	0.0172 *** (*t*=2.69)	0.0200 *** (*t*=3.57)	0.0200 *** (*t*=3.33)
revenue_f	Exogenous, raw	3	0.0178 *** (*t*=3.66)	0.0256 *** (*t*=3.54)	0.0263 *** (*t*=3.41)
revenue_l	Exogenous, raw	2	0.0193 *** (*t*=3.00)	0.0311 *** (*t*=2.80)	0.0352 *** (*t*=3.04)
R^2-*adj*			0.641	0.500	0.446
RMSE			$0.245*10^{-2}$	$0.290*10^{-2}$	$0.318*10^{-2}$
Full Log-L			211.171	207.711	204.984
Diffuse Part of Log-L			19.364	20.519	21.999
AIC			-397.852	-389.421	-383.967

Notes to the table:

[1]One-step-ahead simulations. Presented parameters refer to the forecast produced for 2010, March.

[2]Explanatory series, all – in fixed prices, seasonally adjusted and log-differenced are denoted as follows:
im_c_dur - consumer imports of durables; im_c_ndur - consumer imports of non-durable goods;
maam – VAT payments; revenue_F - revenue of Accommodation services and Restaurants;
revenue_L - revenue of Health Services and Welfare and social work ;
fore.im_c_dur – real-time forecast for consumer imports of durables, simulated upon Google predictors
fore.revenue_serv – real-time forecast for revenue of services, simulated upon Google predictors

[3] T-values are given into parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Appendix 6A. Fit statistics for the state-space with fixed and random coefficients of monthly covariates, estimated ex-post and ex-ante[1] (sample: 1997:2 – 2009:4), by nowcast horizon.

Fit statistics / Effects	R^2-*adj*	*RMSE*	*Log-L*		*AIC*
			Full	*Of which: Diffuse part*	
Panel A. Ex-post estimates					
Fixed effects	0.641	$0.245*10^{-2}$	210.926	19.364	-397.852
Time-varying effects	0.679	$0.221*10^{-2}$	222.050	19.367	-440.100
Panel B. Ex-ante (h=0) estimates					
Fixed effects	0.500	$0.290*10^{-2}$	207.711	20.519	-389.421
Time-varying effects	0.537	$0.279*10^{-2}$	219.300	20.519	-434.600
Panel C. Ex-ante (h=1) estimates					
Fixed effects	0.446	$0.318*10^{-2}$	204.984	21.999	-383.967
Time-varying effects	0.471	$0.313*10^{-2}$	216.630	21.929	-429.300