Bank of Israel Research Department

A Business Conditions Real-time Measure of Output Gap Deviations[1]

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Discussion Paper 2025.11
November 2025

Bank of Israel - http://www.boi.org.il

[1] We thank Amir Yaron (the Governor of the Bank of Israel) and the members of the Monetary Committee of the Bank of Israel for their useful comments. We are also grateful to Nathan Sussman, Alon Eizenberg, Sigal Ribon, Jonathan Benchimol, Eliezer Borenstein, Tim Ginker, Guy Segal, Itamar Caspi, and all other participants of the seminar at the Bank of Israel for their valuable comments and suggestions. We also thank Jonathan Vinograd for his generous assistance with the data.

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Abstract

This study introduces a novel and simple method for estimating the real-time output gap using data from Israel's Business Tendency Survey. We develop an index of excess demand or supply, defined as the difference between reported supply and demand constraints. This index is incorporated into a state space model alongside actual output to estimate the output gap. Our findings demonstrate that the derived output gap measure has a positive and statistically significant impact on three key price indicators in Israel: the Consumer Price Index, Producer Price Inflation, and Business Sector Output Prices.

This measure yields promising results, exhibiting explanatory power that compares favorably to several widely-used alternative output gap estimation methods. Furthermore, our output gap measure demonstrates higher real-time robustness with respect to data revisions than the standard univariate method. The proposed approach complements existing methods, providing valuable insights for economic analysis and policy-making by leveraging real-time survey data and capturing businesses' perceptions of economic constraints.

Keywords: Demand and Supply constraints, Output gap, Inflation, Business Tendency Survey.

אמידה בזמן אמת של פער התוצר במשק הישראלי על סמך סקר המגמות של הלשכה המרכזית לסטטיסטיקה

אלכס אילק ויובל מזר

תקציר

המחקר הנוכחי מציג שיטה חדשה ופשוטה להערכת פער התוצר במשק זמן אמת, תוך שימוש בנתונים מסקר הערכת מגמות בעסקים של הלשכה המרכזית לסטטיסטיקה. המאמר מציג מדד חדש לעודף הביקוש המצרפי במשק, המוגדר כפער בין שקלול של מגבלות ההיצע והביקוש המדווחות על ידי החברות הנסקרות בכל חודש בסקר. מדד זה, ביחד עם התוצר בסקטור העסקי, מאפשר גם לאמוד את פער התוצר במשק. אנו מוצאים כי פער התוצר המתקבל משפיע באופן חיובי ומובהק על מדד המחירים לצרכן כמו גם על מחירי היצרן ומחירי התוצר העסקי בישראל. פער התוצר המוצע מציג רמת הסבר טובה יותר של המחירים לצרכן, היצרן והתוצר העסקי בהשוואה לשיטות האחרות הנפוצות בספרות להערכת פער תוצר. בנוסף, פער התוצר המוצע מציג עמידות גבוהה יותר לרביזיות בנתונים ולהערכת עודף ביקוש או עודף ההיצע במשק בזמן אמת. הגישה המוצעת במאמר לגזירת פער התוצר משלימה שיטות אחרות הקיימות בספרות, ומספקת תובנות חשובות לניתוח כלכלי ולקביעת מדיניות על ידי ניצול נתוני סקר המגמות בזמן אמת, תוך ניצול תפיסות של מנהלי החברות לגבי מגבלות כלכליות במשק הישראלי.

מילות מפתח: מגבלות ביקוש והיצע, פער התוצר, אינפלציה, סקר מגמות בעסקים.

1. Introduction

The measurement of the output gap is central to conducting monetary policy. The output gap represents the difference between the actual observed output and the unobserved potential output of the economy and it is a key macroeconomic indicator used by central banks to evaluate business cycles and inflationary pressures. Real-time output gap estimation is critical for effective monetary policy implementation, and designing monetary policy based on an erroneous evaluation of the output gap can result in poor monetary policy decisions and hinder the achievement of its objectives (Orphanides (2001), Orphanides and van Norden (2002), Coutiño (2016), Segal (2017)).

The literature on various approaches to estimating the output gap is extensive. Canova (2025) compared the output gaps from theoretical New-Keynesian *DSGE* models with those derived from various statistical approaches and found that the polynomial approach was the least distorting and superior to all other output gap measures considered. Álvarez and Gómez-Loscos (2018) present a comprehensive review of various univariate and multivariate estimation methods for deriving output gaps, and discuss the advantages and limitations of these methods.

The study by Blazej et al. (2025) is closely related to our paper. They use Statistics Poland's Business Tendency Surveys and the Annual Non-Financial Enterprises Survey to measure total economic output in the Manufacturing industry by summing firm-level gross value-added. However, they assess each firm's potential production levels by applying the Hodrick-Prescott filter to the components of its production function, a method that could have significant drawbacks (Hamilton, 2018).

This paper introduces a novel and simple method for estimating the real-time output gap in the economy. The approach is based on the Business Tendency Survey in Israel, which collects direct responses from firms' managers. Specifically, the survey captures these managers' subjective assessments about demand and supply constraints affecting their businesses.

The proposed output gap measure presents a complementary approach to assessing the output gap. Our key finding in this paper demonstrates that exploiting the demand and supply constraint data from the survey significantly contributes to the output gap estimator. Additionally, we discover that this new output gap measure more effectively explains in-sample inflation in Israel compared to other methods examined. Furthermore, it exhibits greater resilience to revisions than standard univariate methods.

The intuition behind demand and supply constraints can be explained as follows: A higher supply constraint indicates that firms are experiencing a greater shortage of workers and/or raw materials and equipment needed for producing goods and services. Therefore, a higher supply constraint can be interpreted as a negative supply shift in the economy. Conversely, a higher demand constraint suggests that the demand for goods and services, both domestically and in foreign markets (exports), has weakened. Thus, a higher demand constraint can be interpreted as a negative demand shift in the economy. Consequently, when the supply constraint exceeds the demand constraint, the economy experiences excess demand. This excess demand is expected to exert upward pressure on prices. Conversely, when the demand constraint exceeds the supply constraint, the economy faces excess supply (or demand shortages), leading to downward pressure on prices. The process of translating this excess demand/supply index into an output gap measure for the economy is detailed in Section 3.3. below.

The remainder of this paper is structured as follows: Section 2 describes the data regarding demand and supply constraints, providing the foundation for our analysis. Section 3 presents our proposed method for deriving the output gap. This section includes subsection 3.4, which provides a specific description of how our approach addresses the economic impacts of COVID-19 and the "Swords of Iron" war that started following the 7 October 2023 terror attack on Israel. Section 4 offers a comprehensive comparative analysis, first comparing our resulting measure with existing methodologies, then examining the relationship between various output gap measures and both consumer and producer price inflation. This section also assesses the real-time reliability of our proposed output gap measure. Finally, Section 5 concludes.

2. Data

The Business Tendency Survey, conducted by the Central Bureau of Statistics in Israel since 2013, provides monthly data on production constraints reported by company managers across ten economic sectors (Table A.1). These surveyed represent approximately 85% of the sectors included in the business sector, excluding the public sector and certain smaller industries[1]. In Israel, the public sector accounts for 27 percent of total GDP and has contributed approximately 23 percent to real economic growth over the past three decades.

As an official survey by the Central Bureau of Statistics, it adheres to international standards and employs statistical techniques to address potential response bias.

Roash and Suhoy (2022) utilized this survey to evaluate the informational value of qualitative (soft) data. The found that the survey 'Sentiment' accounts for 21 to 48 percent of output variations within the sample. Moreover, it maintains a reasonable fit outside the sample when the target variable is the initial estimate of the growth rate.

Company managers rate demand and supply constraints on a four-point scale, ranging from ‘no constraint’ to ‘severe constraint.’

There are two types of supply constraints: the labor supply constraint, which gauges the difficulty of recruiting employees, and the material supply constraint, which measures the difficulty of obtaining raw materials and equipment. The demand constraint captures the weakness of both domestic and foreign orders.

There are several key advantages of using survey data:

(1) Micro-founded reliability: Company managers provide direct responses about demand and supply constraints specific to the companies they manage. This ensures that their insights are based on their intimate knowledge of their own operations, rather than on perceptions of the general state of the economy. Therefore, the managers' responses should be considered reliable.

[1] The survey does not cover the remaining 15% of sectors, which comprise smaller industries such as electricity and water supply, agriculture, forestry, and fishing, among others. Most businesses in these sectors have fewer than 5 employees, and the survey is not distributed to them.

(2) Source identification and sectoral analysis: The survey-based measure of the output gap provides valuable insights into its underlying drivers, distinguishing between demand-side and supply-side factors. Furthermore, it enables the quantification of each sector's contribution to overall excess demand or supply.

(3) Timeliness and frequency: The survey is conducted monthly, with results for the previous month reported in the first week of the current month. This allows for prompt utilization of survey data in estimating the output gap.

(4) Stability of survey data and limited revision of output gap estimate: Since managers in the survey do not revise their past responses, the index of excess demand/supply used for estimating the output gap remains unrevised. The only source of potential revision comes from updates to the *GDP* data.

The survey-based method, while useful, has several drawbacks. First, managers lack incentives to provide accurate responses or invest sufficient effort in giving precise answers, as there are no penalties for incorrect information (Charness et al., 2021). Although this could potentially bias the reported data and skew the analysis significantly, several studies indicate that using simple incentivized surveys generates only small biases relative to complex methods (Charness et al., 2021). Second, the limited range of response options, scaled from 0 to 3, restricts nuanced feedback. For example, if a manager considers a constraint to be "very severe," he can only report it as a "severe constraint." This limitation makes it impossible to distinguish between reported severe constraints and those that are truly very severe in the manager's assessment. Third, the subjective nature of survey responses may introduce bias. Managers might disproportionately emphasize certain issues or overstate their concerns about others. To address these potential biases and the scaling issue in converting from an index to an output gap measure, we incorporate measurement errors in the survey data when estimating the output gap using a state space model (see Section 3.3).

To provide preliminary evidence supporting the reliability of the tendency survey prior to estimating the output gap, we conducted a basic regression analysis. Using quarterly *GDP* growth as the dependent variable and the demand constraint as an explanatory variable, we found that the demand constraint alone explains over 50% of *GDP* growth variance. The coefficient of the demand constraint is negative and highly significant, as expected. Together with global demand (proxied by import growth of *OECD* economies), it explains about 80% of the variance in quarterly *GDP* growth. Further regressions on four types of inflation, including demand and supply constraints, showed expected results: a positive effect for the labor supply constraint and a negative effect for the demand constraint, with similar magnitudes (see Appendix B).

3. Method

Our procedure for deriving the output gap involves three stages: First, we derive separate indices for demand and supply constraints on real economic activity, based on the Business Tendency Survey (detailed in Appendix A). Second, we define an index of excess demand as the difference between the supply and demand constraints. Finally, we estimate the output gap using a state space model that incorporates both the index of excess demand/supply from the survey and actual output data.

3.1. Stage 1: Deriving Demand and Supply Constraints

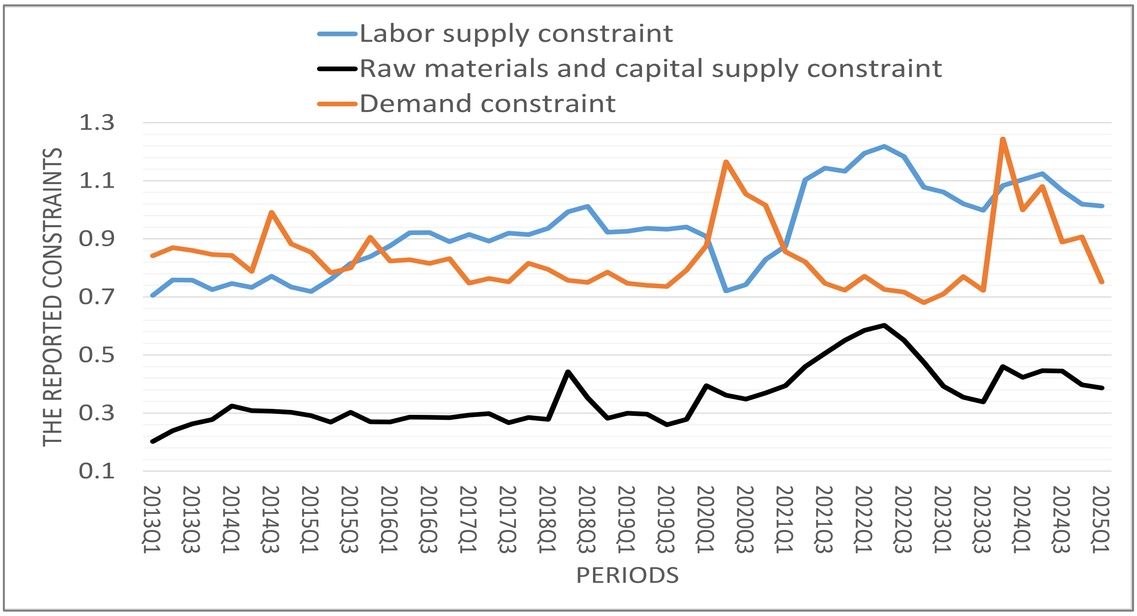
We generate separate, economy-wide indexes for demand and supply constraints by weighting each sector's average constraint level according to its share in business *GDP* (see Table A.1 in Appendix A)[2]. The analysis below adopts time-varying sector weights, recalculated annually from 2013 to 2024.

Figure 1 illustrates two aggregate supply constraints and the aggregate demand constraint. It is evident that the aggregate labor constraint consistently proves more severe than the constraints on raw materials and equipment. The average level of the aggregate labor constraint is 0.93, compared to only 0.35 for raw materials and equipment. This pattern holds true at the micro level as well: with the exception of a

[2] The series of constraints used in the paper are not seasonally adjusted. The reason for this is that the Net Balance Series of the tendency survey—after seasonal adjustment done by the Central Bureau of Statistics (CBS)—were compared to corresponding quantitative series for which the Business Tendency Survey serves as a leading indicator (such as production and employment indices, and turnover indices for the trade and services sectors). This examination revealed that the correlation between the series decreased, casting doubt on the quality of the seasonal adjustment. Given that the original balances of the survey are successfully used by the Bank of Israel to forecast economic growth, the CBS decided at this stage to avoid seasonal adjustment and the publication of seasonally adjusted series.

few outlier observations, the constraint on materials and equipment is consistently weaker than the constraint on workers across all periods and sectors examined. This result is intuitive, as labor is typically harder to acquire than materials or equipment.

Figure 1: Labor and materials supply constraints, and a demand constraint: domestic and foreign orders, Sample period: 2013.Q1-2025.Q1



Note: The figure illustrates three key constraints derived from the Business Tendency Survey: (1) labor supply constraint (blue line), (2) raw materials and equipment supply constraint (black line), and (3) demand constraint (brown line).

3.1.1. Constructing Aggregate Supply Constraint

In our analysis, we aim to formally characterize the supply side of the economy by incorporating both supply constraints. To achieve this, we employ three distinct approaches. The primary differentiation among these approaches lies in the assumed degree of substitutability between labor and raw materials/equipment as production inputs.

1. Two factors of production are fully complementary. This can be characterized by the Leontief production function, $Y = \min\{\alpha L, \beta K\}$, where L represents labor and K represents raw materials and equipment (the parameters α and β represent fixed proportions of inputs in the production function). Given that these two inputs cannot be substituted for one another, only the most binding supply constraint should be considered – in our case, this is the labor supply constraint (as shown in Figure 1).

Thus, the aggregate supply constraint, S, is determined only by labor supply constraint, L^{const}, that is, $S = L^{const}$.

2. Two factors of production are imperfect substitutes[3]. In this scenario, even when the labor constraint is tighter than the equipment constraint, firms can still increase output by utilizing more equipment. Consequently, the aggregate supply constraint is determined by a combination of both the labor supply constraint and the constraint on a raw materials and equipment: $S = \alpha L^{const} + (1-\alpha)K^{const}$.

3. Two factors of production are highly substitutable[4]. In this scenario, when the labor supply constraint remains permanently tighter than the raw materials and equipment constraint (Figure 1), companies can exploit the high degree of substitutability by shifting towards a more capital-intensive operational structure. Consequently, the raw materials and equipment constraint becomes the primary effective constraint for the firm. Thus, the aggregate supply constraint can be expressed as: $S = K^{const}$.

3.2. Stage 2: Constructing the Excess Demand/Supply Index

In the first stage, we calculate the 'Constraints Gap' index, which represents excess demand/supply, for the period from 2013:Q1 through 2025:Q1.

This gap is defined as the difference between the supply constraint and the demand constraint. If the "Constraints Gap" is positive, then the supply constraint is more severe than the demand constraint, indicating excess demand in the economy in terms of real activity. The larger this gap, the stronger the excess demand, and vice versa.

Let us define the index of excess demand/supply as *Excess=S-D*, where S is the aggregate supply constraint and D is the aggregate demand constraint. Based on the three methods of constructing S presented in Section 3.1, we define three constraint gap indexes that measure excess demand/supply:

(1) $L_{excess} = L^{const} - D^{const}$, which is the gap between the labor supply constraint and the demand constraint.

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[3] For example, this relationship can be modeled using a Constant Elasticity of Substitution (CES) production function.

[4] This relationship can be modeled using a linear production function.

(2) $L\&K_{excess} = aL^{const} + (1-a)K^{const} - D^{const}$, which is the gap between the combined supply constraint and the demand constraint[5].

(3) $K_{excess} = K^{const} - D^{const}$, which is the gap between the raw materials and equipment supply constraint and the demand constraint.

Figure 2 illustrates three measures of constraint gap indexes. The first two indexes fluctuate around zero, while the third measure, based on K_excess remains consistently negative throughout the entire sample period. The constraint gap $L\&K\_excess$ consistently falls below the constraint gap L_excess due to the incorporation of K^{const} in the aggregate supply constraint. The raw materials and equipment constraint is persistently lower than the labor constraint (Figure 1), so assigning a positive weight to the former results in a lower $L\&K\_excess$ constraint gap compared to L_excess. In our calibration, we set a relative weight of 25% for the raw materials and equipment constraint[6]. A larger weight would exert more downward pressure on the constraint gap, consequently leading to a lower estimated output gap.

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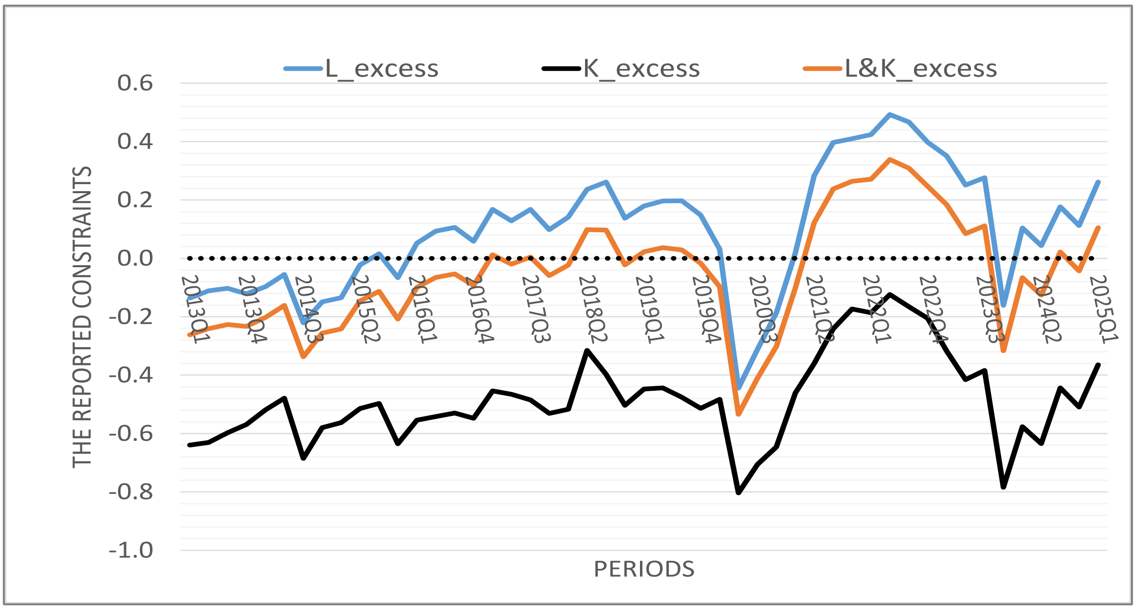
[5] To assess the relative importance of labor versus raw materials and equipment constraints, we estimate: $\log(Y) = c + \delta\log(Trend) + \alpha\log(L^{const}) + (1-\alpha)\log(K^{const})$, where Y is Business GDP, L^{const} is labor constraint, K^{const} is raw materials and equipment supply constraint, and $Trend$ is a time trend. We obtain $\alpha = 0.90$, indicating that the labor constraint is significantly more important for production than the raw-material/equipment constraint. This is higher than the 0.67 used in Argov et al. (2012) for Israel's production function. The difference arises from our use of constraint measures rather than underlying data of production inputs. Based on these results, we calibrate $\alpha = 0.75$, balancing our findings with previous estimates and favoring a conservative approach.

Figure 2: The Evolution of Three Constraint Gaps Indexes, Sample period: 2013.Q1-2025.Q1



Note: *L_excess* represents the gap between the labor supply constraint and the demand constraint. *K_excess* represents the gap between the raw materials and equipment supply constraint and the demand constraint. *L&K_excess* represents the gap between the combined supply constraint and the demand constraint.

Regarding the third constraint gap index based on K_excess, it consistently remains negative throughout the observed period (see Figure 2). This persistent negativity can be primarily attributed to the consistently low values of the equipment and raw materials constraint, as illustrated in Figure 1.

In our subsequent analysis, we omit the presentation and examination of the output gap based K_excess for two reasons: (1) The constraint gap derived from this measure relies on an unrealistic assumption of high substitutability between labor and equipment/raw materials (as discussed in Section 3.1), and (2) The data strongly indicates that the constraint on equipment and raw materials is not binding over the entire sample period (as shown in Figure 1). From a technical standpoint, using K_excess would result in a negative output gap throughout the entire sample, which is not economically plausible.

3.3. Stage 3: Estimating the Output Gap

To use the Constraints Gap index to obtain a measure of the output gap, we construct a simple state space model. This model consists of two main components: signal equations and state equations.

Signal equations:

The first signal equation [1] in our state space model is an identity that exploits the information of the actual output to derive the output gap:

$$(1) \qquad y_t = y_t^n + y_t^{gap},$$

where y_t is the actual GDP of the business sector (in logs), y_t^n is the potential output (in logs), and y_t^{gap} is the output gap.

The second signal equation [2] exploits the information of the Constraints Gap index ($Excess_t$) to derive the output gap. We consider separately two types of Constraints Gap indices: L_{excess} or $L\&K_{excess}$. The unobserved output gap is linked to the chosen $index\ with\ a\ scaling\ factor\ \Upsilon. This\ relationship\ is\ expressed\ as$:

$$(2) \qquad Excess_t = \Upsilon y_t^{gap} + \xi_t^{excess}, \quad \xi_t^{excess} \sim N(0, \sigma_{excess}^2)$$

The residuals ξ_t^{excess} capture the measurement errors in the Constraints Gap index. As noted in Section 2, the responses of survey participants might be biased or underestimated, especially during economic crises. Consequently, the precision of the signal provided by the Constraints Gap index is unknown a priori and depends on the variance of the residuals σ_{excess}^2.

State equations:

The first state equation [3] is an identity, defining variable g as the time-variant growth rate of the potential output:

$$(3) \qquad y_t^n = y_{t-1}^n + g_{t-1}$$

The second state equation [4] describes the evolution of g as a random walk process:

$$(4) \qquad g_t = g_{t-1} + \varepsilon_t^g, \quad \varepsilon_t^g \sim N\left(0, \sigma_g^2\right)$$

The last state equation [5] describes the evolution of the output gap as an *AR(1)* process. This assumption is consistent with the data generating process of $Excess_t$, which exhibits AR(1).

$$(5) \qquad y_t^{gap} = \beta y_{t-1}^{gap} + u_t^{gap}, \quad u_t^{gap} \sim N\left(0, \sigma_{ygap}^2\right)$$

It is important to note that this state space model nests traditional measures of the output gap which rely solely on information from actual output y_t, such as the *HP* filter, linear and quadratic trends, and other univariate approaches.

In these traditional models, only the first signal equation ($y_t = y_t^n + y_t^{gap}$) is included, and under an appropriate choice of variance ratio ($\frac{\sigma^2_{ygap}}{\sigma^2_g}$) one can replicate most of the univariate approaches. Under the assumption that $\Upsilon = 0$, the standard models are nested within our state space framework. In this case, when $\Upsilon = 0$, the Constraints Gap index (L_{excess} or $L\&K_{excess}$) becomes pure noise ($Excess_t = \xi_t^{excess}$), unrelated to the output gap.

We estimate the model using *Kalman Filter* by maximum likelihood. Table 1 presents the estimation results. Column (1) shows the case where the Constraints Gap Index is $Excess_t = L_{excess}$, while Column (2) shows the case where the Constraints Gap Index is $Excess_t = L\&K_{excess}$. Column (3) presents a nested model in which both Constraints Gap Indexes are constrained to be pure noise, which simplifies the model to a univariate standard model.

Table 1: Estimation results of State Space model, Sample: 2013.Q1-2025.Q1

Estimated parameter/ Constraints Gap index	$\boldsymbol{L_{excess}}$ **(1)**	$\boldsymbol{L\&K_{excess}}$ **(2)**	**Standard Model (3)**
$\boldsymbol{\Upsilon}$	4.03 (0.431)	4.21 (0.393)	0
$\boldsymbol{\beta}$	0.821 (0.082)	0.754 (0.099)	0.7497 (0.1364)
$\boldsymbol{\sigma_{excess}}$	0.092 (0.011)	0.086 (0.0096)	0.1972 - 0.209
$\boldsymbol{\sigma_g}$	0.0011 (0.0005)	0.001 (0.0004)	0.0009 (0.0003)
$\boldsymbol{\sigma_{ygap}}$	0.0284 (0.0029)	0.028 (0.0029)	0.0276 (0.003)
Log-Likelihood	128.15	132.55	98.30

Note: The first value represents the estimated parameter. The value in parentheses () represents the standard error (SE) of the estimated parameter. Columns (1)-(2) present the estimation results using the Kalman Filter (KF) of the State Space model based on Constraints Gap index (1) L_{excess} and (2) $L\&K_{excess}$. Column (3) presents the estimation results using the KF of the State Space standard model based only on actual output (excluding Constraints Gap index).

The most important parameters in our analysis are the scaling parameter Υ and the standard error of residuals σ_{excess}. For both Constraints Gap Indexes, we obtain Υ values close to 4 and σ_{excess} values close to 0.09. The standard error (*SE*) of both Constraints Gap Indexes is approximately 0.2 (as shown in Column (3) of Table 1). This implies that about 60% of the variation of the Constraints Gap Indexes in terms of *SE* can be attributed to the output gap, while the remaining 40% is attributed to measurement errors.

A thorough understanding of the parameter Υ in Equation (2) is essential. This parameter maps the metrics of the excess demand index from the survey into the output gap. Specifically, the output gap in the state space model is expressed in percentage points, whereas the excess demand index has uninformed units[6].

Given the choice of the constraint scaling, the model selects the optimal scaling parameter Υ that maximizes the likelihood function. This optimization process is constrained by the fact that the standard univariate model is nested within our expanded model and anchors the scaling of the output gap in terms of percentage points.

In our chosen scaling (between 0 and 3), an increase of one unit in the excess demand index, say from 1 to 2, would be equivalent to an increase in the output gap of 0.25 percentage points [0.25 = 1/(Υ = 4)].[7]

To quantify the impact of incorporating the Constraints Gap Index ($Excess_t$) into the model, we conduct a likelihood ratio test (*LRT*). The *LRT* statistic is calculated as 2× ($LL^{Our\ Model}$ - LL^{Nested}), where $LL^{Our\ Model}$ and LL^{Nested} represent the log-likelihoods of our proposed model and the nested model, respectively. Both log-likelihood values are presented in Table 1. This statistic follows a *Chi-Square Distribution* with one degree of

6 As detailed in subsection 3.2., the excess demand index is calculated as the difference between aggregate supply and demand constraints. Each constraint is arbitrarily scaled between 0 and 3, reflecting the degree of constraint severity (see Appendix A for details). The crucial point is that regardless of the chosen scaling for the constraints (e.g., 100, 200, 300, and 400 or alternatively, 0.1, 0.2, 0.3, and 0.4), a larger excess demand index indicates stronger excess demand in the economy, while a lower index indicates weaker excess demand.

7 For alternative scaling of the excess demand index, such as 0, 100, 200, 300, the scaling parameter Υ would adjust accordingly, in this case to 400.

freedom, since only one restriction is imposed, $\Upsilon = 0$. We find that the *LRT* statistic is equal to 59.7 and 68.5, respectively, which significantly exceeds the critical value of 6.64 under 1% significance level. Thus, we conclude that the inclusion of the Constraints Gap Index in the model significantly contributes to the output gap estimate.

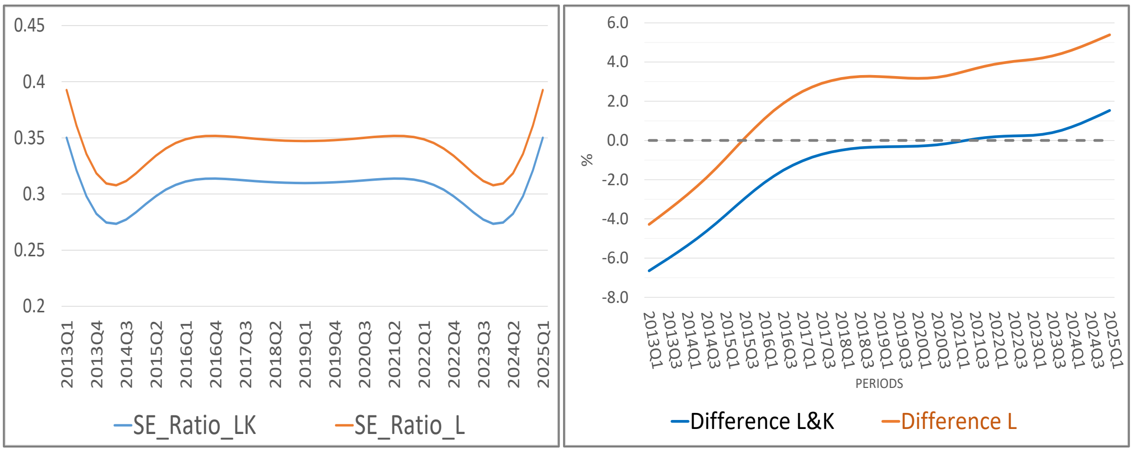
We aim to demonstrate the contribution of the Constraints Gap Index in two ways: First, we analyze its impact on the output gap estimation by examining (a) how it affects the smoothed estimator of the output gap and (b) how it influences the uncertainty of this smoothed estimator[8]. Second, we illustrate its effectiveness in explaining inflation dynamics in Section 4.2. Third, we show the real-time reliability of our output gap measure compared to a standard univariate approach in Section 4.3.

Figure 3 (left) illustrates the difference in smoothed output gap estimates between our model and the standard model (Table 1)[9]. The figure displays two distinct lines:

Upper line: Difference between estimates in Column (1) and Column (3).

Lower line: Difference between estimates in Column (2) and Column (3).

Figure 3: Contribution of Constraints Gap Index to Output Gap Estimation (Smoothed Point Estimate and Standard Error), Sample period: 2013.Q1-2025.Q1



Note: Left Figure: Shows the difference in output gap measures between our model with the Constraint Gap index (Table 1, Columns 1 and 2) and the model without it (Table 1, Column 3). The upper line corresponds to Column 1, the lower to Column 2. Right Figure: Displays the ratio of standard errors (SE) for the smoothed output gap estimate. It compares SEs from our model (Table 1, Columns 1 and 2) to those from the standard model (Table 1, Column 3).

[8] The uncertainty of the output gap estimate is captured in this context through state uncertainty (via disturbance uncertainty).

[9] The standard model's output gap estimate (Table 1) is similar to that from the Hodrick-Prescott (HP) filter.

Figure 3 shows that both Constraints Gap Indexes make a notable quantitative contribution to the smoothed output gap estimate, particularly at the beginning and end of the sample period. The consistently higher position of the first line compared to the second is attributable to L_{excess} being consistently greater than $L\&K_{excess}$ (as illustrated in Figure 2).

Figure 3 (right) illustrates the ratio of the standard error (*SE*) of the smoothed output gap estimate from our model to that of the standard model (Table 1). The graph demonstrates that incorporating the Constraints Gap Indexes into our model significantly reduces the *SE* of the output gap estimate, with the reduction ranging from 60% to 70%.

3.4. Economic Impacts of the COVID-19 Pandemic and the "Swords of Iron" war

3.4.1 COVID-19 Period

It is noteworthy to examine how the supply and demand constraints evolved in response to the COVID-19 crisis, which represents one of the most significant economic disruptions in recent history. Fears of mass infection prompted governments worldwide to impose extensive lockdowns, which greatly affected global economic activity. Consequently, demand constraint increased sharply in 2020, with numerous businesses reporting significant challenges in selling their products (Figure 1).

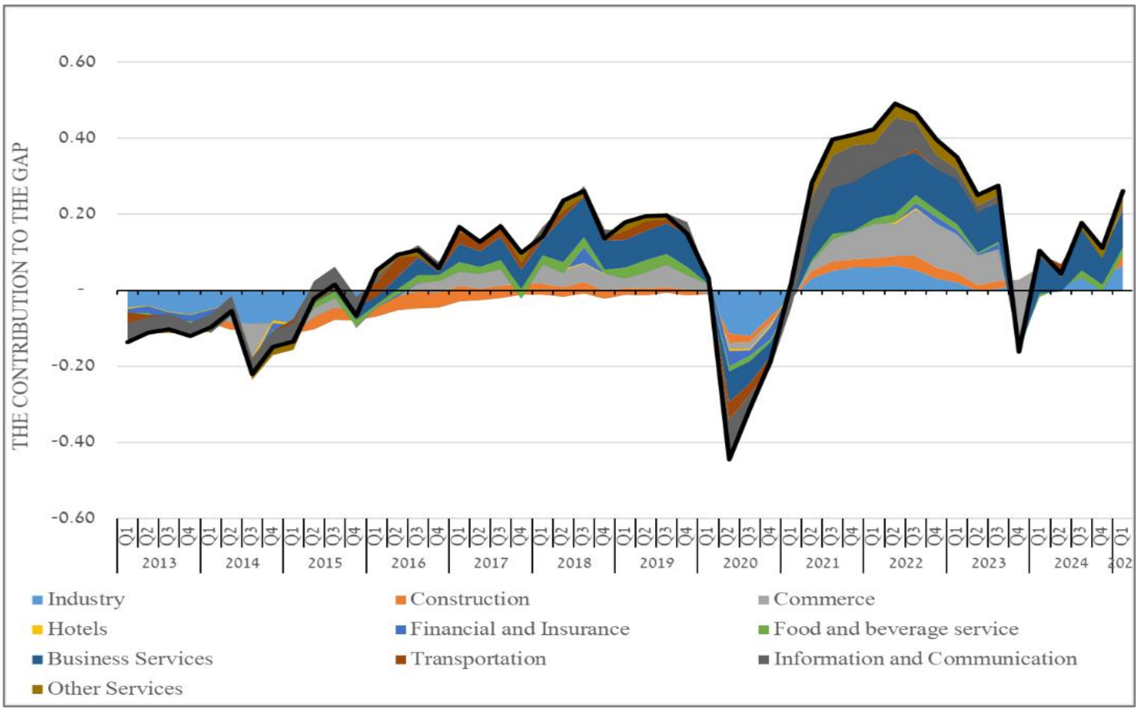
Surprisingly, despite frequent lockdowns, company reports indicated an initial decrease in the labor supply constraint. However, this trend reversed, with the constraint beginning to increase and continuing to rise until mid-2022, marking the initial phase of economic recovery from the crisis. The equipment and raw material supply constraint showed initially limited response to the crisis. However, it subsequently increased, potentially reflecting supply chain disruptions and production challenges during the recovery period. It's worth noting that the equipment and raw material supply constraint remained considerably less pronounced than the labor supply constraint throughout this period.

The initial decline in the labor supply constraint in 2020 can be attributed to the sharp drop in demand during this period. Many companies responded by reducing or halting their recruitment efforts, consequently reporting fewer difficulties in hiring. This dynamic illustrates that when the negative demand shock hit the economy in 2020, the demand constraint reacted more severely than the labor supply constraint, resulting in excess supply (Figure 2).

During the COVID-19 recovery period, a notable increase in demand became evident (as indicated by a decrease in demand constraint). Simultaneously, the economy faced increasing pressure from two types of supply constraints, with the labor constraint demonstrating particular prominence (Figure 1). Consequently, the COVID-19 recovery period displayed excess demand, as measured by the difference between the labor supply constraint and the demand constraint.

Figure 4 illustrates the sectoral contributions to the difference between the labor supply constraint and the demand constraint. It highlights the notable changes in demand and supply constraints across various sectors following the onset of COVID-19. Many sectors, particularly industry, business services, and information and communication, experienced a substantial increase in demand constraint. Interestingly, business services and industry simultaneously faced a decrease in labor constraint and were the primary contributors to excess supply during 2020. The information and communication sector, while strongly affected initially, demonstrated remarkable resilience. It was not only the first to recover but also played a pivotal role in leading the Israeli economy out of the COVID-19 crisis.

Figure 4: Sectoral contributions to the Gap between Labor Supply and Demand Constraints, Sample 2013.Q1-2025.Q1



Note: The figure illustrates the contribution of each of the 10 sectors included in the Business Tendency Survey to the gap between the labor supply constraint and the demand constraint.

It is interesting to observe how the literature addresses the derivation of output gap during the COVID-19 crisis. Several studies adjust their models to account for the onset of the crisis; however, these adjustments often leave the underlying factors driving the output gap measure unidentified. For example, Granados and Parra-Amado (2024) derived the output gap from a reduced-form *VAR* model by adding a scaling factor to residuals during the COVID-19 crisis period. Morley et al. (2023) derived the output gap from a large Bayesian VAR model, applying a similar intervention to model residuals during the COVID-19 pandemic. Júlio and José (2024) derived the output gap from a semi-structural state-space model, in which pandemic innovations were imposed into several model equations, in addition to standard innovations. Barigozzi et al. (2024) estimated the output gap using a rich multivariate model with a common factor. To account for the economic disruptions caused by the COVID-19 pandemic, they incorporated an intervention in the common factor during this period. Their study revealed that financial variables play a crucial role in capturing the excess demand (positive output gap) during the recovery phase following the initial COVID-19 outbreak.

Our analysis, however, suggests that such interventions may not be necessary during crisis periods. This is because our method utilizes survey data, which provides real-time, up-to-date information on excess demand and its breakdown into demand and supply components. The primary limitation of this approach, however, is the potential for survey responses to be both restricted in number and subject to bias during crisis periods, as will be elaborated upon in the following section. Section 3.3 takes into account the potential bias in the survey data when estimating the output gap. Notably, despite the methodological differences, both the aforementioned studies and our approach found a negative output gap during the COVID-19 outbreak. According to our approach, this negative output gap during 2020 is attributed to a negative demand shock.

3.4.2. "Swords of Iron" war 2023-24

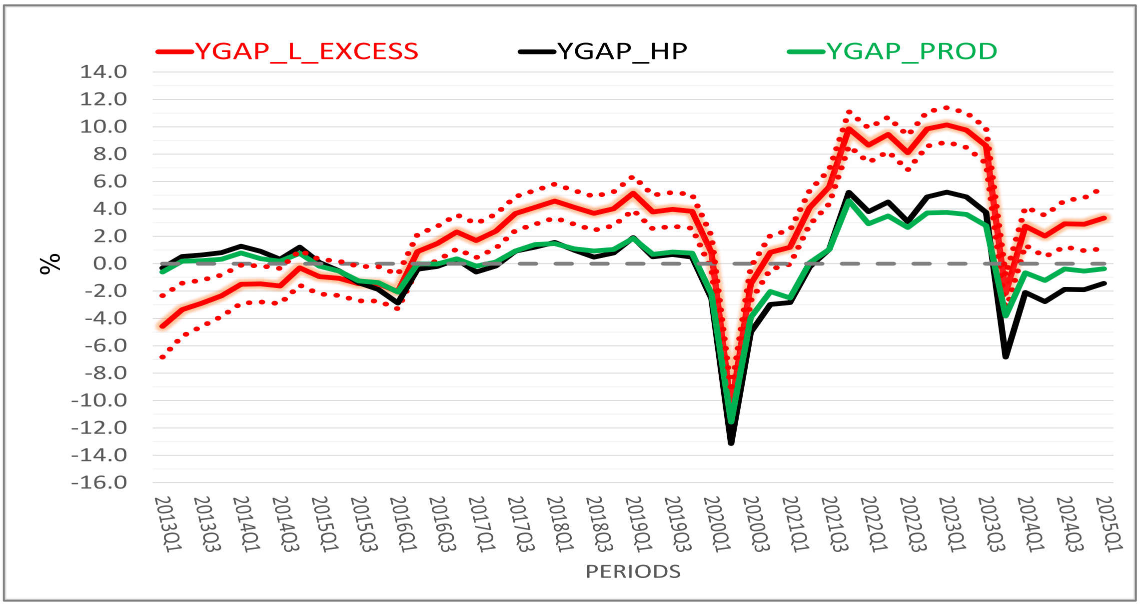
Another interesting episode occurred recently. At the end of 2023, there was a significant surge in the labor supply constraint due to the outbreak of war in Israel (Figure 1). The conflict led to massive reserve recruitment, an immediate and sharp reduction in the number of Palestinian and foreign workers, and the evacuation of many thousands of people from the northern and southern regions of Israel. During 2024, the labor supply constraint eased slightly but remained high. On the demand side, the demand constraint increased at the onset of the war in late 2023, indicating a decline in domestic demand (Figure 1). However, throughout 2024, this constraint gradually eased, suggesting a slow recovery in aggregate demand. Overall, 2024 was characterized by excess demand in the economy, primarily driven by tight labor supply constraint. Examination of sectoral contributions in 2024 reveals that business services and construction made the most substantial positive contributions to excess demand (Figure 4). Both sectors experienced intensified supply constraints. Conversely, the commerce sector exhibited the most significant negative contribution, primarily due to an increase in demand constraint.

4. Empirics

4.1. Evolution of Different Output Gap Estimates

Figure 5 illustrates the evolution of three estimates of the output gap in Israel from 2013.Q1 to 2025.Q1.[10] The first estimate, YGAP_L_EXCESS, is derived from a state space model based on the index of excess demand/supply from the survey, L_{excess} . The second estimate, YGAP_HP, is based on the Hodrick-Prescott filter, using a smoothing parameter of 1600. The third estimate, YGAP_PROD, is based on the production function and it is calculated by the Research Department of the Bank of Israel[11]. The output gap derived from the survey data shows a strong correlation with the other two measures of the output gap. However, there are notable periods of divergence.

Figure 5: Different measures of output gap, Sample period: 2013.Q1-2025.Q1



Note: The figure presents three different output gap estimates: YGAP_L_EXCESS (red line, with dashed lines representing the confidence interval) estimated using a state space model based on the index of excess demand from the survey, L_excess; YGAP_HP (black line) derived from the HP filter; and YGAP_PROD (green line) derived from the production function.

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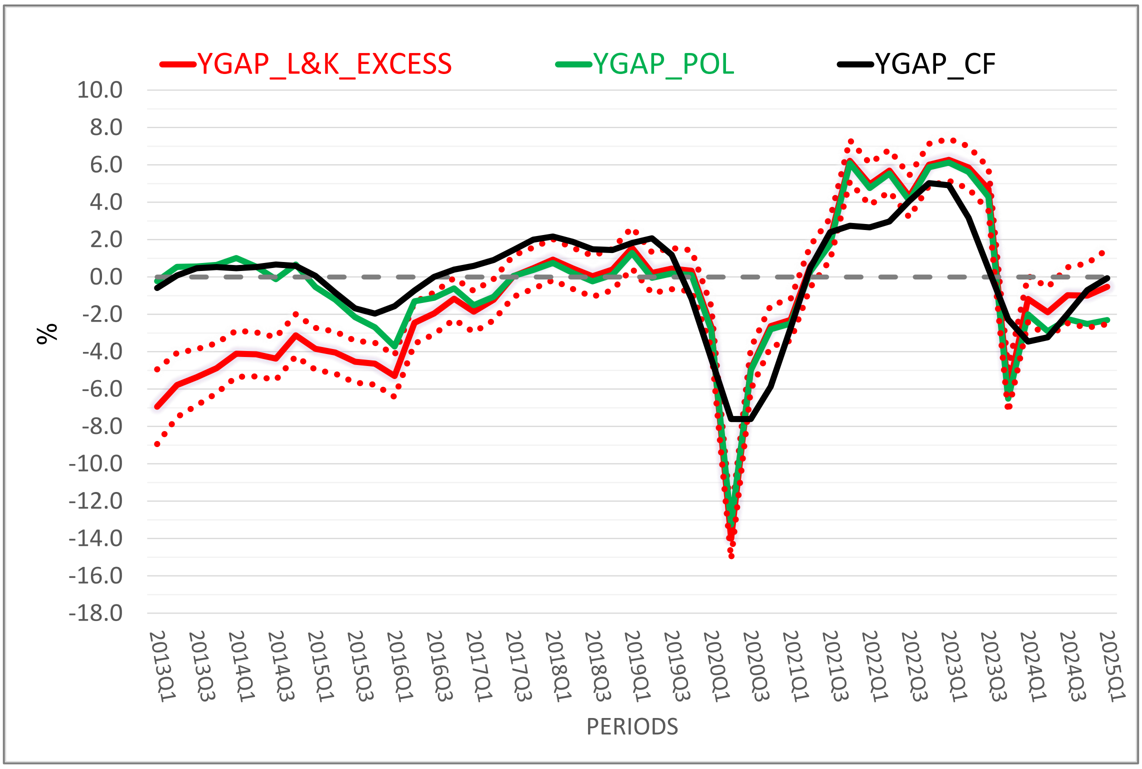
[10] The sample period begins in 2013.Q1, coinciding with the initiation of the survey data collection.

[11] The Cobb-Douglass production function is $Y = TFP \cdot L^{\alpha} K^{1-\alpha}$, where TFP is total factor productivity, L is labor input, and K is capital. L is calculated as (human capital) * (number of workers) * (average weekly hours per worker). It is calculated separately for three groups: prime-age (25-64) Israeli workers, non-prime-age (15-24 and 65+) Israeli workers, and foreign & Palestinian workers, and then aggregated to total labor input. The three groups are characterized by different levels of human capital, which is defined as 1.08*(years of education), where 1.08 is a (gross) return on education. K is calculated as the national capital stock multiplied by capital utilization U. The output gap is calculated as $[tfp - tfp^{HP}] + \alpha[l - l^{HP}] + (1-\alpha)[u - \bar{u}]$, where all variables are in logs and "HP" means that they are detrended by the HP filter with a smoothing factor of 1600. The log of capital utilization (u) is demeaned by long-term average.

At the start of the sample period, YGAP_L_EXCESS shows lower values compared to the other two measures. However, for most of the subsequent period, it exhibits higher values than YGAP_HP and YGAP_PROD. This difference is particularly pronounced during two key periods: the recovery phase following the COVID-19 crisis and the war in Israel in 2024. The divergent behavior can be attributed to the constraints gap, as illustrated in Figure 2. This gap plays a crucial role in the model's output gap estimate, serving as a key driving force (as detailed in Section 3.3). More importantly, during the COVID-19 recovery period and the war in Israel in 2024, the constraint gap indicates excess demand, resulting in a positive output gap. In contrast, the two alternative methods yield negative output gaps during the 2024 war, primarily reflecting the decline in actual output growth rate.

Figure 6 presents two additional statistical measures of the output gap. The first measure, YGAP_POL, is derived from a polynomial trend, while the second measure, YGAP_CF, employs the band-pass filter of Christiano and Fitzgerald (2003) with a 6–32 quarter periodicity. These measures (YGAP_POL and YGAP_CF) generally align with the estimates obtained from the *HP* filter and production function approaches. Moreover, they exhibit a closer resemblance to the measure derived from the state space model based on the survey's combined supply constraint index (YGAP_L&K_EXCESS). However, a notable divergence is observed at the beginning of the sample period, primarily due to excess supply conditions, as illustrated in Figure 2.

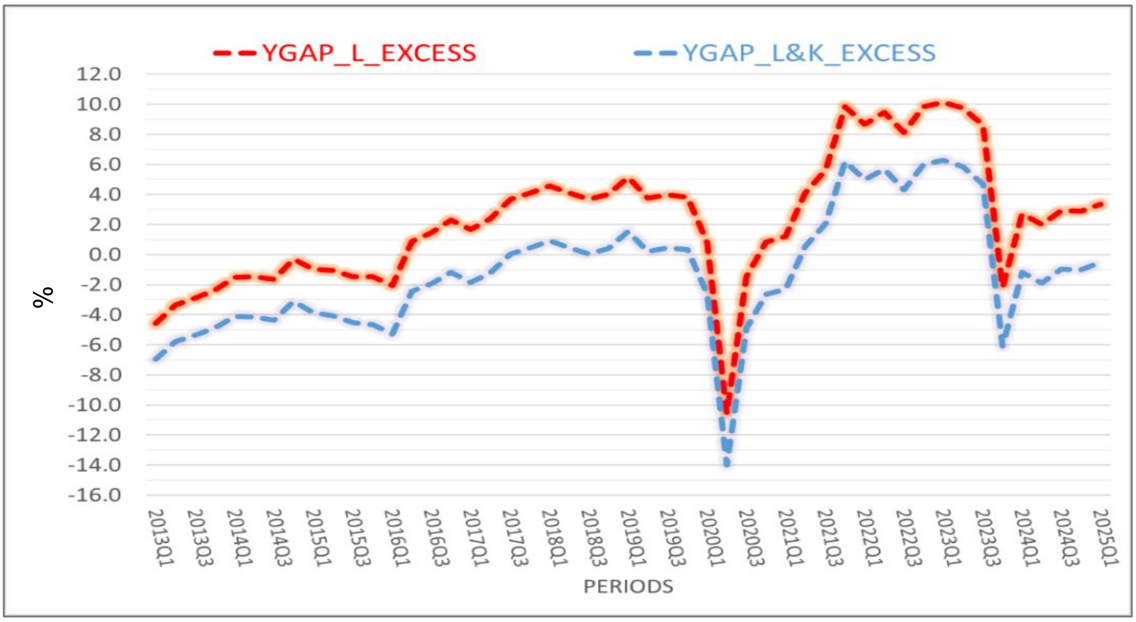
Figure 6: Different measures of output gap, Sample period: 2013.Q1-2025.Q1



Note: The figure displays three output gap estimates: YGAP_L&K_EXCESS (red line, with dashed lines indicating the confidence interval) estimated using a state space model based on the survey's index of excess demand, L&K_excess; YGAP_CF (black line) derived from the Christiano and Fitzgerald (2003) band-pass filter; and YGAP_POL (green line) derived from the quadratic polynomial trend.

Figure 7 illustrates the contrast between YGAP_L_EXCESS and YGAP_L&K_EXCESS. The disparity between these two measures is expected, as it primarily reflects the differences in constrained gaps previously observed in Figure 2. Notably, the graph reveals divergent interpretations of economic conditions in 2024. According to YGAP_L_EXCESS, there was a significant excess demand during this period. In contrast, YGAP_L&K_EXCESS, while showing an upward trend, indicates that the output level remained close to equilibrium (near zero).

Figure 7: Comparison of Output Gap Measures Derived from Survey Data, Sample period: 2013.Q1-2025.Q1



Note: This figure compares two output gap estimates: YGAP_L_EXCESS (red line) and YGAP_L&K_EXCESS (blue line). Both are derived from state space models using different survey indices of excess demand. YGAP_L_EXCESS utilizes L_excess, while YGAP_L&K_EXCESS is based on L&K_excess.

The fundamental difference between statistical univariate methods and the survey-based method lies in how their trend estimates respond to fluctuations in actual output. Statistical methods tend to have trend estimates that "smoothly follow" these fluctuations. Consequently, when actual output falls, the estimated trend also drops—albeit gradually—producing a negative output gap. Canova (2025) demonstrated the fundamental differences between the New-Keynesian output gap and statistical measures, indicating that purely statistical approaches generally cannot fully replicate the New-Keynesian gap.

For instance, Segal (2017) showed that in a New-Keynesian model, a negative technology shock lowers potential output, but due to price rigidity, actual output falls less, resulting in a positive gap and upward inflation pressures. In contrast, statistical methods, upon observing a drop in actual output, would produce a smooth decline in the trend—leading to a negative output gap. This characteristic of pure statistical measures may lead policymakers to draw incorrect conclusions about the output gap. Such misinterpretations could result in either overly accommodative or excessively tight monetary policy, ultimately undermining the effectiveness of monetary policy in achieving its objectives. However, a comprehensive analysis of monetary policy based on different output gap measures lies beyond the scope of this paper. This is because changing monetary policy reactions would induce different economic outcomes, necessitating a general equilibrium model for thorough evaluation.

Although we do not directly compare our survey-based gap with the *New-Keynesian* gap, our goal is to propose a new measure that is neither purely statistical nor fundamentally New-Keynesian. The primary economic potential advantage of our approach may be attributed to its micro-foundations—specifically, the responses provided by numerous company managers regarding their own firms. In this sense, it shares a micro-founded perspective with the New-Keynesian framework. However, unlike the New-Keynesian framework, our output-gap measure does not depend on a specific theoretical model.

4.2. Which Output Gap Measure Best Explains Inflation?

In this subsection, we explore the potential of our survey-based output gap measure in explaining inflation—a crucial aspect relevant to monetary policy. The theoretical relationship between inflation and the output gap (reflecting excess demand) in the New Keynesian framework has been demonstrated by studies such as Clarida et al. (1999) and Galí (2015). According to this framework, inflation is determined by inflation expectations, the output gap, and cost-push shocks. Given that the relationship between prices and their determinants is derived from firms' optimization processes, it is reasonable to expect that firms' perceptions and expectations (or public expectations serving as a proxy) would be most relevant when applying the inflation equation to empirical data. In this context, our survey-based output gap measure, which reflects firm managers' perceptions of excess demand or excess supply, aligns well with these theoretical foundations.

Empirical studies demonstrate advantages in using survey-based expectations, particularly for inflation. Brissimis and Magginas (2008) found support for the forward-looking New Keynesian Phillips curve using professional forecasters' (*PF*) inflation expectations, which largely reduced the need for inflation indexation. Kortelainen et al.

(2016) showed that *PF* expectations improve model performance. Similarly, Smets et al. (2014) found that incorporating *PF* forecasts enhances the New Keynesian model's real-time forecasting for the euro area.

We contribute to the literature by utilizing a survey-based output gap measure to explain inflation. We estimate a simple inflation equation in reduced form for the sample period 2013:Q1-2025:Q1, comparing our measure's performance with other commonly used output gap estimates. We opt for a simple, empirically oriented model rather than a New Keynesian structural model to allow greater flexibility in explaining inflation dynamics. It is crucial to note that, given our relatively short sample period, the results presented here should be interpreted as preliminary indications rather than conclusive evidence.

$$(6) \quad \pi_t^j = c + \sum_{i=0}^{s} \beta_i \Delta s_{t-i} + \sum_{i=0}^{n} \gamma_i \pi_{t-i}^{imp} + \sum_{i=0}^{P} \delta_i ygap_{t-i}^{type} + \epsilon_t,$$

where $\pi_t^j = [\pi_t^a, \pi_t^b, \pi_t^c, \pi_t^p, \pi_t^y]$ and $ygap_t^{type} = [\ ygap\_L_{excess}, ygap\_L\&K_{excess}, ygap_{HP}, ygap_{POL}, ygap_{PROD}, ygap_{CF}]$. π_t^a is quarterly *CPI* inflation, π_t^b is quarterly *CPI* inflation excluding housing and fruit and vegetables. π_t^c is quarterly *CPI* inflation excluding fruit and vegetables and energy. π_t^p is quarterly Producer Price inflation, and π_t^y is quarterly change in the Business Sector output prices. All inflation data is seasonally adjusted. $ygap_t^{type}$ is a set of six versions of output gap considered. Two first measures of the output gap are derived from the Business Sector Tendency Survey, while four additional measures are calculated using statistical methods. We added two additional explanatory variables: the change in the exchange rate of the Shekel against the Dollar (Δs_t) and the change in Israel's import prices in dollars (seasonally adjusted) (π_t^{imp}). These two explanatory variables are needed because Israel is a small open economy; hence, exchange-rate movements and import prices substantially impact both imported final consumption goods and imported intermediate goods.

The estimation results appear in Table 2, which reports the effects of various output gaps on inflation and highlights each gap's contribution to the regression's explanatory power ($R^2_{adj.}$). Setting aside the survey-based output gap for a moment, the polynomial-based measure emerges as the most effective at explaining inflation, showing both the highest impact and consistent statistical significance. Moreover, its contribution to the regression's explanatory power is the greatest. These findings align with Canova (2025), who concludes that the polynomial approach is the least distorting and superior to the other output gap measures considered.

Table 2: The estimated effect of various measures of output gap in Equation (6), Sample: 2013.Q1-2025.Q1

Parameter ϑ/Type of inflation	π_t^a	π_t^b	π_t^c	π_t^p	π_t^y
$ygap\_L_{excess}$ (p=8,10,10,1,11)	0.06 (0.00), 7%	0.11 (0.00), 13.1%	0.03 (0.00), 9.5%	0.07 (0.04), 2.6%	0.03 (0.00), 38.8%
$ygap\_LK_{excess}$(p=8,10,10,1,11)	0.06 (0.01), 6.9%	0.12 (0.00), 12.8%	0.09 (0.00), 9.0%	0.07 (0.04), 2.7%	0.04 (0.00), 37.5%
$ygap_{HP}$ (p=6,8,3,1,11)	0.02 (0.04), 3.5%	0.05 (0.07), 1.2%	-0.06 (0.17), 0.8%	0.04 (0.06), 2.0%	-0.09(0.00), 22.4%
$ygap_{POL}$(p=8,10,10,1,11)	0.09 (0.01), 5.8%	0.17 (0.00), 7.7%	0.15 (0.02), 6.1%	0.04 (0.07), 2.0%	-0.04 (0.00), 30.1%
$ygap_{PROD}$(p=6,8,3,1,11)	0.04 (0.08), 1.6%	0.07 (0.19), -2.1%	-0.05 (0.25), -0.6%	0.07 (0.03), 3.1%	-0.09 (0.00), 37.6%
$ygap_{CF}$(p=4,4,10,3,11)	-0.05 (0.03), 4.8%	-0.05 (0.05), 3.4%	0.01 (0.02), 4.6%	-0.09 (0.13), 0.9%	-0.59 (0.00), 30.3%
R_{adj}^2(basic)	61%	60%	43%	68%	1%

Note: In the table, each row contains three values: (1) the estimated cumulative effect of output gap on inflation $\sum_{i=0}^{P}\delta_i$ in Equation 6, (2) the *p-value* of the Likelihood-ratio test, which tests the redundancy of the output gap in the regression (in parentheses), and (3) the contribution of the output gap to the explanatory power, $R_{adj.}^2$. In all regressions, we include the contemporaneous value and four lags of the shekel-dollar exchange rate and import prices. For each inflation type (π_t^i), we optimized the number of lags for the output gap to maximize explanatory power. The first column shows the optimal number of output gap lags for each inflation measure. The last row shows $R_{adj.}^2(\text{basic})$ when the output gap is omitted from Equation 6.

However, our newly introduced output gap measure ($\mathrm{ygap\_L_{excess}}$ or $\mathrm{ygap\_L\&K_{excess}}$) outperforms the polynomial approach in terms of boosting the regression's explanatory power, contributing to $R^2_{adj.}$ between 2.6% and 38.8%—depending on the inflation measure used (Table 2). It has the most substantial contribution to changes in Business Sector output prices (38.8%), while its influence on Producer Price inflation is minimal (2.6%).

Now we consider an alternative specification for the inflation equation where the dependent variable is the inflation rate over the last four quarters. This alternative specification relies on moving-average trends of the explanatory variables.

$$(7) \qquad \pi 4_t^j = c + \alpha \Delta s\_MA(p)_t + \beta \pi\_MA^{imp}(p)_t + \vartheta ygap\_MA(p)_t^{type} + u_t,$$

where $\pi 4_t^j = [\pi 4_t^a, \pi 4_t^b, \pi 4_t^c, \pi 4_t^p, \pi 4_t^y]$ is an average inflation rate over the last 4 quarters. Each explanatory variable in the regression is a moving average over the last (p) quarters, $x\_MA(p)_t = \frac{1}{p}\left[x_t + x_{t-1} + \cdots + x_{t-p}\right]$, where the choice of lag (p) could be different for each variable.

Table 3 presents the estimation results, highlighting the impact of survey-based measures of the output gap on various inflation indicators. For the first three types of inflation (CPI, Core Inflation 1, and Core Inflation 2), the survey-based output gap measures show a substantially higher contribution compared to other output gap measures, with their contribution approaching 20% for each of these inflation types. The survey-based measures also demonstrate the highest and most significant contribution to Business Sector Output Prices. However, in the case of Producer Price inflation, the survey-based measure's contribution is slightly lower compared to other output gap measures. This pattern suggests that survey-based output gap measures are particularly effective in explaining most types of inflation, with the notable exception of Producer Price inflation. Interestingly, when examining the explanatory power of Equation 7 for Producer Price inflation without including the output gap, import prices and exchange rates alone account for over 90% of the variation. This high explanatory power inherently limits the potential contribution of any type of output gap measure from the outset.

Table 3: The estimated effect of various measures of output gap in Equation (7), Sample: 2013.Q1-2025.Q1

Parameter ϑ/Type of inflation	$\pi4_t^a$	$\pi4_t^b$	$\pi4_t^c$	$\pi4_t^p$	$\pi4_t^y$
$ygap\_L_{excess}$ (p=9,10,9,2,11)	0.09 (0.00), 22%	0.10 (0.00), 21.4%	0.08 (0.00), 20.6%	0.02 (0.41), 0.5%	0.09 (0.08), 10.5%
$ygap\_L\&K_{excess}$(p=10,9,9,2,11)	0.10 (0.00), 22.2%	0.11 (0.00), 21.5%	0.09 (0.00), 20.7%	0.03 (0.42), 0.6%	0.10 (0.07), 10.8%
$ygap_{HP}$ (p=10,10,10,3,5)	0.15 (0.00), 10.3%	0.15 (0.00), 8.1%	0.11 (0.00), 7.5%	0.05 (0.24), 1.0%	-0.09 (0.08), 5.1%
$ygap_{POL}$(p=10,10,10,3,11)	0.17 (0.00), 20.9%	0.18 (0.00), 18.4%	0.14 (0.00), 19.0%	0.06 (0.23), 1.2%	0.15 (0.07), 10.1%
$ygap_{PROD}$(p=10,10,10,3,5)	0.17 (0.00), 11.2%	0.18 (0.00), 9.3%	0.13 (0.00), 8.1%	0.07 (0.15), 1.1%	-0.08 (0.13), 1.6%
$ygap_{CF}$(p=10,10,10,1,5)	0.10 (0.08), 4.2%	0.10 (0.12), 2.9%	0.06 (0.18), 1.9%	0.05 (0.07), 1.0%	-0.10 (0.06), 8.6%
$R^2_{adj}(\text{basic})$	60%	61%	54%	91%	27%

Note: In the table, each row contains three values: (1) the estimated parameter of the output gap (ϑ) in Equation 7, (2) the *p-value* of the Newey-West corrected t-test (in parentheses), and (3) the contribution of the output gap to the explanatory power, $R^2_{adj.}$. For each inflation type ($\pi4_t^i$), we optimized the number of lags for the output gap, exchange rate, and import prices to maximize $R^2_{adj.}$. The optimal number of lags for the exchange rate and import prices was consistently 4 quarters across all inflation types. The first column shows the optimal number of output gap lags for each inflation measure. The last row shows $R^2_{adj.}(\text{basic})$ when the output gap is omitted from Equation 7.

4.3. Real-Time Reliability

In this subsection, we present a brief assessment of the end-of-sample reliability of our proposed output gap estimate compared to a standard univariate model. This analysis evaluates the impact of incorporating survey data on the stability of output gap estimates in real-time compared to ex-post.

Our procedure involves two key steps. First, we calculate the revision in the output gap derived from the univariate standard model (column (3), Table 1) by comparing the smoothed estimate (based on full sample and final vintage *GDP* data) with the filtered estimate (based on real-time and first vintage *GDP* data). Second, we perform a similar calculation for our model, which incorporates the excess demand index from the survey (column (1), Table 1). Here, we compare the smoothed estimate (using full sample, final vintage *GDP* data, and survey data) with the filtered estimate (using real-time and first vintage *GDP* data, along with survey data)[12].

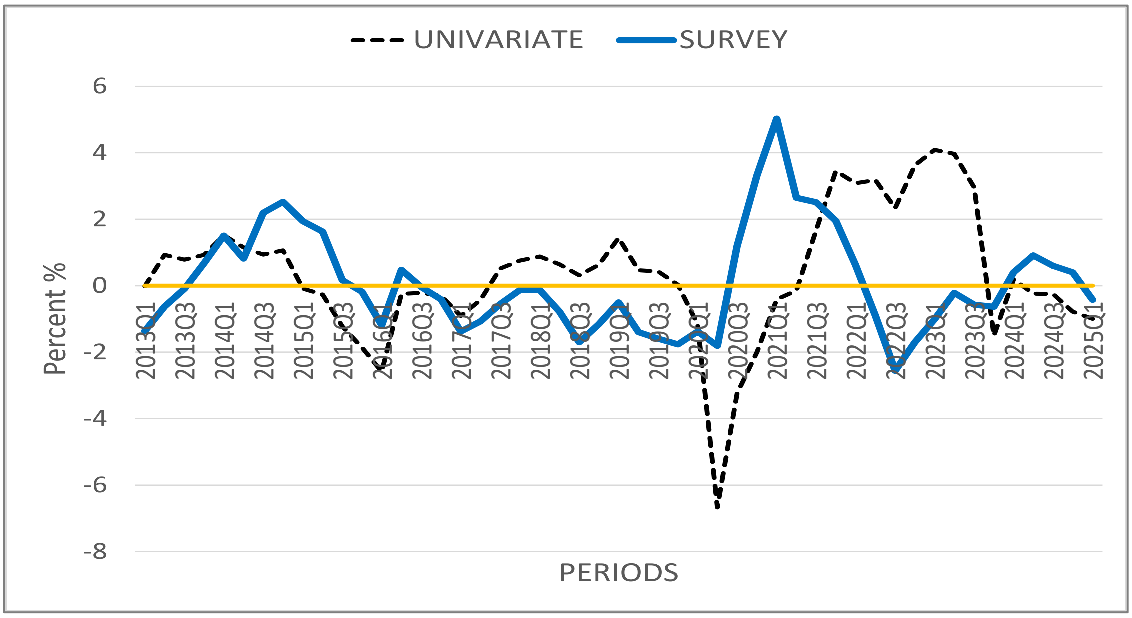
Our examination directly addresses two key sources of uncertainty in real-time output gap estimates. The first source arises from data revisions (Orphanides and van Norden (2002), Kangur et al. (2019)). These revisions can significantly alter the estimated output gap over time, complicating real-time economic analysis. The second source stems from the unreliability of end-of-sample trend estimates (Orphanides and van Norden (2002), Barbarino et al. (2024)). This issue occurs because trend-cycle decomposition methods typically require both past and future data points, which are unavailable in real-time.

Several studies attempt to address the problem of unreliable end-of-sample estimates. Barbarino et al. (2024) suggest improving the end-sample problem by including Okun's law relationship. Similarly, Chalmovianský and Němec (2022) demonstrate that multivariate structural approaches outperform non-structural statistical approaches in terms of stability and assessing business cycles. However, a potential drawback of multivariate approaches is that, although the output gap derived from them is likely to be more stable and less sensitive to end-sample problem and data revisions, these models incorporate additional unobserved variables (such as the natural rate of unemployment in Okun's law relationship). The uncertainty associated with the stochastic processes of these additional unobserved variables introduces more uncertainty to the output gap estimates. On a more positive note, Barigozzi and Luciani (2023) showed that using a large number of variables for the estimation of the output gap in big sample significantly reduces the magnitude of revisions to the output gap estimates.

[12] To eliminate the effect of different samples in real-time versus the full sample on the estimated parameters in the model, we use the model parameters from Table 1 to derive the output gaps in real-time and in the full sample.

Returning to our analysis, Figure 8 presents a comparative visualization of the revisions between two models. The graph illustrates the revisions from the univariate model, depicted by a black dashed line, in contrast with those from our proposed model, represented by a blue continuous line. The analysis reveals that revisions in our survey-based model are more modest compared to the univariate model. Specifically, the standard error (*SE*) of the revisions in our model is 1.55%, lower than the 1.93% observed in the univariate model. Furthermore, the cumulative revisions in our model amount to 4.2%, substantially less than the 16.4% in the standard model and an average revision of 0.09% in our model, compared to 0.33% in the standard model.

Figure 8: Comparison of Output Gap Revisions - Univariate Model vs. Survey-Based Model, Sample period: 2013.Q1-2025.Q1



Note: The blue continuous line depicts the revisions of the output gap estimate based on survey data. The black dashed line illustrates the revisions of the output gap estimate derived from a standard univariate model.

It is particularly noteworthy to examine the revisions during the COVID-19 period. The univariate model exhibited a significant "zig-zag" pattern in its revisions throughout this period. Specifically, during the initial outbreak of the crisis in 2020, we observe substantial negative revisions ranging from 3% to 6%. Subsequently, as the recovery phase unfolded in 2022, the model showed large positive revisions of 3% to 4%.

In contrast, our model shows moderate revisions of 1.8% at most during crisis outbreak in 2020, and modest revisions during the recovery period. The only exception is in the first quarter of 2021, with the highest revision of 5%. This overall pattern of smaller revisions suggests that our model, which incorporates survey data, provides more stable estimates of the output gap in real time, particularly during periods of economic turbulence. The enhanced stability of our model's output gap estimates primarily stems from incorporating an additional indicator from the Business Tendency Survey. This survey data, by nature, is not subject to revisions. Moreover, it provides valuable real-time information about excess demand or supply conditions in the economy.

4.4. Principal component analysis

In our previous analysis, we constructed the constraints gap index which reflects excess demand/supply, based on aggregate supply and demand constraints, weighting each sector by its share in business *GDP* (detailed explanation provided in Appendix A). An alternative approach involves deriving a principal component (*PC*) from the 10 sectors under examination. This method offers several advantages: it extracts the common factor across all 10 sectors, disregards idiosyncratic shocks specific to individual sectors, and does not require consideration of relative sector weights. This *PC*-based approach aligns well with policy objectives, which typically focus on macroeconomic developments rather than sector-specific trends.

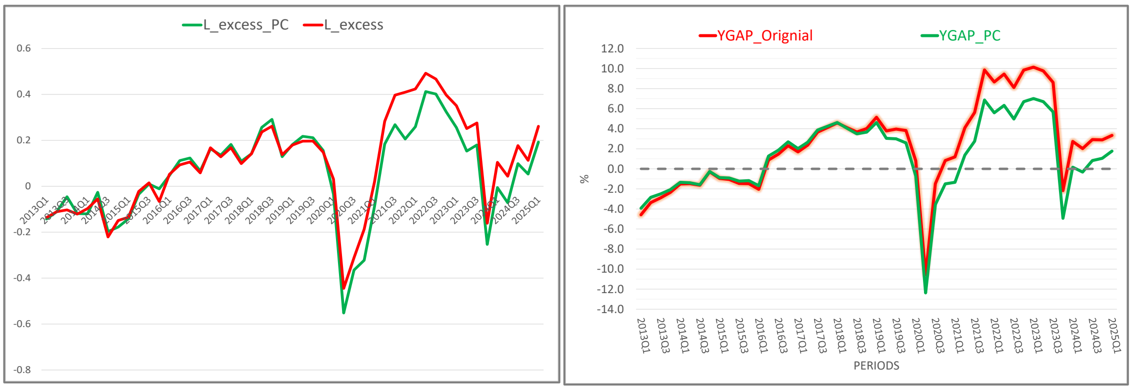
However, the *PC* method has several limitations that should be considered. These include: sensitivity to outliers in the dataset, potential scaling issues that may bias results towards variables with larger magnitudes, and uncertainty regarding the appropriate number of factors to include in the *PC* analysis. Despite these drawbacks, when used judiciously, the *PC* method can provide valuable insights into broader economic trends.

Methodologically, we first derive the *PC* of the labor supply constraint across the 10 sectors, then derive the *PC* of the demand constraint across the same sectors. The constraints gap index, which measures excess demand/supply, is calculated as the difference between these two principal components (PCs)[13].

[13] To ensure comparability with our baseline index, we addressed a scaling issue in the *PC* analysis. We multiplied the *PC*-derived index by 0.27, obtained through a simple regression of the original excess demand index on the *PC*-derived index. This adjustment brings the PC-based index to the same scale as our previously presented baseline index.

Figure 9 presents our findings: the left panel shows the alternative measure of the index of constraints gap index based on the *PC* analysis along with the original measure, while the right panel displays the estimated output gap derived from this *PC*-based index along with the original measure.

Figure 9: Comparison of Original and PC-Based Models: Constraints gap index and Output Gap, Sample period: 2013.Q1-2025.Q1



Note: The left panel displays the original constraints gap index (red) alongside the PC-based index (green). The right panel shows the corresponding original output gap (red) and the PC-based output gap (green).

As evident from Figure 9, the constraints gap index (and consequently, the output gaps) derived from both approaches are nearly identical up until the onset of the COVID-19 crisis. However, in the post-crisis period, the PC-based measure shows slightly lower values compared to the original measure. This suggests a marginally weaker excess demand or stronger excess supply, particularly during the outbreak of the war in late 2023.

5. Conclusions

This study introduces a novel and simple method for deriving the real-time output gap in the economy using data from the Business Tendency Survey. Our approach complements existing methods in the literature, which generally fall into two categories: univariate methods that exploit only actual output data, and multivariate methods that often require additional unobservable variables to estimate the output gap. By incorporating survey data, our method offers a middle ground, potentially combining the simplicity of univariate approaches with the additional information typically associated with multivariate methods.

Our approach offers several key advantages: (1) Easy implementation; (2) Separate estimation of demand and supply constraints as distinct sources of the output gap; and (3) Timely assessment through monthly survey data, enabling real-time evaluation of excess demand or supply. These features provide policymakers with the ability to respond more effectively and promptly to economic changes, which is crucial in uncertain environments. All this may potentially enhance the accuracy and effectiveness of monetary policy decisions.

The proposed approach can be easily implemented worldwide. Many countries already conduct Business Tendency Surveys, which could be enhanced by incorporating specific questions about demand and supply constraints faced by company managers. This addition would enable a more precise real-time assessment of excess demand or supply in the economy, providing valuable input for output gap evaluation.

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Appendix A - Calculation of Supply and Demand Constraints from Business Tendency Survey

Here, we provide a detailed explanation of how supply and demand constraints are constructed. Each month, approximately 1,600 company managers from 10 different sectors in the business sector respond to questions specific to their companies. Among these questions, three focus on the current supply and demand constraints faced by their firms.

Labor Supply Constraint: Company managers are asked to rate the extent to which employee recruitment constraints limit their operations, using a scale of 0 to 3, where:

- 0 - no constraint
- 1 - a slight constraint
- 2 - a moderate constraint
- 3 - a severe constraint

Raw Materials and Equipment Supply Constraint: Company managers are asked to rate the extent to which raw materials and equipment constraints limit their operations, using the same scale of 0 to 3.

Demand Constraint: Company managers are asked to rate their order demand constraints in both domestic and foreign markets (export), using the same 0 to 3 scale. For each company, an average constraint level is calculated by averaging the domestic and export order constraint ratings.

For each of the ten sectors, we calculate the average constraint level by taking the simple average of all firm-level responses within that sector. We then combine these sector-level averages into an economy-wide constraint index by constructing a weighted average, where each sector's weight corresponds to its share in the total GDP of the ten surveyed sectors.

Two sector weighting schemes are available (we implemented the first scheme):

- Time-varying shares, recalculated annually from 2013 through 2024 to capture each sector's evolving share of business GDP
- Constant shares, based on the average share of business GDP for each sector over the entire 2013-2024 sample

Table A.1 presents the average sector shares for the sample period, 2013-2024.

Table A.1: The sample average weights of different sectors based on their shares in the business product.

Sector	Business Services	Other Services	Financial and Insurance	Information and Communication	Food and beverage service	Transportation	Commerce	Construction	Industry	Hotels
Weight (%)	20%	4%	5%	15%	3%	5%	18%	9%	20%	1%

Appendix B

In this Appendix, we examine the effects of demand and labor supply constraints on four types of inflation. We estimate Equation (B.1), assigning separate parameters to each constraint:

$$\text{(B.1)}\quad \pi 4_t^j = \alpha \Delta s\_MA(p)_t + \beta \pi\_MA^{imp}(p)_t + \tau_1 L_{MA(p)_t}{}^{const} + \tau_2 D_{MA(p)_t}{}^{const} + \varepsilon_t,$$

where $\pi 4_t^j = [\pi 4_t^a, \pi 4_t^b, \pi 4_t^c, \pi 4_t^p]$ represents four types of inflation, $L_{MA(p)_t}{}^{const}$ and $D_{MA(p)_t}{}^{const}$ are moving averages of labor constraint and demand constraint, respectively.

Table B.1 presents the estimation results. For all inflation types, the supply constraint coefficient is positive (indicating a negative supply shift, pushing inflation up), while the demand constraint coefficient is negative (indicating a negative demand shift, pushing inflation down). Both coefficients are highly significant, except for the demand constraint in Business Sector output prices (last column). A Wald test examining the equality of the two parameters in absolute value shows that we cannot reject the null hypothesis of equal impacts at the 10% significance level for most inflation types. The only exception is for Business Sector output prices, where the impacts are significantly different. These findings suggest that supply and demand constraints generally have comparable magnitudes of impact on inflation, except for Business Sector output prices.

Table B.1: The estimated separate effect of labor supply constraint and demand constraints in Equation (B.1), Sample: 2013.Q1-2025.Q1

Parameter ϑ/Type of inflation	$\boldsymbol{\pi 4_t^a}$	$\boldsymbol{\pi 4_t^b}$	$\boldsymbol{\pi 4_t^c}$	$\boldsymbol{\pi 4_t^p}$	$\boldsymbol{\pi 4_t^y}$
$\boldsymbol{L\_MA^{const}}$	1.51 (0.00)	1.82 (0.00)	1.29 (0.00)	1.15 (0.01)	0.90 (0.07)
$\boldsymbol{D\_MA^{const}}$	-1.31 (0.00)	-1.83 (0.00)	-1.05 (0.00)	-1.04 (0.05)	-0.40 (0.45)
p-value of Wald Test $\boldsymbol{\tau_1 + \tau_2 = 0}$	0.05	0.07	0.06	0.10	0.00

Note: For each inflation type ($\pi 4_t^i$), the table presents two values: (1) the estimated parameter of the labor supply constraint on inflation, and (2) the estimated parameter of the demand constraint on inflation. Each parameter's *p-value* from the Newey-West corrected t-test appears in parentheses. The number of lags for each explanatory variable was optimally selected to maximize explanatory power ($R^2_{adj.}$). The number of lags for both labor supply and demand constraints was set equally.