

A Business Conditions Real-Time Measure of Output Gap Deviations*

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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 both consumer price index and producer price inflation in Israel. 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 reliability than the standard univariate method. The proposed approach complements existing methods, providing valuable insights for economic analysis and policymaking by leveraging real-time survey data and capturing businesses' perceptions of economic constraints.

JEL Codes: E31, E32, E37.

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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) compares the output gaps from theoretical New Keynesian dynamic stochastic general equilibrium (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 Błażej, Górajski, and Ulrichs (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.

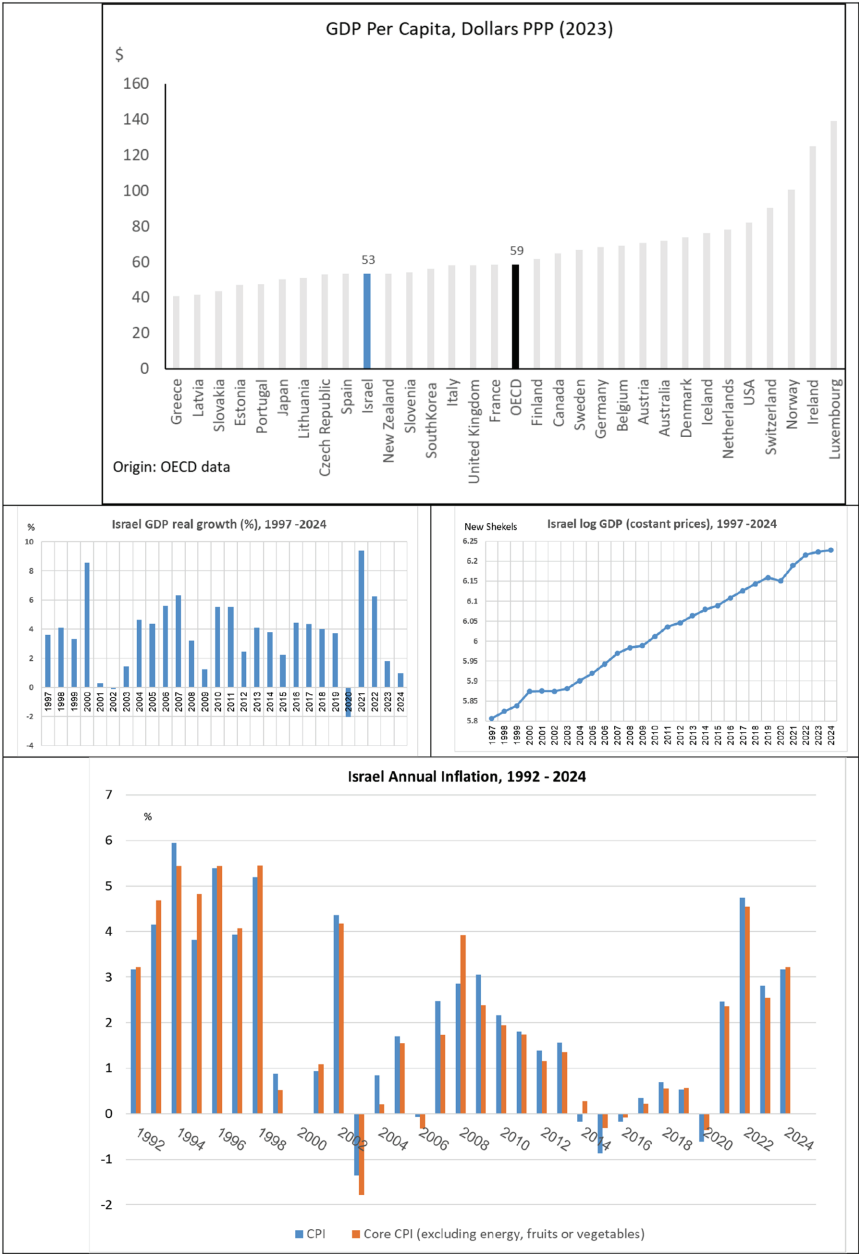
The proposed output gap measure presents a complementary approach to assessing the output gap. Our key finding in this paper

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.

Before proceeding with our analysis, we present some basic facts about the Israeli economy. Israel is a small, open, developed economy that joined the OECD in 2008. The Israeli economy is inclined toward service production, as the weight of services in the gross domestic product is relatively high (about 70 percent) and increasing over the years. As of 2023, Israel's GDP per capita was \$53,000 in terms of purchasing power parity, which is slightly below the OECD average of \$59,000 (Figure 1). The country's population is approximately 10 million people, with an average population growth rate of 1.9 percent—among the highest in the OECD. Since 1997, Israel has experienced an average annual growth rate of 3.7 percent, with about 2.0 percent attributed to per capita growth. The Israeli economy underwent a disinflation process in the 1990s, and since the early 2000s it has operated under an inflation target regime with a range of 1–3 percent. Over the past 20 years, the average annual

Figure 1. Key Economic Indicators for Israel



inflation rate in Israel has been 1.7 percent, aligning with its inflation target range (Figure 1).

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 a military conflict that occurred toward the end of our analysis period. 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 (CBS) in Israel since 2013, provides monthly data on production constraints reported by company managers across 10 economic sectors (see Table A.1). These surveyed sectors represent approximately 85 percent of 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 CBS, the Business Tendency Survey adheres to international standards and employs statistical techniques to address potential response bias. 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

¹The remaining 15 percent of sectors consist of smaller industries such as Electricity and Water Supply, Agriculture, Forestry, and Fishing, among others.

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:

- **Microfounded 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, their responses should be considered reliable.
- **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 quantification of each sector's contribution to overall excess demand or supply.
- **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.
- **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, Gneezy, and Rasocha 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, Gneezy, and Rasocha 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,” they 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 trends 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 percent 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 percent 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).

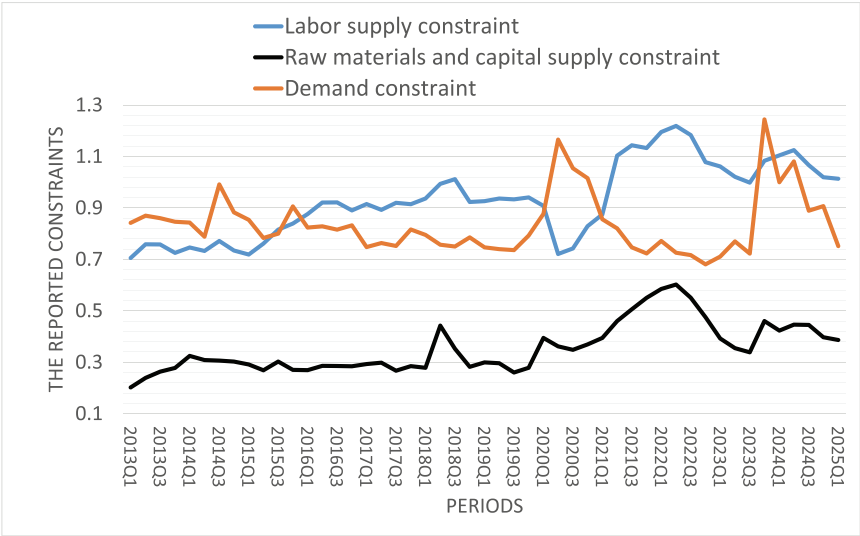
3. Method

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/supply 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 indices 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

Figure 2. Labor and Materials Supply Constraints, and a Demand Constraint: Domestic and Foreign Orders, 2013:Q1–2025:Q1



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

Appendix A).² The analysis below adopts time-varying sector weights, recalculated annually from 2013 to 2024.

Figure 2 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

²The series of constraints used in the paper are not seasonally adjusted. The reason for this is that the Net Balance Series of the trend survey—after seasonal adjustment by the CBS—were compared to corresponding quantitative series for which the trend 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.

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 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.

3.1.1 *Constructing the Aggregate Supply Constraint*

Figure 2 illustrates two distinct supply constraints and one demand 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.

- (i) 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 2). Thus, the aggregate supply constraint, S , is determined only by the labor supply constraint, L^{const} , that is, $S = L^{const}$.
- (ii) 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

³For example, this relationship can be modeled using a constant elasticity of substitution (CES) production function.

supply constraint and the constraint on raw materials and equipment: $S = \alpha L^{const} + (1 - \alpha)K^{const}$.

- (iii) 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 2), companies can exploit the high degree of substitutability by shifting toward 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 “constraint gap” 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 “constraint 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.

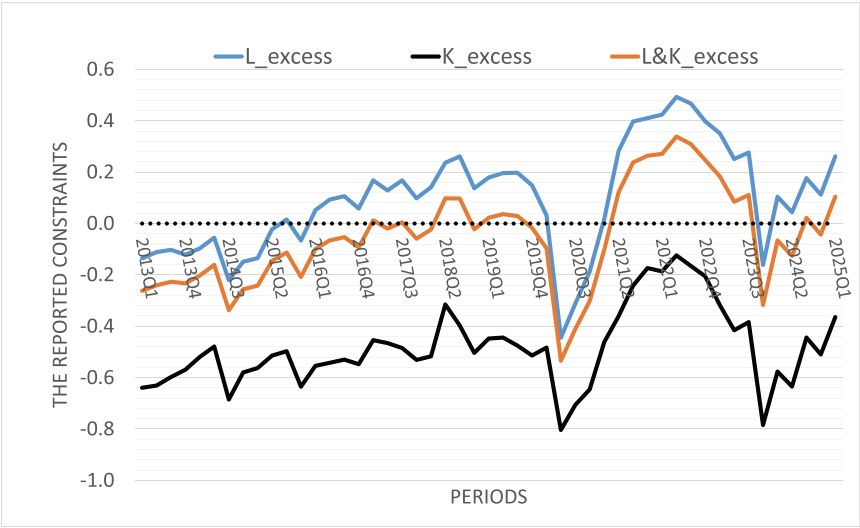
Let us define the index of excess demand/supply as $Excess = S - D$, where S is the aggregate supply constraint and D is the aggregate demand constraint. Based on the three cases of constructing S shown in Section 3.1, we define three measures of excess demand:

- (i) $L_{excess} = L^{const} - D^{const}$, which is the gap between the labor supply constraint and the demand constraint.
- (ii) $L\&K_{excess} = \alpha L^{const} + (1 - \alpha)K^{const} - D^{const}$, which is the gap between the combined supply constraint and the demand constraint.⁵

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

⁵To 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 the labor constraint, K^{const} is the 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 materials/equipment constraint. This is

Figure 3. The Evolution of Three Constraint Gap Indices, 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.

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

Figure 3 illustrates three measures of constraint gap indices. The first two indices 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_excess in the aggregate supply constraint. The raw materials and equipment constraint is persistently lower than the labor constraint (Figure 2), so assigning a positive weight to the former results in

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.

a lower *LEK excess* constraint gap compared to *L excess*. In our calibration, we set a relative weight of 25 percent for the raw materials and equipment constraint. A larger weight would exert more downward pressure on the constraint gap, consequently leading to a lower estimated output gap.

Regarding the third constraint gap index based on *K excess*, it consistently remains negative throughout the observed period (see Figure 3). This persistent negativity can be primarily attributed to the consistently low values of the equipment and raw materials constraint, as illustrated in Figure 2.

In our subsequent analysis, we omit the presentation and examination of the output gap-based *K excess* for two reasons: (i) 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 (ii) the data strongly indicate that the constraint on equipment and raw materials is not binding over the entire sample period (as shown in Figure 2). 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 constraint 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.

3.3.1 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:

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

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 constraint gap index ($Excess_t$) to derive the output gap. We consider separately two types of constraint gap indices: *L excess* or

L&K excess. The unobserved output gap is linked to the chosen index with a scaling factor Υ . This relationship is expressed as

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

The residuals ξ_t^{excess} capture the measurement errors in the constraint 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 constraint gap index is unknown a priori and depends on the variance of the residuals σ_{excess}^2 .

3.3.2 State Equations

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

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

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

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

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 $AR(1)$:

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

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 Hodrick-Prescott (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, $(\frac{\sigma_{ygap}^2}{\sigma_g^2})$, one can replicate most of the univariate approaches. Under the assumption that $\Upsilon = 0$, the standard models are nested

Table 1. Estimation Results of
State-Space Model, 2013:Q1–2025:Q1

Estimated Parameter/ Constraint Gap Index	L_{excess}	$L\&K_{excess}$	Standard Model
	(1)	(2)	(3)
Υ	4.03 (0.431)	4.21 (0.393)	0
β	0.821 (0.082)	0.754 (0.099)	0.7497 (0.1364)
σ_{excess}	0.092 (0.011)	0.086 (0.0096)	0.1972 - 0.209***
σ_g	0.0011 (0.0005)	0.001 (0.0004)	0.0009 (0.0003)
σ_{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 constraint gap index L_{excess} and $L\&K_{excess}$, respectively. Column 3 presents the estimation results using the KF of the state-space standard model based only on actual output (excluding constraint gap index). ***The reported values are the standard deviations of the two excess-demand indices in the data under the assumption that they contain only noise in the standard model.			

within our state-space framework. In this case, when $\Upsilon = 0$, the constraint 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 the Kalman filter by maximum likelihood. Table 1 presents the estimation results. Column 1 shows the case where the constraint gap index is $Excess_t = L_{excess}$, while column 2 shows the case where the constraint gap index is $Excess_t = L\&K_{excess}$. Column 3 presents a nested model in which both constraint gap indices are constrained to be pure noise, which simplifies the model to a univariate standard model.

The most important parameters in our analysis are the scaling parameter, Υ , and the standard error (SE) of residuals, σ_{excess} . For both constraint gap indices, we obtain Υ values close to 4 and σ_{excess} values close to 0.09. The SE of both constraint gap indices is approximately 0.2 (as shown in column 3 of Table 1). This implies that about 60 percent of the variation of the constraint gap indices in terms of SE can be attributed to the output gap, while the remaining 40 percent 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 [$0.25 = 1/(\Upsilon = 4)$].⁷

To quantify the impact of incorporating the constraint gap index ($Excess_t$) into the model, we conduct a likelihood ratio test (LRT). The LRT statistic is calculated as $2 \times (LL^{OurModel} - LL^{Nested})$, where $LL^{OurModel}$ 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 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 percent significance level. Thus, we conclude that the inclusion of the constraint gap index in the model significantly contributes to the output gap estimate.

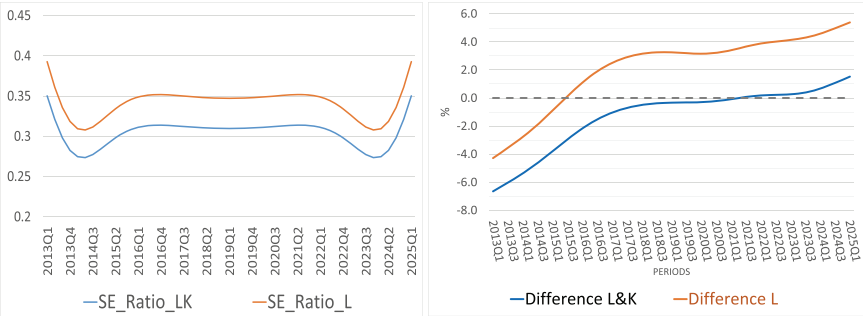
We aim to demonstrate the contribution of the constraint gap index in two ways: First, we analyze its impact on the output gap estimation by examining (i) how it affects the smoothed estimator of the output gap, and (ii) how it influences the uncertainty of this smoothed estimator.⁸ Second, we illustrate its effectiveness in

⁶As 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.

⁷For 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.

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

Figure 4. Contribution of the Constraint Gap Index to the Output Gap Estimation (smoothed point estimate and standard error), 2013:Q1–2025:Q1



Note: The left-hand panel 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. The right-hand panel displays the ratio of standard errors (SEs) 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).

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 4 (left-hand panel) 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 4 shows that both constraint gap indices 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

⁹The standard model’s output gap estimate (Table 1) is similar to that from the HP filter.

is attributable to L_{excess} being consistently greater than $L\&K_{excess}$ (as illustrated in Figure 3).

Figure 4 (right-hand panel) illustrates the ratio of the SE of the smoothed output gap estimate from our model to that of the standard model (Table 1). The graph demonstrates that incorporating the constraint gap indices into our model significantly reduces the SE of the output gap estimate, with the reduction ranging from 60 percent to 70 percent.

3.4 Economic Impacts of the COVID-19 Pandemic and Recent Military Conflict

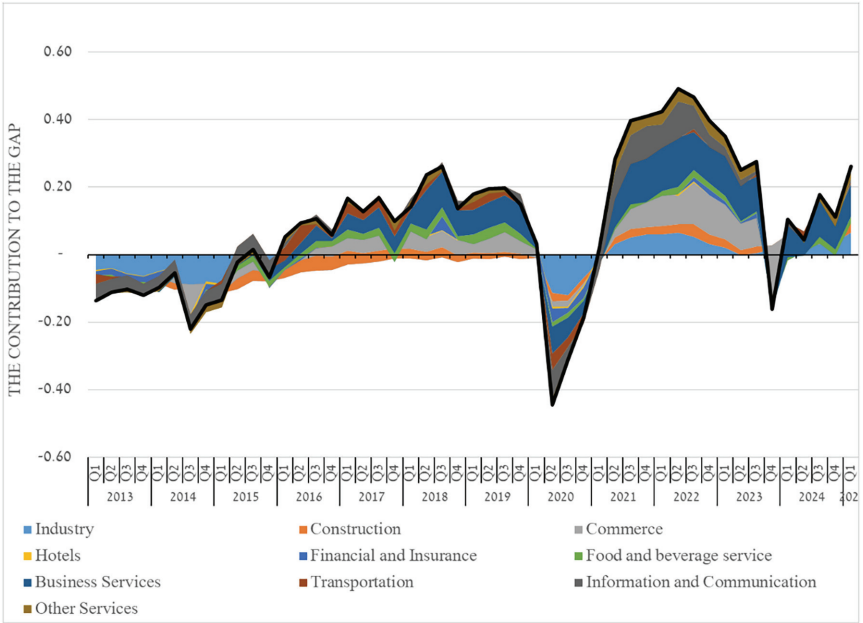
3.4.1 COVID-19 Period

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 is 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

Figure 5. Sectoral Contributions to the Gap between Labor Supply and Demand Constraints, 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.

economy in 2020, the demand constraint reacted more severely than the labor supply constraint, resulting in excess supply (Figure 3).

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 2). Consequently, the COVID-19 recovery period displayed excess demand, as measured by the difference between the labor supply constraint and the demand constraint.

Figure 5 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.

It is interesting to observe how the literature addresses the derivation of the 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 vector autoregression (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 Maria (2024) derived the output gap from a semistructural state-space model, in which pandemic innovations were imposed into several model equations, in addition to standard innovations. Barigozzi, Lissona, and Luciani (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 Military Conflict in 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 2). 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 2). 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 the 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 5). Both sectors experienced intensified supply constraints. Conversely, the commerce sector exhibited the most significant negative contribution, primarily due to an increase in the demand constraint.

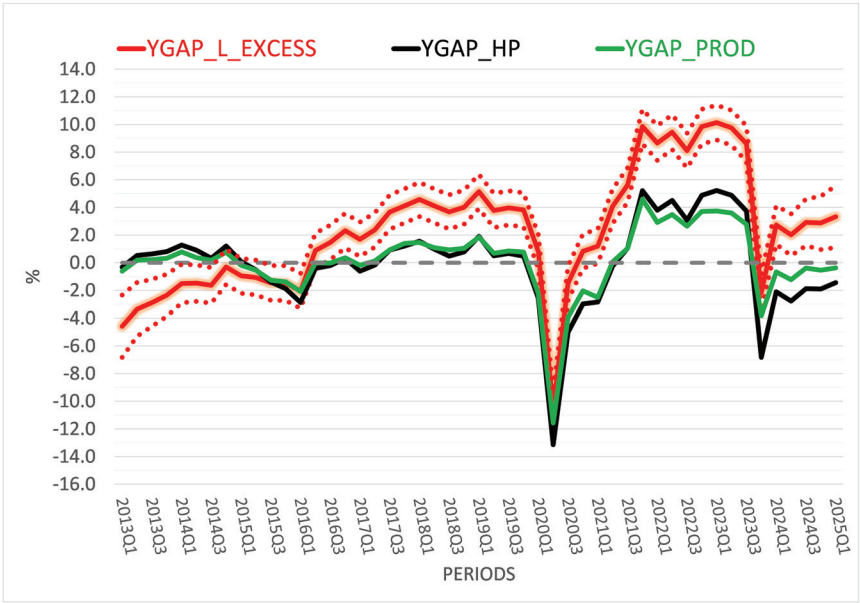
4. Empirics

4.1 Evolution of Different Output Gap Estimates

Figure 6 illustrates the evolution of three estimates of the output gap in Israel from 2013:Q1 through 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 HP filter, using a smoothing

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

Figure 6. Different Measures of the Output Gap, 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.

parameter of 1,600. 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

¹¹The 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 and 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

data shows a strong correlation with the other two measures of the output gap. However, there are notable periods of divergence.

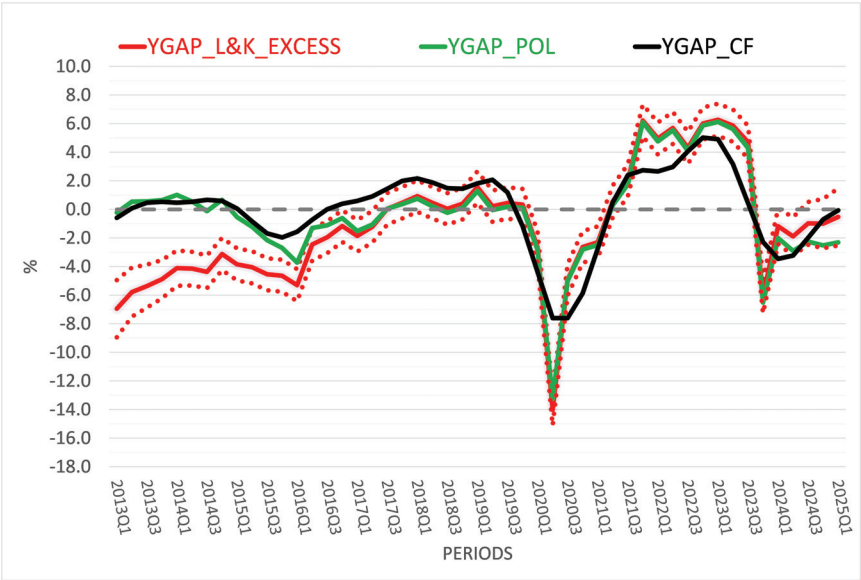
At the start of the sample period, *YGAP_L_EXCESS* shows lower values compared to the other two measures. However, for most of the subsequent period, it exhibits higher values than *YGAP_HP* and *YGAP_PROD*. This difference is particularly pronounced during two key periods: the recovery phase following the COVID-19 crisis and the conflict in Israel in 2024. The divergent behavior can be attributed to the constraint gap, as illustrated in Figure 3. 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 7 presents two additional statistical measures of the output gap. The first measure, *YGAP_POL*, is derived from a polynomial trend, while the second, *YGAP_CF*, employs the bandpass filter of Christiano and Fitzgerald (2003) with a 6- to 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 3.

Figure 8 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 constraint gaps previously observed in Figure 3. Notably, the graph reveals divergent interpretations of economic conditions in 2024. According to *YGAP_L_EXCESS*, there was significant excess demand during this period. In contrast, *YGAP_L&K_EXCESS*, while showing an

“HP” means that they are detrended by the HP filter with a smoothing factor of 1,600. The log of capital utilization (u) is demeaned by long-term average.

Figure 7. Additional Measures of the Output Gap, 2013:Q1–2025:Q1

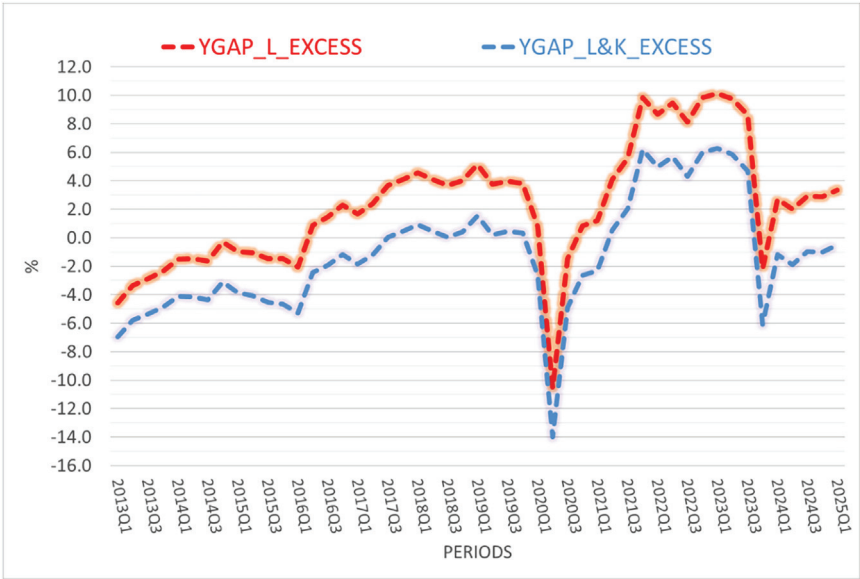


Note: The figure displays three output gap estimates: *YGAP_L&K_EXCESS* (red line, with dashed lines indicating the confidence interval), estimated using a state-space model based on the survey’s index of excess demand, *L&K_{excess}*; *YGAP_CF* (black line), derived from the Christiano and Fitzgerald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

upward trend, indicates that the output level remained close to equilibrium (near zero).

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.

Figure 8. Comparison of Output Gap Measures Derived from Survey Data, 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}*.

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 policy-makers 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 microfoundations—specifically, the responses provided by numerous company managers regarding their own firms. In this sense, it shares a microfounded 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, Galí, and Gertler (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, Paloviita, and Viren (2016) showed that PF expectations improve model performance. Similarly, Smets, Warne, and

Wouters (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:

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

where $\pi_t^j = [\pi_t^a, \pi_t^b, \pi_t^c, \pi_t^p]$ 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, and π_t^p is quarterly producer price inflation. All inflation data are seasonally adjusted. $ygap_t^{type}$ is a set of six output gap versions considered. Two first measures of the output gap are derived from the Business 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_{adj}^2). 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

Table 2. Estimated Effect of Various Measures of the Output Gap in Equation (6), 2013:Q1–2025:Q1

Parameter ϑ /Type of Inflation	π_t^a	π_t^b	π_t^c	π_t^p
<i>YGAP_L_EXCESS</i> ($p = 8, 10, 10, 1$)	0.06 (0.00), 7%	0.11 (0.00), 13.1%	0.03 (0.00), 9.5%	0.07 (0.04), 2.6%
<i>YGAP_L&K_EXCESS</i> ($p = 8, 10, 10, 1$)	0.06 (0.01), 6.9%	0.12 (0.00), 12.8%	0.09 (0.00), 9.0%	0.07 (0.04), 2.7%
<i>YGAP_HP</i> ($p = 6, 8, 3, 1$)	0.02 (0.04), 3.5%	0.05 (0.07), 1.2%	-0.06 (0.17), 0.8%	0.04 (0.06), 2.0%
<i>YGAP_POL</i> ($p = 8, 10, 10, 1$)	0.09 (0.01), 5.8%	0.17 (0.00), 7.7%	0.15 (0.02), 6.1%	0.04 (0.07), 2.0%
<i>YGAP_PROD</i> ($p = 6, 8, 3, 1$)	0.04 (0.08), 1.6%	0.07 (0.19), -2.1%	-0.05 (0.25), -0.6%	0.07 (0.03), 3.1%
<i>YGAP_CF</i> ($p = 4, 4, 10, 3$)	-0.05 (0.03), 4.8%	-0.05 (0.05), 3.4%	0.01 (0.02), 4.6%	-0.09 (0.13), 0.9%
R_{adj}^2 (basic)	61%	60%	43%	68%

Note: In the table, each row contains three values: (i) the estimated cumulative effect of the output gap on inflation $\sum_{i=0}^P \delta_i$ in Equation (6); (ii) the p-value of the likelihood-ratio test, which tests the redundancy of the output gap in the regression (in parentheses); and (iii) 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 (basic) when the output gap is omitted from Equation (6).

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.

However, our newly introduced output gap measure (*YGAP_L_EXCESS* or *YGAP_L&K_EXCESS*) outperforms the polynomial approach in terms of boosting the regression's explanatory power, contributing to R_{adj}^2 between 2.6 percent and 13.1 percent—depending on the inflation measure used. The newly introduced output gap measure has a high contribution to CPI inflation excluding housing and fruit and vegetables and a small contribution to producer price inflation (Table 2).

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:

$$\begin{aligned}\pi 4_t^j = & c + \alpha \Delta s_MA(p)_t + \beta \pi_MA^{imp}(p)_t \\ & + \vartheta ygap_MA(p)_t^{type} + u_t,\end{aligned}\tag{7}$$

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

Table 3 presents the estimation results. The survey-based measures of the output gap show a substantially higher contribution to inflation compared to Table 2. For the first three types of inflation, the contribution is particularly significant, approaching 20 percent. However, for producer price inflation, the survey-based measure's contribution is slightly lower compared to other output gap measures. 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 percent of the variation. This high explanatory power inherently limits the potential contribution of any type of output gap measure from the outset.

Table 3. Estimated Effect of Various Measures of the Output Gap in Equation (7), 2013:Q1–2025:Q1

Parameter ϑ /Type of Inflation	$\pi 4_t^a$	$\pi 4_t^b$	$\pi 4_t^c$	$\pi 4_t^p$
<i>YGAP_L_EXCESS</i> ($p = 9, 10, 9, 2$)	0.09 (0.00), 22%	0.10 (0.00), 21.4%	0.08 (0.00), 20.6%	0.02 (0.41), 0.5%
<i>YGAP_L&K_EXCESS</i> ($p = 10, 9, 9, 2$)	0.10 (0.00), 22.2%	0.11 (0.00), 21.5%	0.09 (0.00), 20.7%	0.03 (0.42), 0.6%
<i>YGAP_HIP</i> ($p = 10, 10, 10, 3$)	0.15 (0.00), 10.3%	0.15 (0.00), 8.1%	0.11 (0.00), 7.5%	0.05 (0.24), 1.0%
<i>YGAP_POL</i> ($p = 10, 10, 10, 3$)	0.17 (0.00), 20.9%	0.18 (0.00), 18.4%	0.14 (0.00), 19.0%	0.06 (0.23), 1.2%
<i>YGAP_PROD</i> ($p = 10, 10, 10, 3$)	0.17 (0.00), 11.2%	0.18 (0.00), 9.3%	0.13 (0.00), 8.1%	0.07 (0.15), 1.1%
<i>YGAP_CF</i> ($p = 10, 10, 10, 1$)	0.10 (0.08), 4.2%	0.10 (0.12), 2.9%	0.06 (0.18), 1.9%	0.05 (0.07), 1.0%
R_{adj}^2 (basic)	60%	61%	54%	91%

Note: In the table, each row contains three values: (i) the estimated parameter of the output gap (ϑ) in Equation (7); (ii) the p-value of the Newey-West corrected t-test (in parentheses); and (iii) the contribution of the output gap to the explanatory power, R_{adj}^2 . For each inflation type ($\pi 4_t^i$), we optimized the number of lags for the output gap, exchange rate, and import prices to maximize R_{adj}^2 . The optimal number of lags for the exchange rate and import prices was consistently four 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_{adj}^2 (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.

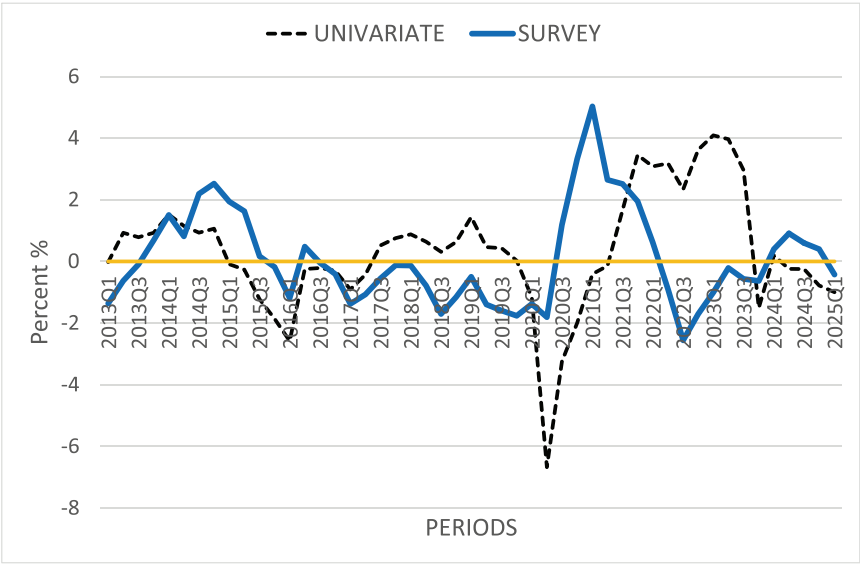
Our procedure involves two key steps. First, we calculate the revision in the output gap derived from the univariate standard model (Table 1, column 3) by comparing the smoothed estimate (based on full sample and final vintage GDP data) with the filtered estimate (based on real-time and first vintage GDP data). Second, we perform a similar calculation for our model, which incorporates the excess demand index from the survey (Table 1, column 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, Berge, and Stella 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, Berge, and Stella (2024) suggest improving the end-sample problem by including an Okun's law relationship. Similarly, Chalmovianský and Némec (2022) demonstrate that multivariate structural approaches outperform nonstructural 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

¹²To 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.

Figure 9. Comparison of Output Gap Revisions—Univariate Model vs. Survey-Based Model



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.

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 an 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 a big sample significantly reduces the magnitude of revisions to the output gap estimates.

Returning to our analysis, Figure 9 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 percent, lower than the 1.93 percent observed in the univariate model. Furthermore, the cumulative revisions in our model amount to 4.2 percent, substantially less than the 16.4 percent in the standard model and an average revision of 0.09 percent in our model, compared to 0.33 percent in the standard model.

It is particularly noteworthy to examine the revisions during the COVID-19 period. The univariate model exhibited a significant “zigzag” 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 percent to 6 percent. Subsequently, as the recovery phase unfolded in 2022, the model showed large positive revisions of 3 percent to 4 percent.

In contrast, our model shows moderate revisions of 1.8 percent at most during the 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 percent. 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. These survey data, by nature, are not subject to revisions. Moreover, they provide valuable real-time information about excess demand or supply conditions in the economy.

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: (i) easy implementation; (ii) separate estimation of demand and supply constraints as distinct sources of the output gap; and (iii) 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.

Data availability: Data are available on request.

Appendix A. Calculation of Supply and Demand Constraints from the 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. Subsequently, for each sector, a simple average of these company-level averages is computed.

For each of the 10 sectors, we calculate the average constraint level by taking the simple mean 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 10 surveyed sectors.

Two weighting schemes are employed:

- (i) time-varying shares, recalculated annually from 2013 through 2024 to capture each sector's evolving share of business GDP
- (ii) 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, 2013–24.

Table A.1. 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. Effects of Demand and Labor Supply Constraints on Inflation

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:

$$\begin{aligned} \pi 4_t^j = & \alpha \Delta s_MA(p)_t + \beta \pi_MA^{imp}(p)_t + \tau_1 L_{MA(p)_t}^{const} \\ & + \tau_2 D_{MA(p)_t}^{const} + \varepsilon_t, \end{aligned}$$

(B.1)

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, and $L_{MA(p)_t}^{const}$ 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 (higher supply constraint represents a negative shift in supply, pushing inflation up), while the demand constraint coefficient is negative (higher demand constraint represents a negative shift in demand, pushing inflation down). Both coefficients are highly significant. The Wald test for equality of the two parameters (in absolute value) indicates that we cannot reject the null hypothesis of equal impacts at the 10 percent significance level for any of the inflation types examined.

Table B.1. Estimated Separate Effect of the Labor Supply Constraint and Demand Constraints in Equation (B.1), 2013:Q1–2025:Q1

Parameter ϑ /Type of Inflation	$\pi 4_t^a$	$\pi 4_t^b$	$\pi 4_t^c$	$\pi 4_t^p$
L_MA^{const}	1.51 (0.00)	1.82 (0.00)	1.29 (0.00)	1.15 (0.01)
D_MA^{const}	−1.31 (0.00)	−1.83 (0.00)	−1.05 (0.00)	−1.04 (0.05)
p-value of Wald Test $\tau_1 + \tau_2 = 0$	0.05	0.07	0.06	0.10

Note: For each inflation type ($\pi 4_t^i$), the table presents two values: (i) the estimated parameter of the labor supply constraint on inflation, and (ii) 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 ($R_{adj.}^2$). The number of lags for both labor supply and demand constraints was set equally.

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