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LUCI: Your Best Friend for Measuring Labor Market Tightness

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Jan Brůha, Adam Ruschka, and Jan Šolc *

Abstract

Which labor market variable best describes labor market developments? What if one series suggests the labor market is tight, while another suggests a different story? To address these questions, we propose a composite index of labor market tightness called the LUCI: the Labor Utilization Composite Index. Its goal is to represent the overall cyclical position of the labor market. From a technical point of view, the LUCI is defined as the first generalized dynamic principal component of the cyclical parts of the labor market variables considered. These cyclical parts are filtered from the data using a multivariate filter that decomposes the data into fundamental cyclical developments, trends, and noise. In addition to being an indicator of overall labor market tightness, we show that the LUCI is a useful analytical tool. The LUCI serves as a measure of economic slack that is useful for the estimation of empirical price and wage Phillips curves. Moreover, based on the LUCI, we construct a measure of demand-driven inflation, called 'supercyclical inflation', which helps disentangle demand- and supply-driven inflation pressures. The LUCI thus enriches the set of analytical tools available to the Monetary Department of the CNB.

Abstrakt

Která veličina trhu práce nejlépe vystihuje vývoj na pracovním trhu? A co když jedna časová řada indikuje, že trh práce je napjatý, zatímco podle jiné je situace odlišná? Abychom mohli na tyto otázky odpovědět, navrhujeme souhrnný indikátor napětí na trhu práce s názvem LUCI (Labor Utilization Composite Index). Cílem tohoto indikátoru je zachytit celkovou cyklickou pozici trhu práce. Z technického hlediska je LUCI definován jako první generalizovaná dynamická hlavní komponenta cyklických složek uvažovaných veličin trhu práce. Tyto cyklické složky jsou filtrovány z dat pomocí vícerozměrného filtru, který data rozkládá na fundamentální cyklický vývoj, trendy a šum. V této práci také dokládáme, že vedle své funkce indikátoru celkového napětí na trhu práce je LUCI rovněž užitečným analytickým nástrojem. LUCI slouží jako ukazatel nevyužitých kapacit, který lze použít pro odhad mzdové a cenové empirické Phillipsovy křivky. Na základě indikátoru LUCI navíc konstruujeme měřítko poptávkové inflace, tzv. „supercyklickou inflaci", s jejíž pomocí lze oddělit poptávkové a nabídkové inflační tlaky. LUCI tak obohacuje sadu analytických nástrojů, které má sekce měnová v ČNB k dispozici.

JEL Codes: E24, E31, E37.
Keywords: Labor market, cyclical position, demand-driven inflation.

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1. Introduction

The labor market plays a crucial role in driving domestic inflationary pressures. To achieve the objective of price stability, it is therefore of utmost importance for a forward-looking central bank to monitor labor market tightness. A comprehensive assessment of the cyclical position of the labor market may be difficult when individual time series send conflicting signals. This may happen especially during turbulent times or periods of unusual shocks, when variables may react with different intensities and timing. The problem of aggregating individual signals then arises.

In addition to the issue of weighting potentially conflicting messages from different labor market variables, the signals may be hard to infer, as a movement in a particular variable could be caused by a reaction to a cyclical shock, a permanent movement unrelated to the business cycle (government regulation or demography), pure noise or simply a mismeasurement. A comprehensive index may be able to suppress non-fundamental movements that can obscure a particular series.

In this paper, we propose a comprehensive aggregate labor market indicator, called the LUCI (Labor Utilization Composite Index), and demonstrate its usefulness in addressing the aforementioned challenges. As far as the authors are aware, this is the only indicator of its kind for the Czech economy, and only a limited number are available for other economies. The primary goal of our proposed indicator is to aggregate information about the cyclical position of the labor market.

Another challenge for monetary policy lies in the identification of the sources of inflationary pressures. There is no straightforward and universally-accepted methodology that would address the question of the decomposition of inflation into demand and supply (or other) pressures. In this paper, we show that the LUCI can be helpful in this task. Given that the labor market is largely related to domestic demand, the LUCI can be used for monitoring not only inflationary pressures stemming from the labor market, but also those originating from the overall demand environment. In addition, we demonstrate that the LUCI can also serve as an alternative indicator of overall economic slack. The LUCI performs well if used in the estimation of price and wage empirical Phillips curves.

The LUCI aggregates information about the cyclical position of a large number of time series into a single index. To achieve this, the model behind the LUCI decomposes the time series into their trend and cyclical components using the simultaneous multivariate Kalman filter. We therefore do not rely on time series prefiltering using a univariate statistical filter. Multivariate filtration increases the efficiency of the trend-cyclical decomposition compared to the use of unrelated univariate filters. The reason is that under multivariate filtration, the identification of the cyclical component of a particular time series depends also on the movements in other series. For example, if many time series comove in a given period, the multivariate filter can take this into account, resulting in a potentially more precise identification of the cycle than if univariate filters are used.

The LUCI aggregates the cyclical parts using a generalized principal component analysis. This approach has not been previously utilized in the context of the aggregate labor market indicator[1]. The model behind the LUCI is formulated as a state-space model, and therefore, the Kalman filter

[1] Methodologically, the closest approach to ours is the one used by Andrle and Brůha (2017) and by Pierluigi et al. (2011). Andrle and Brůha (2017) argue that movements in the trend and cyclical parts of economic variables are likely driven by different sets of drivers and should therefore be modeled and estimated separately. The model behind the LUCI fits into this agenda. Pierluigi et al. (2011) propose an empirical model for the six largest EA economies that treats trends and cycles separately. However, the motivation for and formulation of their model differ from the model behind the LUCI.

machinery can trivially overcome many issues such as missing data, asynchronous data release, and so on. The Kalman filter can also be easily used to incorporate expert judgments.

The LUCI has been under development over the past few years. The first version by Šolc (2017) was essentially the first static principal component analysis applied cyclical components of time series, where the cyclical components were obtained by applying a univariate statistical filter. Šolc and Brůha (2019) then extended the LUCI to a dynamic framework and incorporated multivariate filtration. Since then, the time series entering the model have changed several times and the model has been reformulated and re-estimated. These changes reflected the CNB staff's growing experience with the indicator. This paper presents the current version of the LUCI which is used at the CNB's Monetary Department on a regular basis.[2]

The rest of the paper is organized as follows. The next section 2 reviews the related literature. Section 3 presents the data that enter the LUCI. Section 4 describes the model behind the LUCI and discusses its estimation. Section 5 provides selected applications of the LUCI index conducted at the CNB. The final section 6 concludes.

2. Literature Review

The literature on labor market composite indicators is relatively limited. There are, nonetheless, several papers that serve as an inspiration for us and several papers whose results can be compared to ours.

One of the inspirations was the Kansas City Fed's Labor Market Conditions Indicator (LMCI) described by Hakkio and Willis (2013). The LMCI utilizes twenty-six variables to construct two distinct indicators. The first indicator is designed to describe the level of activity in the labor market, representing the deviation from long-term averages. Meanwhile, the second indicator assesses the rate of change, reflecting the speed of labor market improvement or worsening. Static principal component analysis is employed to derive both measures, yielding the Level of Activity and Rate of Change indicators as the first two computed factors, respectively. Hakkio et al. (2014) demonstrate that their indicator proves to be valuable not only in describing the cyclical position of the economy but also in predicting the future development of the labor market.[3] A similar application of principal component analysis on the same task has been conducted by Zmitrowicz and Khan (2014) from the Bank of Canada. Another interesting example of a composite labor market index was described by Salamaliki (2019). In his paper, Salamaliki uses a dynamic factor model to estimate labor market conditions indicators (LMCI) for Greece. He shows that using the unemployment rate alone to describe the situation on the labor market can be misleading. Baker and Ball (2018) have conducted a thorough overview of labor market indices used by central banks.

Another noteworthy indicator is presented by Armstrong et al. (2016). Their motivation is similar to ours, aiming to derive a reliable indicator that describes the labor market effectively, even when faced with conflicting movements across variables or non-fundamental changes in individual variables. Their labor utilization composite index comprises seventeen variables and, similarly to the approach used in Hakkio and Willis (2013), it is computed using static principal component

[2] The CNB's staff also estimated a simplified version of the LUCI for selected EU countries, see Brůha et al. (2021a). As an avenue for future research, it would be worth considering estimating a more elaborated version of the LUCI for countries other than the Czech Republic.

[3] The same methodology was used by Vasco Botelho and António Dias da Silva in Economic Bulletin Issue 8, 2019 of the European Central Bank in estimating their composite index.

analysis. Armstrong et al. (2016) demonstrate that the results are robust to the exclusion of individual time series and to the estimation period. From the data perspective, out of the seventeen variables, only two pertain to the nominal aspect of the labor market, specifically nominal unit costs and average hourly earnings.

Labor market indexes are obviously not just interesting for central banks, but for other institutions as well. An example is the Conference Board Employment Trends Index (ETI) [4], which aggregates eight labor market indicators to reveal underlying trends in employment conditions. The authors of the ETI methodology focus on variables that exhibit strong predictive power for employment, specifically emphasizing leading indicators. This means that the ETI is forward-looking rather than describing the current state. This may be the reason there is no time series originating from the nominal part of the labor market in the ETI.

Another example of the usefulness of a composite labor market indicator is the 2019–2020 Hayes Global Skills Index.[5] A notable aspect of this index is its division of the seven indicators into supply-side and demand-side variables, which are subsequently combined. Utilizing a consistent methodology across the cross-country data set enables insightful international comparisons.

Finally, it has been shown that a properly constructed labor market index can be useful for empirical models of inflation. For example, Conti (2021) presents an aggregated index of financial and labor market indicators and shows that it works well for explaining inflation when used in the Phillips curve instead of the conventional output or unemployment gap.

3. Data Description

All variables that enter the LUCI are of quarterly frequency. The sample starts in 2000. Although several time series start later, all time series are available from 2005 onwards. Furthermore, all time series have undergone seasonal adjustments to remove any seasonal variations. The time series are also screened for outliers before the computation of the index (and before the estimation as well). We apply a robust version of the LOESS method (Cleveland, 1979) to identify outliers. Observations identified as outliers are not used for filtration[6].

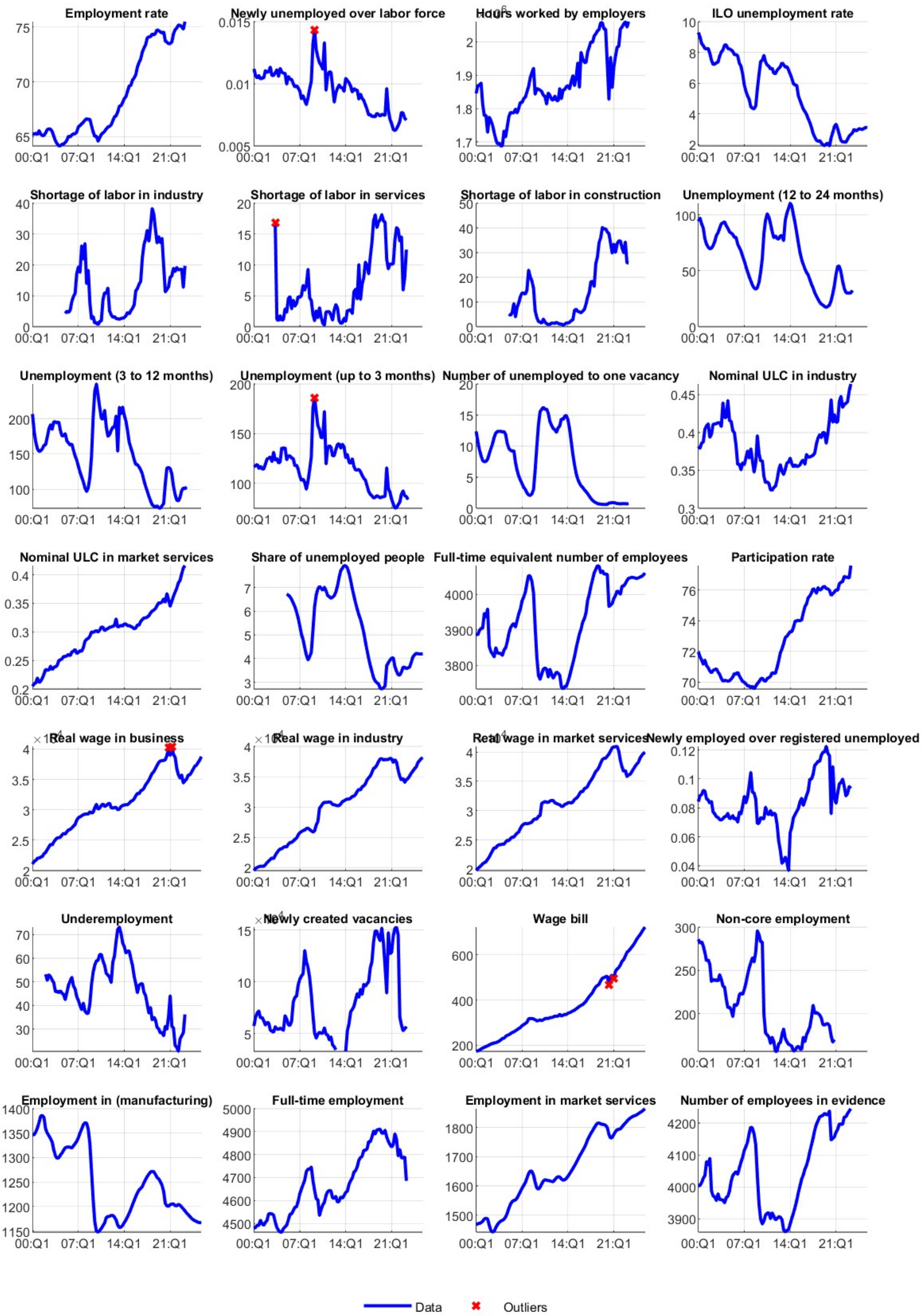
The selection of variables was primarily determined by the data availability and its potential predictive capacity and economic significance. The variables can be broadly categorized into two main groups: those pertaining to the real aspect of the labor market and those related to wages.

Table 1 provides a detailed summary of the variables used, along with its source, the category and the assumed trend, which is crucial for the construction of the underlying model (see next section). Figure 1 then displays the individual time series along with the observations identified as outliers.

The real part of the labor market encompasses indicators that track employment, unemployment, and overall workforce movements. Additionally, it includes variables that describe factors such as the amount of time spent working, the number of job vacancies, and the level of labor force

[4] As of now, there are no published papers available on the ETI; however, additional information can be accessed on the following web page: https://www.conference-board.org/data/eti.cfm.
[5] For further information, please refer to the following web page: https://www.oxfordeconomics.com/resource/the-hays-global-skills-index-2019-2020/.
[6] As the model is formulated in the state-space framework, missing data are straightforwardly handled using the Kalman filter.

Figure 1: Time Series Entering the LUCI



Source: Authors' calculations

Table 1: Overview of All the Variables in the LUCI

Variable	Source	Category	Trend
Employment rate	Labor Force Sample Survey of CZSO	real	I(1)
Newly unemployed over labor force	MoLSA, CZSO and CNB calculations	real	I(1)
Hours worked by employees	National accounts CZSO	real	I(1)
ILO unemployment rate	Labor Force Sample Survey of CZSO	real	I(1)
Shortage of labor limiting production in industry	European Commission	real	I(1)
Shortage of labor limiting production in services	European Commission	real	I(1)
Shortage of labor limiting production in building	European Commission	real	I(1)
Unemployment (12 to 24 months)	MoLSA	real	I(1)
Unemployment (3 to 12 months)	MoLSA	real	I(1)
Unemployment (up to 3 months)	MoLSA	real	I(1)
Number of unemployed to one vacancy	MoLSA	real	I(1)
Share of unemployed people	MoLSA	real	I(1)
Full-time equivalent number of employees	Wage statistics of CZSO	real	I(1)
Participation rate	Labor Force Sample Survey of CZSO	real	I(2)
Newly employed over registered unemployed persons	MoLSA and CNB calculations	real	I(1)
Underemployment	CZSO	real	I(1)
Newly created vacancies	MoLSA	real	I(1)
Non-core employment	Labor Force Sample Survey of CZSO	real	I(1)
Employment in (manufacturing) industry	CNB calculations	real	I(1)
Full-time employment	CNB calculations	real	I(1)
Employment in market services	CNB calculations	real	I(1)
Number of registered employees	Wage statistics of CZSO	real	I(1)
Nominal unit labor costs in industry	National accounts CZSO	wage	I(2)
Nominal unit labor costs in market services	National accounts CZSO	wage	I(2)
Real wage in the business sector (adjusted)	CNB calculations	wage	I(2)
Real wage in industry	CNB calculations	wage	I(2)
Real wage in market services	CNB calculations	wage	I(2)
Wage bill	National accounts CZSO	wage	I(2)

participation. Furthermore, variables that indicate demand for labor, such as shortages of labor limiting production in specific industries, were also considered in the analysis.[7] [8] [9]

The wage part of the labor market comprises variables that encompass various aspects of labor costs. These variables include (real) wages, the wage bill, and nominal unit costs. The disparity in the number of variables between the real part and the wage part of the labor market is primarily attributed to data availability. Nonetheless, it is reasonable to assume that any overheating in the real part of the labor market will swiftly influence wage negotiations. As a result, overall labor market tightness should not be subject to bias, as the effects are interconnected and responsive to changes in each other.

[7] The difference between the Full-time employment and the Registered no. of employees variables is the length of their monthly workload. For example, two registered employees working half-time will constitute one full-time equivalent employee.
[8] Underemployment, as defined by the standard ILO definition, is the underutilization of the productive capacity of the employed population, including those arising from a deficient national or local economic system. It relates to an alternative employment situation in which persons are willing and available to engage.
[9] The variables for labor shortage limiting production come from the business cycle surveys conducted by the CZSO.

4. Model

In this part of the paper, we describe the model behind the LUCI. The starting point is the linear state-space framework, where each time series that enters the LUCI x_{it} is decomposed into the trend component $\bar{x}_{it}$ and the cyclical component $\widehat{x}_{it}$:

$$x_{i,t} = \bar{x}_{i,t} + \widehat{x}_{i,t}.$$

In what follows, denote the vector of the observed time series by $\mathbf{x} = [x_{1,t}, \dots x_{I,t}]^T$, the vector of the trend components by $\bar{\mathbf{x}} = [\bar{x}_{1,t}, \dots \bar{x}_{I,t}]^T$, and the vector of the cyclical components by $\widehat{\mathbf{x}} = [\widehat{x}_{1,t}, \dots \widehat{x}_{I,t}]^T$.

The trend part is modeled either as a random walk, i.e., $I(1)$ process, or as a random walk with drift, which is another random walk, i.e., the trend is an $I(2)$ process.[10] The set of variables for which the $I(1)$ trend is assumed is denoted as J_1, while the set of variables whose trends follow the $I(2)$ process is denoted as J_2. The last column in Table 1 provides information about the assumed trend dynamics for particular variables.

Hence, we have

$$\bar{x}_{i,t} = \bar{x}_{i,t-1} + \bar{\sigma}_i \bar{\varepsilon}_{i,t},$$

for $i \in J_1$ and

$$\bar{x}_{i,t} = \bar{x}_{i,t-1} + \bar{\bar{x}}_{i,t-1},$$

$$\bar{\bar{x}}_{i,t} = \bar{\bar{x}}_{i,t-1} + \bar{\sigma}_i \bar{\varepsilon}_{i,t},$$

for $i \in J_2$.

The innovations $\bar{\varepsilon}_{i,t}$ to the trends are assumed to be i.i.d., with zero mean, unit standard error and independent across time series.

The cyclical components of the model are linked by a stationary VAR(2) model:

$$\widehat{\mathbf{x}}_t = \mathbf{A}_1 \widehat{\mathbf{x}}_{t-1} + \mathbf{A}_2 + \widehat{\mathbf{x}}_{t-2} + \widehat{\Sigma} \widehat{\varepsilon}_t.$$

The whole state equation of the model then reads as follows [11]:

$$\begin{bmatrix} \bar{\mathbf{x}}_t \\ \bar{\bar{\mathbf{x}}}_t \\ \widehat{\mathbf{x}}_t \\ \widehat{\mathbf{x}}_{t-1} \end{bmatrix} = \begin{bmatrix} \mathbf{I} & \mathbf{J} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{A}_1 & \mathbf{A}_2 \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I} \end{bmatrix} \begin{bmatrix} \bar{\mathbf{x}}_{t-1} \\ \bar{\bar{\mathbf{x}}}_{t-1} \\ \widehat{\mathbf{x}}_{t-1} \\ \widehat{\mathbf{x}}_{t-2} \end{bmatrix} + \begin{bmatrix} \bar{\Sigma}_1 \bar{\varepsilon}_t & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \bar{\Sigma}_2 \bar{\varepsilon}_t & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \widehat{\Sigma} \widehat{\varepsilon}_t & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad (1)$$

[10] See Harvey and Jaeger (1993) for the versatility of this process.
[11] Analogically to $\bar{\mathbf{x}}$ and to $\widehat{\mathbf{x}}$, denote the vector of drifts for J_2 series as $\bar{\bar{\mathbf{x}}} = [\bar{\bar{x}}_{j_1,t}, \dots \bar{\bar{x}}_{j_J,t}]^T$, where j_1 is the first component of J_2 and j_J is its last component.

and the observation equation reads as:

$$\mathbf{x}_t = \begin{bmatrix} \mathbf{I} & \mathbf{0} & \mathbf{I} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \bar{\mathbf{x}}_t \\ \bar{\bar{\mathbf{x}}}_t \\ \widehat{\mathbf{x}}_t \\ \widehat{\mathbf{x}}_{t-1} \end{bmatrix} + \Omega v_t, \tag{2}$$

where $\mathbf{J}$ is the matrix that maps drifts to trends for variables in J_2, and v_t is the observation noise, with Ω as its covariance matrix (assumed to be diagonal).

The decomposition of all series to trend and cyclical components is multivariate and the system is linked through the cyclical part. It is assumed (and ex-post verified[12]) that there is a lot of comovement in the cyclical parts of the time series.[13] The Kalman filter machinery can be used to deal with missing data and/or to incorporate expert judgments[14].

The state-space model (1) - (2) depends on unknown parameters that have to be estimated. These parameters enter $\mathbf{A}_1$, $\mathbf{A}_2$, $\bar{\Sigma}$, $\widehat{\Sigma}$, and Ω. We estimate them using the stochastic EM algorithm (Nielsen, 2000).

The LUCI indicator is then defined as the first generalized dynamic principal component of the cyclical parts (Peňa and Yohai, 2016). We use the generalized dynamic principal component to deal with possible lead-lag relationships in the data. In other words, the LUCI $\mathscr{L}$ is defined as follows:

$$\mathscr{L}_t = \sum_{i=1}^{I} w_{0,i}\widehat{x}_{i,t} + \sum_{i=1}^{I} w_{1,i}\widehat{x}_{i,t-1} \sum_{i=1}^{I} w_{2,i}\widehat{x}_{i,t-2}, \tag{3}$$

where $w_{k,i}$ are loadings from the cyclical parts of the LUCI. The weights obtained from the generalized dynamic principal component analysis are displayed in Figure 2.

The resulting LUCI[15] (for data as of October 2023) is displayed in Figure 3. Two peaks related to substantial labor market overheating can be seen in the figure. The first one is related to the period of 2007–2008. In this period, the output gap also suggested the overall overheating of the domestic economy. In late 2008, the situation in the Czech labor market started to cool down in response to the Global Financial Crisis and the related drop in economic activity. As a result, a worsening economic situation brought the LUCI into negative territory where it remained during the following years when the European economy was hit by the sovereign debt crisis. The LUCI returned to positive territory in 2016, and the second peak was reached by the end of 2019, just

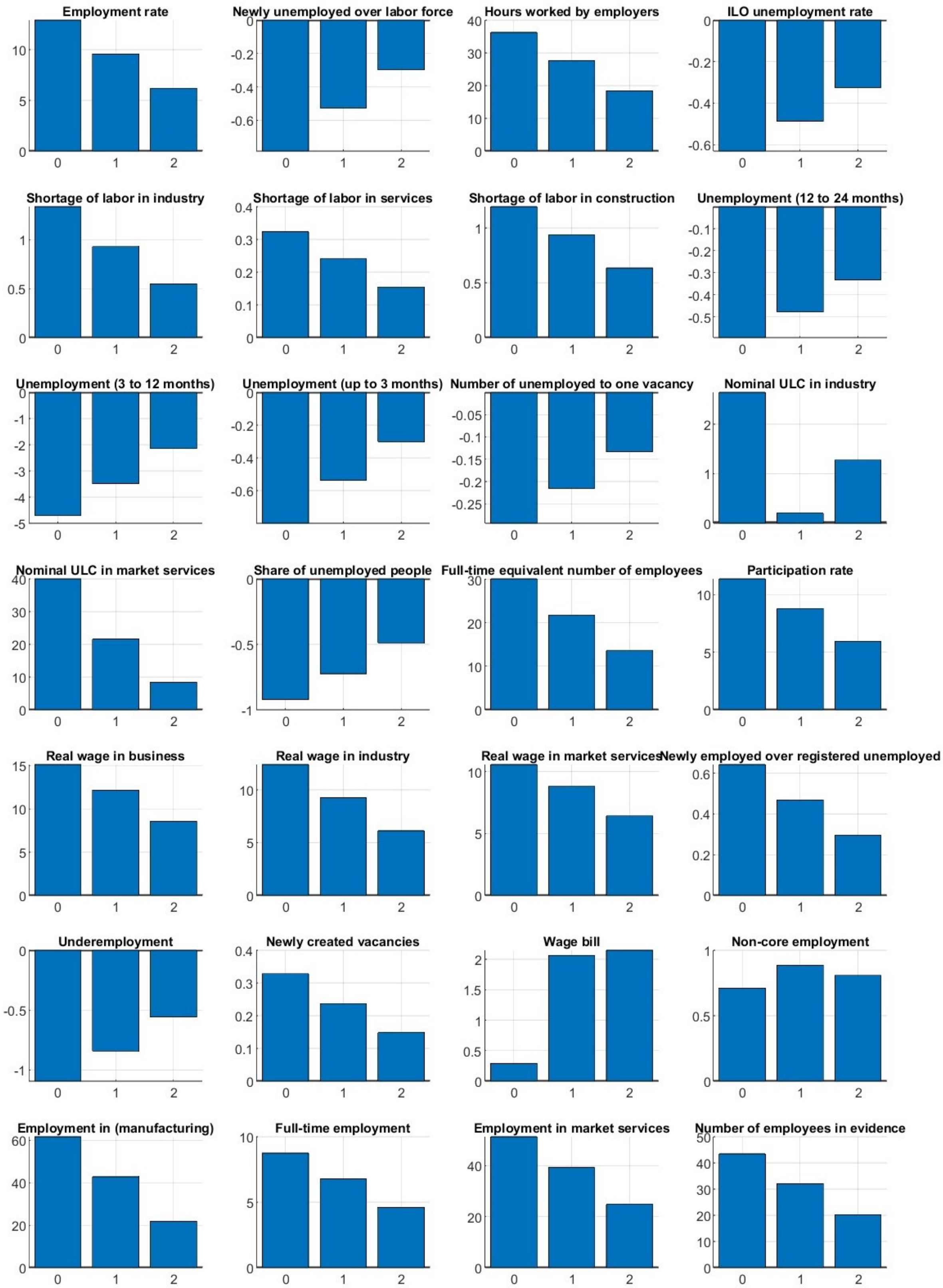
[12] Figure 7 shows the marginal spectral densities of the cyclical parts of the model, along with the first principal component in the frequency domain. Apparently, the first principal component explains more than half of the cyclical variability in the data. Even for variables where the first dynamic principal component of the spectra is not impressive, it peaks at business cycle frequencies. Technically, the figure was generated as follows. Given the estimates of $\mathbf{A}_1$, $\mathbf{A}_2$ and $\widehat{\Sigma}$, it is trivial to compute the multivariate spectral density of $\widehat{\mathbf{x}}_t$ as $f(\omega) = (\mathbf{I} - \mathbf{A}_1 e^{-i\omega} - \mathbf{A}_2 e^{-2i\omega})^{-1}\widehat{\Sigma}(\mathbf{I} - \mathbf{A}_1 e^{-i\omega} - \mathbf{A}_2 e^{-2i\omega})^{-T}$ and the first dynamic principal component is given by the eigendecomposition of $f(\omega)$, see Brillinger (1981) for details.

[13] The comovements of the cyclical components of the labor market are a standard feature of advanced economies. This was demonstrated on a panel of advanced economies, inter alia, by Brůha and Polanský (2015) and by Lafourcade et al. (2016).

[14] This can be trivially done by suitable manipulation of the observation equation (2).

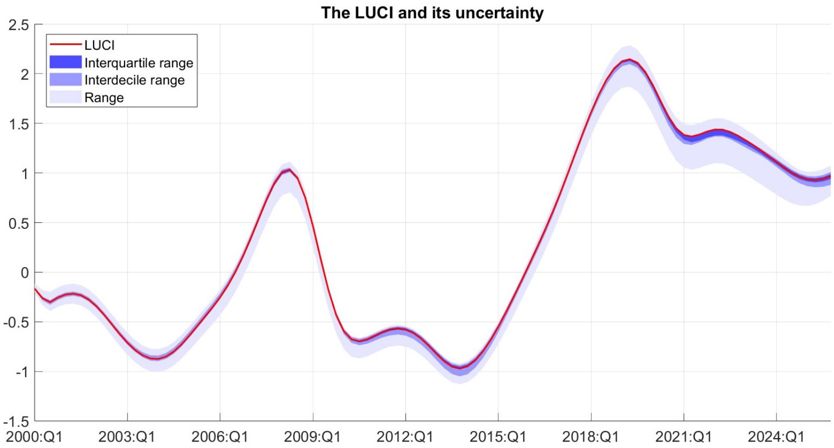
[15] The LUCI results should be read as follows. Positive values indicate a tight labor market, while negative values indicate the opposite. A zero value represents the long-run average – say, the fundamental or steady-state level. By its construction, the LUCI is measured in terms of standard deviations from the steady state.

Figure 2: Weights of Cyclical Parts in the LUCI



Source: Authors' calculations

Figure 3: The LUCI and the Blurred LUCI



Source: Authors' calculations

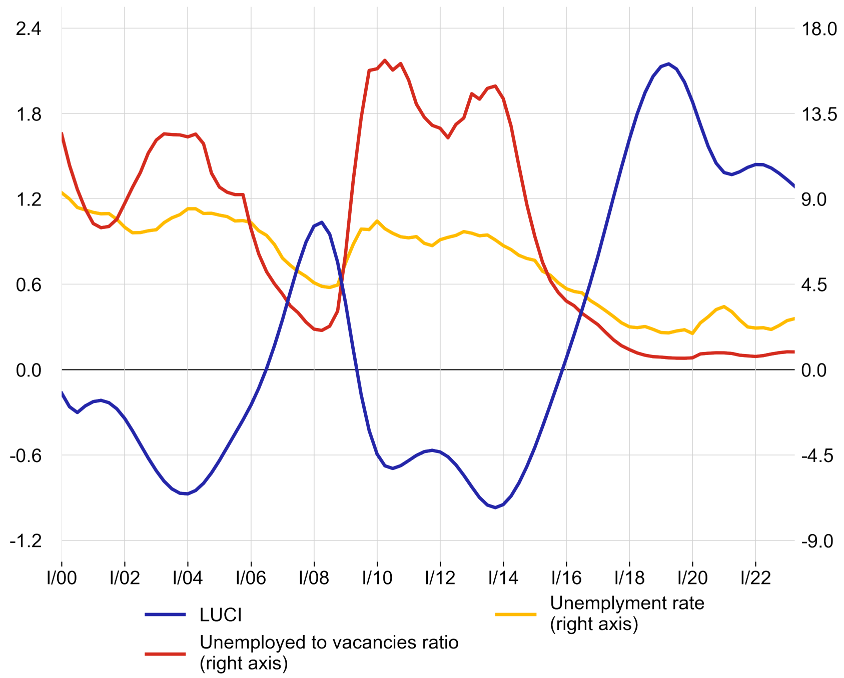
before the Covid-19 pandemic. Contrary to the previous peak, the pandemic and the subsequent economic difficulties related to the surge in energy prices led to only a partial cooling of the labor market[16], and as of the end of 2023, it still remains in positive territory.

A comparison of the LUCI and other commonly used labor market indicators is presented in Figure 4. As illustrated, from 2000 to 2017, the LUCI and other labor market indicators generally convey a similar narrative. There is a marked loosening of the labor market after 2004, a rapid tightening in 2008, and a double-w shaped development from 2010 to 2014, which is characteristic of the Czech economy during this period. However, after 2016, discrepancies between the development of the LUCI and traditional labor market indicators become noticeable. This divergence is primarily due to the inadequacy of the traditional indicators in capturing labor demand, which has been significant during this time, leading to rapid wage growth. A similar rationale explains the effect of the pandemic shock on the labor market. During the outbreak of the pandemic, the Czech labor market witnessed minimal changes in unemployment, also due to government support measures. A further comparison of commonly used slack indicators and the LUCI is detailed in Section 5.

The decomposition of the LUCI into its main categories is illustrated in Figure 5. As briefly mentioned previously, one of the LUCI's strengths lies in its ability to capture influences on the labor market through its decomposition. These influences can significantly impact the labor market's development, the broader economy, and inflationary pressures, yet they are not detected by standard macroeconomic data due to their non-fundamental nature. The consistency and interpretability of the decomposed LUCI were key reasons for the most recent methodological changes in its computation. Retrospectively, the previous method excessively attributed large movements in the LUCI (both historical and forecasted) to labor demand, at the expense of employment, and wages and costs. In the LUCI described in this paper, the contributions of its components more accurately reflect the observed trajectories of labor market variables. These changes are detailed in the

[16] The reader may wonder why the drastic fall in economic activity during the first year of the pandemic did not throw the LUCI into negative territory. One reason is that we interpret this episode as a fall in the potential, not in the gap, i.e., it did not have a cyclical nature, see e.g. Babecká Kucharčuková et al. (2022). The cyclical position of the economy remained positive, which was aided by accommodative monetary and macroprudential policy and large fiscal stimuli including various job retention schemes. The development of the LUCI index during the pandemic is fully consistent with this story.

Figure 4: Comparison of Labor Market Indicators



Source: Authors' calculations

Czech National Bank's Monetary Policy Report – Autumn 2023 (Ruschka, 2023), and the resulting methodology is comprehensively described in this paper.

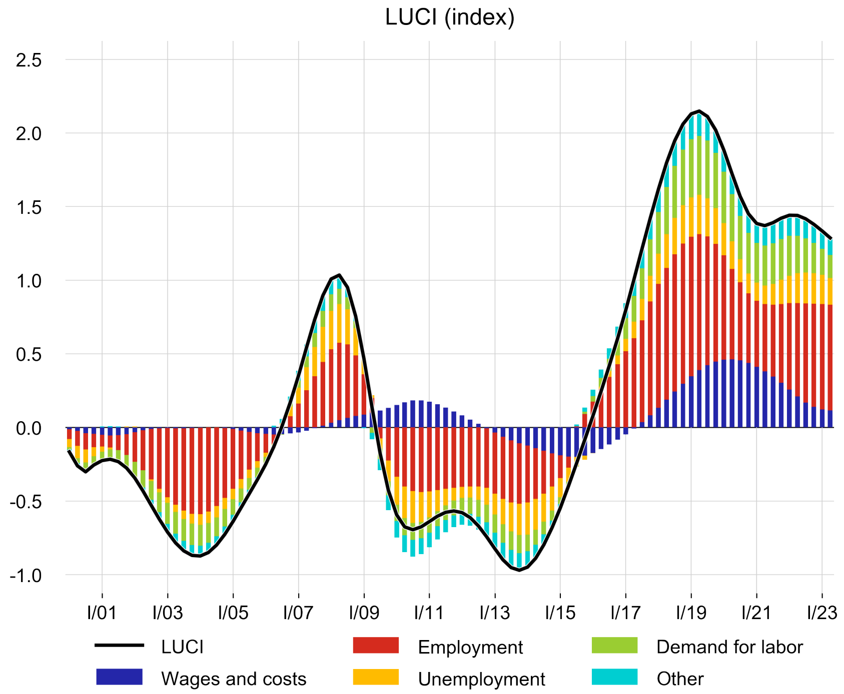
One of the characteristics to be tested is the robustness of the LUCI estimation in terms of the importance of selected variables and the available time span. To check the first characteristics, we recomputed the LUCI under the assumption that one of the time series is not observed. This exercise was repeated for all variables and thus we obtained 28 different LUCIs. In order to assess the importance of the absence of a particular variable, we computed range (min-max), interdecile range, and interquartile range on the set of LUCIs. These statistical characteristics are displayed along with the LUCI including all the data in Figure 3. To conclude, the LUCI is robust with respect to omitting particular time series.

We also looked at the stability of the LUCI in real time. Figure 6 shows the pseudo-real time revisions on the LUCI. Although there are some revisions, they are relatively minor compared to the usual output gap revisions.

5. Applications of the LUCI

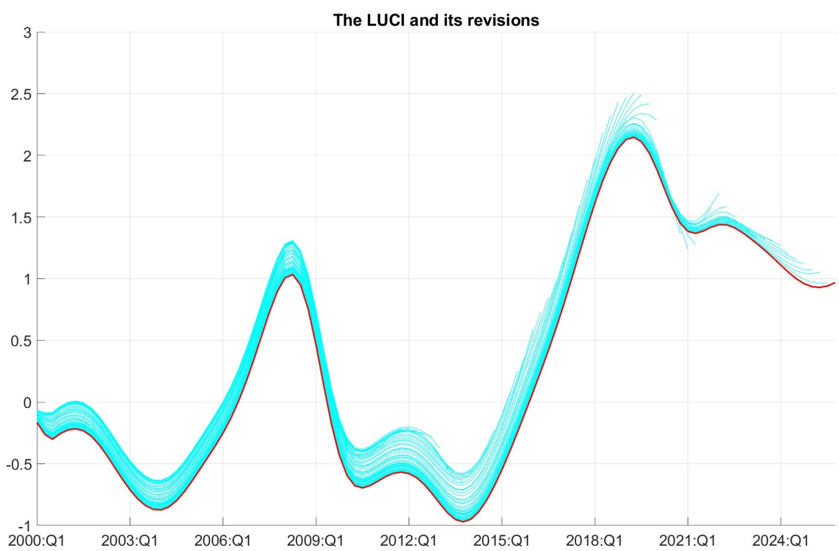
The LUCI is used in the Monetary Department as one of the measures of the cyclical position of the economy. As such, it is compared with the various measures of output gaps. When working with the LUCI in real time during the forecasting rounds, the labor market analysis includes not only an assessment of the current labor market situation, but also its prediction. Obviously, it is not possible to forecast the whole set of series used when computing the LUCI. Therefore, the prediction of the LUCI relies on the nine variables that are forecasted during the preparation of the Monetary Policy Report. These forecasts are employed as if they were data. The set of predicted variables include the

Figure 5: Decomposition of the LUCI



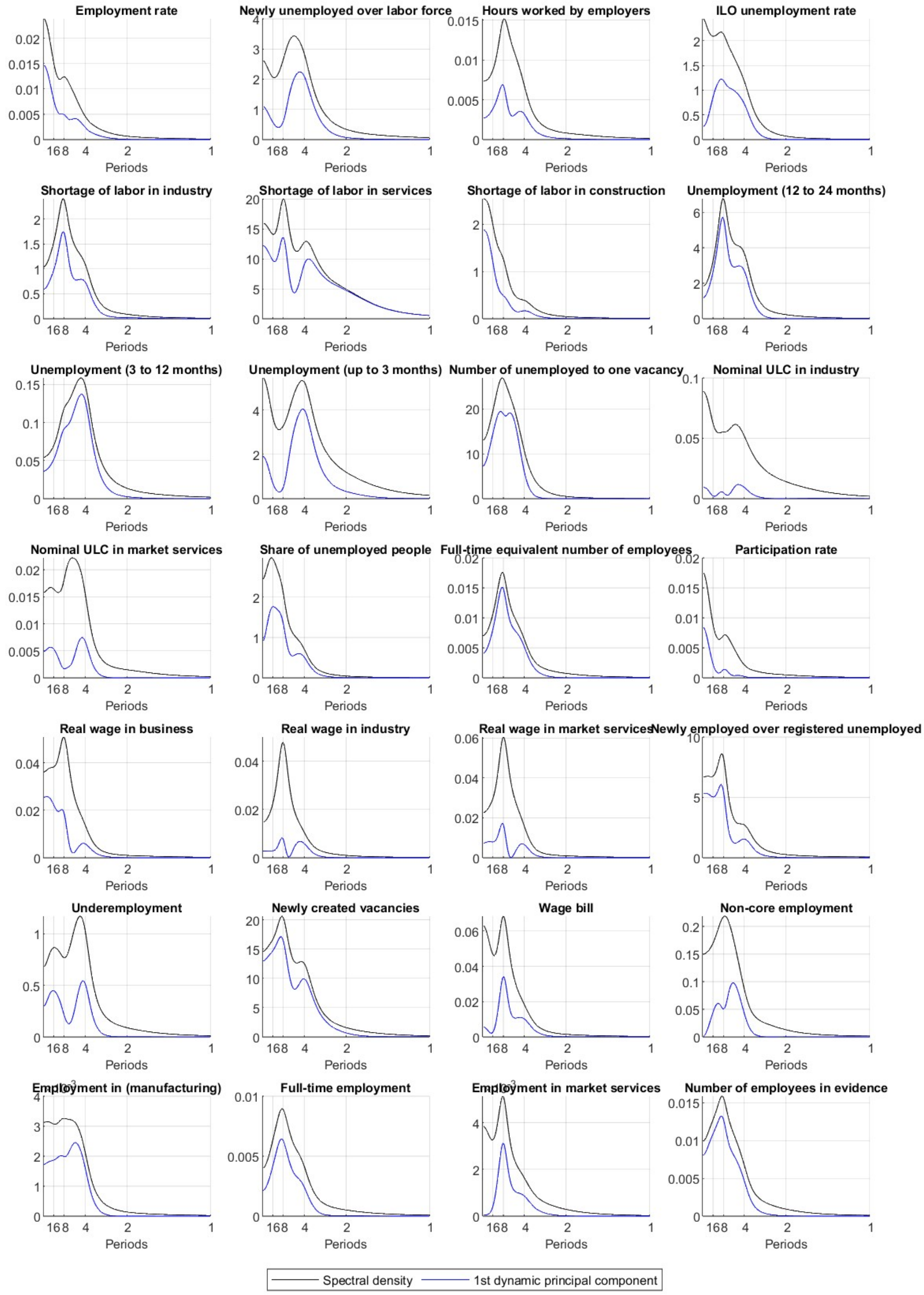
Source: Authors' calculations

Figure 6: Pseudo-real Time Revisions of the LUCI



Source: Authors' calculations

Figure 7: Spectral Densities of the Cyclical Parts



Source: Authors' calculations

ILO (International Labor Organization) unemployment rate, the share of unemployed individuals, the full-time equivalent number of employees, the real wage in the business sector (adjusted)[17], the real wage in the manufacturing industry, the real wage in market services, the wage bill, employment in the manufacturing industry, and employment in market services.

In addition, the LUCI is used for ad hoc analyses. We describe two of such applications. These are (1) an indicator of economic slack that would prove useful for the prediction of wages and inflation in empirical Phillips curves and (2) the decomposition of the supply and demand factors during the recent surge in inflation.

5.1 The LUCI as an Alternative Slack Measure

One of the most significant attributes of the LUCI is its ability to furnish reliable and insightful information regarding the overall economic landscape. While there are numerous possible indicators of economic slack (including common measures like the output gap, capacity utilization, job-finding rate, labor shortages as a production-limiting factor, and labor productivity), we hold the belief that the LUCI excels in both delineating the current economic status and forecasting future developments.

To show this, we employed the aforementioned slack measures, including the LUCI, in the estimation of empirical Phillips curves for year-on-year average nominal wage growth in the business sector and for core inflation. In the estimation of the wage Phillips curve, we utilize lagged wage growth, previous core price inflation, inflation expectations derived from the CIE index, and a slack measure. In parallel, the estimation of the price Phillips curve incorporates a slack measure, inflation expectations, and lagged core inflation. The exercise focuses on two forecasting horizons (specifically, one quarters and four quarters ahead)[18] and two estimation strategies (specifically, an expanding and rolling window)[19]. The comparison between particular slack measures is based on an evaluation of their predictive power. The metric used is the Root Mean Square Error (RMSE). A lower RMSE signifies more accurate predictions, indicating that a given slack measure is better at describing and forecasting economic developments. The analyses are conducted on two periods – one with a standard business cycle and the other with several extraordinary shocks present.

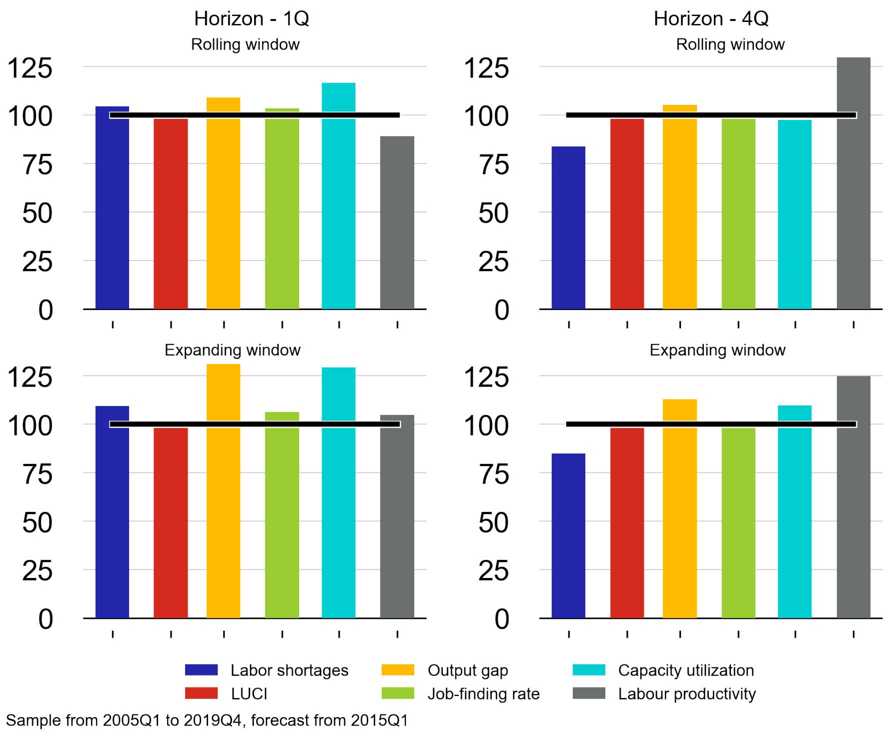
It is important to note that our purpose in conducting this analysis is not to create the optimal model for predicting wage and price growth. Rather, our aim is to compare the various slack measures in terms of their descriptive and predictive capabilities. The outcome of this analysis will provide empirical evidence regarding which variables are the most valuable in informing policy-making decisions, particularly those that pertain to the future development of the economy, such as decisions related to monetary policy.

5.1.1 Best Indicator during Standard Times

In this exercise, we conduct Phillips curve estimations for the period spanning from 2005 to 2019. We have chosen to focus on this timeframe because it is commonly regarded as representative of

[17] The adjustment primarily considers changes in taxation that result in intertemporal shifts of income inflow.
[18] The shorter timeframe is valuable for depicting the current state of the economy, particularly since labor market data often exhibit significant delays in release. Meanwhile, the medium-term horizon provides a means to accurately evaluate the labor market and make informed decisions regarding monetary policy adjustments.
[19] The rolling regression employs a window of 40 quarters, and both the rolling and expanding windows commence their estimations from the first quarter of 2005.

Figure 8: Predictive Power of Slack Measures for Wage Growth



Source: Authors' calculations

a typical economic cycle. During this period, we encountered economic crises in 2008 and 2012, followed by subsequent economic booms so all phases of the economic cycle are included.

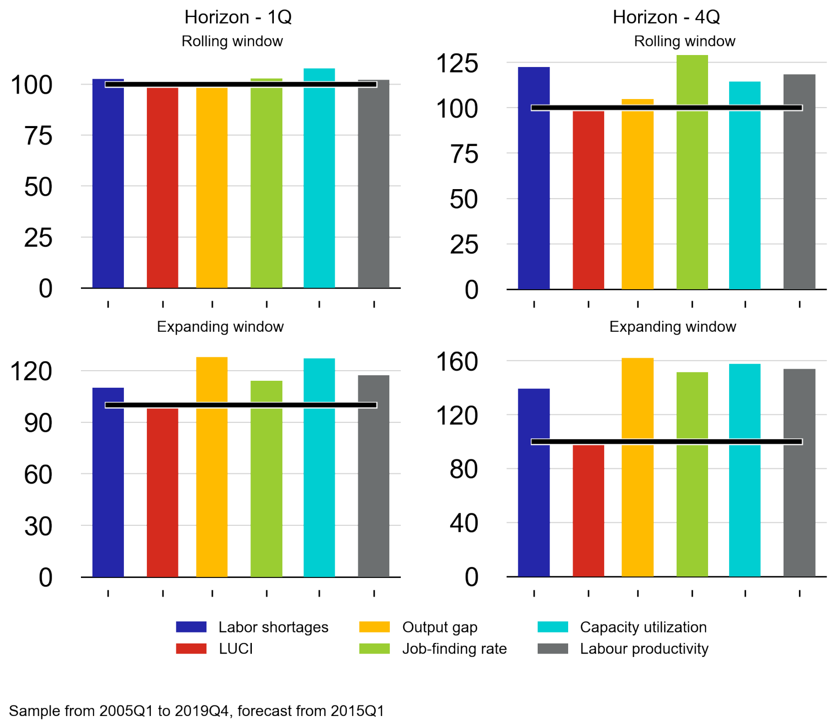
In Figure 8, the relative predictive capabilities for the wage growth of each slack measure are presented. The black line represents the predictive power of the LUCI normalized to 100%. Values below the line exhibit smaller errors and, consequently, have better predictive power than the LUCI, while values above the line perform less effectively in the predictions.

It is evident that there is no single indicator which consistently outperforms the LUCI. Notably, labor shortages exhibited superior performance, but only in the longer term, regardless of the methodology employed. Of particular interest is the comparison to the output gap, which is often used as an indicator of economic conditions. In all four scenarios, the LUCI appears to outshine the output gap as a more effective measure of the economic landscape.

There is a direct connection between the LUCI and wage growth, as the LUCI serves as an approximation of labor market conditions. Recognizing the pivotal role played by the domestic labor market in shaping domestic inflationary pressures, we conducted a parallel estimation for inflation growth. This endeavor aimed to determine whether the LUCI could offer a more accurate forecast of future inflation, which holds crucial significance for policymakers. The outcomes of this analysis are visualized in Figure 9.

There is no slack indicator better in predicting inflation than the LUCI. For both methods and both horizons, the LUCI exhibits the smallest errors. It is again worth noticing that the output gap is again significantly worse in all performed estimations.

Figure 9: Predictive Power of Slack Measures for Inflation



Source: Authors' calculations

We have demonstrated that during a typical economic cycle, the LUCI outperforms other slack indicators in describing and predicting both the labor market (wage growth) and the economy as a whole (core inflation). In the subsequent section, we will undertake a similar analysis, this time focusing on the period spanning from 2020 Q1 to 2023 Q2, to assess the performance of particular slack measures during highly volatile times.

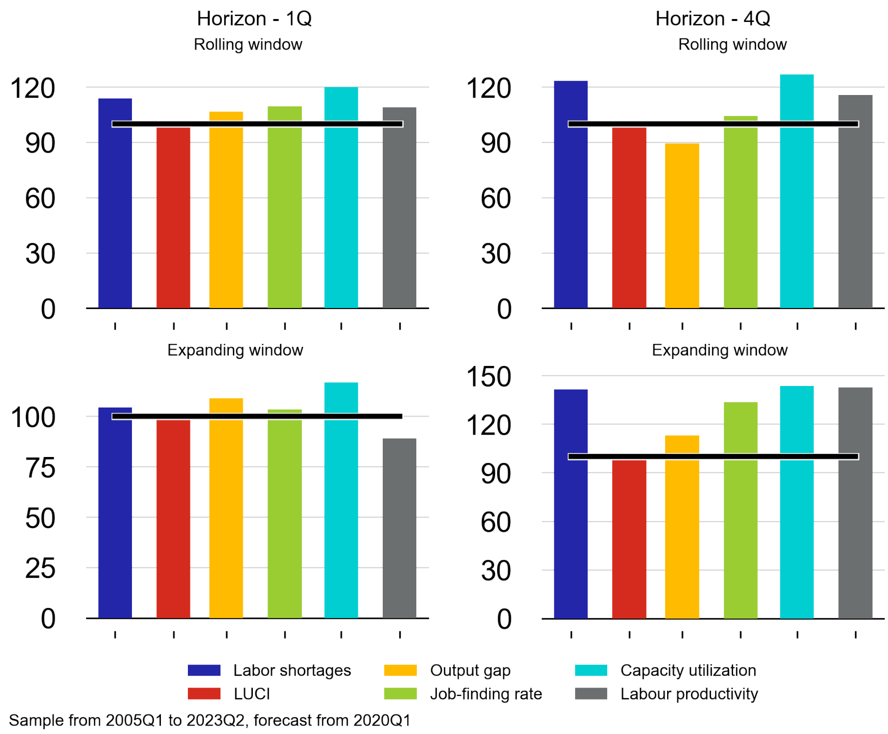
5.1.2 Period of Unconventional Economic Shocks

The last three years have been marked by abrupt shifts in economic dynamics. The impact of the pandemic, Russia's war against Ukraine, energy crises, unprecedented inflation, and stringent fiscal budgets have made policymaking exceptionally challenging. In this section, we once more present estimations of wage and price growth, incorporating various slack measures. Our aim is to assess the performance of particular slack measures and determine whether the LUCI remains the best indicator even during periods of significant economic upheaval.

In Figure 10, it becomes evident that the LUCI maintains its consistency and surpasses the majority of slack measures even during volatile times. Notably, the relative errors are smaller for the LUCI than for other indicators when predicting four quarters ahead. This is a highly valuable characteristic, given the estimation's time horizon and the fact that monetary policy typically influences the economy within 4 to 6 quarters.

Figure 11 illustrates a notable shift in the strong connection between the labor market and inflation that was observed during the standard economic cycle period, as this connection has been disrupted by the economic shocks of the past three years. This transformation is likely a consequence of the fact that a non-negligible part of the inflationary pressures emerged from the supply side of the

Figure 10: Predictive Power of Slack Measures for Wage Growth



Source: Authors' calculations

economy. Consequently, the trajectories of the domestic labor market and inflation have diverged. The results are inconclusive, primarily due to narrow margins and substantial disparities between methods, as evident when comparing the four-quarter horizon results and outcomes from the rolling versus expanding window methodologies. In this specific context, the LUCI appears to perform as effectively as any other indicator.

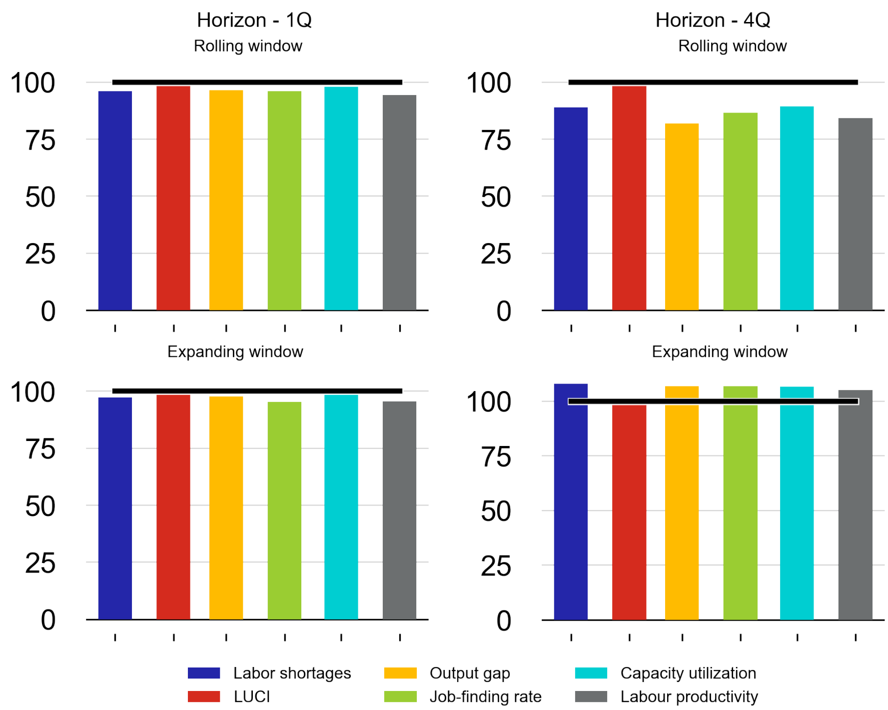
5.1.3 Is LUCI Simply the Best?

Based on the results and discussions presented above, we would contend that the LUCI stands out as the most consistent and reliable indicator of those mentioned for describing the labor market (as characterized by wage growth) or, indeed, the entire economy (as represented by core inflation development). While there might be specific periods or methods where certain indicators offer more precise results, in the majority of cases, the LUCI emerges among the top performers. Notably, the LUCI's predictive accuracy extends not only to the short-term horizon but also to longer-term outlooks. Consequently, the LUCI can serve dual roles: providing a precise depiction of the current economic situation and serving as a foundational basis for policy-making decisions that have implications for the medium-term future.

5.2 Identification of Demand-driven Factors in Overall Price Growth

During the recent upsurge in inflation, policymakers and analysts tried to find out the extent to which prices were driven by demand factors. The reason is obvious – when inflation is fuelled by (external) costs factors, the monetary policy authority has a limited set of tools to deal with it. In such a situation, the aim of the policymaker is to ensure that the effects of this shock will not elevate inflation expectations, thus limiting the possibility of a price spiral. Alternatively, the drivers

Figure 11: Predictive Power of Slack Measures for Inflation



Sample from 2005Q1 to 2023Q2, forecast from 2020Q1

Source: Authors' calculations

of accelerating inflation can be associated with demand factors. In this case, the monetary policy authority should – given its countercyclical function – tighten monetary policy conditions in order to bring the economy to the steady state and return inflation back to the target. Despite its importance, there is no straightforward and widely accepted way of decomposing inflation developments into demand and other factors.

The identification of demand-driven inflation gained in importance during 2021. Brůha et al. (2021b), in their paper focusing on price growth in 2021 Q3, contributed to this quest by introducing a methodology based on the use of the LUCI indicator. The idea was that the LUCI, as a labor market measure, reflects the domestic demand environment.

The approach used by Brůha et al. (2021b) was as follows. The starting point was the division of the consumer basket into 105 items and the related weight scheme provided by the Czech Statistical Office. The quarterly inflation rates for these 105 items were correlated with the LUCI over the 2005–2021 period[20]. As shown in Figure 12, this correlation ranges from both statistically and economically significant values above 0.5 to slightly negative (and insignificant) ones. If the LUCI represents domestic demand pressures, this correlation can be useful in determining the overall strength of demand factors in the recent price growth. In fact, in fall 2021, there was a significant positive association between the correlation with the LUCI and the individual inflation rates. This pointed to the significant component of domestic inflation pressures.

In its analytical framework, the Czech National Bank's Monetary Department divides the items in the consumer basket into five analytical groups, specifically market services, goods (these two groups are parts of core inflation), non-market services (i.e., administered prices), fuels and food prices. With this distribution in mind, we computed the share of demand pressures for each group as a weighted sum of price growth and the above-mentioned correlation. The results are summarized in Figure 13.

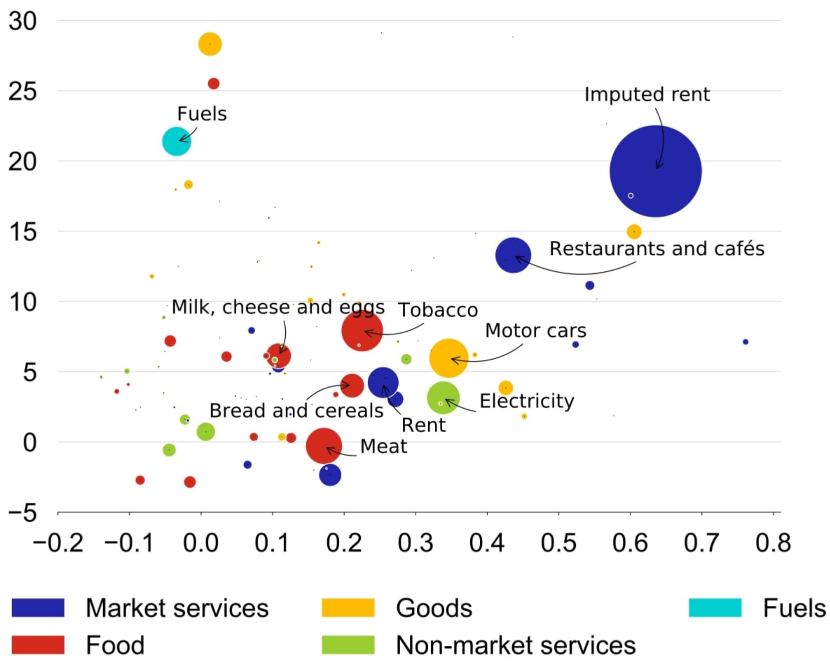
Based on this approach, the share of domestic/demand factors in overall inflation growth in 2021 Q3 reached almost 50% and was thus definitely higher than the "feelings" presented in the then macroeconomic disputes since analysts and commentators tended to attribute the large majority of inflation pressures to external/cost factors.

From the sectoral perspective, demand factors had the strongest impact on price growth in market services, with demand explaining more than 70% of the price increase. The second group of categories included non-market services, goods and food prices where strong demand pressures explained approximately one-third of the price growth in summer 2021. On the other hand, in the case of fuel prices, the effect of the domestic demand environment was – in line with intuition – negligible since fuel prices develop according to costs factors.

This exercise was also repeated in fall 2022, when Brůha et al. (2022) compared their estimation of the demand factor with another methodology based on Shapiro (2022). The share of the domestic inflation pressures was identified as being lower than in 2021, but it was still not negligible. Significantly, the two approaches yielded a similar overall assessment, which reinforces our confidence in the LUCI as a useful tool for measuring the demand component of inflation.

[20] The period prior to 2005 is not taken into consideration since it includes developments in the 1990s related to the transformation of the Czech economy from a centrally-planned to a market-based economy and then the period prior to the country's EU accession in 2004. Both of these periods include non-fundamental price developments and are therefore neglected in our analysis. However, from our perspective, the 2005–2021 period (i.e., more than 15 years of data) is a long enough window to obtain robust results.

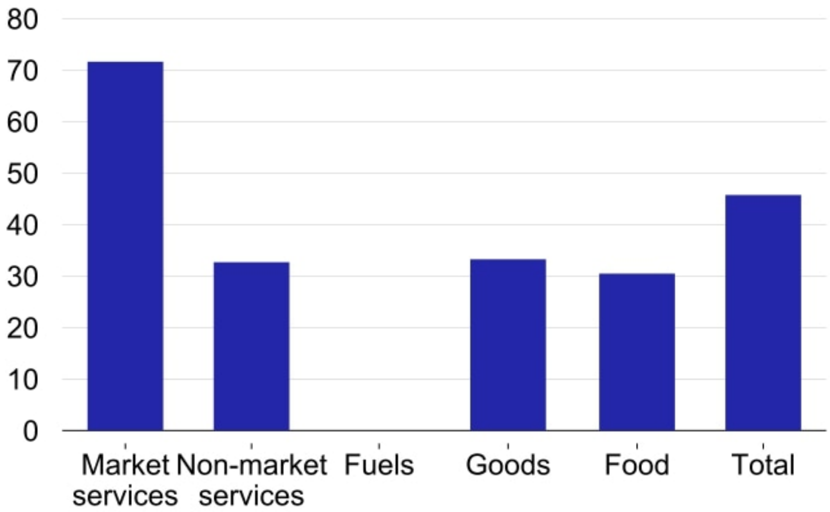
Figure 12: Correlation of the LUCI and Price Growth



Source: Authors' calculations

Note: x-axis: correlation; y-axis: annualised q-o-q price growth in % in 2021 Q3; the color of each bubble corresponds to inclusion in the analytical group; the size of each bubble corresponds to the weight of the category.

Figure 13: Share of Domestic Factors in Price Growth



Source: Authors' calculations

Note: The estimated share of the demand environment on quarterly consumer price inflation in % in 2021 Q3.

5.3 Supercyclical Inflation in the Czech Economy

The aim of economists to focus not only on overall but rather on underlying, or, more specifically, fundamental price growth resulted in the introduction of several alternative measures of inflation. These measures abstract from short-term volatility and their goal is to identify the fundamental inflation pressures. Sometimes, they are used to monitor the likely evolution of inflation in the medium term too[21]. There are various approaches to measuring the underlying inflation; usually based on the exclusion of some items.

Measures of core inflation a priori exclude some volatile (e.g., energy prices, food prices) or non-market driven (e.g. administered prices) items from the consumer basket. Trimmed mean inflation measures (including median inflation as an extreme trimming) exclude items that have large price movements in a given period.

A well-known measures of underlying inflation is supercore inflation published by the ECB. Supercore inflation is based on the idea that after removing volatile items from the consumer basket (i.e., energy and food), analysts should focus on sensitivity to the output gap (as a measure of economic slack). If the item is found to be sensitive to the output gap (in the sense that the inclusion of the output gap helps to beat the naïve AR(1) model in the forecasting exercise), then it is included in the "supercore basket".[22]

We propose the concept of "supercyclical inflation" for the Czech economy. The idea behind it is that the LUCI is in fact also a good measure of economic slack. Moreover, using the LUCI can solve some of the issues related to the use of the output gap – the output gap is often substantially revised which might have an impact on the measure of underlying inflation. To build our measure, we use the correlation between the inflation of item i and the LUCI at lag k and denote it as $\rho_{i,k} = \mathrm{corr}(\mathscr{L}_{t+k}, \pi_{i,t})$ where $\pi_{i,t}$ is the price growth of item i at time t. The maximum correlation within a window of at most two leads to two lags is denoted as follows:

$$\widehat{\rho}_i = \max_{k=-2,\dots,2} \rho_{i,k}.$$

Our supercyclical inflation π_t^{SC} is then defined as follows:

$$\pi_t^{SC} = \sum_i \varpi_i^{SC} \pi_{i,t},$$

and $\varpi_{i,t}^{SC}$ are supercyclical weights that are related to the official CPI weights $\varpi_{i,t}^{CPI}$ as follows:

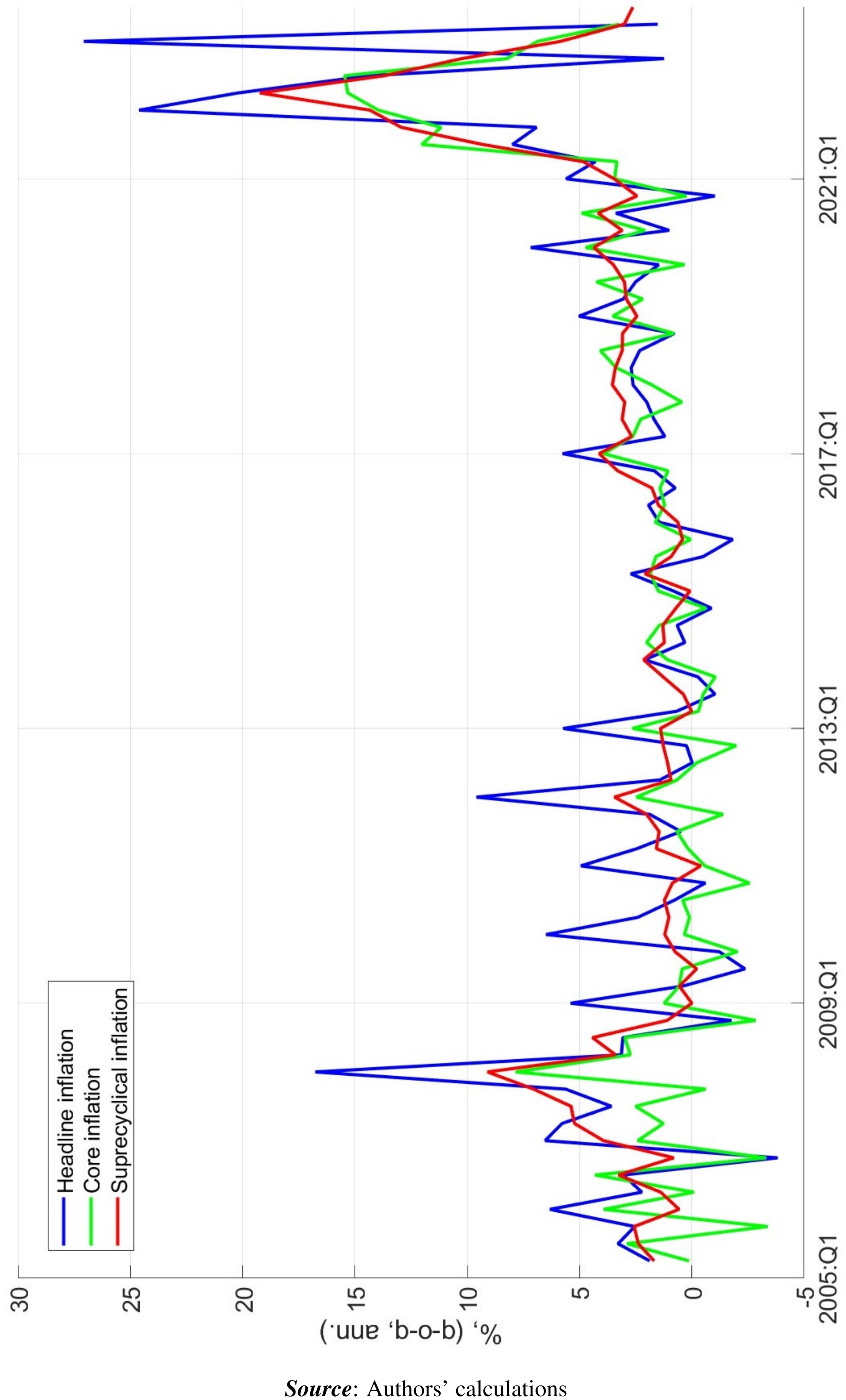
$$\varpi_{i,t}^{SC} = \frac{\widehat{\rho}_i \varpi_{i,t}^{CPI}}{\sum_j \widehat{\rho}_j \varpi_{j,t}^{CPI}}.$$

In other words, the weight of an item in supercyclical inflation equals its official weight in the consumer basket, adjusted by the correlation of its own inflation with the LUCI over ±2 quarters. The supercyclical weights are time-varying because the CPI weights are time-varying too.

[21] Unfortunately, the two tasks, i.e., fundamental inflation pressures and monitoring trends and forecasting power, are sometimes blurred.

[22] As argued by Andrle et al. (2013), the forecasting power of underlying inflation is rather an ad hoc criterion that is not necessarily consistent with economic theory. If it is applied as a criterion, it essentially induces a phase shift of the underlying inflation. Our supercyclical inflation defined below avoids the search for this implicit phase shift.

Figure 14: Comparison of Inflation Rates



Source: Authors' calculations

Figure 14 compares quarterly headline inflation, core inflation and supercyclical inflation. There were two episodes of substantially elevated inflation in our sample. The first one was before the Great Recession (before and in 2008). During this episode, headline inflation was higher than supercyclical inflation, which means that domestic demand pressures were not the predominant factors driving inflation. They were present, just as supercyclical inflation was also elevated, but other – external factors (related *inter alia* to high commodity prices) – also contributed. On the other hand, supercyclical inflation was on average higher than headline inflation from 2017 to 2021, i.e., the prices of CPI items related to the domestic labor market exhibited higher growth than the prices of other items. The domestic demand factors were dominant drivers of inflation in that period. Finally, as energy prices started to surge in late 2021, exogenous inflation pressures took over. Even so, supercyclical inflation has remained strong, which means that the domestic inflation factors have not completely disappeared.

6. Conclusion

In this paper, we introduce an aggregate labor market index called the LUCI. We argue that incorporating the LUCI into macroeconomic models is highly beneficial for understanding labor market developments. The various labor market indicators often provide conflicting signals regarding labor market interpretation. We believe that the LUCI indicator offers a comprehensive overview of labor market conditions, aiding in the formulation of appropriate monetary policy, given that all domestic inflationary demand pressures originate from the labor market. When compared with other methods for computing the aggregate labor market (some of which were mentioned in the literature review), our approach introduces a novel combination of multivariate structural dynamic filtering and principal component analysis. This approach allows us to interconnect all variables through their cyclical components, yielding robust results regarding the cyclical position of the labor market. Additionally, the method's sensitivity to changes in the most recent data enhances the precision of current labor market status estimates. We also discuss the formulation of the model behind the LUCI and its use during the forecasting process at the CNB.

Another benefit of our method is that we can decompose the aggregate LUCI indicator into its main components: wages and costs, employment, unemployment, demand for labor, and other factors. This feature enables us to provide a more detailed and nuanced analysis of labor market developments in the Czech economy. The decomposition aids in understanding the influences on the labor market, particularly in discerning whether movements in labor market tightness are driven by nominal variables (such as wages or nominal unitary costs) or real variables (such as the unemployment rate).

In the second part of this paper, we demonstrate that the LUCI has numerous applications that are significant for monetary policy. Firstly, we show that the LUCI indicator is an effective predictor of future price and wage inflation developments. We conducted a comparative analysis, which revealed that the LUCI performs better than many other commonly used slack measures. Another application uses the LUCI as a proxy for the domestic demand environment, based on the premise that domestic demand is primarily driven by the domestic labor market. By employing the LUCI in this manner, we can decompose inflationary pressures into domestic/demand pressures and external/cost pressures. Our analysis shows that at the beginning of the recent high inflation period, domestic/demand pressures accounted for nearly 50% of Czech inflation, a much higher proportion than previously perceived by analysts and commentators who largely attributed inflation pressures to external/cost factors. Additionally, by linking the LUCI with the inflation of individual goods items, this application allows us to identify sectoral influences on domestic inflation. The final application discussed in this paper uses the LUCI to estimate 'supercyclical inflation', which assesses the underlying or fundamental evolution of domestic inflation. This approach revealed that even though headline inflation was relatively low in the pre-pandemic period, supercyclical inflation indicated significant domestic demand inflationary pressures in the Czech economy.

One of the directions for future research is to compute the LUCI for other EU countries to investigate the synchronization of the labor market in the EU.[23] This can provide insights into the costs and benefits of eurozone entry for EU countries that have yet to adopt the euro. Additionally, incorporating more variables from the nominal side of the labor market would enhance the model's ability to capture labor market developments. However, such enhancements have been challenging thus far due to data accessibility issues.

All in all, we believe that the LUCI is a useful indicator which helps the central bank make timely and appropriate decisions.

[23] A step in this direction was undertaken by Brůha et al. (2021a).

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