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Expanding the Labor Market Lens: Two New Eurozone Labor Indicators*

Ece Fisgin † Joaquin Garcia-Cabo ‡ Alex Haag§ Mitch Lott¶

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Abstract

We present a principal component analysis of euro area labor market conditions by combining information from 22 labor market indicators into two comprehensive series. These two novel indicators provide a systematic view of the current state and forward-looking direction of the euro-area labor market, respectively, and demonstrate superior forecasting performance compared to existing indicators. Crucially, we find significant implications for monetary policy design: a local projection analysis reveals that ECB monetary policy shocks have attenuated effects on both inflation and unemployment when the labor market forward-looking indicator is high. The dampened inflation response calls for tighter policy rate paths than a standard Taylor rule would prescribe. Finally, we show that focusing solely on the official unemployment rate may understate the actual labor market slack, and consequently, the trade-off between labor market health and inflationary dynamics.

JEL Classification: E24, E27, J63
Keywords: employment, unemployment, labor market forecasting, european labor markets

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1 Introduction

Labor market conditions play a crucial role in shaping economic growth and informing monetary policy decisions. Many central banks, including the Federal Reserve and the European Central Bank (ECB), rely on labor market indicators to identify underlying inflationary pressures and gauge overall economic health in guiding their policy choices. Such indicators by themselves, however, may create a puzzling picture of the job market. As a result, policymakers may need to look at a broad set of indicators to extract the correct signal about the health of the market.[1] Moreover, traditional measures such as employment and unemployment rates are inherently backward-looking and come with a lag. This limitation is especially acute for euro area countries, where labor force surveys are usually released on a quarterly basis, potentially leading to delayed policy analysis. While some forward-looking measures exist, they often fail to directly address the specific labor market conditions most relevant to policymakers.

In this paper, we present a systematic approach for analyzing euro area labor market conditions by combining information from 22 labor market indicators into two comprehensive indicators via principal component analysis: *level* and *momentum*.[2] The first indicator, which we define as *level*, effectively captures historical trends, including the impacts of the Eurozone Sovereign Debt Crisis and the COVID-19 pandemic. The second indicator, which we call *momentum*, is forward-looking and adept at detecting changes in labor market dynamics. These two labor market indicators offer policymakers a more comprehensive and real-time view of labor market dynamics compared to traditional single-variable measures to better inform policy choices.

Our findings reveal that the *momentum* indicator outperforms existing forward-looking measures in predicting changes in unemployment rates. Furthermore, we demonstrate that labor market momentum significantly influences the transmission of monetary policy shocks to inflation and unemployment. Specifically, higher labor market momentum dampens the impact of monetary tightening on unemployment and inflation, potentially affecting the expected outcomes of policy interventions.

The methodology employed in this study combines a wide range of labor market indicators from various statistical offices including Eurostat, the ECB, and the European Commission. We use principal component analysis (PCA) to distill information from these 22 variables into two main components at the quarterly frequency from 2010:Q2 onwards: level and momentum. While the indicators provide quarterly values, they are updated in real-time as monthly information refines the model estimates. We assess the robustness of our model through alternative specifications, including a longer time series with fewer incorporated variables. All specifications effectively capture the turns of the euro-area labor market during important recent episodes such as the Eurozone Debt Crisis and the COVID-19 pandemic.

We conduct several forms of analysis to demonstrate the practical applications of our indicators. We start by comparing the forecasting accuracy of our momentum indicator against existing forward-looking measures of labor market health, such as the European Commission's Employment Expectations Indicator (EEI) and the European Labor Market Barometer (LMB). The results indicate that our momentum indicator outperforms both EEI and LMB in predicting future changes in the unemployment rate across several specifications and sampling periods.

We then explore the influence of momentum on the responses of inflation and unemployment

[1] For instance, former Fed Chair Janet Yellen popularized "Janet Yellen's dashboard," a set of 12 labor market and wage indicators: https://www.brookings.edu/articles/introducing-janet-yellens-dashboard.

[2] Our model is a euro-area application of the Kansas City Fed Labor Market Index: https://www.kansascityfed.org/data-and-trends/labor-market-conditions-indicators.

to ECB monetary policy shocks from Jarociński and Karadi (2020) using local projections (Jordà, 2005). This analysis reveals that high labor market momentum significantly dampens the impact of monetary tightening on both inflation and unemployment. We then test the implications for monetary policy design using a calibrated Taylor rule. We demonstrate that periods of strong labor market momentum result in higher policy rates compared to the path that would emerge from a standard Taylor rule when the responses of inflation and unemployment abstract from labor market momentum. These findings underscore the importance of considering the strength and direction of the labor market when designing optimal monetary policy responses.

Lastly, and given the important relationship between unemployment and inflation, we investigate how our model-based measures of labor market slack compare to traditional measures in the context of Phillips Curve estimations. Our results indicate that the model-based unemployment rate exhibits a stronger negative relationship with inflation than official unemployment-based measures of slack, suggesting that focusing solely on the official unemployment rate may understate the actual trade-off between labor market health and inflationary dynamics.

Our study, incorporating a wide range of variables and leveraging advanced statistical techniques, offers economists and policymakers a flexible and robust tool for real-time analysis. The applications demonstrated in this research highlight the potential use cases for these indicators to enhance monetary policy decision-making and deepen our understanding of labor market dynamics in the euro area. As central banks continue to navigate complex economic landscapes, there is outstanding value in developing tools that offer novel insights into labor market conditions when crafting effective monetary policy responses.

2 Related literature

This paper contributes to two main strands of literature. First, we contribute to the existing literature that aims at combining labor market data efficiently using econometric methods for policy analysis. For instance, and most related to our approach, Hakkio and Willis (2013) use a principal component analysis (PCA) approach to develop the monthly Kansas City Fed Labor Market conditions indicator, currently consisting of 24 U.S. labor market variables. This model has provided timely analysis since its inception (Glover et al., 2021). Additionally, Barnes et al. (2007) construct a statistical summary of U.S. labor market variables by applying PCA and demonstrate that wage pressures in recent years correlate better with their measure than with the standard unemployment rate gap, though their measure does not necessarily perform better when focusing on the historical behavior of prices. Chung et al. (2015), using a dynamic factor model, and more recently Gilchrist and Hobijn (2021) via PCA, are other examples using a myriad of labor market variables to summarize economic trends. Our paper complements this literature by analyzing the euro area labor market by implementing a PCA approach. The euro area is composed of 20 European countries sharing a common monetary policy but different fiscal authorities. To our knowledge, we are the first paper to use this procedure for an economy with a labor force of about 200 million workers and facing different labor market institutions and policies than the United States (García-Cabo et al., 2023). For the euro area, the closest available indicators are the European Labor Market Barometer, a survey based measure of 17 European countries on unemployment and employment perspectives and the Employment Expectations Indicator (EEI) from the European Commission. Our approach offers a complementary view by incorporating hard data releases for the aggregate euro area economy as well as individual countries in a timely fashion, allowing for real-time analysis and forecasting of labor market conditions.

Second, to study the effects of such shocks on labor market variables, we follow the literature measuring the effect of monetary policy shocks, specifically for the euro area. We focus on surprises in European Central Bank's (ECB) monetary policy, the common euro area monetary policy authority, as identified in Jarociński and Karadi (2020), from whom we obtain a series of monetary policy surprises in response to 280 ECB policy announcements during the period January 1999 through December 2024. There is ample evidence of the transmission of monetary policy shocks to households (see for instance Cloyne et al. (2019) and Harding and Klein (2022)), as well as the interaction of the transmission with different household variables such as savings (Ferreira et al., 2025). Our work expands on this literature by studying how macroeconomic variables interact with the state of the labor market and how monetary policy transmission is dampened when labor markets are tight.

3 A Principal-Component Analysis: Two indicators

This section describes variable selection for our analysis, including sources, time frame covered, and variable normalization. We then turn to describe how we create our baseline indicators using Principal Component Analysis and provide some robustness analysis.

3.1 Data sources

Our dataset leverages a wide range of labor market indicators from different statistical offices, including the Statistical Office of the European Union (Eurostat) and the ECB and the European Commission, which we mostly obtain via Haver Analytics. We present the full range of indicators and sources in Table A.1.

We first include a set of traditional quarterly indicators like the unemployment plus underemployment rate, underemployed due to involuntary part-time work, long-term unemployment, total hours and hours worked per person, job vacancy rate, employment rate, employment-to-population ratio, labor force participation rate, labor market transition flows, ECB Survey of Professional Forecasters (SPF) euro area unemployment rate forecast (at 8 months ahead), long-term unemployment, and temporary contracts.

We supplement this with monthly indicators aggregated to quarterly averages. Among these monthly releases, we consider several forward-looking measures such as the labor hoarding indicator[3], and the HCOB Eurozone Manufacturing and Services Employment PMI. We also include several country-specific indicators for the largest euro-area economies, including individuals actively seeking work from the French Ministry of Labor (Ministre du Travail, de l'Emploi et de l'Insertion), Kurzarbeit Notices (Short-Time Work Allowance) from the German Federal Employment Agency (Bundesagentur für Arbeit), and Cassa Integrazione Guadagni (Wage Guarantee Fund) from the Italian National Institute for Social Security (Istituto Nazionale Previdenza Sociale) which support firms to maintain employment levels during economic downturns.

Finally, we also incorporate the forward-looking Employment Expectations Indicator (EEI) from the European Commission, a composite measure of managers' hiring intentions across key sectors, standardized to reflect deviations from historical employment expectations.

[3] The European Commission's Labor Hoarding Indicator (LHI) combines responses to two pre-existing questions on expectations with respect to employment and output in the coming 3 months from various surveys associated with its Joint Harmonized EU Programme of Business and Consumer Surveys. The Commission defines labor hoarding as when "firms expect their output to decrease, but their employment to remain stable or even increase."

3.2 Series normalization and time frame

Our baseline analysis defines a unit of observation at the quarterly frequency. For indicators available at the monthly level, we construct the quarterly counterpart by averaging monthly indicators into quarters. All variables are seasonally adjusted. We perform additional checks to ensure homogeneity and consistency of our series. First, when a quarter's final monthly observation is missing, we carry forward the most recent value to complete the quarter. Second, all variables are standardized to have zero mean and unit standard deviation, allowing comparability across indicators. For easier interpretation, countercyclical variables are inverted so that higher values consistently reflect labor market improvement, such as unemployment or labor hoarding. Third, a limited set of variables with short time histories are backcasted to extend coverage using linear regressions on related indicators with longer histories.[4] With the resulting data, we construct two baseline models: one that begins in 2010:Q2 and extends to 2025:Q2 that employs all variables discussed, and a longer model that extends from 2004:Q2 to 2025:Q2 and considers a subset of data available for all years in the range.

3.3 Principal component estimation

We next combine the information from the 22 variables using a Principal-Component analysis for our baseline model. The time series is thus limited by the latest starting point of the series, and as such the baseline model comprises data from 2010:Q2 until 2025:Q2. We subsequently assess the robustness of the model by extending the period analyzed, albeit in a smaller model.

A first inspection of the estimated components conveys that the first two components account for about 80 percent of the total variance of the data.[5] This result is in line with Hakkio and Willis (2013) for the United States. As such, we keep these first two components, which we then rotate using the varimax method and we predict the scores to obtain two indicator series, the main result of this section.

The variables with the largest contributions to the first component are correlated with the level or current health of the euro area labor market, while those with the largest loadings for the second component have a more forward-looking flavor, as presented in Table 1.[6] In particular, the first component obtains the largest contributions from variables regarding the current state of the labor market, namely the unemployment and employment rate, the employment-population ratio, current measures of underemployment and long-term unemployment, as well as the unemployment rate forecast from the Survey of Professional Forecasters. The second component loads largely from forward-looking employment surveys, measures of short-time work and labor under-utilization, as well as hours worked which are a flexible way of adjusting labor utilization in the intensive margin.

As a result of these differences in loadings, with the first component capturing the overall level or current health of the euro area labor market, and the second one the more-forward looking direction, we follow Hakkio and Willis (2014) and refer to these rotated components as the "level" and "momentum" indicators, respectively. We next highlight some similarities and differences between the United States and the euro area resulting indicators. In the case of the United States, Hakkio and Willis (2014) show that the level component exhibits large correlations

[4] We backcast for 2004:Q2-2007:Q4 the unemployment + underemployment rate U6 between using the unemployment rate, and Kurzarbeit Notices using the labor hoarding indicator for Germany; and the job vacancy rate for 2004:Q2-2005:Q4 using the non-agricultural vacancy rate. These sources are presented on Table A.2.

[5] We present the eigenvalues and percentage of variance explained for the first 10 components in Table A.3 in the Appendix.

[6] We present the loadings for the full set of variables on Table A.4 in the Appendix.

Component 1	**Component 2**
Unemployment Rate	EA Labor Hoarding
Employment-Population Ratio	Kurzarbeit in Germany
Employment Rate	Services Employment PMI
Unemployment + Underemployment Rate	Cassa Integrazione in Italy
Long-term unemployment rate	Hours Worked per Employed Person
SPF Unemployment Rate Forecast	Employment Confidence Survey

Table 1: Variables with largest loadings for each component

with measures of unemployment and job separations, as well as long-term unemployment, in line with our findings for the euro-area labor market. For the United States, the largest contributor to the momentum indicator is the ISM manufacturing employment index. In our estimated PCA for the euro area, both services and manufacturing PMI employment indexes are also largely correlated with the momentum indicator. Notwithstanding, the large loadings from measures of short-time work and labor hoarding for the euro area highlight an important difference across U.S. and euro-area labor market institutions. Given the stringent labor market legislation in many euro-area countries, policy-makers have relied in short-time work programs to protect employment in recent downturns. Since hiring and firing costs are significant, the job-finding rate is lower than in the United States, making increases in unemployment very persistent, and as such, these policies protect jobs (García-Cabo et al., 2023). In the United States, where labor market flexibility tends to be higher, firms lay off workers and recall them with little cost, reducing the popularity and usage of short-time work policies. Our PCA analysis validates the incorporation of variables that capture labor market institutions differences to fit the data when applying these methods in a cross-country setting. Having described some of the most salient differences across labor markets, we next turn to describe the historical evolution of the estimated indicators for the euro area.

3.4 A historical overview of level and a *momentum* indicators

Figure 1 depicts the quarterly evolution of the level and momentum indicators between 2010 and 2025. Our baseline indicators start during the brief expansion in 2010 that followed the 2008 financial crisis, right before the euro area Sovereign Debt Crisis in 2011.[7] The level indicator (solid blue line), while recovering during 2010 and early 2011, was still below its long run-average, and it dipped to its historical trough during the first half of 2013, coinciding with an unemployment rate peak of 12.2 percent and the employment rate at a multi-decade low of 55.7 percent. From this trough, the level indicator started a prolonged recovery, turning positive at the end of 2017, that lasted until the first quarter of 2020, when the COVID-19 shock hit. During the COVID-19 pandemic, the indicator quickly turned negative, but this collapse was short-lived, as governments put in place extensive fiscal policies, including labor market subsidies to keep workers attached to firms, that allowed the market to absorb the labor market shock better than in 2011-2012. The latest data suggest that the activity indicator was at the beginning of 2025 at its historical peak, coinciding with the lowest historical record of unemployment in the euro area and high levels of employment and labor force participation.

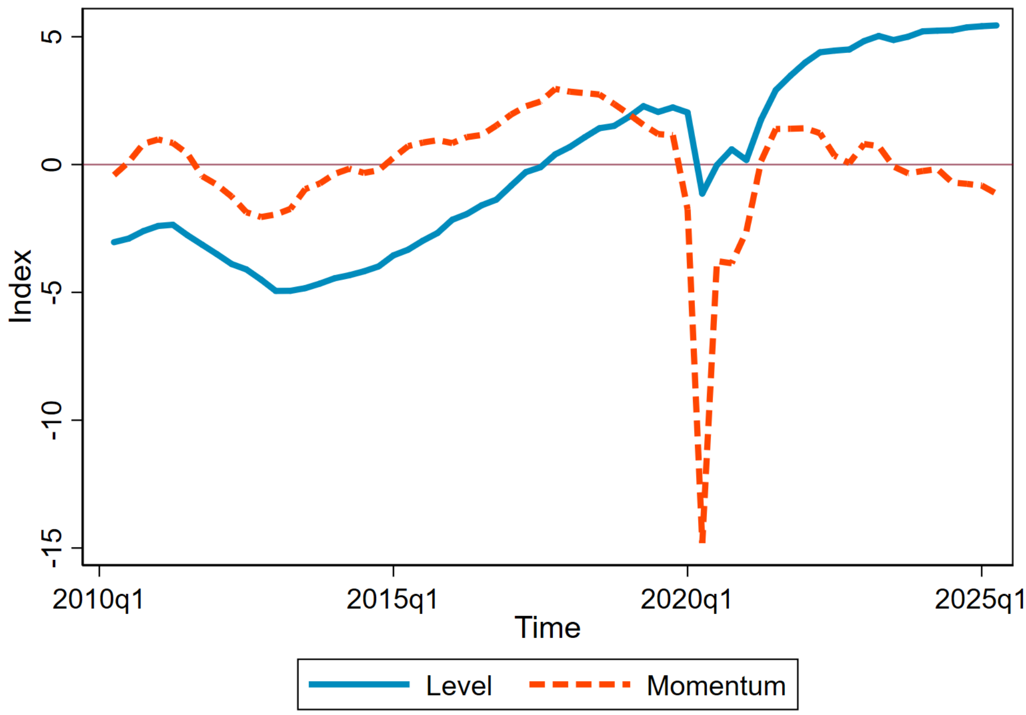
We next turn to describe the momentum indicator (dashed orange line). As a result of the increased optimism about the economy rebounding from the 2008 recession, at the beginning of the sample it signaled a positive forward-looking sentiment, above its long-run average. However, it quickly turned negative, and only returned to above long-run average levels in 2015. The

[7] We assess the robustness of these indicators and alleviate the data horizon limitations by estimating a smaller model with longer time series later.

momentum indicator progressively improved until the end of 2017, when it started a downward trend, although still in positive territory, amid a slow down in growth and a deterioration in some regional labor markets, such as Germany. Interestingly, in turned negative in 2020:Q1, before the level activity reflected the COVID-19 effects on the labor market, and it collapsed in 2020:Q2 to then briefly rebound in 2021. Since 2023, it has been below trend, but fairly stable as consumer sentiment weighed on growth amid high inflation, and moderating employment growth continue weighing on labor demand.

All in all, by combining information from multiple euro-area labor market variables into level and momentum indicators, we provide a more comprehensive and forward-looking view of labor market conditions than any single indicator could offer. We next assess the robustness of these estimators through alternative model specifications.

Figure 1: Euro-area Labor Market Indicators



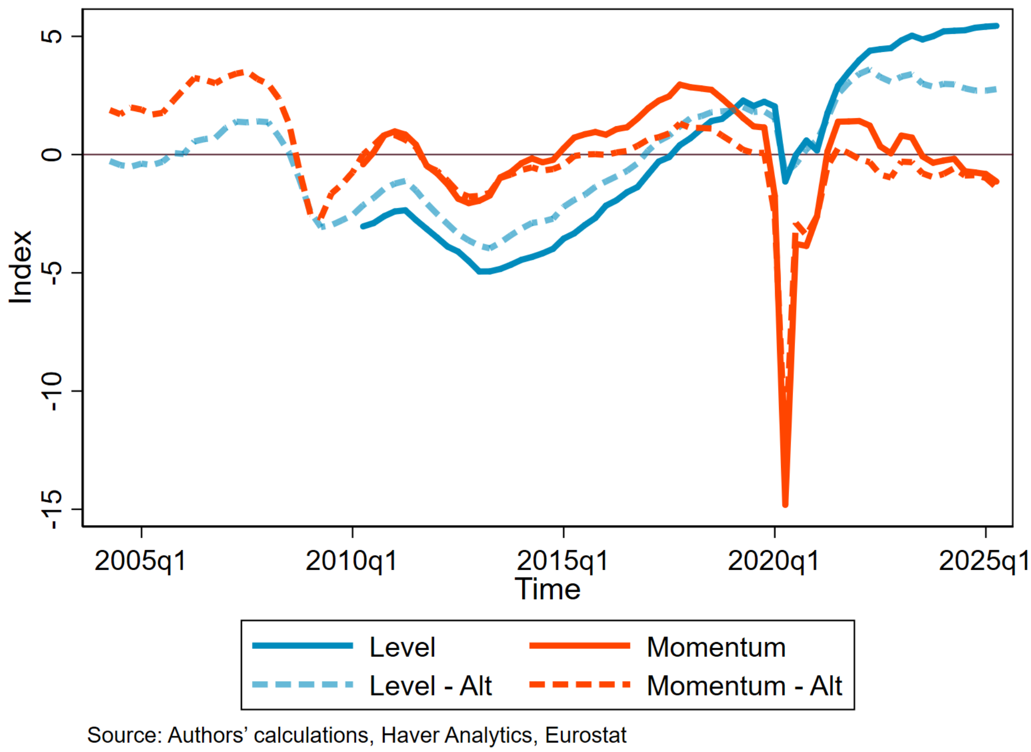
Source: Authors' calculations, Haver Analytics, Eurostat

3.5 Robustness of the estimators: alternative specifications

We now consider an alternative specification involving a longer time frame but a smaller number of variables to assess the robustness of the baseline estimator. In particular, we now restrict the model to a subset of 13 variables starting in 2004:Q2: manufacturing and services employment PMIs, hours worked per person employed, total hours worked in the industry sector excluding construction, the job vacancy rate, the unemployment + underemployment rate, the unemployment rate, the SPF unemployment rate forecast, the French job seekers, the registered unemployed in Spain, the number of workers under kurzarbeit program in Germany, and the European Commission's labor hoarding and employment confidence surveys.

The alternative indicators, presented in Figure 2, track the behavior of the baseline model very closely, alleviating concerns on the long-run behavior of both indicators due to the orthogonalization assumptions on shorter time series. We highlight some slight differences next. First, the alternative model's first two components explain just about 70 percent of the variance, compared to 82 percent on the baseline given the inclusion of a larger set of variables. Second, the level indicator in the smaller alternative model exhibits slightly less variance, with its trough during the sovereign debt crisis and its current peak lower than what the baseline indicator suggests. This is because the baseline model incorporates variables with large loadings that reflect labor market health, such as the employment rate or the employment-to-population ratio. Abstracting from these variables results in a understatement of the state of the labor market. Third, the alternative momentum indicator was virtually identical to the baseline between 2010 and 2015, but it somehow was a bit less optimistic than the baseline in the recovery post-2015. Note how the main loadings into the baseline are almost the same as under the alternative, with the exception of Cassa Integrazione, only available starting 2009. The collapse of the momentum indicator under both models was similar during COVID-19, and more recently, the alternative model has consistently been below its long-run average compared to the baseline. This reflects larger loadings from hours worked per person relative to the baseline, which have failed to recover since the COVID-19 pandemic as measures of hoarding have remained significant. Overall, due to its explanatory power and qualitative behavior, which incorporates information from key labor market variables, this analysis demonstrates a clear preference for the baseline model.

Figure 2: Euro-area Labor Market Indicators: Baseline and alternative specification



Note. Baseline model refers to the 22 variable model spanning 2010:Q2-2025:Q2. Alternative model refers to the 13 variable model described in Section 3.5, spanning 2004:Q2-2025:Q2.

Of note, the model's flexibility and robustness prove particularly valuable if a researcher was interested in assessing how individual variables are affecting indicator dynamics. In particular, one could estimate alternative models by excluding certain variables. While this approach would not provide an exact analysis of variable contributions, it can offer important insights into the recent behavior of both level and momentum indicators vis-à-vis variables of interest. This method provides a nuanced understanding of labor market dynamics, identifying and interpreting trends more effectively. Ultimately, the baseline model's comprehensive nature and adaptability make it a powerful tool for real-time labor market analysis and informed decision-making.

4 Applications

The following section showcases key applications of our developed indicators. First, we demonstrate the superior forecasting capabilities of the momentum indicator compared to existing forward-looking measures of labor market health. This comparison underscores the indicator's value in providing timely and accurate assessments of current labor market conditions. Subsequently, we explore the significant influence of momentum on the responses of inflation and unemployment to monetary policy shocks. Our analysis reveals that the momentum indicator plays a crucial role in shaping these macroeconomic responses, highlighting its importance for optimal monetary policy design.

4.1 Level and momentum and the business cycle

We first assess the effectiveness of indicators as predictors of changes in unemployment and how they compare against existing composite measures of labor market health. Our analysis primarily focuses on the European Commission's Employment Expectations Indicator (EEI), chosen for its extensive time series and timely updates. We also consider the European Labor Market Barometer (LMB), as well as its subcomponent focused on unemployment, though these results are relegated to the appendix. For context, the EEI is a weighted average of managers' employment plans across retail trade, construction, industry, and services sectors, designed to forecast general employment trends. This approach aligns closely with our momentum indicator's aim of capturing early labor market signals. By comparing our indicator's performance against the EEI, we can not only validate our methodology but also highlight the potential advantages of our more comprehensive, data-driven approach over traditional survey-based measures.

We start with a simple regression framework:

$$\Delta Urate_t = \alpha + \sum_{j=1}^{J} \beta_j \Delta Momentum_{t-j} + Z_t + e_t \tag{1}$$

where the dependent variable $\Delta Urate_t$ is the contemporaneous change in the euro area unemployment rate from the previous quarter. We include as regressors the lagged change in momentum (with j indicating the first or second lag, depending on the specification) captured by $\Delta Momentum_{t-j}$, and a series of COVID dummy variables Z_t. We run the same specification for the European Commission's EEI for comparison. We use the fitted estimated regressions to predict the change in the euro area unemployment rate for both series and assess each series' forecasting ability using the root mean squared error (RMSE) of each series' forecasts. Our baseline exercise compares momentum and EEI for the period 2005:Q1–2019:Q4, using one lag for momentum, our preferred specification as a shorter lag is more likely to represent signal on near-term future labor market dynamics, with additional lags tested for robustness in the appendix. [8]

[8] For this exercise, we use the estimated momentum component from the baseline principal-component analysis but we splice it back to 2004 using the smaller model to increase the number of observations. We include additional comparisons for a 2010:Q2–2019:Q4 sample and the 2010:Q2–2025:Q1 sample including the COVID-19 crisis in

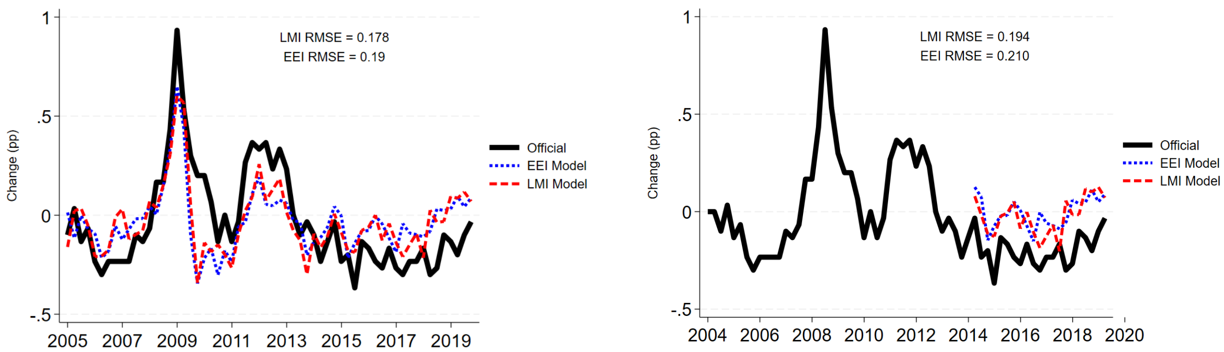
We present the results of this analysis in Figure 3, panel (a). Our in-sample baseline prediction exercise shows that the momentum indicator performs slightly better than the employment expectations index (RMSEs of 0.178 versus 0.19). These results are robust to the second lag of our indicator, shown in the appendix, with RMSEs of 0.195 for momentum and 0.197 for EEI, respectively, although both indicators underperform relative to the first lag specification. In the appendix, we show similar results for alternative specifications using the European Labor Market Barometer (LMB) and its unemployment subcomponent (CompA), with our LMI indicator outperforming both for in-sample prediction. [9]

We also demonstrate LMI's superior out-of-sample forecasting ability using an expanding window 1-step ahead forecast. We use an initial window of 40 quarterly observations (roughly 2/3rds of available data). Our results in Figure 3, panel (b) show that our LMI indicator (RMSE = 0.195) continues to outperform EEI (RMSE = 0.210). Our results are robust to additional window specifications ranging from 30-55 observations, as well as an alternative rolling window specification. While the Momentum LMI indicator RMSE is roughly an 8 percent improvement, on average, over the EEI indicator RMSE, we note that we do not find a statistically significant result when testing the difference in the forecast errors using the modified Diebold-Mariano test. This may, at least in part, be due to the relatively low sample size for each of our forecast errors due to data constraints.

As a result, we are confident that the momentum indicator can be used as a predictor for business cycles, as it performs at least as good or better than other existing indicators by incorporating additional labor market information. Moreover, due to the fact that it incorporates forward-looking information as it is released, it is very timely, adjusting faster than waiting for a specific indicator releases, which usually come with a lag.

Figure 3: Predicted changes in unemployment

(a) In-Sample **(b)** Out-of-Sample



Notes. Chart shows the extended sample results, which extends from 2005Q1 through 2019Q4. Out-of-sample is based on an expanding window 1-step ahead forecast with an initial window of 40 observations. LMI stands for the euro-area Momentum Labor Market Indicator developed in this paper, EEI for the European Commission's Employment Expectations Indicator.

the Appendix.

[9] In the Appendix we show that LMI also outperforms the EEI for 2010:Q2-2019:Q4 and that during the COVID-19 period both indicators have a virtually identical performance, but the fit is not great outside 2020–2022, since the simple linear regression does not do a good job in fitting the large swings observed during this period. We also show that LMI outperforms other indicators, such as the aggregate of the European Labor Market Barometer and its unemployment component, over the varying time horizons discussed.

4.2 Momentum and monetary policy transmission

The evolution of broad labor market conditions aside from the unemployment rate has been shown to be important drivers of monetary policy design (Campolmi and Gnocchi, 2016). The European Central Bank (ECB), while not having a explicit mandate on employment unlike the Federal Reserve, often cites labor market conditions as a motivating factor in determining monetary policy via the economic outlook.[10]

We now turn to empirically document that the level of labor market momentum can lead to different monetary policy implementations. To address this question, we estimate local projections using high-frequency monetary policy shocks from the ECB on macroeconomic aggregates, with a focus on headline inflation and the unemployment rate. Our approach includes a novel interaction of the monetary policy shock on the level of the momentum indicator. We next show how incorporating this interaction results in significantly different responses of inflation and unemployment, which will affect the appropriate monetary policy rule.

In particular, we estimate a standard local projection equation, as pioneered in (Jordà, 2005):

$$\Delta y_{t+h|t-1} = \alpha^h + \beta_1^h \varepsilon_t^m + \beta_2^h (\text{Momentum Indicator}_t) \times \varepsilon_t^m + \gamma^h \mathbf{Z}_{t-1} + e_{t+h} \tag{2}$$

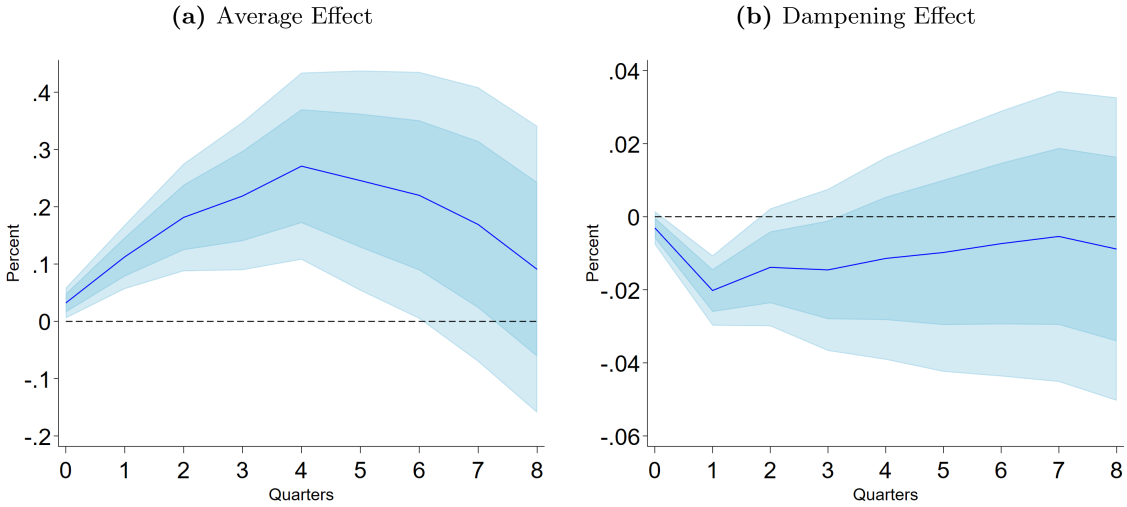
where ε_t^m are the daily monetary policy shocks measured in Jarociński and Karadi (2020), between January 2004 and December 2024, and aggregated at the quarterly level and standardized.[11] $\mathbf{Z}_{t-1}$ is a set of controls that includes three lags of quarterly year-over-year headline HICP inflation for the euro area, quarterly official euro area unemployment rate, the end-of-quarter ECB deposit rate, and the log difference of quarter-over-quarter GDP. We additionally include a time trend control and dummy fixed effects for the COVID-19 pandemic. We interpret our coefficients of interest, β_1^h and β_2^h next. First, β_1^h captures the standard response of the dependent variable at horizon h after the monetary policy shock. Second, and one of the contributions in this paper, β_2^h captures the dynamic effect associated with the interaction of the period's forward-looking momentum indicator with the monetary policy shocks at each horizon h.[12] We will refer this effect as the dampening effect, referring to the marginal dampening effect that high momentum has on monetary policy shocks We focus on the effect of monetary policy shocks on the unemployment rate, inflation, and the employment rate in the euro area due to their importance for monetary policy design, and we relegate the impact on other macroeconomic variables, namely labor force, nominal compensation, and hours worked, to the Appendix.

[10] See for instance, www.ecb.europa.eu/press/press_conference/monetary-policy-statement/2025/html/ecb.is250417~091c625eb6.en.html

[11] We aggregate the daily surprises at the quarterly level with a moving average structure following Gertler and Karadi (2015). We then normalize the shock so it has a standard deviation of one, resulting in a mean value of the shock of about 28 basis points.

[12] For this exercise, we use the estimated momentum component from the baseline principal-component analysis but we splice it back to 2004 using the smaller model to increase the number of observations.

Figure 4: Local projection analysis: Unemployment Rate

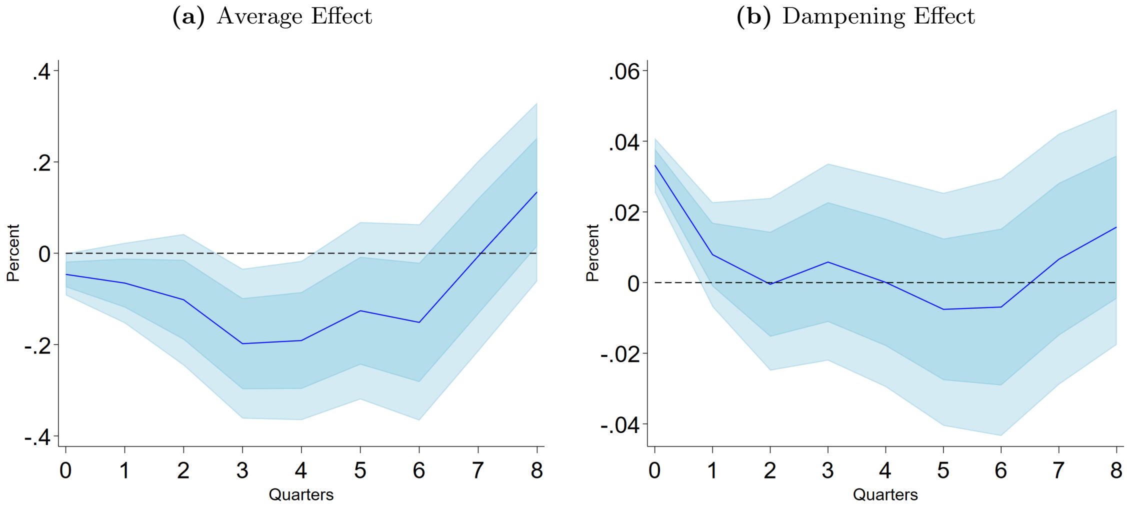


Note. Light shaded areas represent 90 percent confidence intervals, dark shaded areas represent 68 percent confidence intervals, and the solid line represents the mean value.

Figure 4 depicts the unemployment rate response to a monetary policy shock. Panel 4a shows that, unconditionally and standard in the literature, a tightening monetary policy shock increases the unemployment rate by up to around 0.25 percentage points with the effects peaking four quarters after the shock, and exhibiting persistence beyond a year. The estimated dampening effect of momentum, as shown in Panel 4b, is negative and significant the quarter after the shock, exhibiting some persistence albeit at small significance levels. This result implies that when momentum is high, the impact on the unemployment rate might be smaller than one could have anticipated if only looking at the average effect following the shock.

Examining the employment rate–the flip side of the labor market–we observe that a monetary tightening shock negatively impacts euro-area employment (Figure 5). Notably, panel 5b shows that a higher momentum significantly dampens the initial decline in employment following the shock. Specifically, a one-point increase in the momentum indicator nearly offsets the initial impact of the monetary policy shock on employment. These findings underscore the critical role of labor market momentum in determining the responses of both unemployment and employment to monetary policy shocks. High labor market momentum appears to act as a buffer, attenuating the immediate effects of tightening measures. This interaction between monetary policy and labor market dynamics has potential implications for inflation trajectories, a relationship we will explore next.

Figure 5: Local projection analysis: Employment Rate



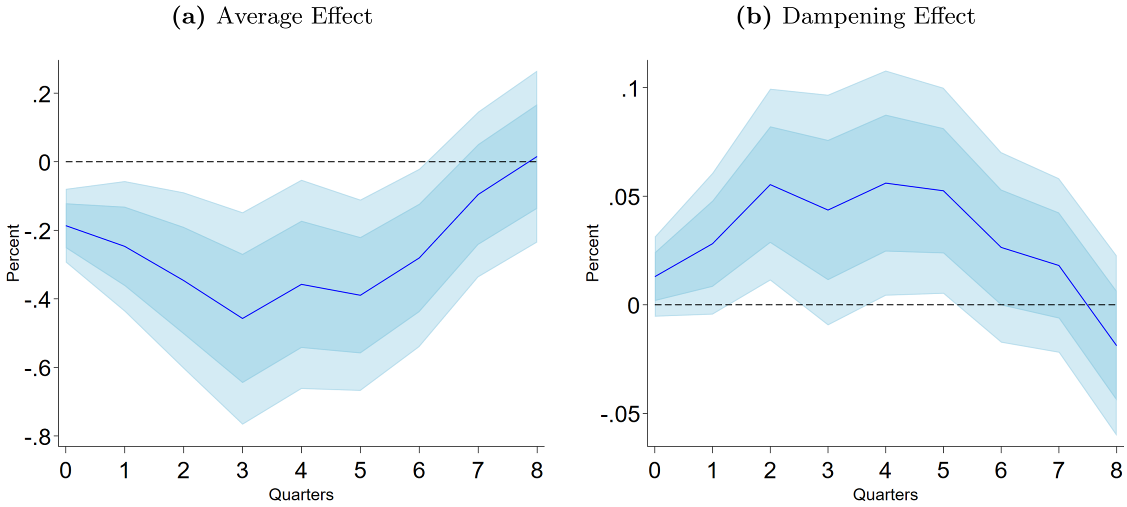
Note. Light shaded areas represent 90 percent confidence intervals, dark shaded areas represent 68 percent confidence intervals, and the solid line represents the mean value.

Of particular interest is the impact of monetary policy shocks on inflation, especially considering how these effects may be affected by labor market momentum. Figure 6 illustrates our findings on this crucial relationship. Panel 6a shows that a monetary policy shock reduces inflation contemporaneously by approximately 0.2 percent, with the effect persisting for four quarters and reaching a peak of about 0.35 percent. This aligns with previous research and the intended outcomes of monetary tightening.

Notably, panel 6b reveals a surprising result: high labor market momentum is positively correlated with a dampening effect on inflation. Take for instance the change of the momentum indicator by one positive unit. This implies a reduction in inflation during the first year after the shock that is 10 percent lower than the average effect, with this effect persisting for nearly two years.

Our findings suggest that commonly used indicators, such as employment and unemployment rates, may not be sufficient to capture labor market health for central bankers' purposes. This points to the likely existence of labor market state-dependence in macroeconomic dynamics, including inflation. A better understanding of the macro responses depending on the state of the economy, as captured by our momentum indicator, can significantly influence the design and transmission of monetary policy. We next explore this channel by demonstrating how accounting for the dampening effect of our labor market momentum indicator can lead to different monetary policy responses using standard Taylor Rule principles.

Figure 6: Local projection analysis: Inflation



Note. Light shaded areas represent 90 percent confidence intervals, dark shaded areas represent 68 percent confidence intervals, and the solid line represents the mean value.

4.2.1 Taylor Rule Implications

Given our previous findings that labor market momentum has a dampening or amplifying effect on monetary policy shocks, we now turn to study the implications of these results for the design of monetary policy following standard monetary policy rules. To address this, we use a calibrated Taylor rule to estimate the projected policy rate under scenarios that account for heterogeneity in labor market momentum.

More concretely, we use the coefficients for the monetary policy shock and its interaction with labor market momentum from our previous local projection analysis to generate inflation and unemployment series under two specifications: 1) a baseline scenario that omits our labor market momentum indicator and 2) and additional scenario where labor market momentum is one standard deviation above its mean value—identified as the positive momentum scenario. For this analysis, we use a one-unit standardized monetary policy shock, or roughly 28 basis points.

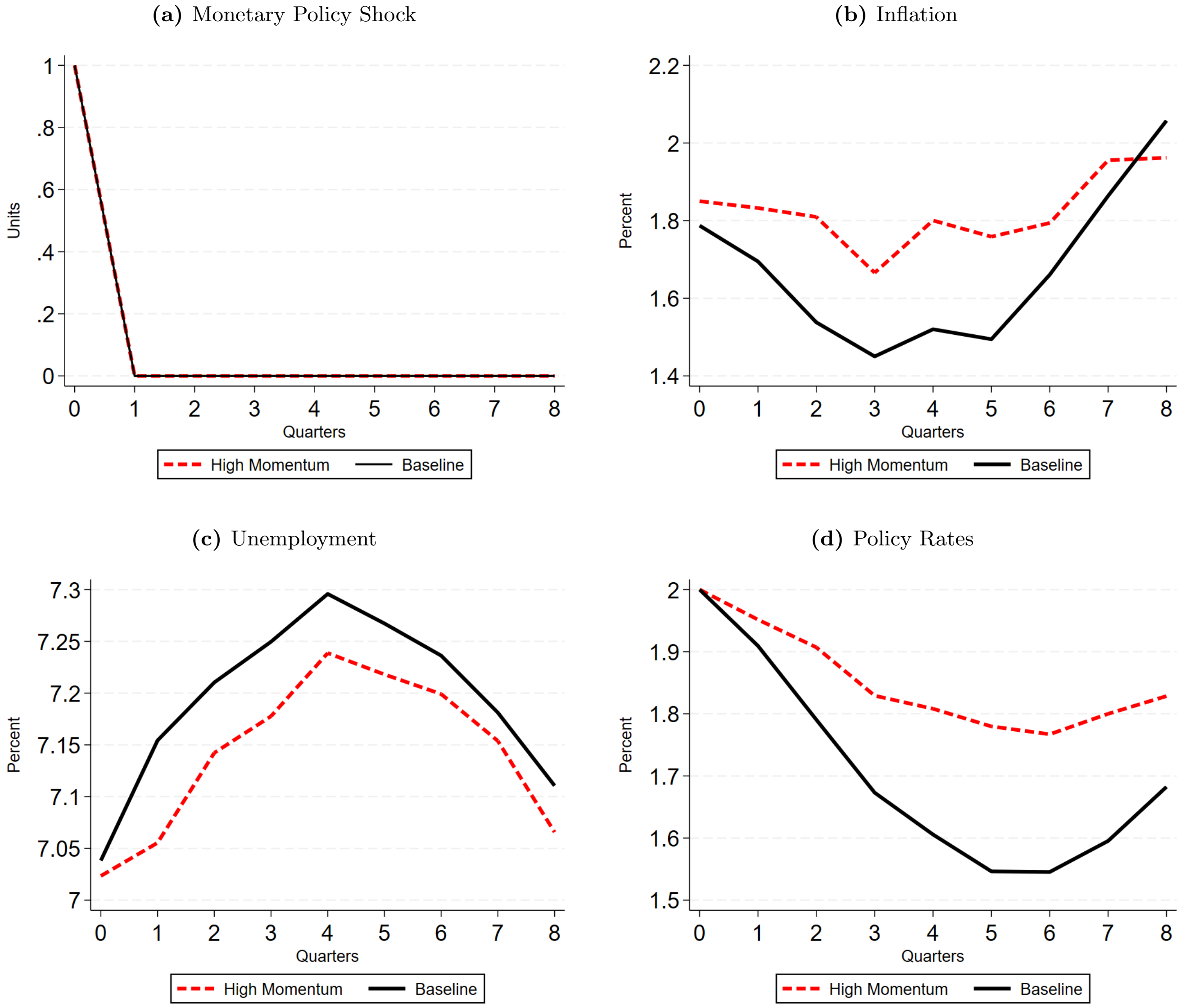
We use these inflation projections within the context of a standard inertial Taylor rule to determine the appropriate policy rate:

$$\log(R_t) - log(\bar{R}) = \phi_R(log(R_{t-1}) - log(\bar{R})) + (1 - \phi_R)[\phi_\pi(log(\pi_t) - log(\bar{\pi}))] + \varepsilon_t^R \qquad (3)$$

where ϕ_π is the response parameter to inflation, ϕ_R is the response parameter to past values of the policy rate, $\bar{R}$ is an estimate of the neutral rate, and $\bar{\pi}$ is the inflation target. ε_t^R represents the i.i.d. monetary policy shock.

We assume an inflation target of 2 percent in all scenarios, with response coefficients $\phi_\pi = 1.4$ and $\phi_R = 0.8$, in line with standard estimates the literature (Taylor, 1999). We also assume, for simplicity, that monetary policy is at the neutral rate in the initial period. Given the high degree of uncertainty surrounding the true value of the neutral rate, we repeat the exercise for several values of the neutral rate between 1.75 and 3 percent, in line with recent estimates from the European Central Bank (Brand et al., 2025).

Figure 7: Impulse responses to a monetary policy shock and implied Taylor Rule



(a) Monetary Policy Shock **(b)** Inflation **(c)** Unemployment **(d)** Policy Rates

The results in Figure 7 shows that inflation (panel 7b) under the assumptions of positive labor market momentum is higher than under negative labor market momentum over the rate setting horizon, with the gap largest 4 to 5 quarters after the initial shock. Unemployment (panel 7c), as expected, is persistently lower under the assumption of positive labor market momentum.

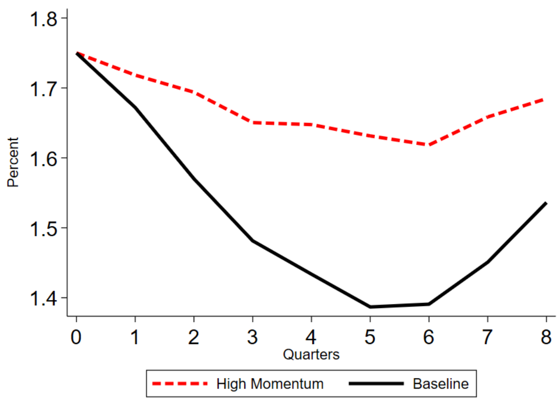
Assuming an initial policy rate of two percent, the expected policy rate in the positive labor market momentum scenario is persistently higher (panel 7d). After four quarters, the expected policy rate under the inertial Taylor rule for the positive-momentum scenario is 11-36 basis points higher than the baseline scenario not incorporating labor market momentum. These results imply that failure to account for the state of momentum in the labor market may, in the case of positive labor market momentum, lead to a monetary policy path that meaningfully undershoots the appropriate level of the policy rate.

We finalize this section by testing the robustness of these results to the choice of the neutral rate of the economy. We study the policy response when the neutral rate is 1.75, 2.25, and 3 percent, as there exists significant uncertainty about the value of this rate and variation over time (see, for example, Benigno et al. (2024) and Ferreira and Shousha (2023)). The results are presented in Figure 8. Our results show that even for these different values in neutral rates, accounting for high momentum leads to different policy rate paths, with larger differences at higher nominal neutral rates.

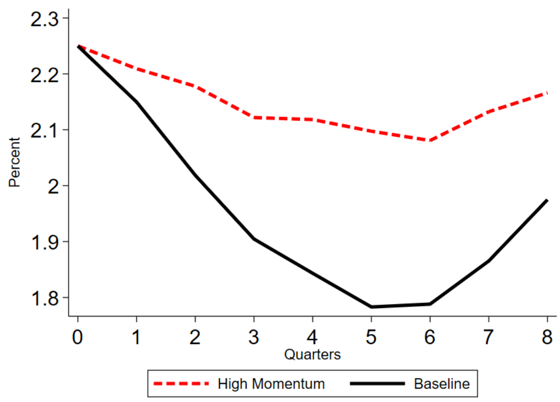
All in all, this section has documented the importance of taking into account labor market health and direction, accounted for by our momentum estimator, for policy makers. Even in the presence of policy tightening, high momentum can dampen the response of unemployment and inflation, reducing the effectiveness and transmission of monetary policy to the economy.

Figure 8: Estimated Policy Rates: Robustness for Additional Neutral Rate Specifications

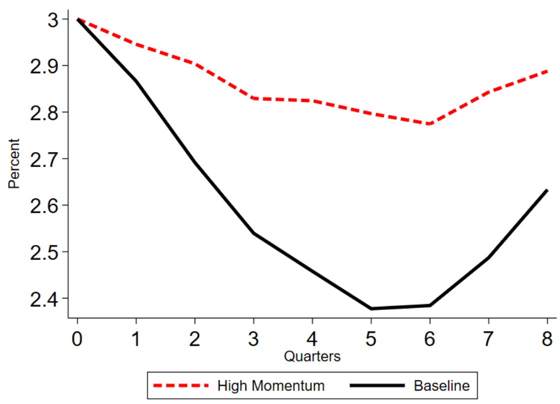
(a) Neutral rate: 1.75 percent



(b) Neutral rate: 2.25 percent



(c) Neutral rate: 3 percent



4.3 Measuring slack and the Phillips Curve

Our last analysis comprises the comparison of standard measures of labor market slack, such as the unemployment rate or the unemployment gap, and those emerging from our indicators. First, we start by comparing the health of the labor market–the unemployment rate–to the one that the additional series summarized in the two indicators generate. We then turn to analyze what the differences across these series represent when assessing the usual relationship between the labor market and inflation via a standard Phillips Curve. We show that by incorporating additional labor market information, slack changes relative to standard measures, leading to a steeper Phillips Curve.

4.3.1 How much slack is there?

In order to evaluate the extent to which the official unemployment rate may be under or overstating broader labor market conditions, we compare the euro-area unemployment rate to the one predicted by our labor market indicators. In our approach, we predict a model-based unemployment rate by regressing the actual unemployment rate on activity, momentum, and an interaction of the two.

Figure 9: Labor Market Indicators Based Unemployment Rate

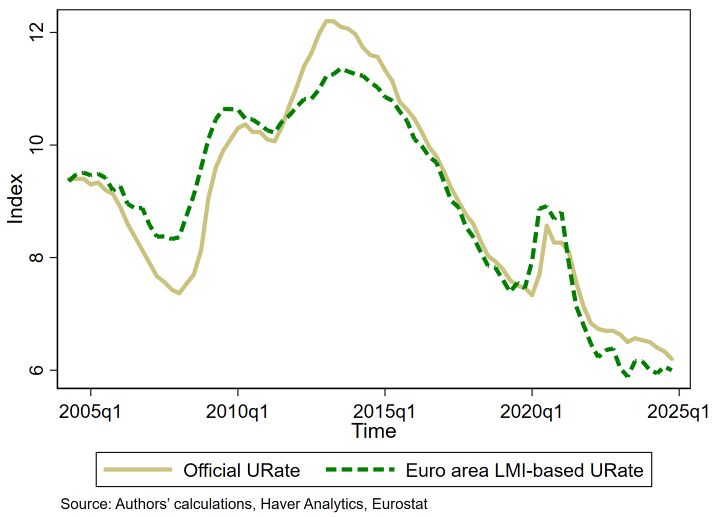


Figure 9 shows the official unemployment rate compared to the indicator-based unemployment rate (EALMI). We see that during the Eurozone crisis, labor market conditions had not deteriorated as severely as implied by the official unemployment rate, since employment and labor force had declined some, but not as sharply as the unemployment rate increased. In contrast, during the COVID-19 crisis, conditions were somewhat worse than the official rate indicated. Particularly important to this period were the rise of short-term work and labor hoarding, which both suppressed the unemployment rate despite significant weaknesses in the labor market. More recently, labor market conditions have been tighter than the official unemployment rate would signal, as employment and labor force participation are at decades-high levels, although conditions seem to have plateaued and the official rate is converging to the predicted one. This example illustrates the importance of looking at a myriad of labor market estimators rather than just one to obtain a better narrative of the state and direction of the labor market.

4.3.2 Implications for Phillips Curve measurement

We next turn to illustrate how the differences between the official unemployment rate and the predicted rate based on the model can result in different empirical correlations between inflation measures and labor market slack, better known as the Phillips curve relationship (Phillips, 1958). The Phillips Curve establishes that periods of lower unemployment are associated with higher inflation, and consequently, the evolution of both series is intertwined, generating an empirical trade-off of great interest to central banks.

In our exercise, we estimate a linear Phillips Curve for 12-month headline inflation changes at the quarterly level and 12-month changes in nominal compensation against various measures of labor market slack: 1) the *naive* quarterly measures of slack given by the official unemployment rate and the predicted rate by our model; 2) the quarterly unemployment gap, calculated as the difference between the measures in 1) and the trend of unemployment extracted using a Hodrick-Prescott filter; and 3) the annual unemployment gap, defined as the difference between the end-of-year measures in 1) and the European Commission's annual non-accelerating wage rate of unemployment (NAWRU) for the euro area.

Table 2 presents the slope estimates for these specifications, underscoring that the model-based unemployment rate exhibits a stronger negative relationship with inflation than the official unemployment-based measures of slack. We choose specification (2) as our preferred specification to visually present and interpret our results next.

	Headline Inflation			Nominal Compensation		
	(1)	(2)	(3)	(1)	(2)	(3)
PC Slope: Official UR						
Coefficient	-0.59^{***}	-0.95^{**}	-0.59^{*}	-0.49^{***}	-0.47	-0.52^{***}
Std. Error	(0.11)	(0.40)	(0.36)	(0.08)	(0.31)	(0.16)
PC Slope: Model-based UR						
Coefficient	-0.72^{***}	-1.37^{***}	-1.11^{***}	-0.60^{***}	-0.89^{***}	-0.87^{***}
Std. Error	(0.11)	(0.36)	(0.42)	(0.08)	(0.28)	(0.17)

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note. Column (1) refers to the specification using the *naive* unemployment rate as regressor, (2) refers to the specification using the HP-filtered unemployment rate to compute the unemployment gap, and (3) uses the European Commission NAWRU to compute the annual unemployment gap.

Table 2: Phillips Curve Estimates: Official vs. Model-Based Unemployment Rates

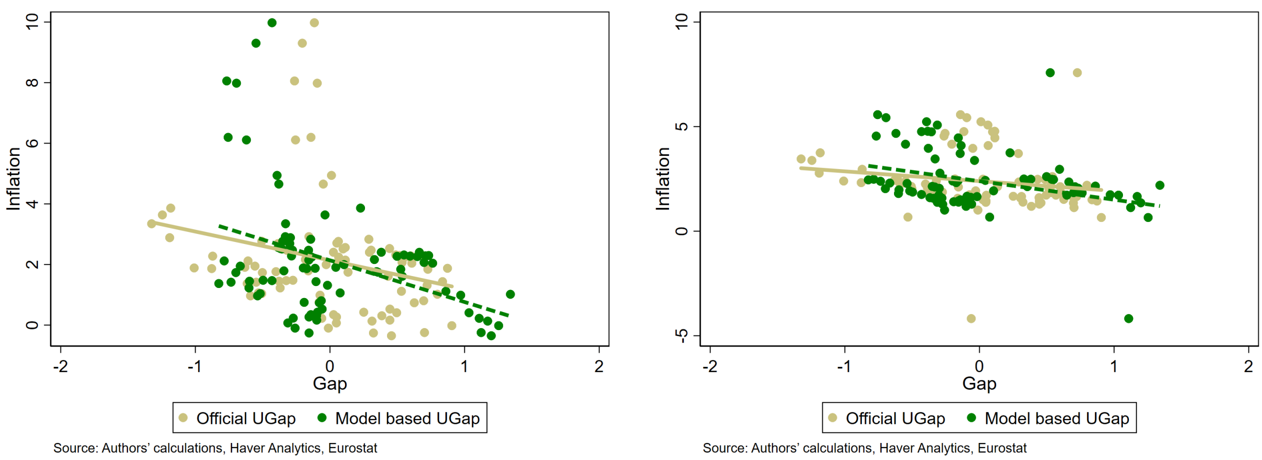
We present in Figure 10 the historical quarterly relationship between inflation (panel 10a and nominal compensation (panel 10b) against the official unemployment rate and the predicted unemployment rate difference relative to the unemployment rate trend (unemployment gap) extracted using a Hodrick-Prescott filter for 2004:Q2-2024:Q4. A positive gap implies that the unemployment rate (official or model-based) is above trend and negative otherwise. The official unemployment rate tends to predict higher slack than the model-based rate, based on the number of observations on the left of both panels. Similarly, the model-based rate seems to assume less slack than the official rate, as it incorporates additional variables, such as labor hoarding, as explained earlier. These differences explain the higher slope of the Phillips curve when using the model-based rate. [13]

As a result, our model-based unemployment rate predicts higher levels of inflation for lower levels of unemployment compared to what the official rate indicates. Similarly to the results shown with the local projections, this is of great importance when assessing how inflation transmits through the economy, second-round effects into wages, and the role of monetary policy. Overall, the applications presented in this paper show that only focusing on one labor market indicator, such as the official unemployment rate, can understate the degree of labor market slack and affect inflation dynamics.

[13]The higher slope at the left-end of the gap suggests the existence of a non-linear fitting, as has been recently discussed for instance in Crust et al. (2023).

Figure 10: Measures of Phillips Curve

(a) Headline inflation **(b)** Nominal Compensation inflation



Note. Ugap stands for Unemployment Gap and it is calculated as the difference between the measure of unemployment depicted and the trend obtained from applying a Hodrick-Prescott filter to the quarterly unemployment rate.

5 Conclusion

This study introduced a novel approach to assessing euro area labor market conditions through the development of two indicators: level and momentum. We combined information from 22 labor market variables using principal component analysis to create a comprehensive and forward-looking analysis of labor market dynamics. Our indicators, particularly the momentum indicator, are successful in predicting changes in unemployment rates and capturing the influence of labor market conditions on monetary policy transmission.

Our research reveals that labor market momentum significantly affects the impact of monetary policy shocks on inflation and unemployment. High labor market momentum tends to dampen the effects of monetary tightening, suggesting that policymakers should consider this factor when setting policy rates to achieve desired outcomes. Moreover, our model-based measures of labor market slack show a stronger negative relationship with inflation compared to official unemployment-based measures, indicating that reliance solely on the official unemployment rate may understate true labor market health and its impact on inflation.

We believe there is a fruitful research agenda stemming from the findings in this paper. One could apply our findings to conduct cross-country analysis within the euro area to examine potential heterogeneity in labor market dynamics and its implications for national and area-wide policies. Additionally, our level and momentum indicators could be integrated into central bank forecasting models to enhance their predictive power for key macroeconomic variables and structural factors driving labor market momentum. These research directions can deepen our understanding of labor market dynamics and provide valuable tools for policymakers in an increasingly complex economic environment.

References

Barnes, M. L., R. Chahrour, G. P. Olivei, and G. Tang (2007). A principal components approach to estimating labor market pressure and its implications for inflation. *Public Policy Brief*.

Benigno, G., B. Hofmann, G. N. Barrau, and D. Sandri (2024, March). Quo vadis, r*? The natural rate of interest after the pandemic. *BIS Quarterly Review*.

Brand, C., N. Lisack, and F. Mazelis (2025). Natural rate estimates for the euro area: insights, uncertainties and shortcomings. *Economic Bulletin Boxes 1*.

Campolmi, A. and S. Gnocchi (2016). Labor market participation, unemployment and monetary policy. *Journal of Monetary Economics 79*, 17–29.

Chung, H. T., B. Fallick, C. J. Nekarda, and D. Ratner (2015, January). Assessing the Change in Labor Market Conditions. Working Papers (Old Series) 1438, Federal Reserve Bank of Cleveland.

Cloyne, J., C. Ferreira, and P. Surico (2019, 01). Monetary policy when households have debt: New evidence on the transmission mechanism. *The Review of Economic Studies 87*(1), 102–129.

Crust, E. E., K. J. Lansing, and N. Petrosky-Nadeau (2023). Reducing inflation along a nonlinear phillips curve. *FRBSF Economic Letter* (2023-17).

Ferreira, T. R., N. Gornemann, and J. L. Ortiz (2025, April). Household Excess Savings and the Transmission of Monetary Policy. *International Journal of Central Banking 21*(2), 1–36.

Ferreira, T. R. and S. Shousha (2023). Determinants of global neutral interest rates. *Journal of International Economics 145*, 103833.

García-Cabo, J., A. Lipińska, and G. Navarro (2023). Sectoral shocks, reallocation, and labor market policies. *European Economic Review 156*, 104494.

Gertler, M. and P. Karadi (2015, January). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics 7*(1), 44–76.

Gilchrist, T. and B. Hobijn (2021). The divergent signals about labor market slack. *FRBSF Economic Letter 2021*(15), 01–06.

Glover, A., J. M. del Rio, and E. Pollard (2021, October). KC Fed LMCI Implies the Labor Market Is Closer to a Full Recovery than the Unemployment Rate Alone Suggests. *Federal Reserve Bank of Kansas City, Economic Bulletin*.

Hakkio, C. S. and J. L. Willis (2013, July). Assessing labor market conditions: the level of activity and the speed of improvement. *Macro Bulletin*, 1–2.

Hakkio, C. S. and J. L. Willis (2014, August). Kansas City Fed Labor Market Conditions Indicators. *Macro Bulletin*, 1–3.

Harding, M. and M. Klein (2022). Monetary policy and household net worth. *Review of Economic Dynamics 44*, 125–151.

Jarociński, M. and P. Karadi (2020, April). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics 12*(2), 1–43.

Jordà, O. (2005, March). Estimation and inference of impulse responses by local projections. *American Economic Review 95*(1), 161–182.

Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the united kingdom, 1861–1957. *Economica 25*(100), 283–299.

Taylor, J. B. (1999, April). A Historical Analysis of Monetary Policy Rules. In *Monetary Policy Rules*, NBER Chapters, pp. 319–348. National Bureau of Economic Research, Inc.

A Appendix A: Data sources and estimation details

Table A.1: Labor Market Indicators: Baseline Model

Indicator	Country	Start date	End date	Source
Unemployment rate	EA20	2000:Q1	2024:Q1	Eurostat, Haver
Unemployment + Underemployment rate	EA20	2008:Q1	2024:Q4	Eurostat, Haver
Long-term unemployment rate	EA20	2009:Q1	2024:Q4	Eurostat, Haver
Underemployed part-time workers	EA20	2009:Q1	2024:Q4	Eurostat, Haver
SPF Unemployment Rate: 8 months	EA20	1999:Q1	2025:Q2	Eurostat, Haver
Participation rate (15-74)	EA20	2009:Q1	2024:Q4	Eurostat, Haver
Employment rate (15-74)	EA20	2009:Q1	2024:Q4	Eurostat, Haver
Employment-Population ratio	EA20	2009:Q1	2024:Q4	Eurostat, Haver
Temporary employment rate	EA20	2009:Q1	2024:Q4	Eurostat, Haver
Employment-Unemployment flows	EA20	2010:Q2	2024:Q4	Eurostat, Haver
Unemployment-Employment flows	EA20	2010:Q2	2024:Q4	Eurostat, Haver
Hours worked per person employed	EA20	2000:Q1	2024:Q4	Eurostat, Haver
Hours worked: Industry ex construction	EA20	2000:Q1	2024:Q4	Eurostat, Haver
Job vacancy rate	EA20	2006:Q1	2024:Q4	Eurostat, Haver
HCOB PMI: Manufacturing employment	EA20	1997:Q2	2025:Q2	S&P Global, Haver
HCOB PMI: Services employment	EA20	1998:Q3	2025:Q2	S&P Global, Haver
Employment expectations	EA20	1985:Q1	2025:Q2	EC, Haver
Labor Hoarding	EA20	2001:Q1	2025:Q2	EC
Kurzarbeit Notices	Germany	2008:Q1	2025:Q1	FEA, Haver
Workers actively seeking work	France	1996:Q1	2025:Q1	MdT, Haver
Registered Unemployment	Spain	1990:Q1	2025:Q1	SEPE,Haver
Cassa Integrazione	Italy	2009:Q1	2024:Q1	INPS, Haver

Note. EC stands for European Commission, FEA for Federal Employment Agency, MdT for Ministre du Travail, SEPE for Servicio Publico de Empleo Estatal, and INSP for Istituto Nazionale Providenza Sociale.

Table A.2: Labor Market Indicators: Additional Sources

Indicator	Country	Start date	End date	Source
Job vacancy rate: non-agricultural	EA20	2004:Q2	2020:Q3	Eurostat, Haver
Labor Hoarding	Germany	2001:Q1	2025:Q2	EC

Note. EC stands for European Commission.

Table A.3: Eigenvalue Analysis of Components

	Component									
	1	2	3	4	5	6	7	8	9	10
Eigenvalue	12.46	5.79	1.65	0.88	0.52	0.28	0.15	0.08	0.05	0.04
Proportion	0.57	0.26	0.08	0.04	0.02	0.01	0.01	0.00	0.00	0.00
Cumulative	0.57	0.83	0.90	0.94	0.97	0.98	0.99	0.99	0.99	1.00

Table A.4: Rotated Component Loadings

Variable	**Component 1**	**Component 2**	**Unexplained**
HCOB PMI: Manufacturing employment	-0.020	0.313	0.421
HCOB PMI: Services employment	0.083	0.356	0.080
Hours worked per person employed	-0.141	0.328	0.226
Hours worked: Industry ex construction	0.154	0.278	0.142
Job vacancy rate	0.265	0.025	0.122
Participation rate (15-74)	0.246	0.075	0.181
Employment rate (15-74)	0.284	0.006	0.012
Employment-Unemployment flows	0.267	0.052	0.077
Unemployment-Employment flows	0.256	0.065	0.133
Employment-Population ratio	0.284	-0.003	0.016
Unemployment + Underemployment rate	0.284	0.016	0.028
Unemployment rate	0.285	0.038	0.026
Underemployed part-time workers	0.259	-0.089	0.189
SPF Unemployment Rate: 8 months	0.278	0.024	0.038
Workers actively seeking work	-0.129	0.016	0.802
Registered Unemployment	0.275	0.032	0.046
Kurzarbeit Notices	-0.040	0.358	0.244
Cassa Integrazione	0.043	0.338	0.254
Long-term unemployment rate	0.279	-0.094	0.063
Temporary employment rate	-0.164	-0.253	0.388
Labor Hoarding	-0.047	0.381	0.144
Employment Expectations Indicator	0.108	0.326	0.128

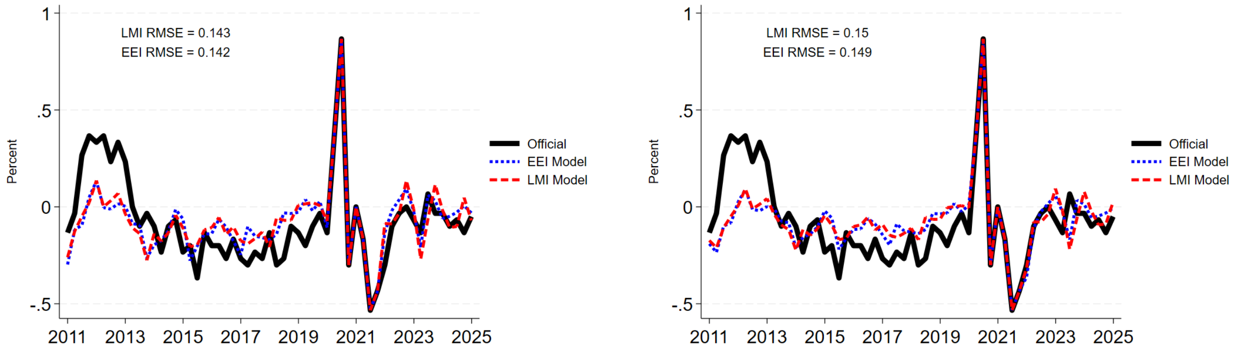
B Appendix B: Business Cycle Robustness Checks

We perform several robustness checks on our momentum indicator across different sample lengths and lag specifications, as well as against multiple forward-looking labor market indicators.

Figure 11 shows the in-sample prediction over the entire sample, including the post-COVID period. This specification includes dummy variables for the several COVID periods reflected in the series. Our LMI predictor (RMSE = 0.143) performs essentially the same as the European Commission's employment expectations indicator (RMSE = 0.142). Under this specification, we see that the fit is particularly poor at the beginning of the sample as the model tries to fit the large swings in the COVID period, even with the dummy variable specification, leading us to focus most of our analysis on the pre-COVID period.

Figure 11: In-Sample Prediction: Full Sample

(a) 1-lag **(b)** 2-lag

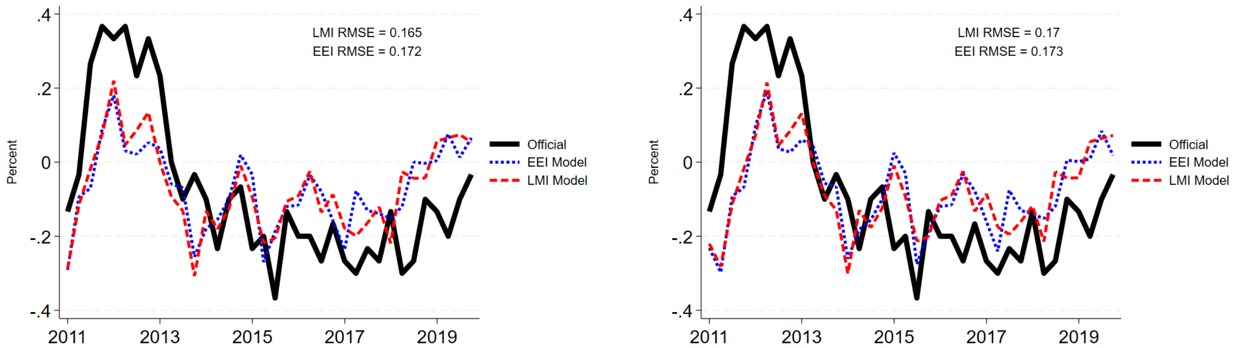


Note. Data extend from 2011Q1 through 2025Q1. LMI stands for the euro-area Momentum Labor Market Indicator developed in this paper, EEI for the European Commission's Employment Expectations Indicator.

The sample focusing on the pre-COVID period (Figure 12) performs much better for both indicators towards the beginning of the sample, with LMI (RMSE = 0.165) outperforming EEI (RMSE = 0.172).

Figure 12: In-Sample Prediction: Pre-COVID Short Sample

(a) 1-lag **(b)** 2-lag

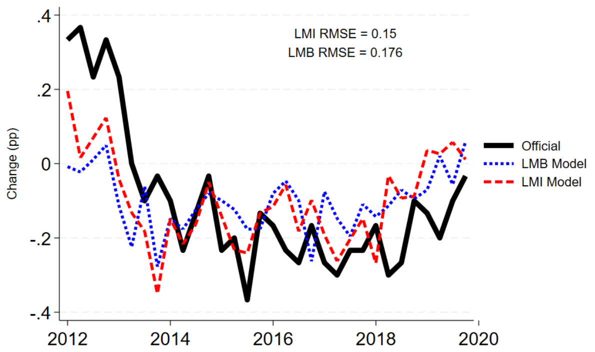


Note. Data extend from 2011Q1 through 2019Q4. LMI stands for the euro-area Momentum Labor Market Indicator developed in this paper, EEI for the European Commission's Employment Expectations Indicator.

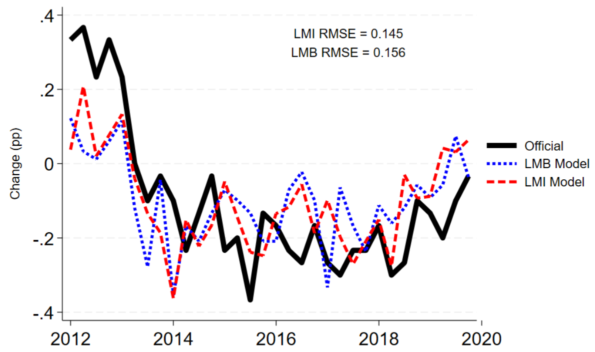
We further test our labor market indicator against the European Labour Market Barometer (LMB). Due to the shorter series of the LMB, we truncate our LMI series for this analysis to ensure comparability of sample periods over the forecast. Figure 13 shows that our LMI model predictions (RMSE = 0.15) again outperform the LMB model (RMSE = 0.176).

Figure 13: In-Sample Prediction: European Labor Market Barometer (LMB)

(a) 1-lag



(b) 2-lag

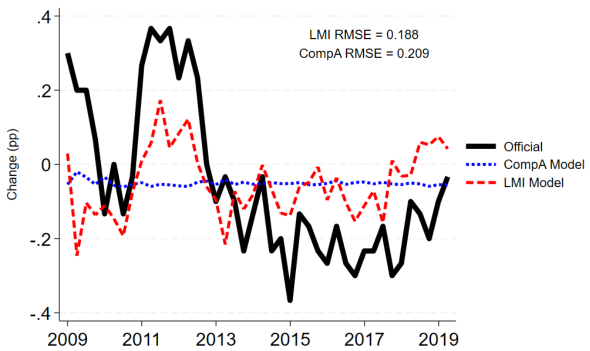


Note. Data extend from 2012Q1 through 2019Q4. LMI stands for the euro-area Momentum Labor Market Indicator developed in this paper.

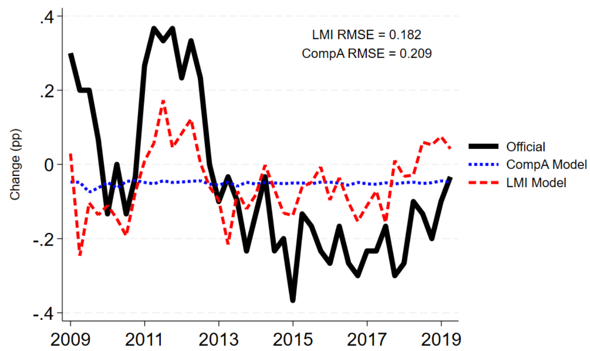
We also test our momentum indicator against the unemployment component (Comp A) of the LMB to assure that momentum's relative performance over LMB is not driven by components unrelated to our dependent variable. Figure 14 shows that visually, Comp A fails to generate meaningful predictions of changes in the unemployment rate in our model setting.

Figure 14: In-Sample Prediction: Component A of LMB

(a) 1-lag



(b) 2-lag

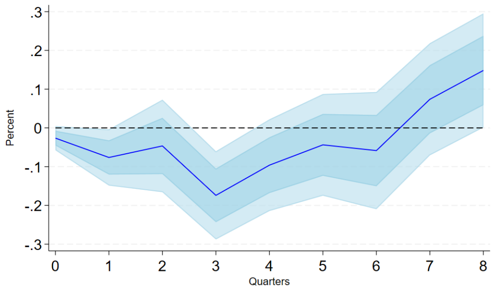


Note. Data extend from 2009Q3 through 2019Q4. LMI stands for the euro-area Momentum Labor Market Indicator developed in this paper, EEI for the European Commission's Employment Expectations Indicator.

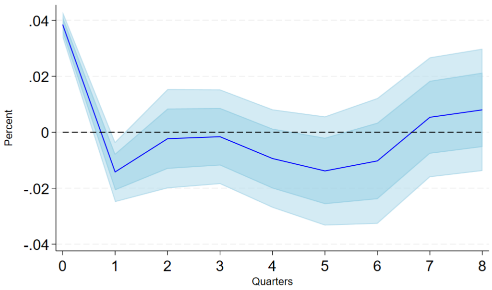
C Appendix C: Additional Local Projection Responses

Figure 15: Local projection analysis: Labor Force Rate

(a) Average Effect



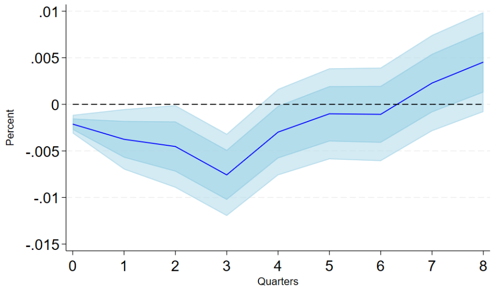
(b) Dampening Effect



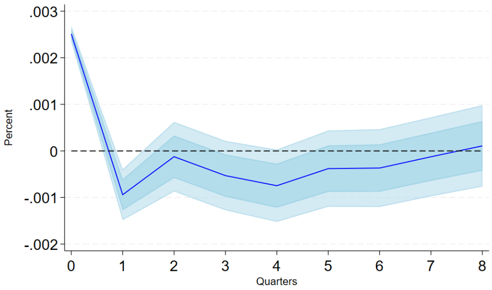
Note. Light shaded areas represent 90 percent confidence intervals, dark shaded areas represent 68 percent confidence intervals, and the solid line represents the mean value.

Figure 16: Local projection analysis: Hours worked per employee

(a) Average Effect



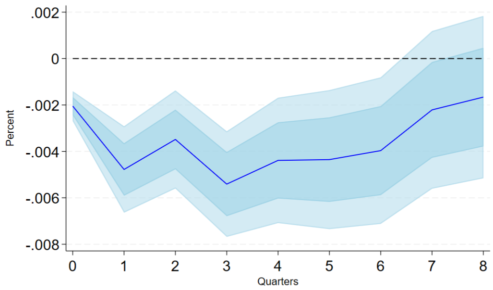
(b) Dampening Effect



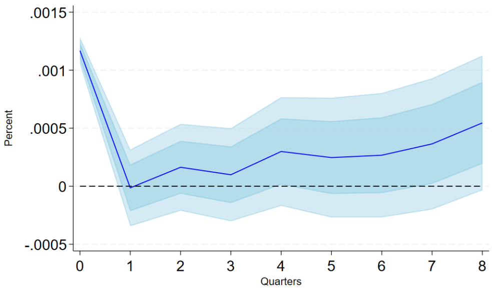
Note. Hours worked per person employed are expressed in log growth rates. Light shaded areas represent 90 percent confidence intervals, dark shaded areas represent 68 percent confidence intervals, and the solid line represents the mean value.

Figure 17: Local projection analysis: Nominal Compensation per Employee

(a) Average Effect



(b) Dampening Effect



Note. Nominal compensation per employee are expressed in log growth rates. Light shaded areas represent 90 percent confidence intervals, dark shaded areas represent 68 percent confidence intervals, and the solid line represents the mean value.