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Eroding Participation in Labor Force Surveys: Evidence, Drivers and Solutions

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Prepared by Eurydice Fotopoulou, Lamya Kejji, Vladimir Klyuev, and Mpumelelo Nxumalo*

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ABSTRACT: The subpar quality of labor market data in many parts of the world can hinder economic policymaking. The challenge is exacerbated by a secular decline in response rates to labor force surveys (LFS) observed in numerous countries, which is also captured partially in labor market data issues flagged in the IMF's Data Adequacy Assessments. This paper documents the evolution of LFS response rates in several countries and explores factors affecting it. By creating a new dataset of LFS characteristics for 39 mostly advanced economies, we find that those with voluntary survey participation have seen the response rates erode 1.5 percentage points per year on average, while the rates have been broadly stable in those with mandatory participation. We also find that survey data collection modalities may affect the response rate. Finally, the paper looks into the effectiveness of various ways in which statistical offices and data users have tried to address the challenges, including adjusting survey methodology and utilizing non-traditional data.

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WORKING PAPERS

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Contents

BOXES

FIGURES

TABLES

Glossary

BEA	Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
CPS	Current Population Survey
DAA	Data Adequacy Assessment
DSI	Data Standards Initiative
Eurostat	Statistical Office of the European Union
IMF	International Monetary Fund
LFS	Labor Force Survey
ONS	Office of National Statistics
SDDS	Special Data Dissemination Standard

Executive Summary

Monitoring labor markets is vital for accurate assessment of economic conditions and policymaking, and as such it requires high quality labor market data. Given this, the persistent decline observed across multiple countries in response rates to Labor Force Surveys (LFS), which have traditionally been a crucial source of information on labor market conditions, is alarming and can affect monetary policy design.

Recently, policymakers, analysts, and the media have expressed significant concerns regarding this trend. The IMF's Data Adequacy Assessments, too, identify broad concerns with the quality of labor market data across a significant share of the membership. A complementary analysis, based on a review of official data releases, documents widespread underperformance in terms of timeliness, frequency, and granularity relative to established benchmarks, particularly among the lower-income economies.

Drawing from these concerns, this paper makes two contributions. First, it examines LFS response rate trajectories in 39 countries, confirming a widespread decrease over the last 10 years. The COVID-19 pandemic intensified the downward trend, and post-COVID-19 recovery has been uneven. To better understand the change, we construct a dataset using publicly available LFS metadata for these 39 countries, which includes LFS response rates, survey participation requirement (mandatory or voluntary), and response collection modalities. At the moment of writing, this dataset is the most exhaustive of its kind. Second, using the dataset we start sketching the factors that may be influencing different response rate trajectories among countries. We find that countries with voluntary survey participation saw response rates erode 1.5 percentage points per year on average during the decade in question, while response rates were broadly stable in those with mandatory participation. We also find that the data collection mode and sampling unit may affect the response rate.

Naturally, declining LFS response rates have prompted various corrective actions to ensure that the data can adequately inform policy. We review traditional methodological and technical solutions from the core toolkit of national statistics offices. While making responses mandatory would appear an impactful intervention, only two countries have taken that route in the last 15 years, Switzerland and Luxembourg, with the former reversing course after political backlash. National statistics offices have experimented with offering participation incentives, altering survey design, sample size, and modalities, and adjusting the way survey data are processed, with varying degrees of success. We also found two cases (Singapore and the UK) that have started experimenting with the use of AI-assisted technologies in data collection.

Less conventionally, digital hiring platforms are increasingly being used for labor market insights outside official statistics. These platforms collect data during their operations, which can be used to shed light on labor market conditions. Hiring platforms have grown in popularity with the exponential growth of the data they collect, although their penetration is still uneven across countries and occupations. Even though these data cannot directly replace official measures of employment and unemployment, they can usually complement and enrich existing data sources. The high degree of granularity and timeliness of non-traditional data hold promise for both structural and conjunctural analysis relevant to policy and decision making.

1. Introduction

Monitoring labor market conditions is essential for effective economic and social policymaking. Timely and accurate labor market statistics are critical inputs for the appropriate setting of monetary policy. Beyond this, reliable labor market data are also important for forecasting inflation, designing labor market policies, allocating social spending, understanding migration, and many other purposes. They are widely used by policymakers, businesses to plan their operations, individuals for career decisions, and researchers to analyze economic trends and patterns. The unemployment rate is perhaps the best known and most cited labor market indicator, but several others are required for a comprehensive picture. These include employment patterns, hours worked, labor force participation, labor underutilization, skills, job turnover, vacancy rates, unemployment duration, wages, and benefits. Labor market data can be regularly published sectoral, regional, and demographic breakdowns.

Labor market statistics are collected from various sources, which traditionally include specific household surveys, establishment surveys, administrative records, and censuses (see Box 1). Labor Force Surveys (LFS) provide data on employment status, job search activities, and demographic characteristics. Establishment surveys offer insights into job vacancies, employment by industry, and wage levels. Administrative records, such as unemployment claims, business registers, or tax records, contribute to understanding labor market flows and trends. Censuses, too, provide snapshots of the labor market and track its evolution over time.

Box 1. Traditional Sources of Labor Market Data

Labor Force Surveys (LFS) remain the principal, and often the only, source for most countries for the estimation of key labor market indicators. These are household surveys that provide fundamental information, as they reflect not only observable labor market outcomes, but also individuals' job-search intentions —information that cannot be captured through other sources easily. LFS outputs are usually published on an annual or quarterly basis, with some countries like the USA publishing labor market indicators monthly, with various degrees of granularity.

Headline indicators such as employment and unemployment levels and rates can also be estimated from administrative data, such as tax records or business registries, or establishment (enterprise) surveys, for instance the U.S. Current Employment Statistics (CES) Survey. The CES provides the headline nonfarm employment estimates, while employment estimates derived from the Current Population Survey (CPS) play a complementary role. Other countries primarily rely on a dedicated LFS or a blend of LFS and administrative data for employment statistics.

Each of these data sources has distinct strengths and limitations. Administrative and enterprise data provide rich information on wages, hours worked, benefits, vacancies, offering valuable context to household-based labor statistics. However, administrative data may suffer from limited timeliness, reducing their usefulness for real-time, data-driven policymaking. Establishment surveys can deliver timely information on employment headcounts and business activity, though they generally lack demographic details that household surveys capture. Ideally, integrating these data sources can produce a more comprehensive and timelier picture of labor market dynamics.

Enterprise surveys face the growing challenge of declining response rates, just like household surveys. The U.S. Bureau of Labor Statistics reports that the CES response rate dropped from 61.0 percent in April 2015 to 42.6 percent in March 2025, while in the United Kingdom, response rates to the Annual Survey of Hours and Earnings fell from an average of 63 percent (1997–2019) to 43 percent since the onset of COVID-19 (Forth et al., 2025).

Recently, the quality of labor market statistics has been found to be lacking. Concerns about the falling LFS response rates and their implications for policy have been expressed by the media, analysts, and policymakers. Additionally, a review of Data Adequacy Assessments (DAAs) in IMF staff reports reveals labor market data gaps in one third of countries assessed. The deficiencies are particularly prevalent in Emerging Market and Developing Economies (EMDEs). Moreover, a comparison with established standards indicates that most Low-Income Countries (LICs) and many Emerging Markets (EMs) fall short of the benchmarks in terms of timeliness, frequency, and granularity of their labor market data.

Declining response rates to statistical surveys could be one reason behind these quality challenges. Information that can be gathered from LFS metadata—mostly for Advanced Economies (AEs)—indicates a declining trend for many countries, although there is no readily available systematic cross-country LFS response rates data for countries at different levels of development. While such trends are harder to discern in EMDEs due to the lack of systematic information, one can surmise that the situation is unlikely to be better there. This paper documents the trends in LFS response rates across 39 countries (mostly AEs) and explores reasons for the observed decline. We focus on the LFS because (i) this is the most widely administered survey across countries, and (ii) it is the source for estimating the unemployment rate, arguably the most important labor market variable for policy.

The first contribution of this analysis is the construction of a dataset—the first of its kind, to our knowledge—comprising LFS response rates, survey modalities and participation which is used for the analysis in the paper. Countries were chosen based on data availability, resulting in heavy representation of advanced economies. We complement this analysis with a summary of labor market data issues flagged in the IMF's DAAs for member countries. Further, the paper highlights structural and resource challenges and discusses the efforts to address them, including using data from digital hiring platforms to complement traditional statistics.

Our analysis advances literature in several ways. It is the first to extract information on labor data gaps from DAAs. It is also the first systematic compilation of response rates in a large dataset since 2018, allowing us to cover COVID-19 and post-COVID-19 developments. Unlike earlier work, our dataset includes not only participation requirement (voluntary vs. compulsory), but also details of survey administration, such as interview mode and sampling unit, which required painstaking metadata collection. These can be useful to other researchers, as well as policy makers interested in ensuring the quality of official labor statistics. We draw on these findings to offer insights into strategies that support higher survey response rates. In examining the role of participation requirements, we identify a significant positive effect of mandatory participation on the rate of change in LFS response rates, thereby extending previous research that primarily emphasized level differences and implicitly assumed their stationarity. Our results suggest that the gap in response rates between voluntary and compulsory participation regimes widens over time, underscoring the lasting influence of mandates on survey performance. We note that this is a correlation, not a clear indication of causality, but given the absolute nature of a compulsory response, one can assume the direction of causality. Finally, we present a comprehensive discussion of current initiatives aimed at improving the quality and reliability of labor market data.

The remainder of the paper is organized as follows. Section 2 reviews labor market data challenges highlighted by IMF DAAs. Section 3 investigates LFS response rates, establishing stylized facts on their recent decline and employing simple econometric methods to differentiate countries with faster versus slower decline. Section 4 considers policy responses to these challenges and the role of big data as a complement to traditional survey sources. Section 5 concludes.

2. Labor Market Data Gaps: Insights from the IMF's Data Adequacy Assessments

Effective surveillance of the circumstances of IMF member countries requires a structured and transparent assessment of the adequacy of their macroeconomic data. To this end, the IMF Board has introduced the Data Adequacy Assessment (DAA) framework. The DAA serves two purposes: first, facilitating policy dialogue with the authorities on data issues and, second, improving prioritization of capacity development efforts (IMF, 2024). In the context of Article IV consultations, the DAA requires IMF staff to assess the adequacy of data provided to the Fund for surveillance purposes, the implications of any data inadequacies for surveillance, and the need for corrective measures. The DAA form includes commentary on five elements: (i) the rationale for the assessment score; (ii) changes in data adequacy since the preceding consultation; (iii) a discussion of necessary corrective actions and capacity development priorities; (iv) explanation for any data used by staff that diverge from official statistics; and (v) the identification of any other data gaps not covered in the standard questionnaire. We focus specifically on these staff-identified "other data gaps."

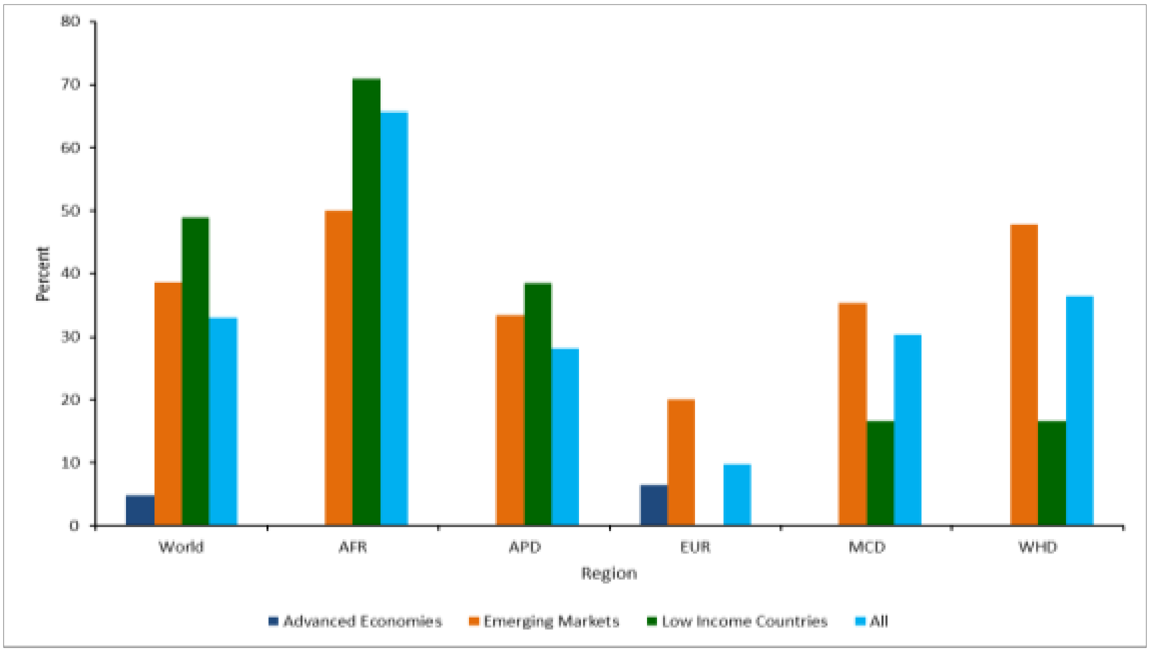
A review of DAA for 161 countries, completed between February 2024 and July 2025 for the purposes of our research, reveals widespread concerns on labor market data.[1] 33 percent of these DAA list labor market statistics in the “other data gaps” section of the form. This is particularly salient given that labor market data are not yet part of the standard DAA template at the time of analysis; concerns about labor market data gaps were volunteered rather than provided in response to a direct question.

Figure 1 shows the distribution of country reports that mention labor data gaps in the DAA by region and by income group.[2] Globally, 49 percent of completed DAA from LICs mention labor data gaps compared to 5 percent of completed DAA from AEs. The Sub-Saharan Africa region (AFR) stands out, with labor data gaps mentioned in approximately 71 percent of DAA from LIC and 50 percent from EMs. This implies systemic challenges in labor data collection and reporting infrastructure across the region. On the other hand, Europe (EUR) shows relatively low percentages across income categories (around 7-20 percent), suggesting more robust labor data systems.

[1] The sample is determined by the timing of the members' Article IV consultations. It covers 84 percent of the IMF's membership and is broadly representative across regions and income groups.

[2] Identification of labor-market-related issues is based on searching for terms such as “labor”, “unemployment”, “employment”, “labor market”, “labor data”, “wages”, “earnings”, “labor force”, “labor force participation”, “employed”, “unemployed”, “income”, “salary”, “wage growth”, “compensation”, “minimum wage”, “real wage”.

Figure 1. DAA Listing Labor Data Gaps, Percent, by Region and Income Group



Source: DAA data, IMF staff calculations.

The three primary challenges identified across the DAA concerning labor market data gaps were: i) frequency and timeliness (affecting 49% of countries), where data collection often occurs only semi-annually or less frequently, consequently hindering real-time policy analysis; ii) coverage and granularity (impacting 30% of countries), specifically relating to inadequate informal sector coverage and insufficient detail for assessing gender dimensions of labor force participation; and iii) methodological and monitoring deficiencies (also impacting 30% of countries), which encompass statistical issues like methodological inconsistencies and the absence of robust monitoring systems necessary for accurately tracking labor market developments.

The labor market data challenges identified in the DAA are corroborated by systematic benchmarking against IMF Data Standards Initiatives requirements, which prescribe quarterly dissemination of employment, unemployment, and wages with a one-quarter lag for countries participating in the Special Data Dissemination Standard (Annex I). For instance, the benchmarking analysis confirms that timeliness issues are most acute in LICs, where a large proportion of countries experience lags of more than 2 years or have no labor data reported at all. Annex I also shows that EUR countries are more likely to provide granular labor statistics including breakdowns by age, sex, education, and economic activity.

3. Response Rates to Labor Force Surveys

The unique breadth of information captured by LFS, unavailable from administrative sources, underscores LFS's essential analytical value. Response rates to LFS[3] have been declining across many countries, a trend that predates COVID-19, but was exacerbated by it and has persisted since. This broad-based decline, observed across multiple survey types, has raised concerns about data quality, representativeness, and continuity. In the UK, the issue has featured prominently in public discussions, with concerns expressed by the press, researchers, and senior policymakers.[4] In the US, cost pressures and falling response rates have fueled concerns that reductions in the in the *Current Population Survey (CPS)* sample size may compromise the reliability of estimates for smaller states or demographic subgroups (e.g., minorities or age brackets), even if national indicators remain robust enough to provide a broad macro picture, (Wilcox, 2024). Similar concerns been expressed in Canada (Lundy, 2023), Sweden (Lindahl, 2019), and elsewhere, reflecting a widespread challenge to sustaining high-quality labor market statistics.

While the issue is not new, there are few systematic multi-country studies of LFS response rates. In addition, there is lack of data to be able to compare the quality and frequency of LFS inputs and outputs across countries. The available cross-country research has limited country coverage, dates back almost a decade, and relies on a single explanatory variable in the analysis. The most comprehensive analyses of declining survey participation are those by de Leeuw et al. (2018) and Beullens et al. (2018). Both examine data from 36 countries, primarily advanced economies - de Leeuw et al. include several non-European advanced economies, while Beullens et al. extend coverage to European emerging markets. Each study documents a broad-based decline in LFS response rates during the pre-COVID-19 period, alongside substantial cross-country variation.

According to de Leeuw et al. (2018), LFS response rates fell by an average of 0.73 percentage points per year between 1980 and 2015, with no statistically significant difference in the rate of decline between the sub-periods 1980–1997 and 1997–2015. They also find that mandatory participation is associated with considerably higher response rates, with an average gap of 11.4 percentage points, both economically and statistically significant. Similarly, Beullens et al. (2018) analyze response patterns across the first seven rounds (2002–2014) of the European Social Survey—a biennial, face-to-face survey—and report a steady deterioration in participation. Response rates declined by 1 to 1.5 percentage points per round, equivalent to 0.5–0.75 percentage points per year, a rate broadly consistent with the findings of de Leeuw et al. The authors discuss a range of potential drivers of declining response rates, including survey fatigue, changing communication habits, and rising privacy concerns, but do not empirically disentangle their effects. Notably, they document increased fieldwork intensity, such as more frequent follow-up contacts with non-respondents, yet note that these efforts did not prevent continued declines in participation.

[3] The response rate to a survey equals the ratio of those who completed the questionnaire to the number of those in the survey sample. While straightforward in principle, some uncertainty may arise in terms of what counts as an attempt to contact an individual or household or how to count partially completed surveys. Frequently the LFS has a longitudinal component, and a partial rotation of the sample (waves), with only a predefined proportion of the sample overlapping across one or more periods. For these reasons, response rates in different countries might not be strictly comparable. That said, the differences should not be overstated, and broad trends can be discerned from observed data. Annex II provides some detail on how LFSs are conducted and how the response rates are calculated.

[4] Examples include Francis-Devine (2023), the Resolution Foundation (2024), Stuart (2024), and Strauss and Borrett (2025).

Cross-country evidence remains limited, but the available country-specific studies corroborate the downward trend and explore its causes. For example, Barnes, Bright, and Hewat (2008) found that the UK LFS response rate fell from 79 percent in 1993 to 58 percent by 2008, with refusals accounting for nearly half of all non-response. In Sweden, Skans (2019) highlights particularly high non-response rates among young adults and foreign-born respondents. In the United States, Czajka and Beyler (2016) document a persistent decline in response rates to the Current Population Survey (CPS) since 1995, while Williams and Brick (2017) report that all six major U.S. government household surveys experienced declining participation between 2000 and 2014, driven by both rising non-contact and refusal rates.

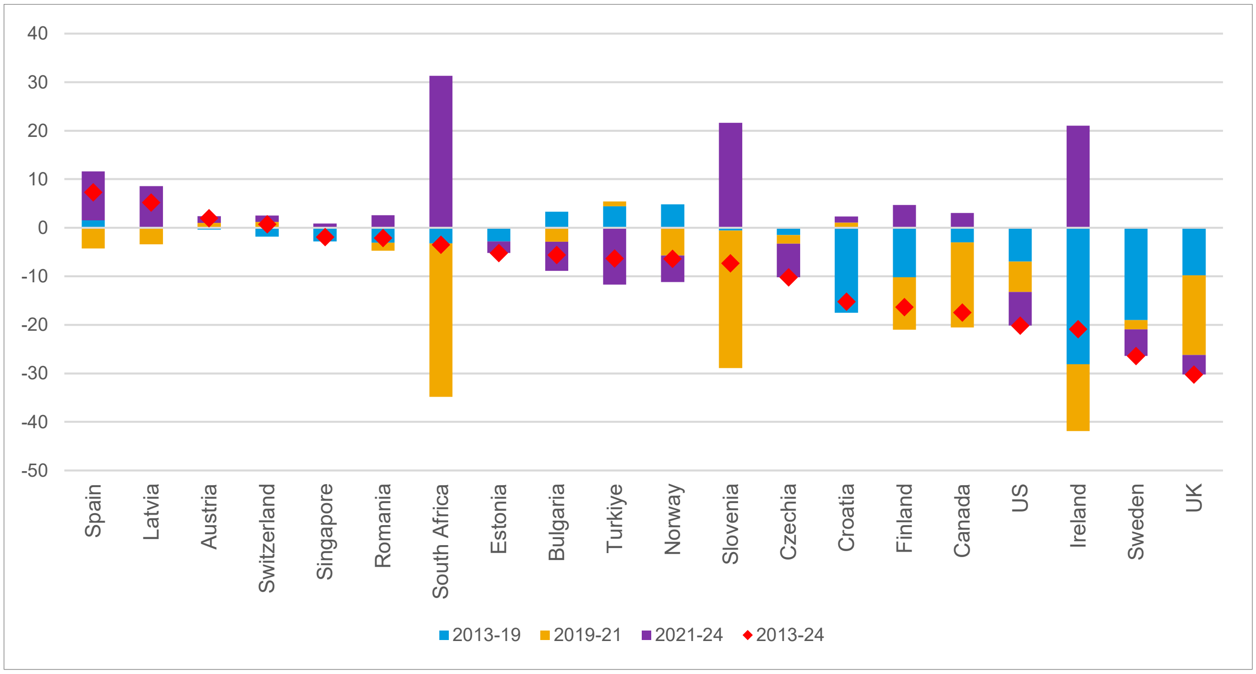
Availability and accessibility of data on LFS response rates exhibit substantial heterogeneity across national contexts. One of the principal contributions of the present analysis is the temporal extension of the datasets mentioned above to encompass the COVID-19 pandemic years, and, for several countries, the subsequent period. Our dataset covers 39 countries, exceeding the coverage of prior cross-country studies (cf. de Leeuw et al., 2018; Beullens et al., 2018). Consistent with these earlier efforts, our sample predominantly comprises European and advanced economies,[5] reflecting considerable challenges associated with broader metadata recording and collection in other regions. Furthermore, we have systematically compiled detailed information regarding survey modalities for all European countries within the sample, which earlier studies do not co. A comprehensive discussion of the data sources and coverage utilized in this study is provided in Annex III.

Figure 2 shows the changes in LFS response rates for 20 countries in our dataset with continuous data coverage spanning the years 2013 through 2024. This analysis disaggregates the observed changes into three distinct temporal phases: the pre-COVID-19 period (2013–2019), the COVID-19 period, and the post-COVID-19 years.[6] Across the entire observation period, the prevailing trend shows a decline in response rates, frequently of a marked magnitude, with only minor exceptions. As expected, response rates in numerous countries experienced a substantial decline during the COVID-19 period. Critically, three-quarters of the countries in the full sample (i.e., the 39 countries with data for both 2013 and 2019) registered declines in the six years preceding the pandemic. Some countries, particularly those that suffered the most significant pandemic-related declines, exhibited recovery in the three years following the pandemic's peak. However, response rates rarely reverted to pre-pandemic levels, and several countries experienced a continued deterioration of response rates during this subsequent three-year period. Individual country response rates are available in Annex IV.

[5] Given the findings in Section 2, one would expect difficulties in LFS data collection to be at least as great outside that group.

[6] While the global pandemic officially ended in March 2023, arguably the peak of COVID-19 was in 2021. Annex IV shows the evolution of response rates for all countries in our sample.

Figure 2. Change in LFS Response Rate, Percentage Points



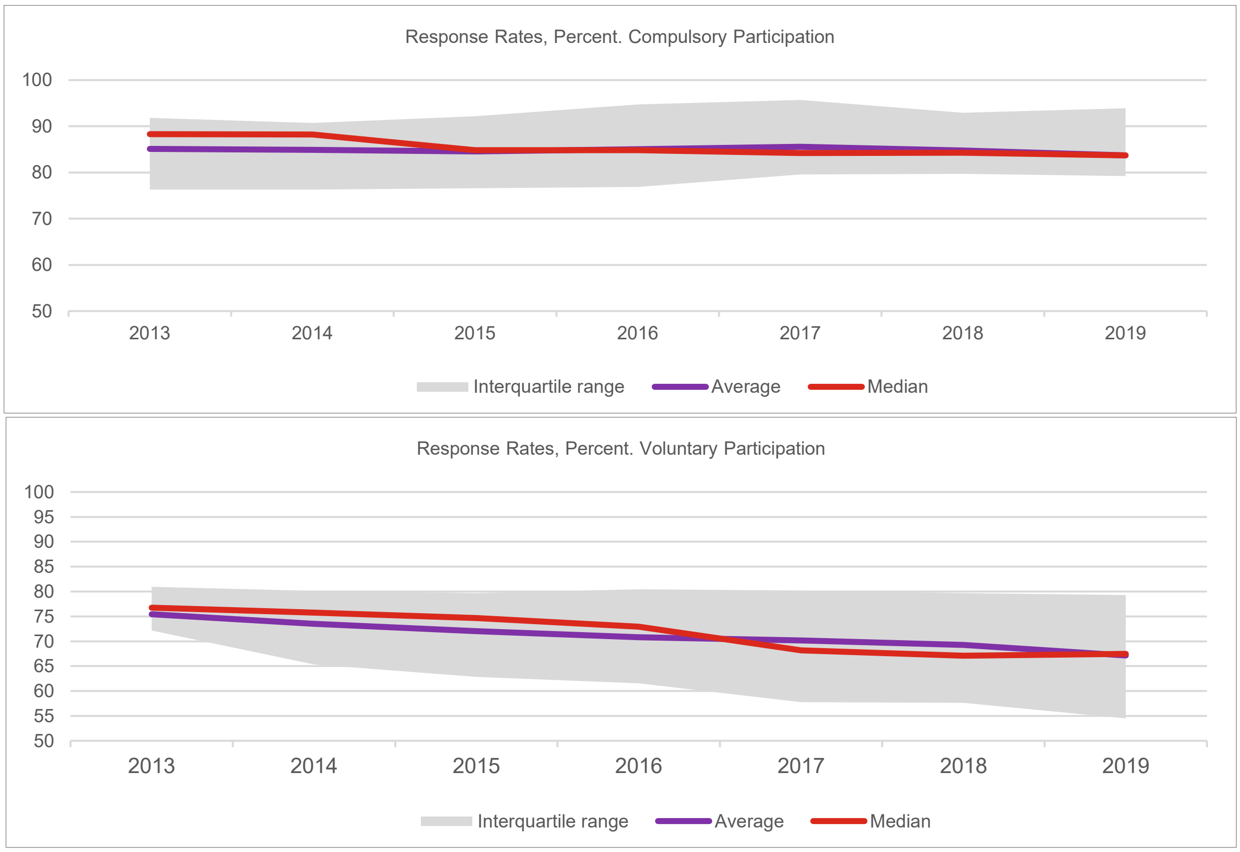
Source: Eurostat and national statistics offices.

There is no shortage of explanations about the causes for the decline in response rates to LFS (which also apply to other surveys). Reduced landline penetration makes it harder to contact survey participants over the phone (Czajka and Beyler (2016); Johnson and Linse (2023)). Smaller households and increased female participation in the labor market make it less likely that someone will be home to respond to a phone call or open the door during business hours (Beullens et al., 2018). Foreign-born residents may be reluctant to talk to field interviewers or be unable to because of the language barrier (Skans, 2019). Some observers have pointed at survey fatigue (Flodberg and Wasén, 2024), or reluctance to respond to field interviewers due to fear of scams (Lindahl, 2019), data privacy concerns, as well as a growing distrust of the government. Several national statistics offices have been citing funding challenges that affect administration of surveys (UNECE, 2025), for instance, cutting down on return visits to households if there was no contact in the first attempt. The concurrence of these attitudes across most countries makes the empirical disentanglement and differentiation of their individual impact a significant challenge, which is beyond the scope of our research.

We start our investigation from the only possible factor that has been tested empirically, **compulsory vs. voluntary participation in surveys**. De Leeuw et al. (2018) find that, other things being equal, response rates are 11.4 percentage points higher for mandatory surveys than for voluntary ones. Given the significant disruption to survey execution and the volatility induced in response rates by the COVID-19 pandemic, coupled with its likely effect on the enforcement of participation, our empirical focus is the pre-pandemic period (2013–2019). This sample period includes 23 countries with voluntary participation and 16 with compulsory participation. A simple inspection of the longitudinal response rate data for this period (Figure 3) immediately establishes a structural difference: countries with compulsory survey participation consistently register higher response rates. This structural divergence is empirically robust, evidenced by the fact that the interquartile ranges of the two groups exhibit near-total separation. Specifically, the 25th percentile for the compulsory group approximates the 75th percentile for the voluntary group.

Furthermore, this structural gap demonstrated a clear expansion over the seven years under consideration, suggesting that the rate of decline in response rates was considerably higher in the countries with voluntary participation methodologies.

Figure 3. Evolution of LFS Response Rates



Source: Eurostat, national statistics offices, and authors' calculations.

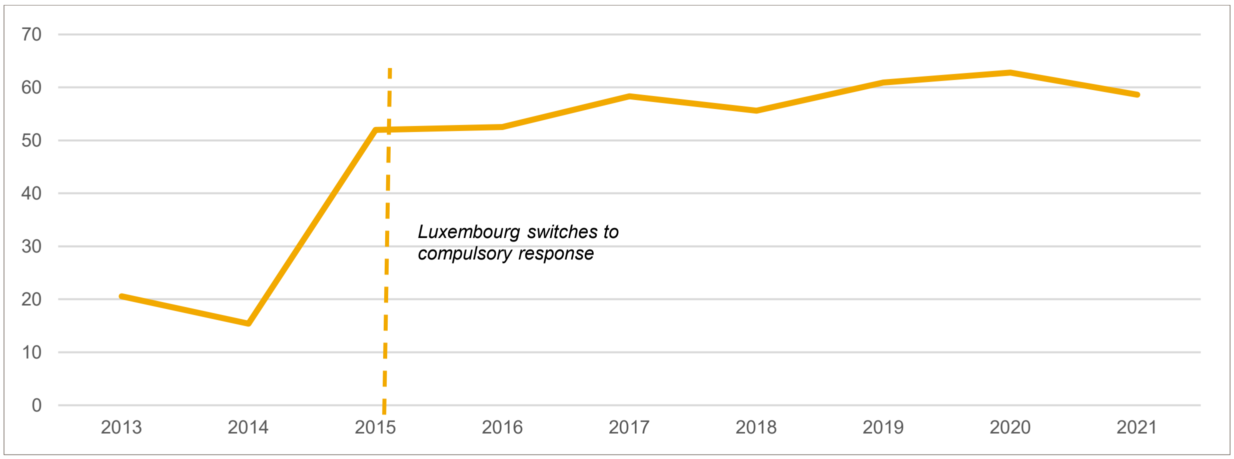
As a result of these trends, by the end of the observation period the response rate was on average 16.6 percentage points higher in the 16 countries with mandatory participation (Table 1). This magnitude directly quantifies the structural leverage afforded by a legal obligation in maintaining survey response integrity, underscoring the necessity of policy enforcement mechanisms, among other measures.

Table 1. LFS Response Rates

	Response rates, 2019, percent		**Change 2013-2019, percentage points**	
	Compulsory	*Voluntary*	*Compulsory*	*Voluntary*
Average	83.7	67.1	-1.4	-8.3
Median	83.7	67.5	-2.8	-5.1
Number of countries reporting	16	23	1	-1

While cross-sectional evidence confirms the effectiveness of mandatory participation, time-series evidence is scant, as countries rarely change their regime. Additionally, we acknowledge that countries that adopt mandatory participation may differ systematically from those that do not do so, in ways that also affect response rate trends, for example having stronger privacy norms, greater institutional capacity, or higher trust in government. Indeed, in the past 10 years only one country in our sample, Luxembourg, switched its policy from voluntary to mandatory, in 2015; Switzerland had attempted that in 2010 but it was short-lived (see Section 4). As Figure 4 demonstrates, Luxembourg's response rate increased sharply after the mandatory rule was introduced and has stayed at that elevated level.

Figure 4. Luxembourg LFS Response Rate, Percent



Source: Eurostat

Motivated by this (limited) evidence we proceed with econometric analysis of factors affecting LFS response rates. We start by looking at compulsory or voluntary participation, then survey administration modalities and finally sampling unit. The details of the analysis are presented in Annex V.

Our key finding indicates that LFS response rates in countries with voluntary **participation** decline on average at a rate of about 1.5 percentage points per year. Conversely, the rate of change in countries with compulsory participation is not significantly different from zero. While our high-level findings align with earlier cross-country studies, particularly de Leeuw et al. (2018), in confirming a broad secular decline in LFS response rates and validating the strong positive effect of compulsory participation, critical structural differences emerge in our analysis. The methodology employed by de Leeuw et al. (2018) hypothesizes a uniform rate of response rate decline across nations, attributing the difference to compulsory versus voluntary participation, albeit restricted to a constant, time-invariant difference in levels. In contrast, our findings reveal that the participation requirement significantly impacts the speed of the response rate decline. This implies a non-stationary and increasing divergence over time between the average response rates of countries with mandatory versus voluntary regimes. This structural refinement provides a more nuanced understanding of the empirical stylized facts. Specifically, the aggregated trend decline of 0.5–0.75 percentage points per year identified in earlier literature (Beullens et al., 2018; de Leeuw et al., 2018) appears to be an average outcome resulting from approximately zero decline in compulsory countries and a highly concerning annual decline of 1.5 percentage points in voluntary countries. We contend that this insight, which isolates the participation requirement as a structural determinant of the rate of decline, constitutes a significant theoretical and empirical contribution to the literature on non-response dynamics.

Turning to **survey data collection modality**, we find that employing a mix of response collection modalities is preferable to relying primarily on one dominant mode. There is some evidence in our analysis that increasing the relative share of web interviewing (CAWI) in the mix correlates positively with an increase in the response rate in our sample, but there is no such effect if it is the dominant mode. That could reflect the fact that, for some demographic groups, internet surveying offers flexible timing for completing the questionnaire, as well as the recent societal tendency away from direct person-to-person interactions. However, there are quality concerns associated with data collected with self-administered web interviewing, while there may be mode effects at play. Additionally, lack of digital literacy, public skepticism, and fatigue around online surveys can reduce response rate to web interviewing. This suggests that a combination of collection techniques may be better suited to reach different population strata, and it requires careful design.

Finally, choosing "person" as a **sampling unit** appears to drive down response rates, perhaps reflecting the extra cost and effort needed to track down all specific individuals, as opposed to households or residents at a fixed address, where a larger target group makes it easier to find a respondent (including using a proxy response). Given the limited sample on which this analysis was conducted, the robustness of these results is not assured. Nonetheless, the impact of these changes is acknowledged in the strategy of national statistics offices to address the declining response rate to LFS. Other considerations, such as cost and accuracy of methods used, can play a role in selecting the optimal collection mode mix, however there was little publicly available information on LFS costs to be able to conduct meaningful analysis. With these caveats, our findings signal that the details of survey administration matter.

4. Addressing the Challenges

This section considers ways to improve the quality of labor market statistics in a budget-constrained environment. We first focus on means to extract more information from labor force surveys and their effectiveness based on country-specific evidence. Subsequently, we consider how traditional labor market indicators can be augmented and complemented by leveraging data obtained from non-traditional labor market data sources to better inform policy.

In response to the pervasive decline in LFS response rates, national statistics offices have primarily relied on **methodological and sampling changes to preserve data quality**. These typically involve adjustments to survey design, interview modes, data processing, and weighting schemes to effectively manage non-response effects. For instance, national statistics offices in Norway and Poland have employed recalibration techniques, integrating adjustments to their rotational sampling (survey waves) and utilizing register-based employment data to mitigate resulting biases (Oguz-Alper, 2018; Saczuk and Zajkowska, 2024). While the UK extensively trialed changes to its sampling methodology and weighting (ONS, 2023), these efforts proved insufficient to overcome the high non-response at the time. This ultimately necessitated a complete LFS redesign, the Transformed Labour Force Survey (TLFS) as a long-term solution – to be fully rolled out in 2026 – while the UK experiments with other adjustments that have yielded promising results in the most recent waves (Benford, 2025). Furthermore, for most countries, estimation processes incorporate a form of weighting adjustment predicated on the differential responsiveness of various sample segments (e.g., urban vs. rural, initial vs. subsequent waves). Additionally, where possible, administrative data can be used to close data gaps or benchmark LFS data, especially using payroll data, or unemployment registers. Crucially, the non-response that remains is not random; while small for the key demographic and labor force status variables, partial non-response is notably larger when economic variables are disaggregated by industry, occupation, and earnings (U.S. Census Bureau, 2019).

For any given level of response rate, the accuracy of estimates can be improved by a carefully considered **expansion of the sample size,** if it targets groups of the population that are more prone to non-response. The ONS has taken this step in the UK, increasing its LFS sample to 55 percent relative to its pre-pandemic size. The expansion resulted in a considerably higher number of responses and better quality of statistics, as indicated by greater coherence between LFS data and other labor market indicators (ONS, 2025). While this approach is straightforward and its impact is predictable, budget constraints can limit its applicability, and care should be taken not to introduce bias. In a similar vein, repeated follow-up attempts to reach potential respondents in case of non-contact, or changing collection modality in case of refusal, may boost the response rate. Nonetheless, such intensified efforts can be costly and may compromise the timeliness of survey results.

Changes in the combinations of data collection modes has also proven effective in maintaining participation rates in some cases, as demonstrated by the experiences of Canada and Poland during COVID-19 (Brochu and Créchet, 2021; Saczuk and Zajkowska, 2024). Likewise, Switzerland has observed an increase in response rates since 2021 with the introduction of web-assisted interviews, alongside telephone ones.[7] Ireland's Central Statistics Office (CSO) has also implemented innovations to counter declining response rates in their LFS over the last 5 years, such as rebalancing the mix of collection modes and refining sampling strategies to improve representativeness. The CSO additionally introduced interviewer dashboards and real-time monitoring tools to boost fieldwork efficiency and data quality, reporting that results were promising—response rates stabilized or improved, and operational efficiency increased (CSO, 2025).

Specific **targeted interventions at data collection level** have proven effective in stabilizing or improving LFS response rates. In Iceland, for example, the strategic use of mobile communication outreach illustrates the success of targeted interventions in enhancing response rates (Sigurðardóttir and Blöndal, 2020). The Australian Bureau of Statistics, similarly, uses a tailored approach to increase engagement with certain demographic groups (Kezilas, Kelly and Wood, 2023). Meanwhile, in the US, the CPS uses alternative language speaking interviewers to overcome refusals to respond due to language barriers. The emergence of Artificial Intelligence (AI) has prompted some countries, such as Singapore[8], to experiment with **AI-assisted interviewing** in LFS, while the UK is exploring the use of Generative AI to improve data collection (Banks and Maspero, 2025), which may provide new insights into maximizing efficiency and response.

Adaptive survey design (ASD) is an increasingly common approach to address non-response, improve representativeness, and optimize survey resource use (see Box 2). For example, the Netherlands, uses ASD to achieve a more balanced response by varying the means of contacting different population groups, combined with mixed mode collection (Van Berkel, 2022). Canada anticipates an improvement in response rates and a reduction in overall survey costs, due to the introduction of ASD (UNECE, 2025). As seen in Box 2, administrative data has often been used to supplement LFS surveys, both in the course of regular statistical production and to close data gaps during periods of high non-response in LFS. During COVID-19 Canada and the European Union successfully integrated administrative data to address data gaps and ensure continuity in labor market analysis (Lucarelli, 2020; Brochu and Créchet, 2022).

[7] Evidence provided directly via correspondence by the Labor Force Section of the Federal Department of Home Affairs of the Swiss Federal Statistical Office (April 2025).

[8] Presentation to the 12th Annual Statistical Forum by the IMF, 2024, available at: p4sessioniiinov20chen-zhihanharnessing-aifor-enhanced-efficiency-and-data-quality-in-government-stat.pdf

Box 2. Adaptive Survey Design Examples

Adaptive Survey Design (ASD) is a framework in which aspects of survey operations—collection mode, number of follow-ups, use of incentives—are dynamically adjusted during the survey process, using auxiliary data and paradata to increase representativeness and cost effectiveness (Schouten, Peytchev and Wagner, 2017).

Table B2.1 Adaptive Survey Design Features in Selected Countries

Aspect	The Netherlands	Canada
Mixed mode collection	The starting mode is Computer-Assisted Web Interviewing (CAWI), and follow-up of CAWI non-response by a combination of Computer-Assisted Telephone Interviewing (CATI) and Computer-Assisted Personal Interviewing (CAPI).	Statistics Canada data collection strategy relies on self-completed *internet response as the first mode of response.* CAPI is used to follow up on non-response.
Targeted outreach	The survey *targets non-response-prone subpopulations* (youths, migrants) and adapts contact times and strategies based on response patterns. For instance, to improve the precision of unemployment figures, i) job seekers registered at the Netherlands Employees Insurance Agency (EIA) are overrepresented, ii) non-western migrants and 15- to 24-year-olds are overrepresented, iii) people aged 65 or over and 14-year-olds are underrepresented.	By combining the integration of auxiliary information and mixed collection mode, Statistics Canada intends to focus efforts on *harder-to-reach groups* and lower the risk of non-response bias.
Use of administrative data	Stratification is done with auxiliary variables from relevant registers.	Statistics Canada is developing methods to use administrative data to develop on-demand survey sampling frames.

Sources: Adaptive Survey Design for the Dutch Labor Force Survey, UNECE, 2025.

The most direct, possibly controversial, way of arresting low response rates may be to mandate **participation**. The present analysis indicates substantial differences between countries with compulsory LFS responses and those relying on voluntary participation, and one could assume that transitioning to a mandatory response status could effectively halt or reverse the erosion of response rates. This is borne out by Luxembourg's experience, where there was a sharp and sustained increase in the response rate after making response mandatory in 2015, following a period of LFS response rate declines. However, imposing a mandate may face resistance, which probably explains why more countries have not followed this tactic. The case of Switzerland illustrates this: the introduction of the obligation in 2010, initially boosted the response rate by about 10 percentage points, but it had to be abandoned two years later, after a backlash. A consideration is the practical enforcement of the obligation to respond, which may present significant operational difficulties. It is worth noting that countries with fewer concerns about data privacy or higher levels of institutional trust may both be more likely to adopt mandatory participation successfully and to maintain higher response rates for other reasons.

A monetary **incentive** to respond could be an alternative strategy for a mandated reply. The Swiss Federal Statistical Office, for instance, began offering vouchers to respondents after the compulsory response was removed. The incentives appear to have been effective in reducing the drop in participation but had to be discontinued in 2024 because of budgetary constraints. Indeed, cost considerations, particularly in the current environment, limit the attractiveness of this approach. Research by the U.S. Bureau of Labor Statistics (BLS) on the use of incentives in surveys (To, 2015) indicates that although they increase response rates in general, they are not always the most cost-effective solution and may increase the administrative burden. Research by the US Census Bureau (2007) reached similar conclusions. Consequently, if incentives are used, it is important to consider the potential for introducing systematic biases into survey results.

In recent years, especially following the COVID-19 pandemic, there has been increased experimentation **using non-traditional data sources**. These sources consist of data collected as a byproduct of routine business activity rather than explicitly for statistical purposes. In the context of labor markets, a prominent example is data generated by digital hiring platforms. The routine operational processes of these platforms yield data that can be used to shed light on labor market conditions. Annex VI provides a brief overview of the most common non-traditional data sources that have been employed for labor market analysis.

Non-traditional data broadly offer two advantages: high degree of granularity and timeliness. As a result, such data can inform policy by facilitating analysis of the hiring rate and labor market tightness (based on posted vacancies and the speed at which they are filled), mismatches comparing users' education and skills against requirements in job advertisements and tracking trends in wages and salaries. The primary sources for these data are job postings and jobseekers' profiles, contain a high level of detail, that extends beyond the capabilities of the LFS. While most of these platforms restrict access to microdata, they offer labor market analytics on variables such as occupational classifications, geographical distribution, employing organizations, remuneration scales, education, skills required and possessed, gender breakdown, and temporal hiring patterns, among others. These data can complement and augment traditional data sources. For some standard labor market variables, such as vacancy or hiring rates, non-traditional sources can furnish a sufficient proxy. However, others—in particular, unemployment or participation rate, which rely on behavioral intentions alongside actions to determine one's labor force status—the quality of the proxies derived from non-traditional data depends on the existence and stability of the underlying behavioral relationships linking the target variable and the proxy.

A significant limitation of non-traditional data, when compared to surveys utilizing representative sampling or administrative data potentially covering the entire relevant population, is its coverage dependency on the market penetration of the specific platforms. This penetration is non-uniform across key dimensions, including demographics, countries (or even geographic regions within countries), and occupations. This may limit the applicability of these data, where there are mostly needed. At a minimum, it necessitates a good understanding of appropriate proxies, the various embedded biases, as well as diligent caveating of results. For instance, a validation exercise conducted by World Bank and LinkedIn found that metrics derived from LinkedIn data favor middle- to high-income countries, and knowledge-intensive and tradable sectors within technology and business occupations (Zhu et al., 2018). The penetration of digital platforms is growing, a trend that will likely mitigate issues with market maturation—although in the meantime the uptrend complicates comparisons over time even within a given country.[9]

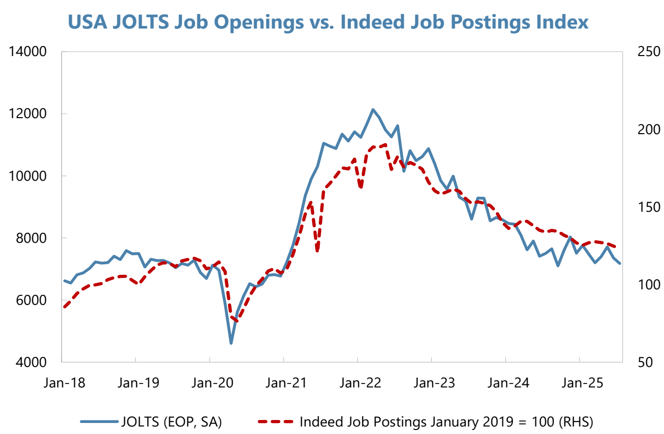
[9] This suggests that analysis focused on ratios rather than raw numbers may be more robust.

A comparison of metrics derived from these sources against official data, as detailed in Box 3, suggests that non-traditional data, while highly informative, generally functions best as a complement rather than a substitute for official statistics. In advanced economies, where online job searching and matching is prevalent, non-traditional data behave similarly to official labor statistics and have the potential to become reliable policy inputs. Conversely, in countries where there is limited coverage of labor markets by digital hiring platforms, non-traditional data alone cannot provide sufficient conclusions about changes in labor markets.

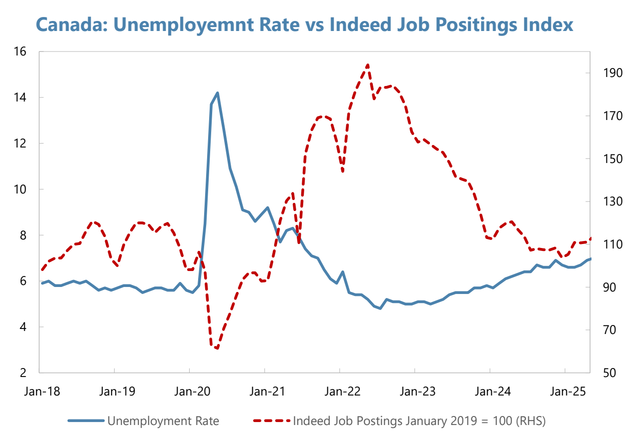
Box 3. Traditional and Non-traditional Data for Policy

LinkedIn's hiring rate and Indeed's job postings count have been found to track reasonably well certain policy-relevant labor market statistics in most economies they cover, although the degree of matching depends on the market penetration of these platforms[10], as well as structural features of the labor markets (e.g., the presence of a large informal sector[11]).

1. Advanced Economies



Vacancy data provided monthly by JOLTS and Indeed job postings for the US exhibit very high correlation, due to the proximity between the two concepts, and Indeed's high penetration of the US labor market (Ardjan and Lyndon, 2024). Job postings data has been one of Indeed's flagship products and has been used in analysis requiring timely information as a consistent and reliable proxy for vacancies (Soh et al, 2022).



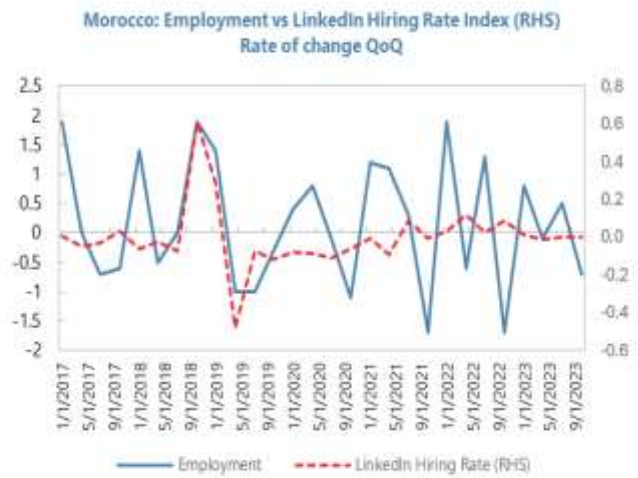
In Canada, as in many other advanced economies, we find that the expected inverse relationship between Indeed's job postings count and the unemployment rate, tends to broadly hold for the period for which data is available (January 2018 - May 2025), and that job postings track well the pace of economic recovery. This observation is consistent with the Beveridge Curve relationship between unemployment and job vacancies. The correlation between the two series is (negative) 74 percent, suggesting that Indeed's job postings count could provide a timely and fairly reliable indicator of labor market conditions.

[10] Indeed offers more granular, real-time microdata for a small number of AEs, while LinkedIn's indices have broader geographical coverage across AEs and EMs with a series of ready-made aggregations. See Annex VI for more details.

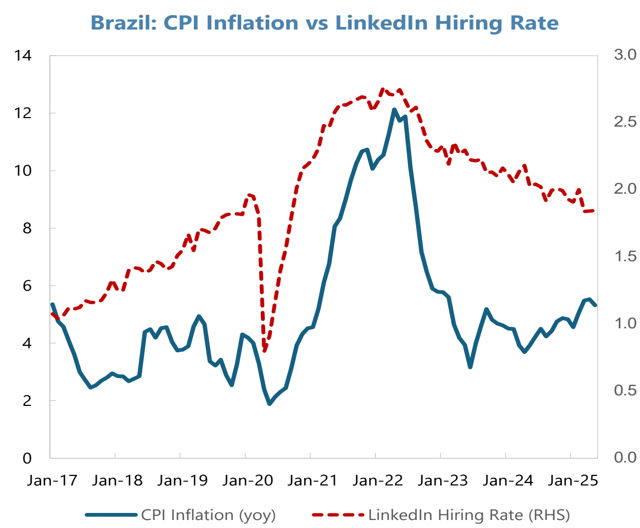
[11] Informal sector jobs can be and frequently are advertised on digital platforms, so one should not think that this is a blind spot. At the same time, the platforms' penetration of the informal sector is lower than for the formal one.

(Box 3 continued)

2. Emerging Market Economies



In Morocco, we observe a moderately positive correlation between the quarter-on-quarter changes in the official rate of employment and the LinkedIn hiring rate. The hiring rate anticipates the direction of the change in employment by one quarter, confirming the expectation that an increase in the hiring rate leads to higher employment levels. However, interpretation is not entirely straightforward for the period that data are available and the magnitude of the change varies considerably. A possible explanation for the variation in magnitude in this case is that LinkedIn data capture mostly white-collar and formal jobs, where online job matching is more common.



In Brazil we observe a clear positive correlation between inflation and LinkedIn hiring rate. During boom periods, strong hiring bids up wages and raises incomes, putting upward pressure on prices. Conversely, a slowdown would lead to a cooling down of prices and a decline in hiring. Hence, the hiring rate could be a useful indicator of cyclical conditions relevant for monetary policy.

Sources: Indeed Job Postings Count (Canada and the USA), Statistics Canada, Bureau of Labor Statistics, Haver Analytics, LinkedIn Hiring Rate (Brazil and Morocco), IMF's International Financial Statistics, and authors' calculations.

The successful integration of any non-traditional data sources into policy analysis is contingent upon a rigorous and multi-faceted assessment of both conceptual alignment and operational feasibility. While these novel data streams offer advantages in timeliness and granularity, their utility is frequently mitigated by methodological challenges, such as establishing the conceptual validity of proxies (e.g., job postings versus true vacancies) and resolving issues of data accuracy and duplication. Addressing these requires not only dedicated resources for dataset acquisition and the development of specialized technical and digital infrastructure and skills, but also a deep understanding of the source data's primary collection process and associated metadata. The adoption of these sources must also navigate complex legal and ethical governance frameworks concerning purpose, data privacy and user consent (Al Bhaghal et al., 2024), underscoring the imperative for a transparent, case-specific cost-benefit analysis to ensure any insights are robust and fit for policy purposes.

5. Conclusion

This paper documents a challenge to one of the empirical foundations of modern economic policy: the systematic erosion of quality in official labor market statistics. Timeliness, frequency, coverage, and granularity may often be insufficient for monitoring economic conditions and policy design. While the accuracy of labor market data is difficult to assess directly, it is almost certainly affected by the decline in response rates to labor force and establishment surveys.

Response rates to various government-conducted surveys have been declining across the world. In this paper we focus on labor force surveys. For the purpose of this analysis, we build a dataset to conduct an exploration into whether survey features affect response rates. We document reductions in LFS response rates over the last decade in 39 countries. In some of these countries, the extent of the decline presents challenges to the quality of economic analysis and policymaking. We also observe that in several countries for which data are available, response rates have not recovered after the predictable dip experienced during COVID-19.

However, the response rate evolution has not been uniform. Cross-country evidence demonstrates that mandated participation in LFS could make a difference. Our analysis indicates that the response rates tend to decline at a rate of around 1.5 percentage points per year on average in countries with voluntary survey participation while they remain broadly stable in those where participation is mandated. This contrasts with earlier (pre-COVID-19) literature that reported a general erosion of about 0.5-0.75 percentage points across all countries and the participation obligation manifesting itself in level rather than change differences.

We also observed a positive impact in the two cases in the last 15 years where such mandates were newly introduced, Luxembourg and Switzerland, although in the latter a backlash resulted in a reversal within two years. Hence, while maintaining the long-existing mandates does not seem to generate particular frictions, imposing new ones might be challenging. Instead of imposing a mandate, monetary incentives for survey participants have been tried in some countries. They seem to make marginal difference, and the size of the payment would have to be substantial to go beyond that, which comes at a cost. There are other potential remedies that could increase the number of responses with more intensive use of resources—such as a greater effort to reach any given individual, expanding the survey size, or outsourcing data collection—but in the current budgetary environment these might not be viable.

Our results suggest that employing a mix of collection modes is preferable to relying on one dominant approach because it allows for better population targeting. We also find that surveying individuals as opposed to households for data collection may have a small, negative impact on response rates, possibly due to behavioral changes and the cost involved. Given our relatively limited sample size, our results should be considered tentative and should be revisited, as many national statistics offices have been adjusting or are considering adjusting their survey design and modalities. Our analysis corroborates the promising avenue of adaptive survey design. Singapore and the UK have started experimenting with the use of AI-assisted technologies in data collection, though it is still early to assess the result of such innovations.

A promising direction is to bring additional data into the picture to enable decision-making, not to replace official statistics. This could be done by statistical offices themselves or by users, for example central banks relying on alternative measures of labor market movements. Such data can come from administrative sources or non-traditional sources. The former is a cost-effective method of closing data gaps and reducing survey burden, where the institutional setting permits data sharing. The latter has grown in popularity, with an exponential growth in the data amassed, although coverage is still uneven across countries and industries. Notwithstanding the cost and ethical concerns, the high degree of granularity and timeliness of non-traditional data hold considerable promise for both structural and conjunctural analysis relevant to policymaking. The limitations associated with the use of non-traditional data sources are being addressed, and their application to analytical research is growing rapidly.

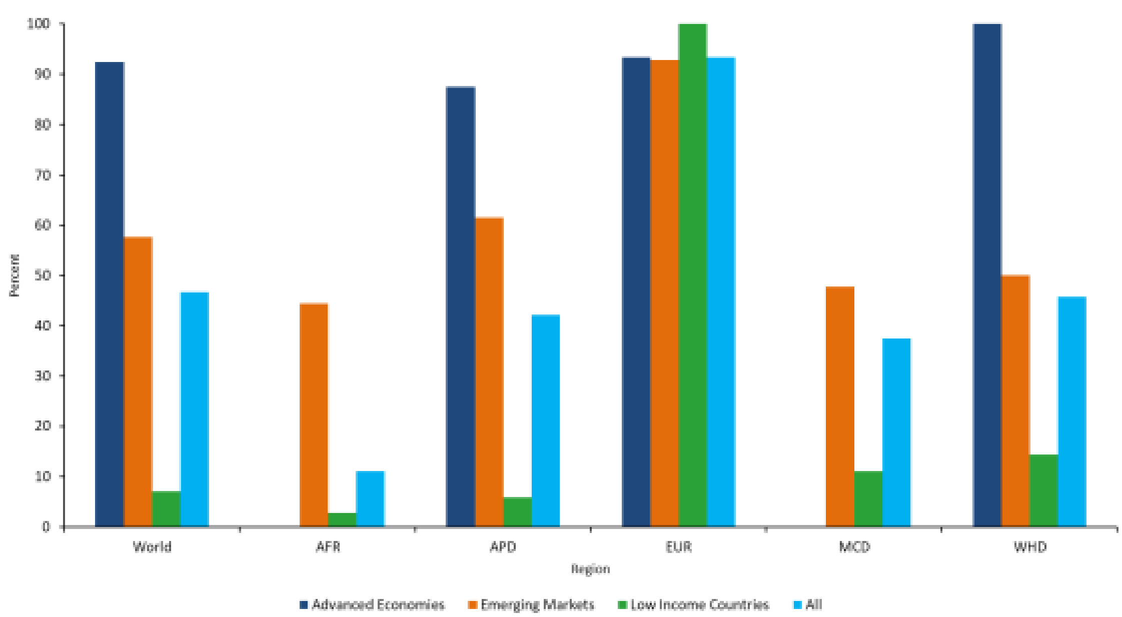
The analysis presented here could provide impetus for further research, using metadata from LFS to extend the dataset we have produced. Further research could test in depth different reasons for the decline in response rates, or the drivers for recovery where this is present. In countries that publish more detailed or frequent labor market data, the analysis can be enhanced by taking into account the quality of inputs and outputs, including the frequency of any labor market publications. Finally, trust in public institutions, or demographic change and attitudes could be integrated into the analysis. This would help national statistics offices choose themselves the most appropriate solution for their specific institutional setting.

Annex I. Benchmarking the Quality of Official Labor Statistics

The IMF Data Standards Initiatives (DSIs) set timeliness and frequency benchmarks for member countries. Countries participating in the second tier of the IMF's DSIs (Special Data Dissemination Standard—SDDS) are prescribed to disseminate employment, unemployment, and wages/earnings (as relevant) on a quarterly basis with a one-quarter lag, allowing for flexibility (IMF, 2013). Countries participating in the third tier—SDDS Plus—are required to disseminate these labor market indicators and encouraged to disseminate gender-disaggregated labor force participation rates. The 2022 Tenth Review of IMF Data Standards Initiatives further proposed to encourage gender-disaggregated labor market data across SDDS tiers (IMF, 2022). Using the quarter lag and quarterly periodicity yardsticks prescribed by SDDS as well as granularity encouraged under the Tenth Review, this annex assesses country performance in these three areas (timeliness, frequency, and granularity) by region and income group.

Timeliness: A review of official labor data releases accessed through Haver Analytics confirms concerns about timeliness identified by the DAAs. By region, Europe (EUR) has the best performance with 93 percent (42 out of 45) countries disseminating within 90 days or less (Figure AI.1). AFR has the poorest timeliness with just 11 percent of countries disseminating labor data within 90 days. By income, Low-Income-Countries (LICs) have a large proportion of countries with lags of more than 2 years, or no data reported at all during the period assessed (2022 to 2024). Advanced Economies (AEs) in all regions have mostly good ratings while Emerging Markets (EMs) show a mix of all three categories.

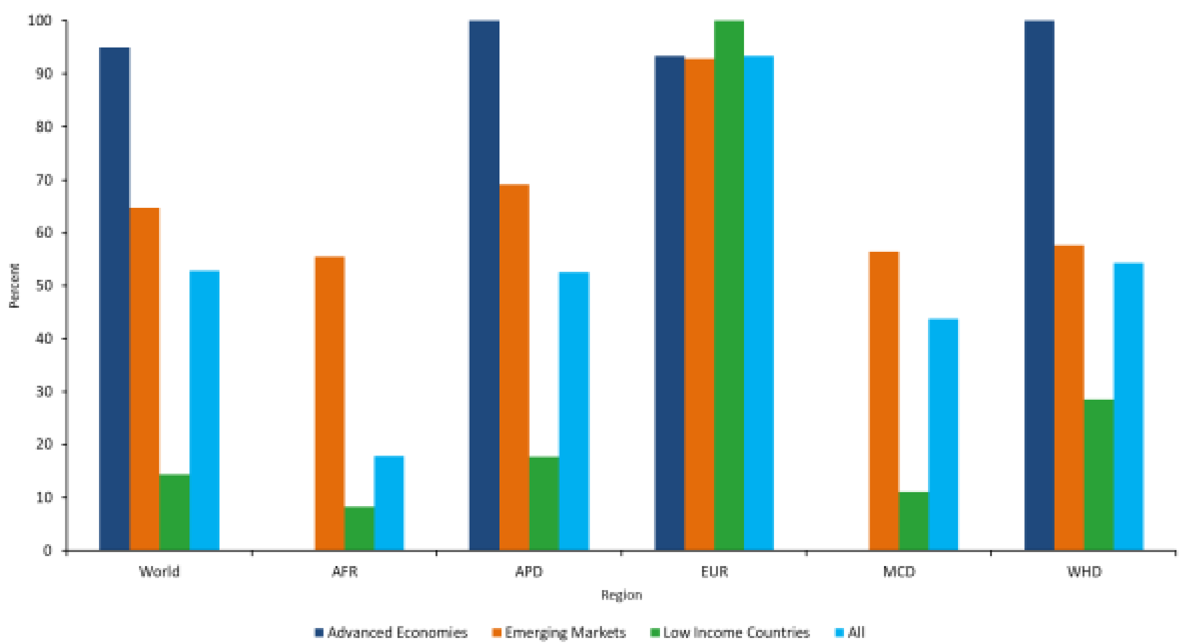
Figure AI.1. Share of countries that meet SDDS requirements for timeliness (90 days)



Source: Authors' analysis using data from Haver Analytics. (Accessed on 7/15/2025).

Frequency: EUR stands out as the region with the best reporting practices for periodicity—93 percent of the countries (42 out of 45) disseminate monthly or quarterly labor data, compared to AFR's 18 percent (Figure AI.2). By income level, AEs across all regions show the best performance with 95 percent (38 out of 40) with monthly/quarterly periodicity. EMs have 65 percent (55 out of 85) of countries with monthly/quarterly frequency. LICs show the lowest frequency with only 14 percent (10 out of 70) disseminating monthly or quarterly data and 62 percent having no data.

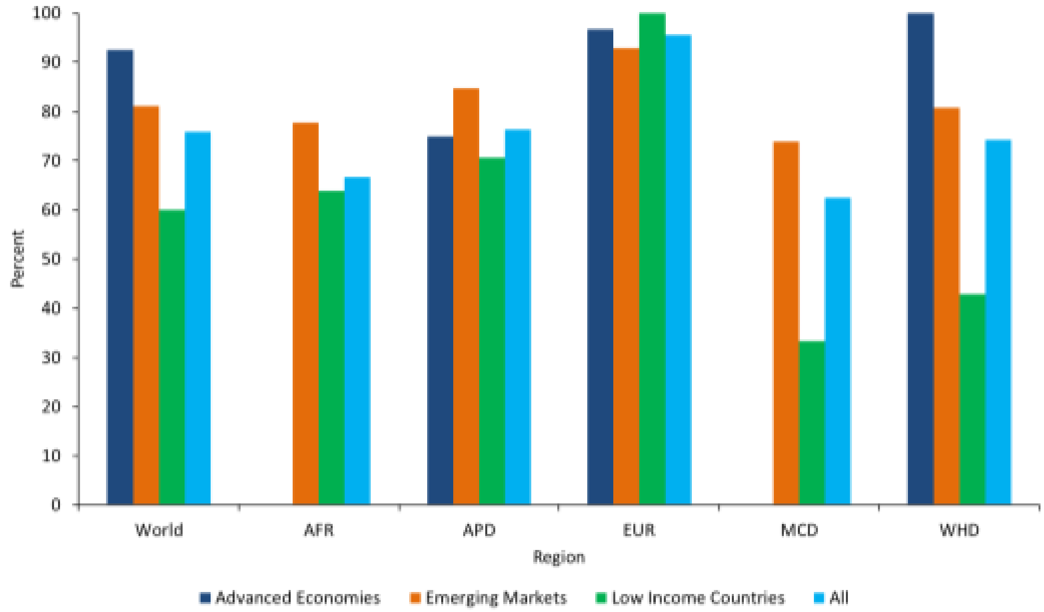
Figure AI.2. Share of countries that meet SDDS requirements for frequency (quarterly)



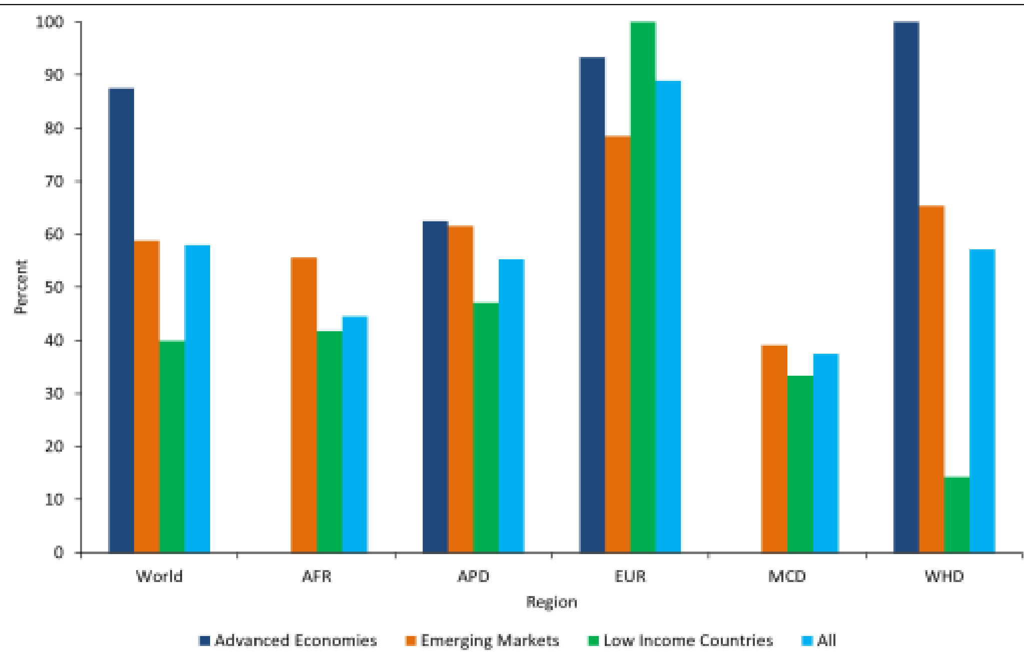
Source: Authors' analysis using data from Haver. (Accessed on 7/15/2025).

Granularity: The lack of granular labor data hampers accurate assessment of wage pressures on inflation, understanding of labor market slack, and evaluation of monetary policy transmission mechanisms. Among LICs, implications may even include inability to effectively target poverty reduction programs; limited ability to assess informal employment; and difficulty in measuring progress toward development goals. Figure AI.3 assesses the extent to which survey data accessed through ILOSTAT facilitate subgroup analysis along four dimensions: sex, age, education, and economic activity. As shown in Figure AI.3a, EUR leads in data granularity of (un)employment series with 96 percent (43 out of 45) of countries assessed having some breakdowns available for at least one of the categories. In AFR and MCD, this ratio is 67 and 63 percent, respectively. Wage data breakdown is less common (Figure AI.3b). Globally, 58 percent of countries have earnings data broken down by at least one of the four categories (sex, age, education, and economic activity). 89 percent of EUR countries have breakdowns by at least one of the four categories compared to 44 percent in AFR and 38 percent of countries in MCD.

Figure AI.3. Granularity of labor data by region and income
a. *Employment data*



b. *Wage data*



Source: Authors analysis using ILOSTAT data. Accessed through ILOSTAT Bulk download facility (ILOSTAT Bulk Download) on 7/15/2025

Note: Granularity assessed based on availability of disaggregation by sex, age group, education level, and industry category

Annex II. Labor Force Survey Response Rate Calculation and Sampling Overview

Labor Force Surveys (LFS) provide insights both into overall conditions (type of employment, wages and benefits, intention for employment, skills and education, etc.) and more specific demographic subsets of the population of interest (such as women, minorities, disabled, long-term sick, or young adults), making them a uniquely rich source of labor market information. LFS can be standalone surveys (e.g., in the UK) or part of other household surveys, for instance the Current Population Survey (CPS) in the US.

Measurement of the LFS response rate

There are slight variations in how the response rate is defined and measured across different countries, even among the ones that are in the same statistical system (such as Eurostat). In general, it is the ratio of the number of successfully completed responses to the total eligible sample.

A detailed formula is provided by the UK:

$$\text{RR} = \frac{FR\ +\ PR}{FR\ + (PR\ +\ OR\ +\ CR\ +\ RHQ\ +\ NC\ +\ RRI)}$$

Where:

RR = Response Rate
FR = Full Response
PR = Partial Response
OR = Outright Refusal
CR = Circumstantial Refusal
RHQ = Refusal to Headquarters
NC = Non-contact
RRI = Refusal to Re-interview

Types of LFS Non-Response

The second part of the denominator of the equation above ($PR\ +\ OR\ +\ CR\ +\ RHQ\ +\ NC\ +\ RRI$) gives total non-response for the UK. Similarly, the US Census Bureau defines total non-response as the number of non-interviews among all eligible households. In Europe, most countries calculate non-response at the household unit, apart from Denmark, Estonia, Luxembourg, Netherlands, Finland, Sweden, Norway and Switzerland, which calculate non-response at the level of the individuals.

There are three types of non-response in these surveys:

i) **Unit non-response** refers to the failure to collect any survey data from an occupied sample housing unit. For example, data may not be obtained from an eligible housing unit in the survey because of impassable roads, a respondent's absence or refusal to participate in the interview, or unavailability of the respondent for other reasons. This is the largest source of non-response, as it includes refusals and non-contact.
ii) **Item non-response (partial response)**, which occurs when a respondent either does not know the answer to a question or refuses to provide the answer. Item non-response tends to be modest.
iii) Finally, less frequently, there is **person non-response**, which occurs when some individuals within an eligible household/dwelling are not interviewed. Person non-response has not been much of an issue

because usually any responsible person aged 15 or over in the household/ dwelling is able to respond for others in it as a proxy.

About two-thirds of unit non-responses in our sample (where data is available) were due to refusals.

Overview of Sampling and Data Collection

LFS collect data usually several times a year using rolling population samples. For example, the US collects and publishes labor market data monthly, while the UK collects data for the LFS in a rotation of 5 waves, dividing the LFS survey year into quarters of 13 weeks. In all cases, rotational sampling ensures some sample overlap (see Table AII.1).

More specifically, the US Current Population Survey (CPS) involves two waves of data collection with each wave consisting of four monthly interviews, with 8 month-in-samples (MIS). Each household in the CPS sample is interviewed for a total of eight months. 75 percent of the sample remains the same from month to month, and 50 percent from year to year. Respondents in the UK are interviewed five times at 13-week intervals, and 20 percent of the sample is replaced each quarter according to the rotation design.

Despite continuous standardization across the countries covered by Eurostat, there is variation in the calculation of non-response correction and recording of non-response, which have been introduced at different times in different countries (e.g., Malta in 2006, Ireland in 2017; relevant information is not always available).

Table AII.1 Data Collection Patterns in Eurostat Countries

SCHEME	INTERVIEW PATTERN	DURATION	QUARTERLY OVERLAP	ANNUAL OVERLAP	COUNTRIES
2-(2)-2	Interviewed 2 consecutive quarters → 2 off → 2 on again	6 quarters	50%	50%	Belgium, Bulgaria, Denmark, Germany, Estonia, Croatia, Italy, Latvia, Lithuania, Malta, Poland, Romania, Slovenia, Switzerland, Serbia, Türkiye
5-	Interviewed every quarter for 5 consecutive quarters	5 quarters	80%	20%	Czechia, Ireland, Luxembourg, Netherlands, Austria, Slovakia
6-	Interviewed every quarter for 6 consecutive quarters	6 quarters	83.3%	33.3%	Greece, Spain, France, Cyprus, Hungary, Portugal
4- ANNUAL	Interviewed once per year for 4 years	4 years	N/A	25%	
3-(1)-2	Interviewed 3 consecutive quarters → 1 off → 2 on again	6 quarters	60%	40%	Finland
8-	Interviewed every quarter for 8 consecutive quarters	8 quarters	87.50%	50%	Sweden, Norway
3-(2)-2	Interviewed 3 consecutive quarters → 2 off → 2 on again	7 quarters	60%	40%	NA in 2021

Annex III. Data

Obtaining data on response rates for Labor Force Surveys (LFS) presents significant challenges due to limited availability and inconsistent reporting across countries. Many national statistics offices do not publish response rates systematically. When data are available, they are often scattered across diverse sources such as quality reports, technical documentation, or research articles. This lack of centralized and standardized reporting hinders efforts to conduct cross-country comparisons or analyze long-term trends. Overall, metadata and methodological transparency around non-response remain limited, making it difficult to assess data quality or replicate studies.

Moreover, documentation practices vary considerably. Some countries provide detailed breakdowns by collection mode, sampling unit, or wave[12] while others report only a single overall figure. The absence of a harmonized reporting framework for LFS response rates necessitates significant manual compilation and verification from secondary sources.

Due to design differences across countries, it could be misleading to compare response rates without context, especially outside of Europe. The bulk of European countries follow Eurostat's harmonized and regularly updated guidance on survey design, sampling, data collection, and analysis, improving comparability. Nonetheless, variations remain. For example, most European countries calculate non-response at the household level, while Denmark, Finland, Sweden, Iceland, Norway, and Switzerland report person-based non-response. Outside of Europe, LFS implementation is more heterogeneous. In regions such as Sub-Saharan Africa and Central Asia, LFSs are often infrequent and inconsistently documented. In many cases, only occasional labor force data are available, often collected through broader household surveys, making it difficult to assess the extent of non-response or data quality.

The compiled dataset covers 39 countries, with data for years between 2004 and 2024. It includes information on survey participation rules, data collection modes, sampling units, and reported annual response rates. Table AIII.1 shows country coverage, and it is available upon request.

[12] The LFS typically uses a rotating panel design, allowing it to track individuals over time (for a limited period). Response rates tend to be higher in later "waves" as those who have already replied to the survey are more likely to do it again. It is not always clear how the statistical offices aggregate across the waves to calculate the overall response rate (or whether they all do it the same way).

Table AIII.1: Countries Covered

Country	Time Coverage*	Participation Type[13]
Austria	2004 - 2024	Compulsory
Belgium	2004 - 2021	Compulsory
Bulgaria	2004 - 2024	Voluntary
Canada	2013 - 2024	Compulsory
Croatia	2004 - 2024	Voluntary
Cyprus	2004 - 2021	Compulsory
Czechia	2004 - 2024	Voluntary
Denmark	2004 - 2021	Voluntary
Estonia	2004 - 2024	Voluntary
Finland	2004 - 2024	Voluntary
France	2004 - 2021	Compulsory
Germany	2004 - 2021	Compulsory
Greece	2004 - 2022	Compulsory
Hungary	2004 - 2021	Voluntary
Iceland	2004 - 2024	Voluntary
Ireland	2004 - 2024	Voluntary
Italy	2004 - 2021	Compulsory
Latvia	2004 - 2024	Voluntary
Lithuania	2004 - 2021	Voluntary
Luxembourg	2004 - 2021	*Voluntary until 2014; Compulsory since 2015*
Malta	2004 - 2021	Compulsory
Montenegro	2019 - 2024	Voluntary
Netherlands	2004 - 2021	Voluntary
North Macedonia	2004 - 2020	Voluntary
Norway	2004 - 2024	Compulsory
Poland	2004 - 2021	Voluntary
Portugal	2004 - 2021	Compulsory
Romania	2004 - 2024	Voluntary
Serbia	2019 - 2024	Voluntary
Singapore	2013 - 2024	Compulsory
Slovakia	2004 - 2021	Compulsory
Slovenia	2004 - 2024	Voluntary
South Africa	2013 - 2024	Voluntary
Spain	2004 - 2024	Compulsory
Sweden	2004 - 2024	Voluntary
Switzerland	2004 - 2024	Voluntary
Türkiye	2004 - 2024	Compulsory
United Kingdom	2002 - 2024	Voluntary
United States	2013 - 2024	Voluntary

**Some countries have incomplete data for the period shown.*

[13] Based on the regime in place for most of the period.

The dataset comprises the variables described in Table AIII.2.

Table AIII.2 Variable Descriptions

Variable	Description
Country	Name of the country
Collection Mode	Main data collection method used in the LFS
LFS Response Rate	Annual reported response rate to the LFS (in percent)
Final Sampling Unit	Whether the LFS sample is based on households, individuals, or dwellings
Participation	Legal status of participation (*compulsory* or *voluntary*)
Year	Year for which the response rate is reported

Data Source Notes

- Sources include national statistics office publications and Eurostat quality reports.
- Where quarterly response rates were available, the average over quarters was used.
- In cases lacking numerical reporting, estimates were derived from charts or narrative descriptions.

Limitations

- **Inconsistency in Definitions**: Countries define and calculate response rates differently; some use gross and others net response, and annualization methods vary.
- **Legal Status Complexity**: While some countries legally mandate participation, enforcement varies and is not always reflected in the observed response rate.
- **Limited Coverage Beyond Europe**: Outside Europe, many countries lack regular LFS implementation or systematic documentation of response rates.

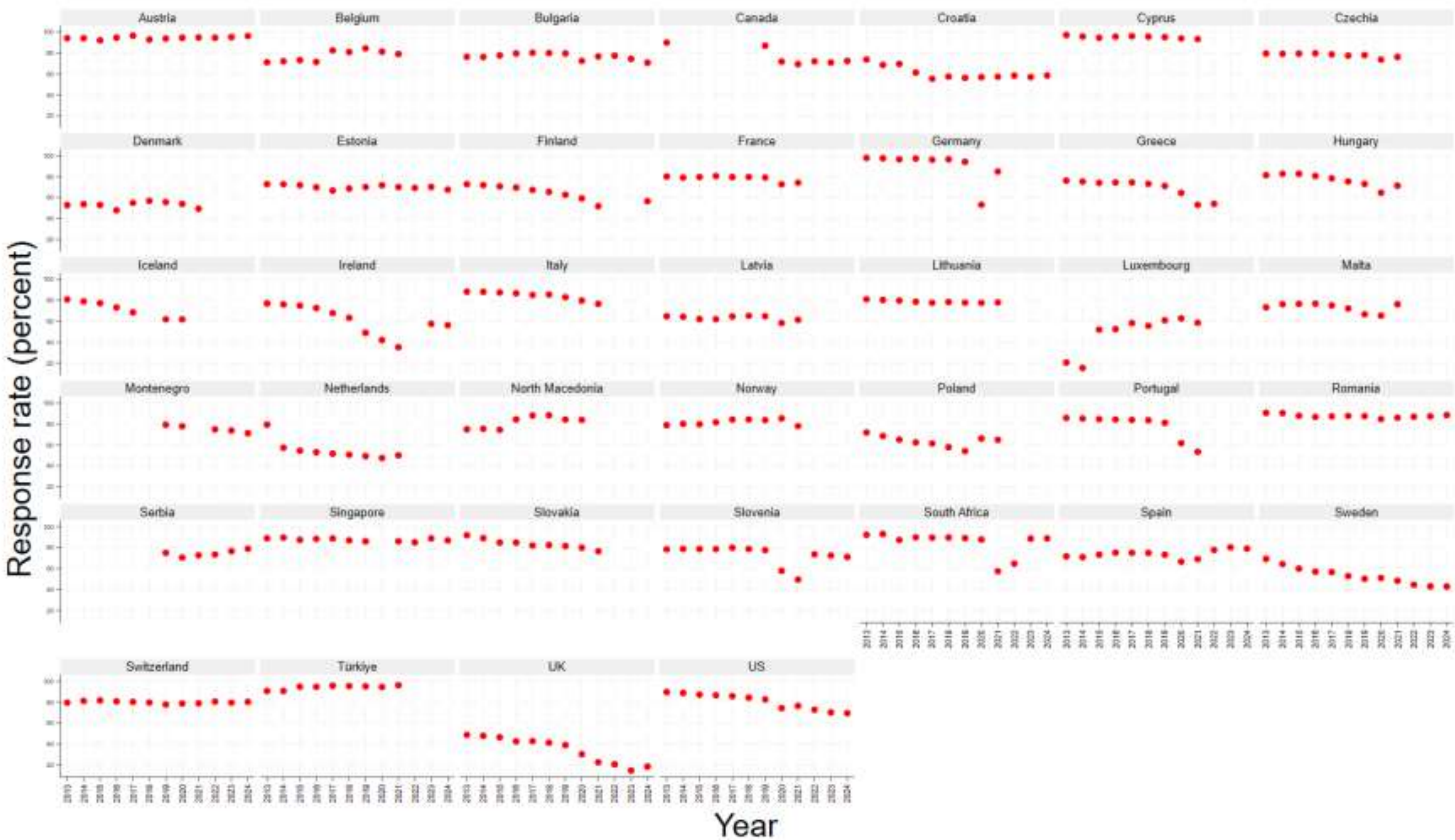
It should be noted that while important details may differ, fundamentally LFS response rates in different countries measure the same concept, so the challenges to comparability should not be exaggerated – and should also be manifested much less in response rate changes over time than in levels as long as countries maintain their methodology.

Data Collection Modes— Eurostat Definitions

- PAPI (Paper and Pencil Interviewing): PAPI is a face to-face interviewing technique in which the interviewer enters the responses into a paper questionnaire. If no interviewer is present and respondents enter the answers themselves, it is considered a self-administered questionnaire.
- CAPI (Computer Assisted Personal Interviewing): CAPI is a face-to-face interviewing technique in which the interviewer uses a computer to administer the questionnaire. Responses are directly entered into the application and control and editing can be directly performed.
- CATI (Computer Assisted Telephone Interviewing): CATI is a telephone surveying technique in which the interviewer follows a questionnaire displayed on a screen. Responses are directly entered into the application. It is a structured system of interviewing that speeds up the collection, control and editing of the information collected.
- CAWI (Computer Assisted Web Interviewing): CAWI is an Internet surveying technique in which respondents follow a questionnaire provided on a website and enter the responses into the application themselves.

Annex IV. Evolution of LFS Response Rates

Figure AIV.1. Labor Force Response Rates, 2013-24



Annex V. Regression Analysis

We start by running simple panel regressions of changes in LFS response rates on the compulsory participation dummy.[1] Given the disruption inflicted by COVID-19, the fact that the severity of the epidemic, as well as its impact on population and various activities differed considerably across countries, the preferred, less biased, estimates come from the pre-COVID-19 period 2013-19. We also try a specification that includes a lagged dependent variable to account for possible serial correlation among error terms, which could be positive if the deviations of changes in individual country response rates from the average were persistent, or negative if the deviations from the trend tended to self-correct. We then extend the estimation period to 2013-24 to increase the sample size and capture the latest developments. To account for the pandemic disruption and subsequent recovery we introduce dummies for each of the COVID-19 years (2020, 2021, and 2022) and the first post-COVID-19 year, i.e. 2023. We take these regressions with a grain of salt, however, since the underlying assumption that COVID-19 impacted the pace of change in LFS response rates equally in all countries is at best a rough approximation.

The results (Table AV.1) for the pre-COVID-19 period indicate that LFS response rates in countries with voluntary participation decline on average at a rate of about 1.5 percentage points per year.[2] Conversely, the rate of change in countries with compulsory participation (given by the sum of the constant term and the coefficient on the dummy) is not significantly different from zero. The coefficient on the lagged dependent variable is negative, large (around 0.5), and statistically significant, indicating that deviations from the common trends tend to be short-lived. Given its statistical significance, we include the lagged dependent variable in subsequent specifications.

The results for the full sample are largely in line with the above findings. Predictably, certain coefficients lose a degree of statistical significance, given that the large pandemic shocks are unlikely to have been picked up fully by the dummy variables. The constant term and the coefficient on the compulsory dummy remain close to their pre-pandemic estimates, and their sum remains insignificantly different from zero, suggesting no slide on average for countries with mandatory responses to the LFS. As expected, the coefficient on the first pandemic year dummy is large, negative, and statistically significant.

[1] The dependent variable is the change rather than the level of response rate since the level is non-stationary. Also, the differences in the way response rates are calculated in different countries are likely persistent and hence affect response rate levels more than yearly changes.

[2] The coefficient on the constant in a regression without a lagged term is negative 1.46. The “steady state” rate of change in the equation with a lagged dependent variable (calculated as the constant divided by one minus the coefficient on the lag) is negative 1.56.

Table AV.1. Baseline Regressions

	(1)	(2)	(3)	(4)
	2013-19	2013-19	2013-24	2013-24
Compulsory	1.721^{**}	2.881^{***}	1.524	2.157^{*}
	(0.797)	(0.779)	(1.092)	(1.101)
Lagged Dep Var		-0.522^{*}		-0.397^{**}
		(0.271)		(0.194)
d20			-5.956^{**}	-5.541^{*}
			(2.529)	(2.870)
d21			0.279	-2.206
			(3.206)	(2.381)
d22			3.221^{*}	4.420^{*}
			(1.703)	(2.364)
d23			1.862	3.279
			(1.652)	(2.082)
Constant	-1.455^{**}	-2.361^{***}	-1.328^{*}	-1.869^{***}
	(0.679)	(0.599)	(0.680)	(0.675)
Observations	249	246	374	366
R-squared	0.015	0.192	0.046	0.174
F-statistic	4.662	6.918	4.123	2.932

Standard errors in parentheses
Dependent variable: Change in Response Rate (Percentage Points)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Next, we introduce the response collection mode (the modes are defined in Box AV.1) in the 2016-19 regressions for countries covered by Eurostat. The start of the period is determined by data availability and the end by COVID-19.[3] We exclude observations where the sum of the shares of different collection methods (the four identified in Box AV.1 and "OTHER," which is supposed to be the residual category) deviates from 100 by more than 5 percentage points, indicating some sort of a problem with share calculations. We include the four modes jointly and individually in the regressions. We also construct a "MIX" variable with a value of one if the dominant collection technique (the one with the largest share) accounts for less than 60 percent of the survey responses and zero otherwise. The rationale for including this variable is the notion that given the diversity of the population, a mix of collection techniques may be better suited to reach various strata.

Table AV.2 presents the results. The first column repeats our baseline specification. The results are very close to those shown in column 2 of Table AV.1 even though the sample is considerably smaller. When collection modes are introduced, the only mode with a statistically significant coefficient is CAWI (computer-assisted web interviewing), suggesting that countries with greater reliance on that modality may experience slower decline in

[3] Information on collection mode is available for 2016-21. In our view, adding the two most turbulent years (2020 and 2021) to the sample is unlikely to improve the quality of the estimates. The regressions over the period 2016-21 produce results qualitatively similar to the one shown below for the 2016-19 sample, but virtually none of the variables are statistically significant.

LFS response rates. The regression results also indicate that having a mixed approach rather than relying on a dominant collection mode might be beneficial.[4]

Table AV.2. Regressions with Collection Mode (2016-19)

	(1) None	(2) All	(3) PAPI	(4) CAPI	(5) CATI	(6) CAWI	(7) MIX
Lagged Dep Var	-0.585**	-0.684***	-0.590**	-0.585**	-0.659***	-0.604**	-0.591**
	(0.279)	(0.233)	(0.281)	(0.274)	(0.235)	(0.280)	(0.283)
Compulsory	2.865**	3.011**	2.954**	2.875**	2.868**	2.937**	2.864**
	(1.146)	(1.198)	(1.178)	(1.142)	(1.129)	(1.202)	(1.139)
PAPI		0.018	0.023				
		(0.040)	(0.015)				
CAPI		-0.009		-0.017			
		(0.046)		(0.023)			
CATI		-0.024				-0.025	
		(0.027)				(0.026)	
CAWI		0.148**			0.143**		
		(0.073)			(0.055)		
MIX							1.856
							(1.144)
Constant	-2.482**	-2.070	-2.856**	-1.952	-3.183***	-1.287*	-3.015**
	(1.080)	(3.882)	(1.235)	(1.675)	(1.137)	(0.709)	(1.276)
Observations	126	126	126	126	126	126	126
R-squared	0.241	0.303	0.247	0.245	0.286	0.250	0.250
F-statistic	4.519	2.948	3.057	4.450	4.515	3.175	3.173

Standard errors in parentheses
Dependent variable: Change in Response Rate (Percentage Points)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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[4] With p-value of 10.7, the coefficient on the MIX variable barely misses being statistically significant at the 10 percent level.

Finally, we check whether the sampling unit—which refers to the entity the survey approaches—makes a difference. The sampling units vary considerably across countries.[5] Table AV.3 shows the way we grouped different characterizations in Eurostat documentation into five broad categories.

Table AV.3. Sample Unit Grouping

Characterization	Group
Households	Households
Dwellings	Dwellings
Persons	Persons
Clusters of Dwellings units	Dwellings
Clusters of Dwellings units (dwellings in DOM)	Dwellings
Clusters (sampling districts) of dwellings	Dwellings
Clusters (sampling districts) of dwellings, households and persons	Mix
Dwellings, households and persons	Mix
Clusters of dwellings	Dwellings
Clusters of households	Households
Addresses	Dwellings
Addresses of selected persons	Other
Household address	Households
Families	Households
Postal addresses/telephone numbers/ Scotland housing units	Mix
Postal addresses/telephone numbers/housing units	Mix

Among the five, Dwellings, Households and Persons are far more prevalent than Mix and Other. Hence, for regression analysis we drop country-years with those last two sampling units (or no information on the sampling unit) and include dummy variables on the first three methods.

As shown in Table AV.4 for the period 2013-19, the dummy on Persons is negative and statistically significant at the 10 percent level.[6] The result suggests that this choice of the sampling unit may increase the pace at which the response rate erodes. This could stem from the fact that tracking separately different people in the same household may be more challenging and resource-intensive.

In all of these experiments, the coefficient on the compulsory survey participation dummy remained large and highly statistically significant. We have also conducted a number of robustness checks, adding measures of country size and wealth (GDP, population, GDP per capita, and growth rates of those variables) as well as a measure of trust in European institutions (for Europe, the average of trust in the European Parliament, trust in the European Commission, and trust in the European Central Bank, available from Eurobarometer) to our baseline regression. None of these variables were statistically significant, nor did their inclusion have a perceptible effect on the participation dummy coefficient.

[5] The information is available from Eurostat, and only for European countries.

[6] Column 1 shows the baseline regression for the group of the countries where information on sampling unit is available. The results are similar to those in Tables AIV.1 and AIV.2.

Table AV.4. Regressions with Sampling Units (2013-19)

	(1)	(2)	(3)	(4)
	None	Households	Dwellings	Persons
Compulsory	3.203**	3.061**	3.148***	3.292**
	(1.297)	(1.226)	(1.165)	(1.279)
Lagged Dep Var	-0.623**	-0.638**	-0.626**	-0.625**
	(0.268)	(0.265)	(0.268)	(0.264)
Households		1.681		
		(1.216)		
Dwellings			-0.440	
			(1.613)	
Persons				-2.162*
				(1.103)
Constant	-2.473**	-3.138*	-2.272***	-2.158
	(1.231)	(1.618)	(0.783)	(1.340)
Observations	104	104	104	104
R-squared	0.269	0.276	0.269	0.276
F-statistic	5.156	3.495	4.350	6.319

Standard errors in parentheses
Dependent variable: Change in Response Rate (Percentage Points)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Annex VI. Alternative Sources of Labor Market Data

Indeed is an easily accessible data source, utilized by central banks to get early information on labor demand and wage levels. It is available on a pro-bono basis, at varying degrees of granularity (regional and by industry) for up to 22 countries. Research has shown that using job vacancies from platforms like Indeed can help identify emerging occupations and skills in high demand, thereby allowing policymakers to better understand labor market dynamics and design effective workforce development programs (Baker et al., 2020). In one of the earliest forays into using online job postings data, in 2019 the Central Bank of Ireland looked into the relationship between labor market tightness and salaries. It investigated what online data can reveal about the Irish labor market and how its "real-time" insights can supplement traditional data sources (Adrjan and Lyndon, 2019). The collaboration between the Central Bank of Ireland and Indeed led to the development of the Indeed Wage Tracker[7] for seven countries in 2022 (Adrjan and Lyndon, 2022). In 2020, the European Central Bank used the number of job postings from Indeed to construct a proxy for changes in labor demand (Benatti et al., 2020). The Bank of England experimented with Indeed data too, to analyze how financial decisions to strengthen balance sheets exacerbated or attenuated labor demand shocks during COVID-19 (Van Dijcke et al., 2023) and to study business creation (Green, Lamby and Quiros, 2022) during the same period. Newer data products include several dashboards that provide information on specific skills demand, too.

LinkedIn's "Data for Impact" program partners with international organizations and governments, including statistics authorities, providing pro-bono data for research and policy solutions for approximately 78 countries. The World Bank collaborated with LinkedIn in 2018 in a large-scale validation exercise of the platform's data, concluding that there were moderate but positive correlations between LinkedIn data metrics and official statistics, and that the occupational categories used by LinkedIn can map closely to standard occupational categories used in official statistics (Zhu et al., 2018). The LinkedIn hiring rate was used in 2020 by the European Central Bank for aggregate and sectoral numbers of hires in the euro area, a nowcasting exercise for the job finding rate, and a deep dive into the evolution of the unemployment rate. These approaches offered timelier information than more traditional statistical sources, albeit focusing on white collar occupations (Benatti et al., 2020). Destatis (nd) found that the LinkedIn hiring rate for Germany matches closely transitions into employment that can be derived from official data—but the official data is only available with a considerable lag (around six months), suggesting that the hiring rate is a good early indicator. LinkedIn has recently introduced an updated measure of labor market tightness based on its members' job applications and the jobs listed on the platform (McCrory and Huang, 2025). It noted a correlation between its measure and frequently used indicators of labor market conditions in the US based on BLS data, such as the ratio of vacancies to hires.

The internet and social media contain vast amounts of relevant data on labor supply and demand scattered across job boards, company websites, user profiles, etc., but collecting, organizing and analyzing that information usually requires significant resources. **Lightcast** is a company that does that, and it provides a particularly rich dataset for 38 countries (at the time of writing) that is available for a fee. Lightcast's comprehensive database of job postings can be leveraged to assess regional labor market conditions and align educational programs with the needs of employers, thereby improving the relevance

[7] GitHub - hiring-lab/indeed-wage-tracker: Measuring growth in wages advertised in job postings

of workforce training initiatives (Harris, 2021). Lightcast data have been used by the OECD in their 2023 Employment Outlook for analysis of skills, employee benefits, and labor market tightness and to reflect on the future of work. Borgonovi et al. (2023) explored demand for AI skills across 14 OECD countries, while Schmidt et al. (2023) examined demand specifically for data skills in Canada, the UK and the US, both using Lightcast data. The Federal Reserve System uses Lightcast data to monitor the evolution of AI skills (Federal Reserve Bank of Atlanta, 2024), demand for short-term employment (Crockett et al., 2024), and occupational mobility (Federal Reserve Banks of Philadelphia and Cleveland, 2024). Lightcast has also been used in surveillance and research work by the IMF. For example, Cevik et al. (2025) used it to analyze the impact of monetary policy shocks on labor markets using data from online job postings in Estonia, Latvia, and Lithuania during 2018–2024, while Burya et al. (2022) studied the interaction between labor market power and monetary policy. A comparison of Lightcast data against traditional statistical labor variables for English-speaking countries conducted by Tsvetkova et al. (2024) and replicated for European countries by Wermuelen and Gutierrez Amaros (2024) found high correlation of Lightcast data for several categories with official statistics.

Other data sources for labor market analysis include online job advertisement platforms *Textkernel* and *Adzuna*, both of which have been used by UK's Office of National Statistics (ONS) in estimates of demand for labor by occupation, regionally disaggregated (ONS, 2024), and during COVID-19 to understand the shift to hybrid/remote employment (ONS, 2021). These are statistics "under development," and the above studies are illustrative examples of how a national statistics office could utilize additional sources to provide information for policy. The ONS, like other organizations using these data, stresses that they are not to replace official statistics. The Federal Reserve Bank of Chicago has experimented with using of *Google Trends* for a study of unemployment (Brave et al. 2023), and although they found that Google Trends' "unemployment" topic traced with high accuracy unemployment insurance in the US, they noted challenges for broader analysis presented by continuous revisions of Google Trend topics and by ambiguous definitions of some topics.

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