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Understanding Unworked Time in Spain

Abstract

This paper explores the evolution of non-working time in Spain over recent years by analysing the results of two surveys conducted by the National Statistics Institute: the Quarterly Survey on Labor Costs and the Labor Force Survey. Using time series models and intervention analysis, potential reasons for the discrepancies between the two surveys are identified and a procedure is proposed to "reconcile" their results. Furthermore, the most notable change found in the behavior of non-working hours has been an increase of around 2% from the second quarter of 2019 as a result of the entry into force of a legal reform that implemented the mandatory recording of working time.

JEL-Codes: C220, C810, C830, J210, J220.

Keywords: labor cost survey, labor force survey, time series, ARIMA models, intervention analysis.

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1 Introduction

Changes in the working practices has accelerated in recent years, among other reasons due to the increased participation of women in the workforce, new forms of workplace organization or the adoption of digital technologies.

One of the habits that has been undergoing significant change is employee unworked time, particularly since the COVID-19 pandemic. This time in the workplace poses a significant challenge to businesses and economies worldwide (Astinova et al., 2024). Spain, like many other countries, has experienced an increase in unworked time rates. This paper explores the complex factors underlying this trend in the Spanish context.

A primary consideration is the identification of sources that provide information on working and unworking time. The Social Security Administration in Spain collects data on sickness benefits, which can be used to estimate unworked time rates. However, while certain private organizations undertake detailed analyses incorporating diverse data, the official statistics that most accurately measure the phenomenon are derived from two surveys administered by the National Statistics Institute (Instituto Nacional de Estadística, INE).

These surveys offer complementary perspectives, with one relying on employer responses and the other on household surveys centered on employed individuals. The Quarterly Labor Cost Survey (Encuesta Trimestral de Coste Laboral, ETCL) provides, among other data, figures on effective hours worked, including hours lost due to sick leave and other forms of absence. On its side, the Labor Force Survey (Encuesta de Población Activa, EPA) is a comprehensive quarterly survey that provides data on the labor market, including employment, unemployment, and unworked time.

The different approaches and techniques used in conducting the two surveys in terms of sources of information, scopes, classifications, or definitions pose significant difficulties on the comparability of their figures. However, taking these differences into account, it is possible to combine the information in a way that allows for a deeper analysis of unworked time in Spain.

The remainder of this paper is organized as follows: Section 2 outlines the key methodological features of both surveys, while Section 3 compares the figures that have similar meaning or interpretation and explores the reasons for the observed discrepancies. Section 4 analyzes the proportion of non-working time according to EPA, disaggregated by sex, which can help to understand the disparities discussed previously. Finally, Section 5 concludes with some comments and reflections.

2 Key methodological properties of the surveys

A detailed description of the methodology employed in both surveys can be found in the respective documents accessible on the INE website^{1 2}. Only those aspects where the differences in both methodological approaches are most notable are highlighted in this section.

As noted earlier, the initial difference between the two surveys is evident in their respective data sources: unlike the ETCL, which draws its information from businesses via their Social Security numbers, the EPA's data are derived from individuals residing in private households. Furthermore, although both investigations are conducted at the national level, they diverge in terms of their respective scopes of application. While ETCL refers to enterprises in all branches of economic activity excluding agriculture, livestock, forestry, fishing, activities of households as employers of domestic staff, and activities of extraterritorial organizations and bodies, EPA focuses on the population residing in private households.

The previous differences provide a sound basis for the probable non-alignment of aggregate unworked time rates derived from the two surveys. However, there are other differences in the definitions of the concepts related to worked time that are worthy of analysis. A detailed breakdown of the related concepts employed in each survey is provided below.

2.1 Quarterly Labor Cost Survey (ETCL)

The ETCL is a quarterly statistical survey designed to monitor trends in the average labor cost per employee and per effective hour worked. It enables a better understanding of time worked and time not worked, its composition, as well as its short-term fluctuations. Following the referenced methodology, "...it makes up part of the set of short-term indicators that the European Commission requires of member states at the request of the European Central Bank in order to verify that the nominal convergence of major economic groups is accompanied by a process of real convergence in labor cost terms by work unit."

Each company is requested to provide aggregate information, including all employees who have been subject to social security contributions for at least one day during the reference month, regardless of their type of contract or working hours. The survey is designed to provide reliable information at national and at regional levels.

¹ ETCL:

https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736045053&menu=metodologia&idp=1254735976596

² EPA:

https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176918&menu=metodologia&idp=1254735976595

Regarding the most important concepts related to working time, the survey provides the following definitions:

- Agreed hours: These are the hours legally established by agreement between the employer and employees.
- Paid hours: This includes both hours worked and remunerated hours not worked.
- Effective hours: These are the hours actually worked, including overtime. They are calculated as the agreed hours plus overtime hours minus hours not worked for various reasons.
- Unworked hours: These refer to the total of agreed hours that were not worked for any reason. The possible reasons are vacations or holidays, temporary incapacity, maternity, adoption, paid leave, technical or economic reasons, medical visits, machine breakdowns, labor disputes, etc. Within this category, the following are detailed due to their particular significance:
 - Hours not worked due to vacations and holidays
 - Hours not worked due to temporary disability
 - Hours not worked due to parental leave



The published figures indicate **the monthly average of each category of hours** per employee. The maximum level of breakdown for economic activity is at the NACE rev. 2 division level (European Union (EU), 2009). The following sections are excluded: A (Agriculture, Forestry and Fishing), T (Activities of Households as Employers), and U (Activities of Extraterritorial Organizations and Bodies). Figure 1 depicts the trend from 2008 onwards of the monthly quantity

of effective, agreed-upon, and paid hours as derived from the comprehensive data of the ETCL across all sectors of the economy.

It can be seen a general downward trend in all three categories, particularly from 2008 to around 2015. After that, the lines seem to stabilize with some fluctuations. The agreed hours consistently remain slightly lower than the paid hours. The seasonal growth observed in the third quarter for both agreed and paid hours may be attributed to the influence of the increase in tourism during the summer months.

For its part, the sharp drop in effective hours in 2020 is likely related to the COVID-19 pandemic and its impact on work patterns. The line also shows a clear seasonal pattern characterized by a perceptible decrease in activity during the summer holiday period. The gap between the effective hours and the agreed-upon constitutes the unworked hours.

2.2 Labor Force Survey (EPA)

The EPA is primarily designed to assess the human dimension of economic activity. It provides data on key population groups in relation to employment (employed, unemployed, and economically active) and offers classifications based on various demographic and socioeconomic characteristics. It is aimed at the population residing in private households. Therefore, neither collective households (hospitals, care homes, military barracks, etc.) nor secondary or seasonal residences are taken into consideration. When a selected household in the sample is occupied, data is collected for the individuals residing in it.

While the EPA utilizes a quarterly reference period for its results, the individual data points are based on information gathered **for the week immediately before the interview**. It provides figures at both the national and regional levels. Most of the published data are presented in absolute values and are measured in thousands (people or hours) except those related to average number of hours that are measured in hours, and those related to wages, measured in euros. And, unlike ETCL, EPA offers individual-level data for all employees allowing for much more detailed analyses by sex, age, or other variables.

Certain concepts within the survey hold particular significance for the analysis of unworked time. The precise definitions of these concepts are provided as follows.

- Occupied population (or people with employment): This category encompasses all individuals aged 16 years and older who were engaged in any type of employment, whether as employees or self-employed workers, during the specified reference week.
- Absent employees: individuals who did not work during the reference week, despite having a prior employment history with the same employer.

- Causes for absence from work while employed: The questionnaire allows respondents to select from a range of reasons for absence, including vacation or personal leave, parental leave, sick leave, temporary disability, summer hours, union activities, strikes or labor disputes, layoffs, personal reasons, or family responsibilities. Data are collected for the following:
 - Number of employees absent due to vacation/holiday
 - Number of employees absent due to illness
 - Number of employees absent due to paternity leave
- Agreed working hours: stipulated working hours each week as per the employment contract.
- Usual hours worked: the total number of hours devoted to the regular occupation each week.
- Effective hours worked: The number of hours actually worked at the job during the previous week.



In Figure 2, the evolution of usual, agreed-upon, and effective weekly hours from 2008 according to EPA data is shown. The graph shows a general downward trend in all three lines over the period from 2008 to 2024. The data reveals a growing alignment between agreed and usual hours starting from 2016 or 2017, probably signifying a decrease in overtime work. Seasonal increases are also observed in the third quarter for both agreed and usual hours. In this case, in addition to the influence of the increase in tourism during the summer, they can be associated with the work of certain agricultural activities. Consistent with the ETCL survey, effective hours experienced a substantial drop during the pandemic. Moreover, these effective hours have maintained a downward trend post-pandemic, suggesting a more enduring shift in work patterns.

As illustrated in Figure 3 and 4, the EPA data series can also be used to obtain information on the percentage of workers who were absent from their jobs. These data can be further disaggregated to show the percentage of absences attributed to leave and/or vacations, illness and parental leave. It can be seen that leaves and/or vacations constitute the primary reason for employee absences in each period, and they are also the main cause of seasonal fluctuations in the overall series. Additionally, it is remarkable that both the series representing the percentage of absent employees and those corresponding to the different reasons for absence exhibit marked increases after 2019 or 2020.



It should be noted that some of the movements in the series may be linked to changes in the survey's methodology. The entry into force of Regulation (EU) 2019/1700 of the European Parliament and the Council of Europe on October 10, 2019, along with other Delegated and Implementing Regulations, required adjustments to certain variable definitions starting from the first quarter of 2021. Specifically, a novel approach was adopted for certain employment absences, categorizing individuals into the economically active or inactive population based on the total duration of the absence. Additionally, the classification of employment status was modified for seasonal workers outside their active periods, fathers on paternity leave, and individuals undergoing job-related training.



Figure 5 illustrates how these methodological changes may influence both the series on effective hours worked and the series on the percentage of absent workers from the first quarter of 2021 onwards, even if in opposite directions.

3 Unworked time and its determinants from both surveys

Before comparing the unworked time estimates, and even though the results of the two surveys are presented with different frequencies, a comparative analysis of the common variables (agreed and effective hours) in Figures 6 and 7 is of particular interest. It is important to note that the scales are different, despite both focusing on quarterly averages of hours. This discrepancy arises from the fact that one survey collects data monthly, while the other gathers data weekly.



The evolution of agreed-upon working hours follows a comparable pattern in both surveys, except from 2021. Regarding effective hours, while both surveys display similar trends up to the pandemic, a divergence emerges thereafter, with the EPA data consistently reporting lower figures. Nevertheless, explanations for these discrepancies may be attributed to (besides sampling errors) the different economic sectors covered by each survey, and the changes in the EPA methodology.

Given the variability in agreed hours, the study of unworked time is more relevant when examined in relation to these hours. With this purpose, we have calculated the average percentage that the non-working hours constitute in relation to the total agreed-upon hours. In both surveys, this variable can be understood as the corresponding estimation of non-working time for the reference quarter, providing comparable estimates in both cases. In Figure 8, both initial estimates of unworked time for the overall economy are shown (in this graph, both series use the same scale). The ETCL series shows a consistently higher level of unworked hours, roughly between 4 and 5 percentage points above the EPA series until 2021. However, after this year both series exhibit more similar growth and levels, indicating that, after the methodological changes in the EPA, unworked time is being measured in a more comparable manner.



Initially, the ETCL's estimate of unworked time can be regarded as the most accurate, given that it is among its primary goals and is conducted using internationally comparable standards. However, EPA data allow us to also consider the influence of socioeconomic factors such as sex, age, and occupation. From this point on, we analyze non-working time and its determinants using the percentage-based variables derived from both surveys, considering their potential limitations and discrepancies.

To assess now the impact of legal reforms, methodological changes and other events, intervention analysis time series (Box & Tiao, 1975) has become a standard statistical method. These authors developed the procedure that can be used to detect and model whether a statistically significant change in the time series occurs after intervention.

The first step is to construct an appropriate seasonal Autoregressive Integrated Moving Average (*ARIMA*) time series model for each series using the Box–Jenkins methodology (Box et al., 2015). The variables to model are percentage variables that show no variation increasing or decreasing with the level, making it unnecessary a previous logarithmic transformation (Hyndman & Athanasopoulos, 2021). The model is identified and estimated using data from the preintervention period. The idea is that the variable would have had the same model at the postintervention period if there had been no intervention. An augmented Dickey–Fuller test (Said & Dickey, 1984) is conducted at the identification stage to see if the series needs to be differenced to make it stationary. Then the estimated autocorrelation and partial autocorrelation functions are used to determine the number of lag observations or autoregressive terms in the model, and the size of the moving average elements. The identified model is estimated by maximum likelihood (Millar, 2011) and then the residuals are checked to be white noise using the Ljung-Box Q statistic (Ljung & Box, 1978), the Jarque-Bera test (Jarque & Bera, 1987) and the Kolmogorov-Smirnov test for normality (Simard & L'Ecuyer, 2011). The seasonal *ARIMA* (*p*, *d*, *q*)(*P*,*D*,*Q*)₄ model for each quarterly percentage of unworked time series X_t can be written as:

$$X_{t} = \frac{\theta(B)\Theta(B)}{\phi(B)\Phi(B)(1-B)^{d}(1-B^{4})^{D}}a_{t}$$
(1)

where $\phi(B) = 1 - \phi_1 B - \dots - \phi_p B^p$ is the autoregressive parameter polynomial, $\Phi(B) = 1 - \Phi_1 B^4 - \dots - \Phi_p B^{4P}$ is the seasonal autoregressive parameter polynomial, $\theta(B) = 1 + \theta_1 B + \dots + \theta_q B^q$ is the moving average parameter polynomial, $\Theta(B) = 1 + \Theta_1 B^4 + \dots + \Theta_q B^{4Q}$ is the seasonal moving average parameter polynomial, B is the backshift operator defined by $B^k(Y_t) = Y_{t-k}$, and a_t is a white noise variable with zero mean and constant variance.

To apply intervention analysis and adequately capture changes on time series data due to external causes, a regression model with *ARIMA* errors model is used (Pankratz, 1991). The term to add to the right-hand side of the previous model expression (1) is $+\sum_{i=0}^{k} w_i I_{i,t}$, where $I_{i,t}$, i = 1, ..., k are the intervention variables accounting for external factors, and w_i are the associated parameters to estimate.

Our aim is to incorporate an intervention variable reflecting the potential impact on the series of a legal reform, specifically Article 10 of Royal Decree-Law 8/2019, which addresses the mandatory recording of working hours starting from May 12, 2019. Thus, the *RDL* variable is a step dummy that begins in the second quarter of 2019, implying a permanent shift in the series from that point forward (Box & Tiao, 1975).

To improve the precision of our estimates, we incorporate additional dummy variables: an *Easter* dummy to control for the seasonal effects of Easter (Bell & Hillmer, 1983), and a *Cov19* dummy to capture the transient impact of the pandemic. This latter variable is built as a decaying impulse-response function with a decay rate of 20% (Box & Tiao, 1975).

3.1 Model for the percentage of unworked time based on the ETCL survey

The final validated model for the ETCL-defined percentage of time not worked is an *ARIMA* $(0,0,1)(0,1,1)_4$ with intervention variables based on the entire sample period:

$$ETCL_{t} = \frac{(1+\theta_{1}B)(1+\theta_{4}B^{4})}{(1-B)^{4}}a_{t} + w_{1}RDL_{t} + w_{2}Easter_{t} + w_{3}Cov19_{t}$$
(2)

The results for the estimation are computed using the *Statsmodel Python* library (Seabold & Perktold, 2010) and presented in Table 1:

Table 1 Parameter estimation for the ETCL unworked time model						
	Coefficient	Standard error	Z	P> z	95% co int	onfidence erval
RDL	2.030	0.333	6.103	0.000	[1.378	, 2.681]
Easter	2.650	0.403	6.571	0.000	[1.860	, 3.441]
Cov19	14.423	2.890	4.990	0.000	[8.758	, 20.088]
ma.L1	0.319	0.118	2.704	0.007	[0.088	, 0.549]
ma.S.L4	-0.796	0.13	-6.105	0.000	[-1.051	, -0.540]

According to the table, the coefficients associated with the three intervention variables are significantly different from 0 and therefore, it can be concluded that they have an impact on the unworked time. Given that this variable is measured as a percentage, the impact of the pandemic is a 14-percentage point increase in the proportion of time not worked in the second quarter of 2020, which rapidly declines in subsequent quarters. In contrast, the effect of the Royal Decree-Law is a 2-percentage point increase that persisted throughout the following quarters. Figure 9 presents the time series of the percentage of time not worked, both the original series and the series adjusted to account for the effects of the Royal Decree-Law and the Covid19 pandemic (the implications of the Easter calendar are irrelevant to this discussion).

Figure 9 Percentage of unworked time based on the ETCL survey Original and adjusted for Royal Decree-Law and Covid19 interventions



The adjusted series indicates that, while the proportion of unworked time has returned to prepandemic levels in recent quarters, a 2% upward adjustment can be attributed to the enforcement of the 2019 Royal Decree-Law, which introduced a requirement for detailed tracking of working hours.

3.2 Model for the percentage of unworked time based on the EPA survey

In this case, to improve the accuracy of the model parameter estimates, in addition to the dummy variables mentioned for the ETCL, a supplementary dummy variable is included in the model

specification to capture the impact of methodological changes implemented in the EPA. Since this impact is expected to persist over time, the variable *Method* is a step dummy starting from the first quarter of 2021 (Box & Tiao, 1975).

The validated model, obtained through the processes of identification, estimation, and validation for the EPA-defined percentage of time not worked is an *ARIMA* $(0,0,0)(0,1,1)_4$ with intervention variables:

$$EPA_{t} = \frac{(1+\theta_{4}B^{4})}{(1-B)^{4}}a_{t} + w_{1}RDL_{t} + w_{2}Easter_{t} + w_{3}Cov19_{t} + w_{4}Method_{t}$$
(3)

and the results obtained appear in Table 2.

Table 2 Parameter estimation for the EPA unworked time model						
	Coefficient	Standard error	z	P> z	95% co int	onfidence erval
RDL	1.936	0.408	4.750	0.000	[1.137	, 2.735]
Easter	1.322	0.631	2.096	0.036	[0.086	, 2.559]
Cov19	20.719	3.482	5.951	0.000	[13.895	, 27.543]
Method	3.609	0.599	6.030	0.000	[2.436	, 4.782]
ma.S.L4	-0.842	0.142	-5.946	0.000	[-1.120	, -0.565]

As in the case of the ETCL, the estimated coefficients for all dummy variables are statistically significant, indicating that they have a non-zero impact on the proportion of unworked time, and can be interpreted as percentage point changes. Their values reveal several key findings. Remarkably, changes in the EPA methodology have had a substantial impact, leading to a 3.6 percentage point increase in the proportion of unworked time. Furthermore, the effect of Royal Decree-Law is consistent with the findings from the ETCL model (2%).

However, what is most interesting is that these results allow us to reconcile the estimates of the proportion of time not worked from both surveys, the ETCL and the EPA. To illustrate this, we constructed a new variable, which we have termed *reconciled_EPA*. This variable consists of adding to the EPA figures up to and including the last quarter of 2020, the estimated coefficient for the variable *Method* which measures the impact of methodological changes on the series. In this way, we obtain a new linked series that reflects the evolution of the EPA in recent times in the same way as the original series, but which also reflects the evolution that the EPA would have had in previous periods if the same methodology had been used as after 2021.

Figure 10 shows the evolution of the percentage of unworked time according to this variable, alongside the estimate derived from ETCL. The discrepancies between the two series are now smaller than those seen in Figure 8 with the original EPA series. They are attributable to various factors, including differences in sectors of activity covered, sources, and the differing methods of measuring working hours during the pandemic, as reported by individuals and companies.



The previous result confirms that the fundamental reason for the differences between the two surveys lies in the methodological changes made in the production of EPA. The significance of this is that it allows for more detailed analysis using the socio-demographic variables of the EPA with new *reconciled* variables.

4 Unworked time from other EPA series

We will now proceed to a more granular analysis using EPA series, focusing on the series of the percentage of unworked time by sex. As will be shown, this can contribute to a more comprehensive understanding of the dummy variables incorporated into the intervention analysis. Following the steps of specification, estimation, and validation, in this case the corresponding models are $ARIMA(0.0.0)(,1,1)_4$ for both series (without logarithmic transformation):

$$EPA_{t} = \frac{(1+\theta_{4}B^{4})}{(1-B)^{4}}a_{t} + w_{1}RDL_{t} + w_{2}Easter_{t} + w_{3}Cov19_{t} + w_{4}Method_{t}$$
(4)

The Tables 3 and 4 display the estimated parameter values.

Table 3 Parameter estimation for the EPA unworked time by men model						
	Coefficient	Standard error	z	P> z	95% co int	onfidence erval
RDL	1.912	0.429	4.451	0.000	[1.070	, 2.753]
Easter	1.345	0.689	4.919	0.051	[-0.006	, 2.696]
Cov19	20.543	3.101	6.624	0.000	[14.465	, 26.622]
Method	3.581	0.728	4.919	0.000	[2.154	, 5.008]
ma.S.L4	-0.776	0.136	-5.713	0.000	[-1.043	, -0.510]

Parameter estimation for the EPA unworked time by women model						
	Coefficient	Standard error	z	P> z	95% co int	onfidence erval
RDL	1.923	0.405	4.746	0.000	[1.129	, 2.717]
Easter	1.317	0.611	2.155	0.031	[0.119	, 2.515]
Cov19	21.031	4.896	4.896	0.000	[12.612	, 29.450]
Method	3.585	0.536	6.692	0.000	[2.535	, 4.635]
ma.S.L4	-0.86	0.153	-5.602	0.000	[-1.160	, -0.559]

Table 4 l

According to the tables, the coefficients associated with the four intervention variables are in both cases significantly different from 0 and similar between them. Figures 11 (a). and (b). show how the corresponding series are adjusted for the impact of Royal Decree-Law, Methodology, and Covid19. It is immediately apparent that women exhibit higher levels of non-working time. And both series return to pre-pandemic levels when the impact of the Royal Decree-Law and the changes in the methodology are removed.



The more curious result, however, is that the estimated parameter is greater for women in relation to both the 2019 Royal Decree-Law variable and the variable capturing methodological changes in the EPA survey. A potential explanation would lie in the choice of dummy variables, as it may be argued that additional variables could have been incorporated. Specifically, during the analyzed period, other legal reforms, such as the progressive increase in paternity leave, may have influenced working hours.

Table 5 Legal reforms amending the paternity leave in Spain					
Regulatory law	Entry into force	Days of paternity leave			
3/2007	01/01/2007	15			
9/2009	01/01/2017	28			
PGE 2018	05/07/2018	35			
6/2019	08/03/2019	56			
6/2019	01/01/2020	84			
6/2019	01/01/2021	112			

Table 5 provides an overview of these legal reforms and the associated number of paid paternity leave days. The table reveals a significant temporal overlap between legal reforms associated with paternity leave, the Royal Decree-Law subject to analysis, and methodological changes to the EPA. This concurrence renders the study of their individual impacts highly difficult. Considering also the relatively small segment of the population affected by paternity leave, the inclusion of additional dummy variables was deemed unnecessary. Consequently, the impact of paternity leave can be taken as additive to the effects of other interventions, especially among men. However, what is found is that slightly higher parameter estimates are observed for women.

Figure 12 displays the *reconciled* time series of the proportion of non-working time, disaggregated by gender. Analogous to the series for the overall population, these series represent the hypothetical evolution of non-working time had the EPA employed its current methodology consistently since before 2021. Both genders exhibit a modest upward trend of approximately 2% subsequent to the implementation of the Royal Decree-Law mandating the recording of working hours from the second quarter of 2019.



5 Final remarks

Before discussing the most significant findings, it is necessary to note that the study of the evolution of non-working time has been conducted by examining the proportion it constitutes relative to the agreed-upon hours, rather than its absolute weekly or monthly duration. This

methodology is deemed more pertinent for our purposes. Moreover, this approach enhances the comparability of the results from both the ETCL and the EPA surveys.

A primary conclusion of this analyses is that the proportion of non-working hours has experienced a remarkable shift in recent years, with an almost 2% increase directly linked to the implementation of the 2019 Royal Decree-Law mandating detailed time recording. The convergence of findings from both the ETCL and EPA surveys, despite their distinct data sources, is particularly noteworthy, as both exhibit statistically significant evidence of this increase. However, it is important to mention that the method employed does not allow us to determine to what extent the small but clear change detected is due to an actual change in workers' time use or simply an adaptation in the way it is recorded.

Another finding relates to the impact of changes in the EPA methodology from 2021 onwards, which can be summarized as an approximate 3.6% increase in non-working hours. Although this could potentially also be attributed to the increase in mandatory paternity leave days from that date, the absence of such an effect in the ETCL data renders methodological changes the more plausible explanation.

This paper also proposes a method based on time series analysis to "harmonize" or "reconcile" the results of both surveys. A more granular approach to reconciliation, involving the reconciliation of series at a lower level and subsequent aggregation, could provide a more refined harmonization.

Finally, it is required to acknowledge that the above-mentioned analyses have been facilitated by the quality of data provided by both INE surveys. This quality is evident in the granular detail of the data as well as the comprehensive supporting documentation.

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