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Gender differences in the duration of sick leave: Economics or biology?

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ABSTRACT

This study addresses the gender gap in workplace sick leave duration, focusing on the underlying economic and biological factors that contribute to this disparity. Using a novel methodological approach, we combine the stochastic frontier technique with an Oaxaca-Blinder-type decomposition to separate sick leave into medically justified and "opportunistic" days. Our analysis, based on detailed administrative data of workplace accidents in Spain, reveals that men and women recover at different rates for the same injuries, with biological differences explaining the majority of the observed gender gap. Additionally, we identify that men tend to use more sick leave days for reasons unrelated to health recovery. The findings offer valuable insights for policymakers and employers, providing an empirical foundation for targeted policies that reduce gender-based discrimination in the workplace and ensure fairer resource allocation. This research contributes to a deeper understanding of the gender gap in occupational health and offers implications for improving workplace equality.

1. Introduction

Workplace accidents continue to reach concerning levels across Europe. Although the number of fatal accidents declined by approximately 70 % between 1994 and 2018, more than 3,000 workers died as a result of workplace accidents in 2019, and over 2.4 million suffered non-fatal injuries (Eurostat, 2023). Following a non-fatal workplace accident, workers typically require a period of inactivity to fully recover, during which they usually receive some form of wage-based compensation to support them through this difficult time. Thus, workplace accidents are not only a matter of occupational health and safety but also a significant economic concern for developed economies. In fact, workplace accidents and occupational diseases accounted for 3.3 % of European GDP in 2019, equivalent to €460 billion (European Commission, 2021).

In most Western countries, women take more sick leave than men. On average, women take 7.6 more sick days per year than men in Europe, 3.1 more in the United States, and 5.2 more in Canada (Ichino and Moretti, 2009). This gender gap may lead to additional discrimination against women if it is not properly examined and fully understood (e.g., employers might avoid hiring women based on these aggregate figures). Several hypotheses have been proposed to explain this gap, including gender differences in the prevalence of certain health conditions, disparities in labor market participation, and the distinct social roles assigned to men and women.

The aim of this paper is to answer the following research questions: To what extent do biological differences between men and women explain the gender gap in sick leave duration following workplace accidents? Can opportunistic behavior in sick leave usage be empirically distinguished from medically justified leave, and does its prevalence differ by gender? How does the decomposition of sick leave duration into biological and economic components reshape our understanding of gender disparities in occupational health?

The contribution of this research is threefold. First, we establish a conceptual framework to analyze the underlying economic and biological factors driving the gender gap in workplace-related sick leave. Second, we develop a methodological approach that, to the best of our knowledge, has not been previously applied in this context. This approach enables us to decompose the gender gap in sick leave duration into components of distinct nature. Third, we provide novel empirical evidence on sex-based differences in sick leave duration, framed within the aforementioned conceptual setting, which offers valuable insights for policymaking. By explicitly distinguishing the portion of sick leave attributable to physiological factors from that related to economic

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behavior, our study equips policymakers with a robust analytical tool to design more targeted and equitable interventions.

The methodology employed in this study combines two distinct techniques which have not previously been applied jointly in this context. First, we use a stochastic frontier approach to estimate the biological and economic components of sick leave duration following workplace accidents, following the framework of Martín-Román and Moral (2017) and Martín-Román et al. (2024). Second, we estimate separate models for male and female workers in order to capture the idiosyncratic features of each group. Finally, we apply an Oaxaca-Blinder-type decomposition to identify and quantify the key parameters required for the empirical analysis.[1]

Regarding the data, we use the full universe of workplace accidents recorded in Spain, which includes detailed information on the duration of each worker's sick leave, the type and severity of the injury, and individual characteristics such as age, sex, and occupational category. Specifically, we rely on the *Statistics of Accidents at Work*, a dataset compiled by the Spanish Ministry of Labor based on mandatory reports of all workplace accidents. This rich administrative source allows us to investigate the underlying factors behind the gender gap in sick leave duration and to decompose this gap into its constituent components.

Our main findings reveal that, although the average duration of sick leave is slightly higher for women (by less than one day) this aggregate difference results from two opposing effects. From a biological standpoint, women experience longer recovery periods, averaging over two additional days compared to men for similar injuries. In contrast, men exhibit a greater tendency toward opportunistic behavior, extending their sick leaves by one to two days due to economic incentives, depending on the model specification. Composition effects also contribute to longer durations among women, as their injury profiles and individual characteristics are associated with slower recovery processes and, in some cases, with a higher likelihood of prolonged leave. Overall, our analysis shows that while biological factors primarily account for the observed gender gap, the higher inefficiency observed among male workers is closely linked to non-medically justified extensions of sick leave.

Our findings have also important implications for the design of health and labor policies. First, we are able to provide rough monetary estimates of the economic cost associated with gender differences in sick leave duration: approximately €130 million over the 2011–2019 period due to longer biologically driven absences among women, and around €215 million attributable to opportunistic extensions of leave by men. These figures offer a benchmark for policymakers to assess the fiscal scope of targeted interventions. Second, the results suggest that current clinical guidelines (often based on average sex-based recovery times) may insufficiently capture the true biological differences in recovery patterns. Enhancing diagnostic and monitoring procedures to better reflect these distinctions could improve fairness and efficiency. Moreover, recognizing the dual nature of sick leave (medical necessity versus behavioral response) highlights the need to strengthen social security oversight, particularly for injuries prone to misuse. At the firm level (Markussen, 2012), rethinking incentive structures and developing sex-sensitive occupational health programs may reduce injury incidence and improve return-to-work outcomes. Overall, an effective policy approach requires combining institutional and employer-level strategies to address both biological and behavioral drivers of the gender gap in sick leave duration.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature and outlines the main hypotheses explaining the gender gap in sick leave duration. Section 3 presents the Spanish institutional context. Section 4 describes the dataset and key variables. Section 5 outlines the empirical strategy. Section 6 discusses the main results, while Section 7 explores their policy implications. Section 8 concludes.

2. Background

2.1. Sick leave duration and gender

When analyzing the duration of sick leave, two primary factors are typically considered: biological determinants and individual behavior. While the academic literature acknowledges the relevance of both, biomedical and public health research tends to emphasize physiological aspects, whereas economic studies focus more heavily on individual decision-making, consistent with the methodological foundations of the economics discipline.

Moreover, the study of sick leave incidence and duration has developed into a substantial research agenda within economics. In Europe, this issue is commonly examined using sick leave records, given the difficulty of obtaining data on unexcused absences from work. Put differently, it is considered absenteeism. In contrast, research in North America often frames the issue within the context of moral hazard related to workplace accident insurance (Butler and Worrall, 1991; Fortin and Lanoie, 2000). In our study, we define absenteeism as the extension of a sick leave period without medical justification (Martín-Román and Moral, 2017). This distinction allows us to build on the literature by separating justified from opportunistic behavior.

Foundational contributions, such as Allen (1981a), (1981b) and Brown and Sessions (1996), establish the main economic mechanisms behind absenteeism, including worker incentives and employer monitoring. Later studies (Barmby et al., 2002; Henrekson and Persson, 2004; Johansson and Palme, 1996) expand on these mechanisms and show how institutional settings shape absence behavior. A parallel cluster of studies documents systematic gender differences in absenteeism (Barmby et al., 1991; Bridges and Mumford, 2001; Ichino and Moretti, 2009; Leigh, 1983; Paringer, 1983; Vandenheuvel and Wooden, 1995; Vistnes, 1997). Together, these contributions highlight the relevance of both gender and incentives, motivating our attempt to disentangle biological from behavioral factors.

However, we argue that the existing literature often conflates physiological and economic determinants without employing a systematic approach to distinguish between the two. Our methodological framework enables a clear separation of these factors, allowing us to isolate genuinely opportunistic behavior from medically justified sick leave. Moreover, we disentangle the pure gender effect from composition effects, providing a more nuanced understanding of the observed gender differences. This distinction constitutes a key contribution of our research and motivates the separate review of the public health and health economics evidence below, each of which provides essential elements for addressing our research question.

2.2. Biomedical and public health evidence

A large body of health literature has shown that women experience longer recovery periods than men (Antczak and Miszczyńska 2021; Casini et al., 2013; Coutu et al., 2021; Fontaneda et al., 2019; Laaksonen et al., 2010; Mastekaasa, 2014; Mastekaasa and Melsom, 2014; Østby et al., 2018). These studies establish that gender differences in sickness duration often originate from differences in the prevalence of illnesses and biological recovery patterns.

Men and women differ systematically in the types of conditions they experience. Women are more likely than men to suffer from musculoskeletal disorders such as anterior cruciate ligament tears, multidirectional shoulder instability, ankle instability, and osteoporosis, among others (Wolf et al., 2015). In addition, women have a higher likelihood of experiencing daily disabling conditions such as rheumatism, anemia, thyroid disorders, eczema, headaches, and mental illnesses. In contrast, men show a higher prevalence of life-threatening conditions such as cardiovascular disease, stroke, lung and kidney disorders, and liver

[1] See Oaxaca (1973) and Blinder (1973).

cirrhosis (Case and Paxson, 2005; Macintyre et al., 1996). As a result, women tend to have higher rates of work disability, which can hinder their return to employment (Coutu et al., 2021).

Biological differences between men and women, particularly in anatomy and hormonal profiles, also contribute to the gender gap in sick leave (Case and Paxson, 2005). For example, women tend to have smaller coronary arteries and a lower overall surface area, which reduces the efficacy of bypass procedures and grafts following cardiac surgery, thereby increasing the likelihood of hospital readmission (Bechtel and Huffmyer, 2020). Additionally, women are more susceptible to developing secondary conditions after surgery or traumatic events such as workplace accidents, including dysphoria, anxiety, and depression, all of which may further delay recovery (Freedman et al., 2002; Kempen et al., 2003; Modica et al., 2014; Oksuzyan et al., 2018). These findings highlight that part of the gender gap in sick leave durations may be medically justified, an important baseline for our study.

In this vein, several studies have also examined the role of reproductive biology in explaining the gender gap in sick leave. Specifically, Herrmann and Rockoff (2012) found that menstruation did not account for the observed gender gap in the duration of sick leave among a sample of public school teachers. However, the same authors (Herrmann and Rockoff, 2013) later found that menstrual problems could explain up to 40 % of the observed difference among U.S. adults, based on two waves of the National Health Interview Survey. Furthermore, improved access to menstrual hygiene has been shown to reduce the likelihood of sick leave by up to 20 % (Krenz and Strulik, 2021). Together, these contributions emphasize that physiological mechanisms can meaningfully contribute to observed gender gaps, reinforcing the need to separate them from behavioral responses.

Although physiological health status remains a key determinant of work absences, psychological and behavioral differences between men and women also influence sick leave duration (Weisberg et al., 2011). This set of studies shows that gender gaps may arise not only from medical conditions but also from differences in pain sensitivity, mental health prevalence, and behavioral responses. For example, women exhibit 30 % higher absenteeism rates, partly due to greater pain sensitivity and higher incidence of mental health issues (Bryan et al., 2021). Personality traits such as neuroticism and extraversion are also associated with longer absences (Løset and von Soest 2022). Moreover, women typically display more cautious health behavior (Idler, 2003) and greater compliance with public health measures (Galasso et al., 2020), which may partly account for longer recovery periods. These findings underscore that behavioral mechanisms may contribute to observed gender differences, reinforcing the need to distinguish them from physiological determinants in our analysis.

2.3. Economic and behavioral determinants

From an economic viewpoint, prior research consistently documents that women exhibit higher absenteeism rates than men (Markussen et al., 2011; Paringer, 1983; Suárez and Muñiz, 2018). Even studies where gender is not the main focus, such as Barmby and Treble (1991), Ichino and Riphahn (2005), and Leigh (1984), frequently find higher absenteeism among women. However, some papers report less consistent differences, such as those by Brown (1994), Chaudhury and Ng (1992), Drago and Wooden (1992), Engellandt and Riphahn (2005), and Kenyon and Dawkins (1989). Overall, this literature documents persistent gender gaps in absenteeism but does not determine whether they stem from biological differences or behavioral responses, precisely the distinction our study aims to identify.

A second set of studies highlights that gender differences in economic preferences and decision-making may shape absence behavior. Foundational work by Croson and Gneezy (2009) shows that women are more risk-averse, less competitive, and more sensitive to context, with subsequent evidence confirming greater social risk aversion and stronger equality preferences (Friedl et al., 2020). These differences are echoed in health-related behaviors: women are more likely to invest in preventive care, seek medical attention (Darkwah, 2024; Gilleskie, 2010), and purchase voluntary health insurance (Kananurak, 2014). As noted by Schünemann et al. (2017), such behavioral differences can produce unequal health outcomes (Bauer et al., 2007; Nelson, 2014; Oaxaca, 1973). This cluster suggests that behavioral channels may generate gender differences in sick-leave duration independently of health status, supporting our objective of separating behavioral responses from medical determinants.

A third strand focuses on moral hazard and incentive effects within sick-leave systems. There is robust evidence that sick-pay generosity affects both the incidence and duration of sick leave (Gilleskie, 1998; Henrekson and Persson, 2004; Jinks, 2023), with men often reacting more strongly to incentives (Ziebarth and Karlsson, 2014). Policy expansions similarly increase take-up (Blanchard et al., 2025; Maclean et al., 2025), though without clear employment or wage effects (Pichler and Ziebarth, 2020). Spanish studies detect patterns of potentially opportunistic behavior among low-skilled women and high-skilled men (Martín-Román and Moral, 2016; Moral de Blas et al., 2012), as well as stronger strategic responses among high-income men when compensation rises (Martín-Román et al., 2024). Yet very long absences appear less prone to opportunism (Ziebarth, 2013). Evidence from other contexts (Spierdijk et al., 2009) shows that gender effects on duration can even reverse depending on controls. These findings point to the importance of controlling for incentive structures to avoid confounding behavioral responses with underlying health differences.

Finally, institutional and social contexts play a crucial role in shaping gendered absence patterns. Job protection increases absenteeism (Ichino and Riphahn, 2005), and union membership amplifies this effect (Goerke and Pannenberg, 2015). Women facing job insecurity show higher absenteeism (Arocena and García-Carrizosa, 2023; Khan and Rehnberg, 2009) and suffer career penalties after long absences (Chadi and Goerke, 2018), helping explain their greater presence in the public sector (Ehlert and García-Morán, 2022). Policies promoting flexible schedules reduce female absenteeism, especially among mothers (Heywood and Miller, 2015), while employment subsidies may influence fertility decisions and future absences (Nieto, 2022). Broader social norms also shape gender gaps: women undertake more unpaid work (Beblo and Ortlieb, 2012; Heywood and Miller, 2015), face a double burden that delays recovery (Côté and Coutu, 2010), and experience earnings penalties amplified by family responsibilities (Goldin et al., 2017). These patterns persisted even during sickness episodes and throughout the pandemic (Farré et al. 2022; Depalo and Pereda-Fernández, 2023). This final cluster emphasizes that institutional and household constraints systematically interact with gender, reinforcing the need to distinguish pure gender effects from composition effects in our empirical approach.

This compilation serves as a reference point for situating our analysis within the broader literature[2]

3. Institutional setting

All Spanish workers are entitled to receive economic compensation when they are on sick leave, but the amount of this benefit depends on whether their temporary incapacity (TI) was due to a work-related (occupational) accident or not. During the TI of the worker, the Social

[2] Table A1 in the Appendix 1 provides a structured overview of previous empirical studies that examine the gender gap in sick leave absenteeism from an economic point of view. For each study, the table summarizes the data source, whether a gender-specific analysis was conducted, the dimension of absenteeism considered (duration or incidence), and whether the observed gender differences were statistically significant. The studies cover a wide range of countries, time periods, and data types, including administrative records, labor force surveys, and firm-level data.

Security Administration covers the medical expenses of the injured worker for 365 days, potentially extendable 180 days more. If a worker is not able to recover his/her health after this period, the National Institute of Social Security decides whether the worker is transferred to the permanent disability system or receives a medical discharge.

Injured workers after a work-related accident receive 75 % of the reference wage[3] the day after his/her general practitioner issues the sick leave certificate, and this benefit is paid by the mutual insurance company. However, if the worker suffers from a non-work-related accident, the first three days after the accident, the worker receives no amount of sick leave. From the 4th to the 20th day the worker receives 75 % of the reference wage and this is paid by the employer until the 15th day, finally, from the 20th day to onwards, the injured worker receives 60 % of the reference wage and this is paid by the Social Security Administration (from day 16th and onwards).

This paper analyzes a database of Spanish private-sector workers who are unable to work due to a work-related accident. The Social Security Law (SSGL) of 1994 regulates the amount of sick leave benefits for this type of accident and it has not undergone any regulatory change to date. The SSGL (Art. 156) establishes the concept of occupational accident as any bodily injury suffered by the worker due to or as a consequence of developing his/her paid job, i.e., this includes all accidents suffered by employees within their workplace, to and from work (*in itinere* accidents) and/or owing to carrying out a union position or any work-related task demanded by the employer (*in mission* accidents). Although this definition excludes occupational diseases (Art. 157 of the SSGL) and common illnesses (Art. 158 of the SSGL), there are some illnesses considered occupational accidents as well. Precisely, there are three types of illnesses excluded from the term "occupational disease" that are considered work-related accidents: diseases in the strict sense, pre-existing or latent diseases, and intercurrent diseases. The diseases in the strict sense are those contracted by workers as a result of carrying out their work duties [Art. 156.2.e of the SSGL]. The pre-existing or latent diseases correspond to those that the worker already holds and that have been aggravated as a consequence of developing his/her job [Art. 156.2.f of the SSGL]. Finally, intercurrent diseases refer to those that are not directly related to the accident but have been exacerbated due to the accident or contracted during the recovery process [Art. 156.2.g of the SSGL].

4. Database

We used the universe of workplace accidents in Spain, provided by the Statistics of Accidents at Work (SAW). This is an annual administrative register of all occupational accidents that occurred in Spain that includes rich information about injured workers (age, sex, occupational class, injured part of the body, severity of the injury, etc.) and conditions of the suffered accident such as the characteristics of the company.

For the estimations, we used a dataset for the period 2011–2019 restricted to private sector workers who work on a full-time basis. This restriction is due to the fact that self-employed individuals follow a different legal framework, and part-time workers receive a lower amount of sick leave benefits that may make them behaviorally react differently when they are on sick leave (e.g., they might try to return to work earlier than full-time workers as their household income loss during their sick leave might be higher). Additionally, we removed some detected registered errors such as ages incompatible with labor market or compensations out of the legally established limits. Our final database consisted of 3,916,249 injured workers due to a work-related accident.

Table 1 presents descriptive statistics from our dataset. As shown, sick leave durations vary significantly depending on the type of injury, the worker's occupation, and the body part affected by the accident. On average, the gender gap in sick leave duration is less than one day; however, for certain types of injuries, such as superficial wounds, psychological trauma, or fractures, female workers take nearly five additional days of leave.

Women also tend to have longer sick leave durations in cases involving neck or back injuries, and among low-skilled workers. Conversely, male workers have slightly longer sick leaves in cases of heart attacks, multiple injuries, lower limb injuries, among high-skilled workers, and in commuting (*in itinere*) accidents.

The workplace accident rate primarily affects men, who account for more than 70 % of total accidents. However, in the case of commuting accidents, the proportion is nearly equal between the sexes throughout the study period. Only in certain high-skilled occupations such as technical staff and scientists (31 %), and administrative staff (36.1 %), the proportion of male workers is lower than that of female workers. When comparing these percentages with the share of men within each occupation, it becomes evident that, for most occupations, the figures are similar, although the percentages are almost always slightly higher in the case of accidents. The main discrepancy is observed among unskilled workers, where the share of men is below 40 %, yet they account for 70 % of all accidents. A possible explanation for this result may lie in the heterogeneity of this occupational group and in the fact that men may be concentrated in tasks that are more prone to accidents.

The evolution of the gender gap in sick leave over the analyzed period further justifies this study. Fig. 1 shows that during the first two years of the analysis (2011 and 2012), the average duration of sick leave was similar for both sexes. In 2013 and 2014, the durations began to diverge with minor differences. However, starting in 2015, the differences became statistically significant. Specifically, in the most recent years analyzed, the average duration of sick leave among women exceeds that of men by more than 3 %.

Another relevant aspect is the influence of territory on the duration of sick leave. To examine this issue, we conduct a spatial analysis to identify provincial-level patterns (see Appendix 2). The results show a Moran's I value of 0.6, indicating a positive spatial correlation in the average duration of sick leave across provinces.

The final descriptive analysis examines the effect of age on differences in duration. Fig. 2 displays gender-based differences in the duration of sick leave across various age groups. In general, there is an upward trend in the duration of sick leave as the age of the injured worker increases. This increase is more pronounced among women, who tend to exhibit shorter absences than men in the younger cohorts but longer sick leave among older workers.

Before outlining our empirical strategy, we begin by estimating an OLS regression to assess the relevance of sex as an explanatory variable for the duration of sick leave. As discussed previously in this section, differences in the duration of sick leave between men and women may be attributed to various factors. Therefore, the presence of a statistically significant coefficient for the variable measuring sex, after controlling for injury type, worker characteristics or occupation, constitutes robust evidence that gender independently influences the duration of sick leave, *ceteris paribus*. This initial regression model is specified as follows:

$$d_i = X_i\beta + M_i\alpha + \varepsilon_i \quad \text{with } d_i = \ln(D_i) \tag{1}$$

Where D_i is the sick leave duration, X_i is a vector of characteristics, β is a vector of coefficients, M_i is a dummy variable that takes 1 if the injured worker is a male, α is the coefficient of the MALE variable, and ε_i is a random error of mean zero and variance σ_ε^2.

Specifically, we estimate the logarithm of sick leave duration using three different model specifications. In the first specification MALE is the

[3] This is calculated from the wage that the worker has earned in the last month before the accident. This reference wage has upper limits that are established in the State General budget each year and they are equal for all professional categories and contingencies (Art. 148 of the SSGL); and lower limits, whose amount depends on the minimum wage of each year increased by one-sixth. The estimation of the contributory base has been unchanged during the period analysis of our study.

Table 1
Mean durations by gender, percentage of males and number of injuries in terms of various characteristics.

	Female	Male	% of males		Obs.
Type of injury					
Not specified	30.8	28.0	69.0		73,802
Superficial Injuries	25.1	21.6	73.1		629,517
Other injuries	23.1	22.8	79.5		615,733
Fractures	79.1	74.1	75.0		286,993
Strains	30.9	29.5	68.9		637,301
Dislocations	33.2	33.2	70.6		276,511
Sprain	29.8	29.4	67.7		1,017,476
Traumatic amputation	80.2	88.4	89.2		9,110
Concussion	32.0	33.4	73.4		223,090
Burns	15.5	20.3	73.5		50,961
Poisoning	17.0	17.3	62.6		6,159
Choking	21.9	21.4	62.5		2,017
Noise, heat	19.9	22.5	75.0		5,737
Psychological trauma	41.6	35.5	64.5		13,330
Multiple injuries	40.8	49.7	68.6		62,723
Heart attack	136.2	164.5	85.9		5,789
Part of the body					
Not specified	37.4	35.8	64.0		16,368
Head	28.5	28.1	75.4		53,623
Face	20.2	19.2	77.8		37,786
Eyes	10.0	10.2	88.0		123,279
Neck (spine)	30.1	26.2	51.9		230,715
Neck (rest)	28.1	24.0	54.8		40,109
Back (spine)	26.2	22.8	73.5		524,022
Back (rest)	25.0	21.5	72.5		133,444
Trunk	28.7	32.0	78.6		166,552
Shoulder	49.3	48.6	69.7		202,420
Arm	44.3	40.7	71.7		209,120
Hand	26.6	27.3	75.8		241,605
Finger (hand)	23.8	27.6	79.0		447,265
Wrist	39.5	35.8	63.7		161,871
Upper limbs (not esp.)	40.6	39.8	70.9		49,100
Leg	40.3	42.2	77.4		460,256
Ankle	30.7	29.8	65.5		268,549
Foot	29.5	31.7	69.3		252,292
Finger (foot)	27.7	30.0	65.9		45,973
Lower limbs (not esp.)	37.9	39.8	71.7		82,249
Multiple parts	37.4	44.3	64.5		169,651
Occupation			***		
			Accidents	***Employment***	
Company management	37.8	41.7	64.4	68.9	13,791
Technical staff and scientists	35.0	36.6	31.0	44.4	144,724
Professional support	32.8	35.0	66.9	62.0	143,180
Administration employees	34.8	36.2	36.1	34.0	188,773
Service workers	31.0	31.0	48.5	40.6	795,967
Skilled agriculture and fishing	32.0	33.1	88.4	80.0	100,537
Crafts and dealers	32.6	31.0	93.8	92.3	947,978
Machine operators	33.2	33.9	93.1	87.1	548,405
Unskilled	31.7	29.1	70.0	39.6	1,032,894
Accident context					
In itinere	38.3	41.6	50.0		479,342
During working hours	30.6	30.6	74.9		3,436,907

Source: Author's own based on SAW data
*** The column reporting the percentage of male workers by occupation is divided into two components. The left-hand side presents the share of male workers in total recorded accidents. The right-hand side reports their share in total employment according to the Labor Force Survey.

sole explanatory variable. The second specification incorporates all medical and physiological variables that may objectively influence the duration of sick leave, including type of injury, affected body part, accident severity, type of medical care received (hospitalization or outpatient), whether the leave corresponds to a relapse, and occupational dummies to account for job-related recovery demands. The third specification further includes variables that may subjectively influence sick leave duration, such as the amount of compensation received, company size, job tenure, employment in the private sector, nationality, and the sector of economic activity or the province in which the accident occurred.

The results of the OLS estimations are presented in **Table A2** (**Appendix 4**), and a summary is depicted in the first panel of Fig. 2. Our findings confirm a highly significant effect of the MALE variable, ranging from −0.090 in Model 1 to −0.058 in Model 2. The coefficient of determination increases as additional explanatory variables are included, exceeding 20 % in the fully specified model.

A placebo test supplements this first analysis to assess whether the observed effect, *ceteris paribus*, is effectively attributable to sex and not to other uncontrolled factors. The first step of this test consists of randomly generating an accessory variable labelled MALE. This variable is then included as a regressor in separate estimations for the male and female subsamples, along with the remaining explanatory variables. Two scenarios are considered for this random assignment: one assuming an equal gender split (50 % male), and another reflecting the actual proportion of injured men in the dataset (70 %). If the MALE variable truly captures the gender effect, this randomly generated variable should not be significant in any specification. Fig. 3 presents the results of this test. In all estimations, the coefficient of the generated MALE variable remains close to zero and statistically insignificant, reinforcing the relevance of sex as a determinant of sick leave duration.

5. Methodology

The purpose of this study is to analyze the differences in the duration of sick leave between male and female workers, and to determine how much of this gap is explained by differences in the types of injuries, biological factors, or the behavior of the injured workers. To address this question, the paper combines two different empirical approaches in a novel way. Firstly, we estimate the duration of sick leave for each gender to identify which part can be attributed physiological/medical factors and which other may instead reflect opportunistic behavior on the worker's side. Secondly, we use decomposition techniques to analyze which factors explain the differences in the average duration of accident-related sick leaves for men and women, both in terms of medical issues and behavior.

5.1. Stochastic frontier estimation

Once the relevance of the MALE variable has been assessed through the OLS estimation, we adopt a stochastic frontier approach to conduct a more in-depth analysis of sick leave duration (Martín-Román and Moral, 2014, 2017; Martín-Román et al., 2024). Following this method, after an injury, there exists a recovery period only attached to medical or physiological factors. That period is identified as 'standard duration' (D_i^s) that marks a lower boundary that can be defined as follows:

$$d_i^s = X_i\beta + v_i \text{ with } d_i^s = \ln(D_i^s) \tag{2}$$

With X_i a vector of characteristics, β a vector of coefficients and v_i a random error of mean zero and variance σ_v^2.

However, insurers do not normally perceive this duration, as they only have information about the actual sick leave duration (D^r). Hence, this actual duration is not only a consequence of medical and physiological factors but also of the worker's capacity to increase his/her recovery period. It is therefore a problem of asymmetric information, which can lead to opportunistic behavior from workers covered by accident insurance. This increase in duration may be linked to inefficiencies in the insurer's sick leave monitoring process.

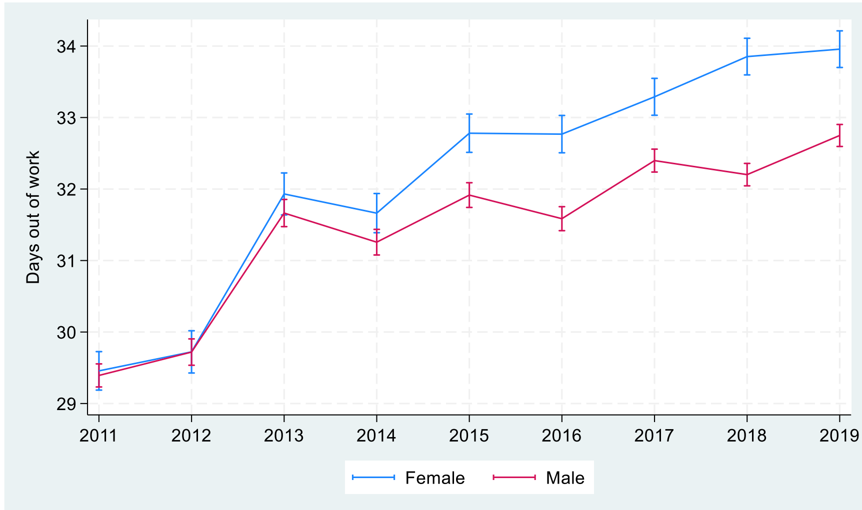

Fig. 1. Mean duration by gender and year, Source: Author's own based on SAW data, Note: 95 % Confidence Intervals.

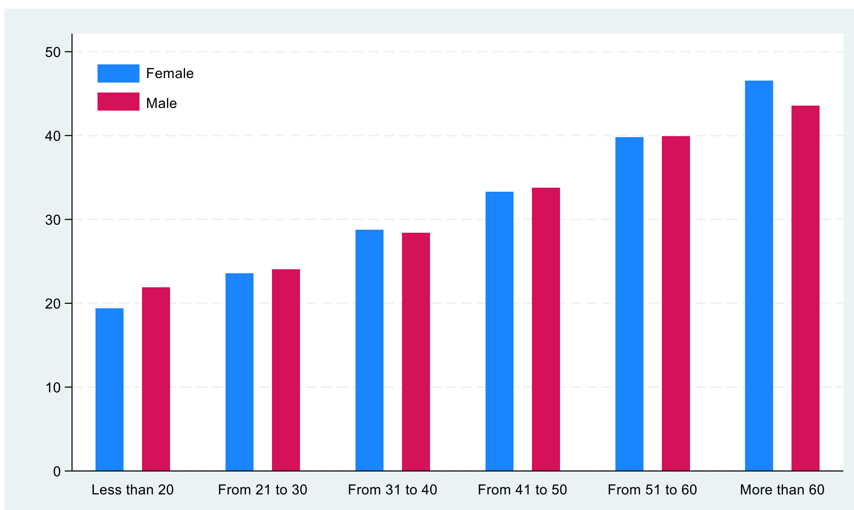

Fig. 2. Mean duration by gender and age group. Source: Author's own based on SAW data.

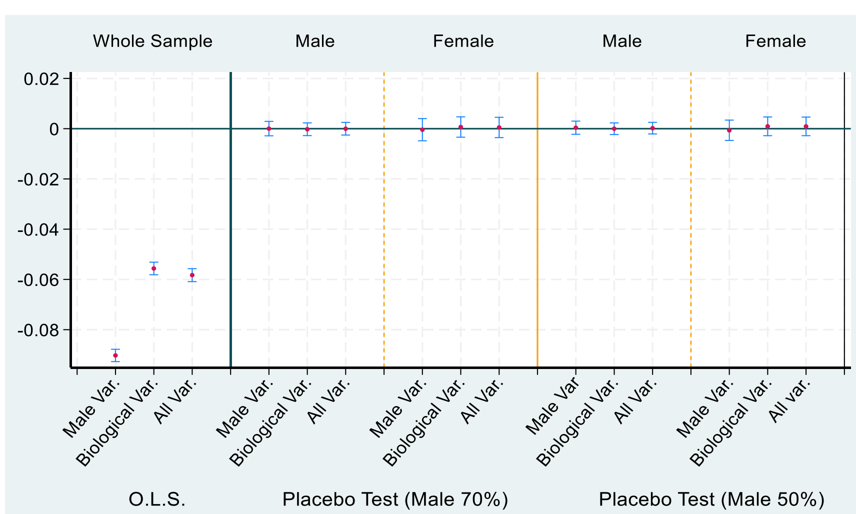

Fig. 3. Coefficient and confidence interval for Male variable (OLS and Placebo test). Source: Author's own based on SAW data.

In formal terms, the actual duration results from adding to the standard duration another random disturbance (u_i) with a positive mean and variance σ_u^2. It can be expressed as follows:

$$d_i^r = d_i^s + u_i \text{ with } d_i^r = \ln(D_i^r) \tag{3}$$

From Eqs. 2 and 3, the final model can be obtained:

$$d_i^r = X_i\beta + v_i + u_i \tag{4}$$

Estimating a composed error model requires addressing two technical aspects. Firstly, assuming independence between the disturbances and the regressors, ordinary least squares yield unbiased, consistent, and efficient estimators. However, the constant term remains inconsistent, and the variances of the two error components cannot be separately identified. On the other hand, introducing an additional disturbance also requires assuming a statistical distribution for it. Some examples of distributions that may be employed are Half-Normal (Aigner et al., 1977), Exponential (Meeusen and van Den Broeck, 1977), Truncated Normal (Stevenson, 1980), or Gamma (Greene 1980a, 1980b). In this case, and following Kumbhakar and Parmeter (2009), the exponential distribution is chosen, as it is commonly used in standard single-tier stochastic frontier models estimated via maximum likelihood.[4]

$$\overline{d^f} - \overline{d^m} = \widehat{\beta_o^f} + \sum_{k=1}^{K}\overline{X_k^f}\widehat{\beta_k^f} - \widehat{\beta_o^m} - \sum_{k=1}^{K}\overline{X_k^m}\widehat{\beta_k^m} + \widehat{\beta_o^m} + \sum_{k=1}^{K}\overline{X_k^f}\widehat{\beta_k^m} - \widehat{\beta_o^m} - \sum_{k=1}^{K}\overline{X_k^f}\widehat{\beta_k^m} = \underbrace{\left(\widehat{\beta_o^f} - \widehat{\beta_o^m}\right) + \sum_{k=1}^{K}\overline{X_k^f}\left(\widehat{\beta_k^f} - \widehat{\beta_k^m}\right)}_{\text{Unjustified effect}} + \underbrace{\sum_{k=1}^{K}\left(\overline{X_k^f} - \overline{X_k^m}\right)\widehat{\beta_k^m}}_{\text{Justified effect}} \tag{7}$$

5.2. Decomposition of the gender gap

Once stochastic frontiers estimations have been obtained separately for men and women, the next step is to decompose the difference between the average duration of sick leave in each group into its different components.

To conduct this type of analysis, the seminal works by Oaxaca (1973) and Blinder (1973) developed a methodology that has been widely applied in economic literature, particularly in the case of wage discrimination. In its original version, the decomposition assumes a linear relationship between the dependent variable (the duration of sick leave) denoted by d and the explanatory variables (X), which must also be independent of the error term (ϵ).[5]

At this point, we can follow Yun's approach (Yun, 2004, 2005) to perform the decomposition for two reasons. Firstly, it allows identification issues to be addressed in the detailed decomposition associated with the use of dummy variable groups in estimation (See **Appendix 3** for technical details). The other option is to use a reference injury determined by the dummy variables removed from the estimation to avoid multicollinearity. Secondly, it puts forward a generalization for any functional relationship that can be extended to the frontier estimation applied in this study.

In formal terms, the decomposition proposed by Oaxaca and Blinder starts with two estimations of the dependent variable (i.e., d in this case), one for each of the groups to be compared (female and male workers, or f and m in this case), as expressed below:

$$d_i^h = \beta_o^h + \sum_{k=1}^{K} X_{ik}\beta_k^h + \varepsilon_i^h \text{ with } h: m, f \tag{5}$$

Where β_o^h and β_k^h are the coefficients resulting from the estimates in each population group, X_{ik} is the corresponding vector of K explanatory variables, and $E(\varepsilon_i^h | X_{ik}) = 0$. At this point, the mean predicted values can be obtained for each group and, with them, a counterfactual estimation. Such a counterfactual results from using the mean values of the variables in the women's group together with the coefficients obtained for the men's group. Its formal specification would be as follows:

$$\overline{d^{fm}} = \widehat{\beta_o^m} + \sum_{k=1}^{K}\overline{X_k^f}\widehat{\beta_k^m} \tag{6}$$

By adding and subtracting the counterfactual within the difference in means of both groups, the duration gap can be decomposed as follows:

The first component (unjustified) reflects that similar characteristics affect each group differently. For the exercise proposed in this study, this component would imply, for example, that similar injuries lead to different recovery processes in men and women. As for the second term, it is considered justified because it is reasonable to assume that different values of the explanatory variables generate differences in the dependent variable. Put simply, if the severity of the injury or the age of the worker differs, the length of the leave may also vary.

Fig. 3 shows a graphical representation of the decomposition, although with certain underlying assumptions. Firstly, a single explanatory variable (X) is considered, which determines the duration of the sick leave. It is also assumed that the duration of leave increases with the values of this variable in both groups at a constant rate $\left(\beta^h\right)$ starting from an initial value indicated by the intercept $\left(\beta_o^h\right)$. Finally, it is assumed that all components of the decomposition operate in the same direction, meaning that the group with a higher initial leave duration also experiences a greater increase in their recovery period as X_i increases. The blue line represents the estimated duration for males, the black line for females, and the green ones are auxiliary lines used to identify the different effects. Both the gap to be explained and the obtained components are shown in bold, and if they are on the right (left) of the bracket, they are considered to have a positive (negative) value.

Based on this well-known decomposition, we can now move on to the case at hand by incorporating the modifications brought by the estimation of stochastic frontiers into the model. As previously explained, the first change generated by the frontier estimation is the inclusion of an additional term associated with inefficiency. Furthermore, if we assume the linearization of the objective function through logarithmic transformation, the individual estimations are expressed as follows:

$$d_i^h = \beta_o^h + \sum_{k=1}^{K} X_{ik}\beta_k^h + u_i^h + \varepsilon_i^h \text{ with } h: m, f \tag{8}$$

Where a new term $\left(u_i^h\right)$ is included, which corresponds to a random disturbance that always takes a positive value and captures the part of

[4] Furthermore, alternative specifications using the half-normal distribution have been tested, and the decomposition results remain robust.

[5] The literature also includes extensions of these types of decompositions for nonlinear models where the dependent variable (continuous or discrete) is a function of a linear combination of regressors. Some examples of these studies are Even and Macpherson (1990), Fairlie (1999), (2005), and Nielsen (1998) for logit and probit models, or Ham et al. (1998) for duration models.

sick leave associated with worker behavior. According to this, the new difference in means could be expressed as follows:

$$\overline{d^f} - \overline{d^m} = \widehat{\beta_o^f} + \sum_{k=1}^{K} \overline{X_{ik}}\widehat{\beta_k^f} + \overline{u^f} - \widehat{\beta_o^m} - \sum_{k=1}^{K} \overline{X_{ik}}\widehat{\beta_k^f} - \overline{u^m} \tag{9}$$

Following this same line of reasoning, the corresponding counterfactual construction that determines the expected duration for women if the variables affected them in the same way as men would be:

$$\overline{d^{fm}} = \widehat{b_o^m} + \sum_{k=1}^{K} \overline{X_k^f}\widehat{\beta_k^m} + \overline{u^{fm}} \tag{10}$$

Where $\overline{u^{fm}}$ represents the expected average duration associated with the inefficiency that women would have if the estimated coefficients for the equation of men are applied to them. By adding and subtracting this counterfactual within the difference in means of both groups, we obtain the following expression for the now modified decomposition:

$$\overline{d^f} - \overline{d^m} = \underbrace{\left(\widehat{\beta_o^f} - \widehat{\beta_o^m}\right) + \sum_{k=1}^{K}\left(\overline{X_k^f} - \overline{X_k^m}\right)\beta_k^m + \sum_{k=1}^{K}\overline{X_k^f}\left(\widehat{\beta_k^f} - \widehat{\beta_k^m}\right)}_{\text{Biological components}} + \underbrace{\left(\overline{u^f} - \overline{u^{fm}}\right) + \left(\overline{u^{fm}} - \overline{u^m}\right)}_{\text{Behavioral components}} \tag{11}$$

Therefore, the analysis effectively consists of two separate decompositions. The first refers to the standard days (the cost frontier), where all components have a biological basis. The second one concerns the differences in inefficiency, whose components are explained by behavioral factors.

Fig. 4 shows this decomposition graphically. Now, the solid lines (blue and black) represent the standard duration values for men and women, respectively. The dashed lines (blue and black) refer to the estimated total sick leave duration for each group. Therefore, the vertical difference between them reflects the inefficiency that men and women exhibit in the labor market. As in the previous graphs, it is assumed that there is a single explanatory variable positively related to the standard duration of sick leave. It is also considered that the difference in intercepts operates in the same direction as the rest of the unjustified component. Furthermore, an additional assumption is included: in this case, it is assumed that the inefficiency component increases as the sick leave duration increases, and thus, the difference between the solid and dashed lines becomes larger. This assumption is sensible when considering efficiency as the ratio between the actual sick leave duration and the minimum expected duration for the recovery of a specific work-related accident. In such circumstances, the longer the sick leave, the more days associated with inefficiency.

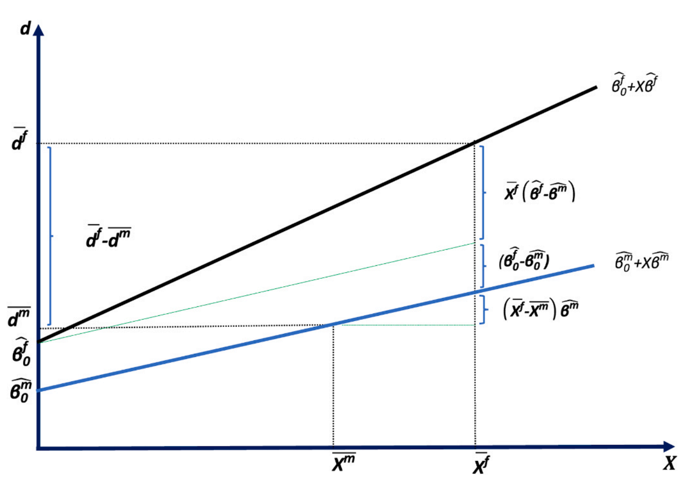

Fig. 4. Standard Oaxaca-Blinder decomposition with all the components operating in the same direction.

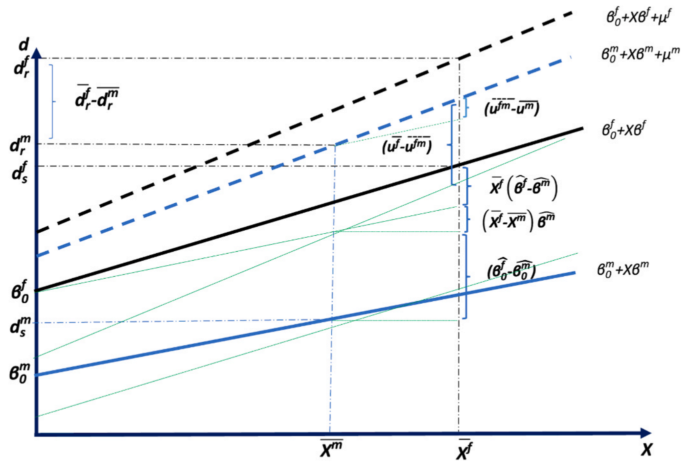

Fig. 5. Nonlinear Oaxaca-Blinder decomposition with SFA estimation and the intercept differences acting in the same direction.

After obtaining the mathematical expression of the decomposition and its graphical representation, the next step is to provide theoretical content to each of its components. As shown in Eq. 11, the first three components have a biological basis and correspond to the standard duration of sick leave. In contrast, the last two components are behavior-driven and account for the days attributable to inefficiency:

- $\left(\widehat{\beta_o^f} - \widehat{\beta_o^m}\right)$: This component can be interpreted in two ways. If the normalized version of the estimation proposed by Yun (2005) is used, it could be interpreted as the difference attributable to the fact that the sick leave generated by an average injury is different for men and women (**biological average injury effect**). If the normalized regression is not used, it would measure the different recovery rates between men and women after a reference injury, which is determined by the dummy variables removed from the estimation to avoid multicollinearity (**biological reference injury effect**). This term also reflects a biological component, as the characteristics captured by the constant have different effects on men and women.
- $\sum_{k=1}^{K}\left(\overline{X_k^f} - \overline{X_k^m}\right)\widehat{\beta_k^m}$: This term refers to the fact that men and women may have different physiological characteristics and also experience different types of injuries. The literature considers these differences as justified because differences in characteristics should generate differences in sick leave duration. In our case, we will refer to it as the **biological composition effect**, which indicates that men and women may have different characteristics or experience different injuries.
- $\sum_{k=1}^{K}\overline{X_k^f}\left(\widehat{\beta_k^f} - \widehat{\beta_k^m}\right)$: In the canonical decomposition, this term is considered as the unjustified difference.[6] However, in the present case, it can be given another interpretation. Specifically, if men and women have different coefficients for the same characteristics, it implies a different recovery period for the same injury depending on the sex of the injured worker. This result could be associated with the different biology of both sexes justifying sick leave durations. For this reason, we dub it the **biological gender effect.** This third component is closely related to the first, since both capture gender-based differences of the same injury.
- $\left(\overline{u^{fm}} - \overline{u^m}\right)$: This is the first term of the decomposition associated with worker behavior, justified by the fact that not all injuries are

[6] This term was originally considered as a wage discrimination measurement in the early literature.

Table 2
Frontier estimations of the logarithm of the sick leave duration by gender (normalized regression).

	Female			*Male*		
	Coeff.	*P > z*	*Coeff. Norm*	*Coeff.*	*P > z*	*Coeff. Norm*
Type of injury						
Not specified			-0.096			-0.133
Superficial Injuries	-0.143	0.000	-0.239	-0.120	0.000	-0.253
Other injuries	-0.141	0.000	-0.237	-0.070	0.000	-0.203
Fractures	1.126	0.000	1.030	1.106	0.000	0.973
Strains	0.019	0.007	-0.077	0.047	0.000	-0.086
Dislocations	0.058	0.000	-0.038	0.118	0.000	-0.016
Sprain	0.033	0.000	-0.063	0.056	0.000	-0.077
Traumatic amputation	0.971	0.000	0.875	1.093	0.000	0.960
Concussion	0.015	0.048	-0.081	0.092	0.000	-0.041
Burns	-0.419	0.000	-0.515	-0.132	0.000	-0.266
Poisoning	-0.388	0.000	-0.483	-0.420	0.000	-0.553
Choking	-0.567	0.000	-0.663	-0.714	0.000	-0.847
Noise, heat	-0.184	0.000	-0.280	-0.155	0.000	-0.288
Psychological trauma	0.084	0.000	-0.012	-0.010	0.366	-0.144
Multiple injuries	0.153	0.000	0.057	0.248	0.000	0.115
Heart attack	0.917	0.000	0.821	0.992	0.000	0.859
Part of the body						
Not specified			0.142			0.090
Head	-0.348	0.000	-0.207	-0.418	0.000	-0.328
Face	-0.567	0.000	-0.425	-0.466	0.000	-0.375
Eyes	-0.966	0.000	-0.824	-0.961	0.000	-0.871
Neck (spine)	0.129	0.000	0.271	0.070	0.000	0.160
Neck (rest)	0.048	0.002	0.189	-0.052	0.000	0.038
Back (spine)	-0.171	0.000	-0.029	-0.260	0.000	-0.170
Back (rest)	-0.184	0.000	-0.042	-0.278	0.000	-0.188
Trunk	-0.181	0.000	-0.039	-0.100	0.000	-0.010
Shoulder	0.235	0.000	0.376	0.270	0.000	0.361
Arm	0.101	0.000	0.243	0.128	0.000	0.219
Hand	-0.183	0.000	-0.041	-0.062	0.000	0.029
Finger (hand)	-0.279	0.000	-0.137	-0.068	0.000	0.023
Wrist	0.041	0.004	0.183	0.043	0.000	0.133
Upper limbs (not esp.)	0.073	0.000	0.215	0.120	0.000	0.210
Leg	0.072	0.000	0.214	0.238	0.000	0.329
Ankle	-0.099	0.000	0.043	0.006	0.577	0.096
Foot	-0.185	0.000	-0.044	-0.059	0.000	0.032
Finger (foot)	-0.550	0.000	-0.409	-0.310	0.000	-0.220
Lower limbs (not esp.)	-0.046	0.002	0.096	0.069	0.000	0.159
Multiple parts	0.084	0.000	0.226	0.193	0.000	0.283
Ambulatory			-0.080			-0.098
Hospital care	0.160	0.000	0.080	0.196	0.000	0.098
No hospitalization			-0.245			-0.318
Hospitalization	0.490	0.000	0.245	0.636	0.000	0.318
Minor			-0.455			-0.525
Serious	0.910	0.000	0.455	1.050	0.000	0.525
Accident			-0.195			-0.201
Relapse	0.390	0.000	0.195	0.402	0.000	0.201
Age						
Less than 20			-0.254			-0.212
From 20 to 30	0.095	0.000	-0.159	0.053	0.000	-0.159
From 30 to 40	0.217	0.000	-0.037	0.151	0.000	-0.061
From 40 to 50	0.301	0.000	0.048	0.248	0.000	0.037
From 50 to 60	0.401	0.006	0.147	0.364	0.000	0.152
More than 60	0.508	0.000	0.255	0.454	0.000	0.242
Occupation						
Company management			-0.057			0.008
Technical staff and scientists	0.050	0.001	-0.007	-0.034	0.003	-0.026
Professional support	0.026	0.077	-0.030	0.013	0.218	0.021
Administration employees	0.013	0.358	-0.043	-0.035	0.002	-0.027
Service workers	0.074	0.000	0.018	-0.021	0.045	-0.013
Skilled agriculture and fishing	0.098	0.000	0.042	0.053	0.000	0.061
Crafts and dealers	0.107	0.000	0.050	-0.029	0.005	-0.021
Machine operators	0.079	0.000	0.022	0.012	0.272	0.019
Unskilled	0.061	0.000	0.005	-0.028	0.008	-0.020
Constant	2.088	0.000	3.326	1.919	0.000	3.308
Observations	1101,551			2814,698		
/lnsig2v	-0.193	0.000		-0.373	0.000	
/lnsig2u	-1.774	0.000		-1.169	0.000	
sigma_v	0.908			0.830		
sigma_u	0.412			0.557		
sigma2	0.994			0.999		
Lambda	0.454			0.672		
LR test of sigma_u= 0	chibar2(01) = 3.2e+ 03			chibar2(01) = 3.5e+ 04		

Source: Author's own based on SAW data

Table 3
Decomposition of the sick leave duration between female and male (Normalized regression).

	Total difference	*Differences in standard duration*			*Differences in efficiency*	
	$\overline{d^{ff}} - \overline{d^{mm}}$	$\left(\widehat{\beta_o^f} - \widehat{\beta_o^m}\right)$	$\left(\overline{X_k^f} - \overline{X_k^m}\right)\beta_k^m$	$\overline{X}_k^f\left(\widehat{\beta_k^f} - \widehat{\beta_k^m}\right)$	$\left(\overline{u^f} - \overline{u^{fm}}\right)$	$\left(\overline{u^{fm}} - \overline{u^m}\right)$
Percentage	100 %	20 %	32 %	208 %	-179 %	18 %
Days	0.778	0.155	0.251	1.622	-1.390	0.140
		2.028			-1.250	

Source: Author's own based on SAW data

expected to result in the same level of inefficiency. The literature has shown that the injuries most likely to induce opportunistic behavior among workers include so-called difficult-to-diagnose injuries (Fortin and Lanoie, 2000), easy-to-conceal injuries (Smith, 1990), or soft tissue injuries (Butler et al. 1996), such as sprains, strains, and lower back pain. Consequently, differences in inefficiency may also arise from men and women exhibiting different characteristics or experiencing different types of injuries. We refer to this term as the ***behavioral composition effect.***

- $\left(\overline{u^f} - \overline{u^{fm}}\right)$: This final component is also behavior-related and reflects the idea that the analyzed group (in this case, women) would exhibit a different level of inefficiency if the coefficients estimated for the other group (men) were applied. In line with the original Oaxaca-Blinder interpretation, this component corresponds to the unexplained gap in inefficiency. Such an unexplained difference may result from men and women behaving differently after the injury has occurred. For these reasons, we refer to this term as the ***behavioral gender effect.***

6. Results

6.1. Stochastic Frontier estimation

After establishing the statistical significance of sex as an explanatory variable, the subsequent step is to estimate stochastic frontier models. As it is explained before, to obtain the mean difference expressed in Eq. 11 it is needed to estimate Eq. 8 for men and women separately. We conducted two different regressions to calculate the standard duration of sick leave. First, to correct the potential multicollinearity and identification problems that arise from using dummy variables (i.e., leave one of them out from the model as a reference category), we calculated a normalized regression (see **Appendix 3**) for men and women separately. Table 2 depicts the results of those regressions. Within each group, the first column shows the estimated coefficients, the second column their significance, and the third column the normalized coefficients. We observe that, for both sexes, injuries such as fractures, traumatic amputations, multiple injuries, and heart attacks implied longer sick leave durations (positive coefficient) than other types of injuries such as superficial injuries, burns, or choking (negative coefficient). The duration of sick leave was also longer for men and women when the injured part of the body was the neck, the shoulder, the arm, the leg, the ankle, or it affected multiple parts of the body. Additionally, if the accident involved hospital care, hospitalization, a serious injury, and/or was a relapse of a previous injury, the duration of sick leave lasted more time for both sexes. The same was also true for workers from the age of 40 and manual workers.

After estimating the duration of sick leave for male and female workers, the gender difference in the duration of sick leave is decomposed as expressed in Eq. 11. Table 3 shows the decomposition of the gender gap in percentage and number of days. The first notable result indicates that, although the overall difference is less than one day, the recovery period attributable to biological factors is two days longer for women. In contrast, men extend their opportunistic sick leaves by more than one day. Of this longer female standard duration, 1.622 days are attributable to the difference in coefficients (*biological gender effect*), 0.251 days reflect differences in baseline characteristics between men and women (*biological composition effect*), and the remaining 0.155 days correspond to the *biological average injury effect*. The greater inefficiency observed in men appears to be explained by a worse opportunistic behavior of men (*behavioral gender effect*), which extends their sick leave by 1.390 days. In contrast, the *behavioral composition effect* would indicate a greater inefficiency in the case of women (0.140 days).

Although the normalized regressions to obtain the duration of sick leave provide a single estimation, the interpretation of results might be difficult as the reference category is an "average injury" that must be interpreted as a notional concept which does not exist in real life. Therefore, the duration of sick leave is also estimated using a regular regression. To do so, the first step is to identify a comparable reference group to interpret the results. This reference group is defined by a combination of injury type and affected body part, representing one of the most frequent cases in our dataset. This is exemplified by "leg sprains", which account for over 150,000 records. Additional selection criteria specify that the injury is minor (not requiring hospitalization or hospital care), is not the result of a recurrent injury, and that the worker is between 30 and 40 years old and belongs to the low-skilled professional category.

Table 4 shows the results of the regular regression for men and women separately. The estimated coefficient and its significance are depicted for both groups. Suffering from a fracture, dislocation, traumatic amputation, multiple injuries, or a heart attack leads to longer sick leave durations compared to suffering from a sprain for men and women alike. This is also true for women suffering from psychological trauma and men suffering from concussions. When the shoulder is the injured body part, the duration of sick leave is also longer compared to injuries affecting the leg. Again, manual and old workers present longer sick leave durations compared to unskilled workers aged from 30 to 40 respectively. Finally, injuries that required hospital care, hospitalization, were serious and/or were a relapse of a previous injury, implied longer sick leave durations compared to a slight injury that did not require hospitalization nor hospital care and was not a relapse of a previous injury.

Once the duration of sick leave has been estimated for both groups, the observed gender gap is decomposed (Table 5). The longer standard duration for women and the greater inefficiency among men remain unchanged. The only variation lies in the reallocation of days across the biological components. Although the *biological composition effect* remains at 0.251 days, using a specific reference group affects the estimation of the intercept, raising the *biological average injury effect* to 1.151 days and reducing the *biological gender effect* to 0.625 days.

6.2. Endogeneity analysis

One of the challenges in frontier analysis is the potential presence of endogeneity,[7] which may arise from correlations between the regressors

[7] There are already studies in the literature that address the treatment of endogeneity in stochastic frontier estimations (Simar et al. 2016). However, we have not applied these methodologies as endogeneity does not appear to be a relevant concern in our case, and their implementation would unnecessarily complicate the proposed decomposition.

and either of the two error components. This issue may be due to the inclusion of endogenous variables, the presence of self-selection in the model, or the omission of variables that are correlated with the dependent variable. From our perspective, we do not consider the first source of endogeneity to be present in this case, given the characteristics of our database. Sick leave duration, as the dependent variable, is an ex-

Table 4
Frontier estimations of the logarithm of the sick leave duration by gender (reference group regression).

	Female		*Male*	
Duration	***Coefficient***	***P > z***	***Coefficient***	***P > z***
Ref.: Sprain				
Not specified	-0.033	0.000	-0.056	0.000
Superficial Injuries	-0.176	0.000	-0.176	0.000
Other injuries	-0.174	0.000	-0.126	0.000
Fractures	1.093	0.000	1.050	0.000
Strains	-0.014	0.000	-0.009	0.000
Dislocations	0.025	0.000	0.062	0.000
Traumatic amputation	0.938	0.000	1.037	0.000
Concussion	-0.018	0.000	0.036	0.000
Burns	-0.452	0.000	-0.188	0.000
Poisoning	-0.421	0.000	-0.476	0.000
Choking	-0.600	0.000	-0.770	0.000
Noise, heat	-0.217	0.000	-0.211	0.000
Psychological trauma	0.051	0.001	-0.066	0.000
Multiple injuries	0.120	0.000	0.192	0.000
Heart attack	0.884	0.000	0.937	0.000
Ref.: Leg				
Not specified	-0.072	0.000	-0.238	0.000
Head	-0.420	0.000	-0.657	0.000
Face	-0.639	0.000	-0.704	0.000
Eyes	-1.038	0.000	-1.200	0.000
Neck (spine)	0.057	0.000	-0.169	0.000
Neck (rest)	-0.024	0.002	-0.291	0.000
Back (spine)	-0.243	0.000	-0.499	0.000
Back (rest)	-0.256	0.000	-0.517	0.000
Trunk	-0.253	0.000	-0.339	0.000
Shoulder	0.163	0.000	0.032	0.000
Arm	0.029	0.000	-0.110	0.000
Hand	-0.255	0.000	-0.300	0.000
Finger (hand)	-0.351	0.000	-0.306	0.000
Wrist	-0.031	0.000	-0.196	0.000
Upper limbs (not esp.)	0.001	0.903	-0.119	0.000
Ankle	-0.171	0.000	-0.233	0.000
Foot	-0.257	0.000	-0.297	0.000
Finger (foot)	-0.622	0.000	-0.549	0.000
Lower limbs (not esp.)	-0.118	0.000	-0.170	0.000
Multiple parts	0.012	0.024	-0.045	0.000
Ref.: Unskilled				
Company management	-0.061	0.000	0.028	0.008
Technical staff and scientists	-0.011	0.002	-0.006	0.194
Professional support	-0.035	0.000	0.041	0.000
Administration employees	-0.048	0.000	-0.007	0.066
Service workers	0.013	0.000	0.007	0.001
Skilled agriculture and fishing	0.037	0.000	0.081	0.000
Crafts and dealers	0.045	0.000	-0.001	0.370
Machine operators	0.018	0.001	0.039	0.000
	Female		***Male***	
	Coefficient	***P > z***	***Coefficient***	***P > z***
Hospital care	0.160	0.000	0.196	0.000
Hospitalization	0.490	0.000	0.636	0.000
Serious	0.910	0.000	1.050	0.000
Relapse	0.390	0.000	0.402	0.000
Ref.: From 30 to 40				
Less than 20	-0.217	0.000	-0.151	0.000
From 20 to 30	-0.122	0.000	-0.098	0.000
From 40 to 50	0.085	0.000	0.097	0.000
From 50 to 60	0.184	0.000	0.213	0.000
More than 60	0.292	0.000	0.303	0.000
Constant	2.471	0.000	2.337	0.000
Observations	1101,551		2814,698	
/lnsig2v	-0.193	0.000	-0.374	0.000
/lnsig2u	-1.766	0.000	-1.165	0.000
sigma_v	0.908		0.830	
sigma_u	0.414		0.559	
sigma2	0.995		1.000	
lambda	0.456		0.673	
LR test of sigma_u= 0	chibar2(01) = 3.2e+ 03		chibar2(01) = 3.5e+ 04	

Source: Author's own based on SAW data

Table 5
Decomposition of the sick leave duration between females and males (reference group regression).

	Total difference	*Differences in standard duration*			*Differences in efficiency*	
	$\overline{d^{ff}} - \overline{d^{mm}}$	$\left(\widehat{\beta_o^f} - \widehat{\beta_o^m}\right)$	$\left(\overline{X_k^f} - \overline{X_k^m}\right)\beta_k^m$	$\overline{X_k^f}\left(\widehat{\beta_k^f} - \widehat{\beta_k^m}\right)$	$\left(\overline{u^f} - \overline{u^{fm}}\right)$	$\left(\overline{u^{fm}} - \overline{u^m}\right)$
Percentage	100 %	148 %	32 %	80 %	-179 %	18 %
Days	0.778	1.151	0.251	0.625	-1.390	0.140
		2.028			-1.250	

Source: Author's own based on SAW data

Table 6
Decomposition of the sick leave duration between females and males with explanatory variables in the inefficiency component (reference group regression).

	Total difference	*Differences in standard duration*			*Differences in efficiency*	
	$\overline{d^{ff}} - \overline{d^{mm}}$	$\left(\widehat{\beta_o^f} - \widehat{\beta_o^m}\right)$	$\left(\overline{X_k^f} - \overline{X_k^m}\right)\beta_k^m$	$\overline{X_k^f}\left(\widehat{\beta_k^f} - \widehat{\beta_k^m}\right)$	$\left(\overline{u^f} - \overline{u^{fm}}\right)$	$\left(\overline{u^{fm}} - \overline{u^m}\right)$
Percentage	100 %	184 %	30 %	83 %	-213 %	16 %
Days	0.778	1.430	0.231	0.649	-1.655	0.123
		2.310			-1.532	

Source: Author's own based on SAW data

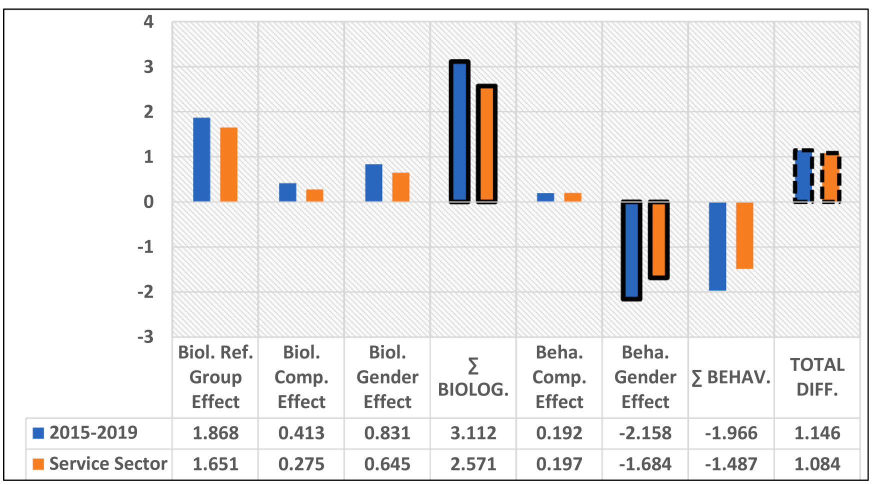

Fig. 6. Robustness check: Decomposition of the sick leave duration between females and males. Service sector and 2015–2019 period (Reference group regressions). Source: Author's own based on SAW data.

post outcome that is determined only after the recovery process has been completed. In contrast, all explanatory variables are fixed at the start of the sick leave, which eliminates the possibility of reverse causality.

In the case of self-selection, one possible source could be that men and women choose different occupations. However, we do not consider this to be a plausible explanation in our context. While such occupational differences may affect the likelihood of experiencing an accident, they should not influence the worker's recovery period once the accident has occurred.

To address potential omitted variable bias, we perform an initial endogeneity test on the OLS estimation to evaluate the robustness of the coefficient on the MALE variable. To this end, nine models with varying specifications were estimated. The results indicate a progressive reduction in the absolute value of the MALE coefficient as additional control variables are introduced, followed by a stabilization in the last four models around a coefficient of approximately −0.580. This stabilization after the inclusion of the observed controls is taken as a sign that omitted variable bias is limited (see **Figure A2** in **Appendix 4**). However, stability alone may not be sufficient to fully assess the potential bias. Therefore, we also compute the delta statistic proposed by Oster (2019), which quantifies the ratio of selection on unobservables to selection on observables. Denoting $\widetilde{R}$ as the R-squared from the regression with controls, and $R_{\max}$ the corresponding value from a hypothetical regression of the outcome on both observed and unobserved controls; Oster proposes to calculate a bias-adjusted coefficient bound using a value of $R_{\max} = 1.3 \times \widetilde{R}$. Under this approach, to argue that the level of stability is consistent with randomized analysis, the δ required should be higher than 1. In this case $\delta = 2.842$, which suggests that the unobservables would need to be about three times as important as the observables so that the coefficient on the MALE variable is equal to zero.

From a stochastic frontier perspective, omitted variable bias may be associated with the one-sided error term that captures inefficiency. From a theoretical standpoint, our framework defines the frontier as a standard duration determined exclusively by medical and/or physiological factors. To estimate this hypothetical duration, we rely on all relevant information available in the dataset. Specifically, we include variables related to the diagnosis (type of injury and affected body part), severity (medical assessment, potential hospitalization, or recurrence of a previous injury), as well as the workers' age and the occupation to which they are expected to return after recovery. Consequently, the inefficiency term may also reflect the influence of explanatory variables that, if omitted, could bias the results. To address this potential source of endogeneity, the one-sided error term is modelled using individual and job-related characteristics that may affect a worker's behavior regarding the extension of sick leave duration. In line with Battese and Coelli (1995), the effects of inefficiency might be explained based on a vector Z of variables, applying the following expression:

$$u_i = Z_i\varphi + \omega_i \qquad with \qquad \omega_i \geq -Z_i\varphi \tag{13}$$

In our specification, Z includes continuous variables such as compensation received, job tenure, and the number of employees within the firm, as well as binary variables capturing nationality, salaried status, occupation, industry sector or the province where the workplace is located. By including these controls, we aim to mitigate potential omitted variable bias and enhance the robustness of our decomposition results.

Table 6 presents the results of the decomposition in the specification that models inefficiency and employs a reference group for the estimation. Overall, the results are consistent with those obtained when no regressors are included in the one-sided error term. All estimated effects preserve their direction, despite some differences in magnitude. The sick leave biological recovery period is now estimated to be 2.310 days longer for women compared to men, of which 0.231 days can be attributed to the *composition effect*. The remaining 2.079 days are distributed between the other two biological components, with greater weight assigned to the difference in the independent terms. On the other hand, there is greater opportunistic behavior among men, amounting to 1.532 days. This effect is mainly explained by the *behavioral gender effect* (1.655 days), as the characteristics of the injuries themselves would predict sick leaves 0.123 days longer for women.

6.3. Robustness checks

We propose two alternative approaches to assess the robustness of our results. First, we rerun the decomposition analysis for the 2015–2019 sample period, during which the average differences in sick leave duration between men and women were statistically significant. Second, we focus the analysis on a specific sector of activity to reduce potential sources of heterogeneity. We selected the service sector, as it is the sector with the highest concentration of accidents (60 % of the total) and a more balanced gender distribution (with women involved in around 40 % of the accidents).

Fig. 6 presents the results of the two robustness checks. A first noteworthy finding is that, in both cases, the average gender gap in sick leave duration exceeds one day. This result is consistent with expectations. In the first analysis, we restricted the period to the years in which the difference in durations was statistically significant. In the second, we excluded male-dominated sectors (agriculture, industry, and construction), where recovery periods may be longer due to the nature of the tasks performed in those sectors. The duration of sick leave remains longer for female workers, particularly concerning the standard component. Specifically, women take more than 3 additional days of leave during the 2015–2019 period and 2.570 additional days in the service sector. Regarding the inefficiency component of sick leave duration, it is again longer for male workers, with the gap ranging from approximately 1.487 days in the service sector to 1.966 days during the 2015–2019 period. This stability in the results is consistent with the statement made in the section addressing endogeneity, where it was argued that self-selection bias appears to be a second-order concern for the present analysis.

When conducting the decomposition analysis for the 2015–2019 period, 0.413 additional days in the longer biological recovery period among women are attributable to a *biological compositional effect*. Furthermore, the largest portion of the gender gap in standard sick leave duration is explained by the *biological reference injury effect*, which partially reflects biological differences. Regarding the gender gap in the inefficiency component, more than 2 days are attributed to the effect of applying male coefficients to female injuries, suggesting longer opportunistic behavior for men. However, the remaining difference of 0.192 additional days in sick leave duration for female workers is attributed to differences in the injury characteristics.

In the case of the service sector, the general conclusions remain similar, although the magnitude of the effects differs. Specifically, within the gender gap in the standard duration of sick leave, the differences in the reference group account for 1.651 days, and the *biological composition effect* contributes 0.275 days. The remaining 0.645 days are the result of the so-called *biological gender effect*. Regarding the inefficiency component, the *behavioral composition effect* explains 0.197 days of the gender gap, while the *behavioral gender effect* accounts for a longer duration of male sick leaves by 1.684 days. Now, the *biological compositional effect* in the standard duration gap is smaller in relative terms, which is consistent with the reduced heterogeneity of sick leave cases when focusing on a single production sector.

7. Policy implications

As a preliminary step toward designing public policy interventions, it is useful to express the observed effects in monetary terms in order to assess their magnitude. According to our processed dataset, women reported 1.1 million work-related injuries, with an average compensation of €43.70 per day in 2019. Therefore, the two additional days of sick leave attributable to biological factors represent an estimated cost of approximately €97.6 million. In comparison, the 2.8 million cases reported by men, with an average daily compensation of €47 and 1.25 additional days of absence linked to opportunistic behavior, imply a cost of around €165.4 million. These estimates should be increased by up to 30 % to account for the data cleaning process, i.e., for the observations excluded for the reasons discussed earlier.

Taking this adjustment into account, a rough estimate of the total economic cost associated with longer biological sick leaves among women amounts to approximately €130 million over the 2011–2019 period, or about €14.5 million per year. This figure provides a useful benchmark for evaluating the fiscal viability of policies aimed at reducing sick leave duration among women. In other words, it serves as a reference point for framing budgetary constraints within a cost-benefit analysis framework.

Similarly, the economic cost associated with opportunistic behavior among male workers is estimated at €215 million for the same period, equivalent to roughly €24 million per year. Following the same reasoning, this amount may be interpreted as an upper bound for public health spending aimed at mitigating opportunistic sick leave extensions among men.

Building on these estimates, it becomes essential to understand the underlying factors that influence the duration of sick leave in order to inform the design of effective health and labor policies. From a biological standpoint, once a sick leave period begins, medical review intervals are set by the attending physician based on the nature of the injury and the worker's individual characteristics. These reference durations often incorporate gender-based adjustment factors, derived from statistical deviations observed in administrative records. However, our findings suggest that such adjustments (typically based on average differences) may fail to adequately capture the true biological disparities in recovery trajectories between male and female workers.

In particular, our analysis indicates that female workers tend to require longer recovery periods not due to inefficiency or behavioral factors, but primarily as a result of anatomical and physiological differences. At the same time, we identify a compositional effect within the opportunistic component of sick leave; that is, some types of injuries are more prone to misuse, leading to extended absences beyond what is medically warranted. Recognizing this duality is essential: while many absences reflect legitimate health needs, others may arise from behavioral responses or systemic inefficiencies. Enhancing the ability of social security systems to distinguish between these scenarios could improve the accuracy of assessments and help reduce unjustified absenteeism.

Finally, we propose a broader set of economic policy recommendations that address both institutional and firm-level dimensions. Tackling the costs identified in this study requires a dual approach. On the employer side, revising incentive structures to reward medically justified leave (rather than leave taken for non-medical reasons) could help better align employee behavior with organizational objectives. In addition, implementing training programs that account for sex-specific occupational risks may contribute to reducing injury rates and improving recovery outcomes across the workforce.

At the institutional level, effective policy design should acknowledge that biological differences contribute to the longer average duration of sick leave among women. This supports the implementation of diagnostic and monitoring procedures that more accurately reflect these differences. At the same time, from a behavioral perspective, policy measures should incorporate more rigorous oversight of male workers, given their greater tendency to extend sick leave beyond medical necessity, particularly in cases involving injuries that are difficult to verify objectively.

8. Conclusions

This paper contributes to a better understanding of the gender gap in the duration of sick leave following workplace accidents by disentangling its biological and behavioral components. Using rich administrative data from Spain and a novel empirical approach that combines stochastic frontier analysis and Oaxaca-Blinder-type decomposition, we are able to separate medically justified recovery time from opportunistic extensions of sick leave. Our results show that, although the overall difference in average sick leave duration between men and women is small, it masks two opposing forces: women tend to experience longer recovery periods due to biological and compositional factors, while men are more likely to extend their leave for non-medical, economically motivated reasons.

These findings have clear implications for the design of labor and health policy. The evidence suggests that current clinical guidelines and monitoring systems may benefit from greater sensitivity to sex-based differences in recovery patterns, as well as from improved tools to detect opportunistic behavior. At the same time, the estimated economic costs associated with both dimensions (biological and behavioral) provide useful benchmarks for cost-benefit assessments of potential interventions. Ultimately, a more nuanced approach to sick leave policy, combining institutional reform with workplace-level initiatives, can promote both equity and efficiency in managing occupational health outcomes.

While this study offers robust evidence on the gender gap in sick leave duration, several avenues remain open for future research. First, although our data capture detailed information on workplace accidents, they do not allow us to track post-recovery labor market outcomes, such as return-to-work quality or long-term health effects. Second, the administrative nature of the data limits our ability to directly observe motivational or psychosocial factors that may also influence opportunistic behavior. Future studies could complement our approach using survey data, qualitative interviews, or experimental designs to better understand the behavioral mechanisms behind sick leave decisions. Additionally, extending the analysis to other institutional contexts would help assess the generalizability of our findings and explore how different labor market regulations, healthcare systems, or cultural norms mediate the biological and economic dimensions of the gender gap in sick leave.

Author Statement

We confirm that the manuscript is original, has not been published previously, and is not under consideration for publication elsewhere. All authors have read and approved the final version of the manuscript and agree to its submission to *Economics and Human Biology*.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest.

Appendix A. Literature review

Table A1
Gender gap in sick leave absenteeism: summary of findings

Author (Year)	Data Source	Gender focus		Gender gap		Statistically significant
		Sex-specific	Control only	Duration	Incidence	
Allen (1981a)	1972–73 Quality of Employment Survey (U.S.)		X	Not specified	Women higher	Yes, mediated by family size or marital status
Arocena and García-Carrizosa (2023)	2015–2019 Statistics of Work Accidents (Spain)		X	Women longer	Not specified	Yes
Barmby and Treble (1991)	Random sample of 250 workers of a firm in 1987 (U.S.)		X	Not specified	Women higher	No
Barmby et al. (1991)	Whole payroll of four factories of a firm from 1987 to 1988 (UK)		X	Women longer	Women higher	Yes
Barmby et al. (2002)	1989–1997 Labor Force Survey data available in the LES (8 European countries + Canada)	X		Not specified	Women higher	Yes
Beblo and Ortlieb (2012)	Selected waves of 1985–2001 German Socio-Economic Panel (SOEP)	X		Not specified	Women higher	Yes

(continued on next page)

Table A1 (*continued*)

Author (Year)	Data Source	Gender focus		Gender gap		Statistically significant
		Sex-specific	Control only	Duration	Incidence	
Bridges and Mumford (2001)	1993 UK Family Expenditure Survey	X		Not specified	Women higher	Yes
Brown (1994)	Four manufacturing firms of Great Britain		X	Not specified	Women higher	No
Bryan et al. (2021)	2009–2018 Labor Force Survey (UK)		X	Not specified	Women higher	Yes
Chadi and Goerke (2018)	1994–2009 German Socio-Economic Panel (SOEP)		X	Not specified	Women higher	No for career advancement
Chaudhury and Ng (1992)	Two questionnaires to 33 organizations in Canada		X	Women longer	Not specified	No
Darkwah (2024)	5th and 6th rounds of the Ghana Living Standard Survey (GLSS)	X		Women longer	Not specified	Yes
Drago and Wooden (1992)	1988 cross-sectional data from 15 Australian plants		X	Not specified	Women higher	Yes but weak (at 10 % level)
Ehlert and García-Morán (2022)	2004–2017 German Socio-Economic Panel (SOEP)		X	Women longer	Not specified	Yes
Engellandt and Riphahn (2005)	Six waves of data from the Swiss Labor Force Survey	X		Not specified	Women higher	No for effort responses
Gilleskie (2010)	1987 National Medical Expenditure Survey (U.S.)	X		Women longer	Not specified	Yes for sick leave coverage changes
Henrekson and Persson (2004)	Administrative data from the National Social Insurance Board (Sweden)		X	Women longer	Women higher	Yes for economic incentives
Herrmann and Rockoff (2012)	Dataset on public school teachers in New York City and Italian bank data	X		Women longer	Not specified	No for effects of menstruation
Herrmann and Rockoff (2013)	2002 and 2007 National Health Interview Survey (U.S.)	X		Women longer	Not specified	Yes
Heywood and Miller (2015)	2004 Workplace Employment Relations Survey (UK)		X	Not specified	Women higher	Yes, reduced by providing of scheduling flexibility
Ichino and Moretti (2009)	Italian bank data	X		Women longer	Women higher	Yes
Kenyon and Dawkins (1989)	1966–1984 Labor Force Survey (Australia)		X	Not specified	Women higher	Yes but weak
Khan and Rehnberg (2009)	2002 Stockholm public health survey	X		Women longer	Not specified	Yes
Krenz and Strulik (2021)	Performance Monitoring and Accountability 2020 (PMA2020) project of the Bill and Melinda Gates Institute for Population and Reproductive Health	X		Not specified	Women higher	Yes, reduced by menstrual hygiene management
Leigh (1983)	1973 Quality of Employment Survey (U.S.)	X		Not specified	Women higher	Yes
Leigh (1984)	1973 Quality of Employment Survey (U.S.)		X	Not specified	Women higher	Yes
Markussen et al. (2011)	2001–2005 Norwegian administrative data		X	Women longer	Women higher	Yes
Martín-Román and Moral (2016)	2002 Statistic of Accidents at Work (Spain)		X	Not specified	Women higher	Yes
Martín-Román et al. (2024)	2011–2019 Statistic of Accidents at Work (Spain)	X		Women longer	Not specified	Yes
Moral de Blas et al. (2012)	1997–2001 Statistic of Accidents at Work (Spain)	X		Women longer	Not specified	Yes
Paringer (1983)	1974 Health Interview Survey data (U.S.)	X		Not specified	Women higher	Yes
Spierdijk et al. (2009)	Data from a private Dutch insurance company		X	Women longer	Not specified	Yes
Suárez and Muñiz (2018)	2014 European Health Survey in Spain		X	Not specified	Women higher	Yes
Vandenheuvel and Wooden (1995)	Data from 61 Australian companies (1994)	X		Not specified	Women higher	Yes
Vistnes (1997)	1987 National Medical Expenditure Survey	X		Women longer	Women higher	Yes
Ziebarth and Karlsson (2014)	1997–2000 German Socio-Economic Panel (SOEP)		X	Women longer	Not specified	No for increased generosity in sick leave benefits

Note: "Gender gap" refers to observed differences in either sick leave duration or incidence between women and men, as reported in each study. "Statistically significant" indicates whether the gender difference was found to be statistically significant according to the authors. "Sex-specific" refers to studies that report separate estimates by sex. "Control only" refers to studies that include gender as a control variable without focusing specifically on gender differences.

Appendix B. Spatial Analysis

To identify territorial differences in sick leave duration, an exploratory spatial data analysis is conducted (**Figure A1**). The right panel displays a quantile map, revealing clusters of provinces with similar average sick leave durations. Notably, provinces located in the northwest and central-eastern regions of the country form a cluster characterized by longer sick leave durations (see right panel of **Figure A1**). To formally assess the presence of spatial patterns, we perform a global spatial autocorrelation test using Moran's I (Moran, 1948). This test is defined as follows:

$$I = \frac{N}{R_o}\bullet\frac{\sum_{i,j}^{N} w_{i,j}\left(D_i-\overline{D}\right)\left(D_j-\overline{D}\right)}{\sum_{i=1}^{N}\left(D_i-\overline{D}\right)^2}$$

where D_i is the sick leave duration in region i, $\overline{D}$ is the sample mean of D, $w_{i,j}$ are the components of the spatial weights matrix, N is the sample size, and $R_0 = \sum_i\sum_j w_{i,j}$.

Moran's I statistic typically ranges from –1 to 1 (although values outside this range can occur), indicating positive spatial autocorrelation when values are close to 1 and negative autocorrelation when values are near –1. A positive value implies that regions with high (low) values of the variable of interest tend to be surrounded by regions with similarly high (low) values. Conversely, a value close to 0 indicates no spatial autocorrelation. In our case, we obtained a Moran's I value of 0.6, which is highly significant, confirming the presence of positive spatial correlation in sick leave durations.

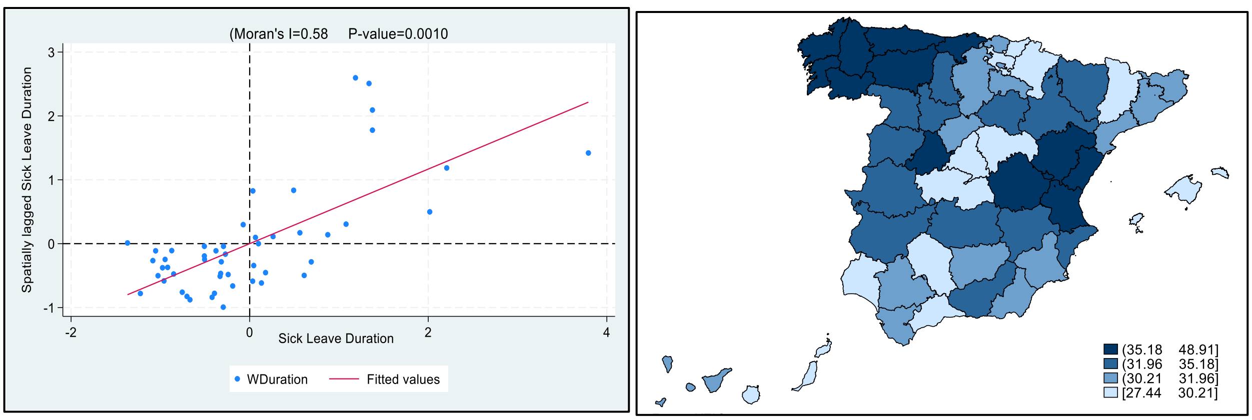

Figure A1. Exploratory spatial analysis of mean duration by province. Source: Author's own based on SAW data

Appendix C. Normalized regression to avoid identification problem

The identification problem arises because when estimating groups of dummy variables, it is necessary to leave out one from the model. In this situation, the independent term not only changes based on the removed variable but also part of the decomposition related to that component. We thus calculated a normalized regression following Yun (2005) to solve this problem. According to Yun, if we start from an estimate of the duration expressed as:

$$\mathrm{d} = \mathrm{b}_0 + \left(\sum_{i=2}^{I}\mathrm{s}_i\mathrm{S}_i\sum_{j=2}^{J}\mathrm{t}_j\mathrm{T}_j\right) + \sum_{k=1}^{K}\mathrm{b}_k\mathrm{X}_k + \mathrm{u}$$

Where S and T are groups of I and J dummy variables, X includes K continuous variables, and u is the inefficiency term. From Eq. 9, we may obtain a normalized regression that does not omit reference groups, and we can calculate it as follows:

$$\mathrm{d} = \mathrm{b}_o^* + \left(\sum_{i=1}^{I}\mathrm{s}_i^*\mathrm{S}_i + \sum_{j=1}^{J}\mathrm{t}_j^*\mathrm{T}_j\right) + \sum_{k=1}^{K}\mathrm{b}_k\mathrm{X}_k + \mathrm{u}$$

Where: $\mathrm{b}_0^* = \mathrm{b}_0 + \bar{\mathrm{s}} + \bar{\mathrm{t}}$, $\mathrm{s}_i^* = \mathrm{s}_i - \bar{\mathrm{s}}$ and $\mathrm{t}_i^* = \mathrm{t}_i - \bar{\mathrm{t}}$

Being: $\bar{s} = \frac{\sum_{i=1}^{I} s_i}{I}$, $\bar{t} = \frac{\sum_{i=1}^{J} t_i}{J}$ and $s_1 = t_1 = 0$

Appendix D. OLS, nonlinear decomposition with control variables in inefficiency and stability test

Table A2
OLS estimation of the logarithm of the sick leave duration

Specification	*Only gender male*		*Biological variables*		*All variables*	
	Coeff.	*P > Z.*	*Coeff.*	*P > Z.*	*Coeff.*	*P > Z.*
Male	**-0.090**	**0.000**	**-0.056**	**0.000**	**-0.058**	**0.000**
Type of injury. (Ref. Sprain)						
Not specified			-0.056	0.000	-0.055	0.000
Superficial Injuries			-0.042	0.000	-0.161	0.000
Other injuries			-0.174	0.000	-0.137	0.000
Fractures			-0.142	0.000	1.018	0.000
Strains			1.024	0.000	-0.013	0.000
Dislocations			-0.008	0.000	0.055	0.000
Traumatic amputation			0.057	0.000	0.996	0.000
Concussion			1.014	0.000	0.049	0.000
Burns			0.032	0.000	-0.270	0.000
Poisoning			-0.284	0.000	-0.441	0.000
Choking			-0.440	0.000	-0.636	0.000
Noise, heat			-0.655	0.000	-0.197	0.000
Psychological trauma			-0.199	0.014	0.035	0.000
Multiple injuries			0.021	0.000	0.180	0.000
Heart attack			0.173	0.000	0.947	0.000
Part of the body (Ref. Leg)						
Not specified			-0.190	0.000	-0.197	0.000
Head			-0.610	0.000	-0.607	0.000
Face			-0.715	0.000	-0.717	0.000
Eyes			-1.215	0.000	-1.215	0.000
Neck (spine)			-0.120	0.000	-0.114	0.000
Neck (rest)			-0.223	0.000	-0.208	0.000
Back (spine)			-0.460	0.000	-0.450	0.000
Back (rest)			-0.475	0.000	-0.460	0.000
Trunk			-0.357	0.000	-0.355	0.000
Shoulder			0.078	0.000	0.081	0.000
Arm			-0.082	0.000	-0.077	0.000
Hand			-0.317	0.000	-0.304	0.000
Finger (hand)			-0.344	0.000	-0.332	0.000
Wrist			-0.169	0.000	-0.163	0.000
Upper limbs (not esp.)			-0.097	0.000	-0.084	0.000
Ankle			-0.254	0.000	-0.248	0.000
Foot			-0.309	0.000	-0.302	0.000
Finger (foot)			-0.606	0.000	-0.598	0.000
Lower limbs (not esp.)			-0.175	0.000	-0.164	0.000
Multiple parts			-0.049	0.000	-0.038	0.000
Hospital care			0.190	0.000	0.189	0.000
Hospitalization			0.621	0.000	0.615	0.000
Serious			1.021	0.000	1.011	0.000
Relapse			0.428	0.000	0.432	0.000
Seniority					4.41E-05	0.000
Compensation					2.76E-04	0.000
Number of workers					4.45E-06	0.000
Salary worker					-0.025	0.000
Age	***No***		***Yes***		***Yes***	
Occupation	***No***		***Yes***		***Yes***	
Industry branch	***No***		***No***		***Yes***	
Nationality	***No***		***No***		***Yes***	
Province	***No***		***No***		***Yes***	
Constant	2.857	0.000	2.952	0.000	2.975	0.000
Observations	3.916.249					
R Squared	***0.001***		***0.197***		***0.208***	

Source: Own elaboration

Table A3
Frontier estimations of the logarithm of the sick leave duration by gender with explanatory variables in the inefficiency component

	Female		*Male*	
Duration	***Coefficient***	***P > z***	***Coefficient***	***P > z***
Ref: Sprain				
Not specified	-0.043	0.000	-0.058	0.000
Superficial Injuries	-0.165	0.000	-0.168	0.000
Other injuries	-0.171	0.000	-0.121	0.000
Fractures	1.090	0.000	1.048	0.000

(*continued on next page*)

Table A3 (*continued*)

	Female		*Male*	
Duration	***Coefficient***	***P > z***	***Coefficient***	***P > z***
Strains	-0.019	0.000	-0.012	0.000
Dislocations	0.027	0.000	0.061	0.000
Traumatic amputation	0.931	0.000	1.033	0.000
Concussion	0.000	0.944	0.048	0.000
Burns	-0.445	0.000	-0.179	0.000
Poisoning	-0.425	0.000	-0.475	0.000
Choking	-0.589	0.000	-0.762	0.000
Noise, heat	-0.193	0.000	-0.215	0.000
Psychological trauma	0.059	0.001	-0.058	0.000
Multiple injuries	0.130	0.000	0.197	0.000
Heart attack	0.864	0.000	0.924	0.000
Ref: Leg				
Not specified	-0.076	0.000	-0.242	0.153
Head	-0.418	0.000	-0.656	0.000
Face	-0.639	0.000	-0.706	0.000
Eyes	-1.046	0.000	-1.198	0.000
Neck (spine)	0.051	0.000	-0.165	0.000
Neck (rest)	-0.023	0.000	-0.281	0.000
Back (spine)	-0.245	0.000	-0.492	0.000
Back (rest)	-0.254	0.000	-0.507	0.000
Trunk	-0.255	0.000	-0.337	0.000
Shoulder	0.156	0.000	0.035	0.000
Arm	0.027	0.000	-0.105	0.000
Hand	-0.254	0.000	-0.289	0.000
Finger (hand)	-0.353	0.000	-0.295	0.000
Wrist	-0.035	0.000	-0.187	0.000
Upper limbs (not esp.)	0.007	0.000	-0.108	0.000
Ankle	-0.171	0.000	-0.228	0.000
Foot	-0.254	0.000	-0.290	0.000
Finger (foot)	-0.622	0.000	-0.541	0.000
Lower limbs (not esp.)	-0.112	0.000	-0.163	0.000
Multiple parts	0.014	0.000	-0.039	0.000
Ref: Unskilled				
Company management	-0.097	0.000	0.008	0.646
Technical staff and scientists	-0.046	0.002	-0.055	0.000
Professional support	-0.050	0.000	0.002	0.675
Administration employees	-0.061	0.000	-0.051	0.000
Service workers	0.019	0.000	-0.013	0.000
Skilled agriculture and fishing	0.055	0.002	0.089	0.000
Crafts and dealers	0.031	0.000	-0.028	0.000
Machine operators	-0.032	0.002	0.008	0.004
Hospital care	0.157	0.000	0.197	0.000
Hospitalization	0.492	0.000	0.633	0.000
Serious	0.912	0.000	1.050	0.000
Relapse	0.395	0.000	0.406	0.000
Ref: From 30–40				
Less than 20	-0.215	0.000	-0.144	0.000
From 20–30	-0.116	0.000	-0.091	0.000
From 40–50	0.074	0.000	0.092	0.000
From 50–60	0.159	0.000	0.201	0.000
More than 60	0.258	0.000	0.291	0.000
Constant	2.528	0.000	2.362	0.000
Modeling inefficiency				
Seniority	4.04E-04	0.000	2.91E-04	0.000
Compensation	-0.001	0.088	0.003	0.000
Number of workers	1.84E-05	0.000	1.07E-05	0.000
Salary worker	0.186	0.000	-0.143	0.000
Occupation	Yes		Yes	
Industry branch	Yes		Yes	
Nationality	Yes		Yes	
Province	Yes		Yes	
Observations	1101,551		2814,698	

Source: Own elaboration

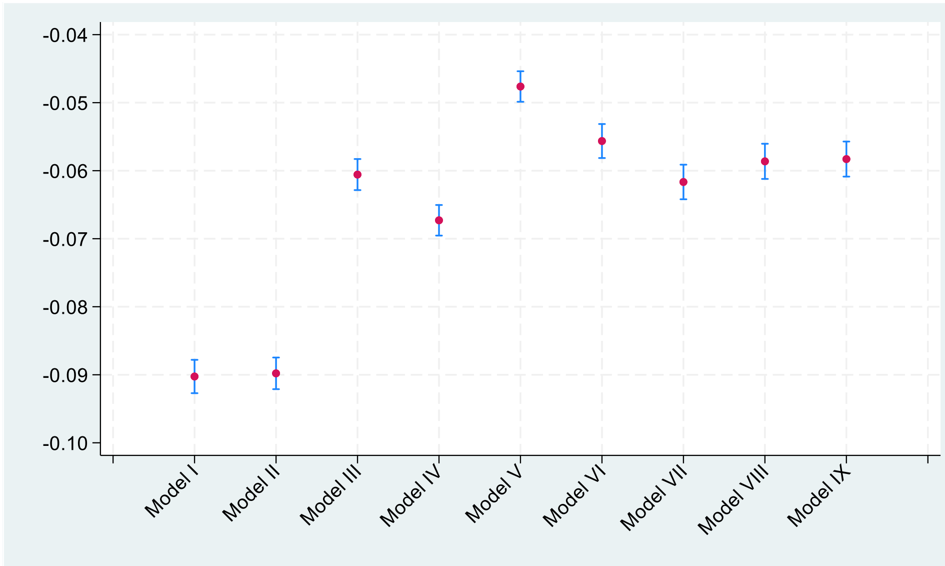

Figure A2. Coefficient and Confidence Interval for Male Variable to test stability (OLS estimation). Notes: Model I includes only the *Male* variable. Model II adds injury-related variables. Model III builds on Model II by incorporating *part of the body* variables. Model IV adds severity controls, and Model V additionally includes age variables. Model VI extends Model V with occupation variables. In Model VII, industry variables are also included. Model VIII adds workplace and nationality variables, and Model IX incorporates territorial controls. 95 % Confidence Intervals

Data availability

Data will be made available on request.

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