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Beyond the added-worker and the discouraged-worker effects: the entitled-worker effect

Ángel L. Martín-Román

University of Valladolid, Spain

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ABSTRACT

This paper identifies and analyses a new effect related to the cyclical behaviour of labour supply: the Entitled-Worker Effect (EWE). This effect is different from the well-known Added-Worker Effect (AWE) and Discouraged-Worker Effect (DWE). The EWE is a consequence of one of the most important labour institutions: the unemployment benefit (UB). We develop a model with uncertainty about the results of the job-seeking and transaction costs linked to such a search process, showing that a kind of moral hazard appears. This creates new incentives for workers and produces an additional counter-cyclical pressure on aggregate labour supply, but with a different foundation from that of the AWE. We present empirical evidence supporting the EWE for the Spanish case. As a forward-looking conclusion, policymakers should rethink their political actions in the future as unemployment might be overstated, particularly in those countries with generous UB systems.

1. Introduction

The analysis of cyclical movements in labour supply is essential to understanding the size of the actual unemployment rate.[1] With the recent Great Recession or Global Financial Crisis, it has become clear that the business cycle is far from being under the control of the policymakers.[2] Therefore, the study of the cyclical evolution of the aggregate labour supply would appear to merit closer attention. Currently, with a difficult macroeconomic situation on the near horizon because of the COVID-19 pandemic, this topic is likely to become central to political and scholarly debates. This issue is particularly important, not only in countries with high unemployment levels like Spain, which for this reason serves to test the main hypothesis of this paper, but in many other countries.

In the literature, two effects have traditionally been considered regarding the cyclical movements of aggregate labour supply: the Added-Worker Effect (AWE) and the Discouraged-Worker Effect (DWE). Whereas the AWE predicts a counter-cyclical behaviour of the participation rate (PR), the DWE predicts pro-cyclical changes on such an aggregate. If the former prevails over the latter, the official unemployment rate is considered to overstate the true unemployment during downturns and, if the DWE is stronger than the AWE, the unemployment will be understated. Recently, the traditional pro-cyclical behaviour of labour supply in Spain has been losing strength. This puzzle has been "solved" by scholarly commentators by simply arguing that the DWE is weaker and/or the AWE is stronger than before. We do not agree with this simplistic way of reasoning and propose a different explanation to account for this fact. In our view, such an explanation is original and rather relevant, particularly from an economic policy standpoint. Furthermore, we test this alternative rationalization by using a rigorous econometric analysis.

Regarding the originality, the contribution of the paper consists of unveiling a theoretical link between the PR and the business cycle, one different from the AWE and the DWE. Although these two competing ideas arose several years ago, they still generate considerable new scientific production (e.g. Österholm, 2010; Congregado et al., 2011; Congregado et al., 2020; Martín-Román et al., 2020; Congregado et al.,

E-mail address: angellm@eco.uva.es.

[1] Throughout the paper, we will use the terms labour supply and participation rate interchangeably. Of course they are not the same: whereas the labour supply is an absolute measure, the participation rate is a relative figure (active population as a percentage of the working-age population). In our model, we do not consider population changes, so in that case, and after normalizing total working age to 100, both terms coincide.

[2] See, for example, Cover and Mallick (2012).

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2021). Nonetheless, the bulk of this sort of research is empirically oriented. Our view is that even though additional and clarifying empirical evidence would be welcome, in order not to misidentify the mechanisms driving the empirical evidence, a theoretical guide is needed. Furthermore, if the cyclical effects operating are not correctly identified, researchers might mislead policymakers when advising them regarding economic policy prescriptions (Granville and Mallick, 2009).

Therefore, this paper contributes to the literature by investigating the following research question: is there another theoretical channel operating together with the AWE and the DWE that accounts for the above-mentioned facts? The answer will be affirmative. Thus, this work aims to identify, define accurately, and, finally, test a new effect related to the cyclical behaviour of labour supply. This effect will be named the Entitled Worker Effect (EWE). The EWE is a consequence of the existence of a labour institution like the Unemployment Benefit (UB). This institution creates a specific type of moral hazard, causing workers to carry out opportunistic behaviour by supplying “fake” labour to be entitled to receive UB.[3]

As to the relevance of the paper, we strongly believe that this research has a sizable significance. This is mainly due to the volume of financial resources devoted to UB by governments in many countries. As will be shown, the EWE predicts a counter-cyclical behaviour of PR. However, the theoretical foundations could not be more different from those of the AWE. The EWE leads to opportunistic behaviour, generating a “fictitious” labour supply motivated by a labour institution such as UB. Needless to say, while it is difficult to fight unemployment overestimation due to AWE from economic policy grounds, it is more feasible to reduce that overestimation because of the EWE by taking political action to monitor this behaviour.

This investigation is also highly relevant owing to the economic policy implications associated with it. The outcomes of this paper are quite helpful for policymakers when managing the aggregate demand policy, particularly during downturns. Another policy implication has to do with aggregate supply policy. The results point to the necessity of monitoring UB claimants more effectively to avoid opportunistic behaviour. This would reduce the natural rate of unemployment and, in turn, would increase the potential output, becoming an efficiency-enhancing mechanism. Finally, it would also help to improve Social Security's financial sustainability.

To address this question, we follow a rigorous procedure, combining theoretical framing to disentangle the different effects conceptually with empirical testing, conducting a number of robustness and sensitivity checks. To begin with, we build a microeconomic model of labour supply, and then we aggregate individual decisions to analyse macroeconomic fluctuations of labour supply. This methodological approach connects this research to the so-called canonical model of labour supply. We utilize this model since it has been the common reference framework to study labour supply choices, particularly the decision to enter the labour market. Nevertheless, it is worth mentioning that several modifications are made to that model, some of them as little associated with neoclassical ideas as the introduction of involuntary unemployment. More precisely, we develop a model with uncertainty about the results of the job seeking and with transaction costs linked to the search process in which a kind of moral hazard appears. Put differently, we combine an extended version of the neoclassical model of labour supply with some elements from job-search theory. In this conceptual framework, new incentives for workers arise that produce an additional counter-cyclical pressure on aggregate supply, but with a different foundation from that of the AWE.

As part of our approach, we also test rigorously the relevance of the EWE with Spanish data. Spain is an excellent “laboratory” due to its extremely high unemployment numbers.[4] At the same time, the cyclical fluctuations in the Spanish labour market are also enormous. Thus, the literature on Okun's Law for Spain has documented an astonishingly large Okun's coefficient, close to 1.[5] With these strong fluctuations in cyclical unemployment, the cyclical patterns in the PR should be easier to measure and identify.

Regarding the theoretical results, we develop a framework where we account for the theoretical channels through which the AWE, the DWE, and the EWE operate. The AWE is a direct result of the neoclassical model, as it arises from the conventional income effect since leisure is habitually considered a normal good. Accounting for the DWE in the model is somewhat less straightforward. This effect is a consequence of involuntary unemployment. For that reason, we consider an expected utility theoretical framework, in which the likelihood of finding a job is determined precisely by the unemployment rate. Furthermore, job-search transaction costs are incorporated into the model because the job-seeking process is costly (in terms of a loss of leisure time). With these two features, we capture the notion of the DWE naturally. Nonetheless, the novelty of this paper is the idea of the EWE. This effect is a sort of moral hazard that arises from the existence of the UB. This labour institution creates economic incentives that might produce an additional counter-cyclical behaviour of the PR. Nonetheless, as will become clear presently, it has nothing to do with the theoretical foundations of the AWE. Indeed, the theoretical channel through which the EWE operates is the change in the likelihood of finding a job (the same as that through which the DWE operates, but with the opposite sign), not the change in non-labour income. The main prediction of the model may be stated as follows: as more individuals are potentially entitled to receive UB, the countercyclical pattern of the PR is strengthened.

As for the empirical results, they seem to support the idea of a significant EWE in Spain in recent years. We provide substantial evidence supporting this hypothesis. We employ three different statistical procedures to gain a measure of the business cycle, two econometric procedures (rolling regression and threshold analysis) to test the hypothesis, two distinct indicators of the generosity of the UB system, two alternative data structures (time series and panel data), and a number of robustness and sensitivity checks. We observe a strong inverse correlation between the cyclical behaviour of the PR and the percentage of potentially entitled workers to receive UB. Thus, all this empirical work appears to uphold the hypothesis posed in this research.

The rest of the paper is organized as follows. Section 2 is devoted to the background regarding the cyclical movements of labour supply, including a few basic concepts and the related literature. Section 3 presents the model to illustrate the EWE. There, the AWE and the DWE are characterized formally, and the EWE is obtained as a cross effect (i.e. a second-order effect). Section 4 explains the empirical strategy employed. Section 5 shows the outcomes. Different approaches are followed to test the main hypothesis, and all of them seem to support the theoretical framework developed in this research. Section 6 examines the economic policy implications of this study. Finally, Section 7 concludes and discusses the results.

2. Background

2.1. AWE versus DWE

The idea behind the AWE can be traced back to the final years of the Great Depression (Woytinsky, 1940; Humphrey, 1940). The argument behind this hypothesis is that when the family's breadwinner loses his/her job during a downturn, his/her spouse would have more

[3] Previous literature has documented significant issues of moral hazard in the Spanish public social insurance system, not only the UB (e.g. Moral-Arce et al., 2019) but also in the sick leave system (e.g. Martín-Román and Moral, 2016, 2017).

[4] See Cuéllar-Martín et al. (2019).

[5] See, for instance, Bande and Martín-Román (2018) or Porras and Martín-Román (2019).

economic incentives to participate in the labour market to replace the income lost. Although quite sophisticated models of family labour supply have been developed to explain this phenomenon,[6] it can be easily formalized within the textbook model of labour supply (see next section).

Regarding the DWE, the works by Long (1953, 1958) outline the concept for the first time. It refers to situations in which workers' expectations about the results of the job search are so bad (during a downturn again) that workers give up seeking. Thus, those previously counted as unemployed workers are now considered out of the labour force. Consequently, we might state that DWE has to do with the uncertainty associated with the job-seeking process. The textbook model of labour supply does not suffice to conceptualize this effect for a very simple reason: it does not consider the uncertainty (associated with involuntary unemployment) regarding the result of the job search.

Although both the AWE and the DWE were originally intended to describe the situation in the labour market during a downturn, the same phenomena take place when the economy is booming, but with the opposite sign. Research has established that the DWE is associated with the pro-cyclical behaviour of the PR and the AWE with the counter-cyclical fluctuations of the PR. Consequently, the DWE is related to an underestimation of the unemployment rate during downturns and an overestimation during booms. On the other hand, if the AWE prevailed, the "actual" unemployment rate would be higher than the official one during recessions (or weak economic growth periods) and lower during economic expansions.

Both effects might be operating at the same time throughout the business cycle. Thus, an observer would see the net effect when checking the data. To illustrate this idea, in panel (a) of Fig. 1, we show a stylized business cycle (let us call it X) with a range of variation between -1 and 1 (i.e. $X \in [-1, 1]$). This cyclical variable is depicted with a solid blue line. For instance, if we assume that every 1-percentage-point increase in X causes a DWE of $+0.6$ percentage points (dotted red line) and an AWE of -0.4 percentage points, we might estimate econometrically a total net effect (TNE) of $+0.2$ percentage points. In this example, we have assumed that the DWE is stronger than the AWE, and, consequently, the TNE is positive.

As regards the studies drawing on aggregate data and employing time-series econometric techniques, Elmeskov and Pichelmann (1994) estimate the elasticity of the participation rates over the business cycle, finding that the DWE is the dominant hypothesis. Darby et al. (2001) find that the DWE is prevalent, stronger in the downward phase of the cycle, and essentially a female phenomenon. Benati (2001), who has produced empirical evidence on the existence of a significant DWE in the US labour market, reviews the literature on time-series econometrics as well, stating that seven studies (Long, 1953, 1958; Hansen, 1961; Wachter, 1972, 1977; Goodman, 1974; Clark and Summers, 1982) do not yield relevant evidence of pro- or counter-cyclicality in labour force or participation rates time series, except for Long, under conditions of severe depression. One study (Wachter, 1974) is inconclusive. Two studies (Barth, 1968; Bowen and Finegan, 1969) present evidence of a weak DWE. Finally, five studies (Tella, 1964, 1965; Mincer, 1966; Perry, 1977; Clark and Summers, 1981) show evidence of a significant DWE.[7] Finally, Wasmer (2009) delves into the bidirectional relationship between unemployment and labour participation, confirming the inverse relationship between the participation rate and the unemployment rate, which gives support to the DWE.

Regarding the literature using cross-sectional analysis, Stephens (2002) finds evidence for the US economy of the prevalence of the AWE in the long-term response of a wife's labour supply to her husband's job loss. Bhalotra and Umana-Aponte (2010), also using microdata and referring to 63 developing and transition countries, find mixed evidence on the AWE and the DWE. They conclude, however, that the AWE is an important issue for certain socio-demographic groups and determined countries. Two papers pointing towards the relevance of the AWE for particular socioeconomic groups are Prieto-Rodríguez and Rodríguez-Gutierrez (2000, 2003).

Congregado et al. (2011), employing a threshold cointegration model with Spanish data, establish that the AWE dominates the DWE, but only when unemployment is below 11.7%. Although by international standards this threshold seems to be rather high, for the Spanish case it is, in fact, quite low. Therefore, the conclusion is that the PR in Spain exhibits a low degree of cyclical sensitivity. Congregado et al. (2014) obtain evidence for a linear DWE for men. The AWE is statistically significant for women, but again, this only applies when the unemployment rates are below a certain threshold.

Finally, in Table 1, we summarize the most relevant empirical literature with regard to the AWE and the DWE published recently. We display the articles according to the year of publication, focusing on those papers published from 2001 onwards and with particular emphasis on those that came out within the last decade. We describe the data employed, the econometric approach used, and the main results obtained.

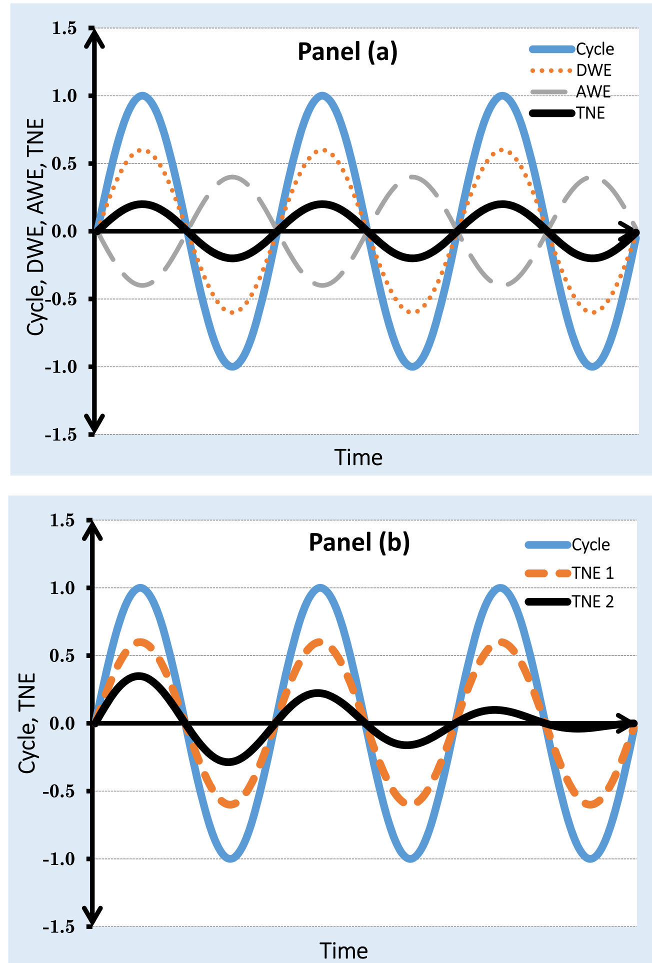

Fig. 1. Business cycle, AWE, DWE and Total Net Effect.
Source: Own elaboration.

2.2. UB and labour supply

Textbooks on macroeconomics consider UB one of the key

[6] See, for instance, Pérez et al. (2015, 2020).

[7] The prevalence of the DWE over the AWE should be qualified. For instance, Parker and Skoufias (2004) detect a significant AWE for women in Mexico. Lee and Parasnis (2014) conclude that the DWE predominates in OECD countries, whereas the AWE prevails in developing countries.

Table 1
Empirical literature review on the AWE and the DWE.

Authors	Data	Econometric Approach	Results
Benati (2001)	Quarterly data from the Current Population Survey	Band Spectrum Regression Techniques	Evidence on the existence of a significant DWE
	United States (1976–1998)		The series displays a clear counter-cyclical pattern both in its male and in its female segments
Darby et al. (2001)	Time series data from the OECD Labour Force Statistics	Structural Time Series Models to compute the trend-cycle decomposition	DWE is prevalent
	United States, France, Japan, and Sweden (1970–1995)	SUR estimates	DWE is strongest in the downward phase of the cycle and is essentially a female phenomenon
Wasmer (2009)	Time series data from the OECD Labour Force Statistics	Structural VAR	In Continental Europe, participation reacts more to unemployment
	United States, France, Germany, and Italy (1956–2002)		Conversely, in the USA, so little of the fluctuations of participation are driven by unemployment
Österholm (2010)	Monthly time series data	Vector Error Correction (VEC)	The unemployment invariance hypothesis has no support in Sweden
	Sweden (1970–2007)	Cointegration	Cointegrating vectors support important discouraged-worker effects in the data
Emerson (2011)	Monthly time series data	Vector Error Correction (VEC)	No evidence supporting the unemployment invariance hypothesis in the USA
	United States (1948–2010)	Cointegration	Some evidence of discouraged worker effects in the United States, especially for men
Congregado et al. (2011)	Quarterly time series data	Threshold cointegration models	The AWE dominates the DWE, but only when unemployment is below 11.7%
	Spain (1976–2008)		Above this threshold, the two effects cancel each other out
Gong (2011)	Longitudinal data from Household, Income and Labour Dynamics in Australia (HILDA)	Linear probability models	A significant AWE for Australian women is found
	Australia (2001–2007)	Panel data probit models	This effect is observed both in terms of increases in full-time employment and in terms of increased working hours
Kakinaka and Miyamoto (2012)	Monthly participation rates data	Vector Error Correction (VEC)	There is a long-run relationship between the PR and the UR for male workers but not for female workers
	Japan (1980–2010)	Cointegration	AWE for young male workers and DWE for middle-aged and old male workers
Fuchs and Weber (2013)	Monthly participation rates from the German Labour Force Survey	Unobserved-components model	The results confirm that both the DWE and the AWE exist
	Germany (1970–2011)	Trend-cycle decomposition	Age groups respond differently to permanent and transitory changes in the unemployment rate
Congregado et al. (2014)	Quarterly time series data	Vector Error Correction (VEC)	Evidence for a linear DWE for men is found
	Spain (1976–2012)	Threshold cointegration models	There exists a significant AWE for women, but only when unemployment rates are below a certain threshold
Lee and Parasnis (2014)	World Bank data	System GMM	The DWE dominates in developed countries
	22 OECD countries and 13 developing countries (1993–2008)		The AWE dominates in developing countries
Oţoiu and Ţiţan (2016)	Quarterly labour force data	Time series models	The unemployment invariance hypothesis holds true for Romania
	Romania (1996–2012)	Cointegration	Results show that there could be evidence of DWE
Tansel et al. (2016)	Quarterly time series data	Vector Error Correction (VEC)	There is no long-run equilibrium relationship between labour force participation and unemployment rates in Turkey
	Turkey (1988–2013)	Cointegration	Support for the unemployment invariance hypothesis in Turkey
Fuchs and Weber (2017)	German Labour Force Survey	Logistic transformation	Short term unemployment cause a DWE for women, young workers, and older men
	Germany (1984–2011)		Short term unemployment produces a AWE for older women and middle-aged men
			For most groups, long term unemployment has a substantial influence on labour participation
Evans (2018)	Monthly time series data from the Australian Bureau of Statistics	Structural VAR	The AWE is dominant in transitions in both directions(inflows and outflows) between unemployment and non-participation
	Australia (1986–2014)		The DWE drives the overall result that non-participation rises during a contraction.
			The overall participation rate is procyclical
Bredtmann et al. (2018)	Longitudinal data from the European Union Statistics on Income and Living Conditions	Probit Models	Evidence of the existence of an AWE for women
	28 European countries (2004–2013)		AWE decreases with the country's female labour force participation rate
Tansel and Ozdemir (2018)	Monthly time series data	Vector Error Correction (VEC)	Lack of support for the unemployment invariance hypotheses
	Canada (1976–2015)	Cointegration	Evidence for AWE for men and DWE for women in Canada
Altuzarra et al. (2019)	Quarterly time series data	Vector Error Correction (VEC)	Support for the unemployment invariance hypotheses in the aggregate case and for males
	Spain (1987–2016)	Cointegration	The unemployment invariance hypotheses does not hold for females
Congregado et al. (2020)	Quarterly LFS data	Non-linear models	Labour force participation rate behaves non-linearly
	Poland (1995–2016)	Threshold Estimation	An unemployment rate higher than 13% implies a DWE
Martín-Román et al. (2020)	Yearly and Quarterly LFS data	Time series models	The results reveal a positive spatial dependence in the cyclical sensitivity of labour force participation
	Spain (1977–2015)	Trend-cycle decomposition	
		Spatial econometrics models	

Source: Own elaboration.

determinants of natural unemployment. The underlying reason is that UB may affect the strength of workers' representatives by enhancing their power in collective bargaining processes.[8] Thus, UB has been established to affect collective labour supply in unionized labour markets. Nevertheless, the theoretical avenue linking UB and labour supply that has attracted more attention among researchers has an individual basis: the job-search theory, which focuses on worker's behaviour when looking for a job, a relevant dimension of labour supply.

Modern job-search theory arose in the 1970s (McCall, 1970; Mortensen, 1970). A good synthesis of this theory can be found in different surveys (e.g. Lippman and McCall, 1976a, 1976b; Mortensen, 1986; Mortensen and Pissarides, 1999; Rogerson et al., 2005; Rogerson and Shimer, 2011). Two elements of the job-search theory are particularly relevant for this paper, and thus we incorporate them into the conceptual setting developed here. First, finding a job implies a search cost in terms of a loss of leisure that can be considered a transaction cost (i.e. to get a job, the worker has to look for one for some time). Second, and even more crucial, the result of that seeking process is uncertain (i.e. after the search, there is no guarantee of finding a job, and the worker might remain unemployed).

Job search models predict in most cases that the more generous UB is, the longer the unemployment spells among those UB beneficiaries are. This suggestive prediction has been tested overwhelmingly within the empirical literature. For example, the early research on this issue, using macroeconomic data, establishes a clear positive relationship between the generosity of UB and the unemployment level (e.g. Layard et al., 1991; Scarpetta, 1996; Nickell, 1997; Bassanini, 2006).

The microeconomic literature on this topic is even more extensive. Two surveying research works on this subject for the early literature are Atkinson and Micklewright (1991) and Pedersen and Westergård-Nielsen (2000). In summary, the empirical evidence indicates significant effects of UB in the United States and the UK, and much weaker effects in Continental Europe (e.g. Holmlund, 1998; Nickell, 1979; Fallick, 1991; Ham and Rea, 1987; Meyer, 1990; Katz and Meyer, 1990; Hunt, 1995; Carling et al., 1996; Winter-Ebmer, 1998). A common denominator in the results of this literature is that when the entitlement for receiving the UB compensation is close to expiring, the likelihood of finding a job increases suspiciously. This outcome has been interpreted as a clear sign of duration moral hazard linked to UB.

More recently, a new strand of research has emerged to isolate the true causal effect of both entitlement and the replacement rate on labour supply. It uses quasi-experimental designs, such as the differences-in-differences estimator or the regression discontinuity design. See, for instance, Card and Levine (2000) for the US, Carling et al. (2001), Bennmarker et al. (2007), Røed and Zhang (2003), and Uusitalo and Verho (2010) for the Nordic Countries, Van Ours and Vodopivec (2006), Lalive et al. (2006), Card et al. (2007), Lalive (2007, 2008), Schmieder et al. (2012), and Caliendo et al. (2013) for Central European countries, and Le Barbanchon (2016), Addison and Portugal (2008), and Centeno and Novo (2006, 2009, 2014) for other European countries. The Spanish case also reveals significant disincentive effects associated with the UB (e.g. Bover et al., 2002; Rebollo-Sanz and García-Pérez, 2015; Rebollo-Sanz and Rodríguez-Planas, 2018). The main conclusion to be drawn from this literature is that there are notable consequences for the unemployment duration if the replacement rate or the potential benefit duration (PBD) changes. To sum up, an extension of the PBD lengthens unemployment duration by about 20% of such PBD time extension. Also, the elasticity of unemployment duration with respect to UB is estimated to be in the range of 0.4–1.0.

2.3. Hypothesis

Economic incentives matter. The job-seeking behaviour of individuals is influenced by both the replacement rate of UB and the entitlement to receive it. Thus, theoretical research has put great effort into modelling these issues. Dynamic macroeconomic models have been used to examine the relationship between unemployment, UB, and labour force participation. For example, Pries and Rogerson (2009) present a modified job-search model to account for labour force decisions. Another theoretical framework, closely related to the previous one, which is used to analyse the unemployment-participation relationship, is the class of real business cycle (RBC) models (e.g. Veracierto, 2008).

The theoretical setting developed in this article takes into account some of the features of this type of modelling, but, at the same time, makes changes to account for the EWE without making the modelling process unnecessarily complex.[9] We are interested in incorporating into the model the idea of uncertainty associated with the seeking activity. This Assumption implies that the individual may remain unemployed after the search and, hence, the notion of unemployment is added to the conceptual framework. Also, we are aware of the fact that job-search is costly for the worker and, consequently, we take this aspect into consideration in the setting.

In the previously mentioned literature, the focus is on the search process. Therefore, whereas the job search is modelled in detail, the treatment of consumption-leisure substitution is kept relatively simple from an analytical point of view. Here, on the other hand, we make the opposite decision, i.e. we focus on the consumption-leisure substitution (which is essential to understand the different nature of the EWE) and keep the job search relatively simple in the modelling task.

The job-search theory is intrinsically dynamic, but we do not need a dynamic model to illustrate how the AWE, the DWE, or the EWE operate. This is why we adopt a static framework[10]. Our interest is not on duration moral hazard, as in dynamic job-search theory, but on incidence moral hazard.[11] We examine how the individual's labour supply behaviour changes when he/she is a beneficiary of the UB, and how this fact ends up affecting the cyclical properties of the aggregate labour supply. The behavioural change analysed is not dynamic in nature, as will be shown in a later section, and therefore the model used is static.

As will be shown, the EWE is a counter-cyclical effect operating only among those workers who are entitled to receive the UB. Therefore, the main hypothesis of the paper could be enunciated as follows:

Hypothesis 1. As the number of individuals entitled to receive the UB increases, so do the counter-cyclical forces affecting the PR cyclical pattern. Therefore, in a labour market A with a higher proportion of UB beneficiaries than in a labour market B, the PR should exhibit a less pro-cyclical or a more counter-cyclical behaviour.

Panel (b) of Fig. 1 illustrates **Hypothesis 1** graphically. We make a distinction there between a total net effect in a labour market without any UB beneficiary, TNE1, and a second scenario in which the number of UB beneficiaries increases progressively, TNE2. Panel (b) of Fig. 1 begins assuming a pro-cyclical pattern of PR. In the second scenario, however, as increasing numbers of individuals gain the right to collect UB, such pro-cyclical behaviour weakens as a consequence of the EWE, ending up in a practically non-cyclical behaviour of the PR.

[8] See, for instance, Cabo and Martín-Román (2019) for a formal analysis.

[9] A different theoretical approach away from job-search theory is adopted by Prescott (2004) and Prescott and Wallenius (2012).

[10] A few papers study how UB affects various aspects of labour supply from a dynamic standpoint. See, for example, Boone (2004), Boone and Van Ours (2006), or Cahuc and Fontaine (2009). None of them, however, model the same behavioural trait addressed in this paper.

[11] See, for instance, Moral-Arce et al. (2019) for a brief discussion of the types of moral hazard affecting the UB.

3. The model

3.1. Theoretical framework

A labour market participation model is built based on the neoclassical framework of choice between leisure-work and consumption-income. As we are interested in the extensive margin of the labour supply, we consider a fixed working week. Hence, labour supply choices coincide with participation decisions (e.g. Boeri and Van Ours, 2013; or Cahuc et al., 2014). The model is extended here to account for the effects of unemployment (i.e. the likelihood of being in the labour force without a job), as in Martin-Roman et al. (2020). Likewise, this paper's model is additionally extended to address the influence of UB on the choice set for the individual.

The UB is considered here as an income linked to the job search. To receive the UB, workers need to spend some time engaged in job-search activities to prove their willingness to work to the unemployment office.[12] Therefore, unemployed workers are individuals who actively look for a job but do not find it. Thus, all UB beneficiaries are in the labour force. We also assume that if workers turn down a job offer, they might lose the right to receive UB with a determined probability.

The rest of the main assumptions of the model are listed below:

Assumption 1. Labour is homogenous, i.e. the wage is the same for all workers[13]

Assumption 2. Labour contracts last one period.

Assumption 3. There exists a certain amount of time associated with labour participation. Before signing a new contract, the worker has to devote s units of time to job-search activities. Here, s is considered a fixed and exogenous sum of time.[14]

Assumption 4. There exists a positive unemployment rate. That rate determines the likelihood p of finding a job, which is the same for all individuals.[15]

Assumption 5. There are two kinds of individuals in the economy. Type-E workers are eligible to receive UB if they fulfil the requirements described below. Type-N workers are not entitled to receive UB. The percentage of individuals of both types is given at every moment[16]

Assumption 6. There exists a UB in the economy, denoted by b. Type-E individuals that have looked for a job for s units of time without finding one are eligible for UB. Furthermore, type-E individuals could reject a job if they found one. If this were the case, the employment authority might sanction an individual with the loss of the right to receive the UB. This occurs with probability $(1 - q)$. With probability q, type-E individuals still receive the UB after turning down a job offer.[17]

Assumption 7. The size of the working week, which we denote by $\bar{l}$, is fixed and exogenously determined.[18]

Assumption 8. The utility function is additive. If C is consumption (or the income because there is no saving) and H is leisure time (i.e. total time minus hours of work), we have: $U(C, H) = \Lambda(C) + \Omega(H)$. As usual, marginal utilities are supposed to be positive and decreasing[19]

The set of alternatives for the worker is shown in Fig. 2. Inside the utility function, the levels of consumption (C) and leisure (H) have been replaced by the corresponding values associated with each decision. Thus, we are already taking into account the budget constraint within the framework of choice. As mentioned, w is the real wage per unit of time, $\bar{l}$ is the duration of the fixed working week, y is the real non-labour income, b is the UB, and s is the job-search duration linked to the participation decision. The total disposable time has been normalized to 1.

Henceforth, type-E individuals will be our baseline reference, those who are potentially eligible to receive UB in case of not finding a job after a search process (i.e. $b > 0$). The analysis of type-N individuals is just a particular case: we only have to assume that $b = 0$. When necessary, we will highlight the differences in behaviour between both groups.

According to Fig. 2, a type-E individual has three options. Each of these options is associated with a level of utility, certain or expected: (1) not to participate,

$$U(y, 1), \tag{1}$$

(2) to participate and reject a job offer if they find one,

$$p(qU(y+b, 1-s) + (1-q)U(y, 1-s)) + (1-p)U(y+b, 1-s), \tag{2}$$

which could be also written as

$$U(y+b, 1-s)(pq + (1-p)) + U(y, 1-s)p(1-q),$$

and (3) to participate and accept a job offer in case of finding one.

$$pU(w\bar{l} + y, 1 - \bar{l} - s) + (1-p)U(y+b, 1-s) \tag{3}$$

3.2. Opportunistic supply of labour (moral hazard)

From expressions (1) to (3), it can be deduced that the worker is going to participate in the labour market whenever expression (4) holds:

$$U(y+b, 1-s)(pq + (1-p)) + U(y, 1-s)p(1-q) \geq U(y, 1) \tag{4}$$

This is so regardless of the real wage prevailing in the labour market. Although the wages were $w = 0$, the individual would participate because the expectancy of collecting UB would compensate for the time spent in job-search activities. In such a case, the individual would deal with labour participation as a game. Such a game offers him/her the opportunity of winning a prize (UB) with likelihood $(pq + (1 - p))$ in exchange for a cost: it is necessary to search for a job during s units of time. Nevertheless, individuals know that if they had the "bad luck" of coming across a job, they would turn it down.

The critical value of the UB (b^*) that induces workers' participation under any circumstances is the one that solves equation (5):

$$U(y+b^*, 1-s)(pq + (1-p)) + U(y, 1-s)p(1-q) = U(y, 1) \tag{5}$$

In other words: if $b \geq b^*$, individuals will opt to look for a job (i.e.

[12] In Spain, as in many other countries, to gain entitlement to UB, it is necessary to fulfil three requisites: (1) not having a job, (2) searching for a job, and (3) being willing to accept a suitable job offer within a brief period.

[13] The mechanism behind the wage formation (i.e. competitive forces, collective bargaining, or a mixture of both) is not significant here. Individuals are wage-takers, whatever the mechanisms for setting the wage to prevail in the economy.

[14] It is outside the scope of the paper to consider s as an endogenous variable, as that lies within the field of job-search theory. See the previous section for some classical surveys of such a theory, or, more recently, Tatsiramos and van Ours (2012, 2014).

[15] In other words, unemployment is primarily involuntary. Obviously, the higher the unemployment rate, the lower the value of p.

[16] It would be possible to endogenize the percentage of type-E and type-N workers in the model. Nonetheless, such a model would require, at least, a two-period horizon. That model would add much complexity with a little gain in predictive capability. For the sake of simplicity, we assume that past labour supply decisions have already been made and the percentages of type-E and type-N workers are given.

[17] This is the origin of the moral hazard which we will elaborate later on.

[18] As mentioned before, since we are interested in the extensive margin of the labour supply, this Assumption allows us to focus on the participation decision.

[19] This Assumption is less restrictive than it seems. Within ordinal utility theory, a logarithmic transformation of the very well-known Cobb–Douglas utility function is also additive, representing an identical set of preferences.

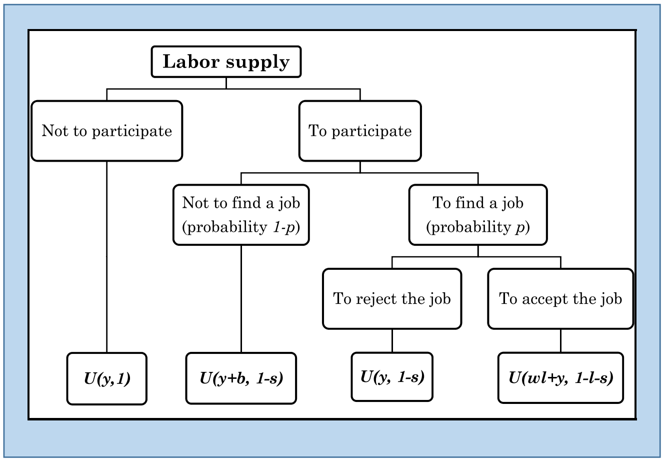

Fig. 2. Set of alternatives for the worker.
Source: Own elaboration.

they will choose to participate), regardless of the wage existing in the market (because in some circumstances they will turn down the job offer). Put differently, if $b \geq b^*$, the reservation wage would be zero ($w^R = 0$). Needless to say, the reservation wage (w^R) has its usual interpretation here.

At this point, the following question arises: assuming that $b \geq b^*$, when is a job offer going to be accepted or rejected? After finding a job, an individual will take it whenever the earnings linked to such a post compensate for the leisure time lost associated with the working week. Nonetheless, we need to point out that the choice of accepting or turning down a job offer does not depend on p. Expression (6) displays the critical wage that equals the utility of accepting or declining a job offer:

$$U(w^*\bar{l}+y, 1-\bar{l}-s) = qU(y+b, 1-s) + (1-q)U(y, 1-s) \tag{6}$$

We label "acceptance wage" as w^* to differentiate it from the notion of reservation wage explained above [20]. It is evident that if $w \geq w^*$, individuals accept the job, and if $w < w^*$, they reject it. Something that will prove useful later is the dependence of w^* on b. From expression (6), we may define an implicit function and demonstrate that w^* is an increasing and concave function of b when represented in the (w, b) space, as in Fig. 3.

$$\frac{\partial w^*}{\partial b} = \frac{qU_C(y+b)}{\bar{l}U_C(w^*\bar{l}+y)} > 0$$

$$\frac{\partial^2 w^*}{\partial b^2} = \frac{qU_{CC}(y+b)}{(\bar{l}U_C(w^*\bar{l}+y))^2} < 0$$

From the preceding discussion, it can be deduced that there exists an opportunistic labour supply for specific values of b and w. If $b \geq b^*$ and $w < w^*$, individuals will participate in the labour market (they will supply a positive number of working hours $\bar{l}$), but this is a "fictitious" labour supply since those working hours cannot be hired by the employers in the economy. From a different standpoint: the UB creates economic incentives that change individuals' behaviour, resulting in a moral hazard issue.

[20] Both may be deemed thresholds to make a decision. We could state that our reservation wage here suits the idea of reservation wage of the (static) neoclassical model of labour supply, whereas our acceptance wage is slightly related to the notion of reservation wage of the (dynamic) job-search theory.

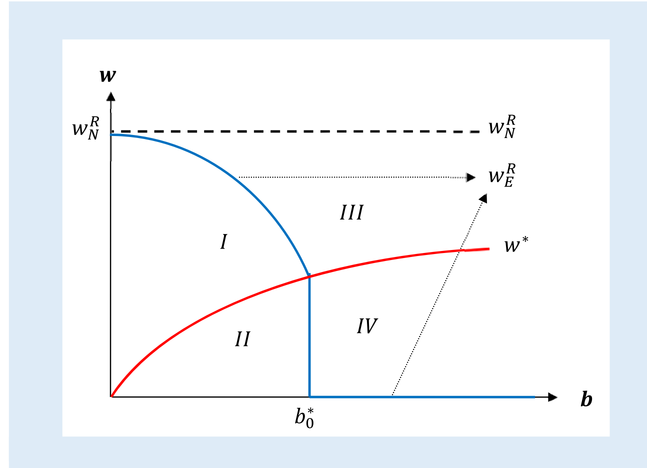

Fig. 3. Reservation wage and UB.
Source: Own elaboration.

3.3. UB and labour supply

Let us now consider the case when $b < b^*$. How is the participation threshold determined under these circumstances? If that were the situation, it would be nonsensical for individuals participating (experiencing a leisure time loss due to the search transaction costs) to reject a job that they find. An individual would participate so as to accept the job. Formally, as the utility value of (2) is lower than that of (1), the only reason for an individual to participate is that the utility value of (3) is higher or equal to that of (1). Consequently, expression (7) provides the participation threshold:

$$pU(w^+\bar{l}+y, 1-\bar{l}-s) + (1-p)U(y+b, 1-s) = U(y, 1) \tag{7}$$

Therefore, we have a two-tier reservation wage. Expression (8) summarizes this situation:

$$w_E^R = \begin{cases} 0 & \text{if } b \geq b^* \\ w^+ & \text{if } b < b^* \end{cases} \tag{8}$$

where w_E^R is the reservation wage for a type-E individual. It is convenient to go deeper into the characteristics of w^+ to understand all the implications of the model. First, it may be shown that w_E^R is a decreasing and concave function of b. From expression (7), and making use of the implicit function theorem, we obtain:

$$\frac{\partial w^+}{\partial b} = -\frac{(1-p)U_C(y+b)}{p\bar{l}U_C(w^+\bar{l}+y)} < 0$$

$$\frac{\partial^2 w^+}{\partial b^2} = -\frac{-(1-p)U_C(y+b)p\bar{l}^2U_{CC}(w^+\bar{l}+y)}{(p\bar{l}U_C(w^+\bar{l}+y))^2} < 0$$

Second, it is easy to see that $w^+ > w^*$ holds (obviously for $b < b^*$, which it is when w^+ is really defined). The proof can be carried out by using the definitions in expressions (6) and (7). Thus, from condition (7), we implicitly know that: $U(w^+\bar{l}+y, 1-\bar{l}-s) > U(y, 1) > U(y+b, 1-s)$. On the other hand, it is evident that: $U(y+b, 1-s) > U(y, 1-s)$. As a consequence, we obtain: $U(w^+\bar{l}+y, 1-\bar{l}-s) > qU(y+b, 1-s) + (1-q)U(y, 1-s)$. Finally, the previous expression together with condition (6) implies that: $U(w^+\bar{l}+y, 1-\bar{l}-s) > U(w^*\bar{l}+y, 1-\bar{l}-s)$, or, in other words, $w^+ > w^*$ provided that $b < b^*$.

Fig. 3 depicts these outcomes. In that figure, the space (w, b) is divided into four parts. A type-E individual whose combination of w and b was located in zone (II) would never participate. If his/her combination of w and b were located in zones (I) or (III), he/she would participate. Furthermore, he/she would accept a job in the case of finding one. Finally, zone (IV) illustrates those situations of moral hazard mentioned above. If this were the case, a type-E individual would enter the labour market, but reject a job offer in any instance.

In Fig. 3 may also be seen the reservation wage for a type-N individual (w_N^R). Formally, this would be a particular case of the more general expression (7). That is, making $b = 0$ in (7), we obtain expression (9):

$$pU\left(w_N^R\bar{l}+y, 1-\bar{l}-s\right)+(1-p)U(y,1-s)=U(y,1) \tag{9}$$

From (9), it is clear that w_N^R is always positive ($w_N^R > 0$)$1 > (1 - s) > (1 - \bar{l} - s)w_N^R\bar{l} > yw_N^R > 0$. As depicted in Fig. 3, w_N^R coincides with the maximum value of w_E^R, reached precisely when $b = 0$. As w_N^R does not depend on b, it is a horizontal line in the space (w, b) represented in Fig. 3.

3.4. Aggregation process

Let us now study the aggregation process. Assuming that workers have different preferences over consumption-income and leisure-work, different non-labour incomes, and differences in their entitlement to receive UB, they will have diverse reservation wages. This heterogeneity of reservation wages $w^R \in [0, +\infty)$ might be represented by a cumulative distribution function $\varphi(\cdot)$. If the rest of the PR determinants do not change (i.e. non-labour income, the likelihood of finding a job, and the UB), the aggregate labour supply could be expressed in formal terms according to (10):

$$L=N\cdot\varphi(\cdot) \tag{10}$$

where L stands for the labour force and N stands for the total working-age population. The PR is simply $\varphi(\cdot)$, as expressed in equation (11):

$$PR=\frac{L}{N}=\varphi(\cdot) \tag{11}$$

Since $\varphi(\cdot)$ is a cumulative distribution function, by definition, it is increasing in its argument, $\varphi_w > 0$. Nevertheless, as shown below, not only the non-labour income but also the likelihood of finding a job and the UB play a significant role in determining PR because they do change. To incorporate this idea, let us call w_M^R the reservation wage for the median individual within the cumulative distribution. Thus, expression (12) describes a stylized PR function:

$$PR=\varphi\left(w, w_M^R\right) \tag{12}$$

As mentioned, $(\partial PR / \partial w) > 0$ by definition. On the other hand, consistent with the concept of reservation wage, $(\partial PR / \partial w_M^R) < 0$. It is worth recalling that w_M^R is in turn a function of some additional arguments. In the model developed here, w_M^R depends on y, p, and b. Besides, we have to point out that both $y(X)$ and $p(X)$ are regarded as functions of the business cycle (X). We assume that if the business cycle X is booming, the state of the economy improves, whereas when X decreases, the economy worsens.[21] As a conclusion, we may rewrite expression (12) as follows:

$$PR=\varphi\left(w, w_M^R[y(X), p(X), b]\right) \tag{13}$$

Equation (13) reveals that PR depends on the business cycle through a double channel. On the one hand, cyclical variations in the median worker's non-labour income give rise to the AWE. On the other hand, cyclical changes in the likelihood of finding a job result in the DWE. More importantly, equation (13) also shows that the level of UB may cause a cross effect or second-order effect ($\partial^2 PR / \partial X \partial b$), which is the origin of the EWE, as explained in greater detail below.

3.5. The Added-Worker Effect

During an economic downturn, some breadwinners lose their job. As a consequence, their spouses experience a reduction in their non-labour incomes which in turn would reduce their reservation wages, and at an aggregate level the PR would rise. The opposite would happen otherwise. Furthermore, this counter-cyclical behaviour of PR would induce an overestimation (underestimation) of the "true" aggregate unemployment rate in downturns (upturns).

This classical result (i.e. the AWE) fits well in our theoretical framework. First, let us analyse type-E individuals. Making use again of the implicit function theorem and computing how w^+ depends on y, we obtain:

$$\frac{\partial w^+}{\partial y}=-\frac{pU_C(w^+\bar{l}+y)+(1-p)U_C(y+b)-U_C(y)}{p\bar{l}U_C(w^+\bar{l}+y)}>0 \tag{14}$$

It is straightforward to derive the positive sign in (14). The denominator is positive. As regards the numerator, a realistic Assumption is that $w^+\bar{l} > b$, which implies that $w^+\bar{l} + y > b + y > yw^+\bar{l} > b$. Since the marginal utilities are decreasing, $U_C(y) > U_C(b + y) > U_C(w^+\bar{l} + y)$. A linear combination of $U_C(b + y)$ and $U_C(w^+\bar{l} + y)$ is less than $U_C(y)$, and, together with the minus sign affecting the whole fraction, (14) has a positive sign.

The effect of y on b^* has also to be studied so as to obtain a complete description of type-E individuals. Using the implicit function theorem again, we have:

$$\frac{\partial b^*}{\partial y}=-\frac{U_C(y+b^*)(pq+(1-p))+U_C(y)p(1-q)-U_C(y)}{U_C(y+b^*)(pq+(1-p))}>0 \tag{15}$$

Finally, it is also necessary to know how w^* changes when y varies, maintaining constant b (and the rest of the factors affecting w^*):

$$\frac{\partial w^*}{\partial y}=-\frac{U_C(w^*\bar{l}+y)-qU_C(y+b)-(1-q)U_C(y)}{\bar{l}U_C(w^*\bar{l}+y)}>0 \tag{16}$$

Expressions (14) to (16) characterize the behaviour of type-E individuals when non-labour income changes, and that is depicted in Fig. 4 (taking a reduction in y as the reference).

The analysis of type-N individuals is easier. From equation (9):

$$\frac{\partial w_N^R}{\partial y}=-\frac{pU_C\left(w_N^R\bar{l}+y\right)+(1-p)U_C(y)-U_C(y)}{p\bar{l}U_C(w_N^R\bar{l}+y)}>0 \tag{17}$$

The positive sign in (17) implies a downward shift of the horizontal line representing w_N^R in Fig. 3 (recall that the reference is a decrease in y).

From the previous discussion, it is quite evident that if we pooled type-E and type-N individuals, a reduction of the non-labour income (as a consequence of a downturn) would decrease the reservation wage of the median worker. This fact, in turn, would encourage labour participation. In more formal terms, and maintaining constant p when the business cycle varies (to disentangle the different effects), we may describe the AWE through (18):

$$\left.\frac{\partial PR}{\partial X}\right|_{\bar{p}}=\frac{\partial PR}{\partial w_M^R}\cdot\frac{\partial w_M^R}{\partial y}\cdot\frac{\partial y}{\partial X}<0 \tag{18}$$

since we know that $\partial y / \partial X > 0$ (by hypothesis), that $\partial w_M^R / \partial y > 0$ (from the discussion in this section), and that $\partial PR / \partial w_M^R < 0$ (from the concept of reservation wage).

[21] We later devote effort to explain how we measure X in statistical terms and its implications.

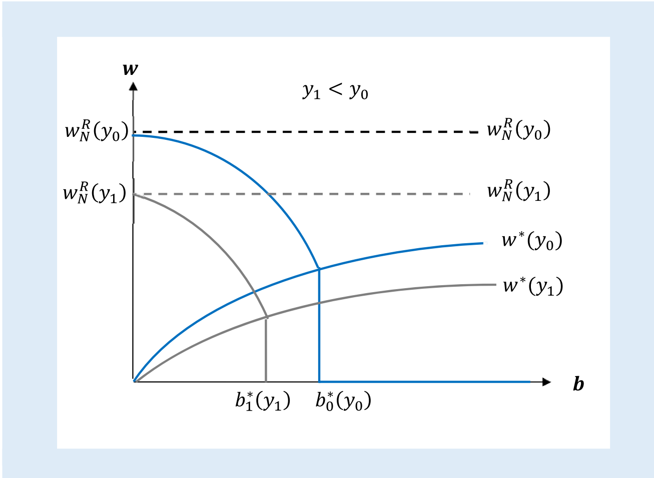

Fig. 4. Reservation wage and non-labor income variations.
Source: Own elaboration.

3.6. The Discouraged-Worker Effect

The original idea of the DWE establishes that when the likelihood of finding a job falls, some workers quit the active job search (i.e. they become inactive), and the opposite occurs otherwise. The rationale behind this is that as the expectations of finding a job worsen, the transaction costs linked to the search process could exceed the expected benefits since these diminish. Therefore, the PR would exhibit a pro-cyclical pattern, and, as a consequence, the "actual" unemployment rate would be underestimated (overestimated) in slumps (in booms).

The way of formalizing the DWE within the model is through p. For the sake of simplicity, and to disentangle the DWE from the EWE, we focus on type-N individuals in this subsection. Evidently, in a world with $b = 0$ for every worker, there is no place for the EWE. Thus, behavioural changes caused by cyclical movements in p can be identified with the DWE in this theoretical setting.[22]

From the reservation wage condition for type-N individuals summarized in equation (9), it is straightforward to compute the effects of changes in p on w_N^R:

$$\frac{\partial w_N^R}{\partial p} = -\frac{U\left(w_N^R\bar{l}+y,1-\bar{l}-s\right)-U(y,1-s)}{p\bar{l}U_C(w_N^R\bar{l}+y)} < 0 \tag{19}$$

The negative sign of (19) is the result of the definition given in (9). First, $U(y,1) > U(y,1-s)$. Second, in order to achieve equality in (9), $U(w_N^R\bar{l}+y,1-\bar{l}-s) > U(y,1) > U(y,1-s)$ must hold. In other words: when p rises (drops), w_N^R decreases (increases).

Thus, a stylized mathematical version of the DWE may be written as expression (20):

$$\left.\frac{\partial PR^N}{\partial X}\right|_{\bar{y}} = \frac{\partial PR^N}{\partial w_M^R}\cdot\frac{\partial w_M^R}{\partial p}\cdot\frac{\partial p}{\partial X} > 0 \tag{20}$$

with the superscript N referring to an economy composed exclusively of type-N individuals. In expression (20), the level of non-labour income has been maintained constant. As before, we can affirm that $\partial p / \partial X > 0$ (by hypothesis), that $\partial w_M^R / \partial p < 0$ (from the discussion in this section), and that $\partial PR^N / \partial w_M^R < 0$ (from the concept of reservation wage).

[22] Indeed, when the DWE was proposed first, the UB system was much less generous than now. Thus, the EWE should have been less important than it might be today in modern welfare states.

3.7. The Entitled-Worker Effect

The model developed can simultaneously rationalize and formalize the AWE and the DWE by means of expressions (18) and (20), respectively. However, the real novelty of this article is to rationalize and formalize the EWE, which operates through the same channel as the DWE (i.e. changes in p) but entails a counter-cyclical behaviour of the PR (like the AWE).

As the EWE is exclusively linked to UB, we primarily focus on type-E individuals in this subsection. The behaviour of type-E individuals is summarized by w_E^R, which in turn depends on the function $w^*(b)$. From condition (6), it is clear that w^* is not affected by changes in p. Nevertheless, that does not imply that b^* is not affected either. From expression (5), we have:

$$\frac{\partial b^*}{\partial p} = -\frac{(q-1)(U(y+b^*,1-s)-U(y,1-s))}{U_C(y+b^*)(pq+(1-p))} > 0 \tag{21}$$

The positive sign in (21) determines a direct relationship between p and b^*. Finally, to complete the analysis of type-E individuals, it is necessary to establish how w^+ varies when p changes:

$$\frac{\partial w^+}{\partial p} = -\frac{U(w^+\bar{l}+y,1-\bar{l}-s)-U(y+b,1-s)}{p\bar{l}U_C(w^+\bar{l}+y)} \gtreqless 0 \tag{22}$$

The sign in (22) can be either positive or negative. This is due to the ambiguity of the sign of the numerator since $U(w^+\bar{l}+y,1-\bar{l}-s) \gtreqless U(y+b,1-s)$. The denominator is always positive. However, it is still possible to reach some conclusions about the pattern of w^+ when p changes. First, let us compare $U(y+b,1-s)$ with $U(y,1)$. Whereas $U(y+b,1-s)$ is an increasing function of b, $U(y,1)$ does not depend on b. Consequently, it is feasible to find a level b^+ for which $U(y+b^+,1-s) = U(y,1)$. For $b < b^+$, we have $U(y+b,1-s) < U(y,1)$, and for $b > b^+$ the following relationship $U(y+b,1-s) > U(y,1)$ holds. We have to point out that always $b^+ < b^*$. This result comes from the definition of b^* in equation (5), which implies that $U(y+b^*,1-s) > U(y,1)$. As, by hypothesis, we have $U(y+b^+,1-s) = U(y,1)$, it follows that $U(y+b^*,1-s) > U(y+b^+,1-s)$, and accordingly that $b^+ < b^*$. In other words, when $b < b^+$, expression (22) has a negative sign, and a positive sign when $b > b^+$. Evidently, when $b = b^+$ we have that $U(w^+\bar{l}+y,1-\bar{l}-s) = U(y+b,1-s) = U(y,1)$, and (22) equals zero.

The implications of the above discussion for type-E individuals' reservation wage are shown in Fig. 5 (with a reduction in the likelihood p as reference). For low levels of UB (i.e. for $b < b^+$), the response of the reservation wage would be qualitatively the same as that of type-N individuals: a decline in p causes a rise in the reservation wage. Fig. 5 also displays the change of w_N^R, although it is just a shift upwards of a parallel to the X-axis line, because w_N^R does not depend on b. Nonetheless, for high enough UB levels (i.e. for $b > b^+$), the relationship between the probability of finding a job and the reservation wage reverses, and we obtain a direct association between p and w_E^R. This is the basis for the EWE: some type-E individuals could be encouraged to look for a job when the perspectives of finding one are worsening because of the institutional prerequisite abovementioned so as to receive the UB payments, which creates the moral hazard issue already explained in Subsection 3.2.

To sum up, in a world with only type-E individuals, some of them would be encouraged (discouraged) to search for a job when the business cycle improves (worsens), but others would be discouraged (encouraged). Formally:

$$\left.\frac{\partial PR^E}{\partial X}\right|_{\bar{y}} = \frac{\partial PR^E}{\partial w_M^R}\cdot\frac{\partial w_M^R}{\partial p}\cdot\frac{\partial p}{\partial X} \gtreqless 0 \tag{23}$$

with the superscript E referring to a world made up only of type-E individuals. What we dub EWE is precisely the possibility of a negative sign

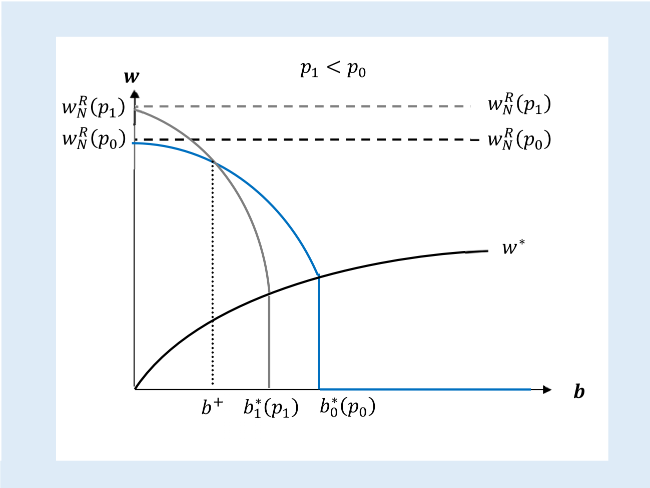

Fig. 5. Reservation wage and the likelihood of finding a job.
Source: Own elaboration.

in (23).

3.8. The total effect

Now, we analyse the three effects jointly. To better understand how the EWE operates, let us imagine a world without UB (i.e. let us suppose that $b = 0$ for all individuals, as in Subsection 3.6). In this case, there would be no difference between type-E and type-N individuals. Indeed, all potential workers in the economy might be considered type-N individuals. Assuming, for instance, that the labour market is heading to a cyclical trough, then the likelihood of finding a job falls and the non-labour income of the median worker decreases. Equations (18) and (20) explain how the PR would respond to this situation. As a consequence of the DWE, the PR should fall, while because of the AWE, the PR should experience an increase. What the researcher may observe directly through the data is the net effect. If we assume, for example, that the DWE is stronger than the AWE, a reduction in the PR would be estimated through econometric methods. This is the scenario depicted in Fig. 1 (a) in section 2.

If we relax the Assumption of $b = 0$ for all potential workers, the difference between type-E and type-N individuals emerges, and, as shown above, these two types of individuals behave differently. For this reason, let us define the proportion of type-E individuals within the total working-age population, θ, as (24) indicates:

$$\theta = \frac{N^E}{N^E + N^N} \tag{24}$$

with N^E and N^N being the number of type-E and type-N individuals, respectively.

In expression (13), it is shown that the level of UB affects the median worker's reservation wage and thus the PR. On the other hand, exogenous changes in θ affect the level of UB for the median worker.[23] Given that we will use an empirical version of θ to test our model in the next section, we switch from (13) to expression (25):

$$PR = \varphi\left(w, w_M^R[y(X), p(X), \theta]\right) \tag{25}$$

which constitutes a key relationship for the empirical strategy.

Traditionally, the literature on this topic has attempted to determine the sign of (26):

$$\frac{\partial PR}{\partial X} = \beta \gtreqless 0 \tag{26}$$

or, put differently, to determine whether the DWE prevails over the AWE or vice versa.

The model developed here, in contrast, has defined a second-order theoretical effect, the EWE, which may be summarized mathematically by (27):

$$\frac{\partial^2 PR}{\partial X \partial \theta} = \frac{\partial \beta}{\partial \theta} < 0 \tag{27}$$

The negative sign in (27) is deduced from the discussion in Subsections 3.5, 3.6, and 3.7. If the starting point is, for example, the prevalence of the DWE over the AWE, the higher the proportion of type-E individuals within the working-age population is, the less pro-cyclical the PR is. This is so because while all type-N individuals will react pro-cyclically to changes in p, some of the type-E individuals will respond pro-cyclically and others counter-cyclically.

This situation is represented in panel (b) of Fig. 1. There, we considered two alternative settings for the Total Net Effect (TNE). The first (TNE 1) only takes into account the aggregation of the AWE and the DWE. This would be the case of an economy without UB (i.e. $b = 0$ for all the individuals). In scenario 2, the Total Net Effect (TNE 2) incorporates the existence of UB. The underlying Assumption behind this second theoretical setting is that the proportion of type-E individuals within the working-age population is monotonically increasing throughout the period considered. Formally: $(\partial \theta(t) / \partial t) > 0$, where t stands for time.

If we interpret β in expressions (26) and (27) as the estimated sensitivity of the PR to the business cycle (e.g. assuming linearity), what panel (b) of Fig. 1 shows is that:

$$\frac{\partial \beta(\theta(t))}{\partial t} = \frac{\partial \beta}{\partial \theta} \cdot \frac{\partial \theta}{\partial t} < 0 \tag{28}$$

In words: as the proportion θ increases, the EWE becomes stronger. For this reason, the pro-cyclical profile of TNE 2 is less pronounced with time. The second cycle peak (trough) is less sharp than the first, and the third peak (trough) is almost negligible. More importantly, this decline in the pro-cyclical sensitivity of PR is a consequence of the EWE, not the AWE. This is the main theoretical outcome of this paper, which will be tested in Section 4.

4. Database and empirical strategy

4.1. Database

To test the central hypothesis posed here, we need statistical information on the PR to be used as the dependent variable in the regressions. Furthermore, as a cyclical indicator, we use the unemployment rate (UR) of prime-age males (35-to-44 age group). In doing so, we minimize the potential problems of simultaneity and reverse causality. Data for PR and UR come from the OECD database.[24] The information about the number of UB beneficiaries comes from the Spanish Ministry of Labour administrative registers.[25] These are all very well-known series.

Nevertheless, three comments regarding the PRs are worth noting. First, we utilize the 16-to-64 age group PR. First, despite the OECD dubbing this group 15-to-64, in Spain the minimum working age is 16.

[23] A higher proportion of type-E workers raises the UB level for the median worker directly because the type-N workers are associated with a level $b = 0$. There are mainly two channels through which the proportion defined in (23) may change systematically: first, legislative changes favouring the entitlement to the UB; and, second, structural changes in the working-age population, creating a more work-committed pool of potential workers (since the entitlement is related to previous work experience).

[24] http://www.oecd.org/.

[25] http://www.empleo.gob.es/index.htm.

Second, although it is possible to find figures before the year 1980 for the Spanish PRs within the OECD database, we limit our analysis to the period 1980–2019 since the number of UB beneficiaries started to be recorded in 1980. Finally, as shown below, there is a relevant discontinuity in the year 2001 due to a notable methodological change in the definition of unemployment that affected the labour force definition as well. For this reason, we include in the econometric regressions a dummy variable that takes the value 1 in the year 2001 and 0 otherwise to capture such a methodological change, and it proved to be highly significant.[26]

4.2. Primary empirical approach: rolling regression

As the theoretical effect that we attempt to identify is a second-order effect, our empirical strategy involves two steps. In the first, we estimate a set of cyclical sensitivities for the PRs in different periods. We implement this stage employing a rolling-window procedure. In the second step, we correlate the coefficients obtained in the first with an empirical measure of the proportion of type-E individuals in the economy.

We have already established that the PR depends on the business cycle (X) and other factors (Z). Thus, we can represent the PR as a general function of a cyclical variable X and a vector Z, as shown in (29):

$$PR = f(X, Z) \tag{29}$$

We also assume that the business cycle affects the PR in the short run, whereas the rest of the factors included in the vector Z influence the PR in the long run. Furthermore, we model econometrically the general function (29) as the linear equation (30):

$$\Delta PR_t = \alpha^{LS} + \beta^{LS} \cdot \Delta UR_t + \varepsilon_t \tag{30}$$

In expression (30), ΔPR_t is the first difference of the PR between year t and year $t-1$. The coefficient α^{LS} reflects a constant linear trend underlying the data and would capture all the long-run factors included in Z. On the other hand, ΔUR_t is the first difference of UR times -1. We change the sign of ΔUR_t to obtain a cyclical indicator for the labour market that varies directly with the booms and downturns of the economy, which facilitates the interpretation of the results. Finally, ε_t stands for a random error term. We denote by β^{LS} the sensitivity of variations in PR to movements in UR, since we calculate it by means of a Least Squares procedure. This approach closely follows that of Pencavel (1987). It is simple and easy to interpret.[27] At the same time, it is flexible enough to make use of the estimated β^{LS} in the second step of our empirical strategy, as will be shown later.

In order to check the robustness and sensitivity of our analysis, we also carry out two additional empirical exercises. With these methods, we first detrend the series and then focus on their cyclical components. In doing so, we avoid potential misleading results associated with spurious correlation as a consequence of the time trends of the series.

Two alternative filters are employed. The first is the Cubic Trend (CT) method. We estimate the time trend of the series with a polynomial of degree 3, and the residuals of that regression are assumed to be the cyclical components of the series.[28] In equation (31), $PRCT_t$ and $URCT_t$ are cyclical components of the PR and the unemployment rate (times -1). β^{CT} is the sensitivity of changes in PR to movements in UR.

$$PRCT_t = \alpha^{CT} + \beta^{CT} \cdot URCT_t + \varepsilon_t \tag{31}$$

The second filtering method is the Hodrick-Prescott (HP) filter, using $\lambda = 100$, as suggested by most research for annual data. As in the previous case, we regress the cyclical component (the gap between the original series and the HP trend) of participation rates ($PRHP_t$) on the cyclical component of the prime-age male unemployment rate ($URHP_t$) in equation (32) [29]:

$$PRHP_t = \alpha^{HP} + \beta^{HP} \cdot URHP_t + \varepsilon_t \tag{32}$$

Fig. 6 is the graphical representation of the time series used in this study. A necessary step to take is to ensure that the series used are stationary, otherwise the estimation of equation (30) through (32) would provide flawed results due to a spurious relationship among the involved variables. We compute standard unit root tests for each of the series employed in the empirical analysis. This is displayed in Table 2. Three different well-known tests have been computed: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS)[30]. Overall, from Table 2, we find that our series are $I(0)$ or stationary and hence the estimates attained from (30) through (32) are reliable.

Comparing and contrasting estimates from (30) through (32) allows us to obtain a point estimate of whether the PR is pro-cyclical or counter-cyclical. However, to test the theory developed in this paper, we have to elaborate more on the empirical strategy. As mentioned, the EWE is a second-order effect, i.e. it refers to how the sensitivity of changes in PR to variations in UR evolves when the percentage of UB beneficiaries varies. Thus, we carry out the second step of our strategy so as to measure this second variation.

In the second step, we make use of the rolling-window regression techniques. This procedure yields different values for the β parameters: one value for each window. As we decided to use 15-year windows, we have 26 values for β, starting in 1980–1994 and ending in 2005–2019.[31]

On the other hand, we need an empirical index of the proportion of type-E workers (PTEW) within the total working-age population. In the theoretical model, labour contracts are signed at the beginning of the period. In real life, however, some workers are employed in a specific moment, other workers are looking for a job (some of them are entitled and others not), and a fraction of the total population is out of the labour force. If we make the Assumption that all workers currently employed are entitled to UB (as they in fact have work experience), and we add them to the pool of UB beneficiaries (which, indeed, are entitled at this time), we have a reasonably good approximation of the volume of type-E individuals.[32] If we then divide them by the total working-age population, we have PTEW as shown in equation (33):

$$PTEW = \frac{B + EM}{N} \tag{33}$$

where B stands for the number of UB beneficiaries, EM is the number of employed, and N refers to the total working-age population. We are

[26] We also tried to identify other relevant methodological changes in the series, but none proved to be very significant.

[27] Moreover, as shown later, the time-series in (30) turned out to be $I(0)$ in first differences (i.e. they are stationary). Thus, we avoid the problems associated with spurious correlation.

[28] We also detrended the series with a polynomial of degree 2 (i.e. we use the Quadratic Trend method). However, the cyclical components thus obtained were not stationary.

[29] It is worth pointing out that the parameters α^{CT} in (31) and α^{HP} in (32) are expected to be statistically non-significant, as the series were previously detrended.

[30] See respectively Dickey and Fuller (1979), Phillips and Perron (1988), and Kwiatkowski et al. (1992). The null hypothesis of the former two is that the series have a unit root, whereas the null hypothesis for the latter is that the series are stationary.

[31] The size of each window is always debatable. For instance, in Knotek (2007), each rolling regression uses a sample period consisting of 13 years of data (with quarterly frequency). Here, the size of the window consists of 15 annual observations, as in Porras and Martín-Román (2019).

[32] Previous work experience is the essential requirement to gain entitlement to UB in Spain. Hence, assuming that current employees are entitled in a (potential) future unemployment spell seems to be a realistic supposition.

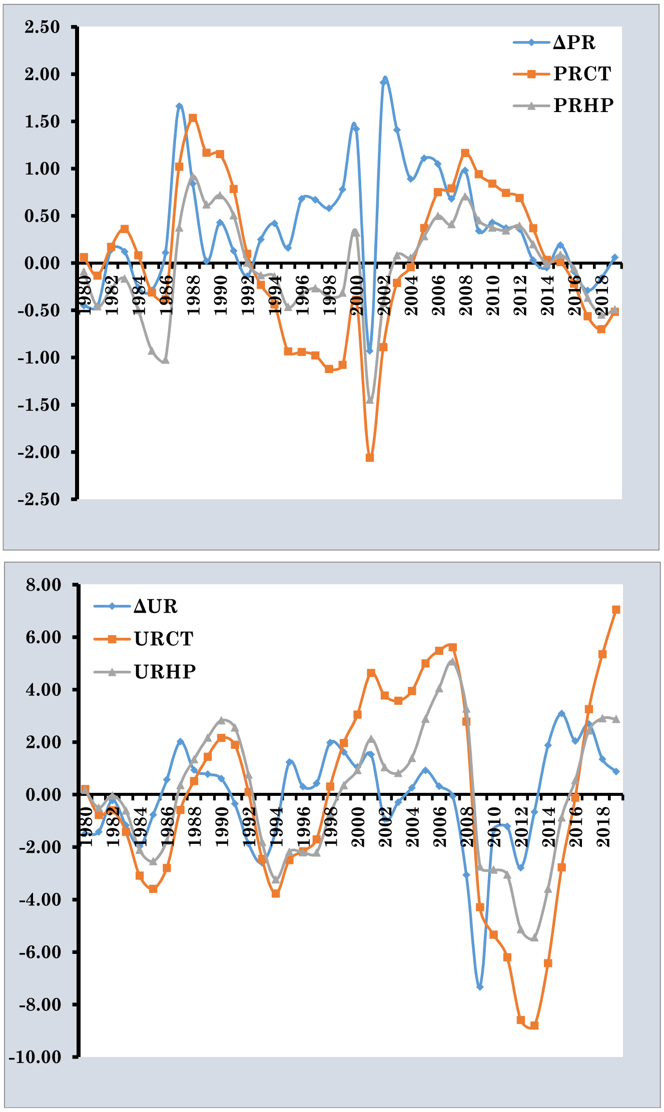

Fig. 6. Cyclical components of the PR and UR.
Source: Own elaboration.

aware that the PTEW index cannot provide the exact figure for the proportion of type-E individuals in a specific year because it is only an approximation. Nonetheless, we deem that it depicts reasonably well the long-run changes in that percentage. Actually, what we use in the second step is the 15-year average of PTEW, and this measure is much less affected by yearly measurement errors, reflecting the relevant movements in the long-run trend of PTEW.

The final stage of our empirical strategy consists in computing the correlation between PTEW and the group of "betas" estimated through the rolling-windows procedure. As mentioned above, we average 15-year periods of PTEW so as to match them to the corresponding estimated β belonging to the same range of years (i.e. within the equivalent window period). We managed to gather data on the number of UB beneficiaries from 1980 onwards (so far as we know, these are the longest time-series that can be obtained).

In Fig. 7, we show these 15-year average observations for PTEW. One of the most remarkable characteristics of that figure is its positive time-trend. A second major feature is the wide variation range of the time-series. Starting with a value of 0.55 in the period 1980–1994, it ends with a value of 0.69 in the period 2005–2019. These 14 percentage points imply an increase of about 25% throughout the whole period. This figure is a significant increase, so if the phenomenon we are analysing in this paper is relevant, such an increase could lead to substantial changes in the size of the estimated β.

Table 2
Unit roots tests.

	ADF		PP		KPSS	
	Statistic	p-value	statistic	p-value	statistic	5% level
ΔPR (16–64)	−4.660	0.000	−4.784	0.000	0.196	0.463
PRCT (16–64)	−2.058	0.039	−2.218	0.027	0.085	0.463
PRHP (16–64)	−3.254	0.002	−3.279	0.002	0.099	0.463
ΔUR	−3.078	0.036	−3.176	0.029	0.085	0.463
URCT	−3.298	0.002	−2.065	0.039	0.069	0.463
URHP	−3.659	0.001	−2.429	0.016	0.052	0.463

Notes: All the tests were carried out for the period 1980–2019. ΔPR stands for the first difference of the participation rate. PRCT is the cyclical gap after the Cubic Trend filtering procedure. PRHP is the cyclical gap attained after the Hodrick-Prescott decomposition. The same applies to the unemployment rate (UR). In the HP and CT tests, neither a constant nor a trend were included. In the first difference transformation, a constant was included but not a trend.

According to the theory previously presented, the higher the percentage of type-E individuals within the total working-age population, the stronger the EWE. Consequently, we expect a negative relationship between the size of the rolling-window estimated betas (β^{LS}_{RW}, β^{CT}_{RW}, β^{HP}_{RW}) and the 15-year average PTEW ($PTEW^{15A}$). equation (34) formalizes **Hypothesis 1** and is the empirical counterpart of equation (27):

$$\frac{\partial \beta^{j}_{RW}}{\partial PTEW^{15A}} < 0 \quad (\forall j = LS, CT, HP) \tag{34}$$

4.3. Complementary empirical approach I: panel data techniques

The main empirical strategy relies on a time-series relationship between the cyclical sensitivity of PR and 15-year average observations for PTEW. As a consequence, underlying time trends might have affected the results. To control for the influence of time, we resort to panel data techniques. This strategy allows us to include fixed time effects in the statistical exercise so as to take into account this potential biasing factor.

Therefore, we use regional data of the 17 NUTS 2 Spanish spatial units and then estimate equation (35) for each Spanish region in a first stage:

$$PRI^{jk}_{it} = \alpha^{jk}_{i} + \beta^{jk}_{i} \cdot URI^{jk}_{it} + \varepsilon^{jk}_{it} \tag{35}$$

where PRI^{j}_{it} is the participation rate index for each estimation procedure j in region i and year t. Thus, to ensure consistency with our previous notation, PRI_{it} can be ΔPR_{it}, $PRCT_{it}$, or $PRHP_{it}$. The same logic applies to URI^{j}_{it}, which is the cyclical index for each estimation procedure j in region i and year t (i.e. URI_{it} can be ΔUR_{it}, $URCT_{it}$, or $URHP_{it}$). The superscript k denotes the period in which the estimates are performed. Finally, ε stands for the error term.

We were able to collect PTEW data for the NUTS 2 Spanish regions from 1982 to 2019. Data for PRs come from the Spanish Statistical Office instead of OECD. Next, we compute equation (35) for two different time periods for each region. As i ranges from 1 to 17 and k from 1 to 2, we obtain a dataset of 34 estimated beta values. Then, with the 34 betas obtained in the first stage, we estimate equation (36) in a second stage:

$$\beta^{jk}_{i} = \vartheta_i + \varphi^{k} + \gamma^{j} \cdot \overline{PTEW}^{k}_{i} + \mu^{jk}_{i} \tag{36}$$

where ϑ_i is a spatial fixed effect capturing the time invariant regional heterogeneity, φ^{k} is a time fixed effect, $\overline{PTEW}^{k}_{i}$ is the average PTEW index in region i and period k, and μ stands for the error term.

Following the main argument developed throughout the paper, with this empirical exercise we would find support for the EWE hypothesis if the gamma parameter estimated in (36) is negative (and statistically significant). Expression (37) captures this idea formally:

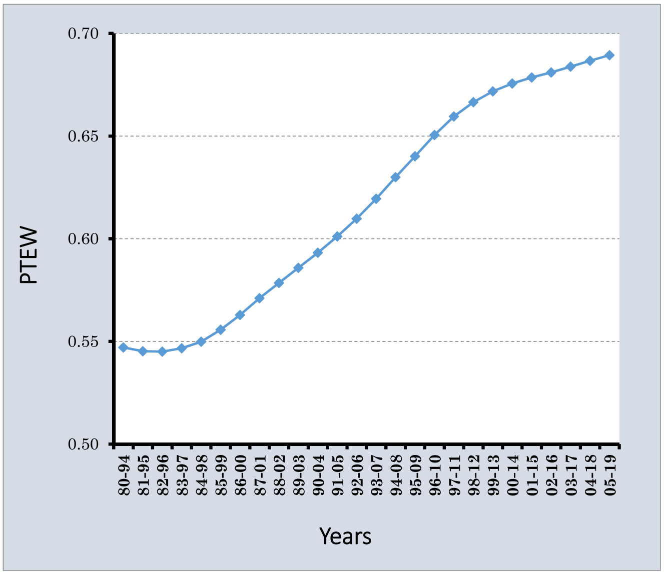

Fig. 7. Evolution of 15-year average of PTEW.
Source: Own elaboration.

$$\frac{\partial \beta_i^{jk}}{\partial PTEW_i^k} = \gamma^j < 0 \quad (\forall j = LS, CT, HP) \tag{37}$$

4.4. Complementary empirical approach II: threshold regression

An alternative way to test the EWE hypothesis is through the threshold regression method. This econometric technique defines a straightforward form of nonlinear regression featuring piecewise linear specifications and regime switching that arises when an observed variable crosses unknown thresholds.

The drop in the cyclical sensitivity of the PR when θ rises might not be smooth and progressive, as equation (27) displays, but sharper.[33] This might yield a discontinuity at the aggregate level in the cyclical sensitivity of the PR as a consequence of a composition effect, yielding two distinct regimes. Expression (38) captures this idea formally:

$$\begin{aligned} PRI_t^j &= \alpha^j + \beta_1^j \cdot URI_t^j + \varepsilon_t^j \quad if \quad 0 \le PTEW_t < \lambda_1 \\ PRI_t^j &= \alpha^j + \beta_2^j \cdot URI_t^j + \varepsilon_t^j \quad if \quad \lambda_1 \le PTEW_t < 100 \end{aligned} \tag{38}$$

where λ_1 is a threshold producing two different regimes, and β_1^j and β_2^j are the two different cyclical sensitivities associated with those two regimes.

Using an indicator function $1(\cdot)$ which takes the value 1 if the expression is true and 0 otherwise, and defining $1_1(PTEW_t, \lambda_1) = 1(0 \le PTEW_t < \lambda_1)$ and $1_2(PTEW_t, \lambda_1) = 1(\lambda_1 \le PTEW_t < 100)$, we may combine the two individual regime specifications into a single equation (39):

$$PRI_t^j = \alpha^j + \sum_{m=1}^{2} \beta_m^j \cdot 1_m(PTEW_t, \lambda_1) \cdot URI_t^j + \varepsilon_t^j \tag{39}$$

The empirical evidence we would expect to find supporting **Hypothesis 1** is that the beta associated with the regime of "low" PTEW should be higher than the beta related to the "high" PTEW regime, as expression (40) formalizes:

$$\frac{\partial PRI_t^j}{\partial 1_1(PTEW_t, \lambda_1) \cdot URI_i^j} = \beta_1^j > \frac{\partial PRI_t^j}{\partial 1_2(PTEW_t, \lambda_1) \cdot URI_i^j} = \beta_2^j \tag{40}$$

[33] We would like to thank an anonymous reviewer for this suggestion.

Thus, condition (40) may be thought of as a discrete version of the expressions (34) or (37) to test **Hypothesis 1**. Although they are not strictly comparable, it must be understood as a complementary manner to find empirical evidence supporting the EWE.

5. Results

5.1. Rolling-regression strategy

Table 3 shows the results of the estimation of equation (30) through (32). We break down the estimates into a twofold classification. First, the set of columns (1)–(3) refers to the three different econometric procedures above-mentioned (LS, CT, and HP). Second, we also carry out the empirical analysis for three different periods. The first covers the whole time horizon and ranges from 1980 to 2019. The other two are the subperiods 1980–1999 and 2000–2019, used to checking the stability of the estimates for the whole period. As a result, we obtain nine estimates for beta.

Overall, the results exhibit a high degree of consistency among the three econometric methods. For the whole period, the LS and CT and HP estimates show no statistically significant effect of the business cycle on the PR. For the sub-period 1980–1999, the three procedures find a positive and significant relationship between the PR and the business cycle (i.e. the PRs are pro-cyclical in these years). Finally, for the sub-period 2000–2019, neither LS nor HP found a statistically significant relationship, while the CT procedure estimates a counter-cyclical behaviour of the PR significant at the 5% level.

At first glance, the absence of a significant relationship between the PR and the business cycle for the whole period could lead the naïve observer to think that the AWE and the DWE are of similar strength and offset each other. However, the reality behind the data is a lack of stability of the estimated parameter. The estimated betas for the two subperiods confirm this view. Within the time span from 1980 to 1999, the cyclical sensitivity of the PR to business cycle movements is estimated significantly in the range of 0.19–0.25. On the other hand, the LS and HP estimates for the period 2000–2019 are not statistically significant, and the CT method produces a beta of −0.05, implying a counter-cyclical behaviour of the PR.

Bearing in mind this empirical evidence, we check whether the decline in the pro-cyclical behaviour in the PR occurs suddenly or whether, on the contrary, it is a gradual phenomenon, and, in the case where it is a gradual phenomenon, we also attempt to determine whether the secular increase of the PTEW shown in Fig. 7 is a major driving factor. With this aim, in a first stage, we calculate a continuum of estimated betas through a set of rolling-window regressions. This is what is displayed in Table 4. Then, in a second stage, we look for evidence of the second-order EWE by correlating the estimated betas with the 15-year average of PTEW.

In order to facilitate the interpretation of the results, we have represented the estimated betas from Table 4 in Fig. 8. Two stylized facts can be observed in Table 4 and Fig. 8. First, there is a clear negative trend in the estimated betas (as we move forward in time). Second, although there are slight differences in the order of magnitude of estimated betas regarding different econometric techniques, we find a high degree of correlation among them. To be more precise, the correlation coefficient between the series of β^{LS} and β^{CT} is $r = 78.2\%$, that between β^{LS} and β^{HP} is $r = 83.7\%$, and that between β^{CT} and β^{HP} is $r = 96.0\%$.

Furthermore, the strong pro-cyclical pattern in the Spanish PR at the beginning of the period should be emphasized. For instance, the LS estimated parameter for the period 1980–1994 indicates that a 1-percentage-point reduction in the unemployment rate would raise the PR by 0.28 percentage points. The CT and the HP estimates yield similar outcomes, 0.26 and 0.25, respectively. Moreover, the estimates are highly significant from a statistical point of view. As we progress in time, there is a steady decrease in the size of the calculated betas. It is also

Table 3
Cyclical sensitivity of PRs.

	(1)		(2)		(3)	
	LS		CT		HP	
	Coeff. (p-value)		Coeff. (p-value)		Coeff. (p-value)	
PR 16–64						
1980–2019						
Constant	0.415***	(0.00)	0.075	(0.54)	0.006	(0.93)
Beta	0.025	(0.53)	−0.016	(0.52)	0.046	(0.14)
D2001	−1.384***	(0.00)	−2.061***	(0.00)	−1.552***	(0.00)
N	40		40		40	
R^2	0.13		0.19		0.26	
$\overline{R^2}$	0.08		0.15		0.22	
1980–1999						
Constant	0.304***	(0.00)	0.155	(0.50)	−0.010	(0.89)
Beta	0.251***	(0.01)	0.191*	(0.06)	0.224***	(0.00)
D2001	–	–	–	–	–	–
N	20		20		20	
R^2	0.47		0.20		0.61	
$\overline{R^2}$	0.44		0.15		0.59	
2000–2019						
Constant	0.551***	(0.00)	0.183	(0.19)	0.127	(0.14)
Beta	−0.053	(0.37)	−0.047**	(0.05)	−0.021	(0.44)
D2001	1.400***	(0.00)	−2.024***	(0.00)	−1.530***	(0.00)
N	20		20		20	
R^2	0.26		0.50		0.52	
$\overline{R^2}$	0.18		0.44		0.46	

Notes: The set of columns (1) trough (3) refers to Least Squares, Cubic Trend and Hodrick-Prescott estimates respectively. The coefficient captures the relationship between the variation of PR and (minus) the variation in prime-age males UR. t-statistics and p-values are calculated using White (1980) heteroskedasticity-consistent standard errors. *** means significance at 1% level, ** significance at 5% level and * significance at 10% level.

worth mentioning that some estimated parameters are no longer statistically significant (at the conventional levels) in the final years, which is logical, as the point estimates are in fact close to zero. In other words, the above-mentioned TNE is close to zero because of the composition effects of the AWE, the DWE, and the EWE. Even more importantly, in the very last years, the three methods produce negative values for the estimated betas, implying a counter-cyclical pattern in the PR.

As illustrated by the previous analysis, the fall in the pro-cyclical

Table 4
Beta estimates of the rolling-window regression.

	(1)			(2)			(3)		
	LS			CT			HP		
	Coeff.	p-val.	R^2	Coeff.	p-val.	R^2	Coeff.	p-val.	R^2
PR 16–64									
1980–1994	0.281	0.033	0.46	0.256	0.000	0.61	0.245	0.001	0.64
1981–1995	0.234	0.062	0.38	0.291	0.000	0.64	0.243	0.000	0.66
1982–1996	0.221	0.064	0.36	0.310	0.000	0.63	0.237	0.000	0.68
1983–1997	0.227	0.048	0.38	0.321	0.000	0.59	0.234	0.000	0.69
1984–1998	0.211	0.036	0.36	0.281	0.001	0.41	0.235	0.000	0.68
1985–1999	0.200	0.042	0.33	0.218	0.051	0.24	0.226	0.000	0.63
1986–2000	0.200	0.027	0.29	0.175	0.091	0.16	0.211	0.000	0.61
1987–2001	0.204	0.029	0.58	0.180	0.113	0.36	0.187	0.000	0.81
1988–2002	0.075	0.474	0.37	0.113	0.255	0.29	0.171	0.001	0.72
1989–2003	0.055	0.614	0.34	0.095	0.208	0.32	0.151	0.002	0.77
1990–2004	0.080	0.473	0.39	0.079	0.169	0.36	0.133	0.008	0.76
1991–2005	0.100	0.376	0.41	0.076	0.101	0.44	0.106	0.007	0.78
1992–2006	0.093	0.447	0.44	0.097	0.058	0.53	0.102	0.002	0.81
1993–2007	0.014	0.921	0.49	0.125	0.017	0.59	0.101	0.000	0.82
1994–2008	−0.081	0.387	0.57	0.155	0.005	0.57	0.119	0.000	0.81
1995–2009	0.023	0.665	0.54	0.089	0.351	0.35	0.098	0.031	0.69
1996–2010	0.047	0.241	0.60	0.013	0.871	0.29	0.063	0.139	0.63
1997–2011	0.055	0.127	0.58	−0.032	0.529	0.33	0.037	0.317	0.61
1998–2012	0.070	0.041	0.58	−0.051	0.110	0.42	0.008	0.762	0.62
1999–2013	0.088	0.006	0.54	−0.043	0.116	0.51	0.004	0.849	0.69
2000–2014	0.052	0.346	0.42	−0.028	0.274	0.58	0.011	0.545	0.74
2001–2015	0.001	0.985	0.38	−0.020	0.441	0.60	0.011	0.565	0.73
2002–2016	−0.023	0.676	0.01	−0.021	0.402	0.04	0.009	0.629	0.01
2003–2017	−0.042	0.390	0.05	−0.017	0.463	0.03	0.004	0.841	0.00
2004–2018	−0.054	0.207	0.11	−0.025	0.331	0.06	−0.009	0.728	0.01
2005–2019	−0.057	0.176	0.12	−0.034	0.201	0.10	−0.018	0.509	0.03

Notes: The set of columns (1) trough (3) refers to Least Squares, Cubic Trend, and Hodrick-Prescott estimates respectively. As mentioned in the text, the coefficient captures the relationship between the variation of PR and (minus) the variation in prime-age males UR. T-statistics are calculated using White (1980) heteroskedasticity-consistent standard errors.

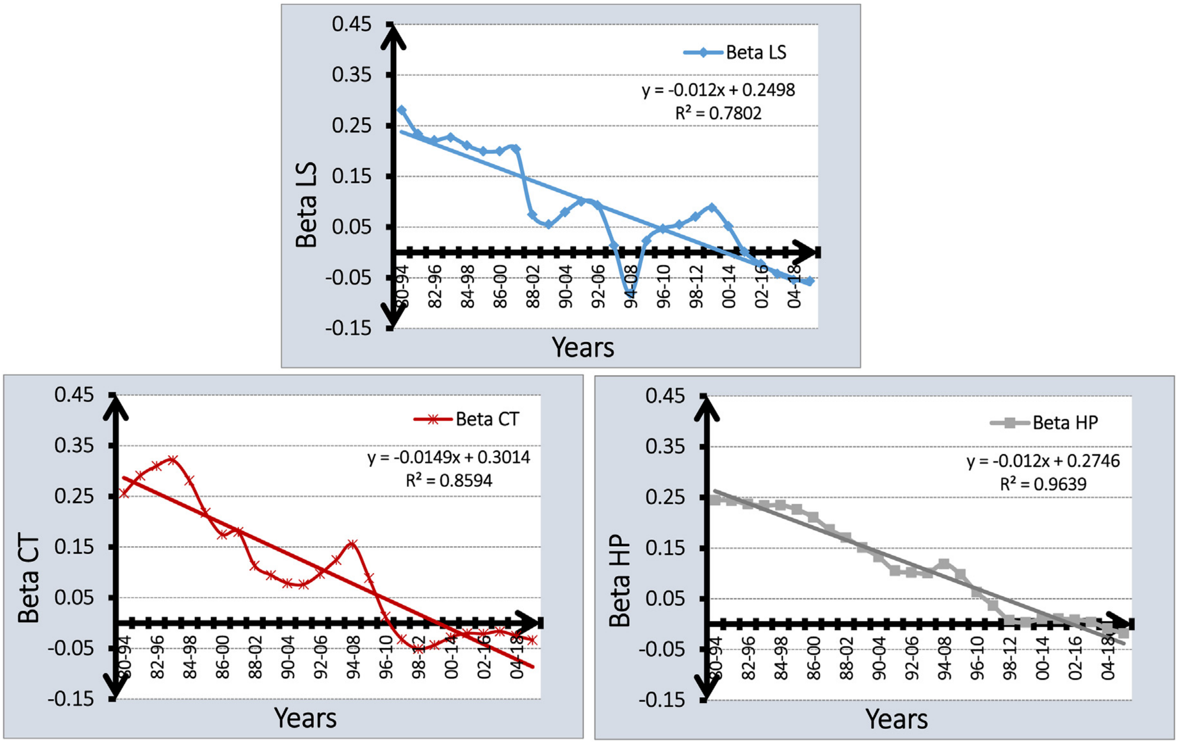

Fig. 8. Beta LS, beta CT, and beta HP.
Source: Own Elaboration.

behaviour of Spanish PR seems to be a progressive process. For this reason, we consider that the loss of procyclicality observed in the Spanish labour supply during the last years is a consequence of structural factors, not of short-term factors. As our theoretical framework establishes, we believe that the EWE is operating more intensively now than in the past, leading consequently to a weakening of the DWE in recent years. Support for this statement can be found in Fig. 7. As can be seen, the PTEW reached its highest levels precisely in the last years.

After having computed the 15-year rolling-window estimates for beta, in the second and final step of the empirical strategy, we proceed to correlate them with their equivalent 15-year average of PTEW. Fig. 9 shows this empirical exercise. We represent PTEW on the X-axis and beta on the Y-axis. In the upper panel, we display the betas obtained through LS, in the bottom-left those calculated with the CT procedure, and in the bottom-right the HP estimates.

Two essential conclusions can be drawn from Fig. 9. First, there exists a negative correlation between the rolling-window betas and PTEW, as predicted by the model. Second, that correlation seems to be fairly high. More specifically, the correlation coefficient in the LS case is $r = 85.6$ %, $r = 93.5$ % for the CT procedure, and $r = 98.8$ % for the HP estimates. These empirical results give credit to the theory developed in this article. In other words, Fig. 9 evidences the importance and significance of EWE.

Anyhow, to test that the correlations between the betas and PTEW in Fig. 9 are not mainly driven by the time trend, we conduct a straightforward test.[34] We include a time trend as a control variable in the regression and check whether the correlations are still significant. In Table 5, we present the results.[35]

Overall, we find a significant correlation between the variables when using detrended time series for two out of the three procedures, i.e. HP and CT. The results for the LS procedure were not significant, though (not reported in the table). From a statistical point of view, the best scenario is found for the HP procedure. This is a feature shared with the rest of the econometric methods used in this paper and, thus, HP estimates are considered as the benchmark hereafter.

It is worth mentioning though that the lack of statistical significance for the LS procedure does not imply a lack of support of the EWE with this method. Using detrended time series is a demanding test that only seeks to verify whether the mechanism driving the results is the time trend, which only occurs in the case of LS. The time trend may also contain relevant economic information regarding the EWE. Thus, by removing the time trend, there is a possibility of incurring a type I error, i.e. rejecting the null hypothesis of a relevant EWE when it is true. For this reason, we keep the LS estimates in the rest of the sections.

In Table 5, we report the estimates for four models, although two of them are entirely instrumental for showing the equivalence between them and the other two. Model 1 adds a linear time trend to the basic specification. Model 2 is a model that associates linearly detrended time series of beta estimates with linearly detrended time series of PTEW. The relevant coefficient for PTEW should be the same in both models, according to basic statistics, and it is. Model 3 adds a linear and a quadratic trend to the basic specification, and Model 4 associates a quadratically detrended series of beta estimates with a quadratically detrended series of PTEW. For the same reasons, the coefficient for PTEW in these two models is the same.

On the whole, we notice that the coefficient of interest keeps its negative sign and reduces its magnitude, but only slightly. This is a common characteristic for both procedures and for the linear and quadratic time trends specifications. For instance, in the case in which a linear trend is included (Model 1 and Model 2), the coefficient takes the value −1.4, whereas it was −1.7 in a specification without trend when using HP filtering. These values are −1.8 (with linear trend) and −2.1 (without linear trend) when using CT filtering. The quadratic trend specification yields virtually the same outcomes. As to the statistical significance, in the case of HP, the coefficient is strongly significant with

[34] We would like to thank an anonymous reviewer for this suggestion.

[35] We also check the influence of time on our results by regressing the first difference of the beta series on the first difference of the PTEW series. The conclusions drawn are virtually the same.

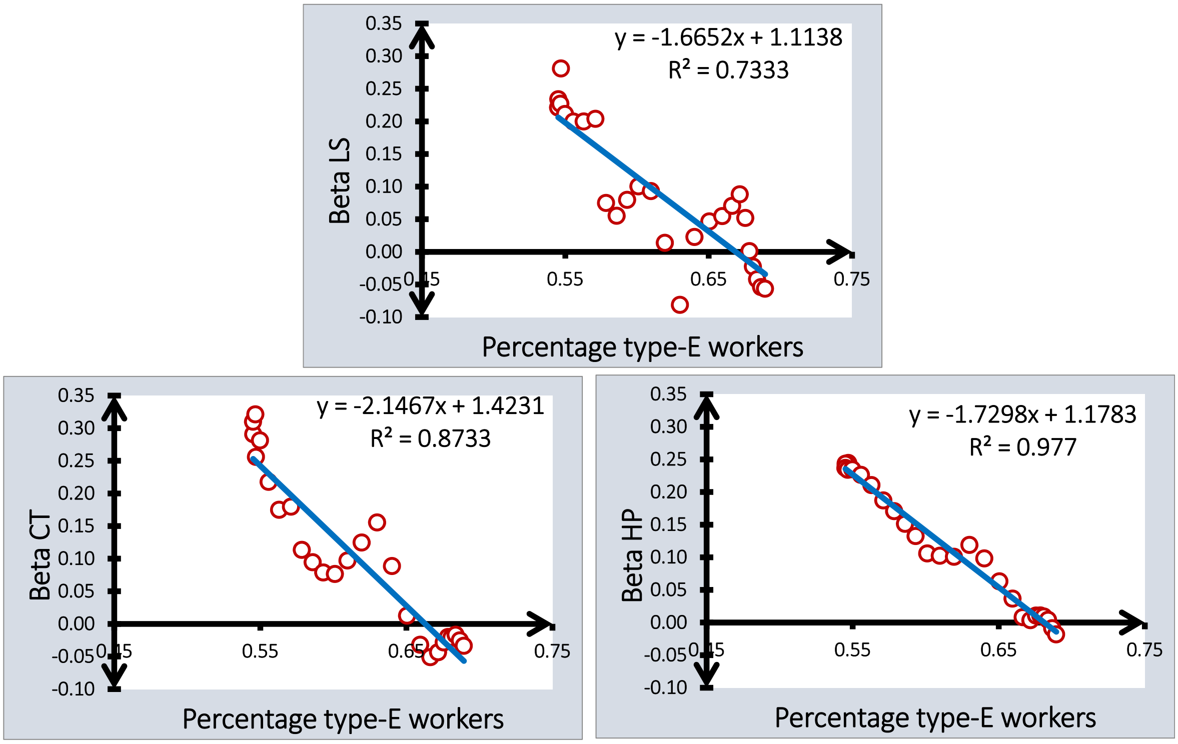

Fig. 9. Correlation between beta and PTEW.
Source: Own elaboration.

Table 5
Rolling beta estimates (PTEW) controlling for time trends.

	HP		CT	
Model 1	Coefficient	t-statistic	Coefficient	t-statistic
Constant	0.981	(6.352)	1.230	(2.572)
PTEW	−1.351	(-4.617)	−1.776	(-1.969)
TIME	−0.003	(-1.408)	−0.003	(-0.439)
R2	0.978		0.874	
N	26		26	
Model 2	Coefficient	t-statistic	Coefficient	t-statistic
Constant	0.000	(0.000)	0.000	(0.000)
PTEWD	−1.351	(-4.716)	−1.776	(-2.011)
R2	0.397		0.102	
N	26		26	
Model 3	Coefficient	t-statistic	Coefficient	t-statistic
Constant	0.982	(6.550)	1.231	(2.823)
PTEW	−1.333	(-4.736)	−1.684	(-2.016)
TIME	−0.005	(-2.407)	−0.014	(-1.777)
TIME SQUARED	0.000	(1.504)	0.000	(2.426)
R2	0.980		0.901	
N	26		26	
Model 4	Coefficient	t-statistic	Coefficient	t-statistic
Constant	0.000	(0.000)	0.000	(0.000)
PTEWD2	−1.333	(-4.946)	−1.684	(-2.105)
R2	0.411		0.114	
N	26		26	

Notes: Model 1 adds a linear time trend to the basic specification. Model 2 is a model that associates linearly detrended time series of beta estimates with linearly detrended time series of PTEW (PTEWD). Model 3 adds a linear and a quadratic trend to the basic specification. Model 4 associates quadratically detrended series of beta estimates with quadratically detrended series of PTEW (PTEWD2).

t-statistics well over 4 in absolute value. In the case of CT, the coefficient exhibits a reasonable level of statistical significance, with t-statistics around 2 in absolute value. These values are remarkable, taking into account that the time series are detrended.

A graphical representation of these outcomes can be found in Fig. 10. In panel (a) of such a figure, we show the linearly detrended time series for beta and PTEW, using HP filtering. In panel (b), we depict the scatter plot diagram showing the correlation between both time series. For other specifications, the results are quite the same. Removing the time trend reduces somewhat the correlation, although it is still remarkably high. In panel (b), it can be seen that most points are located in the northwest and the southeast quadrants. All evidence makes us conclude that the EWE is not mainly driven by the time trends in the series.

5.2. *Sensitivity checks*

To check whether the window size affects the results obtained, we repeated the previous analysis modifying the window length for the three procedures: LS, CT, and the HP. In particular, we used three alternative sizes: 16-year, 17-year, and 18-year windows. Table 6 summarizes all this information, providing further statistical details.[36]

Overall, the estimates display a high degree of consistency. All nine additional beta coefficients are clearly negative, giving support to the EWE and **Hypothesis 1**. Their values range from −1.7 to −2.1, depending on the procedure and the window size. The similarity among the coefficients is remarkable despite the different methods used to calculate them in the first stage. This implies that an increase in the PTEW by 10 percentage points (i.e. a rise by 0.1 in our independent variable) reduces the PR cyclical sensitivity by about 0.2 on average. In conclusion, we may state that the beta estimates are highly stable across

[36] In Table 6, we also include the 15-year window estimates and their associated statistical information. The results of unit root tests for errors in each set of regressions are included as well. They indicate that the errors can be considered stationary.

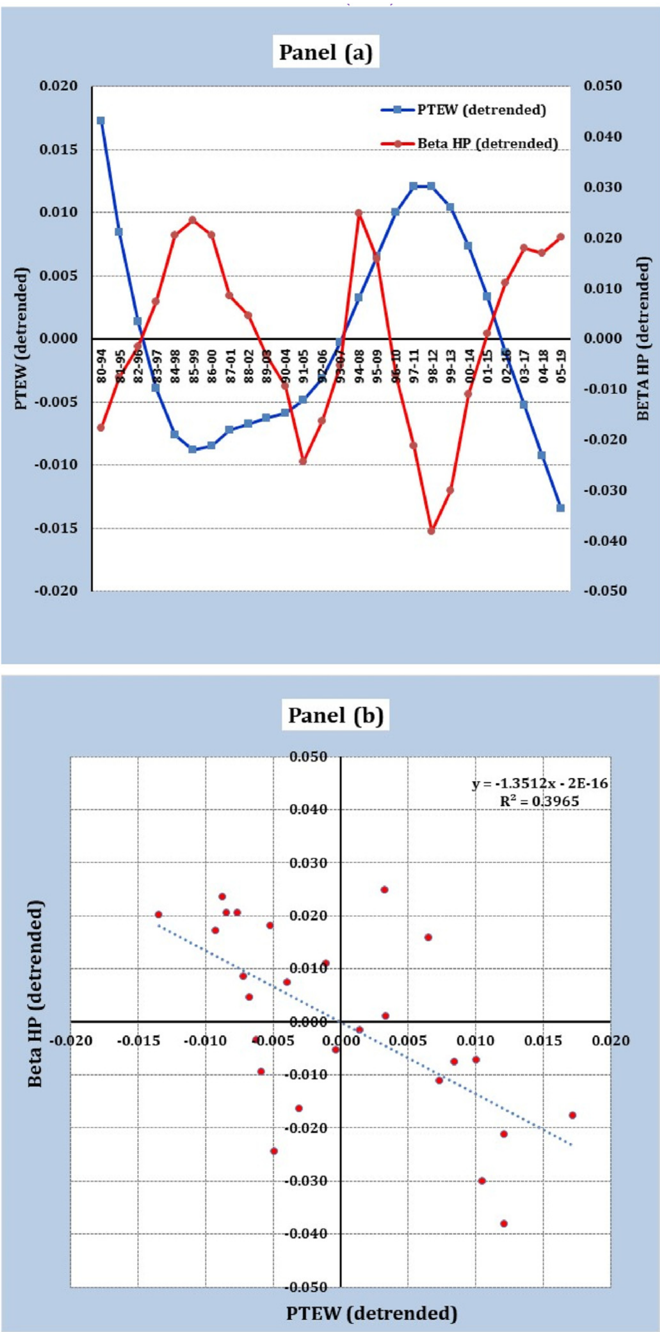

Fig. 10. Correlation between detrended Beta and detrended PTEW (HP).

different empirical exercises.

5.3. Panel data evidence

A major criticism that can be posed against previous empirical evidence is that the results might be driven by underlying time trends in both the series of rolling betas and the moving average of PTEW, at least to some extent.[37] To address this issue, we perform a panel data analysis as explained in section 4.3. Table 7 displays the statistical information regarding equation (36).

Table 6
Rolling beta estimates (PTEW) (different window sizes).

	15-year wind.	16-year wind.	17-year wind.	18-year wind.
LS				
PTEW (coef.)	−1.665	−1.830	−1.951	−2.068
t-statistic	−10.208	−14.425	−16.220	−20.871
N	26	25	24	23
MDV	0.087	0.096	0.094	0.093
R2	0.733	0.877	0.910	0.939
Adjusted R2	0.722	0.872	0.905	0.937
ADF stat.	−2.609	−2.193	−2.231	−2.032
ADF p-value	0.011	0.030	0.028	0.043
PP stat.	−2.737	−2.193	−2.240	−2.091
PP p-value	0.008	0.030	0.027	0.038
KPPS stat.	0.118	0.104	0.116	0.110
KPSS 5%	0.463	0.463	0.463	0.463
CT				
PTEW (coef.)	**−2.147**	**−2.095**	**−2.028**	**−1.909**
t-statistic	−14.861	−12.410	−10.504	−9.183
N	26	25	24	23
MDV	0.100	0.088	0.078	0.068
R2	0.873	0.872	0.844	0.812
Adjusted R2	0.868	0.867	0.837	0.803
ADF stat.	−3.405	−1.823	−3.315	−3.773
ADF p-value	0.002	0.066	0.002	0.001
PP stat.	−2.175	−2.057	−2.136	−2.630
PP p-value	0.031	0.040	0.034	0.011
KPPS stat.	0.094	0.082	0.080	0.071
KPSS 5%	0.463	0.463	0.463	0.463
HP				
PTEW (coef.)	**−1.730**	**−1.846**	**−1.909**	**−1.982**
t-statistic	−51.612	−47.321	−38.990	−34.271
N	26	25	24	23
MDV	0.112	0.115	0.114	0.113
R2	0.977	0.990	0.988	0.983
Adjusted R2	0.976	0.989	0.987	0.982
ADF stat.	−4.046	−3.450	−2.711	−2.399
ADF p-value	0.000	0.001	0.009	0.019
PP stat.	−2.543	−3.480	−2.711	−2.411
PP p-value	0.013	0.001	0.009	0.019
KPPS stat.	0.074	0.093	0.127	0.124
KPSS 5%	0.463	0.463	0.463	0.463

Notes: N= Number of observations; MDV = Mean Dependent Variable; ADF = Augmented Dickey-Fuller; PP=Phillips-Perron (PP); KPSS=Kwiatkowski-Phillips-Schmidt-Shin. T-statistics are calculated using heteroskedasticity-consistent standard errors.

In the upper part, we show the estimates concerning two successive time periods, 1982–2000 and 2001–2019. In the lower section, as a robustness check, we present the estimates for the periods 1982–1996 and 2005–2019. The aim of this second estimation is to compare and contrast the accompanying figures with those from the benchmark model to better understand the role of time in our outcomes. In Table 7, we present the estimates for LS and HP procedures. We discarded estimates for the CT method since, in some regions, the time series used to obtain the beta coefficients in the first stage were not stationary.

In columns (1) and (4), we set $\vartheta_i = \varphi^k = 0$ (i.e. we do not consider region fixed effects or time fixed effects) in equation (36). In columns (2) and (5), we estimate a model with region fixed effects but not time fixed effects (i.e. $\vartheta_i \neq 0$ *and* $\varphi^k = 0$). Both specifications were performed for comparative purposes, as the main interest of this empirical exercise is to control for time effects. Thus, this section's main interest is in figures included in columns (3) and (6).

As a general comment, it may be stated that the condition established in expression (37) is fulfilled for all 12 coefficients shown in Table 7. In all specifications, the gamma parameters are negative and statistically significant at the usual levels, showing that inequality (37) holds. Focusing on the coefficients for the LS procedure in column (3), we find estimates of −2.7 and −3.0, which are slightly higher in absolute value

[37] It is worth pointing out that this fact does not suffice to invalidate the analysis. As was shown in Table 6, the errors of the regressions were stationary. Hence, underlying time trends in both series should not produce spurious results.

Table 7
Panel data estimates.

	LS			HP		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
82–00/01–19						
PTEW (coef.)	**−1.015**	**−1.546**	**−2.566**	**−0.648**	**−0.978**	**−1.376**
t-statistic	−4.232	−8.107	−8.225	−3.349	−8.094	−2.600
p-value	0.000	0.000	0.000	0.002	0.000	0.020
Region FE	NO	YES	YES	NO	YES	YES
Time FE	NO	NO	YES	NO	NO	YES
N	34	34	34	34	34	34
MDV	0.026	0.026	0.026	0.059	0.059	0.059
R2	0.317	0.854	0.868	0.202	0.696	0.699
Adjusted R2	0.295	0.698	0.709	0.177	0.373	0.338
D-W	1.668	2.052	1.984	2.059	2.518	2.544
AIC	−2.041	−2.640	−2.682	−2.333	−2.357	−2.309
SC	−1.951	−1.832	−1.829	−2.243	−1.549	−1.456
82–96/05–19						
PTEW (coef.)	**−0.668**	**−0.934**	**−3.015**	**−0.719**	**−0.995**	**−1.641**
t-statistic	−2.362	−4.179	−6.575	−3.154	−6.626	−3.732
p-value	0.024	0.001	0.000	0.004	0.000	0.002
Region FE	NO	YES	YES	NO	YES	YES
Time FE	NO	NO	YES	NO	NO	YES
N	34	34	34	34	34	34
MDV	0.010	0.010	0.010	0.073	0.073	0.073
R2	0.154	0.682	0.764	0.226	0.706	0.716
Adjusted R2	0.128	0.345	0.482	0.202	0.394	0.375
D-W	1.705	1.949	1.770	1.998	2.199	2.291
AIC	−1.827	−1.866	−2.106	−2.151	−2.178	−2.154
SC	−1.738	−1.057	−1.253	−2.061	−1.370	−1.301

Notes: N = Number of observations; MDV = Mean Dependent Variable; FE = Fixed effects; AIC = Akaike info criterion; SC = Schwarz criterion; D-W = Durbin-Watson statistic. T-statistics are calculated using heteroskedasticity-consistent standard errors.

than the sensitivity found with the same method in Table 6 (e.g. the 18-year window estimate is −2.1). As for the HP figures, shown in column (6), the estimates are −1.4 and −1.6, which are very similar (a bit lower in absolute value) to those obtained by means of rolling regression, displayed in Table 6 (e.g. the 15-year window yielded an estimate of −1.7, while that for the 18-year window was −2.0).

Therefore, it may be stated that the evidence based on panel data is highly consistent with previous empirical findings. This observation allows us to conclude that **Hypothesis 1** is also supported after conducting the panel data analysis. In other words, the EWE is a significant issue according to these results.

5.4. Threshold analysis

A different way to test the relevance of the EWE is through the threshold regression proposed in Section 4.4. Table 8 shows the estimates for this type of econometric analysis. In Table 8, we present nine sets of estimates resulting from combining three different methods to obtain the beta values (i.e. LS, HP, and CT) for three different scenarios.

First, we examine the data and allow them to determine the best model. We use a sequential method to identify threshold values and the associated regression coefficients.[38] The outcome of this procedure is that for the LS and HP methods, the best model was achieved with a threshold value of PTEW = 0.639, entailing one subsample (below the threshold) of 21 observations and another (above the threshold) of 19 observations. On the other hand, in the case of the CT method, the best model was achieved with a threshold value of PTEW = 0.599, associated with a first subsample (below the threshold) of 19 observations, and a second subsample (above the threshold) of 19 observations. We then decided, as a first robustness check, to set the optimal threshold for LS and HP to the case of CT and vice versa. Finally, as a second robustness check, we set the threshold of PTEW = 0.619 in all three cases, which creates two subsamples of 20 observations.

Several outcomes may be highlighted from Table 8. First, and above all, the inequality (40), which is the key condition to validate the EWE, holds for all nine econometric scenarios. This feature is highly relevant, as it adds fundamental empirical evidence supporting **Hypothesis 1**. Furthermore, this new empirical support is structurally different than that of the rolling regression analysis from an econometric standpoint. Thus, we find support for the EWE with two distinct econometric methodologies.

Second, all betas associated with the low PTEW regime are positive and statistically significant, whereas betas in the high PTEW regime are negative and less statistically significant in general terms. If we focus on the best model for each kind of methodology, beta 1 (low PTEW regime) is equal to 0.28 for LS, 0.23 for HP, and 0.23 for CT. Beta 2 (high PTEW regime) is equal to −0.09 for LS, −0.04 for HP, and −0.07 for CT. Finally, we note that in all three cases, a single threshold was identified by the econometric procedure.

5.5. Robustness checks: a different indicator

In this subsection, instead of the percentage of workers potentially entitled to receive unemployment benefits, we use an index measuring policy changes in unemployment benefits so as to test **Hypothesis 1.**[39] We substitute the variable PTEW by an Unemployment Benefit Generosity Index (UBGI), in both the rolling regression and the threshold analyses.

[38] We use Eviews software, which in turn uses the methodologies of Bai and Perron (1998). More precisely, we utilize the procedures dubbed '*Sequential* L+*1 breaks vs. L*'.

[39] We would like to thank an anonymous reviewer for this suggestion.

Table 8
Threshold analysis (PTEW).

	LS		HP		CT	
	Coefficient	t-Statistic (P-value)	Coefficient	t-Statistic (P-value)	Coefficient	t-Statistic (P-value)
	PTEW<0.639	21 obs.	PTEW<0.639	21 obs.	PTEW<0.639	21 obs.
Beta 1	**0.278**	3.656	**0.230**	5.531	**0.143**	1.945
		(0.001)		(0.000)		(0.060)
	0.639≤PTEW	19 obs.	0.639≤PTEW	19 obs.	0.639≤PTEW	19 obs.
Beta 2	**−0.087**	−1.504	**−0.036**	−1.072	**−0.061**	−2.245
		(0.141)		(0.291)		(0.031)
R2	0.258		0.363		0.153	
Prob(F-stat.)	0.004		0.000		0.046	
AIC	1.675		1.145		2.324	
SC	1.802		1.272		2.450	
DW statistic	1.739		1.053		0.343	
	PTEW<0.619	20 obs.	PTEW<0.619	20 obs.	PTEW<0.619	20 obs.
Beta 1	**0.258**	3.472	**0.229**	5.455	**0.184**	2.421
		(0.001)		(0.000)		(0.021)
	0.619≤PTEW	20 obs.	0.619≤PTEW	20 obs.	0.619≤PTEW	20 obs.
Beta 2	**−0.076**	−1.384	**−0.034**	−1.045	**−0.063**	−2.384
		(0.175)		(0.303)		(0.022)
R2	0.211		0.353		0.189	
Prob(F-stat.)	0.013		0.000		0.021	
AIC	1.737		1.161		2.280	
SC	1.864		1.288		2.406	
DW statistic	1.823		1.207		0.503	
	PTEW<0.599	19 obs	PTEW<0.599	19 obs	PTEW<0.599	19 obs
Beta 1	**0.261**	3.217	**0.232**	5.510	**0.232**	3.786
		(0.003)		(0.000)		(0.001)
	0.599≤PTEW	21 obs	0.599≤PTEW	21 obs	0.599≤PTEW	21 obs
Beta 2	**−0.068**	−1.308	**−0.035**	−1.071	**−0.068**	2.548
		(0.199)		(0.291)		(0.015)
R2	0.194		0.360		0.249	
Prob(F-stat.)	0.019		0.000		0.005	
AIC	1.758		1.150		2.203	
SC	1.885		1.277		2.330	
DW statistic	1.758		1.196		0.495	

Notes: AIC = Akaike info criterion; SC = Schwarz criterion; DW = Durbin-Watson statistic. T-statistics are calculated using heteroskedasticity-consistent standard errors.

The UBGI is defined as the ratio of beneficiaries to unemployed persons. It intends to capture the ease of accessing benefits and rises when the system is more generous in accessibility and decreases otherwise. This index is not so strongly affected by secular trends in the time series that make up the PTEW as the PTEW itself. It is reasonable to assume that policy changes in unemployment benefits are the main underlying drivers behind major changes in the UBGI, particularly over long periods of time. This is because the denominator includes unemployed persons, not the working-age population or the labour force.

According to the theory presented, the support for the EWE would be obtained in a similar way as in the case of PTEW. In other words, we expect a negative sign in the second step of the rolling regression procedure, i.e. a negative relationship between the cyclical sensitivity of the PR and the average UBGI for a set window size, as in the case of expression (34). On the other hand, and as to the threshold analysis, we expect a larger value for the coefficient associated with the high UBGI regime (beta 1) than for the coefficient linked to the low UBGI regime (beta 2). As in the case of expression (40), we would expect to find the following relationship: $\beta_1 > \beta_2$.

In Table 9, we show the estimates for the rolling regression method. Note the similarities with Table 6, referring to PTEW. The results ought to be interpreted likewise. The central finding to be highlighted is that all 12 coefficients are negative. This outcome shows that the EWE is also supported by the data when utilizing the UBGI instead of the PTEW. Furthermore, the coefficients are slightly lower in absolute value than those of Table 6, ranging from −1.3 to −1.7 across the different specifications. Nonetheless, we note that they are not strictly comparable. As in the case of Table 6, the high degree of coincidence among the coefficients across the different methods is noteworthy.

In Table 10, we present the results for the threshold analysis. Here, the similarities are with Table 8, and again, these outcomes should be interpreted similarly to that table. As in the case of Table 8, we first let the data speak in order to find the best model for each procedure. The sequential method established that there was a single threshold in all three cases. In the case of LS, that optimal threshold was set for UBGI = 0.438, generating a first subsample with 14 observations in the low UBGI regime and another subsample with 26 observations in the high UBGI regime. Regarding the HP method, the optimal threshold was UBGI = 0.448, creating a low UBGI regime and a high UBGI regime with 16 and 24 observations, respectively. As for the CT method, the threshold was UBGI = 0.454, and the subsamples were made up of 19 (low regime) and 21 (high regime) observations. To check the sensitivity and robustness of these results, we applied the optimal threshold of one procedure for the remaining two other methods. Thus, in Table 10, nine sets of estimates are provided.

In all nine sets of estimates, the condition of beta 1 being larger than beta 2 is fulfilled. If we focus on the optimal model for each method, we obtain $\beta_1^{LS} = 0.38 > \beta_2^{LS} = -0.06$; $\beta_1^{HP} = 0.30 > \beta_2^{HP} = -0.01$; $\beta_1^{CT} = 0.08 > \beta_2^{CT} = -0.06$. The values for beta 1 are more precisely estimated (i.e. more statistically significant) with the LS and HP methods, whereas beta 2 is statistically more significant with the CT method. In any case, the overall picture is clear: in the low UBGI regime the PR is pro-cyclical, and in the high UBGI it is slightly counter-cyclical. This evidence adds further support to the idea that the EWE can play a role in clarifying

Table 9
Rolling beta estimates (UBGI) (different window sizes).

	15-year wind.	16-year wind.	17-year wind.	18-year wind.
LS				
UBGI (coef.)	−1.309	−1.457	−1.555	−1.638
t-statistic	−8.296	−12.542	−15.190	−20.812
N	26	25	24	23
MDV	0.087	0.096	0.094	0.093
R2	0.697	0.862	0.910	0.952
Adjusted R2	0.685	0.856	0.906	0.949
ADF stat.	−2.419	−2.864	−2.197	−2.021
ADF p-value	0.018	0.006	0.030	0.044
PP stat.	−2.419	−2.054	−2.271	−2.127
PP p-value	0.018	0.041	0.025	0.035
KPPS stat.	0.108	0.088	0.094	0.114
KPSS 5%	0.463	0.463	0.463	0.463
CT				
UBGI (coef.)	**−1.745**	**−1.683**	**−1.589**	**−1.440**
t-statistic	−16.432	−12.894	−9.908	−7.969
N	26	25	24	23
MDV	0.100	0.088	0.078	0.068
R2	0.888	0.872	0.815	0.749
Adjusted R2	0.883	0.867	0.807	0.737
ADF stat.	−3.303	−1.911	−3.008	−2.687
ADF p-value	0.002	0.055	0.005	0.010
PP stat.	−2.243	−2.125	−2.145	−2.428
PP p-value	0.027	0.035	0.033	0.018
KPPS stat.	0.083	0.071	0.078	0.094
KPSS 5%	0.463	0.463	0.463	0.463
HP				
UBGI (coef.)	**−1.390**	**−1.470**	**−1.493**	**−1.511**
t-statistic	−34.994	−27.033	−21.068	−16.984
N	26	25	24	23
MDV	0.112	0.115	0.114	0.113
R2	0.970	0.972	0.952	0.925
Adjusted R2	0.969	0.970	0.949	0.921
ADF stat.	−3.401	−1.795	−1.897	−1.408
ADF p-value	0.002	0.070	0.057	0.144
PP stat.	−2.009	−1.868	−1.449	−1.202
PP p-value	0.045	0.060	0.134	0.203
KPPS stat.	0.091	0.203	0.190	0.191
KPSS 5%	0.463	0.463	0.463	0.463

Notes: N= Number of observations; MDV = Mean Dependent Variable; ADF = Augmented Dickey-Fuller; PP=Phillips-Perron (PP); KPSS=Kwiatkowski-Phillips-Schmidt-Shin. T-statistics are calculated using heteroskedasticity-consistent standard errors.

cyclical movements in the PR.

To sum up, evidence based on the UBGI shows a similar scenario to that depicted by the PTEW. Furthermore, the new findings are highly consistent for the two variables in both the case of rolling regression and the threshold analysis. These complementary results reinforce the relevance of Hypothesis 1.

6. Economic policy implications

The policy implications are potentially profound. Traditionally, when the PR exhibited a counter-cyclical behaviour during a downturn, it was assumed that the unemployment rate was overstated. The policy prescription for the government was then to reduce the fiscal stimulus, as the "actual" number of unemployed persons was less than that recorded in the official data. However, aggregate demand management policy should take into account the actual reason behind the behaviour in the PR. According to our results, the fiscal stimulus reduction should focused more on monetary transfers, basically the UB amount, and not so much on government spending cuts. The underlying reason is that in doing so, as our model predicts, opportunistic behaviour would be less financially attractive, discouraging some individuals from such behaviour.

In addition, if the EWE is a major driving factor behind the weakening of the pro-cyclical movements of the PR, policymakers must use supply-side measures to fight the moral hazard problem addressed in this study. Therefore, as the EWE appears to be an issue, economic authorities must monitor the UB system carefully to minimize the underlying opportunistic behaviour. As an economic policy prescription, Public Employment Services (PES), i.e. public agencies dealing with UB provision, should pay closer attention to those unemployment allowances not linked to actual job-search behaviour and scrutinize every potential candidate carefully to avoid fraud.

As a positive side effect, this would incentivize persons to develop a real job-search behaviour, which would lower the natural rate of unemployment, which in turn would raise the potential output, bringing about an efficiency-enhancing mechanism. The efficiency may be further augmented if the matching process in the labour market (between real unemployed persons and vacancies) improves as a consequence of PES monitoring activities.

Moreover, this political action would alleviate the financial difficulties that Social Security systems are facing nowadays in many countries. Public debt is at levels not seen in years in many advanced countries with a developed welfare state. In particular, Social Security budgets have been seriously impacted recently by the COVID-19 pandemic as a result of furlough schemes. At the same time, retirement pensions also depend on the Social Security financial resources, and policymakers must address the issue of ageing populations in countries with generous welfare states. To sum up, PES efficiency-enhancing activities might contribute to the sustainability of welfare state in general and the Social Security system in particular.

7. Discussion and conclusions

This paper identifies and analyses a new effect regarding the cyclical behaviour of labour supply that we dub the Entitled Worker Effect. To this end, we built a formal model in which we explicitly characterized the three recognized theoretical channels: the AWE, the DWE, and the EWE. The key point of this research is that the EWE has its own nature and is different from the two well-known effects regarding the labour supply and the business cycle (i.e. the AWE and the DWE).

The central prediction of the model is that there should be a negative correlation between the cyclical sensitivity of the PR and the PTEW. Put differently, the higher the level of PTEW, the stronger the EWE should be. The rationale for that outcome is, according to the model, that the EWE weakens the DWE and makes the PR less pro-cyclical. However, it is important to stress that the theoretical channel operating has nothing to do with a stronger income effect (i.e. a larger AWE) or with an unexplained change in the way the expectations affect labour supply choices (i.e. an unexplained decrease in the DWE), but rather concerns the moral hazard created by an increasing proportion of people entitled to receive UB.

The empirical evidence seems to support this interpretation of the facts. First, we observe a steady decline in the pro-cyclical sensitivity of the PR to the business cycle from 1980 to the present. Furthermore, the three econometric methods used (LS, CT, and HP) yield a similar evolution of the point estimates for that cyclical sensitivity, which is a sign of the robustness of the results. Second, this continuous decline in the estimated betas with time coincides with a secular increase in the PTEW. The computed correlation between the two variables is very high. Although it is a simple correlation and we do not perform a causality test, it is difficult to think of a reason to expect a reverse causal-effect from cyclical sensitivity to the PTEW. In any case, this might be a field for future research. Interestingly, in the last "windows" of our rolling regression analysis, we detect a counter-cyclical pattern of the PR. Determining whether this empirical regularity will be consolidated in the coming years appears to be an appealing avenue for future research.

Moreover, a number of robustness and sensitivity checks were conducted, all of which supported the idea of a significant EWE. First, we tried different window lengths in our rolling regression procedure and they showed the same basic picture that we obtained with the 15-year

Table 10
Threshold analysis (UBGI).

	LS		HP		CT	
	Coefficient	t-Statistic (P-value)	Coefficient	t-Statistic (P-value)	Coefficient	t-Statistic (P-value)
	UBGI<0.438	14 obs.	UBGI<0.438	14 obs.	UBGI<0.438	14 obs.
Beta 1	**0.377**	4.212	**0.320**	5.310	**0.079**	0.842
		(0.000)		(0.000)		(0.405)
	0.438≤UBGI	26 obs.	0.438≤UBGI	26 obs.	0.438≤UBGI	26 obs.
Beta 2	**−0.061**	−1.461	**−0.008**	−0.287	**−0.043**	−1.599
		(0.153)		(0.775)		(0.118)
R-squared	0.244		0.299		0.057	
Prob(F-stat.)	0.006		0.001		0.335	
AIC	1.694		1.241		2.431	
SC	1.820		1.367		2.557	
DW statistic	1.637		0.864		0.347	
	UBGI<0.448	16 obs.	UBGI<0.448	16 obs.	UBGI<0.448	16 obs.
Beta 1	**0.245**	2.221	**0.301**	6.048	**0.095**	1.075
		(0.033)		(0.000)		(0.289)
	0.448≤UBGI	24 obs.	0.448≤UBGI	24 obs.	0.448≤UBGI	24 obs.
Beta 2	**−0.063**	−1.356	**−0.013**	−0.454	**−0.047**	−1.743
		(0.183)		(0.653)		(0.090)
R-squared	0.151		0.323		0.074	
Prob(F-stat.)	0.048		0.001		0.240	
AIC	1.810		1.205		2.413	
SC	1.936		1.332		2.539	
DW statistic	1.559		1.075		0.374	
	UBGI<0.454	19 obs	UBGI<0.454	19 obs	UBGI<0.454	19 obs
Beta 1	**0.148**	1.612	**0.200**	3.289	**0.076**	1.229
		(0.116)		(0.002)		(0.227)
	0.454≤UBGI	21 obs	0.454≤UBGI	21 obs	0.454≤UBGI	21 obs
Beta 2	**−0.051**	−1.037	**−0.020**	−0.618	**−0.058**	−2.082
		(0.306)		(0.540)		(0.044)
R-squared	0.072		0.222		0.091	
Prob(F-stat.)	0.251		0.010		0.172	
AIC	1.899		1.344		2.395	
SC	2.026		1.471		2.521	
DW statistic	1.447		1.082		0.414	

Notes: AIC = Akaike info criterion; SC = Schwarz criterion; DW = Durbin-Watson statistic. T-statistics are calculated using heteroskedasticity-consistent standard errors.

window. Second, we made use of regional data to build a spatial panel to control for the effect of time in our results. Again, the evidence we obtained was consistent with the rolling regression approach, and the size of the effect was quite similar as well. Third, we conducted a threshold regression analysis. Notably, the results were also strongly supportive of the EWE, despite the fact that it is a markedly different approach from the rolling windows method. Finally, we applied both the rolling regression and the threshold analysis to a different indicator. Instead of using the PTEW as the variable accounting for changes in the unemployment benefit system, we utilized the UBGI. Again, the outcomes of this additional empirical work pointed towards a relevant EWE in the labour market. Thus, two different econometric approaches (i.e. rolling regression and threshold analysis), two distinct indicators (i.e. PTEW and UBGI), two alternative data structures (i.e. time series and panel data), and a number of robustness and sensitivity checks appear to uphold the hypothesis posed in this research.

The economic policy implications are sizeable. They encompass both aggregate demand management and aggregate supply policy intervention. When the EWE is significant, it is preferable to limit the fiscal stimulus during a downturn by means of transfers instead of government spending cuts. On the supply side, public agencies in charge of unemployment benefit allowances ought to screen claimants to avoid false job-search behaviour. This action, in turn, is an efficiency-enhancing mechanism that will help make Social Security budgets more sustainable.

Declaration of competing interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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