Comovement Between Self-Employment and Macroeconomic Variables: Evidence From Spain

Mónica Carmona[1], Emilio Congregado[1], and Antonio A. Golpe[1]

Abstract

The relationship between self-employment and certain macroeconomic variables is often at the heart of the debate about the contributions of self-employment to employment and economic growth; examining this relationship is the aim of this article. This article is devoted to the empirical exploration of the comovement and causality between entrepreneurship and economic performance in both directions. This study searches for basic relationships between self-employment and certain macroeconomic variables in Spain using quarterly data from 1980:1 to 2009:4. From this analysis, four key findings emerge: (a) the relation between self-employment and the business cycle differs across two components of self-employment, that is, employers and own-account workers; (b) the existence of a strong bidirectional causality between self-employment and unemployment and GDP; (c) business cycles contain information valuable for predicting today's employers; and (d) entrepreneurship promotion policies oriented to encourage the emergence of new job creators may be a cornerstone of a new strategy to combat unemployment. These results should be kept in mind when designing entrepreneurship policies.

Keywords

self-employment, entrepreneurship, Spain, time-series models, business cycles

Unemployment in Spain has reached striking levels; it is now the highest in the EU-25. The Spanish unemployment rate reached 22.2% in 2011, and forecasters predict that it will be approximately 23% at the end of this year.

The pessimistic GDP forecasts, combined with a high budget deficit and serious financial problems, do not seem to augur the long-awaited employment recovery.

In this context, the new government has just enacted a deep labor reform (the eighth since 1984) seeking to remove labor rigidities, and they are devising a new self-employment promotion program. These two elements are the primary pillars for combating the dramatic increase in the level of unemployment in an economy affected by the recession.

The logic of promoting self-employment as a way to combat unemployment is quite simple. There are two ways in which self-employment reduces unemployment: directly, by removing a newly self-employed individual from the rolls of the unemployed, and indirectly, because some of these new entrepreneurs will contribute to job creation by hiring workers.

However, inadequate results have cast doubts on public schemes that encourage the long-term unemployed to become self-employed (Congregado, Golpe, & Carmona, 2010; Shane, 2009). The majority of persons participating in the scheme were not qualified to run a business of their own and instead decided to become self-employed as a last resort (Rissman, 2003).

In recessions, lower factor prices (including capital) in combination with lower opportunity costs of paid employment (due to the low job offer arrival rate) tend to lead to an increase in the number of self-employed.[1] As Ghatak, Morelli, and Sjöström (2007) note, the average quality of entrants decreases during recessions, and this phenomenon may prolong the recession. Therefore, promoting entrepreneurship during recessions will reinforce this process of entry into self-employment.

In any case, Lucas (1978) suggests that a large number of these new entrepreneurs will return to paid employment in booms. Thus, the promotion will have only a temporary effect.

In sum, promoting entrepreneurship may not be a panacea for the long-term redeployment of unemployed people. However, the key factor, at least in countries ravaged by unemployment like Spain, is knowing whether the relationship between self-employment and certain macroeconomic variables, such as GDP or the unemployment rate, can help us better understand the possible role of entrepreneurship policies during recessions.

The relationship between self-employment and macroeconomic variables is at the heart of the debate about the

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contribution of self-employment to economic development. In particular, a better understanding of the dynamics of self-employment over the cycle has become crucial for rethinking entrepreneurship promotion policies during a crisis, when policy makers are tempted to use self-employment promotion as a countercyclical policy. The key contribution of this article is to develop this understanding using an empirical basis to clarify the correlation and causality relations between self-employment and macroeconomic variables. In particular, we investigate whether Spanish self-employment influences subsequent economic performance, as suggested by some recent research (e.g., Fritsch & Mueller, 2004; Koellinger & Thurik, 2009; Thurik, Carree, van Stel, & Audretsch, 2008) or as other works claim (e.g., Carmona, Congregado, & Golpe, 2010; Congregado, Golpe, & Parker, 2011), and whether empirical evidence suggests the reverse effect, that is, business cycle fluctuations have a greater effect on self-employment.

We analyze these relations using time-series analysis techniques that allow us to distinguish the different causal relations between self-employment and macroeconomic performance.

From an empirical perspective, the available evidence suggests that individual transitions into entrepreneurship are more numerous in booming economies and lower in bad ones. However, this evidence is usually based on estimates of the sign of time dummies in individual-level studies of occupational choice, rather than being derived from careful analyses of time-series data.

Time-series data have been used to determine how multiple aggregate variables covary over time. However, some standard regression analysis techniques can be vulnerable to the emergence of "spurious" correlations. For this reason, it is crucial to test the robustness of the empirical results via adequate econometric techniques as well as via alternative approaches.

The contribution of this article to existing work on the relation between self-employment and business cycles is twofold. First, we apply time-series techniques to more carefully investigate the relation between self-employment and business cycles. In particular, we apply these techniques to high-frequency macrodatabases containing quarterly observations, which enables us to draw inferences on the causality of the relation. This ability is important because stimulating self-employment is justified only if self-employment causes enhanced macroeconomic performance. Second, when investigating the relation between self-employment and the business cycle, we distinguish between employers and own-account workers. We argue that previous entrepreneurship research seems to have overlooked this distinction. Entrepreneurs who hire external labor ("employers") could exhibit different cyclical behavior compared with entrepreneurs who work on their own ("own-account entrepreneurs"). In booming economies, entrepreneurs can scale up production and expand employment, bidding up wages, thereby drawing relatively low-value own-account entrepreneurs out of entrepreneurship and into paid employment (Lucas, 1978). Furthermore, we might expect some own-account entrepreneurs to start hiring labor (Cowling,

Mitchell, & Taylor, 2004), in which case they switch from own account to employer status. In light of this switching, one might expect the number of employer entrepreneurs to increase relative to the number of own-account entrepreneurs, making cyclical effects positive for employer entrepreneurs and negative for own-account entrepreneurs. Previous studies have obviated this distinction. For this reason, previous results can be biased because own-account workers are the more numerous group within self-employment. Our empirical work will take into account this possible source of bias.

As mentioned, this article takes a macroeconomic approach and focuses as much on the short run as on the long run by analyzing the comovement and the causality between our variables. The next section describes the data set and methods. We begin with the study of comovement. This analysis involves two different approaches: the traditional cross-correlations approach (Burns & Mitchell, 1946) and the use of Vector Autoregression (VAR) forecast errors (den Haan, 2000a). The causality analysis is performed with the analysis of instantaneous and Granger causality. Concluding remarks are given in the last section.

Method

Data and Time-Series Properties

The data used in this article are a sample of quarterly data on nonagricultural[2] employment by status —salaried workers (W_t) and self-employed workers (S_t)—for Spain, covering the period 1980:1-2009:4.[3] Spanish aggregate statistics allow the decomposition of self-employed workers in two components: employers (E_t) and own-account workers (O_t). Finally, the real GDP and unemployment rate are denoted, respectively, by Y_t and U_t.

Self-employment data used in this article are seasonally adjusted quarterly Spanish observations drawn from the Labour Force Survey (LFS, Spanish National Statistics Institute). In the Spanish LFS, workers are asked questions about their main job or business, including, "Were you an employee or self-employed?" If self-employed, the respondent is further asked whether they had any employees. The self-employed in Spain can then be classified as incorporated with or without employees or unincorporated with or without employees.

Finally, for the remainder of the data used in our empirical work, the real GDP is taken from Quarterly National Account database (INE).[4] Figure A1 (in the appendix) plots the original time-series data, which is seasonally adjusted, expressed in logs. Time series are detrended using the Hodrick–Prescott (HP) filter.[5] Figure A1 represents original data and the cycles of each variable using this filter.

Measuring Comovement With Traditional Statistics

This section analyzes comovements between self-employment, real GDP, and unemployment, using the methodology

developed by Burns and Mitchell (1946). This method uses the magnitude of the cross-correlation coefficient, $\rho(j)$, as a measure of the degree of comovement between each pair of series. In particular, the contemporaneous cross-correlation coefficient $\rho(0)$ gives information on the degree of contemporaneous comovement, whereas the cross-correlation coefficient $\rho(j)$, $j \in \{\pm 1, \pm 2, \pm 3, \pm 4\}$, gives information on the phase shift of one series relative to another (Kydland & Prescott, 1990). The comovement between each pair of variables is defined as follows: Two variables are said to commove in the same direction over the cycle if the maximum value in absolute terms of the estimated correlation coefficient is positive; they are said to commove in opposite directions if it is negative, and they are said to not commove if it is close to zero. A large number in (absolute terms) appearing in column $t + i(t - i)$ indicates that the series lags (leads) the cycle by i quarters. If the variable value of the cross-correlation is highest at $i = 0$, then the variable is said to move contemporaneously with the cycle. The results are reported in Tables 1 and 2.

Tables 1 and 2 reports the correlation between labor time series and output (unemployment). We also report, the correlations for the two components of self-employment (employers and own-account workers), to test the existence of "potential" opposite comovements between them over the cycle. The critical value for the correlation coefficient—for the whole sample—is .092.[6] σ_x represents the standard deviation of the variable (in percentage terms), σ_X/σ_Y is the standard deviation of each variable as a fraction of output reflecting its relative variability, and ρ_T is the first-order autocorrelation coefficient, which measures persistence.[7]

Using GDP as a proxy for the business cycle, self-employment and GDP show a peak correlation of .629 at a lag of 0. This means that self-employment is procyclical and adjusts contemporaneously with the GDP cycle.

The results are similar when distinguishing between the two components of self-employment. The own-account worker series shows procyclicality and adjusts contemporaneously with the GDP; however, the correlation between the GDP and employers peaks at .620 with a lag of one quarter. Thus, the GDP leads employers.

To assess the robustness of these findings to the choice of cyclical indicator, Table 2 reports the results of the same exercise but uses unemployment in place of the GDP. In this case, the correlation between self-employment and unemployment achieves a peak correlation of −.660 at a lag of 1, that is, self-employment is countercyclical and adjusts with a lag in comparison with unemployment. Employers and own-account workers are also countercyclical with unemployment. Whereas own-account workers adjust contemporaneously, unemployment leads employers. In sum, self-employment in Spain seems to be contemporaneous with the cycle, whereas the business cycle leads employers' cycles.

Measuring Comovement With VAR Forecast Errors

The previous approach is not the only way to analyze comovements between variables. The comovement between real activity or unemployment and employment series can be also described using the correlation coefficients of forecast errors from vector autoregresive systems at different forecast horizons as proposed in den Haan (2000a). This procedure has advantages over traditional statistics used in the previous section. The previous method focused on only the unconditional correlation, losing valuable information about the dynamic aspects of the comovements of variables. Moreover, as the unconditional correlation coefficient is only defined for stationary variables, the researcher has to transform the data to render it stationary, and there are many ways of doing this—that is, different detrending methods. Finally, this method is suited for the discussion of short-term, medium-term, and long-term correlations.

Following den Haan (2000a), we are going to calculate correlation coefficients of forecast errors at different forecast horizons, obtained from estimations of various specifications of the following VAR model:

$$X_t = \alpha + \beta t + \gamma t^2 + \sum_{t=1}^{l} A_1 X_t + \varepsilon_t, \tag{1}$$

where X_t is the 2×1 vector containing the log of output or the log of unemployment level, and the log of each employment series,[8] α, β, and γ are $N \times 1$ vectors of constants, $\mathbf{A}_1$ are fixed $N \times N$ coefficient matrices, ε is an N-dimensional white noise process that is, $E(\varepsilon_t) = 0$, $E(\varepsilon_t \varepsilon_t') = \psi_\varepsilon$, and $E(\varepsilon_t \varepsilon_t') = 0$ for $s \neq t$, and the total number of lags included is equal to l.

Finally, we define the K-period ahead of the forecast error of each variable X_t as follows:

$$e_{t+K}^X = X_{t+K} - E_t X_{t+K}. \tag{2}$$

Then, we calculate the correlation between these K-period forecast errors and denote it by Corr(K). Note that the use of this approach in a particular horizon of K can be interpreted as a cycle-trend decomposition, where the trend component is given by $E_t X_{t+K}$ and the cycle component is given by $X_{t+K,t}$. Therefore, when we analyze the VAR error forecast error correlation at different horizons, we are studying the comovement between the different cycle components of each pair of variables. Applying this methodology, we must estimate 10 bivariate VARs (5 with regard to GDP and 5 with regard to unemployment).[9]

The correlation coefficients are plotted in Figure 1. The results confirm those of previous studies using traditional statistics. On one hand, as we can see from the figure, the coefficients are significantly positive at all horizons in relation with

Table 1. Correlation of HP-Filtered Labor Market Series and Output at Different Leads and Lags

X_t^{hp}	σ_x	σ_x/σ_y	ρ	cor (X_t^{hp}, GDP$_{t+k}^{hp}$)								
				−4	−3	−2	−1	0	1	2	3	4
W	.019	1.500	.916	.627*	.678*	**.689***	.676*	.612*	.460*	.303*	.173	.047
U	.092	7.180	.921	−.248*	−.394*	−.568*	−.718*	**−.830***	−.818*	−.731*	−.592*	−.407*
S	.020	1.554	.794	.065	.235*	.401*	.551*	**.629***	.528*	.398*	.234*	.078
E	.031	2.407	.705	.298*	.413*	.482*	**.620***	.593*	.514*	.343*	.222**	.096
O	.023	1.785	.780	−.035	.118	.280*	.405*	**.506***	.435*	.358*	.226**	.091

Note: HP = Hodrick–Prescott. The highest correlation coefficients are given in bold.
*, **, and *** denote significance at 1%, 5%, and 10%, respectively.

Table 2. Correlation of HP-Filtered Labor Market Series and Unemployment at Different Leads and Lags

X_t^{hp}	σ_x	σ_x/σ_y	ρ	cor (X_t^{hp}, U_{t+k}^{hp})								
				−4	−3	−2	−1	0	1	2	3	4
W	.019	.209	.916	−.637*	**−.686***	−.679*	−.630*	−.541*	−.382*	−.239**	−.112***	−.000
Y	.013	.139	.805	−.407*	−.592*	−.731*	−.818*	**−.830***	−.718*	−.568*	−.394*	−.248*
S	.020	.216	.794	−.267*	−.456*	−.589*	**−.660***	−0.642*	−.488*	−.326*	−.154***	−.018
E	.031	.335	.705	−.424*	−.533*	**−.601***	−.601*	−0.529*	−.383*	−.226**	−.090	−.002
O	.023	.249	.780	−.142	−.321*	−.455*	−.546*	**−.567***	−.457*	−.341*	−.191**	−.058

Note: HP = Hodrick–Prescott. The highest correlation coefficients are given in bold.
*, **, and *** denote significance at 1%, 5%, and 10%, respectively.

the GDP and significantly negative at all horizons in the unemployment case. In both cases, the correlation coefficients tend to become larger as the forecast horizon increases and then stabilize, typically at forecast horizons of approximately 2 years.

Causality

If we interpret the presence of cross-correlation between output (or unemployment) and self-employment, we should conclude that unemployment and output transmit their cycles to the self-employment cycle. Our objective is now to measure the influence of the business cycle on the self-employment cycle or vice versa, using the VAR's parameters. As they are a transformation of the cross-correlation function, they allow us to make inference about two types of causality: (a) Granger causality and (b) instantaneous causality.

We start looking for Granger and instantaneous causality. To carry out these causality tests, we need to perform the following VAR:

$$\begin{pmatrix} W_t \\ Y_t \\ U_t \\ S_t \end{pmatrix} = \mathbf{c} + \sum_{j=1}^{l} \mathbf{A} \begin{pmatrix} W_{t-j} \\ Y_{t-j} \\ U_{t-j} \\ S_{t-j} \end{pmatrix} + \varepsilon_T, \tag{3}$$

where $\mathbf{A}_j$ is the matrix of coefficients, $\mathbf{c}$ is a vector of deterministic terms, and ε_t is the vector of innovations. At this point, we are interested in the lag length selection of the VAR. To determine the optimal number of lags, we estimate an unrestricted VAR using the data in levels and then choose the appropriate lag length using the Akaike, Schwarz, and Hannan-Quinn information criteria. The lag length was set to 2 on the basis of Hannan-Quinn's and Schwartz's information criteria for a multivariate system (see Table A1 in the appendix).

One could argue that it would be interesting to study whether the variable responds immediately to shocks in other variables. To this end, we will use the concept of instantaneous causality. The *instantaneous causality* concept refers to the possible instantaneous correlation between the cyclical components of various variables. Roughly speaking, a variable x_t is said to be instantaneously causal for another time-series variable z_t if knowing the value of x_t in the forecast period helps to improve the forecasts of z_t. In sum, if the innovation to z_t and the innovation to x_t are correlated, then there is instantaneous causality.[10] The results of the instantaneous causality tests are reported in Table 3. For self-employment and own-account workers (but not the employers), our estimates show an instantaneous causality with the GDP and unemployment. However, the finding of instantaneous correlation between two time series implies that causality can go
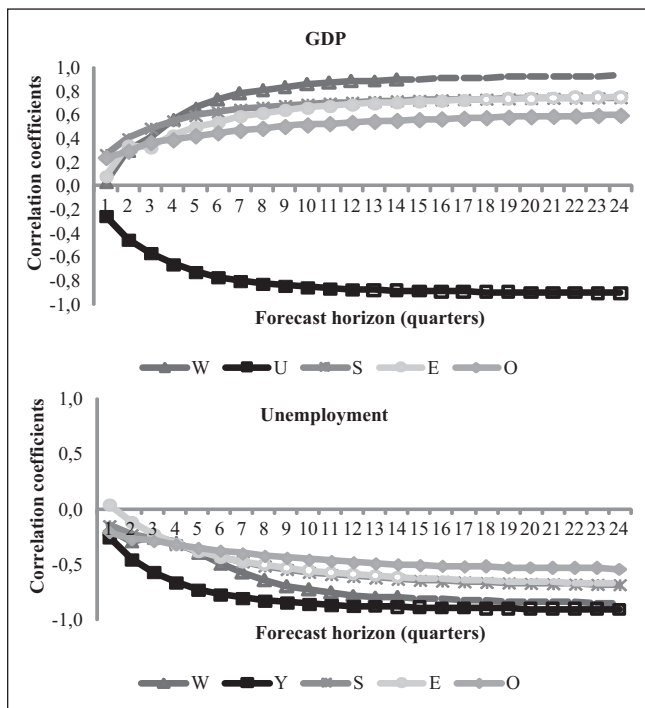
Figure 1. Correlation coefficients of VAR forecast errors
Note: The open squares, circles, or triangles indicate that the estimate is significant at the 10% level and the closed ones indicate that the estimate is significant at the 5% level. A broken line indicates that the estimate is not significant at the 10% level.

either way, that is, the concept of instantaneous causality is fully symmetric, not specifying a causal direction.

To determine the direction of the causality relationship, we use Granger causality. Applying this concept to our case study suggests that the cyclical component of GDP, unemployment, or paid employment does not cause, in a Granger sense, the self-employment (employers or own-account workers) cycle, if lagged cyclical components of GDP, unemployment, or paid employment are not significant in the VAR equation corresponding to cyclical self-employment. In sum, testing for Granger causality between, for example, X and Z consists of checking the significance of the coefficient in the corresponding VAR equation. In other words, X does not Granger-cause Z if the vector has no forecasting power. Each equation represented is estimated separately in testing for Granger causality, and the null hypothesis tested is "X does not Granger-cause Z, and Z does not Granger-cause X."[11] The results of the Granger causality test are reported in Table 3. Each element of the table shows the Granger causality test *p* value from column to row. The results confirm the existence of a bidirectional causality between self-employment and unemployment, whereas the GDP causes self-employment. These results are consistent with some prior evidence of bidirectionality between self-employment and unemployment rates (Faria, Cuestas, & Gil-Alana, 2009; Faria, Cuestas, & Mourelle, 2010; Thurik et al., 2008).

However, if we consider the two self-employment components separately, the results are slightly different: on one hand, the employers' cycle is Granger-caused by the rest of the cycles, but the business cycle is not Granger-caused by the employers; on the other hand, the own-account workers cycle is caused only by unemployment and paid employment. Finally, the employers' cycle is Granger-caused by own-account workers. In sum, causality results reveal that the labor market situation helps to forecast own-account workers, whereas the business cycle phase (GDP or unemployment) contains valuable information for predicting today's employers. Moreover, the results point to the existence of a bidirectional causality between employers and paid employment. Finally, employers appear to adjust immediately in response only to shocks to the wage earners, whereas own-account workers seem to respond immediately to shocks to unemployment and the GDP.

Discussion

The objective of this article was to shed light on the interplay of entrepreneurship and the business cycle, providing new empirical evidence on the development of self-employment over the business cycle to understand what may be expected of public schemes encouraging people to become self-employed in terms of scope and effectiveness. These public schemes are a very highly contested policy issue because entrepreneurship is considered to be a way to combat the current recession.

Our results identified a procyclical relationship with output and unemployment driving cycles in self-employment cycles. However, when we relaxed the assumption of common relationships between the two self-employment components, a different picture emerged. In particular, the own-account workers cycle is driven by the labor market situation, whereas employers' cycle is driven by the business cycle phase and the labor market situation.

From our results, one could argue that the added value of promoting entrepreneurship is given only in terms of job creation because it does not contribute to economic recovery. Furthermore, the promotion's effects are different for the different types of self-employment. On one hand, the promotion of own-account workers only leads to changes in employers' cycles, whereas on the other hand, the promotion of job creators (employers) contributes directly to job creation and reduces unemployment.

In sum, entrepreneurship policies will only have effects on unemployment. However, it should be considered as useful alternatives of active labor market policies.

Some tentative policy recommendations can be advanced on the basis of our results. Countercyclical policies that boost self-employment during economic downturns might be a good complement to other active labor market policies for combating unemployment, but positive effects on output growth should not be expected. Only a promotion aimed at employers could contribute to reduce unemployment; there would be no effect on job creation if the promotion is only targeted at the most numerous group of self-employed: the own-account workers.

Table 3. Causality Analysis

Variable	Granger →W	Instantaneous ↔W	Granger →U	Instantaneous ↔U	Granger →Y	Instantaneous. ↔Y	Granger →S	Instantaneous ↔S	Granger →E	Instantaneous ↔E	Granger →O	Instantaneous ↔O
W			**.000**	0.218	.727	**.031**	**.033**	**.021**	**.000**	**.000**	**.072**	0.945
U	**.000**	.218			**.000**	**.001**	**.000**	**.001**	**.000**	.856	**.008**	**0.000**
Y	**.000**	**.031**	.129	**.001**			**.060**	**.005**	**.000**	.488	.354	**0.001**
S	.143	**.021**	**.003**	**.001**	.111	**.005**						
E	.590	**.000**	**.002**	0.856	.153	.488					.628	0.975
O	.945	.945	.151	**.000**	.159	**.001**			**.012**	.975		

Note: Bold values indicate *p* values less than 10%. Null Hypothesis: X_t does not cause Z_t.

Appendix
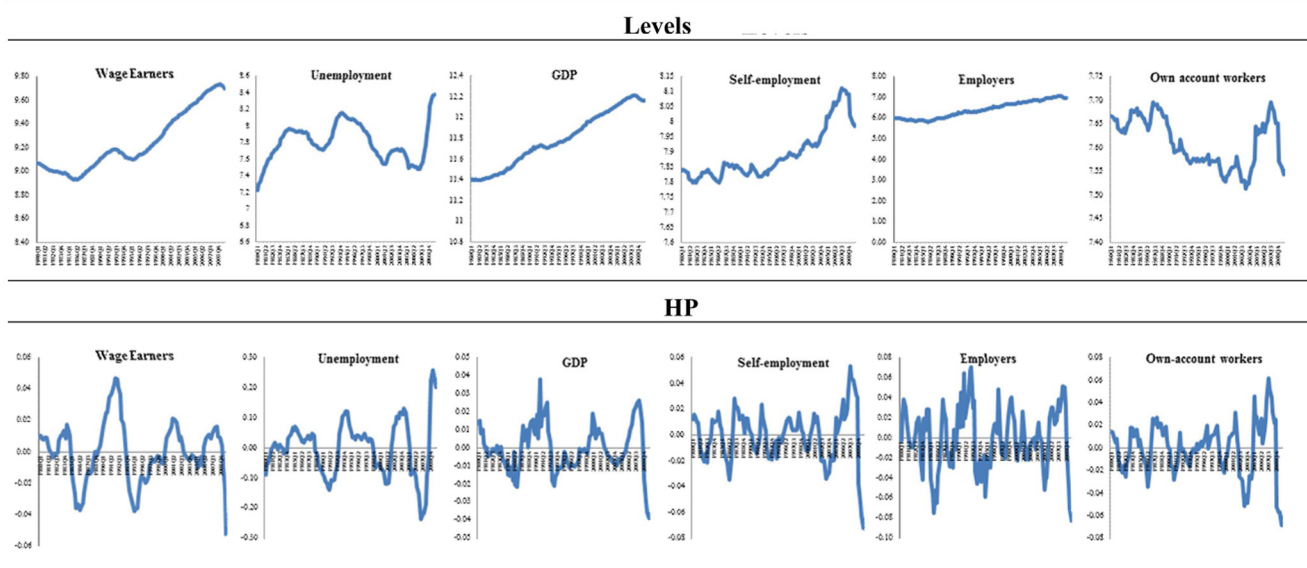
Figure A1. Graphs and results

Table A1. AIC, SC, and HQ Statistics (VAR Lag Length)

Hodrick–Prescott

Lags	AIC	SC	HQ
1	−25.80729	−25.41893	−25.64972
2	−26.40065	−25.62394*	−26.08551*
3	−26.40037	−25.23529	−25.92766
4	−26.63296	−25.07953	−26.00269
5	−25.80729	−25.41893	−25.64972

Note: AIC = Akaike Information Criteria; SC = Schwarz Information Criteria; HQ = Hannan-Quinn Information Criteria
* indicates lag order selected

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Notes

1. See the recession-push effect discussed by Storey (1994) or the emergence of marginal worker cooperatives formed during recessions, as Ben-Ner (1998) and Pérotin (2006) note.
2. Workers in the agricultural sector are excluded because this sector is structurally different from the rest of the economy. This exclusion is a common practice in the existing literature.
3. Self-employment statistics by sector were not available in Spain until this quarter.
4. They are expressed in 1995 prices and seasonally adjusted.
5. The Hodrick–Prescott (HP) filter is a standard method of removing trend movements. The smoothing parameter λ of the filter, which penalizes acceleration in the trend relative to the cycle component, needs to be specified. By using quar-

terly data, it is a common practice in the business cycle literature to use a λvalue of 1,600, as the work of Hodrick and Prescott (1997) suggests.

6. See McCandless and Weber (1995) or Hoel (1954). The standard deviation of the correlation coefficient can be computed as $(n - 3)^{-1/2}$, where *n* is the sample size.

7. The measure of persistence is the cycle correlation with its first lag (Campbell & Mankiw, 1987).

8. Let us remember that these series are in logs and seasonally adjusted.

9. The lag length and the inclusion of linear and quadratic trends are based on the Akaike information criterion. Ninety percent confidence intervals are calculated by using bootstrap methods. Each estimated VAR and its bootstrapped errors generate 2,500 repetitions.

10. Following Lütkepohl (1991), instantaneous causality may be viewed as a measure of the instantaneous relation between two variables when all intertemporal relations have been accounted for.

11. See Lütkepohl and Krätzig (2004) for a detailed explanation.

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