UNIVERSIDAD DE HUELVA

DOCTORAL THESIS

Self-employment at the Macro-Level: Drivers, Inhibitors and Fluctuations

Author:
Ana María Rodríguez Santiago

Supervisors:
Dr. Máximo Camacho
Dr. Emilio Congregado

A thesis submitted in fulfillment of the requirements for the degree of Philosophy in the Doctoral Program in Economics, Business, Finance and Computer Science
University of Huelva and International University of Andalusia

Department of Economics

June 2022

A mis almas gemelas

"The important thing is not to stop questioning. Curiosity has its own reason for existence."

– Albert Einstein

"Nothing in life is to be feared, it is only to be understood. Now is the time to understand more, so that we may fear less."

– Marie Curie

Index

Preface

I would like to express my deepest gratitude to my supervisors, Emilio Congregado and Máximo Camacho, for their support and supervision during these fruitful years. Emilio, the most helpful and decisive professor, and the best supervisor I could ever imagine. And Máximo, one of the brightest people I have ever had the pleasure to know. I could not think of a better tandem team. Thank you for teaching me so much and walking me through this path. You both made me love what I do.

Besides my supervisors, I would like to express my gratitude to Jesús Crespo for his invitation and support during my stay at the Vienna University of Economics and Business. Furthermore, I also want to thank all the people who were part of the MSc and PhD in Economics, Finance and Computer Science.

My special thanks to my colleagues and friends from the Spanish Entrepreneurship Research Group and the University of Huelva, Concepción Román, Mónica Carmona, Inmaculada Vílchez, Javier García, Pablo Casas, José Carlos Vides, Maribel de Andrés, Marisa Vílchez, Montse Pereira, Antonio Golpe, Alejandro Almeida, Jesús Iglesias or Juanma Martín. It has been a pleasure to learn from all of you and to share so many special moments together.

My deepest thanks to my family. I thank mum and dad for the unconditional support and admiration. I also want to thank my brother Marcial, the smartest person I know, because you have always been an inspiration to me.

Very especially, I am grateful to my friends, the family I chose. To Mis puntitos Anna, Francesco, Arantza and Bryan, for the good energy and unmeasurable moments of pure joy, you all just make me happy and a better person whenever I am with you. To my two halves, María and María del Mar, for the good moments and endless love. To my own couple, Cinta and Borja, for being there all along the way. To Ana Blanco for her inspiration and encouragement. To Inma for appearing the last year and making it

awesome. And to so many other friends that I have the pleasure to share my life with: Wanda, Ale, Juanma Catela, Juanma Papurri, Isa, Ángela, Antonio, Marina, José Pablo, Josemi, Paco, Pablo and all my T-guys, you all have made my life easier these years. Thank you for being there to celebrate each achievement.

I am honored that you all believed in me.

Huelva, June 2022

Ana M. Rodríguez Santiago

Part I: Introduction

Chapter 1: Introduction

1.1. Motivation, aims and scope

Recent self-employment dynamics have triggered a renewed interest among scholars and analysts, being common the association between self-employment growth and the deterioration of labor market conditions. These phenomena have run parallel both to weak employment intensity of growth since the onset of the financial crisis, the persistent elevated level of involuntary part-time work (Bell and Blanchflower, 2021; Valletta et al., 2020; Borowczyk-Martins and Lalé, 2018, 2020) and the emergence of the growth of "non-standard" or "alternative" forms of work linked to the on-demand economy –gig economy– enabled by digital labor platforms (Congregado et al., 2019, 2022; Bracha and Burke, 2021).

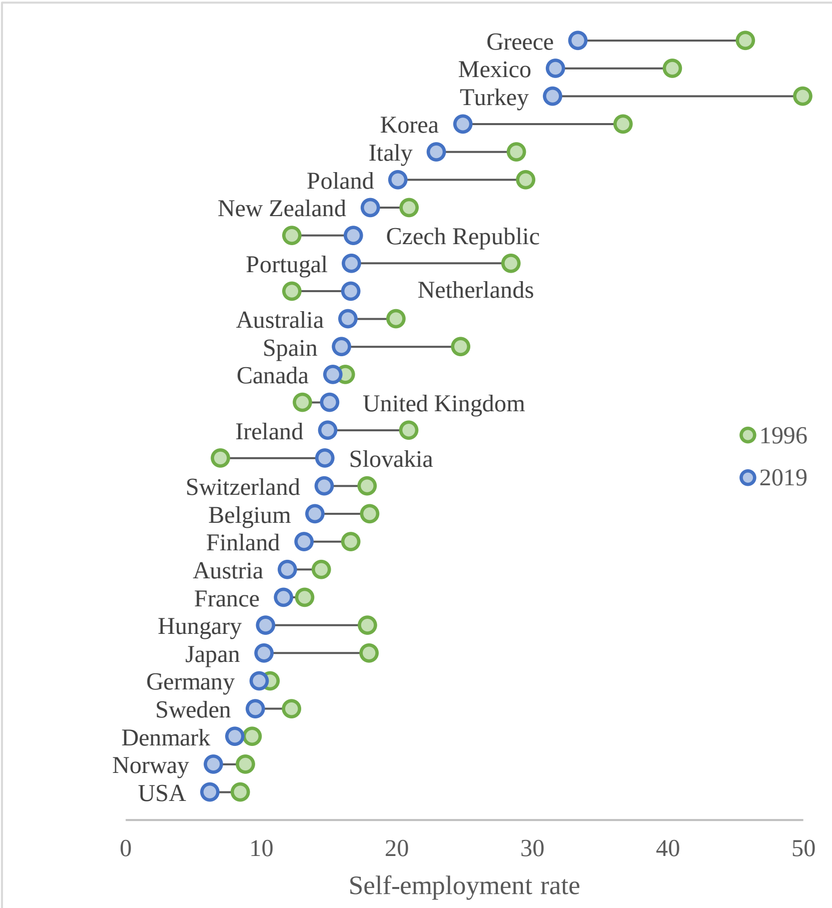
After the Great Recession, some developed countries reached the highest levels of self-employment since its records began. The cases of the United Kingdom, the Netherlands and Canada, among others, are representative of this evolution (see figure 1 and 2). In addition, most part of the new employment created during the recovery phase after the Great Recession of 2008, was due to the growth in solo self-employment (Boeri et al., 2020)[1].

However, the most surprising and shocking fact, before the COVID-19 crisis, was that there has been no real change in the proportion of people choosing to enter self-employment, but a significant drop in the proportion

[1] This expression in the entrepreneurship/self-employment literature, refers to those within the self-employment sector, who work entirely on their own account, without employees. They are the group of own-account workers or independent contractors –self-employment without employees– defined in the International Classification of Status in Employment (Congregado, 2007; Iversen et al., 2007; Ahmad and Hoffman, 2008; Ahmad and Seymour, 2008).

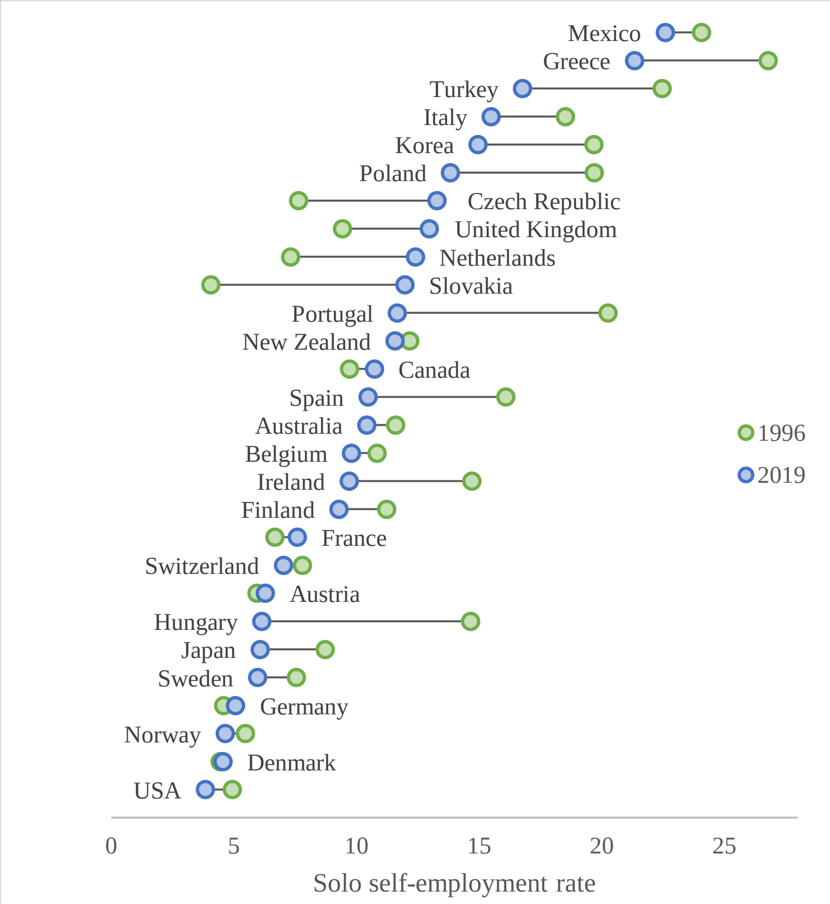
leaving self-employment[2] –maybe due to the lack of opportunities in the traditional employee-employer labor market–.

Figure 1. Self-employment rates in 28 OECD countries, 1996 and 2019



[2] Turning unemployment into self-employment was a common practice during the Great Recession as way to combat unemployment since traditional active labor market policies did not work. However, one would expect that the phase of recovery after a crisis was characterized by transitions from self-employment to work as an employee, at least for the so-called "necessity" entrepreneurs (Fairlie, 2013; Cima et al., 2017). However, during the recovery phase following the Great Recession, this was not the case: these marginal entrepreneurs did not transition back into salaried employment.

Figure 2. Solo self-employment rates in 28 OECD countries, 1996 and 2019



In other words, the counter cyclicality of (solo) self-employment breaks after the Great Recession. In this new phase of recovery the impossibility to find a full-time job offer in the wage sector, due to an insufficient employment intensity of growth, causes that, now, even when the economy is booming, a great part of the self-employed workers are associated to marginal entrepreneurs, groups of secondary and vulnerable workers, including women, young workers, the elderly, immigrants, and workers whose jobs are precarious –gig workers–, who remain "trapped" in the self-employed sector (Boeri et al., 2020; Giupponi and Xu, 2020), some of them as precarious self-employed workers (Reuschke and Zhang, 2022).

Nevertheless, not all the rise in self-employment was associated to precarious jobs in the gig sector. Along with this, there is also a rise associated to professionals, scientific and technical activities, and the emergence of new forms of self-employment –hybrid, dependent, and underemployed among others– running in parallel to the new forms of employment and to the emergence of the so-called digital labor platforms (Congregado et al., 2022).

However, this phenomenon is not entirely new. In fact, the emergence of the so-called digital labor platforms only deepens and accelerates trends that began decades ago. As production technologies made it possible to divide tasks with low transaction costs, the phenomenon of outsourcing and the hiring of professionals –self-employed workers– from outside the company gained ground over the characteristic employer-employee relationship of traditional employment. Furthermore, we cannot rule out that stricter labor market regulations encouraged the growth of self-employment, insofar as firms attempted to circumvent the constraints and costs of employment protection legislation (henceforth, EPL) by substituting activities carried out in the framework of regular employment with self-employed persons hired to perform work on-demand (Robson, 2003; Román et al., 2011). Under certain circumstances, more employment protection for salaried employees could lead large firms to adopt flexible production strategies relying more heavily on external independent contractors. This creates new market niches for self-employed professionals, that is, reduces uncertainty, increases opportunities for self-employed workers making self-employment failure less likely (Arum et al., 2000).

As if this was not enough, the legacy of the Great Recession was a flexibilization of the labor market institutions and a substantial reduction of the EPL, which together with the recent introduction of job retention schemes for self-employed workers during the COVID-19 crisis, have notably altered the opportunity cost of being self-employed.

All these developments might have deep effects on the composition of labor market, on the national self-employed sector, and ultimately on its capacity for contributing to economic growth and employment.

Despite all this, and although there are many who consider that the upturn in self-employment is associated with the deterioration of employment, governments continue to use policies to promote self-employment and entrepreneurship as key pillars of their political action agenda, allocating large amounts of resources to encourage transitions to self-employment and to achieve a more entrepreneurial society (Audretsch, 2009; Elert et al., 2019).

Given the clarity with which these policies are being advocated, it is to be hoped that practitioners and policy makers will design these policies on the basis of the solid propositions and the empirical evidence provided by previous literature, in terms of which factors are drivers and which are inhibitors for achieving an entrepreneurial society and on how to manage the effects of policy and economic shocks on the entrepreneurship dynamics over the business cycle, on how self-employment responds to business cycles.

The empirical research at the micro- and meso-level provides a robust and exhaustive evidence while at the macro level the evidence is controversial (Kim et al., 2016). The evidence is mixed and not too robust at the macro level, largely due to the availability of low-dimensional datasets which has limited the application of some econometric approaches and a deep analysis of the dynamics. The aim of this thesis is to provide a deepen macro analysis thanks to the availability and exploitation of new data sources in both cross-sectional and longitudinal dimensions that facilitate, not only revisiting the results on the determinants of entrepreneurship across countries, but also addressing the study of the cyclical behavior of entrepreneurship with appropriate macro-econometric techniques.

In this context, some issues particularly intriguing, at the time of writing, are: revisiting the interplay between entrepreneurship and economic growth; identifying its determinants, specially how some macroeconomic variables and labor market institutions affect to the opportunity cost of being self-employed; and providing evidence for understanding the new dynamics of self-employment across the business cycle and the resilience into self-employment, since the onset of the financial crisis.

To this end, this dissertation aims to shed new light on these main issues: (1) the new dynamics of self-employment including issues related to persistence/hysteresis; (2) the role of the country-specific macroeconomic and institutional characteristics as drivers or inhibitors of entrepreneurship; and (3) the empirical identification of homogeneous groups of countries in terms of the productivity of their national self-employment sectors, identifying the factors that increase the probability of transition from a low productivity group to a higher productivity group.

1.2. Research gaps and contributions

Once the research gaps have been identified, the next step is describing the different strategies and ways to address the above-mentioned issues and a preview of the main contributions of this thesis.

Data and indicators

Entrepreneurship is a multifaceted concept which encompasses a range of roles including the innovation, the reduction of inefficiencies, the discover of profit opportunities and the strategic decision making in an uncertain environment (Lyalkov et al., 2020). Any single measure of entrepreneurship is unlikely to do justice to all these facets. At the macro level, the most common measure used in practice is self-employment rates, reflecting the widespread availability of aggregate data for a range of countries[3]. In some extent, and although self-employment is not a perfect measure of entrepreneurship, self-employed workers (independent worker or business owners) correspond to the Kirznerian and Knightian entrepreneur. In sum, the self-employment definition has the merit of inclusiveness and convenience specially for cross-country studies. There are different ways to operationalize entrepreneurship. Although entrepreneurship and self-employment are not the same thing, self-employment is often used as a way to operationalize empirically the concept. Self-employment and entrepreneurship are used in this dissertation as interchangeable concepts.

---

[3] Labor Force Surveys are the most common source of data for operationalize entrepreneurship. The classifications of employment by status provide internationally harmonized data on the occupational choice decisions in both micro- and macro-level. The International Labour Office Statistics currently provide updated time series for cross-country analysis. Previous essays to provide internationally comparable data at the macro-level includes the COMPENDIA data base (Van Stel, 2005; Van Stel et al., 2010) and the OECD-Eurostat entrepreneurship indicators program. Special attention should be paid to the attempt of the Global Entrepreneurship Monitoring Consortium to provide a measure of the entrepreneurial dynamism at the macro-level. The early-stage entrepreneurial activity (TEA) indicator has become a benchmark in empirical studies. However, the low frequency and the short cross-sectional and longitudinal dimensions available in this dataset, discourage its use for the analysis of the entrepreneurship drivers (Reynolds et al., 1999, 2001; Minniti et al., 2007; Bosma, 2013).

The self-employment/entrepreneurship data used are mainly extracted from the International Labour Organization Statistics (ILOSTAT) database. Based on the employment status we can distinguish between two categories of the total employed: (a) wage and salaried workers (also known as employees); and (b) self-employed workers. The self-employed group is broken down in the subcategories: self-employed workers with employees (employers), self-employed workers without employees (own-account workers), members of producers’ cooperatives and contributing family workers (also known as unpaid family workers). Data are drawn from labor force surveys and household surveys and the series is part of the ILO estimates and it is harmonized to ensure comparability across countries and over time by accounting for differences in data source, scope of coverage, methodology, and other country-specific factors. The estimates are based mainly on nationally representative labor force surveys, with other sources (population censuses and nationally reported estimates) used only when no survey data are available.

Monthly and quarterly self-employment rate, as the percentage of the labor force that is self-employed, is used for the study of hysteresis and analysis of cycle in the UK. For the first of them, furthermore real GDP in billions of chained 2005 British pounds is used (from Quarterly National Accounts database); and for the second work, monthly unemployment rate (from ILOSTAT database) and business confidence index series (from OECD Statistics) are used to explore the causality relationships between these two series and the self-employment series.

For the third part of the thesis, annual data have been used. A complete panel of 187 countries for 30 years has been created, and different subsamples of countries in different spans have been used depending on data availability for the focus variable as well as for the other variables included in our empirical models.

A balanced panel from 2005 to 2019 is used to evaluate the role of stages of economic development when determining self-employment rates across 117 countries, using covariates related to GDP and components, technological progress, human capital, labor market, population and institutions. Statistics are taken from different sources such as ILOSTAT, the World Bank database, the index from the World Intellectual Property Organization (WIPO), the Penn World Tables (PWT), and indicators from the Doing Business and World Governance Indicators (WGI).

This panel is reduced to 28 OECD countries in the period 1996-2019, for revisiting the interplay between self-employment and labor market rigidities. In this case, we use the Employment Protection Legislation Index, distinguishing between temporary and regular employment, and the Rule of Law as an indicator of compliance as focus variables and a set of controls described above.

Finally, our data-driven search of clusters of countries in terms of self-employment productivity and the underlying idiosyncratic characteristics, is run by using a panel of 120 countries in the period 1991-2019. In this case, we use GDP converted to international dollars using purchasing power parity rates, in constant 2017 international dollars, and the number of self-employed workers taken from World Bank and ILOSTAT databases, respectively. In this exercise, the four covariates are: national unemployment rates (taken from ILOSTAT); the value added by industry as a percentage of GDP (World Bank database); the digital adoption index (World Bank database) and the labor market legislation rigidity index (LAMRIG, created from Botero's index of employment protection legislation and NATLEX, the ILO depository of labor laws).

Cyclical behavior, persistence, and causality

This thesis addresses different issues related to the behavior of self-employment over the business cycle. In addition to applying dating techniques to the main aggregate self-employment series[4], it also deals with the causality –both linear and non-linear–, and the role of two potential leading indicators: the unemployment rate and the business climate, linking with the literature on opportunity and necessity entrepreneurs (Fairlie and Fossen, 2020; Fossen, 2021) and on linear and non-linear causality relationships between labor time series (Pérez and Sánchez, 2011; Lamo et al., 2012, Carmona et al., 2012; Congregado, Carmona and Golpe, 2012; Parker et al., 2012a). It also applies different techniques to test for the existence of hysteresis in these series –that is, to test whether a transitory shock becomes permanent–, as a macro way of anticipating and evaluating the potential effects of policies, by using alternative approaches commonly used in previous

---

[4] Following the strategy adopted by Camacho et al. (2006), we provide a dating of self-employment cycles turning points, providing new stylized facts to this type of literature.

literature: unit roots and unobserved component models (Congregado, Golpe and Parker, 2012; Parker et al., 2012b; Gil-Alana and Payne, 2015).

Determinants of self-employment at the macro-level

There is an extensive empirical literature devoted to the analysis of the factors that determine the differences in national/regional self-employment rates, i.e., the determinants of macro-level entrepreneurship (see e.g., Wennekers et al., 2002; Thai and Turkina, 2014; Pietrobelli et al., 2004; Gindling and Newhouse 2014; Arin et al., 2015; Rodríguez-Santiago, 2022; and Cueto (2010), Cueto et al. (2015) and Golpe and Van Stel (2008), for the Spanish regions). Although entrepreneurship scholars tend to agree on the drivers and inhibitors of entrepreneurship –the factors influencing entrepreneurship–, evidence provided by this literature is very often mixed, it is common to find differences with regard to the relative importance of each driver and at times with opposite effects (Bjørnskov and Foss, 2016). For instance, it is possible to find contradictory studies where the same driver is positive, negative related or even unrelated to national rates of entrepreneurship.

The causes of this lack of robustness can be found in the low adequacy of the available data for international analysis[5], in how the longitudinal/cross-sectional dimension of the databases used conditions the econometric strategy adopted and the statistical significance of the results –cross-sectional vs panel data and short panels vs long-panels[6]–, and even in the operationalization used to measure entrepreneurship/self-employment at the macro-level[7]. In any case, the methodological scheme in this type of literature is common: based on structural or *ad hoc* specifications, in which some

[5] In these empirical investigations, it is common for scholars to face a trade-off between having more and better indicators versus having more units of observation –countries/regions– and a greater temporal dimension.

[6] The use of cross-section models or static models with short panels raises serious concerns about the validity of estimates since the potential unobservable heterogeneity or the introduction of dynamics will not have been controlled.

[7] For instance, the use of TEA indicator, provided by the Global Entrepreneurship Monitor, instead of self-employment rates, as proxy of national entrepreneurship, imposes serious limits for exploiting the longitudinal dimension.

predictor is set as the "focus" variable, the influence of this factor and some controls on the national entrepreneurship variation is estimated.

Two chapters included in the third part of this thesis are pieces of research directly related with this body of literature. The first one revisits the analysis of determinants of self-employment at the macro-level, investigating the heterogeneity across countries, by using the GDP as focus variable. To this end and, in order to avoid the discretionary choice of predictors –the so-called model uncertainty–, our estimates are derived adopting a Bayesian model averaging approach. By using a new panel dataset of 117 countries in the 2005-2019 period, our model allows to consider, not only fixed effects, but also the effect of different interactions between our focus variable and other controls.

The second one, focuses on the role of employment protection legislation as a driver or inhibitor of self-employment. This paper provides new evidence to help overcome the controversy about the effect that the greater or lesser stringency of employment protection legislation has on occupational choice. A priori and from a theoretical point of view, two competing explanations exist to explain this relationship. While it is true that greater EPL increases the opportunity cost of self-employment, it is not less true that the greater the regulation of salaried employment is, the greater the incentive for firms to adopt flexible production strategies that allow them to outsource activities and replace traditional employer-employee labor relations by relations with independent contractors. If the latter were the case, we would agree that it would be somewhat ironic if greater EPL was translated into increased opportunities for potential self-employed by increasing market niches and making entrepreneurial success more likely.

Empirical evidence should be a natural way to solve a controversy of these characteristics. However, evidence has not provided unambiguous results. We will argue that the mixed set of results in earlier studies are partly due to econometric specification problems, but mainly because higher EPL does not immediately translate into higher rigidity, this regulation is not guaranteed to be complied with. It is from the interaction between the degree of employment protection and compliance that a given net effect on national self-employment is given. The use of Bayesian model averaging methodology with interactions allows us to shed light on whether self-employment is responding to labor market rigidities.

Econometric approaches

As we mentioned above, mixed evidence and the scarcity of work on the dynamics of self-employment is not due to the lack of ability of scholars. Some of the controversies and apparently contradictory results might be due to the low quality of data, at least in part. The availability of short panels, data with low frequency, or the lack of long time series of internationally comparable data have conditioned the progress in this area. One of the major contributions of this thesis is to have imported/applied to this field, for the first time, business cycle dating methods to the analysis of self-employment cycles (Camacho et al., 2006). In this thesis we also apply fractional unit roots (Gil-Alana and Hualde, 2009) and the non-linear unobserved component model proposed by Pérez-Alonso and Di Sanzo (2010), in order to explore hysteresis in self-employment.

Bayesian methods have been used for revisiting the study of the determinants of the variation in rates of entrepreneurship across countries. In particular, we apply the Bayesian model averaging framework for panel data allowing interactions in order to avoid problems linked to model uncertainty, since this approach selects the best predictors avoiding the discretionary selection of regressors (Raftery, 1995; Fernandez et al., 2001; Crespo-Cuaresma and Slacik, 2009; Moral-Benito, 2010, 2012; Crespo-Cuaresma, 2011; Crespo-Cuaresma et al., 2014). The new availability of data allows to extend the work of Arin et al. (2015) with pooled data, controlling for unobservable heterogeneity and including interactions among covariates.

In the last paper, we use a finite mixture model for identifying different groups of countries in terms of their entrepreneurship productivity. Finite mixture model is a Bayesian approach for clustering time series proposed by Frühwirth-Schnatter (2006) that allows to find hidden groups within time series. All time series in a group can be estimated using the same econometric model. The estimation is data-driven, therefore the number of groups, the group membership and the group-specific parameters are unknown a priori.

Following the approach of Frühwirth-Schnatter and Kaufmann (2008), Kaufmann (2010) and Hamilton and Owyang (2011), the prior probability of the group indicator is estimated by a multinomial logistic model that allows to include country-specific characteristics to identify the intensity of every variable when classifying a country into a certain group.

Heterogeneity into self-employment

Whenever the data permit it, this thesis attempts to explore the existence of asymmetric effects among the different groups of self-employed. The motivations at entry –necessity vs. opportunity entrepreneurs–, the distinctions in terms of genuine and non-genuine entrepreneurs, or dependent vs. independent (Román et al., 2011), the degree of business success in terms of job creation –self-employed vs. employers–, the group of hybrid entrepreneurs, and whether they are vulnerable/precarious or not –underemployed or involuntary part-time workers– might be, among other things, behind the mixed evidence observed when the heterogeneity among groups of self-employed workers is ignored (Dvouletý, 2018; Cieślik and Dvouletý, 2019).

We would argue that in much of previous entrepreneurship research, important distinctions between different types of entrepreneurs seem to have been overlooked. The importance of recognizing the potential effects of heterogeneity is supported by the differences observed in micro-, meso- and macro-level studies when any cause of heterogeneity among the self-employed is explicitly considered.

For instance, entrepreneurs who hire external labor (employers) belong to a distinct group and they have different motivations to become entrepreneurs, different probabilities of success (Millán et al., 2012) and resilience (Millán et al., 2014; Congregado, Carmona and Golpe, 2012). They also experience different levels of job satisfaction (Millán et al., 2013), and could exhibit different cyclical behavior (Parker et al., 2012a) compared with entrepreneurs who work on their own (own-account entrepreneurs).

Our empirical estimates below will shed light on these conjectures.

1.3. Chapters overview

This thesis consists of six self-contained essays structured as follows. It mainly consists of two parts leaving aside this introduction.

Part II includes three essays and deals with time series analysis regarding topics of cycle dating, causality, and persistence on UK self-employment.

Chapter 2 can be seen as an introduction to the techniques used on the analysis of self-employment cycles, since frictions in labor market by itself can generate unemployment/employment cycles, and variations in the cyclical variation in the employment composition by status. In this chapter we analyze the business cycle dynamics in the European Union (EU-28) and the potential changes in cyclical linkages among countries introduced after the Great Recession based on the similarities in their cyclical features and synchronization, following the strategy adopted by Camacho et al. (2006). We apply a methodology for detecting turning points in GDP time series. Then, we provide a dating of expansions and recessions of every country, which allows us to analyze the length, depth, and shape for different cycles, joint to the synchronization between them. The cyclical pattern observed after the 2008-financial crisis, compared with the results obtained from the period before, shows that recessions become longer and deeper during the Great Recession.

Chapter 3 explores and checks whether the self-employed sector is responding in the same way as it did in previous economic recovery episodes after previous crises. By using the business confidence index and the unemployment rate as indicators for the UK, we provide: (1) a dating of the self-employment cycles; (2) the characteristics of these cyclical phases; (3) an analysis of the synchronization between the self-employment, unemployment, and business confidence cycles; and (4) a (linear and non-linear) causality analysis between these three variables. Our empirical analysis shows that self-employment rate development is not caused by the unemployment dynamics; but rather, it is now caused by the business climate, proxied by the confidence index. However, this causal impact is only found for positive shocks. As a result, one might speculate that the dynamics of the so-called opportunity-driven entrepreneurship governs the dynamics of the self-employment.

Chapter 4, reports evidence of unit roots –conventional and fractional– and estimates from an unobserved components model, as alternative ways of testing the existence of hysteresis in entrepreneurship and of evaluating the robustness of our empirical findings. Defining hysteresis in terms of the interdependent evolution of a nonstationary natural rate and a stationary cyclical component, thereby distinguishing hysteresis from natural rate shocks, the chapter provides robust evidence of hysteresis in entrepreneurship based on UK data. This implies that economic and/or non-economic shocks in the UK have cyclical and permanent effects on rates of entrepreneurship.

Part III provides different analyses about drivers and inhibitors when determining self-employment rates and productivity at the macro-level.

Chapter 5 re-evaluates the relationship between stages of economic development and entrepreneurship. To circumvent problems related to model uncertainty we use a Bayesian model averaging to evaluate the robustness of determinants of self-employment in a dataset of 117 countries, investigating the existence of heterogeneity allowing interactions between GDP, as focus variable, and a set of 20 potential entrepreneurship determinants. Our empirical results shows that the variation of self-employment rates across countries are mainly determined by variations in the unemployment, the stage of economic development and the variations in labor market frictions. When interactions are taken into account, results confirm that there is a differential effect of labor market frictions in countries with different levels of income. Frictions in labor market may encourage becoming self-employed in richer countries. These results are in line with those obtained in the previous literature, which suggests that entrepreneurship plays a different role in countries in different stages of economic development (Van Stel et al., 2005) and with the idea that a different scope for entrepreneurship policy should be devised across subsequent stages of development (Wennekers et al., 2005).

This last result leads us directly to the controversy, based in the mixed evidence about whether self-employment is a response to labor market rigidity as Arum et al. (2000) suggests. At the macro-level, mixed results on the relationship between labor market institutions and self-employment can be found, at least, in the works of Centeno (2000), Robson (2003) or Torrini (2005). The impact of employment protection legislation on self-employment is ambiguous.

Chapter 6 revisits this controversy exploring whether employment protection legislation (EPL, henceforth) stringency in conjunction with the regulatory compliance/enforcement encourages or inhibits national self-employment. We use time series of cross-national macro data of entrepreneurship, from a sample of 28 OECD countries, and apply Bayesian model averaging as a way to circumvent problems related to model uncertainty, regarding the choice of the best predictors and considering the interaction between institutions and enforcement/flexibility. We find empirical support of our main hypothesis according to which employment protection legislation can either boost or contract the self-employment rate depending on the degree of practical compliance with employment legislation –regular and temporary–, although differences are observed between job creators and solo self-employed.

Chapter 7 provides a data-driven categorization of economies in terms of the productivity of entrepreneurship by using a panel of 120 countries during 1991-2019. Using a Bayesian approach for clustering time series based on Markov chain Monte Carlo methods for finite mixture models (Frühwirth-Schnatter and Kaufmann, 2008), we allow the data to define clusters of countries on the basis of comovement in national entrepreneurial productivity and other national characteristics. We provide evidence of the existence of three clusters of countries defined in terms of the national self-employed worker's productivity. The labor market dynamics –national unemployment– and the degree of digitalization matter for cluster determination –leading transitions between clusters of countries–, but other factors, such as the share of industrial added value or the existence of rigidities in the labor market are not determinants of such transitions. These clusters might be identified with three major groups of countries usually considered in the entrepreneurship literature: factor-, efficiency-, and innovation-driven countries, and with the literature on managed vs. entrepreneurial societies (Audretsch and Thurik, 2004; Okamuro et al., 2017).

Part IV concludes the study with a last work, chapter 8, containing some concluding remarks and the future research agenda. Table 1 summarizes the general structure of the thesis.

Table 1. Thesis structure

CHAPTER	OBJECTIVES	SCOPE	DATA AND SOURCES	ECONOMETRIC FRAMEWORK
2	Analyzing the business cycle dynamics in the European Union after the Great Recession	EU-28	Growth rate of GDP at market prices, seasonally and working day adjusted 1953:1-2017:2 (quarterly data) OECD, National Statistics Institutes or Central Banks	Business Cycle dating, characteristics and synchronization Multidimensional Scaling
3	Reconsidering the push/pull hypothesis, controlling by non-linear causality between self-employment and unemployment vs. business confidence index	UK	Self-employment rates, unemployment rates, business confidence index 1992:5-2019:2 (monthly data) ILOSTAT database, OECD	Turning points dating, characteristics of cycle Non-linear Granger causality
4	Testing the existence of hysteresis in the self-employment rate in the UK	UK	Self-employment rate 1992:4-2019:4 (quarterly data) Labour Force Survey	Unobserved components model
5	Evaluating the role of stages of economic development when determining self-employment rates	World (117)	Self-employment rate and covariates related to: GDP (focus) and components, technological progress, human capital, labor market, population and institutions 2005-2019 (annual data) ILOSTAT, World Bank, WIPO, PWT, Doing Business WGI	Bayesian model averaging
6	Assessing model uncertainty over determinants of self-employment rates depending on the employment protection legislation	OECD (28)	Self-employment rate and covariates related to: GDP and components, technological progress, human capital, labor market, population and institutions (focus EPL) 1996-2019 (annual data) ILOSTAT, World Bank, WIPO, PWT, WGI, OECD	Bayesian model averaging
7	Finding clusters of countries and idiosyncratic characteristics driving the different levels of self-employment productivity	World (120)	GDP by Self-employed, unemployment rate, value added by industry, LAMRIG and digital adoption index 1991-2019 (annual data) ILOSTAT and World Bank	Finite mixture model

1.4. Publications

Some chapters of this PhD thesis are based on pieces of research published or submitted to academic journals. The chapters can be read independently of each other.

Chapter 2 is based on a paper that was published in Journal of Business Cycle Research in 2019. The origin of this article was my Master Thesis, awarded as Best Research Dissertation Award at MSc in Economics, Finance and Computer Science, International University of Andalusia. This work was supervised by Máximo Camacho. It also was previously presented at the XVIII Conference on International Economics, in June 2017.

A very early version of chapter 3, a work jointly done with Emilio Congregado and Mónica Carmona, was presented at the Global Workshop on Freelancing & Self-employment Research (London, April 2018). Two updated and extended versions were presented at the XIII Labour Economics Meeting (Islantilla, June 2019) and at the XXIV Applied Economics Meeting (University of Balearic Islands, June 2022).

The contents of chapter 4 correspond with the article published in 2020, jointly with Elisabeth López-Pérez and Emilio Congregado. A first draft of this paper was previously discussed at the XIII Labour Economics Meeting (Huelva, June 2019).

Chapters 5 and 6 were initiated during my stay as a visiting researcher in the Department of Economics at the Vienna University of Economics and Business (Austria, 2021).

Chapter 5 is based on a paper that was published in International Journal of Interactive Multimedia and Artificial Intelligence, and previously presented at the doctoral course on Topics in Macroeconomics delivered by Prof. Jesús Crespo-Cuaresma in Vienna University of Economics and Business (Winter term 2020/21) and at the XIV Labour Economics Meeting (UNIR, June 2021).

A first draft of chapter 6, coauthored by Emilio Congregado and Concepción Román, has been presented at the XV Labour Economics Meeting (University of Castilla Mancha, July 2022) and at the 8th International conference on Time Series and Forecasting (Canary Islands, June 2022).

Finally, Chapter 7 is based on a paper jointly written with Máximo Camacho and Emilio Congregado. A first preliminary draft was presented at the doctoral course on Bayesian Econometrics delivered by Prof. Sylvia Frühwirth-Schnatter in Vienna University of Economics and Business (Winter term 2020/21).

References

Ahmad, N., & Hoffman, A. (2008). *A framework for addressing and measuring entrepreneurship,* OECD Statistics Working Paper, No° 2008/02.

Ahmad, N., & Seymour, R. (2008). *Defining Entrepreneurial Activity,* OECD Statistics Working Paper, No° 2008/01.

Arin, K. P., Huang, V. Z., Minniti, M., Nandialath, A. M., & Reich, O. F. (2015). Revisiting the determinants of entrepreneurship: A Bayesian approach. *Journal of Management*, *41*(2), 607-631.

Arum, R., Budig, M., & Grant, D. S. (2000). Labor market regulation and the growth of self-employment. *International Journal of Sociology*, 30(4), 3-27.

Audretsch, D. B. (2009). The entrepreneurial society. *The Journal of Technology Transfer*, *34*(3), 245-254.

Audretsch, D. B., & Thurik, R. (2004). A Model of the Entrepreneurial Economy. *International Journal of Entrepreneurship*, *2*(2), 143-166.

Bell, D. N., & Blanchflower, D. G. (2021). Underemployment in the United States and Europe. *ILR Review*, *74*(1), 56-94.

Bjørnskov, C., & Foss, N. J. (2016). Institutions, entrepreneurship, and economic growth: what do we know and what do we still need to know?. *Academy of Management Perspectives*, *30*(3), 292-315.

Boeri, T., Giupponi, G., Krueger, A. B., & Machin, S. (2020) Solo self-employment and alternative work arrangements. *The Journal of Economic Perspectives*, *34*(1), 170-195.

Borowczyk-Martins, D., & Lalé, E. (2018). The welfare effects of involuntary part-time work. *Oxford Economic Papers*, *70*(1), 183-205.

Borowczyk-Martins, D., & Lalé, E. (2020). The ins and outs of involuntary part-time employment. *Labour Economics*, *67*, 101940.

Bosma, N. (2013). The Global Entrepreneurship Monitor (GEM) and its impact on entrepreneurship research. *Foundations and Trends® in Entrepreneurship*, *9*(2), 143-248.

Bracha, A., & Burke, M. A. (2021). How big is the gig? The extensive margin, the intensive margin, and the hidden margin. *Labour Economics*, *69*, 101974.

Camacho, M., Pérez-Quirós, G., & Saiz, L. (2006). Are European business cycles close enough to be just like one? *Journal of Economic Dynamics &* Control, *30*, 1687-1706.

Carmona, M., Congregado, E., & Golpe, A. A. (2012). Comovement between self-employment and macroeconomic variables: evidence from Spain. *Sage Open*, *2*(2), 2158244012448665.

Centeno, M. (2000). Is self-employment a response to labour market rigidity. *Economic Bulletin*, 37-44.

Cieślik, J., & Dvouletý, O. (2019). Segmentation of the Population of the Solo Self-employed. *International Review of Entrepreneurship*, *17*(3).

Cima, J., Costa, J., Pinto, C., & Pinto, T. (2017). The Dynamics of Self-Employment and Unemployment During the Great Recession. *International Review of Entrepreneurship*, *15*(3).

Congregado, E. (Ed.). (2007). *Measuring entrepreneurship: building a statistical system* (Vol. 16). Springer Science & Business Media.

Congregado, E., Carmona, M., & Golpe, A. A. (2012). Self-employment and Job Creation in the EU-12. *Revista de economía mundial*, (30), 133-155.

Congregado, E., de Andrés, M. I., & Román, C. (2019). Explorando la heterogeneidad en el empleo mediado por plataformas digitales: Intensidad y localización. *Revista de Economía Laboral*, *16*(2), 69-103.

Congregado, E., de Andrés, M. I., Román, C., & Nolan, E. (2022). Heterogeneity among Self-Employed Digital Platform Workers. Evidence from Europe. *International Review of Entrepreneurship*, *20*(1), 45-68.

Congregado, E., Golpe, A. A., & Parker, S. C. (2012). The dynamics of entrepreneurship: hysteresis, business cycles and government policy. *Empirical Economics*, *43*(3), 1239-1261.

Crespo-Cuaresma, J. (2011). How different is Africa? A comment on Masanjala and Papageorgiou. *Journal of Applied Econometrics*, *26*(6), 1041-1047.

Crespo-Cuaresma, J., & Slacik, T. (2009). On the determinants of currency crises: The role of model uncertainty. *Journal of Macroeconomics*, *31*(4), 621-632.

Crespo-Cuaresma, J., Doppelhofer, G., & Feldkircher, M. (2014). The determinants of economic growth in European regions. *Regional Studies*, *48*(1), 44-67.

Cueto, B. (2010). Explaining regional differences in self-employment rates in Spain. *Discussion Papers on Applied Economics*. Department of Applied Economics. University of Oviedo. DPAE/09/02.

Cueto, B., Mayor, M., & Suárez, P. (2015). Entrepreneurship and unemployment in Spain: a regional analysis. *Applied Economics Letters*, *22*(15), 1230-1235.

Dvouletý, O. (2018). How to analyse determinants of entrepreneurship and self-employment at the country level? A methodological contribution. *Journal of Business Venturing Insights*, *9*, 92-99.

Elert, N., Henrekson, M., & Sanders, M. (2019). *The entrepreneurial society: a reform strategy for the European Union* (p. 173). Springer Nature.

Fairlie, R. W. (2013). Entrepreneurship, economic conditions, and the great recession. *Journal of Economics & Management Strategy*, *22*(2), 207-231.

Fairlie, R. W., & Fossen, F. M. (2020). Defining opportunity versus necessity entrepreneurship: Two components of business creation. In *Change at home, in the labor market, and on the job*. Emerald Publishing Limited.

Fernandez, C., Ley, E., & Steel, M. F. (2001). Model uncertainty in cross-country growth regressions. *Journal of applied Econometrics*, *16*(5), 563-576.

Fossen, F. M. (2021). Self-employment over the business cycle in the USA: a decomposition. *Small Business Economics*, *57*(4), 1837-1855.

Frühwirth-Schnatter, S. (2006). *Finite Mixture and Markov Switching Models*.

Frühwirth-Schnatter, S., & Kaufmann, S. (2008). Model-based clustering of multiple time series. *Journal of Business and Economic Statistics*, *26*(1), 78-89.

Gil-Alana, L. A., & Hualde, J. (2009). Fractional integration and cointegration: an overview and an empirical application. *Palgrave handbook of econometrics*, 434-469.

Gil-Alana, L. A., & Payne, J. E. (2015). A time-series analysis of US entrepreneurship: Evidence from fractional integration. *Applied Economics Letters*, *22*(7), 521-524.

Gindling, T. H., & Newhouse, D. (2014). Self-employment in the developing world. *World development*, *56*, 313-331.

Giupponi, G., & Xu, X. (2020). What does the rise of self-employment tell us about the UK labour market?. London: *Institute of Fiscal Studies*.

Golpe, A. A., & Stel, A. V. (2008). Self-employment and unemployment in Spanish regions in the period 1979-2001. In *Measuring Entrepreneurship* (pp. 191-204). Springer, Boston, MA.

Hamilton, J. D., & Owyang, M. T. (2011). The propagation of reginal recessions. *NBER Working Paper Series*.

Iversen, J., Jørgensen, R., & Malchow-Møller, N. (2007). Defining and measuring entrepreneurship. *Foundations and Trends® in Entrepreneurship*, *4*(1), 1-63.

Kaufmann, S. (2010). Dating and forecasting turning points by Bayesian clustering with dynamic structure: A suggestion with an application to Austrian data. *Journal of Applied Econometrics*, *25*(2), 309-344.

Kim, P. H., Wennberg, K., & Croidieu, G. (2016). Untapped riches of meso-level applications in multilevel entrepreneurship mechanisms. *Academy of Management Perspectives*, *30*(3), 273-291.

Lamo, A., Pérez, J. J., & Schuknecht, L. (2012). Public or private sector wage leadership? An international perspective. *The Scandinavian Journal of Economics*, *114*(1), 228-244.

Lyalkov, S., Carmona, M., Congregado, E., Millán, A., & Millán, J. M. (2020). Trademarks and their association with Kirznerian entrepreneurs. *Industry and Innovation*, *27*(1-2), 155-183.

Millán, J. M., Congregado, E., & Román, C. (2012). Determinants of self-employment survival in Europe. *Small Business Economics*, *38*(2), 231-258.

Millán, J. M., Congregado, E., & Román, C. (2014). Entrepreneurship persistence with and without personnel: The role of human capital and previous unemployment. *International Entrepreneurship and Management Journal*, *10*(1), 187-206.

Millán, J. M., Hessels, J., Thurik, R., & Aguado, R. (2013). Determinants of job satisfaction: a European comparison of self-employed and paid employees. *Small business economics*, *40*(3), 651-670.

Minniti, M., Bosma, N., & Quill, M. (2007). The 2006 Global Entrepreneurship Monitor Technical Assessment. *London Business School and Babson College, London, UK and Wellesley, MA*.

Moral-Benito, E. (2010). Determinants of Economic Growth: A Bayesian panel data approach. *Documentos de trabajo del Banco de España*, (31), 1-40.

Moral-Benito, E. (2012). Determinants of economic growth: A Bayesian panel data approach. *Review of Economics and Statistics*, *94*(2), 566-579.

Okamuro, H., Van Stel, A., & Verheul, I. (2017). Understanding the drivers of an 'entrepreneurial' economy: lessons from Japan and the Netherlands. In *Exploring the Entrepreneurial Society*. Edward Elgar Publishing.

Parker, S. C., Congregado, E., & Golpe, A. A. (2012a). Is entrepreneurship a leading or lagging indicator of the business cycle? Evidence from UK self-employment data. *International Small Business Journal*, *30*(7), 736-753.

Parker, S. C., Congregado, E., & Golpe, A. A. (2012b). Testing for hysteresis in entrepreneurship in 23 OECD countries. *Applied Economics Letters*, *19*(1), 61-66.

Pérez, J. J., & Sánchez, A. J. (2011). Is there a signalling role for public wages? Evidence for the euro area based on macro data. *Empirical Economics*, *41*(2), 421-445.

Pérez-Alonso, A., & Di Sanzo, S. (2010). Unemployment and hysteresis: a nonlinear unobserved components approach. *Studies in Nonlinear Dynamics & Econometrics*, *15*(1).

Pietrobelli, C., Rabellotti, R., & Aquilina, M. (2004). An empirical study of the determinants of self-employment in developing countries. *Journal of International Development*, *16*(6), 803-820.

Raftery, A. E. (1995). Bayesian model selection in social research. *Sociological methodology*, 111-163.

Reuschke, D., & Zhang, M. (2022). Precarious self-employment in urban Europe. *European Urban and Regional Studies*, 09697764221095756.

Reynolds, P. D., Camp, S. M., Bygrave, W. D., Autio, E., & Hay, M. (2001). Global entrepreneurship monitor: 2001 executive report.

Reynolds, P. D., Hay, M., & Camp, S. M. (1999). Global entrepreneurship monitor. *Kansas City, Missouri: Kauffman Center for Entrepreneurial Leadership*.

Robson, M. T. (2003). Does stricter employment protection legislation promote self-employment?. *Small Business Economics*, *21*(3), 309-319.

Rodríguez-Santiago, A. (2022). Re-Evaluating the Relationship Between Economic Development and Self-Employment, at the Macro-Level: A Bayesian Model Averaging Approach. *International Journal of Interactive Multimedia & Artificial Intelligence*, *7*(3), 20-25.

Román, C., Congregado, E., & Millán, J. M. (2011). Dependent self-employment as a way to evade employment protection legislation. *Small Business Economics*, *37*(3), 363-392.

Thai, M. T. T., & Turkina, E. (2014). Macro-level determinants of formal entrepreneurship versus informal entrepreneurship. *Journal of Business Venturing*, *29*(4), 490-510.

Torrini, R. (2005). Cross-country differences in self-employment rates: The role of institutions. *Labour Economics*, *12*(5), 661-683.

Valletta, R. G., Bengali, L., & Van der List, C. (2020). Cyclical and market determinants of involuntary part-time employment. *Journal of Labor Economics*, *38*(1), 67-93.

Van Stel, A. (2005). COMPENDIA: Harmonizing business ownership data across countries and over time. *The International Entrepreneurship and Management Journal*, *1*(1), 105-123.

Van Stel, A., Carree, M., & Thurik, R. (2005). The effect of entrepreneurial activity on national economic growth. *Small business economics*, *24*(3), 311-321.

Van Stel, A., Cieślik, J., & Hartog, C. M. (2010). Measuring business ownership across countries and over time: Extending the COMPENDIA data base. *EIM Business and Policy Research, Scales Research Reports*, (H201019).

Wennekers, S., Van Stel, A., Thurik, R., & Reynolds, P. (2005). Nascent entrepreneurship and the level of economic development. *Small Business Economics*, *24*(3), 293-309.

Wennekers, S., Uhlaner, L. M., & Thurik, R. (2002). Entrepreneurship and its conditions: a macro perspective. *International Journal of Entrepreneurship Education*, *1*(1): 25-68.

Part II: Cyclicality, dating, causality and persistence

Chapter 2: What has changed after the Great Recession on the European cyclical patterns?

This article analyzes the business cycle dynamics in the European Union (EU28) during recent decades. Following Camacho et al. (2006), we extend the analysis of European cycles to a broader range of countries, including new entrants. In addition, we update their sample by including the Great Recession data with the aim of exploring whether the financial crisis led to changes in cyclical features across these countries. Our results indicate that the Great Recession has undermined European cyclical linkages. Notably, we succeeded in detecting that the European economies do not follow more closed dynamics, despite the fact that the countries are showing more similar cyclical characteristics.

2.1. Introduction

The study of economic cycles is currently a hot policy issue in Europe, as some countries are rethinking the new role played in the European Union (EU), and new member states are reconsidering the effects of economic integration. In some sense, one could expect that economic integration should lead to similar patterns in macroeconomic dynamics. The inexistence of a common cycle should imply the adoption of different treatments for member countries of the European Union. It is important to know whether every country follows the same cyclical pattern to adapt the economic policies that are developed by the European Union Commission for the purpose of common welfare and, especially, the European Central Bank, responsible for monetary policy and financial supervision of the economic and monetary union (EMU).

The analysis of heterogeneity between member countries is especially relevant for the application of monetary policy, since the application of a "one-size-fits-all" policy by the EMU or European Commission could not have the expected effect if the countries are showing diverging economic dynamics, in words of Feldstein (1997): "Uniform monetary policy and inflexible exchange rates will create conflicts whenever cyclical conditions differ among the member countries". In this context, this piece of research attempts to provide empirical evidence on the existence, or not, of a business cycle pattern among member countries and on the potential effect of the 2008-financial crisis on such a pattern.

The finding of patterns in business cycles (BC), the study of linkages among different formations of countries and the provision of explanations for these stylized facts have been the core of a body of theoretical and empirical literature devoted to the study of the business cycle (see the survey conducted by De Haan et al., 2008). Most authors studying European economic cycles have focused on synchronization, rather than on any other characteristic of the cycle, with few exceptions, such as Krolzig and Toro (2005) or Camacho et al. (2008). After the enlargement of the European Union, the focus was placed on the search for a core-periphery pattern in the group but taking into account only the synchronization between countries or some presupposed central core (Camacho et al., 2006; Darvas and Szapáry, 2008; Gomez et al., 2011; König and Ohr, 2013; and Wortmann and Stahl, 2016). There is still a gap in the literature about the effects of the Great Recession on the cycles of European Union countries, with some exceptions, such as Antonakakis et al. (2016), who explained the debt crisis by the shocks on the periphery countries, Grigoraş and Stanciu (2016), who stated that European economies are less synchronized after the crisis, or Ahlborn and Wortmann (2018), who applied fuzzy clustering to explain changes in European clusters after the crisis.

The issues we address in this paper are how to provide evidence on the business cycle similarities and dynamics before and after the beginning of the Great Recession. To this end, first, we check if the length, depth, shape and synchronization of business cycles across European Union countries are now following more similar dynamics than before; second, and after more than a decade, we can extend the analysis to the new entrants and provide a comprehensive analysis once the lately adhered economies to the European Union have been established; and last, we explore if the 2008-financial crisis has introduced some changes in the cyclical linkages across this set of European countries and whether the crisis has changed the way in which relationships between countries were established before the crisis.

Our results point to the reconsideration of linkages across economic cycles of member countries of the European Union. The Great Recession seems to have changed patterns in cyclical linkages since the results obtained show a desynchronization between European economies, despite the fact that the countries are now showing more similar business cycle characteristics, as a consequence of the severity of the crisis experienced during the late 2000s.

The rest of this paper is structured as follows: Section 2 describes the methodology and data for analyzing business cycle characteristics and synchronization. Section 3 develops and applies the methodologies for identifying groups of countries with similar patterns in cycles. Finally, section 4 presents some general conclusions about the research and the study.

2.2. Business cycle analysis

Data

Our study is focused on the cycles of the 28 member countries of the European Union group because of the recent interest in the linkages between countries forming the group after the accessions in recent decades. The EU foundation occurred in 1957 with six member countries as founders, and from there, successive incorporations have been taking place until the last and current composition of the EU28 group (the date of accession can be consulted in Table A1).

For the analysis of the business cycle of the member countries of the European Union, we use the quarterly growth rate of GDP at market prices, seasonally and working day adjusted. Although most of the time series were obtained from the Organization for Economic Co-operation and Development database (OECD), some of them were obtained from national statistics institutes or central banks of the countries. We used the available data for each country. Table 1 shows the periods of each sample, the source of the data, the assigned country code for identification and the year of accession of each country to the European Union.

Table 1. Data description

COUNTRY	CODE	PERIOD	SOURCE	DATE OF ACCESSION	BEGINNING OF THE CRISIS
AUSTRIA	AT	1969/Q1 – 2017/Q2	OECD	01/01/1995	2008Q2
BELGIUM	BE	1960/Q2 – 2017/Q2	OECD	**25/03/1957**	2008Q3
BULGARIA	BG	2000/Q2 – 2017/Q2	Statistical Institute	01/01/2007	2009Q1
CROATIA	HR	2001/Q1 – 2017/Q2	Statistical Institute	01/07/2013	2008Q3
CYPRUS	CY	1995/Q2 – 2017/Q2	Statistical Institute	01/05/2004	2008Q4
CZECH REP.	CZ	1994/Q2 – 2017/Q2	OECD	01/05/2004	2008Q4
DENMARK	DK	1960/Q2 – 2017/Q2	OECD	01/01/1973	2008Q1
ESTONIA	EE	1995/Q2 – 2017/Q2	Statistical Institute	01/05/2004	2008Q1
FINLAND	FI	1960/Q2 – 2017/Q2	OECD	01/01/1995	2008Q1
FRANCE	FR	1953/Q1 – 2017/Q2	Statistical Institute	**25/03/1957**	2008Q2
GERMANY	DE	1960/Q2 – 2017/Q2	OECD	**25/03/1957**	2008Q3
GREECE	EL	1960/Q2 – 2017/Q2	OECD	01/01/1981	2007Q3
HUNGARY	HU	1995/Q2 – 2017/Q2	OECD	01/05/2004	2008Q3
IRELAND	IE	1960/Q2 – 2017/Q2	OECD	01/01/1973	2008Q1
ITALY	IT	1960/Q2 – 2017/Q2	OECD	**25/03/1957**	2007Q4
LATVIA	LV	1995/Q2 – 2017/Q2	OECD	01/05/2004	2007Q4
LITHUANIA	LT	1995/Q2 – 2017/Q2	Statistical Institute	01/05/2004	2008Q3
LUXEMBOURG	LU	1960/Q2 – 2017/Q2	OECD	**25/03/1957**	2008Q2
MALTA	MT	2000/Q2 – 2017/Q2	Central Bank	01/05/2004	2008Q4
NETHERLANDS	NL	1960/Q2 – 2017/Q2	OECD	**25/03/1957**	2008Q3
POLAND	PL	1995/Q2 – 2017/Q2	OECD	01/05/2004	2008Q4
PORTUGAL	PT	1960/Q2 – 2017/Q2	OECD	01/01/1986	2008Q2
ROMANIA	RO	1995/Q2 – 2017/Q2	Statistical Institute	01/01/2007	2008Q4
SLOVAKIA	SK	1993/Q2 – 2017/Q2	OECD	01/05/2004	2009Q1
SLOVENIA	SI	1995/Q2 – 2017/Q2	Statistical Institute	01/05/2004	2008Q3
SPAIN	ES	1969/Q1 – 2017/Q2	OECD	01/01/1986	2008Q2
SWEDEN	SE	1969/Q1 – 2017/Q2	OECD	01/01/1995	2008Q3
UK	UK	1955/Q2 – 2017/Q2	OECD	01/01/1973	2008Q3

Methodologies for dating turning points

A recession is the period between a peak and a trough, while expansion is the period between a trough and a peak. In this context, a peak is identified as the last moment of an expansion, and the trough is therefore the last moment of a recession. To establish the cycles, it seems necessary to detect the turning points, which are the moments when the cycle passes from an expansion to a recession (peak) and from a recession to an expansion (trough).

Turning points identification is made by the Economic Cycle Research Institute (ECRI) for seven countries forming the European Union group (AT, FR, DE, IT, ES, SE and UK). This institute dates peaks and troughs from the behavior of certain economic variables. For detecting business cycles, the ECRI uses variables such as GDP, IPI, labor market, rent and sales. However, this organization does not elaborate on the identification of turning points for the rest of the countries forming the group.

For the rest of countries, we have applied the methodology of Harding and Pagan (2002) to find maxima and minima from the series of rebuilt GDP. Harding and Pagan provided an algorithm to locate turning points and a measure of pro-cyclicality on quarterly data[1]. Their approach allows us to dissect cycles in terms of the contributions made by their different components, i.e., trend, volatility, serial correlation and non-linear effects.

The algorithm provides us a binary variable that takes the value of one on the date when a recession takes place. This variable is used to establish the peaks and troughs that a time series experienced and then analyze the cycle characteristics, distinguishing between expansions and recessions.

Business cycle characteristics and synchronization

Although there are a wide range of features identified across the empirical literature about business cycles, we have selected a set of necessary characteristics to describe the cycle from the GDP time series, apart from the business cycle synchronization between countries. The analyzed features of the business cycle refer to the length, depth and shape of the cycles, which can be measured by the duration, amplitude and both excess and cumulative

---

[1] This methodology is a refinement of the dating algorithm for monthly data suggested by Bry and Boschan (1971). Although is it possible to employ a different algorithm, such as the Markov Switching model proposed by Hamilton (1989), the literature has successfully proved the preference of BBQ over other methods due to being the most effective, easy and having the fewest restriction requirements (see Ahking (2015) on this issue).

movement of the cycles, respectively, as Harding and Pagan (2002) considered.

Concerning the length of the cycles, duration is the time spent between peak and trough in the case of a recession or between trough and peak when an expansion takes place. In our case, duration is represented as the number of quarters for each phase for each one of the countries, and the average refers to the mean duration that cycles last in the entire group of the European Union.

Regarding the depth of the cycle, we measure the amplitude, which is referred as the total gain or loss between peak and trough, and vice versa, experienced in a phase. To measure the amplitude, the GDP of every phase is rebuilt to compare the last trough/peak of the phase and the initial value. Amplitude is represented by the rate of loss or gain, which is the mean percentage that the GDP has increased during expansions or decreased during recessions.

Finally, the last characteristic is the deepness, which is associated with the shape of the cycle. It can be measured by the so-called excess, which measures how the actual time series behaves against a hypothetical linear path between two consecutive turning points. In terms of Harding and Pagan (2002), once we have the duration and amplitude of a phase, we obtain the excess cumulated movements by the triangle approximation to the cumulative movements ($C_{Ti} = 0.5\, D_i\, A_i$, where D is the duration and A is the amplitude) and the actual cumulative movements or *cumulation*, calculated as the sum of every period's amplitude in a phase. The calculation of the excess in every phase (E_i) may be approximated by

$$E_i = (C_{Ti} - C_i + 0.5\, A_i)/D_i,$$

where the term $0.5\, A_i$ removes the bias that arises in using a sum of rectangles (cumulation C_i) to approximate a triangle.

Considering the way that the excess is calculated, a negative value refers to a concave evolution against the linear path, and a positive sign would indicate a convex evolution with respect to a linear growth/decrease. In this way, a concave expansion and a convex recession evolve more sharply at the beginning of a phase and in a smooth manner at the end of a phase. In contrast, convex expansions and concave recessions present a moderate evolution at the start of the phase and become more abrupt at the end. To illustrate these concepts, check Figure A1, where a representation of different types of expansions and recessions, depending on the sign of the excess, and the concepts of amplitude and duration are represented.

Furthermore, to study the synchronization between different business cycles, the concordance index between cycles of countries i and j (IC_{ij}) has been calculated as Harding and Pagan (2006) proposed[2], with R_{it} being the binary variable that takes a value of 1 when country i is in recession.

$$IC_{ij} = \frac{1}{T}\sum_{t=1}^{T}\{ R_{it}\, R_{jt} + (1 - R_{it})(1 - R_{jt})\}.$$

The index represents the proportion of time in which two nations experience the same state of the economy. In this way, the difference between 1 and the concordance would represent the pairwise distances in business cycle synchronization.

Results

For a better understanding of the results, Table 1 indicates the effective sample period per country as well as when the crisis started for each of the countries. It is worth mentioning that for some of the countries that accessed the EU long ago, the OECD has data since 1960 for most of the countries (1949 for France and 1955 for United Kingdom), and for the last entries, the sample of GDP starts between 1994 and 2000[3].

Table 2 presents the average and standard deviation of the business cycle features for the entire sample of data, the period before the Great Recession started in 2008 and the period since it started until the last data point that we have at our disposition (refer to tables A2 to A4 to see the individual characteristics of the countries).

[2] McDermott and Scott (2000), Harding and Pagan (2002), Krolzig and Toro (2005) and Harding and Pagan (2006) regard the use of the concordance index as being a better tool in measuring business cycle synchronization. As advocated by Harding and Pagan (2002) and McDermott and Scott (2000) the concordance indicator is a better metric, focusing on the fraction of time when the reference cycle and the specific cycle are in the same state.

[3] This is except for France, Sweden, Austria and Spain, whose samples have had to be shortened, since the dating of the cycles is made by the ECRI, which only provides data from 1953 for France and 1969 for the other 3 countries.

Table 2. Summary of BC features

	Duration		Amplitude		Excess		Cumulation	
	E	R	E	R	E	R	E	R
Entire sample	22.79	5.45	29.24	-4.10	1.24	0.12	5.03	-0.17
(28)	(7.47)	(3.00)	(11.96)	(2.88)	(1.06)	(0.34)	(3.45)	(0.15)
Before crisis	25.44	4.79	37.08	-2.20	1.79	0.05	6.60	-0.07
(24)	(8.81)	(2.64)	(16.17)	(1.81)	(2.05)	(0.36)	(4.82)	(0.09)
Since crisis	16.80	6.06	12.98	-6.51	0.07	0.08	1.53	-0.32
(28)	(9.21)	(4.35)	(9.18)	(4.70)	(0.78)	(0.67)	(1.63)	(0.41)

Note: Standard error in parentheses.

Starting with the length of the cycles, as we expected, expansions last much longer than recessions. The average duration for the EU28 group takes a value of 22.8 quarters, while recessions have a mean duration of 5.5 quarters. The cases of the United Kingdom and Spain, whose expansions last on average 44.6 and 36.8 quarters, much longer than the mean on EU28, are remarkable. There are also countries whose expansions are much shorter than the average of the group, such as Croatia, Greece, Malta and Poland, with expansions of 14.3, 12.3, 10.2 and 14 quarters, respectively. Concerning the recessions, the case of Spain, where recessions last a mean of 15.7 quarters, is striking.

The amplitude analysis shows an average depth of 29.2% of the GDP during expansions and -4.1% during recessions. Although most of the countries present similar results, some countries have a much higher increase in GDP during expansions, such as Slovakia, Estonia and Lithuania, whose gains rise between 46% and 48%, and Ireland, presenting an average amplitude of 65% during expansions. On the other hand, there are countries such as Croatia, Denmark, Hungary, and Poland that present more modest growth (below 18%). With regard to recessions, some special cases are Estonia and Lithuania, whose loss in recessions is between 9% and 12%.

Respecting the shape of the cycles, the mean of excess takes a positive value for both expansions and recessions (1.24 and 0.12, respectively), which means that expansions tend to be smoother at the beginning and more abrupt at the end of the phase. Conversely, during recessions, the drop is more noticeable at the beginning, and it evolves in a smoother way to the end of the recession. This reflects the presence of convex expansions and recessions on average across the EU28.

The main point in our analysis of cyclical characteristics is the one referring to the situation since the late 2000s crisis started. We analyze the characteristics of the cycles for each of the countries for the period before and after the Great Recession started. This financial crisis had effects worldwide, with more or less repercussion depending on the country, but a generalized fact is that it started between the end of 2007 and the beginning of 2008. With regard to dating for business cycles, a date for the start of the crisis period has been established for every country[4].

The characteristics of the business cycles before the crisis started[5] and the results for the period after the crisis (that can be consulted in individual detail in tables A3 and A5) show that the average duration before the crisis was 25.4 quarters during expansions and 4.8 in recessions, while the average duration after the crisis was 16.8 quarters and 6.1. Expansions have become shorter, while recessions have become longer. The characteristics of the depth show relevant information since expansions before the crisis presented an amplitude of 37.1% during expansions and -2.2% during recessions, changing to a growth of 13% in expansions and a loss of 6.5% in recessions during the period since the crisis started. Finally, the measure of excess seems to be similar during recession between the period before and after the crisis (from excess of 0.05 to 0.08), but the excess on expansions has been shortened (from 1.79 to 0.07), meaning that expansions are less convex now.

Regarding the synchronization between countries (whose individual results can be consulted in tables A5 to A7), we can see that, considering the entire sample of data, the smallest concordance indexes are approximately 0.51-0.59, and the average shows a value of 0.81, with Croatia and Greece being the countries with the smallest concordance indexes. For the period before the crisis, which has been considered to end in 2007 for every country, the average concordance index between the entire set of countries is situated in 0.87 and 0.74 during the period since the crisis started, which would demonstrate a decrease in synchronization between the European Union, in line with the study of Bierbaumer-Polly et al. (2016). We can check this by analyzing the minima concordance index that takes a value of 0.53 before and 0.29 after the crisis, being before the less synchronized countries

[4] The moment that we consider the crisis started for each of the countries is clarified in Table 1. It has been determined based on the peak that the countries showed during the years 2007-2008.

[5] Bulgaria, Croatia, Cyprus and Slovenia have been excluded from the sample due to lack of a complete business cycle during the period before the crisis.

of the group Croatia, Cyprus, Greece, Italy and Spain, and after Romania and Germany[6].

Although the comment on the economic reasons behind the heterogeneity found on cyclical characteristics could be discussed longer, it is kept out of the paper's scope, since it basically is to comment the evolution of dynamics between the countries of the European Union after the Great Recession. Section 3 presents the methodology and results to complete the analysis of cycle dynamics.

2.3. Cycle dynamics

Data and methodology

Once we have obtained the cycle characteristics and the concordance index for the member countries of the European Union, the next step in our analysis is to determine whether business cycles are similar between these countries and/or are now following more closed dynamics, in addition to analyzing this relationship, in other words, if there are one or more groups of countries presenting similar cycles. Furthermore, we try to see whether there are some differences between relationships between the subsample pre-crisis and the period since the crisis started. Unlike Grigoraş and Stanciu (2016), we are not limited to analyzing only the cycle features or the synchronization with a presupposed core central country. We let the data speak by itself, by not assuming any central core of the EU aggregation, and analyzing the concordance of the cycle phases between every country with each other; in order to analyze the distribution of dissimilarities for both characteristics and concordance between countries, and study the changes that may have occurred after the Great Recession.

To study the existence of patterns between the countries, we use a clustering method that finds similar behaviors on cycles' characteristics. We apply the method of multidimensional scaling (MDS), a type of multivariate data analysis. Noted by Cox and Cox (2000), supposing a set of *n* objects, where between each pair of objects, there is a measurement of the dissimilarity, MDS application searches for a low-dimensional space, usually Euclidean, in which points in the space represent the objects and such that the

[6] Bulgaria, Croatia, Cyprus and Slovenia have also been deleted from the sample of synchronization due to the interference that they provide as consequence of little data.

distances between the points in the space match, as well as possible, the original dissimilarities. This analysis projects the pairwise cycle distances in a map such that the distances among the countries plotted in the layout approximate the economic cycle dissimilarities. In the resulting map, countries that present high economic cycle dissimilarities have representations in the layout that are not close to one another.

The MDS that we apply is the classical one, whose aim is to find a configuration in a low number of dimensions that, in our case, is two. This method treats the distances as Euclidean distances by going from a data matrix to a Euclidean distance matrix[7]. The Euclidean distance between two points is the length of the line segment connecting them.

First, and having access to the average features that we have obtained from business cycles, we apply MDS to the results from the entire sample of data, the period before the crisis and the period since it started to build the MDS maps. Then, we perform the same process directly using the pairwise distances of business cycle synchronization, obtained as 1 minus the concordance index.

The aim is to represent in a map the different countries of the EU28 to find relationships among groups of them. The maps allow us to visually understand which countries show similar patterns about business cycle features and synchronization[8].

After that, to prove the veracity of the results, we apply a non-parametric density estimation approach to examine the distribution of the pairwise distances that we have previously calculated. Once we have obtained the distances between each pair of countries for the characteristics and using the pairwise distances of synchronization, we represent a kernel density distribution. The Gaussian kernel density estimator smooths out the contribution of each observed pairwise distance using an optimal bandwidth h, which is the optimal width of the density window around each point that would minimize the mean integrated squared error. Representing the distribution of the entire sample and both pre- and post-crisis subsamples, we can check if there are any changes between the cyclical patterns of characteristics and synchronization before and after the crisis started.

---

[7] We are aware of the sensitivity of Euclidean distances to outliers and composition of the sample itself.

[8] Note that in these maps, axes are meaningless; thus, they have been deleted. Every MDS map plots the country code, whose meanings are collected in Table 2.

Furthermore, to provide robustness, we also present a summary of the descriptive statistics including skewness and kurtosis of the different pairwise distances calculated and apply the Kolmogorov-Smirnov test of equality on the distributions of two different samples, which not only evaluates the difference in central tendency but also evaluates the shape and skewness on the distributions.

Finally, to test for the number of modes of the distributions with the purpose of checking the existence of a core-periphery structure, we use the test suggested by Silverman (1981). The null hypothesis states that a density function has at most k modes, against the alternative hypothesis that it has more than k modes. Establishing a critical bandwidth h_k* of the kernel density estimate for which it has k modes as maximum, it is possible to resample the pairwise distances by bootstrapping techniques and repeat this process many times to test the probability of having more than the number of modes k given h_k*. The probability that the resulting critical bandwidths given k are larger than the critical bandwidth established can be used as the *p-value* of the test.

Results

The maps of dissimilarities in average business cycle features using multidimensional scaling are represented in Figures 1 to 3. Regarding the maps, it is possible to check how there is not an approximation among countries based on the date of accession to the European Union[9], similar to the result that Gomez et al. (2012) and Wortmann and Stahl (2016) stated. Regarding the complete sample, we can identify two separated central cores that gather most of the countries. The right periphery of the main core gathers countries such as Croatia, Poland and Malta, which present shorter expansions, or Finland, Hungary and Denmark, which have shown the smallest gain during expansion. On the left side of the map, at the periphery of the core, Slovakia, Lithuania and Estonia, with larger amplitudes during expansions, are together. The UK and Spain, which had longer expansions, are represented farther away from the core, as well as Ireland, which shows a much longer average gain during expansions. Although there appears to be no relation between the date of accession to the EU and the approximation among countries, with the exception of the UK and Spain, the oldest members of the group are closer among themselves.

[9] In every MDS map, the founders and oldest members of the European Union are represented in red, the members who acceded between 1973-1995 are plotted in blue, and the new members, since 2004, are represented in black.

The MDS analysis of the distances in business cycle features before the beginning of the Great Recession, represented in Figure 2, shows a similar pattern: there is a core with the smallest distances between the countries, and the countries on the periphery are the same as those on the complete sample analysis. The MDS map for the period since the crisis started (Figure 3) seems to show that countries are now represented with a greater distance between them.

Figure 1. MDS map of BC features. Entire sample

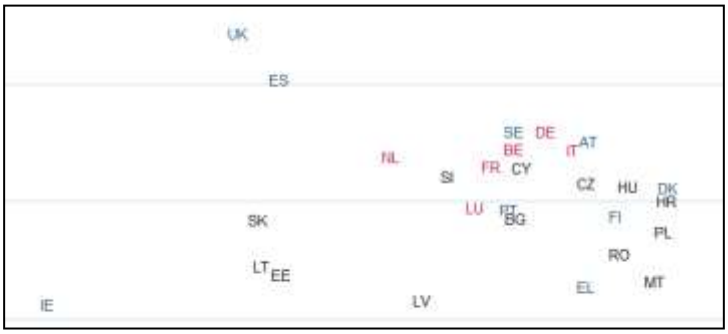


Figure 2. MDS map of BC features. Period before the crisis

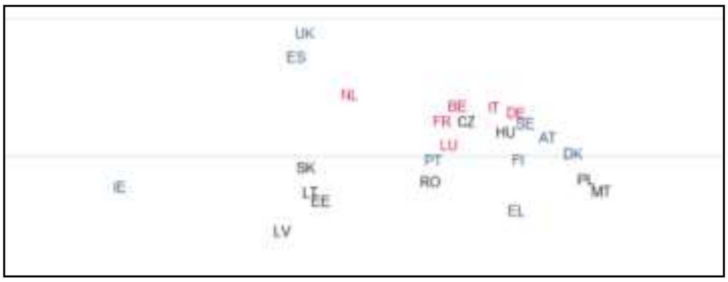


Figure 3. MDS map of BC features. Period since the crisis started

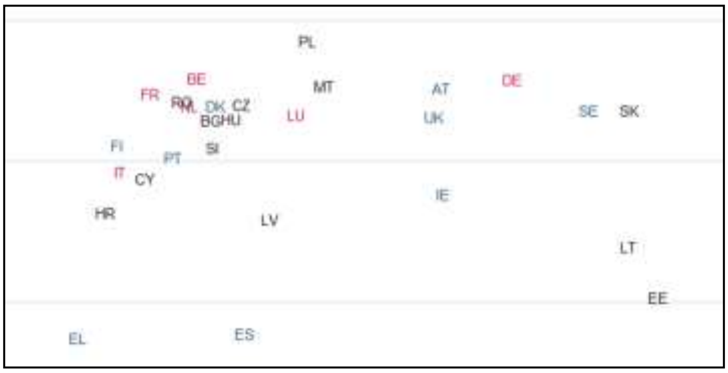
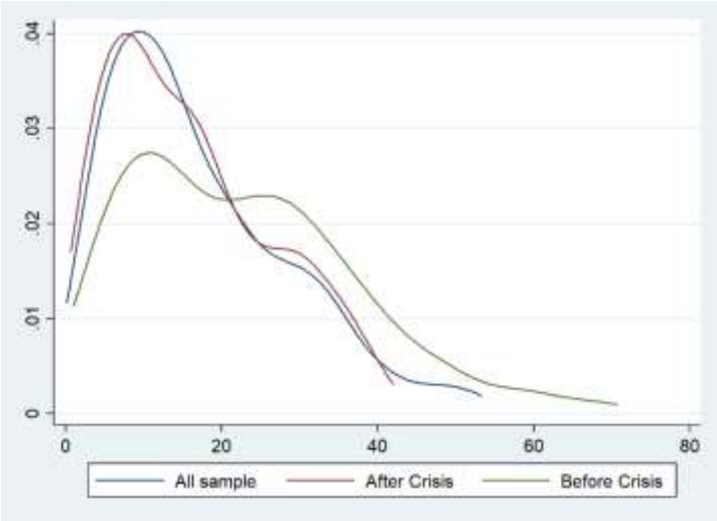


Figure 4. Kernel density function of distances in BC features. Original samples



However, analyzing the different kernel density functions of distances in business cycle features, represented in Figure 4, it is possible to check that there were more dissimilarities and larger distances during the period before 2008. The distribution of distances in business cycle features during the period since the crisis started shows the reduction of dissimilarities and distances between countries.

We can confirm that since the beginning of the Great Recession, the characteristics of the business cycles of countries belonging to the European Union group have become more similar. It is also possible to see that there is not a symptom that makes us think in a pattern across new or old members of the European Union, relationships based on date of accession to the group do not seem to be defined by a pattern, and countries are showing more similar behaviors than previous decades, due to the experienced crisis.

Table 3. Statistics of distances in BC features and synchronization

	MEAN	STD. DEV.	VARIANCE	SKEWNESS	KURTOSIS
BC CHARACTERISTICS					
Entire sample	17.135	11.560	133.639	0.908	3.253
Before crisis	22.765	14.532	211.189	0.760	3.237
Since 2008	15.995	10.372	107.587	0.571	2.318
BC SYNCHRONIZATION					
Entire sample	0.202	0.074	0.005	0.604	3.503
Before crisis	0.172	0.071	0.005	0.749	3.921
Since 2008	0.280	0.143	0.020	0.594	2.732

Table 4. Silverman test of multimodality. P-values

	Entire sample		Before crisis		Since 2008	
	Critical BW	p-value	Critical BW	p-value	Critical BW	p-value
BC characteristics						
1 mode	3.101	0.42	4.563	0.46	2.819	0.44
2 mode	1.998	0.92	3.248	0.62	2.509	0.02
BC synchronization						
1 mode	0.012	0.56	0.025	0.38	0.033	0.66
2 mode	0.014	0.58	0.020	0.10	0.028	0.44

Table 5. Kolmogorov-Smirnov test of the equality of pairwise distances distributions. P-values

	Before vs since 2008	All vs before crisis	All vs since 2008
BC characteristics	0.000	0.000	0.785
BC synchronization	0.000	0.000	0.000

To support this statement, summary statistics including skewness and kurtosis, multimodality and equality of distributions are also presented. If we observe the skewness and kurtosis presented in Table 3, the values corresponding to the distances in features for the period before the crisis (S=0.76, K=3.23) are higher than the values obtained considering the period since the crisis started (S=0.57, K=2.31), which shows the reduction in dissimilarities. The results from the Silverman test of multimodality, presented in Table 4, show that we cannot reject the hypothesis of unimodality for the three samples considered. Furthermore, to confirm the changes in business cycle characteristics after 2008, the results from the Kolmogorov-Smirnov test, presented in Table 5, show that it is possible to reject the null hypothesis comparing the equality between the samples before and after the crisis started.

These results point towards the reconsideration of the analysis about business cycle features made by Camacho et al. (2008). They refused the existence of an attractor in cycles of member countries of the European Union; thus, it is reasonable to think that the Great Recession has introduced considerable changes in cyclical patterns. Their study only covered the sample until the last accessions in 2004; consequently, if our analysis shows the existence of that European common cycle, it is acceptable to think that studying the update sample has led to the discovery of the change in cyclical characteristics after the experienced financial crisis.

Considering the analysis of synchronization, Figures 5 to 7 show the MDS maps of dissimilarities between business cycle synchronization for the entire sample, before the crisis started and since 2008. It is possible to identify a central core that gathers most of the countries; Germany, Portugal, Italy, Spain and Cyprus are located on the periphery, but there is still a great distance between them, and much farther away, we can find Malta, Romania, Croatia and Greece. As was the case with dissimilarities between business cycle characteristics, there appears to be no relation between date of accession to the EU and distance with other countries in terms of business cycle synchronization. The map for the period until the crisis started, presented in Figure 6, shows that countries are gathered in the center, with the exception of Germany, Sweden, Romania, Malta and Latvia. The MDS map for the period since the crisis started, plotted in Figure 7, shows the same situation. The change we can appreciate is that the main core gathers more countries now, with the exception of Latvia, situated below the core, and Italy, Cyprus, Croatia, Spain and Greece, represented at the left-hand side of this center, due to the similarities of the Great Recession between these countries, which was considerably longer and stronger. As before, we find no differences for the last added countries to the group in terms of synchronization with the rest of EU members.

Figure 5. MDS map of BC synchronization. Entire sample

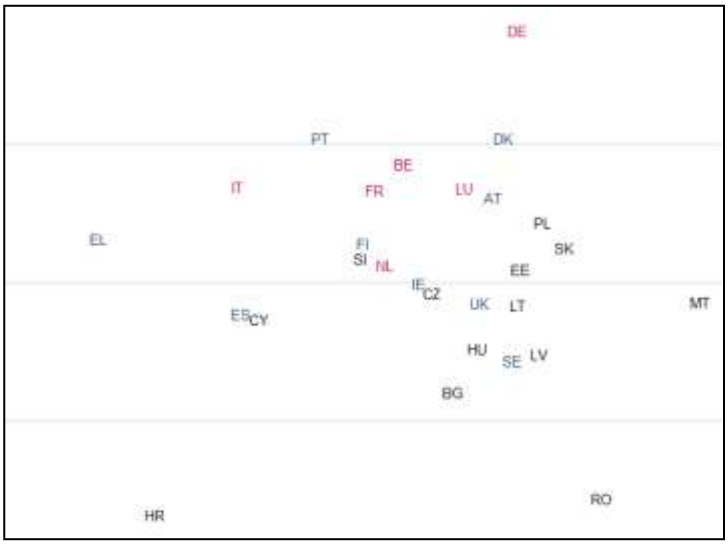


Figure 6. MDS map of BC synchronization. Period before the crisis

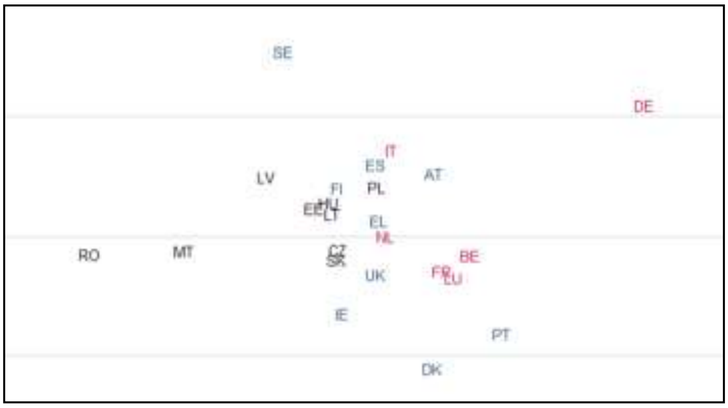
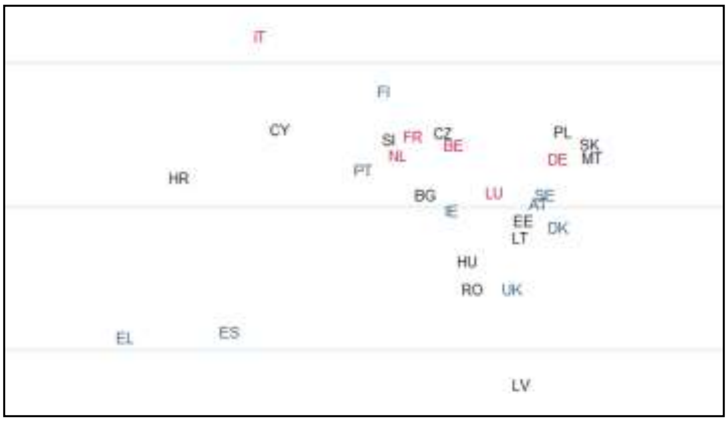
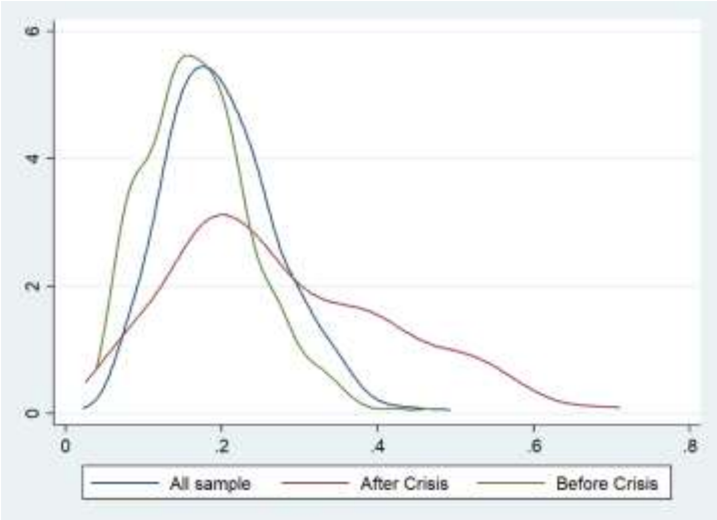


Figure 7. MDS map of BC synchronization. Period since the crisis started



For a more visual proof, Figure 8 shows the three Kernel density distributions of distances in business cycle synchronization. While the distribution for the period before the crisis presents a smaller right-hand tail what means homogeneous synchronization, since the crisis started, we can see that the dissimilarities between countries have increased, which means that the countries are not currently following closer dynamics.

Figure 8. Kernel density function of distances in BC synchronization. Original samples

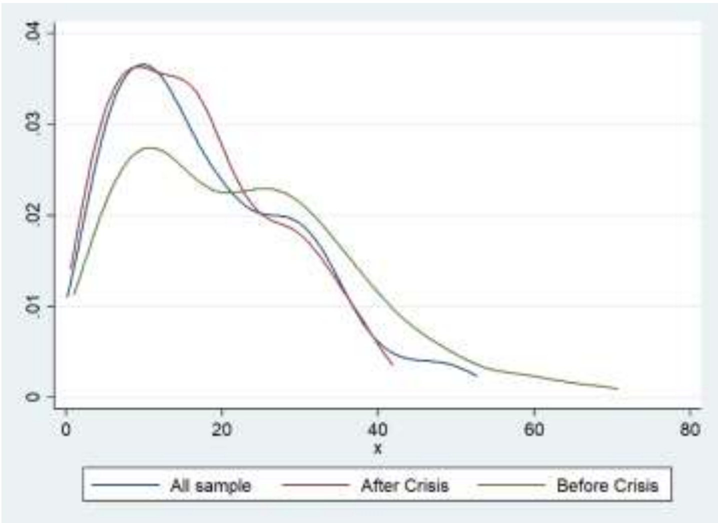


Observing the skewness and kurtosis values (Table 3), it seems that these values have been reduced during the period since the Great Recession began (kurtosis passing from 3.92 to 2.73, and skewness from 0.75 to 0.59). The results of the Silverman test analysis (Table 4) show that we cannot reject the null hypothesis of unimodality for any of the three samples. The Kolmogorov-Smirnov test of equality of pairwise distances in synchronization (Table 5) shows that the distribution before the crisis and the one since it began are not similar.

In line with Camacho et al. (2020), we can prove that differences in behaviors during the crisis and the speed of overcoming it between the countries have provoked an increase in synchronization dissimilarities. This is due to the fact that the countries have suffered different levels of impact of the recession and the idiosyncratic characteristics of the countries make the recovery phase differ in terms of duration and amplitude. Our results differ from those by Degiannakis et al. (2014), who stated the emergence of two groups of countries, and only demonstrated a decrease in synchronization of the countries out of the EMU group, while we showed that there is not proof of the existence of two cores, as well as from the conclusion achieved by Ahlborn and Wortmann (2018), which stated that the southern periphery is showing a diverging pattern while the Eastern periphery is showing convergence.

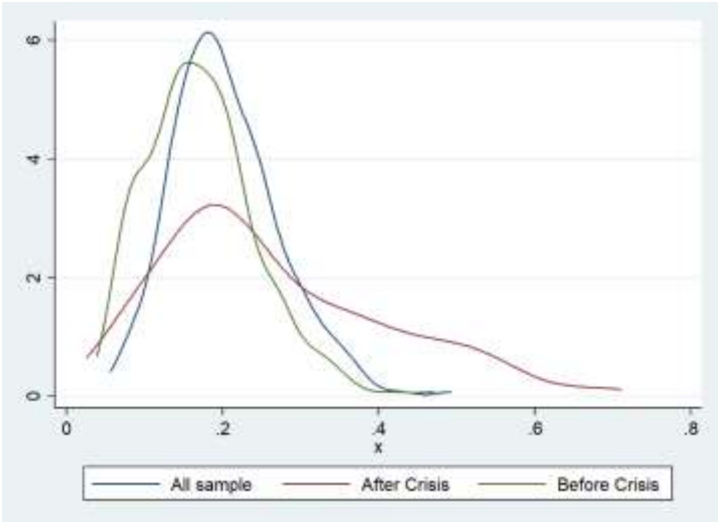
Since the sample for the period before the crisis started needed to be shortened due to a lack of complete cycles, the exercise was carried out for the three different samples excluding the same four countries (Bulgaria, Croatia, Cyprus and Slovenia) to compare pre- and post-crisis samples that actually include the same countries, obtaining the same general results[10]. We have obtained the pairwise distances between business cycle synchronization and other features, represented by the kernel density distribution and a summary of statistics. Figures 9 and 10 plot the kernel density distributions of both business cycle characteristics and synchronization, respectively. They show the same general shape as the ones that were previously calculated.

Figure 9. Kernel density function of distances in BC features. Reduced samples



[10] The completed results of the exercise with the reduced samples are available upon request.

Figure 10. Kernel density function of distances in BC synchronization. Reduced samples



Regarding the summary statistics in Table 6, although we can check how the entire sample shows smaller skewness and kurtosis values, the sample before crisis still presents a higher variance value, that confirms the reduction of dissimilarities of business cycle characteristics from the period before the crisis to the period post-crisis, which means that countries are now showing more similar cyclical characteristics. On the other hand, analyzing synchronization between countries, we can check that the skewness value is also higher for the sample since the crisis started. Furthermore, the increase in the variance indicates that there are more dissimilarities between the countries' synchronization, which we can visually check regarding the long right tail and the shift to the right side that the density function has experienced.

Table 6. Summary statistics of distances in business cycle characteristics and synchronization. Reduced samples

	MEAN	STD. DEV.	VARIANCE	SKEWNESS	KURTOSIS
BC CHARACTERISTICS					
Entire sample	18.314	11.880	141.130	0.748	2.894
Before crisis	22.765	14.532	211.190	0.760	3.237
Since 2008	16.759	10.224	104.524	0.482	2.293
BC SYNCHRONIZATION					
Entire sample	0.204	0.069	0.005	0.687	3.812
Before crisis	0.173	0.071	0.005	0.748	3.921
Since 2008	0.265	0.146	0.021	0.775	3.009

2.4. Conclusions

In this paper, we study and analyze possible changes in cyclical linkages among countries of the European Union introduced after the Great Recession based on the similarities in their cyclical features and synchronization. To some extent, this paper is an update and an extended version of previous works performed within the European Union. In particular, the consideration of a wide set of countries during an additional decade and the severity of the Great Recession seem to be behind these new empirical findings and the change in the relationship.

To summarize, we report the results obtained by applying a methodology for detecting turning points in GDP time series for each country. These turning points help to date expansions and recessions of every country, which allows us to analyze the length, depth and shape for different cycles, in addition to the synchronization.

Perhaps the most important contribution of our analysis emerges from the cyclical pattern observed after the 2008-financial crisis. In particular, cyclical characteristics after the crisis compared with the results obtained from the period before. Basically, recessions become longer and deeper during the Great recession.

On the other hand, focusing on the linkages between countries, and to check potential changes in the relationship after the crisis, we carried out an exhaustive analysis of distances in business cycle features and synchronization, for the entire sample, the period before 2008 and the period since the Great Recession started. In doing so, we apply a multidimensional scaling methodology to represent, in a map, every country by using their distances in features and synchronization of the business cycle. No evidence of a definite linkage among countries is found. In other words, it is not possible to establish definite relationships depending on the date of the entry to the group. To check the robustness of these findings, we represent the density distribution by kernel estimator on each of the distances for the characteristics and synchronization in business cycles.

Finally, we check the existence of an attractor in these distributions and verify the hypotheses that the 2008-crisis has probably powered linkages among countries, making their cyclical characteristics more similar, given that the Great Recession has had similar effects across the European Union, besides the fact that the countries are now more desynchronized due to the different evolutions of the cycles since the Great Recession started.

All in all, these results are important to distinguish different groups of economies in terms of heterogeneous dynamics and groups with close linkages. Identifying these groups is a key element for improving the effectiveness of European policies and especially the monetary policies developed by the European Central Bank in order to promote economic stabilization.

References

Ahking, F. W. (2015). Measuring U.S. business cycles: A comparison of two methods and two indicators of economic activities. *Journal of Economic and Social Measurement*, *39*, 199-216.

Ahlborn, M., & Wortmann, M. (2018). The core-periphery pattern of European business cycles: A fuzzy clustering approach. *Journal of Macroeconomics*, *55*, 12-27.

Antonakakis, N., Chatziantoniou, I., & Filis, G. (2016). Business Cycle Spillovers in the European Union: What is the Message Transmitted to the Core? *The Manchester School*, *84*(4), 437-481.

Bierbaumer-Polly, J., Huber, P., & Rozmahel, P. (2016). Regional Business-Cycle Synchronization, Sector Specialization and EU Accession. *Journal of Common Market Studies*, *54*(3), 544-568.

Bry, G., & Boschan, C. (1971). Cyclical analysis of time series: Selected procedures and computer programs. *National Bureau of Economic Research*.

Camacho, M., Caro, A., & Lopez-Buenache, G. (2020). The two-speed Europe in business cycle synchronization. *Empirical Economics*, *59*(3), 1069-1084.

Camacho, M., Perez-Quiros, G., & Saiz, L. (2006). Are European business cycles close enough to be just like one? *Journal of Economic Dynamics & Control*, *30*, 1687-1706.

Camacho, M., Perez-Quiros, G., & Saiz, L. (2008). Do European business cycles look like one? *Journal of Economic Dynamics & Control*, *32*, 2165-2190.

Cox, T. F., & Cox, M. A. (2000). Multidimensional Scaling. *Chapman and Hall*.

Darvas, Z., & Szapáry, G. (2008). Business cycle synchronization in the enlarged EU. *Open Economies Review*, *19*(1), 1-19.

De Haan, J., Inklaar, R., & Jong-A-Pin, R. (2008). Will business cycles in the euro area converge? A critical survey of empirical research. *Journal of economic surveys*, *22*(2), 234-273.

Degiannakis, S., Duffy, D., & Filis, G. (2014). Business Cycle Synchronization in EU: A Time-Varying Approach. *Scottish Journal of Political Economy*, *61*(4), 348-370.

Feldstein, M. (1997). The political economy of the European Economic and Monetary Union: Political sources of an economic liability. *Journal of Economic Perspectives*, *11*(4), 23-42.

Gomez, D. M., Ortega, G. J., & Torgler, B. (2012). *Synchronization and diversity in business cycles: A network approach applied to the European Union* (No. 2012-01). CREMA Working Paper.

Grigoraş, V., & Stanciu, I. E. (2016). New evidence on the (de)synchronisation of business cycles: Reshaping the European business cycle. *International Economics*, *147*, 27-52.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, *57*(2), 357-384.

Harding, D., & Pagan, A. (2002). Dissecting the cycle: a methodological investigation. *Journal of Monetary Economics*, *49*, 365-381.

Harding, D., & Pagan, A. (2006). Synchronization of cycles. *Journal of Econometrics*, *132*(1), 59-79.

König, J., & Ohr, R. (2013). Different Efforts in European Economic Integration: Implications of the EU Index. *JCMS: Journal of Common Market Studies*, *51*(6), 1074-1090.

Krolzig, H., & Toro, J. (2005). Classical and modern business cycle measurement: the European case. *Spanish Economic Review*, *7*, 1-22.

McDermott, C. J., & Scott, A. (2000). Concordance in business cycles. *Technical report, IMF*.

Silverman, B. W. (1981). Using kernel density estimates to investigate multimodality. *Journal of the Royal Statistical Society. Series B (Methodological)*, 97-99.

Wortmann, M., & Stahl, M. (2016). One Size Fits Some: A Reassessment of EMU's Core-periphery Framework. *Journal of Economic Integration*, *31*(2), 377-413.

Appendix

Table A1. Chronological enlargement of the European Union

DATE	COUNTRIES	DATE	COUNTRIES
1957 Founders	Belgium	**2004**	Cyprus
	France		Czech Republic
	Germany		Estonia
	Italy		Hungary
	Luxembourg		Latvia
	Netherlands		Lithuania
			Malta
1973	Denmark		Poland
	Ireland		Slovakia
	United Kingdom		Slovenia
1981	Greece	**2007**	Bulgaria
			Romania
1986	Portugal		
	Spain	**2013**	Croatia
1995	Austria		
	Finland		
	Sweden		

Table A2. Business cycle features for the entire sample

	DURATION (Q)		AMPLITUDE (%)		EXCESS (%)		CUMULATION	
	E	R	E	R	E	R	E	R
AUSTRIA	23.4	5	19.66	-0.58	0.44	0.22	2.44	-0.02
BELGIUM	25.5	3.6	25.21	-1.93	1.53	0.05	4.80	-0.05
BULGARIA	20	4.5	27.81	-3.57	1.65	0.40	3.79	-0.11
CROATIA	14.3	11.5	15.71	-7.11	0.39	0.68	2.06	-0.44
CYPRUS	24	8.5	25.82	-6.88	1.72	0.43	5.46	-0.44
CZECH REP.	20.3	4	21.07	-3.11	1.40	0.06	2.74	-0.07
DENMARK	18	3.1	15.98	-2.52	0.04	-0.10	2.27	-0.05
ESTONIA	26	5.5	47.60	-11.70	1.90	-0.51	6.99	-0.42
FINLAND	16.8	4.4	19.89	-3.66	0.38	0.10	3.26	-0.16
FRANCE	24.1	5.1	28.06	0.08	0.96	-0.03	5.77	0.02
GERMANY	25.6	8.3	23.84	-1.39	0.67	-0.26	3.05	-0.02
GREECE	12.3	5.8	24.50	-7.22	0.74	-0.35	3.33	-0.42
HUNGARY	18.3	4	18.01	-2.98	0.78	0.54	2.90	-0.12
IRELAND	29.6	3.7	65.34	-2.46	3.66	0.20	16.83	-0.10
ITALY	22.4	7.1	21.34	-1.95	-0.04	0.13	3.06	-0.11
LATVIA	17.3	5	37.65	-6.83	3.43	0.22	4.38	-0.43
LITHUANIA	26.3	5	48.04	-9.84	1.89	0.49	6.89	-0.36
LUXEM-BOURG	22.6	3.3	30.49	-2.81	1.70	0.00	4.00	-0.08
MALTA	10.2	1.6	20.08	-1.00	0.55	-0.12	1.31	-0.01
NETHER-LANDS	28.6	4.8	34.04	-3.68	0.74	-0.46	10.35	-0.09
POLAND	14	1	17.28	-1.13	0.14	0.00	1.45	-0.01
PORTUGAL	21.4	4.5	27.81	-3.82	0.95	-0.16	3.68	-0.12
ROMANIA	13.4	4.4	21.14	-4.42	1.79	-0.02	2.57	-0.18
SLOVAKIA	30.7	2.5	46.59	-7.63	3.12	0.59	6.55	-0.15
SLOVENIA	26	5.5	30.48	-7.08	2.75	-0.19	5.92	-0.20
SPAIN	36.8	15.7	40.82	-3.38	-0.41	0.11	9.50	-0.39
SWEDEN	25.5	8.6	23.60	-2.52	0.28	0.43	4.40	-0.15
UK	44.6	6.5	40.79	-3.77	1.52	0.88	11.18	-0.21
Average EU28	22.79	5.45	29.24	-4.10	1.24	0.12	5.03	-0.17

Table A3. Business cycle features before the crisis started

	Duration (Q)		Amplitude (%)		Excess (%)		Cumulation	
	E	R	E	R	E	R	E	R
AUSTRIA	22.00	5.00	20.85	0.34	0.54	0.36	2.50	0.00
BELGIUM	29.30	3.40	31.58	-1.78	2.18	0.03	6.23	0.03
BULGARIA	35.00	-	64.63	-	4.41	-	10.09	-
CROATIA	30.00	-	38.70	-	0.89	-	5.73	-
CYPRUS	54.00	-	66.75	-	4.66	-	15.84	-
CZECH REP.	27.00	4.00	31.45	-1.60	2.33	-0.02	4.70	-0.04
DENMARK	18.70	2.90	18.06	-2.19	0.04	-0.01	2.63	-0.04
ESTONIA	23.50	4.00	55.46	-2.50	3.74	-0.29	7.66	-0.05
FINLAND	20.40	4.00	25.83	-3.18	0.60	0.30	4.39	-0.17
FRANCE	27.10	5.20	34.76	0.68	1.13	0.08	7.33	0.04
GERMANY	24.30	9.40	24.82	-0.33	0.91	-0.05	3.00	-0.01
GREECE	13.60	3.90	28.64	-5.68	0.89	-0.33	3.93	-0.14
HUNGARY	23.00	3.50	26.56	-0.90	1.30	0.09	4.97	-0.02
IRELAND	35.80	3.00	79.37	-0.61	5.46	-0.02	22.46	-0.01
ITALY	26.70	6.00	27.49	-0.49	-0.13	0.31	4.03	-0.02
LATVIA	22.00	3.00	62.03	-2.14	7.53	-0.28	7.40	-0.03
LITHUANIA	24.50	4.00	56.73	-2.89	3.49	-0.34	7.77	-0.06
LUXEM-BOURG	24.70	3.20	35.08	-2.12	2.46	0.02	4.73	-0.06
MALTA	10.30	1.50	17.15	-1.94	-0.24	-0.08	1.05	-0.02
NETHER-LANDS	35.00	4.50	44.92	-3.89	0.70	-0.56	14.32	-0.09
POLAND	12.80	1.00	18.48	-1.68	-0.17	0.00	1.59	-0.02
PORTUGAL	24.10	3.80	34.29	-3.02	1.14	0.06	4.63	-0.09
ROMANIA	20.00	7.00	39.59	-5.50	3.31	-0.36	5.36	-0.33
SLOVAKIA	29.50	4.00	55.46	-6.15	4.79	1.19	7.33	-0.20
SLOVENIA	53.00	-	74.84	-	6.70	-	16.66	-
SPAIN	44.00	12.50	50.72	-0.29	-0.77	0.03	12.40	0.00
SWEDEN	23.80	9.80	23.31	-1.57	-0.02	0.47	4.53	-0.15
UK	48.50	6.30	47.19	-3.46	1.84	0.53	13.42	-0.17
Average EU28	25.44	4.79	37.08	-2.20	1.79	0.05	6.60	-0.07

Table A4. Business cycle features since the crisis started

	DURATION (Q)		AMPLITUDE (%)		EXCESS (%)		CUMULATION	
	E	R	E	R	E	R	E	R
AUSTRIA	32	5	12.53	-5.17	-0.16	-0.51	2.12	-0.13
BELGIUM	14	4	6.10	-2.32	-0.41	0.12	0.51	-0.06
BULGARIA	12.5	4.5	9.40	-3.57	0.27	0.40	0.64	-0.11
CROATIA	6.5	11.5	4.22	-7.11	0.14	0.68	0.23	-0.44
CYPRUS	9	8.5	5.36	-6.88	0.25	0.43	0.27	-0.44
CZECH REP.	13.5	4	10.70	-3.86	0.47	0.11	0.79	-0.09
DENMARK	15	4	6.61	-3.81	0.04	-0.49	0.62	-0.10
ESTONIA	31	7	31.87	-20.89	-1.80	-0.72	5.66	-0.79
FINLAND	7.3	5.3	4.06	-4.76	-0.18	-0.37	0.24	-0.13
FRANCE	13.5	5	4.63	-1.74	0.34	-0.36	0.31	-0.03
GERMANY	33	3	17.99	-6.67	-0.77	-1.34	3.31	-0.09
GREECE	5	15	1.72	-14.91	-0.13	-0.40	0.07	-1.81
HUNGARY	13.5	4.5	9.45	-5.05	0.26	1.00	0.83	-0.23
IRELAND	14	5	30.26	-6.17	-0.81	0.62	2.75	-0.27
ITALY	9.5	10	2.88	-5.61	0.24	-0.32	0.13	-0.33
LATVIA	12.5	7	13.26	-11.52	-0.67	0.72	1.36	-0.82
LITHUANIA	30	6	30.65	-16.78	-1.31	1.32	5.14	-0.67
LUXEM-BOURG	15	3.5	14.40	-4.88	-0.96	-0.05	1.43	-0.13
MALTA	10	1.7	23.01	-0.37	1.34	-0.14	1.58	-0.00
NETHER-LANDS	12.5	5.5	6.84	-3.28	0.85	-0.26	0.42	-0.08
POLAND	16.5	1	14.88	-0.29	0.76	0.00	1.17	-0.00
PORTUGAL	12	6.5	5.11	-6.20	0.29	-0.80	0.35	-0.20
ROMANIA	9	2.7	8.84	-3.71	0.77	0.20	0.72	-0.08
SLOVAKIA	33	1	28.85	-9.12	-0.20	0.00	4.97	-0.09
SLOVENIA	12.5	5.5	8.31	-7.08	0.78	-0.19	0.56	-0.20
SPAIN	15	22	11.12	-9.55	0.65	0.26	0.79	-1.16
SWEDEN	34	4	25.05	-6.34	1.82	0.27	3.77	-0.17
UK	29	7	15.20	-4.72	0.22	1.92	2.22	-0.32
Average EU28	16.80	6.06	12.98	-6.51	0.07	0.08	1.53	-0.32

Table A5. Business Cycle Synchronization

	AT	BE	BG	HR	CY	CZ	DK	EE	FI	FR
AT	1.00									
BE	0.88	1.00								
BG	0.81	0.84	1.00							
HR	0.65	0.71	0.79	1.00						
CY	0.75	0.83	0.88	0.91	1.00					
CZ	0.82	0.89	0.93	0.77	0.85	1.00				
DK	0.82	0.84	0.75	0.59	0.72	0.83	1.00			
EE	0.87	0.83	0.86	0.70	0.78	0.81	0.85	1.00		
FI	0.77	0.84	0.78	0.77	0.85	0.85	0.75	0.83	1.00	
FR	0.82	0.86	0.86	0.73	0.84	0.86	0.80	0.82	0.77	1.00
DE	0.86	0.81	0.71	0.55	0.71	0.76	0.77	0.80	0.75	0.79
EL	0.69	0.74	0.67	0.77	0.79	0.68	0.70	0.67	0.71	0.71
HU	0.85	0.80	0.88	0.76	0.79	0.80	0.80	0.81	0.75	0.79
IE	0.82	0.86	0.87	0.74	0.85	0.89	0.82	0.92	0.82	0.83
IT	0.84	0.81	0.75	0.83	0.90	0.81	0.75	0.76	0.79	0.83
LV	0.81	0.73	0.78	0.65	0.70	0.71	0.78	0.88	0.73	0.72
LT	0.85	0.84	0.90	0.74	0.81	0.82	0.82	0.92	0.80	0.81
LU	0.85	0.86	0.84	0.68	0.81	0.85	0.83	0.88	0.81	0.84
MT	0.83	0.77	0.78	0.62	0.70	0.83	0.77	0.84	0.71	0.75
NL	0.88	0.87	0.91	0.82	0.89	0.90	0.83	0.84	0.76	0.85
PL	0.87	0.88	0.86	0.67	0.80	0.85	0.81	0.87	0.81	0.84
PT	0.78	0.86	0.78	0.74	0.79	0.81	0.81	0.76	0.76	0.92
RO	0.74	0.69	0.87	0.71	0.67	0.80	0.71	0.79	0.64	0.70
SK	0.85	0.85	0.88	0.67	0.78	0.84	0.81	0.87	0.79	0.81
SI	0.84	0.92	0.91	0.82	0.91	0.92	0.81	0.84	0.88	0.93
ES	0.82	0.78	0.81	0.89	0.88	0.81	0.71	0.76	0.74	0.84
SE	0.83	0.79	0.87	0.71	0.83	0.89	0.73	0.92	0.82	0.74
UK	0.84	0.86	0.88	0.76	0.84	0.86	0.82	0.91	0.83	0.80

Table A5. *Continued*

	DE	EL	HU	IE	IT	LV	LT	LU	MT
DE	1.00								
EL	0.65	1.00							
HU	0.74	0.66	1.00						
IE	0.73	0.73	0.82	1.00					
IT	0.77	0.76	0.71	0.78	1.00				
LV	0.70	0.69	0.82	0.82	0.69	1.00			
LT	0.81	0.66	0.84	0.89	0.73	0.82	1.00		
LU	0.84	0.70	0.82	0.83	0.80	0.78	0.87	1.00	
MT	0.75	0.51	0.78	0.80	0.65	0.74	0.86	0.80	1.00
NL	0.79	0.75	0.83	0.84	0.84	0.74	0.85	0.86	0.81
PL	0.84	0.63	0.81	0.85	0.76	0.76	0.88	0.85	0.87
PT	0.79	0.73	0.73	0.81	0.80	0.66	0.75	0.86	0.71
RO	0.65	0.57	0.75	0.71	0.62	0.80	0.78	0.75	0.83
SK	0.78	0.62	0.79	0.87	0.73	0.74	0.92	0.87	0.90
SI	0.80	0.76	0.83	0.92	0.88	0.74	0.85	0.90	0.78
ES	0.75	0.80	0.78	0.78	0.85	0.75	0.78	0.77	0.65
SE	0.79	0.66	0.87	0.77	0.79	0.82	0.93	0.76	0.88
UK	0.81	0.70	0.90	0.83	0.76	0.85	0.94	0.89	0.84

Table A5. *Continued*

	NL	PL	PT	RO	SK	SI	ES	SE	UK
NL	1.00								
PL	0.87	1.00							
PT	0.84	0.79	1.00						
RO	0.74	0.76	0.64	1.00					
SK	0.86	0.89	0.78	0.76	1.00				
SI	0.98	0.87	0.88	0.74	0.84	1.00			
ES	0.85	0.74	0.82	0.69	0.71	0.88	1.00		
SE	0.79	0.92	0.70	0.78	0.91	0.92	0.78	1.00	
UK	0.86	0.89	0.80	0.76	0.90	0.89	0.76	0.81	1.00

Table A6. Business Cycle Synchronization before the crisis

	AT	BE	CZ	DK	EE	FI	FR	DE	EL	HU	IE	IT
AT	1.00											
BE	0.88	1.00										
CZ	0.82	0.85	1.00									
DK	0.79	0.85	0.89	1.00								
EE	0.80	0.84	0.84	0.80	1.00							
FI	0.79	0.85	0.93	0.76	0.92	1.00						
FR	0.82	0.86	0.87	0.81	0.86	0.79	1.00					
DE	0.84	0.80	0.73	0.75	0.73	0.76	0.78	1.00				
EL	0.76	0.79	0.82	0.76	0.84	0.74	0.75	0.71	1.00			
HU	0.86	0.78	0.78	0.82	0.78	0.86	0.80	0.67	0.78	1.00		
IE	0.81	0.85	0.93	0.82	0.92	0.82	0.84	0.71	0.77	0.86	1.00	
IT	0.90	0.84	0.91	0.79	0.90	0.79	0.84	0.81	0.79	0.84	0.81	1.00
LV	0.82	0.78	0.78	0.75	0.90	0.86	0.80	0.67	0.82	0.84	0.86	0.88
LT	0.80	0.84	0.84	0.80	0.92	0.92	0.86	0.73	0.84	0.78	0.92	0.90
LU	0.83	0.87	0.87	0.82	0.86	0.84	0.83	0.83	0.75	0.80	0.84	0.83
MT	0.81	0.77	0.90	0.77	0.90	0.90	0.81	0.58	0.77	0.84	0.90	0.87
NL	0.90	0.87	0.93	0.85	0.92	0.78	0.84	0.80	0.79	0.86	0.85	0.87
PL	0.86	0.90	0.86	0.82	0.90	0.94	0.88	0.78	0.86	0.80	0.94	0.92
PT	0.79	0.88	0.84	0.84	0.82	0.79	0.92	0.80	0.76	0.76	0.83	0.82
RO	0.69	0.65	0.80	0.69	0.80	0.73	0.67	0.53	0.65	0.71	0.73	0.71
SK	0.81	0.86	0.85	0.81	0.88	0.92	0.85	0.68	0.83	0.78	0.93	0.86
ES	0.88	0.82	0.93	0.77	0.92	0.80	0.87	0.81	0.79	0.86	0.82	0.91
SE	0.79	0.77	0.93	0.69	0.92	0.85	0.73	0.75	0.74	0.86	0.76	0.85
UK	0.82	0.87	0.93	0.82	0.92	0.87	0.82	0.79	0.75	0.86	0.84	0.81

Table A6. *Continued*

	LV	LT	LU	MT	NL	PL	PT	RO	SK	ES	SE	UK
LV	1.00											
LT	0.82	1.00										
LU	0.80	0.86	1.00									
MT	0.87	0.90	0.81	1.00								
NL	0.86	0.92	0.87	0.90	1.00							
PL	0.84	0.90	0.88	0.87	0.94	1.00						
PT	0.76	0.82	0.87	0.74	0.83	0.84	1.00					
RO	0.82	0.76	0.67	0.90	0.73	0.75	0.63	1.00				
SK	0.78	0.96	0.88	0.90	0.93	0.86	0.85	0.73	1.00			
ES	0.86	0.92	0.81	0.90	0.88	0.94	0.83	0.73	0.88	1.00		
SE	0.86	0.92	0.72	0.90	0.79	0.94	0.69	0.73	0.90	0.85	1.00	
UK	0.86	0.92	0.90	0.90	0.89	0.94	0.83	0.73	0.93	0.79	0.78	1.00

Table A7. Business Cycle Synchronization after the crisis

	AT	BE	BG	HR	CY	CZ	DK	EE	FI	FR
AT	1.00									
BE	0.87	1.00								
BG	0.74	0.82	1.00							
HR	0.47	0.61	0.63	1.00						
CY	0.58	0.71	0.79	0.84	1.00					
CZ	0.82	0.95	0.87	0.61	0.76	1.00				
DK	0.92	0.79	0.66	0.39	0.50	0.74	1.00			
EE	0.95	0.82	0.74	0.47	0.58	0.76	0.92	1.00		
FI	0.71	0.79	0.61	0.61	0.66	0.74	0.68	0.71	1.00	
FR	0.82	0.84	0.82	0.61	0.71	0.84	0.74	0.76	0.68	1.00
DE	0.95	0.87	0.74	0.47	0.58	0.82	0.87	0.89	0.66	0.82
EL	0.39	0.47	0.50	0.71	0.61	0.47	0.42	0.45	0.53	0.53
HU	0.84	0.82	0.84	0.63	0.68	0.82	0.76	0.84	0.61	0.76
IE	0.87	0.89	0.76	0.55	0.66	0.84	0.84	0.92	0.79	0.79
IT	0.58	0.66	0.58	0.74	0.79	0.66	0.55	0.58	0.82	0.76
LV	0.79	0.66	0.63	0.42	0.47	0.61	0.82	0.84	0.55	0.61
LT	0.92	0.84	0.82	0.55	0.66	0.79	0.84	0.92	0.63	0.74
LU	0.95	0.82	0.79	0.53	0.63	0.82	0.87	0.89	0.66	0.87
MT	0.84	0.76	0.68	0.42	0.53	0.76	0.76	0.79	0.55	0.71
NL	0.79	0.87	0.84	0.68	0.74	0.87	0.71	0.74	0.66	0.92
PL	0.87	0.84	0.76	0.45	0.61	0.84	0.79	0.82	0.63	0.79
PT	0.74	0.76	0.74	0.68	0.63	0.76	0.66	0.68	0.61	0.92
RO	0.82	0.74	0.76	0.50	0.61	0.79	0.74	0.76	0.53	0.74
SK	0.89	0.82	0.79	0.42	0.58	0.82	0.82	0.84	0.61	0.76
SI	0.79	0.92	0.84	0.68	0.79	0.92	0.71	0.74	0.71	0.92
ES	0.55	0.63	0.66	0.82	0.71	0.63	0.47	0.55	0.47	0.68
SE	0.97	0.89	0.76	0.50	0.61	0.84	0.89	0.92	0.68	0.79
UK	0.89	0.82	0.79	0.58	0.63	0.76	0.82	0.89	0.61	0.71

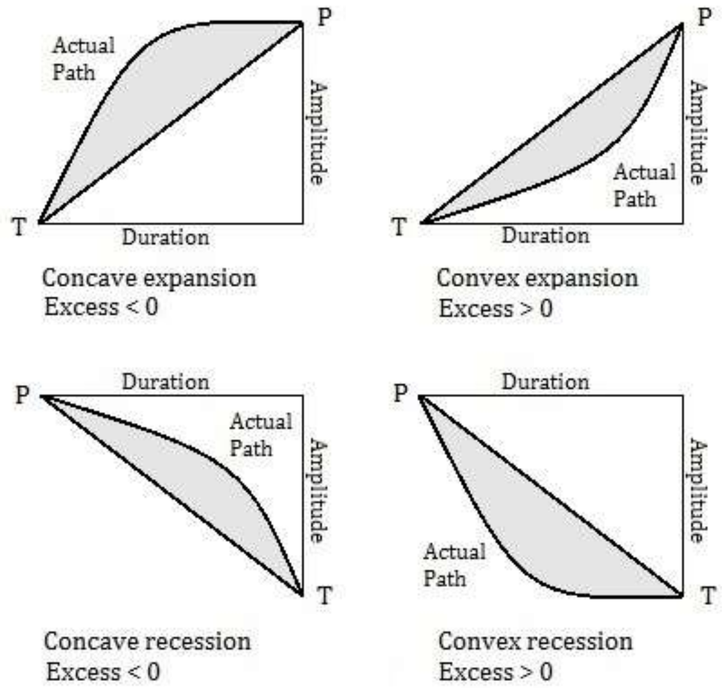
Table A7. *Continued*

	DE	EL	HU	IE	IT	LV	LT	LU	MT
DE	1.00								
EL	0.34	1.00							
HU	0.84	0.50	1.00						
IE	0.82	0.53	0.76	1.00					
IT	0.58	0.61	0.53	0.66	1.00				
LV	0.74	0.50	0.79	0.76	0.42	1.00			
LT	0.92	0.42	0.92	0.84	0.50	0.82	1.00		
LU	0.89	0.45	0.84	0.82	0.63	0.74	0.87	1.00	
MT	0.89	0.29	0.74	0.71	0.47	0.63	0.82	0.79	1.00
NL	0.79	0.55	0.79	0.76	0.68	0.58	0.76	0.84	0.74
PL	0.92	0.32	0.82	0.74	0.55	0.66	0.84	0.82	0.87
PT	0.74	0.61	0.68	0.71	0.68	0.53	0.66	0.79	0.68
RO	0.82	0.47	0.82	0.68	0.50	0.76	0.79	0.87	0.76
SK	0.95	0.29	0.79	0.76	0.53	0.68	0.87	0.84	0.89
SI	0.79	0.55	0.79	0.82	0.74	0.58	0.76	0.84	0.68
ES	0.50	0.84	0.66	0.63	0.61	0.61	0.58	0.61	0.45
SE	0.97	0.37	0.87	0.84	0.55	0.76	0.95	0.92	0.87
UK	0.89	0.45	0.95	0.82	0.47	0.84	0.97	0.84	0.79

Table A7. *Continued*

	NL	PL	PT	RO	SK	SI	ES	SE	UK
NL	1.00								
PL	0.76	1.00							
PT	0.89	0.71	1.00						
RO	0.76	0.79	0.66	1.00					
SK	0.74	0.92	0.68	0.82	1.00				
SI	0.95	0.76	0.84	0.76	0.74	1.00			
ES	0.71	0.47	0.76	0.63	0.45	0.71	1.00		
SE	0.82	0.89	0.71	0.84	0.92	0.82	0.53	1.00	
UK	0.74	0.82	0.63	0.82	0.84	0.74	0.61	0.92	1.00

Figure A1. Duration, amplitude and excess. Stylized pictures of expansions and recessions depending on the excess



Chapter 3: Procyclical and countercyclical components in aggregate self-employment dynamics

We revisit the macrodynamics of entrepreneurship in the UK from a new perspective. We ask whether entrepreneurship exhibits a new cyclical behavior after the Great Recession, providing self-employment turning point dating and establishing a new strategy to disentangle the preponderance of recession-push and prosperity-pull effects. We carry out an analysis of (nonlinear) causality applied to the bidirectional relationships between the self-employment rate and two indicators, the unemployment rate and the business confidence index, as a way to explore the prevalence of opportunity-based or necessity-driven entrepreneurship depending on the business cycle phase. First, after a literature review, our empirical analysis shows that self-employment rate development is not caused by labor market evolution; rather, it is now caused by the business climate, that is, confidence in the economy. However, this causal impact is only found for positive shocks. As a result, the dynamics of so-called opportunity-driven entrepreneurs govern the dynamics of self-employment in the UK. Furthermore, the results reveal that both positive and negative shocks in self-employment will cause shocks in the business climate. These effects can be both the same or the opposite signs. A rationale for this last result is provided.

3.1. Introduction

The macrodynamics of the self-employment rate remain a source of controversy among scholars, summarized in the so-called push and pull hypotheses (see Fairlie and Fossen (2020); Caliendo and Kritikos (2009)), as well as in the distinction between opportunity and necessity entrepreneurs, perceived as two different components of business creation with potentially opposite dynamics over the business cycle (Dawson and Henley (2012); Congregado et al. (2012)). There is renewed interest in this issue due to recent developments in self-employment rates in some OECD countries after the

Great Recession. The issue of whether entrepreneurship/self-employment is procyclical or countercyclical and whether it lags or leads business cycles has usually been associated with the study of the macro dynamics not only between self-employment and unemployment but also between self-employment development and the pace of economic activity.

The relationship between self-employment and unemployment has been the most intriguing relationship for both scholars and practitioners. The empirical estimates of the self-employment/unemployment relationship aspire only to capture a "net" effect of the recession-push and the prosperity-pull effects. For the latter, turning unemployment into self-employment is often seen by policymakers as an alternative to traditional active labor market policies to combat unemployment, Laffineur et al. (2017). Transitions into entrepreneurship can reduce unemployment rates, both directly–since each self-employee creates their own job– and indirectly, because some of these new entrants turn into employers creating additional jobs for others; see for instance Baumgartner and Caliendo (2008), Earle and Sakova (2000), and Congregado et al. (2010).

However, some theoretical models (Lucas, 1978) predict that participation in the self-employment sector will be temporary, since many of them – especially marginal entrepreneurs– will return to wage-earning employment during an economic upturn. In this way, the self-employment episode for these unemployed workers had been nothing more than a transitory occupation, as a refuge from unemployment (Rissman, 2003) avoiding human capital depreciation (Congregado et al., 2019) and providing a way of earning a living at least until recovery enabled them to gradually return to wage-earning employment.

However, the economic upturn after the Great Recession seems to show different patterns from previous recovery patterns. In some OECD countries, self-employment rates have shown persistence during the recovery reaching figures not seen before, in a context in which unemployment has been replaced by chronic underemployment and the emergence of new forms of employment and marginal entrepreneurs, including involuntary part-time ones (Congregado et al., 2019). Some analysts have suggested that the persistent elevated level of underemployment represents labor market slack during recovery, such as Bell and Blanchflower (2011), which is associated with the business cycle. Alternatively, this persistence and the emergence of new forms of self-employment – or nonstandard forms, including the work arrangements associated with the gig economy (Bracha and Burke, 2018) – may be due to new structural features of the labor market; see for instance, Valletta et al. (2020) and Green and Livanos (2017).

The case of the UK is a paradigmatic and extreme example of this new pattern during the recovery phase of the business cycle, becoming a particularly suitable case of study (Giupponi and Xu, 2020). UK self-employment rate figures after the Great Recession seem to show persistence. Self-employment rate numbers are similar to the rates before the recovery phase. The large increase of opportunity-driven entrepreneurs, and the survival of necessity entrepreneurs because the “new” full employment is now operating differently (i.e., emergence of non-standard forms of [self-] employment) are competing explanations for understanding this evolution. In this context, the challenge is to determine what kind of self-employment is behind the recent evolution of self-employment figures and check whether the self-employed sector is responding in the same way as British entrepreneurship did in previous economic recovery episodes (Cowling and Mitchell, 1997; Henley, 2021).

There is a large body of empirical literature that explores the cyclicality and countercyclicality of these two different species of entrepreneurs by using different econometric strategies and data –see Parker (2012) and López-Pérez et al. (2020) for a survey. Some of this literature has even gone so far as to try to provide operational definitions of opportunity versus necessity entrepreneurship by using readily available nationally representative data –Fossen (2020) and Neymotin (2020)–, and applying time series techniques to check the macrodynamics of opportunity and necessity self-employment during the business cycle.

However, this method raises serious concerns. First, the distinction between the two categories of self-employed workers is based on revealed intentions; second, time series are too short to make inferences; and third, the initial motivation does not necessarily lead to higher probabilities of success (survival).

To circumvent these problems in measuring, we avoid the use of these two components of self-employment time series to disentangle the relationship, separating the evolution of self-employment into two relationships: one related to labor market performance –as the push and as Lucas’ hypotheses state– and a second one depending on the opportunities for profit. In particular, and by using a non-linear causality test developed by Hatemi-J (2012), we explore whether labor market performance precedes the turning points of self-employment and whether a leading indicator, the business confidence index –which provides information about the future state of the economy and profit seeking opportunities– allows us to identify and forecast self-employment cycles. In addition, this empirical framework allows us to examine the degree of synchronization between self-employment and these two leading indicators.

In summary, this analysis might help us to understand the new stylized facts: what are the reasons why self-employment is higher and more persistent than before; to what extent do new economic trends affect labor market performance; and to what extent do economic agents make occupational decisions?

Our econometric approach consists of two strategies: by using a modified version of the Business Cycle Dating Algorithm by Bry and Boschan (1971), we detect and date turning points of the self-employment/unemployment and business index cycles.

The second analysis is based on the asymmetric causality analysis proposed by Hatemi-J (2012). An empirical analysis of (non-linear) causality applied to the relationships between self-employment, unemployment and business confidence index as a way to explore the prevalence of opportunity-based entrepreneurship or necessity-driven entrepreneurship depending on the business cycle phase.

The structure of the rest of this article is as follows. In Section 2, we conduct a brief description of the data and the methodology that we employ. Section 3 describes the empirical results, and finally, Section 4 concludes.

3.2. Methods and data

The aim of this article is to analyze the nature of the relationships between self-employment and macrodynamics, taking into consideration both labor-market dynamics and the countries' business cycle phase.

To this end, we conduct two types of analysis: first, the detection of turning points in the time series cycles and second, the exploration of causality relationships between self-employment and the other two time series.

Data

The data used are monthly observations from May 1992 to February 2019 for the UK, extracted from the ILOSTAT[1] database (self-employment and unemployment rates) and from the OECD Statistics (Business Confidence Index). Before conducting the empirical analysis, the data were seasonally adjusted and converted to natural logarithms. The time plots of the series are shown in Appendix Figure I.

Dating turning points

Using an adapted methodology for detecting turning points of the business cycle, we dated turning points and analyzed the cycles of the self-employment rate, unemployment rate and business confidence index. As usual, we assumed the definition of the cycle of Burns and Mitchell (1946) as a recurrent fluctuation of two regimes (recessions and expansions) in the dynamic evolution of the time series. In this way, a recession would be the period between a peak and a trough and expansions the period between trough and peak.

In this context, a peak is identified as the last moment of an expansion, and the trough is therefore the last moment of a recession. Starting from these definitions, the detection of these turning points (peaks and troughs) seems to be necessary to establish the cycle lengths.

It seems necessary to clarify the economic meaning of the cycle in the different series. A recession to the self-employment rate would mean that the rate is suffering a decrease and is considerably increasing during an expansion. The cycle of the unemployment rate could be defined as a decrease in unemployment during a recession phase and an increase in unemployment during expansions. Similar to the Business Confidence Index, confidence in the economy decreases during a recession and increases during an expansion.

Although there are many methods for the dating of cycles, we apply the methodology of Harding and Pagan (2002) to locate turning points and obtain an initial idea on the cyclicality, which is a refinement of the dating algorithm suggested by Bry and Boschan (1971).

[1] International Labour Organization Statistics.

The algorithm identifies a first set of turning points, the turning points within 6 months of the beginning or the end of the series are disregarded and then assesses a criterion of minimum duration of the phases, with 6 months being the minimum duration of a single phase and 15 months being the minimum duration of a complete cycle.

Finally, the algorithm gives us a binary variable that takes value one on the date when a recession takes place. This variable is used to establish the peaks and troughs of a sample time series, distinguishing between expansions and recessions, and then to analyze the cycle characteristics. Once the cycles have been extracted, we characterize the cycles based on the length, depth and shape, which can be measured by duration, amplitude and both excess and cumulative movement of the cycles, respectively.

Concerning the length of the cycles, duration is the average number of months spent between peak and trough in the case of recessions or between trough and peak during expansions.

Regarding the depth of the cycle, we measure the amplitude, which refers to the total gain or loss between the peak and trough, and vice versa, experienced in a phase. This value is represented by the rate of loss or gain, which is the mean percentage that the series have increased during expansions or decreased during recessions. Finally, the last characteristic is the deepness, which is associated with the shape of the cycle. It can be measured by the so-called excess, which measures how the actual time series behaves against a hypothetical linear path between two consecutive turning points.

Following Harding and Pagan (2002), once we have the duration and amplitude of a phase, we obtain the excess cumulated movements by the triangle approximation to the cumulative movements ($C_{Ti} = 0.5\, D_i\, A_i$, where D is the duration and A is the amplitude) and the actual cumulative movements or *cumulation*, calculated as the sum of every period's amplitude in a phase. The calculation of the excess in every phase (E_i) may be approximated by $E_i = (C_{Ti} - C_i + 0.5\, A_i)/D_i$, where the term $0.5\, A_i$ removes the bias that arises in using a sum of rectangles (cumulation C_i) to approximate a triangle.

Considering the way that the excess is calculated, a negative value refers to a concave evolution against the linear path, and a positive sign would indicate a convex evolution with respect to linear growth/decrease. In this way, a concave expansion and a convex recession evolve more sharply at the beginning of a phase and more smoothly at the end of it. In contrast, convex expansions and concave recessions present a moderate evolution at the start of the phase and become more abrupt at the end.

Concordance Index

Furthermore, to study the synchronization between the self-employment cycle and the unemployment or BCI cycle, the concordance index between self-employment i and unemployment/BCI j (IC_{ij}) has been calculated by Harding and Pagan, where R_{it} is a binary variable that takes value 1 when self-employment is in recession.

$$IC_{ij} = \frac{1}{T}\sum_{t=1}^{T}\{ R_{it}\, R_{jt} + (1 - R_{it})(1 - R_{jt})\} \tag{1}$$

The index represents the proportion of time in which the two variables experience the same phase of the cycle. The concordance index was calculated for the same moment of both variables and lagging unemployment or BCI cycles from 1 to 12 months to analyze the lagged response on concordance between self-employment and unemployment or BCI. Furthermore, the concordance index is divided by concordance during recessions and expansions.

Granger causality

The second part of our empirical strategy is to determine the possible existence of Granger causality relationships between self-employment, unemployment and the business climate using an alternative econometric approach to check the robustness of these relationships. The common way to study causality relationships is by using the Granger causality definition by using estimates from VAR models. The work of Toda and Yamamoto (1995) extends this traditional approach, suggesting a modified version of the Granger causality test based on augmented VAR models in levels and extra lags. This approach circumvents the problems stemming from the cointegration relationship and non-stationarity of the data series since the Toda-Yamamoto test can be applied irrespective of the order of integration or whether the time series are co-integrated.

Following this approach, our benchmark model for each of the two studied relationships is defined as follows[2]:

$$S_t = \alpha_1 + \sum_{i=1}^{p+d_{max}} \beta_{1i} S_{t-i} + \sum_{j=1}^{p+d_{max}} \gamma_{1j} U_{t-j} + \varepsilon_{1t} \tag{2a}$$

$$U_t = \alpha_2 + \sum_{i=1}^{p+d_{max}} \beta_{2i} U_{t-i} + \sum_{j=1}^{p+d_{max}} \gamma_{2j} S_{t-j} + \varepsilon_{2t} \tag{2b}$$

$$S_t = \alpha_3 + \sum_{i=1}^{p+d_{max}} \beta_{3i} S_{t-i} + \sum_{j=1}^{p+d_{max}} \gamma_{3j} B_{t-j} + \varepsilon_{3t} \tag{3a}$$

$$B_t = \alpha_4 + \sum_{i=1}^{p+d_{max}} \beta_{3i} B_{t-i} + \sum_{j=1}^{p+d_{max}} \gamma_{3j} S_{t-j} + \varepsilon_{4t} \tag{3b}$$

where S is self-employment, U is unemployment, B is business confidence index, p is the optimal lag length structure for the VAR model, according to the Akaike Information Criterion (AIC) and where d_{max} are the extra lagged explanatory variables –i.e., the maximum order of integration. Gaussian distributions with noise processes are assumed for the error terms.

To test the Granger causality between these variables, we must focus on the statistical significance of $\sum_{j=1}^{p+d_{max}} \gamma_{1j}$, $\sum_{j=1}^{p+d_{max}} \gamma_{2j}$, $\sum_{j=1}^{p+d_{max}} \gamma_{3j}$ and $\sum_{j=1}^{p+d_{max}} \gamma_{4j}$. For instance, if $\sum_{j=1}^{p+d_{max}} \gamma_{1j} \neq 0$, U_t Granger causes S_t whereas $\sum_{j=1}^{p+d_{max}} \gamma_{2j} \neq 0$, implies that S_t Granger causes U_t. Moreover, we cannot ignore the case in which both hypotheses are rejected. In this last case, there exists a bidirectional causality relationship. The same applies in equations 3a and 3b for the relationship between the business climate index and self-employment.

In addition, we cannot rule out the possibility of nonlinearities in the relationship. Assuming linearity might be the cause of rejecting Granger causality between any pair of variables. To address this issue, we also apply the Granger causality test suggested by Hatemi-J (2012) to address this issue. The econometric framework proposed by Hatemi-J determines whether cumulative positive and negative shocks can cause different impacts on the causal relationship, i.e., looking for asymmetry in the causality relationship by decomposing the potential causal impact of positive (negative) shocks from that of positive (negative) shocks. Applying this strategy to our two

---

[2] Results are suppressed for brevity but are available from the authors upon request.

analyzed relationships, we first represent the three variables by means of random walk processes:

$$S_t = S_{t-1} + \varepsilon_{1t} = S_0 + \sum_{i=1}^{t} \varepsilon_{1t} \tag{4}$$

$$U_t = U_{t-1} + \varepsilon_{2t} = U_0 + \sum_{i=1}^{t} \varepsilon_{2t} \tag{5}$$

$$B_t = B_{t-1} + \varepsilon_{3t} = B_0 + \sum_{i=1}^{t} \varepsilon_{3t} \tag{6}$$

where $t = 1,2, \ldots T$; the constants S_0, U_0 and B_0 are the initial values; and the variables ε_{1i}, ε_{2i} and ε_{3i} are white-noise error terms. We also allow the existence of both positive and negative shocks as follows: $\varepsilon_{1i}^{+} = max\{\varepsilon_{1i}, 0\}$, $\varepsilon_{2i}^{+} = max\{\varepsilon_{2i}, 0\}$, $\varepsilon_{3i}^{+} = max\{\varepsilon_{3i}, 0\}$, $\varepsilon_{1i}^{-} = min\{\varepsilon_{1i}, 0\}$, $\varepsilon_{2i}^{-} = max\{\varepsilon_{2i}, 0\}$, and $\varepsilon_{3i}^{-} = max\{\varepsilon_{3i}, 0\}$. We can rewrite equations (4) to (6) as follows:

$$S_t = S_{t-1} + \varepsilon_{1t} = S_0 + \sum_{i=1}^{t} \varepsilon_{1t}^{+} + \sum_{i=1}^{t} \varepsilon_{1t}^{-} \tag{7}$$

$$U_t = U_{t-1} + \varepsilon_{2t} = U_0 + \sum_{i=1}^{t} \varepsilon_{2t}^{+} + \sum_{i=1}^{t} \varepsilon_{2t}^{-} \tag{8}$$

$$B_t = B_{t-1} + \varepsilon_{3t} = B_0 + \sum_{i=1}^{t} \varepsilon_{3t}^{+} + \sum_{i=1}^{t} \varepsilon_{3t}^{-} \tag{9}$$

Therefore, positive and negative shocks for the three variables can be summarized as follows:

$$S_t^{+} = \sum_{i=1}^{t} \varepsilon_{1i}^{+} \tag{10}$$

$$S_t^{-} = \sum_{i=1}^{t} \varepsilon_{1i}^{-} \tag{11}$$

$$U_t^{+} = \sum_{i=1}^{t} \varepsilon_{2i}^{+} \tag{12}$$

$$U_t^{-} = \sum_{i=1}^{t} \varepsilon_{2i}^{-} \tag{13}$$

$$B_t^{+} = \sum_{i=1}^{t} \varepsilon_{3i}^{+} \tag{14}$$

$$B_t^{-} = \sum_{i=1}^{t} \varepsilon_{3i}^{-} \tag{15}$$

To check the two causal relationships, we should explore the following 8 combinations:

$$(S_t^{+}, U_t^{+}), (S_t^{-}, U_t^{-}), (S_t^{+}, U_t^{-}), (S_t^{-}, U_t^{+}), (S_t^{+}, B_t^{+}), (S_t^{-}, B_t^{-}), (S_t^{+}, B_t^{-}), (S_t^{-}, B_t^{+})$$

To this end, we first must estimate a vector autoregressive model for every combination and then run a Wald test, where the null hypothesis of non-Granger causality must be rejected at the level of significance α depending on the bootstrap critical values.

3.3. Results

Dating turning points

Table 1 shows the turning point dating of the three series[3], and the characteristics of the different cycles are presented in Table 2. Both expansions and recessions of self-employment rate last on average approximately 2 years, while the phases of business confidence index present a length of approximately one year and half, and the duration of the unemployment cycle phases is on average one year and half for expansions and almost 4 years for recessions. This finding is to be expected considering that recessions of unemployment can be linked with expansions of business cycles and vice versa, and economic expansions tend to last much longer than recessions.

Regarding depth, we can see that the amplitude of the self-employment rate is higher during expansions (5.4%) than during recessions (-3.9%), which implies a general increase during the period considered. The unemployment rate shows a different behavior, with a reduction of 34.5% during recessions and an increase of 15.7% in expansions. The depth of the BCI shows similar gain/loss during both phases (2.3% in expansions and -2.1% in recessions).

[3] Consult Figure A2 in the appendix for a more visual representation. It shows the self-employment rate over the BCI and unemployment cycles (1 means recession and 0 means expansion).

Table 1. Turning Points Dating

		SELF-EMPLOYMENT	UNEMPLOYMENT	BCI
92-94	P		02/1993	
	T	11/1992		
95-96	P	01/1995		02/1995
	T			05/1996
97-98	P			11/1997
	T			11/1998
99-01	P			12/1999
	T	11/2000	04/2001	12/2001
02-03	P	09/2003	08/2002	07/2002
	T			06/2003
04-06	P			06/2004
	T	01/2005	09/2004	01/2006
07-09	P	02/2007	01/2007	05/2007
	T	08/2008	12/2007	03/2009
10-11	P		03/2010	03/2011
	T		02/2011	11/2011
14-15	P	06/2012	10/2011	
	T	05/2013		
16-17	P	04/2014		06/2014
	T	04/2015		12/2015
18-19	P	12/2016		07/2017
	T			

Note: P for peak, T for through.

Table 2. Features of cycles

		DURATION	AMPLITUDE	EXCESS	CUMULATION
SE	E	23.857	5.36	-0.001	0.769
	R	22.143	-3.90	0.002	-0.984
U	E	17.600	15.67	-0.011	2.127
	R	46.800	-34.49	0.005	-14.958
BCI	E	19.556	2.30	-0.002	0.271
	R	16.222	-2.09	-0.001	-0.173

Note: E for expansion, R for recession. Duration expressed in months. Amplitude expressed in percentage.

Respecting the shape of the cycles, all the series show excess values close to zero, which means that both expansions and recessions behave in a similar way to a hypothetical linear path between turning points on average.

Table 3. Concordance index between SE and U/BCI

	SE	SE (1)	SE (0)		SE	SE (1)	SE (0)
u	0.606	0.407	0.199	bci	0.587	0.261	0.326
u_1	0.592	0.402	0.190	bci_1	0.611	0.274	0.336
u_2	0.584	0.400	0.184	bci_2	0.628	0.284	0.344
u_3	0.577	0.398	0.179	bci_3	0.646	0.295	0.351
u_4	0.569	0.396	0.173	bci_4	0.657	0.302	0.355
u_5	0.562	0.394	0.167	bci_5	0.669	0.309	0.360
u_6	0.547	0.389	0.158	bci_6	0.680	0.316	0.364
u_7	0.530	0.381	0.149	bci_7	0.683	0.317	0.365
u_8	0.513	0.373	0.140	bci_8	0.678	0.315	0.363
u_9	0.495	0.364	0.131	bci_9	0.668	0.310	0.358
u_10	0.481	0.356	0.125	bci_10	0.651	0.301	0.349
u_11	0.466	0.347	0.119	bci_11	0.633	0.293	0.341
u_12	0.452	0.339	0.113	bci_12	0.610	0.281	0.329

Table 3 presents the concordance index between the self-employment cycle and unemployment/BCI cycles, considering lags up to 12 months and differentiating between general concordance and during expansions (0) and recessions (1). While the synchronization between self-employment and unemployment decreases as the number of lagged months increases on unemployment, the synchronization with the business confidence index increases to reach the maximum at a 7-month lag and starts decreasing afterwards. The meaning of this trend is explained by a higher synchronization between self-employment and unemployment at the same moment, with both series increasing or decreasing and a reduction of concordance with lagged unemployment. However, self-employment is more synchronized with the business confidence index after some months of changes in this index, which means that self-employment shows increasing (decreasing) behavior after some months of increase (reduction) in the confidence index during expansions (recessions), reaching the maximum concordance at a 7-month lag.

Granger Causality

Based on the econometric strategy described above, in this subsection, we now present the empirical findings on the Granger causality relationships established between the self-employment rate (SE) and the other two variables: the unemployment rate (U) and the business confidence index (BCI). Thus, we use the methodology of Hatemi-J to allow non-linear behavior between the variables. In Tables 4 and 5, we report the tests for the relationships unemployment at and self-employment and vice versa, whereas Tables 6 and 7 present the results for the relationship between self-employment and the business confidence index and between the index and the self-employment rate, respectively[4].

Based on these results, it is evident that only the null hypothesis that self-employment shocks do not Granger cause shocks in business climate can be rejected. The null of no Granger causality cannot be rejected for the other three linear relationships: SE-U, U-SE and BCI-SE.

Table 4. Causality between self-employment and unemployment

	Test statistic	Bootstrap critical values		
		1%	5%	10%
$SE \nRightarrow U$	7.223	15.445	11.590	9.522
$SE^+ \nRightarrow U^+$	2.211	11.497	7.524	6.077
$SE^- \nRightarrow U^-$	0.193	9.139	5.997	4.576
$SE^+ \nRightarrow U^-$	0.766	8.887	6.031	4.418
$SE^- \nRightarrow U^+$	1.288	12.768	8.702	6.337

Table 5. Causality between unemployment and self-employment

	Test statistic	Bootstrap critical values		
		1%	5%	10%
$U \nRightarrow SE$	4.552	15.937	11.924	9.544
$U^+ \nRightarrow SE^+$	4.466	11.697	8.270	6.666
$U^- \nRightarrow SE^-$	1.400	9.960	6.613	4.730
$U^+ \nRightarrow SE^-$	4.820	11.862	8.738	6.752
$U^- \nRightarrow SE^+$	0.525	9.163	6.033	4.423

In addition, the results indicate that we can reject the null hypothesis that negative shocks in self-employment do not Granger cause negative shocks in the business climate (i.e., negative shocks in self-employment can be considered a leading indicator of business confidence). Apparently contradictory to this, our results suggest that positive shocks in self-employment cause negative shocks in the business confidence index. We hypothesize that this relationship can prevail during recessions, when expansions in the numbers of necessity entrepreneurs are usually associated with a worsening economic situation.

The null hypothesis of no Granger causality cannot be rejected for the other cases except for the combination of positive shocks between the

[4] For these tables, *, **, ***, imply statistical significance at 10%, 5% and 1%, respectively. Critical values are obtained from 5000 bootstrap replications. The symbol A⇏B means that A does not cause B.

business confidence index and self-employment. The results show that the null hypothesis that positive BCI shocks do not cause a positive shock in self-employment can be rejected at the 10% significance level. Then, a relationship of causality can be established between self-employment and the business confidence index but only for positive shocks. To some extent, positive shocks in business confidence lead to positive effects on opportunity-driven entrepreneurs.

Table 6. Causality between self-employment and BCI

	TEST STATISTIC	BOOTSTRAP CRITICAL VALUES		
		1%	5%	10%
$SE \nRightarrow BCI$	11.554**	15.887	10.882	9.372
$SE^{+} \nRightarrow BCI^{+}$	0.477	11.248	7.989	6.337
$SE^{-} \nRightarrow BCI^{-}$	13.447**	15.165	9.808	7.847
$SE^{+} \nRightarrow BCI^{-}$	15.072**	15.469	11.443	9.177
$SE^{-} \nRightarrow BCI^{+}$	4.075	11.823	8.351	6.679

Table 7. Causality between BCI and self-employment

	TEST STATISTIC	BOOTSTRAP CRITICAL VALUES		
		1%	5%	10%
$BCI \nRightarrow SE$	3.494	14.757	11.465	9.495
$BCI^{+} \nRightarrow SE^{+}$	7.610*	12.471	7.680	6.143
$BCI^{-} \nRightarrow SE^{-}$	4.183	13.489	9.545	7.737
$BCI^{+} \nRightarrow SE^{-}$	2.028	11.761	8.393	6.491
$BCI^{-} \nRightarrow SE^{+}$	0.923	16.880	11.320	9.320

Different theories and models predict a range of different possibilities in terms of relationships of causality, including both unidirectional and bidirectional relationships between cycles in output, entrepreneurship and unemployment –see Parker et al. (2012) for a survey. As Ghatak et al. (2012) hypothesize, procyclicality with bidirectional causality is the most plausible theoretically grounded outcome when entrepreneurship is operationalized in terms of self-employment rates. By using UK data up to 2010, previous findings seemed to support this hypothesis because entrepreneurship is affected not only by the economic cycle but it also seems to affect it; more specifically, bidirectionality, with cycles in entrepreneurship causing and being caused by cycles in output and unemployment.

Our new empirical results support the idea that self-employment impacts the rest of the economy. In that sense, these results are broadly consistent with previous empirical findings that have related self-employment rates to subsequent aggregate economic performance but not to unemployment. The new and nonstandard forms of (self-) employment and the deep changes in labor market institutions may support these new relationships.

3.4. Conclusions

The empirical goal of this paper was to explore and check whether the self-employed sector is responding in the same way as entrepreneurship in previous economic recovery episodes by analyzing the case of the UK.

We applied time series techniques for checking the macrodynamics of opportunity and necessity self-employment during the business cycle, avoiding the use of the existent time series, and separating the evolution of self-employment into two relationships: one related to labor market performance –as the push theory states–and a second hypothesis depends on the opportunities for profit –pull hypothesis.

By using the business confidence index (BCI) and the unemployment rate (U) as indicators, we provided evidence on: (1) turning points dating of self-employment rate time series to establish a self-employment cycle; (2) the characteristics of the cycle phases; (3) an analysis of the synchronization between the self-employment cycle and the cycles of unemployment and business confidence; and (4) a non-linear causality analysis between these sets of variables.

In summary, we checked that self-employment phases of expansion show a higher amplitude even if the average duration is similar to recessions. The dating of turning points of unemployment and BCI time series allows us to analyze the synchronization between SE and both series, showing a higher concordance with unemployment at the same moment and a higher concordance with confidence in economy with a delayed response of seven months.

Our empirical findings extend and qualify the previous ones to understand what are the leading indicators for monitoring and forecasting the self-employment evolution during the business cycle.

In conclusion, the analysis provided new specific facts and revisited some relationships but leaves some questions open: (1) what are the reasons why self-employment in the UK is higher and more persistent than before; (2) to what extent do new economic trends, such as the development of the gig economy, affect the relative labor market performance of some economies and the way in which economic agents make their occupational decisions;

and (3) a micro-look at the determinants of the transitions from and into self-employment before and after the Great Recession may shed light on some of these questions.

References

Baumgartner, H. J., & Caliendo, M. (2008). Turning unemployment into self-employment: effectiveness of two start-up programmes. *Oxford Bulletin of Economics and Statistics*, *70*(3), 347-373.

Bell, D. N., & Blanchflower, D. G. (2011). Underemployment in the UK in the Great Recession. *National Institute Economic Review*, *215*, R23-R33.

Bracha, A., & Burke, M. A. (2018). Wage inflation and informal work. *Economics Letters*, *171*, 159-163.

Bry, G., & Boschan, C. (1971). Cyclical Analysis of Time Series: Selected Procedures and Computer Programs. *National Bureau of Economic Research.*

Burns, A. F., & Mitchell, W. C. (1946). Measuring business cycles. *National Bureau of Economic Research.*

Caliendo, M., & Kritikos, A. S. (2009). "I want to, but I also need to": start-ups resulting from opportunity and necessity. *IZA Discussion Papers No. 4661.*

Congregado, E., de Andrés, M. I., & Román, C. (2019). Explorando la heterogeneidad en el empleo mediado por plataformas digitales: intensidad y localización. *Revista de Economía Laboral*, *16*(2), 69-103.

Congregado, E., Golpe, A. A., & Van Stel, A. (2012). The 'recession-push'hypothesis reconsidered. *International Entrepreneurship and Management Journal*, *8*(3), 325-342.

Congregado, E., Millán, J. M., & Román, C. (2010). From own-account worker to job creator. *International Review of Entrepreneurship*, *8*(4), 277-302.

Cowling, M., & Mitchell, P. (1997). The evolution of U.K. Self-Employment: A Study of Government Policy and the Role of the Macroeconomy. *The Manchester School*, *65*, 427-442.

Dawson, C., & Henley, A. (2012). "Push" versus "pull" entrepreneurship: an ambiguous distinction? *International Journal of Entrepreneurial Behavior & Research.*

Earle, J. S., & Sakova, Z. (2000). Business start-ups or disguised unemployment? Evidence on the character of self-employment from transition economies. *Labour Economics*, *7*(5), 575-601.

Fairlie, R. W., & Fossen, F. M. (2020). Defining opportunity versus necessity entrepreneurship: Two components of business creation. In Polachek, S. W., & Tatsiramos, K. *Change at home, in the labor market, and on the job*. Emerald Publishing Limited.

Fossen, F. M. (2020). Self-employment over the business cycle in the USA: a decomposition. *Small Business Economics*, 1-19.

Ghatak, M., Morelli, M., & Sjöström, T. (2012). Entrepreneurial income, occupational choice, and trickle up policies. *Journal of Economic Theory*, *137*(1), 27-48.

Giupponi, G., & Xu, X. (2020). What does the rise of self-employment tell us about the UK labour market? *The IFS Deaton Review.*

Green, A., & Livanos, I. (2017). Involuntary non-standard employment in Europe. *European Urban and Regional Studies*, *24*(2), 175-192.

Harding, D., & Pagan, A. (2002). Dissecting the cycle: A methodological investigation. *Journal of Monetary Economics*, *49*(2), 365-381.

Hatemi-J, A. (2012). Asymmetric causality tests with an application. *Empirical Economics*, *43*(1), 447-456.

Henley, A. (2021). The rise of self-employment in the UK: entrepreneurial transmission or declining job quality? *Cambridge Journal of Economics*, *45*(3), 457-486.

Laffineur, C., Barbosa, S. D., Fayolle, A., & Nziali, E. (2017). Active labor market programs' effects on entrepreneurship and unemployment. *Small Business Economics*, *49*(4), 889-918.

López-Pérez, E., Rodríguez-Santiago, A., & Congregado, E. (2020). Persistence in Self-Employment Rates before the Great Lockdown: The Case of the UK. *Sustainability*, *12*(16), 6429.

Lucas, R. E. (1978). On the size distribution of business firms. *The Bell Journal of Economics*, 508-523.

Neymotin, F. (2020). Necessity and Opportunity Entrepreneurship in Canada. *Review of Economic Analysis*, *12*(3).

Parker, S. C. (2012). Theories of entrepreneurship, innovation and the business cycle. *Journal of Economic Surveys*, *26*(3), 377-394.

Parker, S. C., Congregado, E., & Golpe, A. A. (2012). Is Entrepreneurship a Leading or Lagged Indicator of the Business Cycle? Evidence from UK Self-employment Data. *International Small Business Journal*, *30*(7), 736-753.

Rissman, E. (2003). Self-employment as an alternative to unemployment. *Working Paper Series Federal Reserve Bank of Chicago No. WP-03-34.*

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector auto regressions with possibly integrated processes. *Journal of Econometrics*, 66, 225-250.

Valletta, R. G., Bengali, L., & Van der List, C. (2020). Cyclical and market determinants of involuntary part-time employment. *Journal of Labor Economics*, *38*(1), 67-93.

Appendix

Figure A1. Time series plots

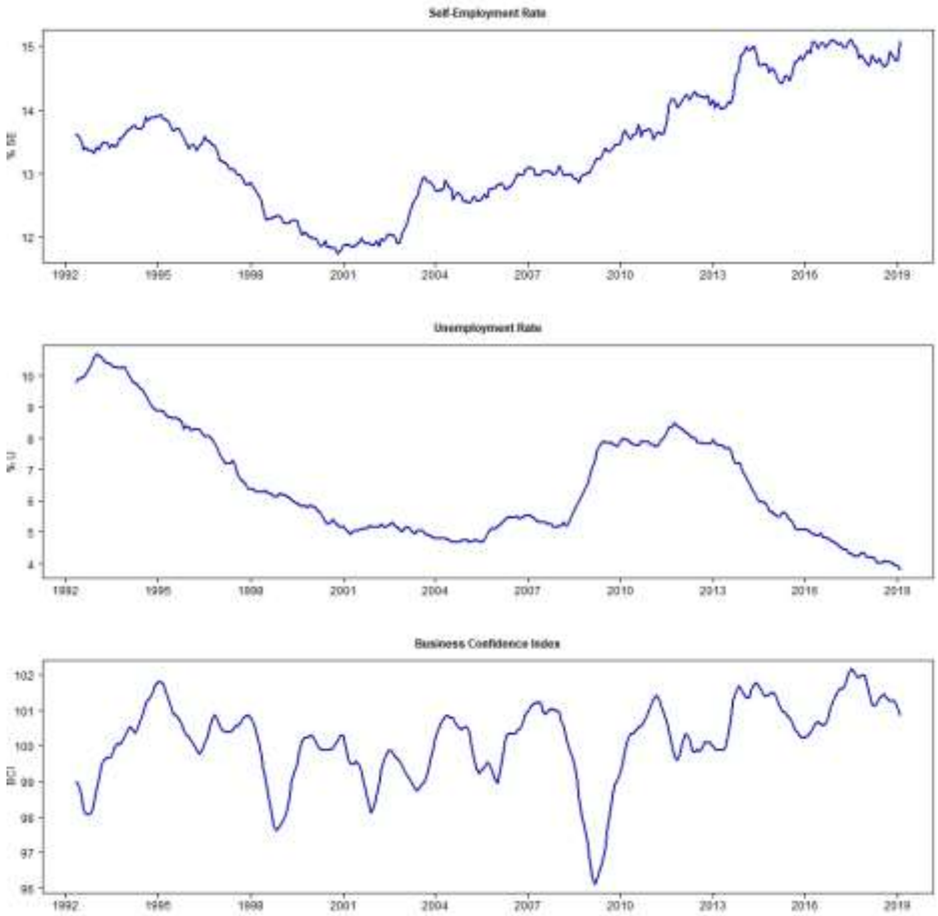


Figure A2. Self-Employment rate over the BCI and Unemployment cycles

Chapter 4: Persistence in self-employment rates before the Great Lockdown: The case of UK

A growing body of empirical literature, both on the micro and macro scale, is devoted to exploring the existence of hysteresis –or at least persistence– in self-employment, i.e., whether policy, economic or external shocks have transitory or persistent effects on the probability of survival, and in turn, on the natural rate of self-employment. In aggregate time series studies, the usual method to address this issue has been to look for unit roots by using alternative tests or by using unobservable components models. In this research, we performed a battery of tests and competing approaches to check the robustness of our results with UK self-employment time series. The UK is a suitable case for study because the recent evolution of the UK self-employment rate figures shows a steady growth since the beginning of the millennium. This long-term rise in UK self-employment has attracted the attention of scholars, at least, before the Great Lockdown. We find evidence of hysteresis, while business cycle output variations significantly affect self-employment rates. The article discusses the implications of the findings.

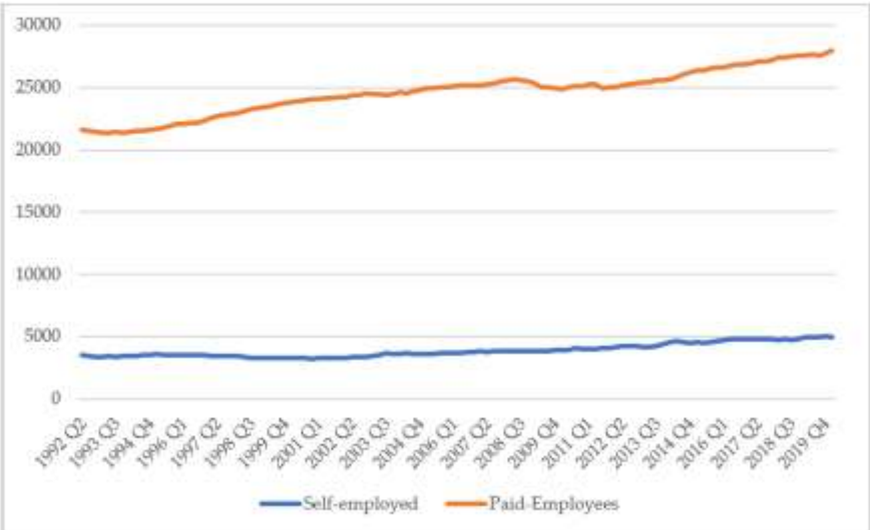
4.1. Introduction

In December 2019, more than five million people were self-employed in the UK (15.3% of all employed people), the highest number and self-employment ratio since records began. Some analysts hypothesize that the increase in self-employment has been caused mainly by a decrease in people leaving self-employment rather than an increase in people entering it, that is, a certain degree of persistence after the last recession, due to multiple factors, such as the lack of opportunities to work as an employee since the onset of the economic downturn or the emergence of the platform economy (see Congregado et al., 2019; Broughton and Richards, 2016; Kenney and Zysman, 2016). However, this rise in self-employment involves not only precariat, part-time and older workers but also professionals and freelancers (IPSE, 2020).

However, what does this trend tell us about the state of the UK economy? Does the trend indicate the emergence of new entrepreneurs who are pushed into self-employment due to the lack of job opportunities and therefore a temporary shock to occupational decisions, or is it a permanent structural change in a labor market, which is, or was, close to full employment at the start of 2020?

In hindsight self-employment in the UK rose rapidly in the 1980s, decreased during the mid-1990s, and rose again in the 2000s, showing a particularly large jump after the crisis, and a significant steady rise in the self-employment rate in the coming years (see Saridakis and Papaioannou, 2014; Parker et al., 2012a; Wales and Agyiri, 2016; Tomlinson and Corlett, 2017).

Figure 1. UK unemployment and self-employment (thousands).



Several factors might be behind the observed large jump in UK self-employment (see Figure 1). On the one hand, one could speculate that it is the result of the reaction to the British economy creating too little paid employment and the opportunity cost of self-employment being relatively low. If that were true, marginal entrepreneurs (and in particular those that were formerly unemployed, or necessity entrepreneurs) might show a high survival rate more closely linked to the lack of employment opportunities than to success (Caliendo, Goethner and Weißenberger, 2020).

In addition, the existence of different schemes of entrepreneurship promotion could reinforce the effects of this self-employment revival (Dvouletý and Lukeš, 2016; Boeri et al., 2020).

Another explanatory factor is related to the emergence of different forms of dependent self-employment. In particular, to circumvent the most onerous elements of the (paid-) employment protection legislation, some wage earners are induced to switch to self-employment with a guaranteed demand by the employer, substituting the costs and rights associated with paid – sometimes subsidized (see Román et al., 2011a; Böheim and Muehlberger, 2006, 2009)– employment by self-employed workers.

A third potential explanation could be that the upswing shown in self-employment data could be the result of crowding out effects, i.e., non-subsidized firms or self-employed workers may be displaced by supported start-ups (Caliendo and Künn, 2011; Caliendo, Künn and Weißenberger, 2020).

In sum, turning unemployment into self-employment is one of the most common causes behind this revival in self-employment in many countries around the world, especially during the Great Recession.

However, the above factors are not all the factors that we can take into account to explain the determinants of the substantial rise in UK self-employment.

On the one hand, the UK labor market has become more flexible than those in other European countries, thanks to the institutional framework that favors labor market flexibility.

On the other hand, one could argue that the flexible labor market should place the UK economy in a better position to respond to unemployment, but it can encourage a growing percentage of individuals to change their initial occupational choice and decide to become entrepreneurs, given that this flexibility tends to equalize the relative valuation of paid employment and self-employment, countering the rights and safety that characterize paid employment versus self-employment (see Román et al., 2011b; Torrini, 2005; Baumann and Brändle, 2012; Robson, 2003).

Finally, a final explanation could apply. As Acs (2006) argues, average firm size was an increasing function of the wealth of the economy in intermediate stages of economic development and a source of decreasing self-employment because marginal entrepreneurs find that they can earn more money by being employed by somebody else (Lucas, 1978). However, it seems that as the economy becomes more developed, the self-employment rate increases because the development of business services and the improvements in information technologies provide more opportunities for entrepreneurship. In other words, a U-shaped relationship may characterize the relationship between entrepreneurship and the stage of economic development.

This interpretation is consistent with the evidence provided by Blanchflower and Sandforth (2007), who analyzed the evolution of self-employment in the UK over the past four decades, as well as the time series analysis carried out by Cowling and Mitchell (1997), for the 1972-1992 period.

In sum, and whatever the cause of this upward trend –policy or economic shocks– the key question is to know if the effects of these shocks are temporary or permanent, given that one could argue that only those individuals who decide to become entrepreneurs on the basis of voluntary participation –opportunity entrepreneurship– will represent permanent transitions into self-employment, while as the number of self-employees becoming involved in necessity entrepreneurship increases, temporary transitions increase, with people abandoning self-employment when the economy and labor market show symptoms of recovery.

One could argue that looking for hysteresis in UK self-employment is a hot policy issue and a good research question at the time of writing, when policy makers and analysts are probing the deep causes and perspectives of this evolution. In sum, the UK is a suitable case for study, and the use of alternative (and competing) strategies for checking persistence is a good way to address these questions (Blundell and Machin, 2020).

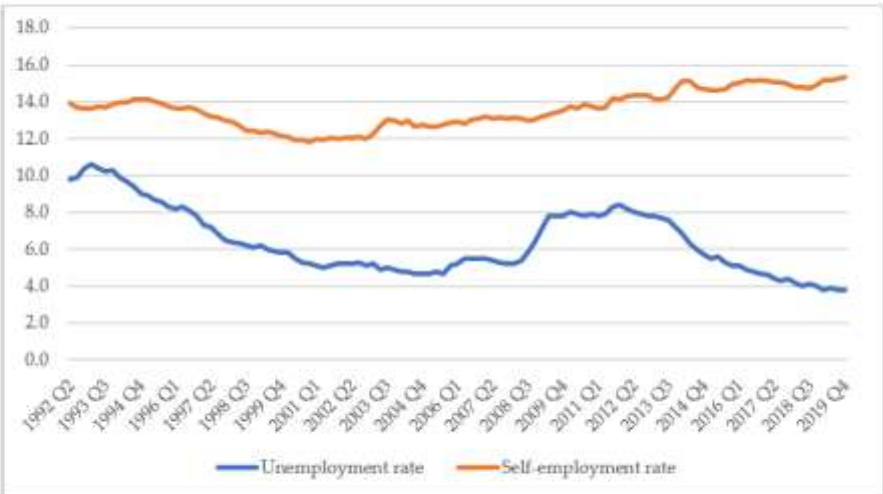
Therefore, the goal of this paper is to explore persistence in the UK aggregate rate of self-employment in the UK. We do so with quarterly time series data on self-employment rates for the UK. The self-employment development in the UK has attracted analysts' attention since UK self-employment experienced a sustainable increase during the 1980s, likely thanks to government intervention and liberalization in the context of rapid economic growth, with the UK labor market becoming one of the more flexible ones in Europe.

If this were the case, low employment protection alongside a favorable tax system and the reduction of the credit constraints people face could be a more likely reason for the self-employment boom in the UK.

Therefore, the UK is a suitable case of study, given that labor market conditions and the tax system seem to point to highly sensitive self-employment responses to changing macroeconomic conditions.

Furthermore, there is another reason for suggesting the analysis of UK self-employment as a singular case: in several previous studies, UK self-employment has been considered an outlier (see Blanchflower and Shadforth, 2007; Thurik, 2003; Faria et al., 2009; Carmona et al., 2010). In particular, the relationship between entrepreneurship and unemployment in the UK seems to have a specific nature such that entrepreneurship contributes less to alleviating the unemployment problem in the UK than elsewhere (Carmona et al., 2010), while the most important determinant of the proportion of the workforce in self-employment is the income differential between self-employed and employed workers (Blanchflower and Shadforth, 2007), i.e., in response to macroeconomic conditions and not in response to labor market conditions (Figure 2).

Figure 2. UK unemployment and self-employment rates



The remainder of this article has the following structure. The next section briefly discusses the theoretical and empirical evidence on hysteresis in entrepreneurship. The third section describes the data, presents and discusses the results and performs different robustness checks for our findings. The final section concludes with a discussion of policy implications.

4.2. A selective survey of previous literature

We will agree that the durability of shocks to entrepreneurship –policy or economic shocks– should be an important research question in the economics of entrepreneurship. In that sense, there is a growing body of empirical literature devoted to exploring the existence of hysteresis or at least persistence in entrepreneurship. This question is important from at least two different perspectives. On the one hand, persistence in self-employment can be seen as a way of success and, if applicable, survival in entrepreneurship signals the long-term effects of past entrepreneurship promotion policies. On the other hand, another important issue is to check if after crisis times, non-genuine entrepreneurs (i.e., necessity and false self-employed persons who entered into self-employment as a "last resort") remain as entrepreneurs or whether, on the contrary, they return to paid employment when the economic circumstances improve (à la Lucas).

A broad body of empirical literature has addressed these issues. This literature includes both microeconometric and macroeconometric evidence using different approaches.

The first group of works –based on cross/pooled sectional micro-data files– explores this question either by estimating models of survival for different groups of self-employed workers or by exploring the determinants and characteristics of those self-employed who decide to abandon self-employment to enter another state (paid-employment, unemployment or inactivity). The outcomes of these works are well summarized in Caliendo, Goethner and Weißenberger (2020) and Millán et al. (2012, 2014). This branch of literature has evolved from a first generation of works with apparently contradictory or at least non-robust results to a second wave of literature in which the explicit recognition of the heterogeneity among self-employed workers has contributed decisively to solve the previous puzzle shedding new light on these hypotheses (Millán et al., 2014). The available evidence suggests the presence of persistence in entrepreneurship. Thus, the probability of exit from solo self-employment to employership is higher than the probability of switching to other states (Millán et al., 2012). Furthermore, in adverse conditions employers opt to become solo self-employed before exploring other options (see Millán et al., 2014; Lechmann and Wunder, 2017; Baptista et al., 2014).

The alternative to this body of evidence based on estimates of different dummies in individual-level studies of occupational choice is to perform careful analyses of time series data (macro approach).

Pieces of research provided by Congregado, Golpe and Parker (2012), Parker et al. (2012b) and Gil-Alana and Payne (2015) have examined, using time series analysis and panel data unit roots, whether entrepreneurship exhibits hysteresis as a way to check whether policy shocks, economic shocks or the shocks induced in the occupational choice decisions by a new employment legislation or a new tax treatment for employees' and self-employees' earnings have only temporary effects on self-employment or if, by contrast, they have a permanent character, that is, they are persistent.

Gil-Alana and Payne (2015) applied fractional integration to explore the existence of hysteresis using monthly time series data on US self-employment rates. The results suggest the existence of nonstationary behavior, supporting previous evidence provided by Congregado, Golpe and Parker (2012) for American entrepreneurship.

In a time series context, hysteresis can be defined and measured in various ways. The most popular approach in the empirical literature simply equates hysteresis with the existence of a unit root in a variable by using integer or fractional integration.

An alternative approach proposed by Jaeger and Parkinson states that hysteresis exists if and only if cyclical changes affect the natural rate of a variable, even as the natural rate follows a unit root process. In this case, temporary shocks have permanent effects, while the business cycle does not evolve independently of the natural rate; then, it follows that a unit root is a necessary but not sufficient condition for hysteresis. To test for hysteresis in this way, we follow Jaeger and Parkinson (1990) and decompose entrepreneurship into two unobservable components: a nonstationary "natural rate" component and a stationary "cyclical" component. These components can be estimated by maximum likelihood using the Kalman filter. This is the third approach carried out in this paper.

This methodology must enable us to assess not only the question of the persistence but also the relationship between entrepreneurship and business cycle, i.e., to investigate the economic forces shaping the aggregate relationship between self-employment, business cycles and the labor market, summarized in the controversy between the recession-push and the prosperity-pull hypotheses. The recession-push hypothesis states that in times of high unemployment individuals are pushed into self-employment for lack of alternative sources of income such as paid employment. The prosperity-pull hypothesis represents an opposite (but equally possible) interpretation of this relationship. At times of crisis, the risk of business failures increases, and thus, individuals are pulled out of entrepreneurship. The empirical performance of competing hypotheses like those is very important for gaining more in-depth knowledge about the relationship between entrepreneurship and some macroeconomic variables (Congregado, Golpe and Van Stel, 2012). This is the secondary goal of this paper.

4.3. Methods and results

This section describes the indicators and data sources used as proxies for entrepreneurship and the general strategy for checking the presence of hysteresis in UK self-employment series.

Data and Measurement Issues

Similar to most previous studies, entrepreneurship is defined in this paper in terms of self-employment, reflecting data availability at the time series level. Entrepreneurship is difficult to measure and operationalize for empirical work. The most commonly used indicators of entrepreneurship are divided into three categories: (1) stock measures (self-employment or firm data), (2) flow measures (firm or self-employment entry/exit rates) and (3) indirect indicators of entrepreneurship such as competitiveness, patents, etc. In a strict sense, self-employment data are related to the Knightian entrepreneur who assumes all the uncertainty connected with the firm (see Congregado (2007) for a detailed discussion).

Our empirical analysis uses seasonally adjusted quarterly data on self-employment rates for the UK. The self-employment rate, S_t, is defined as the share of the workforce that is self-employed. British self-employment data are seasonally adjusted quarterly observations drawn from the Labour Force Survey (LFS, Office for National Statistics).

The sample starts in 1992:4 and ends in 2019:4. It should be noted that independent owner–managers and directors of incorporated enterprises are classified as employers, i.e., in the survey, workers were asked questions about their main job or business, including, “Are you an employee or self-employed?” If self-employed, the respondent was further asked whether they had any employees. Finally, real GDP is denoted by Y_t. Data on British real GDP are taken from the Quarterly National Accounts database. These data are seasonally adjusted and are expressed in billions of chained 2005 British pounds.

Methodology

The most common approach for testing hysteresis in economic time series matches the presence of hysteresis in a time series with a unit root process. This approach has two potential sources of bias. The first one is that results obtained from traditional batteries of unit roots tests might be taken with caution, given the low power of these procedures if the alternatives are of a fractional form. To avoid this possibility, we used the framework proposed by Gil-Alana and Hualde (2009) as a way to check the robustness of the results of our first approach (see Appendix B). The second one is that the defining feature of hysteretic processes in time series is that changes to the cyclical component of a time series induce permanent changes in the natural rate of the series (Jaeger and Parkinson, 1994). This is not the case in a unit root process.

Several macroeconomic studies equate hysteresis in a time series with a unit root process. Independent of the use of an integer or fractional unit, the problem with these two approaches is that the existence of a unit root in the self-employment time series is a necessary but not sufficient condition for hysteresis.

Alternatively, Congregado, Golpe and Parker (2012) argued that hysteresis in self-employment arises if and only if changes to the cyclical component of a time series induce permanent changes to its natural rate.

To test this definition of persistence, Jaeger and Parkinson (1990) proposed a framework from a decomposition of the time series into the sum of two unobservable components: the natural rate and the cyclical component.

To illustrate the approach applied to our case under study, let us decompose the UK self-employment series, S_t, into the sum of its two (unobservable) components: the nonstationary natural rate component, S_t^N, and the stationary cyclical component, S_t^c:

$$S_t = S_t^N + S_t^c, \tag{1}$$

Now, we will define the natural rate component as a random walk plus a term capturing a possible hysteresis effect:

$$S_t^N = S_{t-1}^N + \beta S_{t-1}^c + \varepsilon_t^N, \tag{2}$$

where the β coefficient measures, in percentage points, how much the natural rate increases if the economy experiences a cyclical self-employment rate increase of one percent.

Evidently, we can check whether a unit root in the self-employment rate is a necessary but not sufficient condition for the existence of hysteresis since a unit root could be generated by an accumulation of shocks to the natural rate while $\beta = 0$ simultaneously. In contrast, there is hysteresis if $\beta > 0$.

The specification of the model is completed by writing the cyclical component of the self-employment rate as a stationary second-order autoregressive process:

$$S_t^C = \phi_1 S_{t-1}^C + \phi_2 S_{t-2}^C + \alpha \Delta Y_{t-1} + \varepsilon_t^C , \tag{3}$$

augmented with a term, $\alpha\Delta Y_{t-1}$, which relates cyclical self-employment to lagged output growth, where Y_{t-1} is lagged real GDP. This enables the relationship between the business cycle and entrepreneurship to be analyzed.

The random shocks ε_t^N and ε_t^C are assumed to be mean-zero draws from the normal distribution with variance–covariance matrix Ω; the state-space form of the model can be written as

$$S_t = \begin{pmatrix} 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} S_t^N \\ S_t^C \\ S_{t-1}^C \end{pmatrix} \tag{4}$$

$$\begin{pmatrix} S_t^N \\ S_t^C \\ S_{t-1}^C \end{pmatrix} = \begin{pmatrix} 1 & \beta & 0 \\ 0 & \phi_1 & \phi_2 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} S_{t-1}^N \\ S_{t-1}^C \\ S_{t-2}^C \end{pmatrix} + \begin{pmatrix} 0 \\ \alpha \\ 0 \end{pmatrix} \Delta Y_{t-1} + \begin{pmatrix} \varepsilon_t^N \\ \varepsilon_t^C \\ 0 \end{pmatrix} \tag{5}$$

$$\Omega = \begin{pmatrix} \sigma_N^2 & 0 & 0 \\ 0 & \sigma_C^2 & 0 \\ 0 & 0 & 0 \end{pmatrix} \tag{6}$$

To summarize, hysteresis is inferred if the coefficient β is significantly different from zero, whereas pro- or anti-cyclical variation is inferred depending on whether the coefficient α is positive or negative, respectively.

The coefficients of models (4) - (6) are estimated with maximum likelihood using a Kalman filter.

The estimation of the linear unobserved components model outlined above enables hysteresis to be tested directly and the existence of business cycle effects to be examined.

Finally, ignoring asymmetry when it is present leads to a misspecified model that produces erroneous inferences in hypothesis testing (Jaeger and Parkinson, 1994). Additionally, potential asymmetries according to how self-employment absorbs positive or negative shocks should be considered too. Therefore, we follow the non-linear specification of the unobserved components model developed by Pérez-Alonso and Di Sanzo (2010). This asymmetric approach can be summarized by the following set of equations:

$$S_t = S_t^N + S_t^c \tag{7}$$

$$S_t^N = S_{t-1}^N + \beta_1 S_{t-1}^c I(\Delta Y_{t-1} \geq \tau) + \beta_2 S_{t-1}^c I(\Delta Y_{t-1} < \tau) + \varepsilon_t^N, \tag{8}$$

$$S_t^C = \varphi_1 S_{t-1}^c + \varphi_2 S_{t-2}^c + \alpha \Delta Y_{t-1} + \varepsilon_t^c, \tag{9}$$

where I is the Heaviside indicator function.

As was done for the previous model, the estimations are carried out via the maximum likelihood and Kalman filter methods. The threshold parameter needs to be estimated together with the rest of the parameters of the model, i.e., β_1 and β_2.

From the perspective of this specification, we can analyze the potential asymmetry by testing for linearity, with the null hypothesis being $H_0: \beta_1 = \beta_2$ and the alternative being $H_0: \beta_1 \neq \beta_2$; that is, the existence of a single regime against the presence of two different regimes. Rejecting the null hypothesis implies that there is evidence of non-linear persistence in the self-employment rate, which means that the cyclical shocks cause asymmetric changes in the natural rate component of the time series. As Pérez-Alonso and Di Sanzo (2010) pointed out, it may be necessary to resort to bootstrap methods to provide reliable approximations for the sampling distribution of the test statistic.

4.4. Results and discussion

Unit roots

As a preliminary check, given that several studies equal hysteresis to unit roots, we performed standard unit root tests on the series.

The results based on Augmented Dickey-Fuller and Phillips-Perron tests are reported in Table 1, and they show that the series of the UK self-employment rate is integrated of order one, i.e., *I(0)* stationary in first differences. Then, the shocks are mean reverting. This finding buttresses our conclusion that a unit root exists in the self-employment rates. As noted above, a unit root is a maintained assumption needed to test for Jaeger and Parkinson's notion of hysteresis. We now test it.

Table 1. Conventional unit root tests

	I(1) vs. I(0)						
	ADF	PP	Ng-Perron				
Variable	Test	Test	MZa	MZt	MSB	MPT	Lags
Self-employment rate	-1.644 (0.769)	-1.755 (0.720)	-2.147	-0.954	0.444	38.182	1
GDP	-1.288 (0.886)	-1.423 (0.849)	-9.361	-2.058	0.220	10.174	1
Unemployment rate	-3.279 * (0.076)	-1.547 (0.807)	-4.517	-1.502	0.333	20.169	2

Notes: For the Augmented Dicky-Fuller (ADF) (based on Akaike Information Criterion) and Phillips-Perron (PP) test (based on the Bartlett kernel and Newey-West Bandwidth), we used Mackinnon (1996) one-sided p-values for the null hypothesis of a unit root. The critical values for the Ng-Perron test are tabulated in Ng and Perron (2001). The Modified Akaike Information criterion was used to select the autoregressive truncation lag, k, as proposed in Ng and Perron (1995). * Denotes significance at 10% level.

In the Appendix (Table A1) we also report an alternative method, fractional integration, in order to test the robustness of traditional unit roots. Results seem to reinforce the presence of hysteresis.

An unobserved component model

Table 2 presents the results of estimating models (4) through (6) for aggregate self-employment rates. The parameter β is statistically significant, which implies that self-employment exhibits hysteresis.

Table 2. Linear unobserved component model

	3 LAGS	4 LAGS
	NATURAL RATE EQUATION	
β	1.842*** (0.082)	1.893*** (0.040)
σ_N	0.089*** (0.030)	0.000 (0.001)
	CYCLICAL RATE EQUATION	
ϕ_1	-0.469*** (0.303)	-0.611*** (0.079)
ϕ_2	0.391*** (0.092)	0.287*** (0.076)
σ_C	0.115*** (0.030)	0.149*** (0.012)
α	0.821*** (0.058)	0.808*** (0.060)
δ	1.038** (0.504)	0.490** (0.248)
σ_D	0.467*** (0.057)	0.480*** (0.050)

Notes: Standard errors in parentheses. ***, **, * Rejects null hypothesis at 1%, 5% and 10% significance level respectively.

The estimate of α reported in the fourth row suggests that only the aggregate self-employment series S_t also exhibits a significant impact of business cycle variations in output on cyclical self-employment. As we mentioned above, we should take into account the potential existence of asymmetries. To this end, we ran the test of linearity based in bootstrap test, proposed by Pérez and Di Sanzo (2010). The results in Table 3 seem to point out that the linear model was adequate, since the test does not allow the rejection of the null hypothesis of linearity. Estimates of the non-linear version of this model are reported in Appendix (Table A2).

Table 3**.** Test of linearity Ho: $\alpha_1 = \alpha_2$.

Bootstrap p value	0.25

We also report estimates (Table 4) of our baseline unobserved linear component model, substituting GDP by the unemployment rate, in order to check the robustness and whether the cyclical pattern of self-employment is also linked to the labor market evolution. The results point to this positive effect of unemployment rate on the self-employment rate (recession push effect) reinforcing the result of resilience too in line with previous findings by Carmona et al. (2016).

Table 4. Linear unobserved component model. Using unemployment

	3 LAGS	4 LAGS
	NATURAL RATE EQUATION	
β	1.945** (1.175)	1.192*** (0.146)
σ_N	0.123*** (0.012)	0.000 (0.014)
	CYCLICAL RATE EQUATION	
ϕ_1	0.520*** (0.210)	0.037 (0.162)
ϕ_2	-0.068 (0.055)	0.178* (0.132)
σ_C	0.048 (0.040)	0.148*** (0.012)
α	0.4812*** (0.107)	0.485*** (0.101)
δ	2.071 (9.393)	0.519 (2.236)
σ_D	3.035*** (0.213)	3.036*** (0.213)

Notes: Standard errors in parentheses. ***, **, * Rejects null hypothesis at 1%, 5% and 10% significance level respectively.

4.5. Conclusions

This paper reported evidence of unit roots and estimated an unobserved components model for testing the existence of hysteresis in the self-employment rate in the United Kingdom. Defining hysteresis in terms of the interdependent evolution of a nonstationary natural rate and a stationary cyclical component, thereby distinguishing hysteresis from natural rate shocks, the results provide robust evidence of hysteresis in entrepreneurship. This implies that economic and/or non-economic shocks have cyclical and permanent effects on rates of entrepreneurship.

For policy makers and trade unions, our results should be interpreted as great news. For both, tackling unemployment and maintaining employment is a major challenge. Policies to promote entrepreneurship (genuine or not) and self-employment income support schemes (oriented to support self-employed workers in bad times when cost cutting, shrinkage and retrenchment is not sufficient for survival) impose sizeable costs on the taxpayer.

However, our findings appear to indicate that the long-term effects of these policies are guarantees in the UK.

Further research is needed to determine whether it is different national and institutional conditions, or structural changes which lead to different findings.

Similarly, further research will be required to gather more information concerning the long-term effects of the new support income schemes approved for combating the effects the Great Lockdown on the UK self-employment sector.

References

Acs, Z. (2006). How is entrepreneurship good for economic growth. *Innovations*, *1*(1), 97-107.

Baptista, R., Karaöz, M., & Mendonça, J. (2014). The impact of human capital on the early success of necessity versus opportunity-based entrepreneurs. *Small Business Economics*, *42*(4), 831-847.

Baumann, F., & Brändle, T. (2012). Self-employment, educational attainment and employment protection legislation. *Labour Economics*, *19*(6), 846-859.

Blanchflower, D. G., & Shadforth, C. (2007). Entrepreneurship in the UK. *Foundations and Trends® in Entrepreneurship*, *3*(4), 257-364.

Blundell, J., & Machin, S. (2020). *Self-employment in the Covid-19 crisis*. Centre for Economic Performance, London School of Economics and Political Science.

Boeri, T., Giupponi, G., Krueger, A. B., & Machin, S. (2020). Solo self-employment and alternative work arrangements: A cross-country perspective on the changing composition of jobs. *Journal of Economic Perspectives*, *34*(1), 170-95.

Böheim, R., & Muehlberger, U. (2006). Dependent Forms of Self-employment in the UK: Identifying Workers on the Border between Employment and Self-employment.

Böheim, R., & Mühlberger, U. (2009). Dependent self-employment: workers between employment and self-employment in the UK. *Zeitschrift für Arbeitsmarkt Forschung*, *42*(2), 182-195.

Broughton, N., & Richards, B. (2016). Tough gig: Low paid self-employment in London and the UK. *Social Market Foundation: London, UK*.

Caliendo, M., & Künn, S. (2011). Start-up subsidies for the unemployed: Long-term evidence and effect heterogeneity. *Journal of Public Economics*, *95*(3-4), 311-331.

Caliendo, M., Goethner, M., & Weißenberger, M. (2020). Entrepreneurial persistence beyond survival: Measurement and determinants. *Journal of Small Business Management*, *58*(3), 617-647.

Caliendo, M., Künn, S., & Weißenberger, M. (2020). Catching up or lagging behind? The long-term business and innovation potential of subsidized start-ups out of unemployment. *Research Policy*, *49*(10), 104053.

Carmona, M., Congregado, E., & Golpe, A. A. (2010). Co-movement and causality between self-employment, unemployment and business cycle in the EU-12. *International Review of Entrepreneurship*, *8*(4), 1-35.

Carmona, M., Congregado, E., Golpe, A. A., & Iglesias, J. (2016). Self-employment and business cycles: searching for asymmetries in a panel of 23 OECD countries. *Journal of Business Economics and Management*, *17*(6), 1155-1171.

Congregado, E. (Ed.). (2007). *Measuring entrepreneurship: building a statistical system* (Vol. 16). Springer Science & Business Media.

Congregado, E., de Andrés, M. I., & Román, C. (2019). Explorando la heterogeneidad en el empleo mediado por plataformas digitales: Intensidad y localización. *Revista de Economía Laboral.*, *16*(2), 69-103.

Congregado, E., Golpe, A. A., & Parker, S. C. (2012). The dynamics of entrepreneurship: hysteresis, business cycles and government policy. *Empirical Economics*, *43*(3), 1239-1261.

Congregado, E., Golpe, A. A., & Van Stel, A. (2012). The 'recession-push'hypothesis reconsidered. *International Entrepreneurship and Management Journal*, *8*(3), 325-342.

Cowling, M., & Mitchell, P. (1997). The evolution of UK self-employment: a study of government policy and the role of the macroeconomy. *The Manchester School*, *65*(4), 427-442.

Dvouletý, O., & Lukeš, M. (2016). Review of empirical studies on self-employment out of unemployment: do self-employment policies make a positive impact?. *International Review of Entrepreneurship*, *14*(3).

Faria, J. R., Cuestas, J. C., & Gil-Alana, L. A. (2009). Unemployment and entrepreneurship: A cyclical relation?. *Economics Letters*, *105*(3), 318-320.

Gil-Alana, L. A., & Hualde, J. (2009). Fractional integration and cointegration: an overview and an empirical application. *Palgrave handbook of econometrics*, 434-469.

Gil-Alana, L. A., & Payne, J. E. (2015). A time-series analysis of US entrepreneurship: Evidence from fractional integration. *Applied Economics Letters*, *22*(7), 521-524.

IPSE. Exploring the Rise of Self-Employment in the Modern Economy. Available online: https://www.ipse.co.uk/uploads/assets/uploaded/59868faa-841d-496d-bba6891d417a7e94.pdf (accessed on 25 May 2020).

Jaeger, A., & Parkinson, M. (1990). Testing for hysteresis in unemployment an unobserved components approach. In *Hysteresis Effects in Economic Models* (pp. 77-90). Physica-Verlag HD.

Jaeger, A., & Parkinson, M. (1994). Some evidence on hysteresis in unemployment rates. *European economic review*, *38*(2), 329-342.

Kenney, M., & Zysman, J. (2016). The rise of the platform economy. *Issues in science and technology*, *32*(3), 61.

Lechmann, D. S., & Wunder, C. (2017). The dynamics of solo self-employment: Persistence and transition to employership. *Labour Economics*, *49*, 95-105.

Lucas, R. E. (1978). On the size distribution of business firms. *The Bell Journal of Economics*, 508-523.

MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of applied econometrics*, *11*(6), 601-618.

Millán, J. M., Congregado, E., & Román, C. (2012). Determinants of self-employment survival in Europe. *Small Business Economics*, *38*(2), 231-258.

Millán, J. M., Congregado, E., & Román, C. (2014). Entrepreneurship persistence with and without personnel: The role of human capital and previous unemployment. *International Entrepreneurship and Management Journal*, *10*(1), 187-206.

Ng, S., & Perron, P. (1995). Unit root tests in ARMA models with data-dependent methods for the selection of the truncation lag. *Journal of the American Statistical Association*, *90*(429), 268-281.

Ng, S., & Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica*, *69*(6), 1519-1554.

Parker, S. C., Congregado, E., & Golpe, A. A. (2012a). Is entrepreneurship a leading or lagging indicator of the business cycle? Evidence from UK self-employment data. *International Small Business Journal*, *30*(7), 736-753.

Parker, S. C., Congregado, E., & Golpe, A. A. (2012b). Testing for hysteresis in entrepreneurship in 23 OECD countries. *Applied Economics Letters*, *19*(1), 61-66.

Pérez-Alonso, A., & Di Sanzo, S. (2010). Unemployment and hysteresis: a nonlinear unobserved components approach. *Studies in Nonlinear Dynamics & Econometrics*, *15*(1).

Robson, M. T. (2003). Does stricter employment protection legislation promote self-employment?. *Small Business Economics*, *21*(3), 309-319.

Román, C., Congregado, E., & Millán, J. M. (2011a). Dependent self-employment as a way to evade employment protection legislation. *Small Business Economics*, *37*(3), 363-392.

Román, C., Congregado, E., & Millán, J. M. (2011b). The role of labor market institutions on entrepreneurship dynamics in times of crisis: Evidence from European countries. In *Entrepreneurship and Global*

Competitiveness in Regional Economies: Determinants and Policy Implications. Emerald Group Publishing Limited.

Saridakis, G., & Papaioannou, G. (2014). Forecasting self-employment in the UK. *The Empirical Economics Letters*, *13*(9), 923-930.

Thurik, R. (2003). Entrepreneurship and unemployment in the UK. *Scottish Journal of Political Economy*, *50*(3), 264-290.

Tomlinson, D., & Corlett, A. (2017). A tough gig? The nature of self-employment in 21st Century Britain and policy implications. *Resolution Foundation*.

Torrini, R. (2005). Cross-country differences in self-employment rates: The role of institutions. *Labour Economics*, *12*(5), 661-683.

Wales, P., & Agyiri, A. (2016). Trends in Self-Employment in the UK: 2001 to 2015. *ONS: London, UK*.

Appendix

Fractional Integration

The objective of this paper is to evaluate the robustness of hysteresis in UK self-employment rates by using alternative econometric models other than traditional unit root tests. The first alternative is the employment of fractional integration –see Gil-Alana and Hualde (2009) for a survey– to infer the existence of hysteresis in UK self-employment rates. This approach has been recently applied to the field of the economics of entrepreneurship by Gil-Alana and Payne (2015). The key difference between the traditional time series approach and fractional integration is that the number of differences required for rendering a series *I(0)* stationary is a fractional value rather an integer one. In particular, we will consider that the British self-employment rate can be *I(0)* stationary (i.e., $d = 0$), nonstationary and non-mean-reverting (if $d \geq 1$), stationary with long memory (if $0 < d < 0.5$) or nonstationary but mean reverting (if $0.5 \leq d < 1$). In other words, the larger the value of d, the greater the degree of dependence on the past data and the longer the effects of shocks (more persistence).

Table A1. Estimates of the fractional parameter

	Coefficient	Std. Error	t-Value	t-Prob
d parameter	0.776	0.053	4.29	0.000
Constant	11.049	7.849	1.41	0.161

Notes: Log-likelihood: -1129.51; No. observations: 227; No. parameters: 3; AIC: 9.97; ARFIMA (0, d, 0).

We estimate the fractional differencing parameter d. The estimate of the fractional differencing parameter is displayed in Table 2. We observe that the value of d is the interval (0, 1), implying long memory ($d > 0$) and mean reverting ($d < 1$) behavior. We notice that the estimated value of d implies a long memory, i.e., nonstationary but mean reverting. Then, the shocks are mean reverting. This finding buttresses our conclusion that a unit root exists in the self-employment rates.

Table A2. Non-linear unobserved component model

	3 Lags		4 Lags		6 Lags	
Regime	$i = 1$	$i = 2$	$i = 1$	$i = 2$	$i = 1$	$i = 2$
β_i	0.037 *	0.038 *	0.043 ***	0.040 **	3.146 **	1.851 **
	(0.022)	(0.026)	(0.018)	(0.021)	(1.409)	(1.102)
α	0.573 ***		0.592 ***		0.773 ***	
	(0.149)		(0.146)		(0.061)	
τ	-0.0040		0.0302		0.0286	
% obs.	54.13%	45.87%	46.79%	53.21%	47.71%	52.29%

Notes: Standard errors in parentheses. ***, **, * Rejects null hypothesis at 1%, 5% and 10% significance level respectively.

Part III: Drivers and inhibitors

Chapter 5: Re-evaluating the relationship between economic development and self-employment

We re-evaluate the relationship between stages of economic development and entrepreneurship, at the macro level. We first conduct a literature review of previous empirical research on cross-country determinants of entrepreneurship in order to put our contribution in perspective. To circumvent problems related to model uncertainty we use Bayesian Model Averaging (BMA) to evaluate the robustness of determinants of self-employment in a new dataset of 117 countries in the 2005-2019 period, allowing fixed effects and investigating the existence of heterogeneity allowing interactions of our focus variable with other regressors. Our empirical analysis then shows that the variation of self-employment rates across countries are mainly determined by variations in the unemployment, the stage of economic development and the variations in labor market frictions. When interactions are taken into account, results confirm that there is a differential effect of labor market frictions in countries with different levels of income. Frictions in labor market may encourage becoming self-employed in richer countries.

5.1. Introduction

The empirical literature on the macro-level determinants of entrepreneurship/self-employment[1] has analyzed a wider set of predictors as potential entrepreneurship drivers. These potential determinants relate to human

---

[1] Throughout this paper, we use the terms entrepreneurship and self-employment synonymously and interchangeably. This operationalization of entrepreneurship as self-employment is dictated by data availability considerations.

capital[2], the level of development[3] and institutions[4]. There is a great number of studies in which a large set of regressors are included in so-called *ad hoc* regressions, based on previous hypotheses and theoretical propositions[5].

Whatever the type of specification is –structural or not[6]– and independently of the inclusion of a focus variable, we have a set of theories and propositions not mutually exclusive and, as in other fields of economics research, most of the empirical results in previous literature on the determinants of entrepreneurship at the macro-level have potential problems of model uncertainty, that is, regarding the choice of predictors.

To the best of our knowledge, we only can find two previous attempts to circumvent these potential problems. On the one hand, Giménez-Nadal et al. (2019) adopted an algorithmic approach based on resampling and bootstrap techniques in a cross section of 69 countries for the year 2014, using data drawn from the Global Entrepreneurship Monitoring Database (henceforth, GEM). In short, the method is a step-by-step approach for finding the subset of explanatory variables leading the best possible prediction accuracy. With this strategy they select the more relevant regressors for explaining the national total entrepreneurship activity (TEA). The strength of

[2] Educational attainment and sociodemographic characteristics.

[3] Economic development, macroeconomic stability –unemployment, inflation, government size–, financial development and access to finance and technological progress.

[4] Labor market institutions, Globalization, Administrative complexity and the rule of law, Taxes and Government.

[5] These works may be classified into two groups: with or without focus variable. For example, among the former are the works of Robson (2003), Spencer and Gómez (2004), Kanniainen and Vesala (2005), Torrini (2005), Sobel et al. (2007), Bjørnskov and Foss (2008), Nyström (2008), Kim et al. (2012), Stenholm et al. (2013), Thai and Turkina (2014), Autio and Fu (2015), Aparicio et al. (2016), Poschke (2019) and Shapiro and Mandelman (2021), and among the latter the works of Pietrobelli et al. (2004), Arin et al. (2015) and Giménez-Nadal et al. (2019).

[6] The adjective structural describes how the specification is derived from a theoretical model. As Low and Meghir (2017) state, this approach allows to understand how the model is identified. The works of Kanniainen and Vesala (2005), Torrini (2005), Poschke (2019) and Shapiro and Mandelman (2021) are examples of this approach in the empirical literature on the determinants of entrepreneurship.

Innovation and research and the level of entrepreneurial education are the best predictors in their analysis. Arin et al. (2015) adopted an alternative solution. They applied a Bayesian model averaging (henceforth, BMA) to address the issue of model uncertainty in the framework of the literature on the determinants of self-employment, following the seminal contribution of Raftery (1995), who combined the Bayesian Information criteria model weights and maximum likelihood estimates for model selection, later revisited in the works of Fernández et al. (2001b) and Ley and Steel (2009). By using 32 predictors, aggregated into three groups – human capital, level of development and Institutions–, they use the BMA approach for correcting model uncertainty. With a short panel of 80 observations drawn from the GEM, the gross domestic product per capita, the unemployment and tax rates and the volatility of inflation are identified as the best predictors of the entrepreneurship rate, when model uncertainty is corrected for.

Despite the advantages of this last approach, the poor quality of the database and short period of observation and the non-consideration of interactions awake serious concerns about the robustness of the last two previous contributions. The problem may be particularly worrying if the relationship between self-employment and the potential regressors was dependent on the state of economic development, as suggested several previous contributions: Acs et al. (1994), Carree et al. (2002), Wennekers et al. (2005) and Acs et al. (2008).

The present study aims to re-evaluate the robustness of the statistical significance of 21 macrolevel variables as predictors of the cross-country differences in the level of self-employment taking into account the potential parameter heterogeneity according to country development level. To this end, we use an extension of the BMA, suggested by Crespo-Cuaresma (2011), to re-evaluate the robustness of 21 determinants of self-employment in a new larger dataset of 117 countries during the period from 2005 to 2019, and investigate the existence of parameter heterogeneity allowing interactions between potential regressors and the stage of economic development based in panel data with fixed effects.

This article contributes to the previous empirical literature on self-employment determinants on the following grounds.

First, we provide new (and updated) empirical evidence on the drivers of self-employment in a much larger dataset than in the available empirical literature, including both developed and developing countries. As usual in prior related literature joint to our focus variable –the economic development proxied by GDP per capita–, a set of control variables are also included

–e.g., proxies of different type of institutions, human capital, openness and technological progress, among others–.

Second, although previous empirical literature devoted to the identification the drivers of entrepreneurship across countries is considerable, there is a lack of consensus. Empirical evidence has not provided unambiguous results and as a result some controversies, about what are the drivers (and barriers) of entrepreneurship, have emerged, with deep policy implications. These inconsistencies may be due to the poor quality of data, to problems related with measurement issues of some variables and to the discretionary choice of predictors, the so-called model uncertainty (Young, 2009)[7]. To circumvent this problem of specification we use an extended version of the BMA for panel data allowing interactions and parameter heterogeneity based on Moral-Benito (2012) and Crespo-Cuaresma (2011) in which inference is based on a weighted average of all possible model specifications, not in a particular one. To the best of our knowledge this contribution is the first attempt to use the BMA approach with interactions in the context of the empirical literature on the determinants of entrepreneurship/self-employment.

Third, the data collected in the new database have been drawn from different sources –International Labor Organization Statistics, OECD Statistics, Penn World Tables (10.0), World Bank and World Intellectual Property Organization–. For measuring some explanatory variables, alternative indicators were taken into consideration to enlarge the sample.

Empirical support is found for the view that national self-employment rate is affected by unemployment, labor market frictions and the level of economic development –a non-linear relationship consistent with the observed U-shape relationship between GDP and self-employment–. When interactions are considered, the key finding is that labor market frictions for the most advanced countries economic are found to be associated with higher self-employment rates.

The paper proceeds as follow. In Section 2 we conduct a brief description of the methodology that we employ and data. Section 3 describes the empirical results and, finally, Section 4 concludes.

---

[7] The potential bias of ignoring this uncertainty is discussed in the works of Acs et al. (1994), Acs et al. (2008), Crespo-Cuaresma (2011) and Young (2009). See Moral-Benito (2015) for a detailed and recent survey.

5.2. Methods and data

Data

Our sample consists of a balanced panel dataset formed by 117 economies over the period 2005–2019. Entrepreneurship is operationalized in terms of self-employment, reflecting data availability at the time series level[8]. Entrepreneurship is defined as the self-employment rate, which is the number of business owners –employers and solo self-employed workers– divided by the total labor force[9]. The self-employment rate is drawn from the International Labor Organization Statistics (ILO-Statistics).

To explain the cross-national variations on self-employment rate, we include the 21 following variables (see Table A2 in the appendix for sources and descriptive statistics):

GDP per capita on purchasing power parity (PPP): gross domestic product converted to international dollars using purchasing power parity rates. Data are in constant 2017 international dollars.

Agriculture, Services and Industry correspond to the ISIC divisions 1-5, 50-99 and 10-45, respectively.

Exports/Imports of goods and services represent the value of all goods and other market services provided/received to/from the rest of the world.

Patent applications are worldwide patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office for exclusive rights for an invention.

Internet users. This indicator captures the proportion of individuals using the Internet based on results from national household surveys.

---

[8] Table A1 and Figure A1 in the appendix show a list of the countries included on the sample and a map with the average self-employment rate over the sample period, respectively.

[9] This is a common practice, for convenience although it is aware that entrepreneurship is a multifaceted concept and look for better indicators is a major challenge for empirical research.

Human capital index. Index provided by the Penn World Tables based on the average years of schooling and an assumed rate of return to education, based on Mincer equation estimates around the world.

Female Labor force participation rate. Proportion of females aged 15 and older who are economically active.

Frictions in Labor Markets. Following Poschke (2019), we use the unemployment-wage employment ratio as an indicator of labor market frictions. He argues that labor market frictions make it more difficult to find a job and cause high levels of unemployment relative to wage employment, reducing the opportunity cost of self-employment.

Unemployment (Youth unemployment). Share the labor force that is without work but available for and seeking employment (in the age interval 15-24, for the younger age group).

Rural population. It refers to people living in rural areas as defined by national statistical offices. It is calculated as the difference between total population and urban population.

Total population. It is "de facto" definition of population, which counts all residents regardless of legal status or citizenship.

Inflation. Proxied by the annual growth rate of the GDP implicit deflator.

Taxes. The total tax and contribution rate measures the amount of taxes and mandatory contributions borne by the business in the second year of operation, expressed as a share of commercial profit. The labor tax and contributions rate measures all government mandated labor contributions that are borne by the business in the second year of operation, expressed as a share of commercial profit.

Doing Business. The score for starting a business is the simple average of the scores for each of the component indicators: the procedures, time and cost for an entrepreneur to start and formally operate a business, as well as the paid-in minimum capital requirement.

Control of Corruption. This index captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.

Government Effectiveness. It captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.

Methodology

As we mentioned, our objective is to select the appropriate specification or statistical model for the determinants of self-employment avoiding the personal discretion of the researcher. Consider the general model,

$$y = \alpha + X_k\beta_k + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2 I), \tag{1}$$

where y is the self-employment rate and k is the number of regressors included, from all the possible regressors K. We are interested in the effect β of every particular variable and interaction included in X. With 21 possible variables, the cardinality of the model space including interactions would be 2^{41}, number of combinations of the 41 variables/interactions in models of size from 1 to 41. It is not possible to estimate around 2.199 billion models. If we could estimate all the models and get the probabilities of every model, the posterior distribution of the parameter β would be a weighting of the estimate of β from every particular model M_i times the probability that this model is true given the data.

$$p(\beta|y) = \sum_{i=1}^{2^K} p(\beta|y, M_i)\, p(M_i|y), \tag{2}$$

We use a BMA approach, first introduced by Raftery (1995), to assess the implicit uncertainty across models. With BMA we assign a prior probability to a set of models and update it according to the data. Then, the posterior model probabilities (PMP) of the top models are averaged to calculate the posterior inclusion probabilities (PIP) for the potential determinants.

The PMP of every model is approximated by the marginal likelihood times the prior probability of the model, not conditional on the data.

$$p(M_i|y) \propto p(y|M_i)\, p(M_i) \tag{3}$$

The researcher is in charge of including the prior beliefs on the model prior. Non-informative prior will assume $p(M_i) = 1/2^K$, assessing the same probability to all the possible models. Under this prior, the posterior model probability will be proportional to the marginal likelihood. It is the likelihood function after integrating away all the parameters of the model (α, β, σ):

$$p(y|M_i) = \iiint p(y|\, M_i, \alpha, \beta_k, \sigma)\, p(\alpha, \beta_k, \sigma)\ d\alpha\ \ d\beta_k\, d\sigma \qquad (4)$$

Priors for model-specific parameters. Setting uninformative prior, we let the data speak. We establish non-informative priors on intercept $p(\alpha) \propto 1$ and on the deviation $p(\sigma) \propto 1/\sigma$. But, in order to find an analytical solution of the marginal likelihood, we need barely informative prior for coefficients β. We assume informative prior on β given σ by the g-prior by Zellner (1986)

$$p(\beta_k|\sigma) \sim \mathcal{N}(0, \sigma^2(gX'X)^{-1}) \qquad (5)$$

This prior requires only elicitation of g. The variance-covariance matrix of β has the same structure of the variance-covariance matrix of OLS estimator, scaled with g, that determines the shrinkage in the regression parameters

$$E(\beta|y, M_i) = \frac{1}{1+g}(X'X)^{-1}X'y = \frac{1}{1+g}\hat{\beta}_{OLS} \qquad (6)$$

The marginal likelihood for model M_i is given by

$$p(y|M_i)\ \propto \left(\frac{g}{1+g}\right)^{\frac{k_i}{2}} \left[\frac{1}{1+g}y'M_X\, y + \frac{g}{1+g}(y-\bar{y}_n)'(y-\bar{y}_n)\right]^{-\frac{n-1}{2}} \qquad (7)$$

with the residual matrix $M_X = (I - X(X'X)^{-1}X')$.

The Bayes factor comparing $M_i$to the null model is given by

$$BF[M_i\ :\ M_0] = \frac{p(y|M_i)}{p(y|M_0)} = \left(1+\frac{1}{g}\right)^{\frac{n-k_i-1}{2}} \left[1+\frac{1}{g}(1-R_i^2)\right]^{-\frac{n-1}{2}} \qquad (8)$$

Fixing g, the marginal likelihood depends on how well the model fits the data and the size of the model. The use of the g-prior leads to a marginal likelihood which incorporates Occam's razor properties: For a given value of k_i, $p(y|M_i)$ and $BF[M_i\ :\ M_0]$ increase as goodness of fits increases, and for a given goodness of fit, $p(y|M_i)$ and $BF[M_i\ :\ M_0]$ increase as k_i decreases.

Literature has provided different options when choosing g. Unit Information Prior (UIP), proposed by Kass and Wasserman (1995), establishes $g = n$, which implies that the Bayes Factor mimics BIC (Liang et al., 2008). Risk Inflation Criterion (RIC), proposed by Foster and George (1994), sets $g = K^2$, that minimizes the maximum increase in risk due to selecting rather than knowing the correct predictors. According to Fernández et al. (2001a), we use the Benchmark prior (BRIC), $g = \max(n, K^2)$, that will decide between UIP or BIC depending on the number of potential regressors K and the sample size n.

Priors over the model space. We follow Ley and Steel (2009) for the specification of the prior model probabilities. We establish a fully random prior for the model and a binomial-beta hyperprior over prior inclusion probability with prior expected model size $\tilde{k} = K/2$. This hyper-prior leads to flat prior inclusion probability[10].

Related predictors. In order to know the different determinants of self-employment rate depending on the income level, we include in our model interactions of all the variables with the GDP per capita. Since we want to analyze the determinants of the self-employment comparing different level of development, we need to control by the effect of individual variables to compare the effect of the interactions. Following Crespo-Cuaresma (2011), we include the specification of strong heredity principle based on Chipman (1996), which is a special case of George's dilution priors (George, 1999). This way, we define prior probabilities across models where interactions are not present or are present with parent variables, and assign zero prior probability to models with interactions where some parent variable is not present.

The rationale behind this specification is that using a uniform prior over the model space we are interpreting an interaction term as an exclusive effect of that particular product of covariates and ignoring the independent effects of the interacted variables. Since we want to assess the differential effect of the covariates depending on GDP, we need to evaluate the significance of these interactions in a model which contains linear terms in both variables in addition to the interaction variable.

Computational Issues. Sampling from the model space. Following Fernández et al. (2001b), we use Markov Chain Monte Carlo Model

[10] In order to check robustness, we tried an informative specification for expected model size ($\tilde{k} = 5$). Results do not show significant change.

Composition (MC3) to approximate the posterior model probability. Starting with a random model with a random number of variables, we compute the posterior model probability and then propose a candidate model in the neighborhood of the first model, with one variable more or less, randomly chosen. Then, we can compare the posterior model probability with the previous one and keep the model with a higher value, that will be compared with a new candidate from the neighborhood. This procedure will visit models with higher non-negligible posterior model probability. Convergence of the MC3 sampler can be checked by computing the correlation between analytical and frequency-based posterior model probabilities for a region of the model space. We estimate 5.000.000 draws, discard the first 1.000.000 draws as the burn-in sample, and compute the results based on the top 100 models visited by the Markov chain.

Using the extension of the BMA methodology (Fernández et al., 2001b) to a panel data framework by Moral-Benito (2012), we estimate a country fixed effects panel, including interactions terms with GDP per capita under the strong heredity prior over the model space. We present posterior inclusion probabilities (PIP)[11], the mean of the posterior distribution for each parameter (and interaction) and the corresponding posterior standard deviation (SD).

5.3. Results

Table 1 presents the results of the BMA exercise. We use the benchmark BRIC prior and establishes a binomial-beta prior on a prior expected model size of $K/2 = 20.5$. Using the strong heredity priors, we only evaluate models which contain the parent variables when interaction terms are included.

Figure 1 shows the variables inclusion of variables with highest PIP on the top visited models and the sign when included. Our analysis, based on 21 covariates and the interaction of GDPpc with all the variables, presents a posterior mean model size of 11 variables but identifies only five variables/terms as significatively determinants of the self-employment.

[11] PIP is considered robust when higher than the prior inclusion probability (π), which is expected model size by the number of variables. For the flat prior over the model space $\tilde{k} = K/2, \pi = \tilde{k}/K = 0.5$.

First, GDP per capita presents a negative and statistically significant relationship with self-employment rate, in line with previous literature (Poschke, 2019; Pietrobelli et al., 2004; Arin et al., 2015). Cross-country analysis shows that self-employment rates are lower in richer countries (Poschke, 2019), while some propositions and theories have attempted to provide a rationale for this negative relationship (Yamada, 1996; Kuznets, 1966).

Acs et al. (2008) distinguishes three major stages of development in self-employment rates. The first is characterized by high rates of non-agricultural self-employment. The second is characterized for a growing number of transitions to the wage-employment sector. As the economy becomes more developed fewer people become self-employed. In the third, the business sector expanded relative to manufacturing and the improvement in information technologies increase the returns of entrepreneurship. From this perspective, a U-shape relationship between self-employment and economic development emerges. Both arguments suggest a non-linear relationship as the significance of the coefficient associated to the quadratic GDPpc seems to indicate (Wennekers et al., 2010).

The next variables appearing as dominant determining the self-employment rates are related to the labor market. Unemployment rate emerges as negative and statistically significant, providing support to the entrepreneurial-pull hypothesis. As Congregado et al. (2012) state, it has been a traditional source of controversy among economists, caused by the two competing hypotheses provided by the theory. The recession-push hypothesis which states that in times of crisis the lack of job opportunities pushes unemployed into self-employment. By contrast, the prosperity-pull mechanism suggests a positive comovement between self-employment and economic opportunities. If this relationship prevails in times of crisis, entrepreneurs are "pulled" out of self-employment, suggesting the existence of negative relationship between unemployment and self-employment. Previous empirical literature provides a large array of different results. As a result, the exact nature of the relation is still not clear, since we can only aspire to capture the net effect (Pietrobelli et al., 2004; Arin et al., 2015). Our results support the prosperity pull hypothesis.

Finally, the frictions on the labor market are found to be a determinant of the variation of self-employment across countries. The relationship between the ratio unemployed by wage employees and self-employment is significant and negative. When checking the importance of interaction terms of GDPpc, only the one with the ratio U/WE appears to be significant. It means that economies with more frictions on the labor market tend to present lower self-employment rate, unless they have higher level of development, in which case the relationship between frictions and self-employment turns positive. This outcome is in line with the results provided by Robson (2003), Kanniainen and Vesala (2005) and Poschke (2019).

Table 1. BMA results

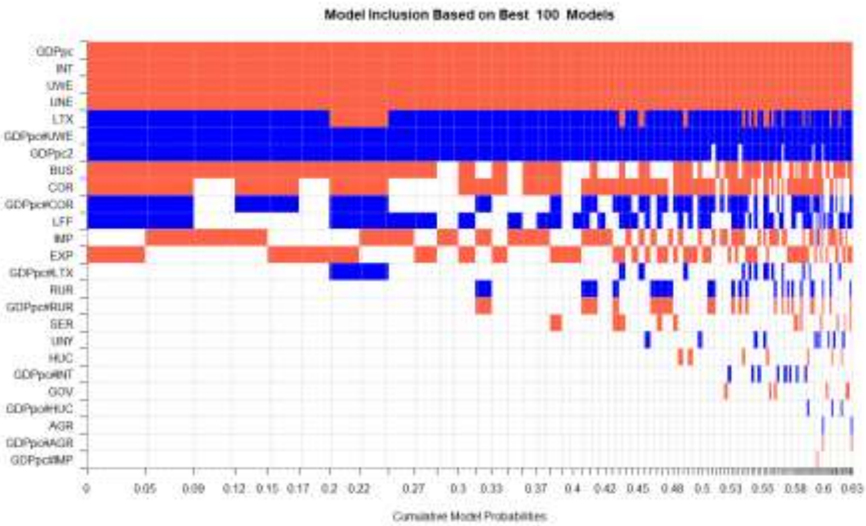
VARIABLE	PIP	M	SD
GDPpc	**1.00**	-40.71***	12.23
AGR	0.05	0.03	0.17
EXP	0.48	-0.01	0.01
IMP	**0.53**	-0.01	0.02
SER	0.11	0.00	0.02
IND	0.02	0.00	0.00
PAT	0.01	0.00	0.00
INT	**1.00**	-0.03	0.03
HUC	0.08	-0.40	2.15
LFF	**0.56**	0.04	0.05
UWE	**1.00**	-171.20***	12.28
UNE	**1.00**	-1.28***	0.10
UNY	0.08	0.00	0.03
RUR	0.21	0.14	0.31
POP	0.01	0.00	0.00
INF	0.02	0.00	0.00
TTX	0.05	0.00	0.01
LTX	**1.00**	0.03	0.17
BUS	**0.70**	-0.01	0.01
COR	**0.73**	-5.24	4.60
GOV	0.05	-0.03	0.25
GDPpc2	**0.95**	1.70***	0.59
GDPpc x AGR	0.04	0.00	0.02
GDPpc x EXP	0.01	0.00	0.00
GDPpc x IMP	0.02	0.00	0.00
GDPpc x SER	0.00	0.00	0.00
GDPpc x IND	0.00	0.00	0.00
GDPpc x PAT	0.00	0.00	0.00
GDPpc x INT	0.06	0.00	0.00
GDPpc x HUC	0.03	0.03	0.20

Table 1. *Continued*

VARIABLE	PIP	M	SD
GDPpc x LFF	0.01	0.00	0.00
GDPpc x UWE	**1.00**	23.94***	1.60
GDPpc x UNE	0.01	0.00	0.01
GDPpc x UNY	0.00	0.00	0.00
GDPpc x RUR	0.19	-0.02	0.03
GDPpc x POP	0.00	0.00	0.00
GDPpc x INF	0.00	0.00	0.00
GDPpc x TTX	0.01	0.00	0.00
GDPpc x LTX	0.17	0.01	0.02
GDPpc x BUS	0.01	0.00	0.00
GDPpc x COR	**0.57**	0.49	0.47
GDPpc x GOV	0.00	0.00	0.02
PMS	**11.77**		
Corr. PMP	0.9998		

Notes: PIP, Posterior inclusion probability; M, mean of the posterior distribution parameter; SD, posterior standard deviation of the parameter; PMS, posterior mean model size; PMP, posterior model probability. Statistics based on the 100 most visited models by the Markov chain. Bold entries refer to variables who PIP>0.5. *, p<0.10; **, p<0.05; ***, p<0.01.

Figure 1. Selected models probabilities. Inclusion and sign of variables



5.4. Conclusion

The contribution of this paper was to provide empirical evidence on the drivers of self-employment in a new and much larger –and harmonized– dataset than in the available empirical literature including 117 countries observed 15 periods and a set of 21 potential entrepreneurship determinants. As usual in prior related literature, joint to our focus variable –the economic development proxied by GDP per capita– a large battery of control variables is also included –e.g., GDP per capita square, institutions, human capital, openness and technological progress, among others– and data and we include a new proxy for capturing frictions in the labor market suggested by Poschke (2019). To circumvent problems associated to model uncertainty we adopted a BMA approach for panel. Our results provide a new explanation of the cross-country differences in the level of self-employment. We show that the unemployment rate, the frictions in the labor market and the stage of economic development are strong determinants of self-employment across the 117 countries included in our sample. Other potential drivers are not significantly correlated with self-employment.

References

Acs, Z. J., Audretsch, D. B., & Evans, D. S. (1994). *Why does the self-employment rate vary across countries and over time?* (No. 871). CEPR Discussion Papers.

Acs, Z. J., Desai, S., & Hessels, J. (2008). Entrepreneurship, economic development and institutions. *Small Business Economics*, *31*(3), 219-234.

Aparicio, S., Urbano, D., & Audretsch, D. B. (2016). Institutional factors, opportunity entrepreneurship and economic growth: Panel data evidence. *Technological Forecasting and Social Change*, *102*, 45-61.

Arin, K. P., Huang, V. Z., Minniti, M., Nandialath, A. M., & Reich, O. F. (2015). Revisiting the determinants of entrepreneurship: A Bayesian approach. *Journal of Management*, *41*(2), 607-631.

Autio, E., & Fu, K. (2015). Economic and political institutions and entry into formal and informal entrepreneurship. *Asia Pacific Journal of Management*, *32*(1), 67-94.

Bjørnskov, C., & Foss, N. J. (2008). Economic freedom and entrepreneurial activity: Some cross-country evidence. *Public Choice*, *134*(3), 307-328.

Carree, M., Van Stel, A., Thurik, R., & Wennekers, S. (2002). Economic Development and Business Ownership: An Analysis Using Data of 23 OECD Countries in the Period 1976-1996. *Small Business Economics*, *19*(3), 271-290.

Chipman, H. (1996). Bayesian variable selection with related predictors. *Canadian Journal of Statistics*, *24*(1), 17-36.

Congregado, E., Golpe, A. A., & Van Stel, A. (2012). The 'recession-push'hypothesis reconsidered. *International Entrepreneurship and Management Journal*, *8*(3), 325-342.

Crespo-Cuaresma, J. (2011). How different is Africa? A comment on Masanjala and Papageorgiou, *Journal of Applied Econometrics*, *26*, 1041-1047.

Fernández, C., Ley, E., & Steel, M. F. (2001a). Benchmark priors for Bayesian model averaging. *Journal of Econometrics*, *100*(2), 381-427.

Fernández, C., Ley, E., & Steel, M. F. (2001b). Model uncertainty in cross-country growth regressions. *Journal of applied Econometrics*, *16*(5), 563-576.

Foster, D. P., & George, E. I. (1994). The risk interaction criterion for multiple regression. *The Annals of Statistics*, *22*(4), 1947-1975.

George, E. I. (1999). Discussion of Bayesian model averaging and model search strategies by M. A. Clyde. *Bayesian Statistics*, *6*, 175-177.

Giménez-Nadal, J. I., Lafuente, M., Molina, J. A., & Velilla, J. (2019). Resampling and bootstrap algorithms to assess the relevance of variables: applications to cross section entrepreneurship data. *Empirical Economics*, *56*(1), 233-267.

Kanniainen, K., & Vesala, T. (2005). Entrepreneurship and labor market institutions, *Economic Modelling*, *22*(5), 828-847.

Kass, R., & Wasserman, L. (1995). A reference Bayesian test for nested hypotheses and its relationship to the Schwarz criterion. *Journal of the American Statistical Association*, *90*(431), 928-934.

Kim, Y., Kim, W., & Yang, T. (2012). The effect of the triple helix system and habitat on regional entrepreneurship: Empirical evidence from the US. *Research Policy*, *41*(1), 154-166.

Kuznets, S. S. (1966). *Modern economic growth*. Yale University Press.

Ley, E., & Steel, M. F. (2009). On the effect of prior assumptions in Bayesian model averaging with applications to growth regression. *Journal of applied econometrics*, *24*(4), 651-674.

Liang, F., Paulo, R., Molina, G., Clyde, M. A., & Berger, J. O. (2009). Mixtures of g priors for Bayesian variable selection. *Journal of the American Statistical Association*, *103*(481), 410-423.

Low, H., & Meghir, C. (2017). The use of structural models in econometrics. *Journal of Economic Perspectives*, *31*(2), 33-58.

Moral-Benito, E. (2012). Determinants of economic growth: a Bayesian panel data approach. *Review of Economics and Statistics*, *94*(2), 566-579.

Moral-Benito, E. (2015). Model averaging in economics: An overview. *Journal of Economic Surveys*, *29*(1), 46-75.

Nyström, K. (2008). The institutions of economic freedom and entrepreneurship: evidence from panel data. *Public choice*, *136*(3), 269-282.

Pietrobelli, C., Rabellotti, R., & Aquilina, M. (2004). An empirical study of the determinants of self-employment in developing countries. *Journal of International Development*, *16*(6), 803-820.

Poschke, M. (2019). Wage Employment, Unemployment and Self-Employment across Countries. IZA Working Paper DP No. 12367.

Raftery, A. E. (1995). Bayesian model selection in social research. *Sociological methodology*, 111-163.

Robson, M. T. (2003). Does stricter employment protection legislation promote self-employment?. *Small Business Economics*, *21*(3), 309-319.

Shapiro, A. F., & Mandelman, F. S. (2021). Digital adoption, automation, and labor markets in developing countries. *Journal of Development Economics*, *151*, 102656.

Sobel, R. S., Clark, J. R., & Lee, D. R. (2007). Freedom, barriers to entry, entrepreneurship, and economic progress. *The Review of Austrian Economics*, *20*(4), 221-236.

Spencer, J. W., & Gómez, C. (2004). The relationship among national institutional structures, economic factors, and domestic entrepreneurial activity: a multicountry study. *Journal of business research*, *57*(10), 1098-1107.

Stenholm, P., Acs, Z. J., & Wuebker, R. (2013). Exploring country-level institutional arrangements on the rate and type of entrepreneurial activity. *Journal of business venturing*, *28*(1), 176-193.

Thai, M. T. T., & Turkina, E. (2014). Macro-level determinants of formal entrepreneurship versus informal entrepreneurship. *Journal of Business Venturing*, *29*(4), 490-510.

Torrini, R. (2005). Cross-country differences in self-employment rates: The role of institutions. *Labour Economics*, *12*(5), 661-683.

Wennekers, S., Van Stel, A., Carree, M., & Thurik, R. (2010). The Relationship Between Entrepreneurship and Economic Development: Is It U-shaped?. *Foundations and Trends in Entrepreneurship*, *6*(3), 167-237.

Wennekers, S., Van Stel, A., Thurik, R., & Reynolds, P. (2005). Nascent entrepreneurship and the level of economic development. *Small business economics*, *24*(3), 293-309.

Yamada, G. (1996). Urban informal employment and self-employment in developing countries: theory and evidence. *Economic development and cultural change*, *44*(2), 289-314.

Young, C. (2009). Model uncertainty in sociological research: an application to religion and economic growth. *American Sociological Review*, *74*(3), 380-397.

Zellner, A. (1986). Bayesian estimation and prediction using asymmetric loss functions. *Journal of the American Statistical Association*, *81*(394), 446-451.

Appendix

Table A1. Countries in the sample

Albania	Cote d'Ivoire	Indonesia	Moldova	Serbia
Algeria	Croatia	Iran	Mongolia	Sierra Leone
Angola	Czech Rep.	Iraq	Morocco	Singapore
Argentina	Denmark	Ireland	Mozambique	Slovak Rep.
Australia	Dominican Rep.	Israel	Namibia	Slovenia
Austria	Ecuador	Italy	Nepal	South Africa
Bangladesh	Egypt	Jamaica	Netherlands	Spain
Belgium	El Salvador	Japan	New Zealand	Sri Lanka
Belize	Estonia	Jordan	Nicaragua	Sudan
Benin	Eswatini	Kazakhstan	Nigeria	Sweden
Bolivia	Fiji	Kenya	Norway	Switzerland
Botswana	Finland	South Korea	Pakistan	Thailand
Brazil	France	Kyrgyz Rep.	Panama	Tunisia
Bulgaria	Gabon	Latvia	Paraguay	Turkey
Burkina Faso	Gambia	Lithuania	Peru	Uganda
Burundi	Germany	Luxembourg	Philippines	Ukraine
Cambodia	Ghana	Madagascar	Poland	UA Emirates
Cameroon	Greece	Malawi	Portugal	United Kingdom
Canada	Guatemala	Malaysia	Romania	United States
Chile	Haiti	Mali	Russia	Uruguay
China	Honduras	Mauritania	Rwanda	Vietnam
Colombia	Hungary	Mauritius	Saudi Arabia	Zambia
Rep. of Congo	Iceland	Mexico	Senegal	Zimbabwe
Costa Rica	India			

Table A2. Variable description, source and statistics

COVARIATE	CODE	SOURCE	MEAN	MIN	MAX
Dependent					
Self-employed (% of total employment)	SE	ILOSTAT	39.67	2.94	94.79
GDP and components					
Log GDP per capita, PPP (constant 2017 $)	GDPpc	WB	9.42	6.62	11.66
Agriculture, forestry, and fishing (% of GDP)	AGR	WB	10.03	0.03	60.28
Exports of goods and services (% of GDP)	EXP	WB	41.32	5.32	228.99
Imports of goods and services (% of GDP)	IMP	WB	44.29	9.00	208.33
Services (% of GDP)	SER	WB	54.53	12.81	79.33
Industry, including construction (% of GDP)	IND	WB	27.18	0.96	66.76
Technological Progress					
Patent applications, per million people	PAT	WIPO	217.75	0.00	4212.02
Individuals using the internet (% of population)	INT	WB	42.18	0.22	99.15
Human Capital					
Human Capital Index	HUC	PWT	2.62	1.12	4.35
Labor Market					
Labor force participation rate, female	LFF	ILOSTAT	51.73	11.28	87.12
Ratio Unemployed by Wage employees	UWE	ILOSTAT	0.17	0.00	1.13
Unemployment (% of total labor force)	UNE	ILOSTAT	7.50	0.39	29.25
Unemployment, youth (% of labor force 15-24yo)	UNY	ILOSTAT	16.58	0.60	58.00
Population					
Rural population (% of total population)	RUR	WB	39.65	0.00	90.63
Population, total in millions	POP	WB	55.00	0.28	1397.72
Institutions					
Inflation, GDP deflator	INF	WB	5.66	-26.10	95.41
Profit tax (% of profit)	TTX	DB	44.96	14.10	285.90
Labor tax and contributions (% of profit)	LTX	DB	19.17	0.00	68.00
Score-Starting a business	BUS	DB	76.36	13.09	99.98
Control of Corruption	COR	WGI	0.06	-1.53	2.47
Government effectiveness	GOV	WGI	0.15	-2.08	2.44

Notes: WB, World Bank; WIPO, World Intellectual Property Organization; PWT, Penn World Tables; DB, Doing Business; WGI, Worldwide Governance Indicators.

Figure A1. Average self-employment rate, 2005-2019

Chapter 6: Is employment protection legislation a driver or an inhibitor of entrepreneurship? The interaction between stringency and enforcement

In this work, we use time series of cross-national macro data of entrepreneurship, from a sample of 28 OECD countries and revisit the interplay between the stringency of employment protection legislation (henceforth, EPL), the regulatory compliance and entrepreneurship at the macro-level. In doing so we report estimates by using a Bayesian model averaging methodology as a way to circumvent problems related to model uncertainty, that is, regarding the choice of the best predictors, focusing on the interaction between EPL and the rule of law, exploring the heterogeneity among "solo" self-employment and employer entrepreneurship. Our results point to: (1) EPL –regular and temporary– can either boost or contract the aggregate self-employment rate depending on the degree of practical regulatory compliance; (2) the relations only hold for "solo" self-employment but not for employer entrepreneurship; and (3) these effects are non-linear in terms of the degree of compliance. Our results can help us to understand the existence of mixed results on the role of EPL as an inhibiting factor or as a driver of entrepreneurship.

6.1. Introduction

Self-employment dynamics in OECD countries, between the 2008 and 2020 crises, has triggered a renewed interest among scholars and analysts, being common the association between self-employment growth and the deterioration of labor market conditions (Henley, 2022; Wieteke and Schippers, 2019). Between the Great Recession and the Great Pandemic, at the same time that some of the countries where self-employment was most prevalent, witnessed a sharp decline in their self-employment rates (e.g., Greece, Portugal or Turkey), other countries, like the Netherlands and the United Kingdom, reached the highest levels of self-employment since records began: more than 5 million in the UK and almost 1.4 million in the Netherlands

(Eurostat, 2019). In fact, great part of the new employment created during the recovery phase, was due to an increase in "solo" self-employment (Giupponi and Xu, 2020). However, the most surprising and shocking fact was that there has been no real change in the proportion of people choosing to enter self-employment, but a significant drop in the proportion leaving self-employment (Valleta et al., 2020)[1]. In other words, the counter cyclicality of self-employment breaks, perhaps because of the impossibility to find a full-time job offer in the wage sector, due to an insufficient employment intensity of growth (Borowczyk-Martins and Lalé, 2020).

With the above arguments, it may seem that what characterizes the inter-crisis period is that a great part of the new self-employment is associated to marginal entrepreneurs, groups of secondary and vulnerable workers, and that they are all "trapped" in the self-employed sector[2]. Nevertheless, not all the rise in self-employment was associated to precarious jobs or on-demand labor in the gig sector. In addition to this, there is also a rise associated to professional, scientific, and technical activities, and an upsurge of transitions to self-employment motivated by the search of a better work-family balance and flexible hours (Molina, 2020), running in parallel to changes in the industrial structure and technologies of production and the rapid growth of digitally enabled forms of work (Congregado et al., 2019, 2022).

To this we must add that the conjunction of instruments encouraging the transition to becoming self-employed[3], the potential use of self-employment

---

[1] Several countries implemented policies to foster entrepreneurship among unemployed during the Great Recession, as an active labor market policy with the objective of turning unemployment into self-employment. In other words, many of these new "solo" self-employed were marginal entrepreneurs/non-genuine entrepreneurs. What was new was that the opportunities to move from self-employment to working as an employee after the recession has been limited and often as an involuntary part-time worker. This phenomenon may be reflecting the lack of opportunities in traditional employment since the onset of the recovery, the general weakness in the labor market.

[2] Giupponi and Xu (2020) document that in the post-recession period, the UK has reached record numbers of self-employed who are earning lower wages and working longer than other workers.

[3] The introduction of a flat rate for new self-employed (Cueto et al., 2017), the potential capitalization of unemployment benefits for turning unemployment into self-employment (Caliendo and Künn, 2011; Mayor et al., 2015), and tax

as a way to avoid taxes and social security contributions, and to circumvent regulations and protection, alter the opportunity cost of being self-employed, thus changing the composition of employment pushing individuals to self-employment.

This whole order of things has deep implications not only for government revenues (lower social security contributions and lower rates of taxation), but also on the public expenditure: taken together, these interventions often impose sizeable costs on the taxpayer (Congregado et al., 2012).

But budget issues aside, there are implications for the effectiveness of labor policies. Specifically, labor market rigidity leads to a push-effect to self-employment and inhibits or erodes employment protection legislation, by encouraging self-employment as a way to evade and circumvent the effects of certain labor market institutions. As consequence, there is a loss of rights and protection by replacing the regular labor relation between employer-employee by relations between firms and independent contractors[4]. The only way to prevent these practices is through strict compliance with the norm that avoids these distortions.

In strictly regulated labor markets, employers have greater incentives to rely on contracting outside of the firm increasing the opportunities for self-employed, creating market niches that reduce uncertainty and makes entrepreneurial success more viable. This context is conducive to the emergence of dependent forms of self-employment, agreed or not by workers and employers, who can make use of incentives schemes for achieving a more "advantageous" and "cheaper" relationship, avoiding labor market regulation and institutions.

The paradox is that a highly protective employment legislation, in the absence of an adequate guarantee of compliance and in the presence of incentive schemes to promote self-employment, can become ineffective, transforming employer-employee labor relations into relations based on work on

---

deductions and benefits for the self-employed (Bruce, 2002) are just some of these incentives.

[4] These types of distortions in occupational choice have intensified because of the irruption of digitally enabled on-demand work and the strategies of flexible production incentives to outsource production substituting relations employer-employee by contracts with self-employed professionals –democratized to low skill workers in the gig economy– external to the firm.

demand and leading to the absolute loss of workers' rights, inhibiting the intended effect of the protective labor market legislation (Arum et al., 2000).

In this context, revisiting the interplay between the employment protection legislation, the degree of compliance with the regulatory framework, and the opportunity cost of being self-employed is particularly intriguing. To this end, this work aims to shed new light on the role of these country-specific institutional characteristics –that are parts of the so-called national systems of entrepreneurship in terms of Szerb et al. (2013) and Acs et al. (2014)– as driver or inhibitor of entrepreneurship.

From this perspective, this paper relates to the extensive empirical literature dedicated to the analysis of the factors that determine the differences in national self-employment rates, i.e., the determinants of macro-level entrepreneurship[5]. Evidence provided by this type of works is very often mixed. The causes can be found in the low adequacy of the available data for international analysis[6], in how the longitudinal/cross-sectional dimension(s) of the used databases conditions the econometric strategy adopted and the statistical significance of the results, and even in the operationalization used to measure entrepreneurship/self-employment at the macro-level –see, Dvouletý (2018) for a recent and detailed discussion about measurement issues and potential consequences in this type of studies[7]–.

[5] There are also international studies based on micro-data or multilevel analysis (see for instance, Román et al., 2011b or Block et al., 2019, as examples of these two types of analyses).

[6] In this body of literature there is no shortage of studies based on cross-sectional data and short panels, in which a limited number of controls are used as predictor of cross-national variation in the aggregate self-employment. As a result, some scholars expressed serious concerns about some previous and apparently contradictory empirical findings (see, Koellinger and Thurik, 2012; Iversen et al., 2007; Congregado, 2008; Coviello and Jones, 2004).

[7] Total entrepreneurship activity (henceforth, TEA) –aggregate measure of start-ups collected by the Global Entrepreneurship Monitor (henceforth, GEM)– and aggregate self-employment (taken from Labour Force Surveys Statistics, henceforth, LFS) are some of the most common measures of self-employment/entrepreneurship used in this type of studies at the macro-level.

From a methodological perspective, the scheme in this type of literature is usually quite common: based on structural or *ad hoc* specifications –in which some predictor is set as the "focus" variable[8]– the influence of this factor and some controls[9] (and its interactions) on the national/regional entrepreneurship is estimated.

In relation to our research question, special mention should be made to the body of literature that focuses on the role of institutional design and quality. Among these are those focused on the quality of institutions (Autio and Fu, 2015; Valdez and Richardson, 2013), on the role of fiscal systems (Torrini, 2005), and those focused on the effect of certain labor market institutions (Grubb and Wells, 1993; Kanniainen and Vesala, 2005; Liebregts and Stam, 2019) or on the role of the greater or lesser degree of employment protection and/or flexibility conferred by these institutions (OECD, 1999; Robson, 2003; Centeno, 2000; Torrini, 2005; Baker et al., 2018)[10].

Focusing on the impact of the employment protection legislation's stringency on self-employment, the evidence seems to yield ambiguous results, finding support for a negative impact in the works of Grubb and Wells (1993) or OECD (1999); positive, in the works of Centeno (2000) or Robson (2003); while others seem to support different impacts for different groups

---

[8] Doing a selective review of the literature according to the "focus" variable, we find papers focusing on the role of the level of economic development (Acs et al., 1994; Pietrobelli et al., 2004, Rodriguez-Santiago, 2022), unemployment (Blanchflower, 2000; Poschke, 2019), education (Van der Sluis et al., 2005), the degree of openness and foreign trade (Sobel, 2008), the economic freedom (Nyström, 2008; Sobel et al., 2007; Bjørnskov and Foss, 2008; Bailey and Thomas, 2017), the role of innovation and technology (Giménez-Nadal et al., 2016), the financial development (Hurst and Lusardi, 2004), the digital adoption (Shapiro and Mandelman, 2021), the role of the macroeconomic environment/stability (Arin et al., 2015) and, the labor market rigidity (Grubb and Wells, 1993; OECD, 1999; Centeno, 2000; Robson, 2003; Torrini, 2005; Baker et al., 2018).

[9] GDP per worker, human capital endowments, the relative weight of de different sectors in the economic activity, and some macroeconomic indicators, labor market aggregates, and institutional variables are some of the most common controls.

[10] There are also international studies with micro data and multi-level studies, i.e., the so-called micro- and meso-studies (Davidsson and Wiklund, 2007).

of workers (Baker et al., 2018) or point to the non-existence of effects (Torrini, 2005).

From our point of view, and leaving aside the possible influence of the sample and the selection of proxies to measure the entrepreneurship and the "focus" variable, we would argue that previous mixed results might be due to some of following reasons: (1) the econometric approximation and, more specifically, due to specification problems (Arin et al., 2015); (2) the non-consideration of interactions between the focus variable and the control variables, as Centeno (2000) suggests, because the greater or lesser rigidity introduced by employment protection legislation may be conditioned by degree of compliance, or in other terms, with the difficulty of evading its application (Torrini, 2005); and (3) previous research seems to have overlooked the heterogeneity in self-employment, and we cannot rule that labor regulation could have a different impacts on entrepreneurs who hire external labor compared with entrepreneurs who work on their own.

To deal with these three hypotheses in a single framework, we propose to revisit the impact of the stringency of employment protection legislation on the aggregate rate of self-employment across 28 OECD countries, by using an empirical approach defined by the three following pillars. Firstly, controlling the model uncertainty, i.e., the selection of predictors used as controls. Secondly, following the extension of the Bayesian model averaging methodology (henceforth, BMA) to a panel data framework (Moral-Benito, 2012) with interactions (Crespo-Cuaresma, 2011), we report estimates in a model in which we check the impact of the stringency employment protection legislation and its interaction with the rule of law. Thirdly, we also report separate estimates for employers and "solo" self-employed workers because we cannot rule different impacts of EPL stringency among different groups of self-employed.

In this way, our estimates shed new light about the prevalence of crowding-out or crowding-in effects of the stringency of EPL on self-employment, depending on the ease with which compliance with the law can be evaded.

Our results point to: (1) EPL –regular and temporary– can either boost or contract the aggregate self-employment rate depending on the degree of practical regulatory compliance; (2) the relations only hold for "solo" self-employment but not for employer entrepreneurship; and (3) these effects are non-linear in terms of the degree of compliance.

In short, our results show how important it is to take into account compliance and the unintended effects that employment protection legislation can have on the occupational choice, generating distortions in the composition of employment.

The rest of this paper is organized as follows. Section 2 presents a selective review of related literature. Section 3 describes the dataset used to find the determinants of self-employment rate among OECD countries. Section 4 presents the methodology used and section 5 describes the results. Finally, conclusions are presented on section 6.

6.2. A selective review of related literature

From a theoretical point of view, the nature of the relationship between the employment protection legislation and self-employment rates allows for two competing hypotheses which could it be referred to as the crowding-out and crowding-in hypotheses. On the one hand, one can argue that greater protection of salaried employment directly influences the opportunity cost of self-employment by unbalancing the choice of occupation in favor of paid-employment (Baker et al., 2018)[11]. However, it is no less true that, from the employer's perspective, greater protection introduces rigidity and higher costs in hiring (both explicit and implicit), which may lead them to devise mechanisms that allow them to avoid the most onerous and harmful elements of employment protection legislation. That is, by trying to replace traditional employer-employee relationships with service leasing relationships with self-employed persons or by trying to avoid the rule of law by encouraging the development of dependent forms of self-employment, either under the legal formula of economically dependent self-employed workers or directly through different forms of false self-employment (Roman et al., 2011a)[12].

Grubb and Wells (1993) argued that regulation might reduce regular paid-employment since employers may attempt to circumvent the effects of regulations contracting-out work to self-employed contractors. As a result, the emergence of non-genuine forms of self-employment like the so-called false

[11] They suggest that this effect might be stronger among high-skilled workers.

[12] Perhaps, this effect will be prevalent among low-employability groups of workers who will become marginal entrepreneurs and non-genuine self-employed workers.

self-employment (Román et al., 2011a), can help to understand the evidence on the positive effect of the national labor market regulation on self-employment rates. Similar results are obtained by the OECD (1999) by using a panel data of 23 OECD countries and including different measures of employment protection legislation. By using different summary measures of the strictness of employment protection legislation (overall, regular employment, temporary contracts, and collective dismissals), they provide evidence of a positive and statistically significant relationship between the strictness of employment –for the overall and regular employment measures– and the share of self-employment in OECD.

However, subsequent studies showed that evidence on the (positive) relationship between self-employment and the strictness of EPL was weak, non-robust. Robson (2003), argued that contrary to the results of previous studies, once that control variables and country-fixed effects are introduced into the analysis, the evidence of a positive relationship disappears. Centeno (2000) illustrated another key drawback of previous research on self-employment and labor market rigidities. In his influential paper, he offers an alternative explanation to the lack of previous robust evidence based on the inclusion of controls and interactions with the focus variable. In particular, he reports evidence on the sensitivity of the finding of a positive relationship between labor market rigidity and the share of self-employment to the inclusion of controls capturing the costs of self-employment. Proxying these costs with the ratio of social security contributions per self-employed to the nominal GDP per capita, his main result suggests that higher contributions by the self-employed reduce the effect of EPL stringency on self-employment. From our point of view, the key contribution of this work resides in the fact that calls for taking into account of interactions with controls, since in some conditions, some factors might inhibit the ability of our focus variable to explain the variation of self-employment.

Kanniainen and Vesala (2005) and Torrini (2005) also explore the impact of labor market institutions on enterprise formation. The work of Torrini (2005), focused on the determinants of the cross-country variation in self-employment, is another contribution with a substantial added value to this brand of literature. Torrini, by using a panel of OECD countries in a span of 21 years, reports estimates of a structural model in which, joint to a set of economic and institutional determinants, he also considers the institutional context and rules of the game, under which self-employed workers operate[13]. Although, he does not provide evidence to support the notion that stricter employment protection legislation promotes self-employment, the value of his contribution is the jointly exploration of the role of taxation and tax evasion opportunities, for exploring the idea that not only the institutional framework but also the institutional quality are important predictors of self-employment. Some recently works, have revisited the relationship by introducing heterogeneity, that is, reconsidering the effects for different groups of self-employed workers. A prime example is the work of Poschke (2019) which finds empirical evidence supporting a positive causal effect of labor market rigidities and self-employment but limited to "solo" self-employment. Another example is Baker et al. (2018) who explore the stringency of EPL distinguishing between low- and high-skilled workers. Importantly, they find a contrasting impact on self-employment across skill types and no impact on aggregate self-employment. This result, once again, reaffirms the importance of considering heterogeneity in self-employment.

Finally, our work also has its roots in the literature on the determinants of self-employment/entrepreneurship, and in particular, in how did this brand of literature evolved over time, in terms of the type of econometric approach. Much of this literature consists of cross-section analysis and estimates from short panels conditioned by the availability of data. The inclusion of controls (Robson, 2003), country fixed effects (Pietrobielli et al., 2004), and interactions (Centeno, 2000), as well as the different forms to circumvent endogeneity bias (Kaniannien and Vesala, 2005), have marked the evolution of this body of empirical literature. Irrespective of this, most of the empirical results in previous literature on the determinants of entrepreneurship at the macro-level have potential problems of model uncertainty, that is, regarding the choice of predictors.

An attempt to circumvent this problem is due to Giménez-Nadal et al. (2016) who adopted an algorithmic approach based on resampling and

[13] To some extent, this idea runs in parallel with the works of Sobel (2008), Bjørnskov and Foss (2008), Nyström (2008) and Autio and Fu (2015) about the effect of the institutional quality, the rules of game, as determinants of the productive and unproductive entrepreneurship (in the Baumol's sense), the total entrepreneurial activity, the rate of business owners and of the formal and informal entrepreneurship, respectively.

bootstrap techniques in a cross section of 69 countries for the year 2014, using data drawn from the Global Entrepreneurship Monitor Database. In short, the method is a step-by-step approach for finding the subset of explanatory variables leading the best possible prediction accuracy. With this strategy, they select the more relevant regressors for explaining the national total entrepreneurship activity. The strength of innovation and research and the level of entrepreneurial education are the best predictors in their analysis.

Particularly remarkable are the works of Arin et al. (2015) and Rodríguez-Santiago (2022) who applied a BMA model to address the issue of model uncertainty in the framework of the literature on the determinants of entrepreneurship/self-employment, following the seminal contribution of Raftery (1995), who combined the Bayesian information criteria model weights and maximum likelihood estimates for model selection, later revisited in the works of Fernández et al. (2001a) and Ley and Steel (2009). By using 21 predictors, Rodriguez-Santiago (2022) uses the BMA approach for correcting model uncertainty. With a panel drawn from different sources, the unemployment rate, the frictions in the labor market and the stage of economic development are strong determinants of self-employment across the 117 countries included in the sample, when model uncertainty is corrected for. Other potential drivers are not significantly correlated with self-employment.

Table 1 presents a summary of this selective review of related literature about the determinants of self-employment at the macro-level.

Table 1. A selective review of cross-country studies about determinants of self-employment/entrepreneurship at the macro-level

AUTHORS	DEPENDENT VARIABLE	PROXY DEPENDENT VARIABLE(S)	DATA SOURCES	SAMPLE	FOCUS VARIABLE / MACRO-LEVEL PREDICTORS	CONTROL VARIABLES - OTHER COVARIATES	METHOD	RESEARCH GAP / FOCUS	RESULTS
Grubb and Wells (1993)	SE [1]	Self-employment including employers and unpaid family workers	EU- Labor Force Survey	11 European Countries (1989)	Overall regulation of dependent work	NA	Cross country correlations	Effect of regulation	Regulation reduces regular employment and increases non-standard works
OECD (1999)	SE [1]	Share of self-employment	OECD	23 OECD countries (1985-1997)	Strictness of EPL indicators Overall, regular employment, temporary employment, collective dismissals	NA	Random Effects GLS estimates	Self-employment and strictness of employment protection legislation distinguishing different types of protection	Stricter EPL (overall and for regular employment) is strongly associated with higher rates of SE when other factors are controlled
Centeno (2000)	SE [1]	Share of non-agricultural self-employment	OECD Labor Force Statistics	18 OECD countries (1984-1997)	Flexibility Self-employed workers Social Security Contributions	Log GDP pc U [2] Social Security contribution per self-employed	Panel, fixed effects	Relationship between Labor Market rigidities and self-employment in previous literature provided mixed	Self-employment channel of employment flexibility inhibiting EPL stringency
Robson (2003)	SE [1]	Share of non-agricultural self-employment	OECD Labor Force Statistics	Panel Data 13 OECD (1965-1995) Cross section 15 OECD (1999)	Strictness of EPL indicators Overall, regular employment, temporary employment, collective dismissals	Log GDP pc U [2] LFPT [3] Income tax rate Payroll tax rate Benefit replacement ratio	OLS in both Panel data and cross section specifications	Check the robustness of previous results by introducing controls, country fixed effects and non-agricultural SE	Findings of a positive relationship between EPL and self-employment reported in previous studies are non-robust
Torrini (2005)	SE [1]	Log self-employment rate	OECD Economic Outlook Database International Transparence	Panel 19-25 OECD countries (1979-2000)	Tax Wedge Replacement rate	GDP per worker U [2] EPL PML [4] Corruption index Public sector size	Pooled and fixed effects estimates from panel data	Role of institutions and compliance	No relationship between self-employment and employment protection legislation. Effect of Taxation depends on the country attitude towards tax evasion.
Kanniainen and Vesala (2005)	E [5]	Ratio of non-agricultural employers and people working on their own account	OECD Statistics	5 years interval cross section data 19 OECD economies (1978-98)	Labor Market Institutions: replacement ratio; EPL; labor union power; trade union density; bargaining coverage rate; wage bargaining; coordination across trade unions; unemployment rate.		OLS pooled estimates of a Panel	Structural model incorporating a three years lag for avoiding simultaneity and reversed causality bias	Predictors: economic risks, unemployment compensation, union power, and labor protection variables
Aparicio et al. (2016)	E [5]	Opportunity entrepreneurship	GEM data [6] World Bank	Unbalanced panel 43 countries (2004-2012)	Control of corruption	NA	Three stage least-square	Formal and informal institutions	Informal institutions have a higher impact on opportunity entrepreneurship than formal institutions (Control of corruption, confidence and private coverage)

Table 1. *Continued*

AUTHORS	DEPENDENT VARIABLE	PROXY DEPENDENT VARIABLE(S)	DATA SOURCES	SAMPLE	FOCUS VARIABLE / MACRO-LEVEL PREDICTORS	CONTROL VARIABLES - OTHER COVARIATES	METHOD	RESEARCH GAP / FOCUS	RESULTS
Giménez-Nadal et al. (2016)	E [5]	Overall total entrepreneurship activity (TEA rate)	GEM data [6]	Cross Section 69 countries (2014)	Innovation; Sociocultural environment; Entrepreneurial education; R&D transfers; Government subsidies		Algorithmic approach based on resampling and bootstrap techniques	Step by step approach for finding the subset of explanatory variables leading the best possible prediction accuracy. Selection of the more relevant regressor(s)	Strength of Innovation and Research, and of Entrepreneurial Education Selection of the more relevant regressor(s)
Baker et al. (2018)	SE [1]	Aggregate self-employment (own account and employers)	EUROSTAT data	21 countries (1995-2013)	EPL regular and temporary	Tax wedge, unemployment benefit, minimum wage, ALMP, output gap, share of ICT	Dynamic panel data	Evaluation of the impact of different labor market institutions and imposition on aggregate self-employment and self-employed groups (unemployment benefits, active labor market policies, EPL, minimum wage and tax wedge)	No impact of EPL stringency on aggregate self-employment. Positive impact among low-skilled workers. Negative impact among high-skilled workers
Poschke (2019)	SE [1]	Aggregate self-employment (own account and employers)	IPUMS [7]	58 countries (developed and least developed countries)	Ratio U/U+W [8]	Log GDP per capita Employment share industry Minimum wage Severance payment Tertiary education enrollment	Panel Data	Role of frictions in the entry into self-employment and entrepreneurship	Positive effects of Labor market frictions on low productivity own-account work (not employers)
Arin et al. (2015)	E [5]	Overall total entrepreneurship activity (TEA rate)	GEM data [6]	43 countries (1995-1997)	32/21 predictors: Human capital: population, education, unemployment		BMA [9]	Correct model uncertainty	Predictors: GDPpc, Unemployment, tax rate, volatility of inflation
Rodríguez-Santiago (2022)	SE [1]	Self-employment rate	ILO data	117 countries (2005-2019)	Level of development: GDP per capita, Financial Development, Technological Progress Institutions: Administrative Complexity, Globalization, Taxes, Inflation		BMA [9]	Correct model uncertainty + interactions	Predictors: unemployment rate, frictions in the labor market and stage of economic development

Notes:
(1) Self-employment
(2) Unemployment rate
(3) Female Participation rate
(4) Product market regulation
(5) Entrepreneurship
(6) Global Entrepreneurship Monitoring
(7) International Integrated Public Use Microdata Surveys
(8) Wage-earners
(9) Bayesian Model Averaging

6.3. Data

Entrepreneurship is a multifaceted concept which encompasses a range of roles including the innovation (Schumpeter, 1934, 1939), the reduction of inefficiencies (Leibenstein, 1968), the discover of profit opportunities (Kirzner, 1979), and the strategic decision making in an uncertain environment (Knight, 1921). Any single measure of entrepreneurship is unlikely to do justice to all these facets. At the macro level, and in cross-country analyses, the most common measure used in practice is self-employment rates, reflecting the widespread availability of aggregate data for a range of countries[14]. To some extent, and although self-employment is not a perfect measure of entrepreneurship, the self-employment definition has the merit of inclusiveness and convenience (Ahmad, 2008; Ahmad and Seymour, 2008; Congregado, 2008), specially for cross-country studies. We must be aware, however, that the self-employment may represent the response to institutional structures rather than the entrepreneurial dynamism.

For these reasons, and to describe the role of institutions as determinants of self-employment, we use a balanced panel dataset formed by 28 OECD countries, with annual data spanning from 1996 to 2019. The self-employment rate is drawn from the International Labor Organization Statistics (ILO-Statistics) and is defined as the percentage of total workers that are employers, members of producers' cooperatives, contributing family workers or own account workers. Taking into account the heterogeneity within self-employment, our analysis will be disaggregated into total self-employment, employership and own-account work.

[14] Labor Force Surveys are the most common source of data for operationalize entrepreneurship (Dvouletý, 2020). The classifications of employment by status provide internationally harmonized data on the occupational choice decisions. Previous essays to provide internationally comparable data at the macro-level includes the COMPENDIA data base (Van Stel, 2005; Van Stel et al., 2010). Of special mention is the attempt of the Global Entrepreneurship Monitoring Consortium in order to provide a measure of the entrepreneurial dynamism at the macro level. The early-stage entrepreneurial activity (TEA) has become a benchmark in empirical studies. However, the low frequency and the short cross-sectional and longitudinal dimensions available in this dataset, discourage its use for the analysis of the entrepreneurship drivers.

To identify the key factors determining the cross-national differences on self-employment (employership or own-account work) rate, as it is common in this kind of literature, our database includes a set of 17 variables representing different aspects related to the level of development, technological progress, the development of the financial sector, the human capital endowment and the role of different institutions among others. The list and description of these variables is as follows[15]:

GDP per capita (and squared GDP per capita) on purchasing power parity (PPP): Gross domestic product per worker, converted to international dollars using purchasing power parity rates. Data are in constant 2017 international dollars.

Agriculture, Industry and Services correspond to the ISIC divisions 1-5, 10-45 and 50-99, respectively, as a percentage of GDP.

Trade openness: Exports plus imports of goods and services, that represent the value of trade as a percentage of GDP.

Rural population: It refers to people living in rural areas as defined by national statistical offices. It is calculated as the difference between total population and urban population.

Patent applications by million population: Worldwide patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office for exclusive rights for an invention.

Internet users: This indicator captures the proportion of individuals using the Internet based on results from national household surveys.

Human capital index: Index provided by the Penn World Tables based on the average years of schooling and an assumed rate of return to education, based on Mincer equation estimates around the world.

Female Labor force participation rate: Proportion of females aged 15 and older who are economically active.

[15] See Table A1 for variables' sources and descriptive statistics, and Table A2 for a list of the countries on the sample.

Unemployment (Youth unemployment): Share the labor force that is without work but available for and seeking employment (in the age interval 15-24, for the younger age group).

Inflation: Proxied by the annual growth rate of the GDP implicit deflator.

Government expenditure: All government current expenditures for purchases of goods and services, including compensation of employees and most expenditures on national defense and security, as a percentage of GDP.

Rule of Law: This index includes several indicators which measure the extent to which agents have confidence in and abide by the rules of society, including perceptions of the incidence of crime, the effectiveness and predictability of the judiciary, and the enforceability of contracts.

Employment Protection Legislation of regular contracts[16]. Synthetic indicator of the strictness of dismissals of workers on regular contracts, both individual and collective dismissals.

Employment Protection Legislation of temporary contracts[17]. Synthetic indicator of the strictness of regulation on the use of temporary contracts.

The aim of this paper is the study of the role of EPL as a driver of entrepreneurship and, particularly, whether the effect is different depending on

[16] For every country, EPL is described along with 21 items. Protection of regular workers against individual dismissal includes 9 units: Notification procedures, delay involved before notice can start, length of the notice period at, severance pay at, definition of justified or unfair dismissal, length of trial period, compensation following unfair dismissal, possibility of reinstatement following unfair dismissal and maximum time to make a claim of unfair dismissal. Furthermore, there are 4 additional units to measure protection against collective dismissals: definition of collective dismissal, additional notification requirements, additional delays involved before notice can start and other special costs to employers. For more information regarding the calculation of summary indicators of EPL strictness, see OECD (1999), Chapter 2, annex 2.B.

[17] The regulation of temporary forms of employment is described by these 8 units: valid cases for use of fixed-term contracts (FTC), maximum number of successive FTC, maximum cumulated duration of successive FTC, types of work for which temporary work agency (TWA) employment is legal, restrictions on number on renewals, maximum cumulated duration of TWA assignments, authorization, or obligations to set-up a TWA, and equal treatment of regular workers at firms.

the compliance of labor market laws, measured by the rule of law index. Furthermore, distinction between EPL of regular and temporary contracts is taken into account.

6.4. Methodology

Consider the general model,

$$y_{it} = \alpha_i + X_{k,it}\beta_k + \varepsilon_{it}, \qquad \varepsilon \sim N(0, \sigma^2 I), \tag{1}$$

where y_{it} is the self-employment rate of country i, observed over the period t and k is the number of regressors included, from all the possible regressors K. We are interested in the effect β of every particular variable and interaction included in X.

With 17 possible variables, the cardinality of the model space, including the interaction between EPL and rule of law, would be 218, number of combinations of the 18 variables/interaction in models of size from 1 to 18. It is not possible to estimate around 262 thousand models. If we could estimate all the models and get the probabilities of every model, the posterior distribution of the parameter β would be a weighting of the estimate of β from every particular model M_i times the probability that this model is true given the data.

$$p(\beta|y) = \sum_{i=1}^{2^K} p(\beta|y, M_i)\, p(M_i|y), \tag{2}$$

We use a Bayesian model averaging approach, first introduced by Raftery (1995), to assess the implicit uncertainty across models. With BMA we assign a prior probability to a set of models and update it according to the data. Then, the posterior model probabilities (PMP) of the top models are averaged to calculate the posterior inclusion probabilities (PIP) for the potential determinants.

The posterior model probability of every model is approximated by the marginal likelihood times the prior probability of the model, not conditional on the data.

$$p(M_i|y) \propto p(y|M_i)\, p(M_i) \tag{3}$$

The researcher is in charge of including the prior beliefs on the model prior. Non-informative prior will assume $p(M_i) = 1/2^K$, assessing the same probability to all the possible models. Under this prior, the posterior model probability will be proportional to the marginal likelihood. It is the likelihood function after integrating away all the parameters of the model (α, β, σ):

$$p(y|M_i) = \iiint p(y|\, M_i, \alpha, \beta_k, \sigma)\, p(\alpha, \beta_k, \sigma)\; d\alpha\;\, d\beta_k\, d\sigma \qquad (4)$$

Priors for model-specific parameters. Setting uninformative prior, we let the data speak. We establish non-informative priors on intercept $p(\alpha) \propto 1$ and on the deviation $p(\sigma) \propto 1/\sigma$. But, in order to find an analytical solution of the marginal likelihood, we need barely informative prior for coefficients β. We assume informative prior on β given σ by the g-prior by Zellner (1986).

$$p(\beta_k|\sigma) \sim \mathcal{N}(0, \sigma^2(gX'X)^{-1}) \qquad (5)$$

This prior requires only elicitation of g. The variance-covariance matrix of β has the same structure of the variance-covariance matrix of OLS estimator, scaled with g, that determines the shrinkage in the regression parameters

$$E(\beta|y, M_i) = \frac{1}{1+g}(X'X)^{-1}X'y = \frac{1}{1+g}\hat{\beta}_{OLS} \qquad (6)$$

The marginal likelihood for model M_i is given by

$$p(y|M_i) \propto \left(\frac{g}{1+g}\right)^{\frac{k_i}{2}} \left[\frac{1}{1+g}y'M_X\, y + \frac{g}{1+g}(y-\bar{y}_n)'(y-\bar{y}_n)\right]^{-\frac{n-1}{2}} \qquad (7)$$

with the residual matrix $M_X = (I - X(X'X)^{-1}X')$.

The Bayes factor comparing $M_i$to the null model is given by

$$BF[M_i : M_0] = \frac{p(y|M_i)}{p(y|M_0)} = \left(1+\frac{1}{g}\right)^{\frac{n-k_i-1}{2}} \left[1+\frac{1}{g}(1-R_i^2)\right]^{-\frac{n-1}{2}} \qquad (8)$$

Fixing g, the marginal likelihood depends on how well the model fits the data and the size of the model. The use of the g-prior leads to a marginal likelihood which incorporates Occam's razor properties: For a given value of k_i, $p(y|M_i)$ and $BF[M_i : M_0]$ increase as goodness of fits increases, and for a given goodness of fit, $p(y|M_i)$ and $BF[M_i : M_0]$ increase as k_i decreases.

Literature has provided different options when choosing g. Unit Information Prior (UIP), proposed by Kass and Wasserman (1995), establishes $g = n$, which implies that the Bayes Factor mimics BIC (Liang et al., 2009). Risk Inflation Criterion (RIC), proposed by Foster and George (1994), sets $g = K^2$, that minimizes the maximum increase in risk due to selecting rather than knowing the correct predictors. According to Fernández et al. (2001a), we use the Benchmark prior (BRIC), $g = \max(n, K^2)$, that will decide between UIP or BIC depending on the number of potential regressors K and the sample size n.

Priors over the model space. We follow Ley and Steel (2009) for the specification of the prior model probabilities. We establish a fully random prior for the model and a binomial-beta hyperprior over prior inclusion probability with prior expected model size $\tilde{k} = K/2$. This hyper-prior leads to flat prior inclusion probability.

Related predictors. In order to know the different determinants of self-employment, employership or own-account work rates depending on the role of institutions and compliance, we include in our model the interaction between rule of law and EPL (on regular or temporary contracts). Since we want to analyze the determinants of the self-employment comparing different situations regarding compliance of the labor market regulation, we need to control by the effect of individual variables to compare the effect of the interaction. Following Crespo-Cuaresma (2011), we include the specification of strong heredity principle based on Chipman (1996), which is a special case of George's (1999) dilution priors. This way, we define prior probabilities across models where interactions are not present or are present with parent variables and assign zero prior probability to models with interactions where some parent variable is not present.

The rationale behind this specification is that using a uniform prior over the model space we are interpreting an interaction term as an exclusive effect of that particular product of covariates and ignoring the independent effects of the interacted variables. Since we want to assess the differential effect of the covariates depending on dichotomized EPL, we need to evaluate the significance of this interactions in a model which contains linear terms in both variables in addition to the interaction variable. This way, we obtain effect of the covariates when EPL is low (individual effect) and the effect when EPL is high (interaction effect).

Sampling from the model space. Following Fernández et al. (2001b), we use Markov Chain Monte Carlo Model Composition (MC3) to approximate the posterior model probability. Starting with a random model with a random number of variables, we compute the posterior model probability and then propose a candidate model, in the neighborhood of the first model, with one variable more or less, randomly chosen. Then, we can compare the posterior model probability with the previous one and keep the model with a higher value, that will be compare with a new candidate from the neighborhood.

This procedure will visit models with higher non-negligible posterior model probability. Convergence of the MC3 sampler can be checked by computing the correlation between analytical and frequency-based posterior model probabilities for a region of the model space. For every model, we estimate 6 million draws, discard the first million as the burn-in sample, and compute the results based on the top 100 models visited by the Markov chain.

Using the extension of the Bayesian model averaging methodology (Fernández et al., 2001b) to a panel data framework, by Moral-Benito (2012), estimations of a baseline panel and a panel including the interaction term between rule of law and EPL are carried out for self-employment, employership and own-account work rates as dependent variables, and differentiating between EPL for regular and temporary contracts. We present posterior inclusion probabilities (PIP)[18], the mean of the posterior distribution for each parameter (and interaction) and the corresponding posterior standard deviation (SD) for each of the twelve different analyses carried out.

6.5. Results

This section presents the main results of the empirical analysis developed to shed new light on the role of EPL as a driver of entrepreneurship. Table 2 presents the results of BMA exercises for baseline panel and for the panel including an interaction between EPL for regular employment and Rule of

---

[18] PIP is considered robust when higher than the prior inclusion probability (π), which is expected model size by the number of variables. For the flat prior over the model space $\tilde{k} = K/2, \pi = \tilde{k}/K = 0.5$.

Law[19]. Then, taking into consideration the existing heterogeneity within self-employment as a group, tables 3 and 4 present results for employership and own-account work rates separately. Finally, tables 5 to 7 reproduce the previous analysis but considering EPL for temporary employment instead of EPL for regular employment.

In tables 2 to 7 we report the posterior inclusion probability of each variable (PIP), which is computed as the sum of the posterior probability of the models including that variable, together with the mean of the posterior distribution of the parameter attached to the variable (PM) and its standard deviation (SD). The PIP can be interpreted as the probability that a given variable belongs to the true model. Under this criterion the set of regressors with a PIP-value in bold are predictors of the variation of the self-employment (employership or own account work) rates across countries.

As stated previously, the main research question of this paper is about the role of the EPL as a driver of entrepreneurship and, in particular whether this effect is modulated depending on the compliance of labor market laws, i.e., by the rule of law. Our results point to a positive impact of EPL –either for regular and temporary employment– on aggregate self-employment rates, that becomes smaller the greater the rule of law is (see tables 2 and 5).

On the one hand, these results contrast with the weak evidence obtained by Robson (2003), Torrini (2005) and Kanniainen and Vesala (2005) –in their studies EPL has little impact on self-employment– and support the importance of considering the interaction between the policy and institutional factors as Centeno (2000) suggests. On the other hand, the self-employed sector is highly heterogeneous, and we cannot rule that the interplay rigidity-compliance impacts differently on solo self-employment and on the share of employer entrepreneurship. In fact, we found robust impacts to the use of different measures of EPL on the share of aggregate self-employed and holds for own account workers (Poschke, 2019) and for low-skilled workers (Baker et al., 2018).

Our results qualify and extend the previous ones providing support to the crowding-out hypothesis, that is the stringency of employment protection legislation in rule of law contexts encourage that firms and workers try to

[19] We use the benchmark BRIC prior and establishes a binomial-beta prior on a prior expected model size of $K/2$. Using the strong heredity priors, we only evaluate models which contain the parent variables when the interaction term is included.

circumvent the higher costs associated with strict regulation pushing individuals to "solo" self-employment. This mechanism does not work for employers. We do not find that EPL and the rule of law play a significant role in determining the share of self-employed with employees. Finally, it should come as no surprise that EPL stringency and compliance appear also significantly related to the aggregate share of self-employed. As previous literature states (Carmona et al., 2012), is possible that the impact of our focus variable differs across the two components of self-employment, that is, employers and own-account workers and since the composition of aggregate self-employment is mainly composed of "solo" self-employment, it is highly probably that the nature of the impact for the aggregate is the same as that found for "solo" self-employment[20].

Finally, the effects are not linear. Thus, focusing on the impact of EPL for temporary employment on own-account work rates (Table 7), we observe that an increase on EPL strictness may increase own-account work rates if rule of law is below 2.06, whereas that the impact of EPL on own-account work rates would be negative if rule of law is above this figure. Countries whit the highest compliance of laws, like Finland, Denmark, Sweden, Norway or New Zealand, will experience a negative impact of employment protection legislation on own-account work rates.

6.6. Conclusions

The interaction between labor market rigidities and entrepreneurship has been the subject of controversy due to the lack of an unambiguous result. Being commonly accepted that stringency of employment protection legislation inhibits entrepreneurship, there is room for arguing that the presence of a stringent employment legislation can lead unexpected effects on national self-employment rates turning unemployment and traditional employment into (false/necessity/non-genuine) self-employment/entrepreneurship.

[20] Results concerning the rest of control variables seem to show, in general, the expected sign. These results support the different nature of own-account work and employership (Roman et al., 2013). On the one hand, as distinct from determinants of own-account work, employership rates may be affected by GDP, the sectoral composition, openness, number of patents or inflation. And on the other hand, aspects like human capital, rural population or unemployment have impact on own-account work rates but not on employership.

In this paper, we revisited this issue at the macro-level focusing on the effects of the greater or lesser employment protection legislation stringency in conjunction with compliance for aggregate self-employment and, distinguishing between "solo" self-employment and employer entrepreneurship.

Our results point to a positive relationship between aggregate and "solo" self-employment and EPL –either for regular and temporary employment–, that becomes smaller the greater the rule of law is. The impact of EPL for temporary employment on own-account work rates becomes negative when the compliance of law exceeds a certain threshold, while employership rates seem to be unaffected by labor market rigidities and compliance.

This result can help us to understand the existence of mixed and sometimes controversial results on the relationship between the role of labor market institutions as an inhibiting or driver factor of entrepreneurship.

Finally, we cannot rule out the possibility that our results are affected by data limitations. Thus, a potential extension to the current paper would entail testing whether different effects can be found if we consider other aspects of heterogeneity into entrepreneurship –necessity vs. opportunity entrepreneurs; formal vs. informal; or productive vs unproductive among others–. We believe that this is an interesting avenue for future research. In any case, our results should be considered as a good starting point for an in-depth analysis of the effect of rigidities in the labor market considering also the enforcement of labor laws.

Table 2. BMA results. Self-Employment rates (EPL regular contracts)

	BASELINE				INTERACTION		
	PIP	M	SD		PIP	M	SD
GDP	0.31	0.893	8.60	GDP	0.48	1.660	11.59
GDP2	0.33	-0.099	0.42	GDP2	**0.52**	-0.192	0.56
AGR	**1.00**	0.949***	0.19	AGR	**0.99**	0.685***	0.20
IND	**1.00**	-0.412***	0.11	IND	**1.00**	-0.437***	0.10
SER	**0.92**	-0.233**	0.10	SER	**0.99**	-0.271***	0.08
RUR	**1.00**	-0.136***	0.02	RUR	**1.00**	-0.155***	0.02
OPN	0.34	-0.003	0.00	OPN	0.17	0.000	0.00
PAT	**0.98**	0.001***	0.00	PAT	**1.00**	0.001***	0.00
INT	0.17	0.001	0.01	INT	0.26	0.003	0.01
HUC	**1.00**	-4.150***	0.72	HUC	**1.00**	-4.507***	0.70
INF	0.13	-0.002	0.01	INF	0.25	-0.008	0.02
GOV	**1.00**	-1.124***	0.08	GOV	**1.00**	-1.110***	0.08
LFF	**0.71**	-0.075	0.06	LFF	**0.89**	-0.103*	0.05
UNE	**0.94**	-0.372**	0.15	UNE	**0.99**	-0.433***	0.13
UNY	**1.00**	0.244***	0.07	UNY	**1.00**	0.260***	0.06
ROL	**0.96**	-2.599***	0.99	ROL	**1.00**	4.395***	1.66
EPLR	**1.00**	2.104***	0.28	EPLR	**1.00**	8.040***	1.23
				EPLR#ROL	**1.00**	-2.789***	0.56

Note: PIP, Posterior inclusion probability; M, mean of the posterior distribution parameter; SD, posterior standard deviation of the parameter. Bold entries refer to variables with PIP>0.5. *, p<0.10; **, p<0.05; ***, p<0.01.

Table 3. BMA results. Employership rates (EPL regular contracts)

	Baseline				Interaction		
	PIP	M	SD		PIP	M	SD
GDP	**1.00**	50.309***	6.97	GDP	**1.00**	50.379***	6.95
GDP2	**1.00**	-2.350***	0.33	GDP2	**1.00**	-2.355***	0.33
AGR	**0.99**	0.193***	0.05	AGR	**0.99**	0.184***	0.06
IND	**1.00**	-0.162***	0.03	IND	**1.00**	-0.164***	0.03
SER	**1.00**	-0.086***	0.02	SER	**1.00**	-0.088***	0.02
RUR	0.37	-0.004	0.01	RUR	0.48	-0.006	0.01
OPN	**0.87**	0.003*	0.00	OPN	**0.89**	0.004**	0.00
PAT	**0.91**	0.000**	0.00	PAT	**0.92**	0.000**	0.00
INT	**1.00**	-0.012***	0.00	INT	**1.00**	-0.012***	0.00
HUC	0.15	-0.019	0.08	HUC	0.21	-0.041	0.12
INF	**0.99**	-0.029***	0.01	INF	**0.99**	-0.030***	0.01
GOV	**1.00**	-0.239***	0.02	GOV	**1.00**	-0.238***	0.02
LFF	0.16	0.001	0.01	LFF	0.20	0.002	0.01
UNE	0.22	-0.001	0.02	UNE	0.25	-0.002	0.02
UNY	**0.91**	0.021**	0.01	UNY	**0.91**	0.021*	0.01
ROL	0.13	-0.010	0.07	ROL	0.46	0.369	0.53
EPLR	**1.00**	0.263***	0.07	EPLR	**1.00**	0.619	0.49
				EPLR#ROL	0.39	-0.165	0.23

Note: PIP, Posterior inclusion probability; M, mean of the posterior distribution parameter; SD, posterior standard deviation of the parameter. Bold entries refer to variables with PIP>0.5. *, p<0.10; **, p<0.05; ***, p<0.01.

Table 4. BMA results. Own-account work rates (EPL regular contracts)

	BASELINE				INTERACTION		
	PIP	M	SD		PIP	M	SD
GDP	**0.66**	17.336	24.27	GDP	**0.64**	15.553	23.74
GDP2	**0.79**	-1.014	1.17	GDP2	**0.77**	-0.935	1.14
AGR	0.34	0.084	0.15	AGR	0.26	0.048	0.11
IND	**0.95**	-0.165*	0.09	IND	**0.93**	-0.168*	0.09
SER	**0.60**	-0.072	0.07	SER	**0.71**	-0.087	0.07
RUR	**1.00**	-0.096***	0.02	RUR	**1.00**	-0.102***	0.02
OPN	0.11	0.000	0.00	OPN	0.13	0.000	0.00
PAT	**0.54**	0.000	0.00	PAT	0.41	0.000	0.00
INT	**0.65**	0.010	0.01	INT	**0.78**	0.012	0.01
HUC	**1.00**	-2.694***	0.55	HUC	**1.00**	-2.991***	0.55
INF	0.41	-0.016	0.02	INF	**0.71**	-0.034	0.03
GOV	**1.00**	-0.724***	0.06	GOV	**1.00**	-0.697***	0.06
LFF	0.18	-0.001	0.02	LFF	0.14	0.000	0.01
UNE	**1.00**	-0.487***	0.09	UNE	**1.00**	-0.491***	0.08
UNY	**1.00**	0.281***	0.04	UNY	**1.00**	0.277***	0.04
ROL	**0.88**	-1.186*	0.61	ROL	**1.00**	1.791	1.20
EPLR	**1.00**	1.570***	0.20	EPLR	**1.00**	4.318***	1.01
				EPLR#ROL	**0.96**	-1.303***	0.47

Note: PIP, Posterior inclusion probability; M, mean of the posterior distribution parameter; SD, posterior standard deviation of the parameter. Bold entries refer to variables with PIP>0.5. *, p<0.10; **, p<0.05; ***, p<0.01.

Table 5. BMA results. Self-Employment rates (EPL temporary contracts)

	Baseline				Interaction		
	PIP	M	SD		PIP	M	SD
GDP	**0.63**	25.214	33.90	GDP	**0.92**	66.036*	35.05
GDP2	**0.69**	-1.325	1.63	GDP2	**0.95**	-3.338**	1.68
AGR	**1.00**	0.886***	0.20	AGR	**0.96**	0.568***	0.22
IND	**1.00**	-0.454***	0.10	IND	**1.00**	-0.447***	0.10
SER	**0.97**	-0.282***	0.10	SER	**1.00**	-0.319***	0.08
RUR	**0.93**	-0.065**	0.03	RUR	0.36	-0.013	0.02
OPN	0.18	-0.001	0.00	OPN	0.13	0.000	0.00
PAT	**1.00**	0.002***	0.00	PAT	**1.00**	0.002***	0.00
INT	0.14	0.000	0.00	INT	0.19	-0.002	0.01
HUC	**1.00**	-5.105***	0.80	HUC	**1.00**	-4.137***	0.73
INF	0.17	-0.004	0.02	INF	0.25	-0.009	0.02
GOV	**1.00**	-0.914***	0.08	GOV	**1.00**	-0.811***	0.08
LFF	0.28	-0.018	0.04	LFF	0.20	-0.008	0.03
UNE	**1.00**	-0.499***	0.13	UNE	**1.00**	-0.653***	0.12
UNY	**1.00**	0.273***	0.06	UNY	**1.00**	0.374***	0.06
ROL	**1.00**	-3.080***	0.79	ROL	**1.00**	1.046	0.89
EPLT	**0.93**	0.735**	0.32	EPLT	**1.00**	4.216***	0.58
				EPLT#ROL	**1.00**	-1.773***	0.28

Note: PIP, Posterior inclusion probability; M, mean of the posterior distribution parameter; SD, posterior standard deviation of the parameter. Bold entries refer to variables with PIP>0.5. *, p<0.10; **, p<0.05; ***, p<0.01.

Table 6. BMA results. Employership rates (EPL temporary contracts)

	BASELINE				INTERACTION		
	PIP	M	SD		PIP	M	SD
GDP	**1.00**	53.179***	7.06	GDP	**1.00**	53.153***	7.09
GDP2	**1.00**	-2.492***	0.34	GDP2	**1.00**	-2.491***	0.34
AGR	**0.98**	0.180***	0.06	AGR	**0.97**	0.178***	0.06
IND	**1.00**	-0.172***	0.03	IND	**1.00**	-0.173***	0.03
SER	**1.00**	-0.102***	0.02	SER	**1.00**	-0.103***	0.02
RUR	0.12	0.000	0.00	RUR	0.10	0.000	0.00
OPN	**0.88**	0.003*	0.00	OPN	**0.85**	0.003*	0.00
PAT	**0.98**	0.000***	0.00	PAT	**0.98**	0.000***	0.00
INT	**1.00**	-0.012***	0.00	INT	**1.00**	-0.012***	0.00
HUC	**0.62**	-0.249	0.24	HUC	**0.57**	-0.228	0.24
INF	**0.99**	-0.029***	0.01	INF	**0.98**	-0.029***	0.01
GOV	**1.00**	-0.220***	0.02	GOV	**1.00**	-0.221***	0.02
LFF	0.17	0.002	0.01	LFF	0.13	0.001	0.01
UNE	0.26	-0.007	0.02	UNE	0.22	-0.006	0.02
UNY	**0.94**	0.023*	0.01	UNY	**0.93**	0.022*	0.01
ROL	0.24	-0.059	0.14	ROL	0.21	-0.051	0.13
EPLT	0.14	-0.004	0.03	EPLT	0.12	-0.004	0.03
				EPLT#ROL	0.01	0.000	0.01

Note: PIP, Posterior inclusion probability; M, mean of the posterior distribution parameter; SD, posterior standard deviation of the parameter. Bold entries refer to variables with PIP>0.5. *, p<0.10; **, p<0.05; ***, p<0.01.

Table 7. BMA results. Own-account work rates (EPL temporary contracts)

	Baseline				Interaction		
	PIP	M	SD		PIP	M	SD
GDP	**0.93**	55.042**	26.86	GDP	**0.96**	61.637**	25.82
GDP2	**0.96**	-2.808**	1.29	GDP2	**0.98**	-3.140**	1.24
AGR	0.31	0.092	0.17	AGR	0.26	0.054	0.13
IND	**0.80**	-0.166	0.11	IND	**0.61**	-0.107	0.10
SER	**0.75**	-0.123	0.08	SER	**0.58**	-0.088	0.09
RUR	**0.97**	-0.055***	0.02	RUR	**0.58**	-0.023	0.02
OPN	0.09	0.000	0.00	OPN	0.11	0.000	0.00
PAT	0.10	0.000	0.00	PAT	0.13	0.000	0.00
INT	**0.71**	0.011	0.01	INT	**0.51**	0.007	0.01
HUC	**1.00**	-4.115***	0.56	HUC	**1.00**	-3.420***	0.59
INF	0.36	-0.016	0.03	INF	**0.68**	-0.036	0.03
GOV	**1.00**	-0.561***	0.07	GOV	**1.00**	-0.472***	0.07
LFF	0.16	0.006	0.02	LFF	0.26	0.012	0.03
UNE	**1.00**	-0.547***	0.09	UNE	**1.00**	-0.641***	0.09
UNY	**1.00**	0.290***	0.04	UNY	**1.00**	0.347***	0.04
ROL	**1.00**	-1.948***	0.47	ROL	**1.00**	0.087	0.73
EPLT	0.09	0.010	0.06	EPLT	**0.99**	1.832***	0.46
				EPLT#ROL	**0.99**	-0.888***	0.22

Note: PIP, Posterior inclusion probability; M, mean of the posterior distribution parameter; SD, posterior standard deviation of the parameter. Bold entries refer to variables with PIP>0.5. *, p<0.10; **, p<0.05; ***, p<0.01.

References

Acs, Z. J., Audretsch, D. B., & Evans, D. S. (1994). *Why does the self-employment rate vary across countries and over time?* (No. 871). CEPR Discussion Papers.

Acs, Z. J., Autio, E., & Szerb, L. (2014). National systems of entrepreneurship: Measurement issues and policy implications. *Research policy*, *43*(3), 476-494.

Ahmad, N. (2008). A proposed framework for business demography statistics. In *Measuring entrepreneurship* (pp. 113-174). Springer, Boston, MA.

Ahmad, N., & Seymour, R. G. (2008). Defining entrepreneurial activity: Definitions supporting frameworks for data collection.

Aparicio, S., Urbano, D., & Audretsch, D. B. (2016). Institutional factors, opportunity entrepreneurship and economic growth: Panel data evidence. *Technological Forecasting and Social Change*, *102*, 45-61.

Arin, K. P., Huang, V. Z., Minniti, M., Nandialath, A. M., & Reich, O. F. (2015). Revisiting the determinants of entrepreneurship: A Bayesian approach. *Journal of Management*, *41*(2), 607-631.

Arum, R., Budig, M., & Grant, D. S. (2000). Labor market regulation and the growth of self-employment. *International Journal of Sociology*, *30*(4), 3-27.

Autio, E., & Fu, K. (2015). Economic and political institutions and entry into formal and informal entrepreneurship. *Asia Pacific Journal of Management*, *32*(1), 67-94.

Bailey, J. B., & Thomas, D. W. (2017). Regulating away competition: The effect of regulation on entrepreneurship and employment. *Journal of Regulatory Economics*, *52*(3), 237-254.

Baker, M., Égert, B., Fulop, G., & Mourougane, A. (2018). To what extent do policies contribute to self-employment?. *OECD Economic Department Working Papers*, (1512), 1-31.

Bjørnskov, C., & Foss, N. J. (2008). Economic freedom and entrepreneurial activity: Some cross-country evidence. *Public Choice*, *134*(3), 307-328.

Blanchflower, D. G. (2000). Self-employment in OECD countries. *Labour economics*, *7*(5), 471-505.

Block, J. H., Fisch, C. O., Lau, J., Obschonka, M., & Presse, A. (2019). How do labor market institutions influence the preference to work in family firms? A multilevel analysis across 40 countries. *Entrepreneurship Theory and Practice*, *43*(6), 1067-1093.

Borowczyk-Martins, D., & Lalé, E. (2020). The ins and outs of involuntary part-time employment. *Labour Economics*, *67*, 101940.

Bruce, D. (2002). Taxes and entrepreneurial endurance: Evidence from the self-employed. *National Tax Journal*, *55*(1), 5-24.

Caliendo, M., & Künn, S. (2011). Start-up subsidies for the unemployed: Long-term evidence and effect heterogeneity. *Journal of Public Economics*, *95*(3-4), 311-331.

Carmona, M., Congregado, E., & Golpe, A. A. (2012). Comovement between self-employment and macroeconomic variables: evidence from Spain. *Sage Open*, *2*(2), 2158244012448665.

Centeno, M. (2000). Is self-employment a response to labour market rigidity?. *Economic Bulletin*, Banco de Portugal, December, 37-4.

Chipman, H. (1996). Bayesian variable selection with related predictors. *Canadian Journal of Statistics*, *24*(1), 17-36.

Congregado, E. (Ed.). (2007). Measuring entrepreneurship: building a statistical system (Vol. 16). Springer Science & Business Media.

Congregado, E., de Andrés, M. I., & Román, C. (2019). Explorando la heterogeneidad en el empleo mediado por plataformas digitales: Intensidad y localización. *Revista de Economía Laboral*, *16*(2), 69-103.

Congregado, E., de Andrés, M. I., Nolan, E., & Román, C. (2022). Heterogeneity Among Self-employed Digital Platform Workers. Evidence from Europe. *International Review of Entrepreneurship*, forthcoming.

Coviello, N. E., & Jones, M. V. (2004). Methodological issues in international entrepreneurship research. *Journal of Business Venturing*, *19*(4), 485-508.

Crespo-Cuaresma, J. (2011). How different is Africa? A comment on Masanjala and Papageorgiou, *Journal of Applied Econometrics*, *26*, 1041-1047.

Cueto, B., Mayor, M., & Suárez, P. (2017). Evaluation of the Spanish flat rate for young self-employed workers. *Small Business Economics*, *49*(4), 937-951.

Davidsson, P., & Wiklund, J. (2007). Levels of analysis in entrepreneurship research: Current research practice and suggestions for the future. *Entrepreneurship*, 245-265.

Dvouletý, O. (2018). How to analyse determinants of entrepreneurship and self-employment at the country level? A methodological contribution. *Journal of Business Venturing Insights*, *9*, 92-99.

Dvouletý, O. (2020). Classifying self-employed persons using segmentation criteria available in the Labour Force Survey (LFS) data. *Journal of Business Venturing Insights*, *14*, e00199.

Eurostat (2019). *Labor Force Survey*, Employment by sex, age and professional status.

Fernández, C., Ley, E., & Steel, M. F. (2001a). Benchmark priors for Bayesian model averaging. *Journal of Econometrics*, *100*(2), 381-427.

Fernández, C., Ley, E., & Steel, M. F. (2001b). Model uncertainty in cross-country growth regressions. *Journal of applied Econometrics*, *16*(5), 563-576.

Foster, D. P., & George, E. I. (1994). The risk interaction criterion for multiple regression. *The Annals of Statistics*, *22*(4), 1947-1975.

George, E. I. (1999). Discussion of Bayesian model averaging and model search strategies by M. A. Clyde. *Bayesian Statistics*, *6*, 175-177.

Giménez-Nadal, J. I., Lafuente, M., Molina, J. A., & Velilla, J. (2016). *Resampling and bootstrap to assess the relevance of variables: a* *new algorithmic approach with applications to entrepreneurship data* (No. 9938). IZA Discussion Papers.

Giupponi, G., & Xu, X. (2020). What does the rise of self-employment tell us about the UK labour market?. *London: Institute of Fiscal Studies*

Grubb, D., & Wells, W. (1993). Employment regulation and patterns of work in EC countries. *OECD Economic studies*, 7-7.

Henley, A. (2022). Is rising self-employment associated with material deprivation in the UK?. *Work Employment and Society*.

Hurst, E., & Lusardi, A. (2004). Liquidity constraints, household wealth, and entrepreneurship. *Journal of political Economy*, *112*(2), 319-347.

Iversen, J., Jørgensen, R., & Malchow-Møller, N. (2007). Defining and measuring entrepreneurship. *Foundations and Trends® in Entrepreneurship*, *4*(1), 1-63.

Kanniainen, K., & Vesala, T. (2005). Entrepreneurship and labor market institutions, *Economic Modelling*, *22*(5), 828-847.

Kass, R., & Wasserman, L. (1995). A reference Bayesian test for nested hypotheses and its relationship to the Schwarz criterion. *Journal of the American Statistical Association*, *90*(431), 928-934.

Kirzner, I. (1979). Producer, Entrepreneur, and the Right to Property. In *Perception, Opportunity, and Profit*, 185-99. Chicago: University of Chicago Press.

Knight, F. K. (1921). Risk, Uncertainty, and Profit. Houghton Mifflin, Boston.

Koellinger, P. D., & Roy Thurik, A. (2012). Entrepreneurship and the business cycle. *Review of Economics and Statistics*, *94*(4), 1143-1156.

Leibenstein, H. (1968). Entrepreneurship and development. *The American economic review*, *58*(2), 72-83.

Ley, E., & Steel, M. F. (2009). On the effect of prior assumptions in Bayesian model averaging with applications to growth regression. *Journal of applied econometrics*, *24*(4), 651-674.

Liang, F., Paulo, R., Molina, G., Clyde, M. A., & Berger, J. O. (2009). Mixtures of g priors for Bayesian variable selection. *Journal of the American Statistical Association*, *103*(481), 410-423.

Liebregts, W., & Stam, E. (2019). Employment protection legislation and entrepreneurial activity. *International Small Business Journal*, *37*(6), 581-603.

Mayor, M., Cueto, B., & Suárez, P. (2015). Fostering the Self-Employment in Spain: An Evaluation of the Capitalisation of Unemployment Benefits Programme. In *Geographical labor market imbalances* (pp. 335-352). Springer, Berlin, Heidelberg.

Molina, J. A. (2020). Family and entrepreneurship: New empirical and theoretical results. *Journal of Family and Economic Issues*, *41*(1), 1-3.

Moral-Benito, E. (2012). Determinants of economic growth: a Bayesian panel data approach. *Review of Economics and Statistics*, *94*(2), 566-579.

Nyström, K. (2008). The institutions of economic freedom and entrepreneurship: evidence from panel data. *Public choice*, *136*(3), 269-282.

OECD. (1999). The employment outlook (Chap. 2). Paris: OECD.

Parker, S. C. (2009). *The economics of entrepreneurship*. Cambridge University Press.

Pietrobelli, C., Rabellotti, R., & Aquilina, M. (2004). An empirical study of the determinants of self-employment in developing countries. *Journal of International Development*, *16*(6), 803-820.

Poschke, M. (2019). Wage Employment, Unemployment and Self-Employment across Countries. IZA Working Paper DP No. 12367.

Raftery, A. E. (1995). Bayesian model selection in social research. *Sociological methodology*, 111-163.

Robson, M. T. (2003). Does stricter employment protection legislation promote self-employment?. *Small Business Economics*, *21*(3), 309-319.

Rodríguez-Santiago, A. (2022). Re-Evaluating the Relationship Between Economic Development and Self-Employment, at the Macro-Level: A

Bayesian Model Averaging Approach. *International Journal of Interactive Multimedia & Artificial Intelligence*, *7*(3).

Román, C., Congregado, E., & Millán, J. M. (2011a). Dependent self-employment as a way to evade employment protection legislation. *Small Business Economics*, *37*(3), 363-392.

Román, C., Congregado, E., & Millán, J. M. (2011b). The role of labor market institutions on entrepreneurship dynamics in times of crisis: Evidence from European countries. In *Entrepreneurship and Global Competitiveness in Regional Economies: Determinants and Policy Implications*. Emerald Group Publishing Limited.

Román, C., Congregado, E., & Millán, J. M. (2013). Start-up incentives: Entrepreneurship policy or active labour market programme?. *Journal of Business Venturing*, *28*(1), 151-175.

Schumpeter, J. A. (1912). 1934, The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest and the Business Cycle. *Harvard edition. Harvard Economic Studies*.

Schumpeter, J. A. (1939). *Business cycles*. New York: Mcgraw-hill.

Shapiro, A. F., & Mandelman, F. S. (2021). Digital adoption, automation, and labor markets in developing countries. *Journal of Development Economics*, *151*, 102656.

Sobel, R. S. (2008). Testing Baumol: Institutional quality and the productivity of entrepreneurship. *Journal of Business Venturing*, *23*(6), 641-655.

Sobel, R. S., Clark, J. R., & Lee, D. R. (2007). Freedom, barriers to entry, entrepreneurship, and economic progress. *The Review of Austrian Economics*, *20*(4), 221-236.

Szerb, L. A., Acs, Z., & Autio, E. (2013). Entrepreneurship and policy: The national system of entrepreneurship in the European Union and in its member countries. *Entrepreneurship research journal*, *3*(1), 9-34.

Torrini, R. (2005). Cross-country differences in self-employment rates: The role of institutions. *Labour Economics*, *12*(5), 661-683.

Valdez, M. E., & Richardson, J. (2013). Institutional determinants of macro-level entrepreneurship. *Entrepreneurship theory and practice*, *37*(5), 1149-1175.

Valletta, R. G., Bengali, L., & Van der List, C. (2020). Cyclical and market determinants of involuntary part-time employment. *Journal of Labor Economics*, 38(1), 67-93.

Van der Sluis, J., Van Praag, M., & Vijverberg, W. (2005). Entrepreneurship selection and performance: A meta-analysis of the impact of education in developing economies. *The World Bank Economic Review*, *19*(2), 225-261.

Van Stel, A. (2005). COMPENDIA: Harmonizing business ownership data across countries and over time. *The International Entrepreneurship and Management Journal*, *1*(1), 105-123.

Van Stel, A., Cieslik, J., & Hartog, C. (2010). Measuring business ownership across countries and over time: Extending the COMPENDIA data base. *EIM Business and Policy Research, Scales Research Reports*, (H201019).

Wieteke, C., & Schippers, J. (eds) (2019). Self-employment as Precarious Work: A European Perspective. Cheltenham: Edward Elgar Publishing.

Zellner, A. (1986). Bayesian estimation and prediction using asymmetric loss functions. *Journal of the American Statistical Association*, *81*(394), 446-451.

Appendix

Table A1. Variable description, source and statistics

COVARIATE	CODE	SOURCE	MEAN	MIN	MAX
Dependent variables					
Self-employed (% of total employment)	SE	ILOSTAT	18.03	6.22	49.95
Employers (% of total employment)	EMP	ILOSTAT	4.65	1.37	8.34
Own-account workers (% of total employment)	OWN	ILOSTAT	11.20	3.84	26.79
Independent variables					
GDP and components					
Log GDP per capita, PPP (constant 2017 $)	GDP	World Bank	10.54	9.49	11.37
Agriculture, forestry, and fishing (% of GDP)	AGR	World Bank	2.46	0.55	16.85
Industry, including construction (% of GDP)	IND	World Bank	25.78	13.68	40.29
Services (% of GDP)	SER	World Bank	62.29	48.16	77.66
Trade openness: Exports + Imports (% of GDP)	OPN	World Bank	81.97	18.35	239.22
Population					
Rural population (% of total population)	RUR	World Bank	24.05	1.96	48.23
Technological Progress					
Patents applications, per million people	PAT	WIPO	671.20	3.52	4212.02
Individuals using the internet (% of population)	INT	World Bank	56.95	0.19	98.05
Human Capital					
Human Capital Index	HUC	Penn World Tables	3.21	1.88	3.85
Labor Market					
Labor force participation rate, female	LFF	World Bank	51.47	23.05	64.83
Unemployment (% of total labor force)	UNE	World Bank	7.54	1.93	27.47
Unemployment, youth (% of labor force 15-24yo)	UNY	World Bank	16.70	3.58	58.00
Institutions					
Inflation, GDP deflator	INF	World Bank	3.24	-5.21	143.64
Government final consumption expenditure (% of GDP)	GOV	World Bank	18.95	8.12	27.94
Rule of Law	ROL	World Governance Indicators	2.02	0.00	2.83
Employment protection legislation, regular	EPLR	OECD	2.17	0.09	4.58
Employment protection legislation, temporary	EPLT	OECD	1.71	0.13	4.88

Table A2. OECD Countries on the sample

COUNTRY	CODE	COUNTRY	CODE
Australia	AUS	Korea, Rep.	KOR
Austria	AUT	Mexico	MEX
Belgium	BEL	Netherlands	NLD
Canada	CAN	New Zealand	NZL
Czech Republic	CZE	Norway	NOR
Denmark	DNK	Poland	POL
Finland	FIN	Portugal	PRT
France	FRA	Slovak Republic	SVK
Germany	DEU	Spain	ESP
Greece	GRC	Sweden	SWE
Hungary	HUN	Switzerland	CHE
Ireland	IRL	Turkey	TUR
Italy	ITA	United Kingdom	GBR
Japan	JPN	United States	USA

Chapter 7: An inquiry into the drivers of an entrepreneurial economy: a Bayesian clustering approach

In this paper we provide an empirical categorization of economies in terms of the quality of entrepreneurship by using a new compendium of cross-national data by using a panel of 120 countries during 1991-2019. We provide evidence of the existence of three clusters of countries defined in terms of the productivity of the national self-employment sector and associated to some economic and institutional factors which lead the transitions between groups. These groups might be identified with three major categories of countries usually considered in the entrepreneurship literature: factor-, efficiency/managed-, and innovation-driven/entrepreneurial countries. The results show that digitalization enhance the probability to switch from the group of factor-driven countries to the group of efficiency-driven countries and thereon to the innovation-driven group. A second finding indicates that higher levels of unemployment reduce the probability from the efficiency- to innovation-driven group. Finally, results also point to that neither the weight of the industry nor the strictness of the employment protection legislation, are determinants in the transition between groups. Some suggestive rationales for these results, limitations and implications for the entrepreneurship policy agenda are also provided.

7.1. Introduction

The conventional thinking among many scholars, policy makers and other observers is that entrepreneurial activity should be encouraged. Indeed, although there are no obvious direct linkages between the "size" of self-employment sector and productivity/economic growth, its potential positive impacts on economic growth[1], job creation and innovation have become a mantra for policy makers who have no doubts when they affirm that self-employment promotion and the support to small and medium firms are drivers of economic growth. Many governments, as consequence, devise and implement portfolios of policies to promote self-employment/entrepreneurship, as the solution to weak economic performance and to deficient job creation. From this perspective the research of the determinants of the most "productive" entrepreneurship[2] –i.e., the essential requirements to this end or pillars for an entrepreneurial ecosystem (Stam, 2015)– is particularly important for devising a national strategy of competitiveness.

The strong cross-country negative association between the incidence of self-employment and levels of income per capita among the less developed and developing countries[3] and the mixed evidence on the impact of entrepreneurship on growth at the macro-level constitute strong indications of that there is something wrong in the dominant view (Pietrobelli et al., 2004; Acs, 2006; Wennekers et al., 2010; Arin et al., 2015; Rodríguez-Santiago, 2022). In some extent we would argue that the dominant view seems to have overlooked that behind the significant variation in rates of self-employment across countries there is a (growing) heterogeneity into self-employment; that is, how different impacts would be expected according to the entrepreneurial predominance –self-employment composition–.

---

[1] The relationship between entrepreneurship and economic growth is a certainly different matter. Audretsch and Keilbach (2004) suggest that entrepreneurship is an important mechanism in facilitating the spillover of knowledge providing empirical evidence that regions with higher levels of entrepreneurship exhibit stronger growth in labor productivity. Similarly, Wennekers et al. (2005) argue that for the most advanced nations, improving incentive structures for business start-ups and promoting the commercial exploitation of scientific findings offer the most promising approach for public policy.

[2] We should clarify that the term productive entrepreneurship does not coincide here with the expression popularized by Baumol (1990) to distinguish true entrepreneurs from rent-seekers.

[3] This relationship is now positive in the group of developed countries. This reversal trend is mainly based on the developments in the ICT technologies and in the new forms of employment and labor market dynamics.

Some of these sources of heterogeneity with deep consequences in the aggregate entrepreneurship quality are: the prevalence of high- vs. low[4]-ability entrepreneurship (Poschke, 2013, 2018, 2019); the proportion opportunity- vs. necessity-entrepreneurs (Acs, 2006); the relative weight of the informal sector in the economy (Gerxhani, 2004; Maloney, 2004); the relative importance of solo self-employed with regard to self-employed with employees (Congregado et al., 2010; Allub and Erosa, 2019); and, the extent of dependent/bogus, involuntary part-time, and hybrid self-employment, i.e., the new forms of employment emerged in parallel to extension of the digital labor platforms (Congregado et al., 2022)[5].

This explains to a certain extent that, it is very common the shared use of policy instruments in the entrepreneurship promotion and in the promotion of entry into self-employment[6] –in the belief that both concepts are interchangeable–, even though the target to promote entrepreneurship among opportunity entrepreneurs or individuals with high ability entrepreneurship (Acs and Szerb, 2007) has nothing to do with turning unemployment into self-employment (Baumgartner and Caliendo, 2008), with promoting transitions among early retired as a bride to self-employment (Zissimopoulos and Karoly, 2007), with encouraging the participation among some groups of secondary workers (Justo et al., 2021), or with the search of ways for poverty alleviation (Sutter et al., 2019).

In sum, the new reality is more complex than the traditional binary division between full-time self-employed and paid-employed workers. This element argued in favor of reconsidering and redefining the treatment groups in order to adapt entrepreneurship and active labor market policies to the transformation of work. Policies to support the self-employment in the labor markets of the future should consider these new elements clarifying its objectives and redefining its policies.

---

[4] The so-called "marginal" entrepreneurs (Lucas, 1978).

[5] In some of these digital platforms, self-employed workers are in a situation that resembles to the one of employees in terms of dependence –i.e., they work for the same employer in a percentage higher than 75%– and lack of autonomy.

[6] It is common that the devise of horizontal policy instruments with no eligibility criteria or with criteria non-based in the quality and viability of the project. And, in many cases, there is no mentoring/monitoring.

From this perspective and, in line with the body of literature that warns that encouraging more people to become entrepreneurs might represent a bad public policy (Blanchflower, 2004; Acs and Mueller, 2008; Shane, 2009; Lerner, 2010; Congregado et al., 2010; Stam, 2015), it is important to: (1) establish what are the countries where start-up ventures create the real economic growth and job creation; and (2) explore pillars for an entrepreneurial ecosystem conducive to productive entrepreneurship/self-employment within a particular economy, contributing to unraveling the puzzle about the determinants of self-employment.

To this end, this paper uses an approach for big data, the version of the Bayesian approach for clustering time series proposed by Frühwirth-Schnatter and Kaufmann (2008) –finite mixture model for clustering– for a novel dataset: a compendium of productive entrepreneurship data and its determinants, internationally comparable, for 120 countries during the last three decades.

By using this dataset, we classify the countries included in our sample by using level and trend of the productivity per self-employed worker. This approach, versus other alternative clustering methods, such as K-means or ANOVA, reports a set of controls indicating the keys of forming part of a group or not. In other words, results not only provide homogeneous groups of countries in terms of the quality of entrepreneurship but also what are the institutions or elements in the national entrepreneurial ecosystem that enable productive entrepreneurship within a particular country.

Furthermore, results allow policy makers to know which are the characteristics and elements that help a country to become more productive, in terms of changing from one cluster to another.

This analysis gives new insights for public policy decision making to formulate and implement entrepreneurship policies and to take into account the elements for devising a policy in order to get an entrepreneurial economy.

From our data-driven analysis, three groups of countries emerge. These clusters might be identified with three major groups of countries usually considered in the entrepreneurship literature: factor-, efficiency-, and innovation-knowledge-driven countries (see e.g., Alvarez et al., 2014 or Hechavarría and Ingram, 2019, among others), and with the literature on managed vs. entrepreneurial societies (Audrestsh and Thurik, 2004; Okamuro et al., 2017).

Even being aware of the limited scope of our results, it seems that they suggest that: (1) digitalization proves crucial to advance positions in terms of productivity, either to leave the group of those with lower productivity or to catch up with those with higher productivity; (2) maintaining high unemployment rates favors the entry into self-employment of marginal entrepreneurs who erode average productivity hindering becoming an entrepreneurial economy; (3) employment protection stringency, at least by itself, does not seem to have an impact on productivity; and (4) the relative weight of the industrial sector, although it may be key to the average firm size, does not seem to be the key today to a more productive entrepreneurship.

The outline of the rest of the paper is as follows. Section 2 is devoted to present a selective review of previous related literature. Section 3 describes variables, available indicators and the dataset. Section 4 presents the methodology, and section 5 presents and discuss the results. Finally, section 6 concludes with a discussion of policy implications and some promising avenues for future research.

7.2. A selective review of related literature

Self-employment rates across countries exhibit a large variability in the cross-section and, from a dynamic perspective, we are witnessing a resurgence of self-employment in some developed countries that had previously experienced a steady decline. Indeed, since 1970s and 1980s, self-employment rates appeared to increase in many industrialized countries in such a way that the trend of self-employment rates seemed to show a structural shift in terms of a revival –*U*-shape– or at least a stabilization –*L*-shape– (Carree et al., 2002, 2007; Wennekers et al., 2010). A large body of theoretical and empirical literature has sought to explain the large disparities observed in self-employment rates and its dynamics, suggesting different hypotheses and theoretical propositions and exploring empirically the determinants of the cross-country differences in self-employment rates at the macro-level.

Theoretical models and hypotheses

The Lucas (1978) model predicted that the average size of firms would continue to increase with progressive economic development. This would be the case because higher capital per capita ratios raise the opportunity costs of managing a firm (i.e., wages) relative to the marginal managerial rents. This, in turn, would induce "marginal" entrepreneurs to become employees, thereby increasing average firm size.

In the Lucas model individuals are homogeneous with respect to productivity in paid-employment, but they differ with respect to managerial ability in entrepreneurship. Individuals freely choose between becoming an entrepreneur with an expected return or becoming a wage-worker earning a fixed wage. Entrepreneurs maximize profits which are an increasing function of managerial ability.

In the solution of the model, the more able entrepreneurs run the largest firms. Concerning the role of capital in determining the distribution of the workforce between wage-workers and entrepreneurs, assuming that the elasticity of factor substitution between capital and labor is less than unity, entrepreneurs benefit less from an increase in capital stock than wage-workers do. This will cause "marginal" entrepreneurs (those who are indifferent –in terms of income– between entrepreneurship and paid-employment) to become employees, thereby increasing the wage-earners to entrepreneurs ratio.

This occupational choice model has been extended in different ways. Jovanovic (1994) extends the Lucas model allowing heterogeneity in abilities. Recently, Poschke (2018) develops a frictionless *occupational choice model à la Lucas with skill-biased change in entrepreneurial technology*[7] for explaining the firm-size development, predicting not only that average firm size rises with development but also the size dispersion. Allub and Erosa (2019) explore another source of heterogeneity. For them, cross-country differences in entrepreneurship are explained by self-employment differences, i.e., the relative weight of self-employed with employees and solo self-employment in the national self-employment sector[8]. From a similar perspective, Acs and Varga (2005) argue that only opportunity entrepreneurship has effect on economic development.

These works are also related to the body of literature addressing the contribution of entrepreneurship to GDP growth and the relationship between new firm entry and the stages of development, and some attempts to explain

---

[7] In words of Poschke (2018) "(...) *technological change does not benefit all potential entrepreneurs equally, and an individual's potential payoffs in working and in entrepreneurship are positively related*".

[8] To go further into depth on knowledge on issues concerning solo self-employment and employership, see Congregado et al. (2012), Cowling and Wooden (2021), Boeri et al. (2020).

the dynamics. On the one hand, Van Stel et al. (2005) provide evidence supporting the idea that entrepreneurship plays a different role in countries in different stages of economic development, while Wennekers et al. (2005) suggest that “the ‘natural rate’ entrepreneurship is to some extent governed by ‘laws’ related to the level of economic development”.

On the other hand, Acs (2006) distinguishes three major stages of development, each of which shows a different development in self-employment rates. The first one, the early stage of economic development, is characterized by high rates of self-employment mainly consisting of solo self-employed workers. In the second stage, as economy becomes wealthier the average firm size should increase and fewer people become self-employed. The relationship between economic development and entrepreneurial activity turns into a negative one. The third phase, likewise, is characterized by a combination of the predominance of larger corporations, joint to a drop in the average firm size and a bout of self-employment. He also provides some rationales potentially behind this observed development including: (1) the expansion of the business sector and service firms relative to manufacturing; and (2) the improvements in information technologies which may increase the returns to entrepreneurship reducing the importance of liquidity constraints.

Aquilina et al. (2006), provide another argument for explaining this evolution. For them, increases in the aggregate elasticity of substitution between capital and labor might also explain this evolution to more entrepreneurs and smaller firms associated to higher levels of development.

In addition, other potential factors discussed in previous literature are: (1) the fragmentation of large firms and the propensity towards contracting out (Taylor, 2004); (2) deep changes in the industry composition (Blanchflower and Shadforth, 2007); (3) the rise of necessity-driven entrepreneurs as a result of the lack of other options in the labor market (Fairlie and Fossen, 2020; Cowling and Wooden, 2021); (4) the rise of dependent forms of self-employment, especially in countries where labor markets are highly regulated (Román et al., 2011; Carrasco and Hernanz, 2022); (5) the emergence of the so-called atypical, non-standard or new forms of employment (Mandl and Biletta, 2016; Malo, 2018; Giupponi and Xu, 2020); and (6) the rise of digital labor platforms (Scholz, 2012; Sundararajan, 2016; Pesole et al., 2018; Congregado et al., 2019; Urzi Brancati et al., 2020; Gómez and Hospido, 2022).

This description/interpretation of the different development in self-employment rates depending on the stage of development, runs in parallel to the phases set out by the World Economic Forum. According to this classification, economies can be clustered in three major groups: (1) factor-driven economies, composed by the least developed countries, where subsistence agriculture, extraction businesses, and unskilled labor are prevalent. In this context high levels of entrepreneurship are mainly linked too few wage-earning job opportunities; (2) efficiency-driven economies are increasingly competitive, with more-efficient production processes, and potentially associated to lower self-employment rates; and (3) innovation-driven economies, i.e., the most developed. Since businesses are more knowledge-intensive, and the service sector expands, the self-employment sector expands too, and the average firm size decreases.

By using a close categorization –considering managed vs. entrepreneurial economies–, Audrestch and Thurik (2001, 2004) provides a theoretical framework including the factors conducive becoming an entrepreneurial economy, that is identified with the scientific and knowledge leadership.

At this point, one could argue that a substantial part of the differences across countries, in terms of the different paths by which entrepreneurship can impact on productivity growth and employment, are likely to be due to differences in the types and/or qualities prevailing in the self-employment sector.

Thus, the challenge is to find clusters of countries, homogeneous groups in terms of the entrepreneurship/self-employed productivity, identifying which determinants effectively engage the most "productive" entrepreneurship, that is, those with which to achieve the scientific-technological leadership that will give them the necessary market power to join the group of the world's richest economies. The results should provide tentative guidelines to policy makers to orient the entrepreneurial ecosystem to one that stimulate productive entrepreneurship and economic performance, i.e., to an innovation-driven economy.

To this end, the role of labor market regulation, taxation, corruption, financial frictions, macroeconomic stability and the institutional environment are, to some extent, candidates for explaining the productivity of entrepreneurship (see, Alvarez et al., 2014, for a survey).

Indeed, the role of macroeconomic factors and institutional variables in determining the cross-country variation in self-employment rates at the macro level include at least the works of: Acs et al. (1994) who focus on differences in capital per worker and industry composition; Pietrobelli et al. (2004), Arin et al. (2015) and Rodríguez-Santiago (2022) who explore the role of the income per worker as a determinant of the self-employment rates and also confirm that macroeconomic instability discourages long-term contracts and relations necessary for successful entrepreneurship; Blanchflower (2000), Centeno (2000), Robson (2003), and Torrini (2005) who investigated the role of labor market dynamics and regulation –frictions and employment protection legislation–; and Fölster (2002), Torrini (2005), Anokhin and Schulze (2009), Djankov et al. (2010), Estrin et al. (2012), Belitski et al. (2016) and Dutta and Sobel (2016) who examined the role of corruption and taxation. Likewise, several articles have examined the effects of institutions and the institutional quality on entrepreneurship (Sobel, 2008; Acs et al., 2008; Estrin et al., 2012; Bjørnskov and Foss, 2016; and Urbano et al., 2020).

A general overview of this literature on the macro-level showed a rather disappointing picture in terms of robustness. The lack of adequate datasets and the omission of the heterogeneity advise us the adoption of alternative strategies. This work is aimed at filling this gap in the entrepreneurship literature. In the next section we present our empirical strategy.

7.3. Methodology

Let $\{y_{it}\}, i = 1, \dots, N;\ t = 1, \dots, T$, be a panel consisting of country-year observations available of the self-employment productivity. On the basis of this panel, we investigate pooling within a panel of time series using finite mixture models. We assume that K hidden groups are present whereby all time series within a certain group may be characterized by the same econometric model and information from all time series in the group can be used for estimation.

We consider a finite mixtures model, composed by a mean and a trend effect, where the parameters are different among K groups:

$$y_{it} = \mu^k + \alpha^k t + \varepsilon_{it}, \quad \varepsilon_{it} \sim N\left(0, \frac{\sigma^2}{\lambda_i}\right), \ k = 1, \dots, K. \qquad (1)$$

We pursue a fully Bayesian approach, using Markov chain Monte Carlo (MCMC) methods based on data augmentation, where we draw heavily from previous work on MCMC methods for finite mixture models (Frühwirth-Schnatter, 2006). An important feature of our approach is the assumption that group membership of a certain time series is unknown a priori and is estimated along with the group-specific parameters.

The approach pursued in this article is based on formulating a time series model for each univariate time series $y_i = \{y_{i1}, \ldots, y_{iT}\}$ in terms of the sampling density $p(y_i|\vartheta)$, where $\vartheta = \{\vartheta_1, \ldots, \vartheta_K\}$ collects the unknown parameters taking values in a parameter space Θ.

We assume that the N time series arise from K groups, whereby within each group, say k, an econometric model based on the same parameter ϑ_k could be used for all time series for inference and forecasting. In other words, we could pool all time series within a cluster. Toward this aim, a latent group indicator S_i is introduced for each time series y_i, which takes a value out of the discrete set $\{1, \ldots, K\}$, indicating to which group the time series belongs; that is, $S_i = k$ if time series y_i belongs to group k. Thus knowing S_i is equivalent to knowing the unit-specific parameter, $p(y_i|S_i, \vartheta_1, \ldots, \vartheta_K) = p(y_i|\vartheta_{S_i})$.

$$p(y_i|\vartheta_{S_i}) = \begin{cases} p(y_i|\vartheta_1), & if\ S_i = 1 \\ \quad\ldots & \\ p(y_i|\vartheta_K), & if\ S_i = K \end{cases} \tag{2}$$

Model (2) implicitly assumes that in all clusters the same model is valid, but with different parameters. Furthermore, independence of the y_i's is assumed within each cluster.

Therefore, the joint sampling distribution reads as

$$p(y_1, \ldots, y_N|S_1, \ldots, S_N, \vartheta_1, \ldots, \vartheta_K) = \prod_{k=1}^{K} \prod_{i:S_i=k} p(y_i|\vartheta_k) \tag{3}$$

An important aspect of model (2) is that we do not assume to know a priori the number of groups and which time series belong to which group. For each time series, the group indicator S_i is estimated along with the group-specific parameters $\vartheta_1, \ldots, \vartheta_K$ from the data. The Bayesian classification rule combines the information in the data with the prior probability of group indicator S_i to obtain the inference on group membership.

To complete the model specification, we must formulate a probabilistic model for the group indicators $S = (S_1, \ldots, S_N)$. This probabilistic model determines the prior probability of group indicator S_i within a Bayesian classification rule. In general, we assume that $S_1, \ldots, S_N$ are a priori independent and define for each $i = 1, \ldots, N$ the probability that time series y_i belongs to group k, $Pr(S_i = k)$.

Following the approach of Frühwirth-Schnatter and Kaufmann (2008), Kaufmann (2010) and Hamilton and Owyang (2011), we consider a multinomial logit model to include prior information on a particular series into the estimation of the group probability

$$Pr(S_i = k \mid \gamma_2, \dots, \gamma_K) = \frac{\exp(Z_i \gamma_k)}{1 + \sum_{l=2}^{K} \exp(Z_i \gamma_l)} \tag{4}$$

where the first group is the baseline group with $\gamma_1 = 0$. The variable Z_i for $i = 1, \dots, N$, may be a vector of the series-specific features which are thought to determine the classification into a specific group. In our model, we will use unemployment rate, value added by industry, labour market rigidity index and digital adoption index. The parameters $\gamma = (\gamma_2, \dots, \gamma_K)$ are unknown but group-specific values and they allow to estimate the prior classification probabilities of a country into a certain group depending on the variables Z, which are stable over time and determine country-specific characteristics of the labor market structure during the sample period. Furthermore, the parameters γ are used to determine the intensity of every structural variable when classifying a country into a certain group.

The model estimation is carried out within a Bayesian framework with the aid of Markov Chain Monte Carlo (MCMC) simulation methods to obtain a posterior inference on the augmented parameter vector which includes the model parameters ϑ, the group indicator S and the series-specific variance weights λ.

MCMC estimation is carried out through the technique of data augmentation. The posterior distributions are obtained by updating the prior distribution with the information given in the data.

Priors. The parameter vector is further broken down into parameter blocks, for all of which we assume standard prior distributions: The prior distribution of the group-specific parameters $(\mu^1, \dots, \mu^K, \alpha^1, \dots, \alpha^K) \sim N(m_0, M_0)$; the variance of the error terms and the series-specific variance weights follow an inverse Gamma and a Gamma distribution respectively: $\sigma^2 \sim IG(g_0, G_0)\ and\ \lambda_i \sim G\left(\frac{v}{2}, \frac{v}{2}\right), i = 1, \dots, N$; the parameters governing the prior group probabilities under the logit structure follow a normal distribution for each coefficient, $\gamma \sim N(0, \tau I_g)$, where g is the dimension of vector Z.

Estimation. The sampling scheme to draw from the posterior follows Frühwirth-Schnatter and Kaufmann (2008) and involves the iteration between the following three steps:

(1) Classification for fixed parameters. For each $i = 1, \ldots, N$, time series y_i is classified as a whole into one of the K groups by sampling the group indicator S_i from the posterior distribution $Pr(S_i = k|y, \vartheta_1, \ldots, \vartheta_K, \lambda_i, \gamma), k = 1, \ldots, K$, making use of the sampling density $p(y_i|\vartheta)$, defined for each time series in (2), as well as the prior classification probabilities (4),

$$Pr(S_i = k|y, \vartheta_1, \ldots, \vartheta_K, \lambda_i, \gamma) \propto p(y_i|\vartheta_k, \lambda_i) Pr(S_i = k|\gamma), \quad k = 1, \ldots, K. \tag{5}$$

(2) Estimation for a fixed classification. Conditional on known indicator $S = (S_1, \ldots, S_N)$ and $\lambda = (\lambda_1, \ldots, \lambda_N)$, the group-specific parameters $(\vartheta_1, \ldots, \vartheta_K)$ and $(\gamma_2, \ldots, \gamma_K)$ are conditionally independent. Estimation is carried out by sampling the group-specific parameters from the posterior $p(\vartheta_1, \ldots, \vartheta_K|S, y, \lambda)$, and the parameters γ relevant for prior classification from the posterior $p(\gamma|S, y)$.

(3) Sampling the scale factors $\lambda = (\lambda_1, \ldots, \lambda_N)$. For each $i = 1, \ldots, N$, the scale factors λ_i are sampled independently from Gamma distributions.

All posterior distributions are conjugate to the priors, except for the posterior distribution of γ, the parameters influencing the group probabilities under a logit-type structure.

Sampling the group-specific parameters $\vartheta_1, \ldots, \vartheta_K$ is particularly easy since the groups share no common parameters. Each group parameter ϑ_k is estimated by pooling every time series that currently belong to group k.

Sampling the parameters influencing the group probabilities γ is not standard under the logit-type structure. For the posterior $p(\gamma|S_1, \ldots, S_N)$, a Metropolis-Hasting algorithm is used to sample them, following Scott (2011).

Identification and clustering. After a burn-in-phase, M values of the MCMC draws are retained for inference. In what follows, we use the superscript (m) to refer to MCMC draws; for example, $S_i^{(m)}$ represents the mth draw of the group indicator S_i. The MCMC draws may be used to perform unit-specific inference, to recover individual parameters, and to obtain forecasts for each individual time series. The unit-specific estimated parameter $\tilde{\vartheta}_i$ of time series y_i may be expressed as $\tilde{\vartheta}_i = \sum_{k=1}^{K} \vartheta_k \, I_{\{S_i=k\}}$, where the indicator function $I_{\{S_i=k\}}$ takes the value 1 iff $S_i = k$ and 0 otherwise. Therefore, posterior draws of the unit-specific parameters are given by $\tilde{\vartheta}_i^{(m)} = \sum_{k=1}^{K} \vartheta_k^{(m)} \, I_{\{S_i^{(m)}=k\}}$. The unit-specific draws $\tilde{\vartheta}_i^{(m)}$, together with MCMC draws of all model parameters, may also be used to sample future paths for each time series y_i.

To perform posterior classification and to estimate the group-specific parameters, the finite mixture model must be identified through some inequality constraint on the group-specific parameters, to avoid label-switching[9]. We restrict the classification by the mean value of the self-employment rate of each group, identifying the model by $\mu_1 > \mu_2 > \cdots > \mu_K$.

Once the model has been identified, it is possible to classify the time series into the various groups by estimating for each time series the posterior classification probability from the MCMC draws,

$$Pr(S_i = k|y) \approx \frac{1}{M} \sum_{m=1}^{M} I_{\{S_i^{(m)}=k\}} \tag{6}$$

Number of clusters. In practice, the number K of groups will be unknown. Each model specification with a fixed number K of groups will be denoted by $\mathcal{M}_K$. The marginal likelihood $p(y|\mathcal{M}_K)$, defined by

$$p(y|\mathcal{M}_K) = \int p(y_1, \dots, y_N|\psi, K)p(\psi)d\psi, \tag{7}$$

is combined through Bayes' theorem with the prior probability $Pr(\mathcal{M}_K)$ to obtain the posterior probability of each model, $Pr(\mathcal{M}_K|y) \propto p(y|\mathcal{M}_K)Pr\,(\mathcal{M}_K)$.

The usual is choosing the model with the highest marginal likelihood, but this method tends to choose a model with a large number of groups. For this reason, we consider to choose the model with the number of groups that maximizes the quality of the classification, by introducing the entropy what

[9] See Frühwirth-Schnatter (2006) for an extensive discussion of this issue.

measures how well the data are classified given a mixture distribution. Entropy, defined as

$$EN_k = -\sum_{i=1}^{N}\sum_{k=1}^{K} p(S_i = k|y_i, \vartheta) \log p \ (S_i = k|y_i, \vartheta), \tag{8}$$

takes value of 0 for a perfect classification, otherwise the entropy may be considerably larger that increases as the quality of the classification deteriorates.

7.4. Data and results

In this paper we adopt the strategy of using the productivity of self-employment as focus variable –a proxy of the quality of entrepreneurship–. As we mentioned, if we consider self-employment rates or other measure of the total entrepreneurship activity[10], one allows implicitly the inclusion of any type of informal self-employment or unproductive entrepreneurship. Then high levels of entrepreneurship/self-employment may mean simply that the economy is creating too few wage-earning job opportunities. Under these circumstances high levels of entrepreneurship would correlate with unproductive entrepreneurship or slow economic growth.

GDP per person self-employed represents entrepreneurship productivity, i.e., the output per self-employed worker, analogous way to other inputs. To compare productivity levels across countries, GDP is converted to international dollars using purchasing power parity rates which take account of differences in relative prices between countries[11]. Self-employed workers are those workers who, working on their own account or with one or a few partners or in cooperative, hold the type of jobs defined as self-employment

[10] Startup rates, the relative share of SMEs and self-employment rates are the most usual measures at the macro level. GEM is an annual large scale international study on the prevalence of entrepreneurship – rate of entrepreneurial activity–conducted since 1999 in 52 countries into different stages of economic development – developing, transition and developed–.

[11] Gross domestic product converted to international dollars using purchasing power parity rates, in constant 2017 international dollars, from World Development Indicators database, World Bank and Eurostat-OECD PPP Programme.

jobs. These data are taken from ILOSTAT database (International Labor Office). Self-employed workers include four sub-categories of employers, own-account workers, members of producers' cooperatives, and contributing family workers.

The dataset of covariates to help on the classification of every country in a specific group by a logistic prior is created with four variables that try to catch differences regarding: (1) the average unemployment rate, as percentage of total labor force that is without work, but seeking work in a recent past period, and currently available for work, to capture the labor market situation, taken also from ILOSTAT database; (2) the average industry added value as percentage of GDP, including ISIC divisions 05-43, from World Bank national accounts data and OECD National Accounts Statistics; (3) the average of the labour market legislation rigidity index (LAMRIG), elaborated by Campos and Nugent (2012), and based on the Botero et al. (2004) index of employment protection legislation and NATLEX, the ILO depository of labor laws; and (4) the digital adoption index (DAI), that measures countries' digital adoption across three dimensions of the economy: people, government, and business, from Data World Bank. To interpret results, since data has been normalized, countries with values over 0 will be above the sample average, and vice versa.

The model requires completely balanced panel; therefore, our final data set is composed by the annual self-employment productivity (GDP by self-employed in thousands) of 120 countries, spanning from 1991 to 2019, and the set of four country-level covariates. The list of countries, their code, average GDP by self-employed for the period, as well as the values of covariates can be consulted on Annex 1.

We estimate different models, where μ_k and α_k will indicate the mean self-employment productivity and trend effect of the countries belonging to group k, respectively. Estimation is based on the following priors: for group-specific parameters, $(\mu_k, \alpha_k) \sim \mathrm{N}(0{,}1000)$, the unit-specific variances, $\varepsilon_{it} \sim N(0, \sigma^2/\lambda_i)$ with $\sigma^2 \sim IG(1{,}1)$ and $\lambda_i \sim G(4{,}4)$, and the parameters of the logistic model, $\gamma \sim N(0, \tau I_g)$, with $\tau = 20$ and $g = 4$, the dimension of Z.

For each run of the MCMC sampler, after a burn-in-phase of 1000 iterations to remove dependence on starting condition, 4000 draws are kept to evaluate the estimation. We check the quality of classification, measured by the entropy, to choose the number of groups of our model.

Table 1 presents the results of bridge sampling marginal likelihood, log likelihood and entropy of models with $K = 2,3,4,5,6$ for models with unit-specific variance.

The preferred model specification is the one that divides into 3 groups. Table 2 contains the posterior means of estimated parameters (standard deviation in parenthesis, all of them appear to be significant at 95% of confidence), which shows a division of countries into groups with average high, medium and low self-employment productivity. The group's membership of every country can be consulted on Figure 1. The group 1, showing higher levels of entrepreneurship productivity, is composed by the most of the countries of Europe (with the exception of Portugal, Poland, Ukraine and Greece), United States, Saudi Arabia, Oman, Japan and Australia. The formation of this group could be related with the innovation-driven economies. Group 2 is formed by the rest of European countries, south of Africa, Mexico, Brazil, Argentina, Chile and Uruguay, Algeria, Egypt, Turkey, Iran, Kazakhstan, South Korea and Malaysia. These countries show a middle productivity of self-employment and are mainly classified as developing and emerging economies. The last group is composed by the rest of countries, mainly less developed economies, that are showing low levels of self-employment productivity.

The analysis allows us to know the individual characteristics that are driven the groups formation. Table 3 shows the posterior means of the estimated logistic coefficients influencing the group probabilities (standard deviation in parenthesis, in bold when significant at 95% of confidence). The coefficients have the following interpretation: the probability of inclusion in clusters 2 and 3 may be lower than the probability of inclusion in cluster 1 when a country show a value above average on one characteristic included if the coefficient is negative. We can conclude that countries that show higher unemployment rate, will have lower odds to enter the first group with respect to the second one. Furthermore, countries with high levels of digitalization will lower their probabilities to enter the second and third group, which means that higher levels of digitalization increase the probability of a country belonging to the most productive group, the first one. The significance of this informative prior on classification probability is shown in Figure 2. It shows the posterior distribution of the effects of the different covariates (unemployment rate, value added by industry, LAMRIG and DAI) into groups. For the prior probability of classification into groups 2 (black line) and 3 (red line), the posterior distribution of the effects of DAI are clearly shifted away from zero, while the posterior distribution of the effects of unemployment is only significant for the probability of classification into group 2.

Let us contextualize our results with those obtained in previous literature. First, in our study, the results do not support the idea that labor market flexibility favors the transition toward the groups of countries with higher productivity, like the most part of the studies which evaluate the impact of EPL restrictiveness on aggregate self-employment (Robson, 2003; Torrini, 2005; Kanniainen and Vesala, 2005). However, we cannot rule that a significant impact could be obtained if we could extend our analysis to account for heterogeneity in self-employment –as in the work of Baker et al. (2018) or Poschke (2019)– or the degree of regulatory compliance[12].

Secondly, our statistical evidence does not seem to support the idea that the weight of the industrial sector is associated with the emergence of larger companies and a growth in salaried employment opportunities, which leads a good number of marginal entrepreneurs to move from self-employment to salaried employment, decreasing the quantitative composition of the business fabric and increasing productivity per self-employed. At this point we can only speculate and suggest a possible explanation that has to do with outsourcing processes and the growth of the service sector that characterizes post-industrial societies.

Thirdly, our statistical results suggest that there is a relationship between the labor market dynamics (the reduction of unemployment) and the likelihood of moving from being an efficiency-driven economy to becoming an entrepreneurial economy. In some extent, in those economies where unemployment is low, turning unemployment into self-employment will be more unlikely. In this way, the relative weight of the needy/marginal entrepreneurs with respect to the opportunity entrepreneurship will be lower, thus increasing the productivity of entrepreneurship (Acs, 2006; Acs et al., 2008; Van der Zwan et al., 2016).

Fourthly, the results point to the fact that digitalization seems to be a factor favoring the transition from a factor-driven to an entrepreneurial driven society. The intuition is that digitalization has become a key competitive factor, both for a managed economy in which competitiveness is based on efficiency, and for capturing the best profit opportunities that favor technological and economic leadership. Not only for the most advanced nations, but also for the less developed ones, improving incentive structures for business start-ups associated to digitalization and promoting the introduction of

---

[12] These potential extensions involve sacrificing units of observation in our data-driven analysis.

a new culture of data-driven management offer promising avenues for public policy.

Figure 3 gives some idea of the role played by the countries characteristics and observed self-employment productivity in associating countries with particular groups. The first column, the prior probabilities of classification based only on the explanatory variables, $Pr(S_i = k|z_i)$, summarizes the inference we would draw if we knew nothing about the country other than the characteristics, and the second column reports the posterior group probabilities based on explanatory variables plus observed self-employment productivity, $Pr(S_i = k|z_i, y_i)$. The lightest grey countries in the map are out of sample. Prior and posterior classification probabilities of group 3 have much in common. This appears to be related to the fact that countries included in group 3 are mainly less developed countries, showing the lowest levels of digitalization. For group 1, the information content in the prior based on characteristics is not as sharp, but also shows that most developed economies have higher probabilities of belonging to the most productive group of countries.

Focusing on the relevant factors determining the classification of countries, the plot of the prior probability $Pr(S_i = 2|z_i)$ as a function of unemployment rate (Figure 4), indicates that countries with unemployment rate above the average have a high probability of belonging to the second group. As unemployment rate decreases, the prior chance of belonging to this second group decreases. The same way, the plot of the prior probability $Pr(S_i = 1|z_i)$ as a function of digital adoption index shown in Figure 5, shows that countries with high levels of digitalization have a high probability of belonging to the first group, formed by innovation-driven economies. Indeed, checking the posterior probability of pertaining to group 1, we can check that the most of countries with higher levels of digitalization actually belongs to this innovation-driven group

7.5. Conclusions

This paper reexamined the diversity in the level and dynamics of the self-employment rate across countries, in terms of productivity. We explored if a substantial part of the differences across countries in the effects of entrepreneurship employment, innovation and economic growth are due to differences in the composition of the self-employment sector –types and qualities–.

To this end we apply a non-conventional approach based on a Bayesian clustering which allows, not only reveal homogeneous groups in terms of the stage of development, but also the factors that rule the transition from a group to a more productive one.

By using a new and more complete dataset that covers a wide range of countries –including less developed, developing and developed countries–, during three decades, our results point to the existence of three groups in terms of the entrepreneurship productivity. These groups are many parallels regards the so-called factor- efficiency- and innovation-driven economies and close to the classification of countries according three different stages of economic development: developing, transition and developed countries.

The main contributions of this paper have been the identification of groups of countries on the basis of the productivity of their self-employment sectors, the determinants of the membership to a particular group of countries, and more importantly, how different factors affect to the probability of transition between groups.

The labor market dynamics –national unemployment– and the degree of digitalization matters for cluster determination –leading transitions between clusters of countries–, other factors, such as the share of industrial added value or the existence of rigidities in the labor market are not determinants of such transitions. These clusters might be identified with three major groups of countries usually considered in the entrepreneurship literature: factor-, efficiency-, and innovation-knowledge-driven countries, and with the literature on managed vs. entrepreneurial societies.

Taken together, these results should guide the shift towards policy for entrepreneurial economy, taking the quality of self-employment as a focal point. However, we cannot rule the potential effect of other dimensions although the incorporation of some of them involve the loss of observational units limiting the scope of our data-driven analysis.

References

Acs, Z. J. (2006). How is entrepreneurship good for economic growth. *Innovations*, *1*(1), 97-107.

Acs, Z. J., & Mueller, P. (2008). Employment effects of business dynamics: mice, gazelles and elephants. *Small Business Economics*, *30*(1), 85-100.

Acs, Z. J., & Szerb, L. (2007). Entrepreneurship, economic growth and public policy. *Small Business Economics*, *28*(2), 109-122.

Acs, Z. J., Audretsch, D. B., & Evans, D. S. (1994). *Why does the self-employment rate vary across countries and over time?* (No. 871). CEPR Discussion Papers.

Acs, Z. J., Desai, S., & Hessels, J. (2008). Entrepreneurship, economic development and institutions. *Small Business Economics*, *31*(3), 219-234.

Acs, Z. J., & Varga, A. (2005) Entrepreneurship, agglomeration and technological change. *Small Business Economics*, *24*, 323-334.

Allub, L., & Erosa, A. (2019). Financial frictions, occupational choice and economic inequality. *Journal of Monetary Economics*, *107*, 63-76.

Álvarez, C., Urbano, D., & Amorós, J. E. (2014). GEM research: achievements and challenges. *Small Business Economics*, *42*(3), 445-465.

Anokhin, S., & Schulze, W. S. (2009). Entrepreneurship, innovation, and corruption. *Journal of business venturing*, *24*(5), 465-476.

Aquilina, M., Klump, R., & Pietrobelli, C. (2006). Factor substitution, average firm size and economic growth. *Small Business Economics*, *26*(3), 203-214.

Arin, K. P., Huang, V. Z., Minniti, M., Nandialath, A. M., & Reich, O. F. M. (2015). Revisiting the Determinants of Entrepreneurship: A Bayesian Approach. *Journal of Management*, *41*(2), 607-631.

Audretsch, D. B., & Fritsch, M. (2002). Growth regimes over time and space. *Regional Studies*, *36*(2), 113-124.

Audretsch, D. B., & Keilbach, M. (2004). Entrepreneurship and regional growth: an evolutionary interpretation. *Journal of evolutionary economics*, *14*(5), 605-616.

Audretsch, D. B., & Thurik, A. R. (2001). What's new about the new economy? Sources of growth in the managed and entrepreneurial economies. *Industrial and corporate change*, *10*(1), 267-315.

Audretsch, D. B., & Thurik, A. R. (2004). A model of the entrepreneurial economy (No. 1204). *Papers on Entrepreneurship, Growth and Public Policy*. EIM, Erasmus Universiteit Rotterdam.

Baumgartner, H. J., & Caliendo, M. (2008). Turning unemployment into self-employment: Effectiveness of two start-up programmes. *Oxford Bulletin of Economics and Statistics*, *70*(3), 347-373.

Baumol W. J. (1990). Entrepreneurship: productive, unproductive and destructive. *Journal of Political Economy*, *98*(5), 893-921.

Belitski, M., Chowdhury, F. & Desai, S. (2016). Taxes, corruption, and entry. *Small Business Economics*, *47*(1), 201-216.

Bjørnskov, C., & Foss, N. J. (2016). Institutions, entrepreneurship, and economic growth: what do we know and what do we still need to know?. *Academy of Management Perspectives*, *30*(3), 292-315.

Blanchflower, D. G. (2000). Self-employment in OECD countries. *Labour economics*, *7*(5), 471-505.

Blanchflower, D. G. (2004). Self-employment: More may not be better. *Swedish Economic Review*, *11*, 15-73.

Blanchflower, D. G., & Shadforth, C. (2007). Entrepreneurship in the UK. *Foundations and Trends in Entrepreneurship*, *3*(4): 257-364.

Boeri, T., Giupponi, G., Krueger, A. B., & Machin, S. (2020). Solo self-employment and alternative work arrangements: A cross-country perspective on the changing composition of jobs. *Journal of Economic Perspectives*, *34*(1), 170-95.

Botero, J., Djankov, S., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2004). The regulation of labor. *The Quarterly Journal of Economics*, *119*(4), 1339-1382.

Campos, N. F., & Nugent, J. B. (2012). The dynamics of the regulation of labour in developing and developed countries since 1960. *The Political Economy of Structural Reforms in Europe*, (6881), 75-88.

Carrasco, R., & Hernanz, V. (2022). Dependent self-employment across Europe: Involuntariness, country's wealth and labour market institutions. *Applied Economics*, *54*(14), 1568-1583.

Carree, M., Van Stel, A., Thurik, R., & Wennekers, S. (2002). Economic Development and Business Ownership: An Analysis Using Data of 23 OECD Countries in the Period 1976-1996. *Small Business Economics*, *19*(3), 271-290.

Carree, M., Van Stel, A., Thurik, R., & Wennekers, S. (2007). The Relationship Between Economic Development and Business Ownership Revisited. *Entrepreneurship and Regional Development*, *19*(3), 281-291.

Centeno, M. (2000). Is self-employment a response to labour market rigidity?. *Economic Bulletin*, Banco de Portugal, December, 37-4.

Congregado, E., de Andrés, M. I., & Román, C. (2019). Explorando la heterogeneidad en el empleo mediado por plataformas digitales: Intensidad y localización. *Revista de Economía Laboral*, *16*(2), 69-103.

Congregado, E., de Andrés, M. I., Román, C., & Nolan, E. (2022). Heterogeneity Among Self-employed Digital Platform Workers. Evidence from Europe. *International Review of Entrepreneurship*, *20*(1), forthcoming.

Congregado, E., Golpe, A. A., & Carmona, M. (2010). Is it a good policy to promote self-employment for job creation? Evidence from Spain. *Journal of Policy Modeling*, *32*(6), 828-842.

Cowling, M. L., & Wooden, M. (2021). Does solo self-employment serve as a 'stepping stone'to employership?. *Labour Economics*, *68*, 101942.

Djankov, S., Ganser, T., McLiesh, C., Ramalho, R., & Shleifer, A. (2010). The effect of corporate taxes on investment and entrepreneurship. *American Economic Journal: Macroeconomics*, *2*(3), 31-64.

Dutta, N., & Sobel, R. (2016). Does corruption ever help entrepreneurship?. *Small Business Economics*, *47*, 179-199.

Estrin, S., Korosteleva, J., & Mickiewicz, T. (2012). Which institutions encourage entrepreneurial growth aspirations?. J*ournal of Business Venturing*, *28*(4), 564-580.

Fairlie, R. W., & Fossen, F. M. (2020). Defining opportunity versus necessity entrepreneurship: Two components of business creation. In *Change at home, in the labor market, and on the job*. Emerald Publishing Limited.

Fölster, S. (2002). Do Lower Taxes Stimulate Self-Employment?. *Small Business Economics*, *19*, 135-145.

Frühwirth-Schnatter, S. (2006). *Finite Mixture and Markov Switching Models*.

Frühwirth-Schnatter, S., & Kaufmann, S. (2008). Model-based clustering of multiple time series. *Journal of Business and Economic Statistics*, *26*(1), 78-89.

Gerxhani, K. (2004). The informal sector in developed and less developed countries: A literature survey. *Public choice*, *120*(3), 267-300.

Giupponi, G., & Xu, X. (2020). What does the rise of self-employment tell us about the UK labour market?. *London: Institute of Fiscal Studies*.

Gómez, M., & Hospido, L. (2022). The challenge of measuring digital platform work. *Banco de España Article*, *3*, 22.

Hamilton, J. D., & Owyang, M. T. (2011). The propagation of reginal recessions. *NBER Working Paper Series*.

Hechavarría, D. M., & Ingram, A. E. (2019). Entrepreneurial ecosystem conditions and gendered national-level entrepreneurial activity: A 14-year panel study of GEM. *Small Business Economics*, *53*(2), 431-458.

Jovanovic, B. (1994). Firm formation with heterogeneous management and labor skills. *Small Business Economics*, *6*(3), 185-191.

Justo, R., Congregado, E., & Román, C. (2021). Becoming self-employed from inactivity: an in-depth analysis of satisfaction. *Small Business Economics*, *56*(1), 145-187.

Kaufmann, S. (2010). Dating and forecasting turning points by Bayesian clustering with dynamic structure: A suggestion with an application to Austrian data. *Journal of Applied Econometrics*, *25*(2), 309-344.

Lerner, J. (2010). The future of public efforts to boost entrepreneurship and venture capital. *Small Business Economics, 35*(3), 255-264.

Lucas, R. E. (1978). On the Size Distribution of Business Firms. *Bell Journal of Economics*, 508-523.

Malo, M. A. (2018). New forms of employment: From atypical employment to digital platforms, *Papeles de Economía Española*, *156*, 146-158.

Maloney, W. F. (2004). Informality revisited. *World development*, *32*(7), 1159-1178.

Mandl, I., & Biletta, I. (2016). Overview of new forms of employment. *Bulletin of comparative labour relations (94). New forms of employment in Europe*.

Nyström, K. (2008). The Institutions of Economic Freedom and Entrepreneurship: Evidence from Panel Data. *Public Choice*, *136*(3-4), 269-282.

Okamuro, H., Van Stel, A., & Verheul, I. (2017). Understanding the drivers of an 'entrepreneurial' economy: lessons from Japan and the Netherlands. In *Exploring the Entrepreneurial Society*. Edward Elgar Publishing

Parker, S. C., & Robson, M. T. (2004). Explaining International Variations in Self-employment: Evidence from a Panel of OECD Countries. *Southern Economic Journal*, *71*, 287-301.

Pesole, A., Brancati, U., Fernández-Macías, E., Biagi, F., & Gonzalez Vazquez, I. (2018). Platform workers in Europe. *Luxembourg: Publications Office of the European Union*.

Pietrobelli, C., Rabellotti, R., & Aquilina, M. (2004). An empirical study of the determinants of self-employment in developing countries. *Journal of International Development*, *16*(6), 803-820.

Poschke, M. (2013). Who becomes an entrepreneur? Labor market prospects and occupational choice. *Journal of Economic Dynamics and Control*, *37*(3), 693-710.

Poschke, M. (2018). The firm size distribution across countries and skill-biased change in entrepreneurial technology. *American Economic Journal: Macroeconomics*, *10*(3), 1-41.

Poschke, M. (2019). Wage Employment, Unemployment and Self-Employment across Countries. IZA DP No. 12367.

Robson, M. T. (2003). Does stricter employment protection legislation promote self-employment?. *Small Business Economics*, *21*(3), 309-319.

Rodríguez-Santiago, A. (2022). Re-Evaluating the Relationship Between Economic Development and Self-Employment, at the Macro-Level: A Bayesian Model Averaging Approach. *International Journal of Interactive Multimedia & Artificial Intelligence*, *7*(3).

Román, C., Congregado, E., & Millán, J. M. (2011). Dependent self-employment as a way to evade employment protection legislation. *Small Business Economics*, *37*(3), 363-392.

Scholz, T. (Ed.). (2012). *Digital labor: The internet as playground and factory*. Routledge.

Scott, S. L. (2011). Data augmentation, frequentist estimation, and the Bayesian analysis of multinomial logit models. *Statistical Papers*, *52*, 87-109.

Shane, S. (2009). Why encouraging more people to become entrepreneurs is bad public policy. *Small business economics*, *33*(2), 141-149.

Sobel, R. S. (2008). Testing Baumol: Institutional quality and the productivity of entrepreneurship. *Journal of Business Venturing*, *23*(6), 641-655.

Stam, E. (2015). Entrepreneurial ecosystems and regional policy: a sympathetic critique. *European planning studies*, *23*(9), 1759-1769.

Sundararajan, A. (2016). *The Sharing Economy: The End of Employment and the Rise of Crowd-based Capitalism*. Cambridge, MIT Press.

Sutter, C., Bruton, G. D., & Chen, J. (2019). Entrepreneurship as a solution to extreme poverty: A review and future research directions. *Journal of business venturing*, *34*(1), 197-214.

Taylor, M. (2004). Self-employment in Britain: when, who and why?. *Swedish Economic Policy Review*, *11*(2), 141-173.

Torrini, R. (2005). Cross-country differences in self-employment rates: The role of institutions. *Labour Economics*, *12*(5), 661-683.

Urbano, D., Audretsch, D. B., Aparicio, S., & Noguera, M. (2020). Does entrepreneurial activity matter for economic growth in developing countries? The role of the institutional environment. *International Entrepreneurship and Management Journal*, *16*(3), 1065-1099.

Urzi Brancati, M. C., Pesole, A., & Fernández-Macías, E. (2020). New evidence on platform workers in Europe. *Results from the second COLLEEM survey*.

Van der Zwan, P., Thurik, R., Verheul, I., & Hessels, J. (2016). Factors influencing the entrepreneurial engagement of opportunity and necessity entrepreneurs. *Eurasian Business Review*, *6*(3), 273-295.

Van Stel, A., Carree, M., & Thurik, R. (2005). The effect of entrepreneurial activity on national economic growth. *Small business economics*, *24*(3), 311-321.

Wennekers, S., Van Stel, A., Carree, M., & Thurik, R. (2010). The Relationship Between Entrepreneurship and Economic Development: Is It U-shaped?. *Foundations and Trends in Entrepreneurship*, *6*(3), 167-237.

Wennekers, S., Van Stel, A., Thurik, R., & Reynolds, P. (2005). Nascent entrepreneurship and the level of economic development. *Small business economics*, *24*(3), 293-309.

Zissimopoulos, J. M., & Karoly, L. A. (2007). Transitions to self-employment at older ages: The role of wealth, health, health insurance and other factors. *Labour economics*, *14*(2), 269-295.

Tables and Figures

Table 1. Marginal likelihood of various model specifications

K	Bridge Sampling	Log-Likelihood	Entropy
2	-19555.93	-19469.62	0.43
3	-18435.95	-18338.91	0.08
4	-18055.51	-17799.37	0.29
5	-17281.36	-17006.90	0.87
6	-16978.62	-16684.56	1.52

Table 2. Posterior means of estimated model parameters

		S_i	
	1	2	3
μ	281.06	99.94	7.44
	(8.34)	(2.77)	(0.53)
α	16.95	2.87	0.27
	(0.51)	(0.16)	(0.03)

Table 3. Posterior means of estimated logistic coefficients

S_i	u	$industry$	$lamrig$	dai
2	**1.13**	0.46	0.12	**-0.85**
	(0.44)	(0.33)	(0.28)	(0.3)
3	-0.33	0.43	0.23	**-4.84**
	(0.45)	(0.43)	(0.39)	(0.72)

Figure 1. Group membership

Figure 2. Posterior distribution of the effects of covariates for the prior probability of classification into group 2 (black line) and group 3 (red line)

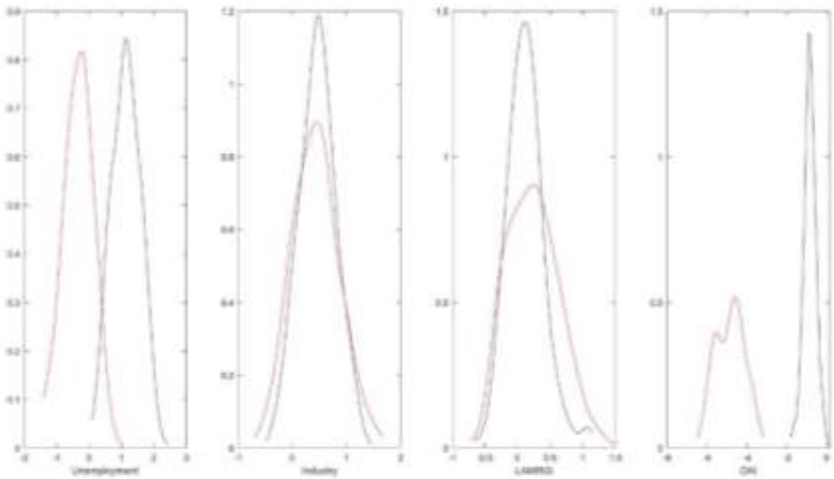


Figure 3. Probabilities of group classification based on covariates (first column) and based on covariates plus observed self-employment productivity data (second column).

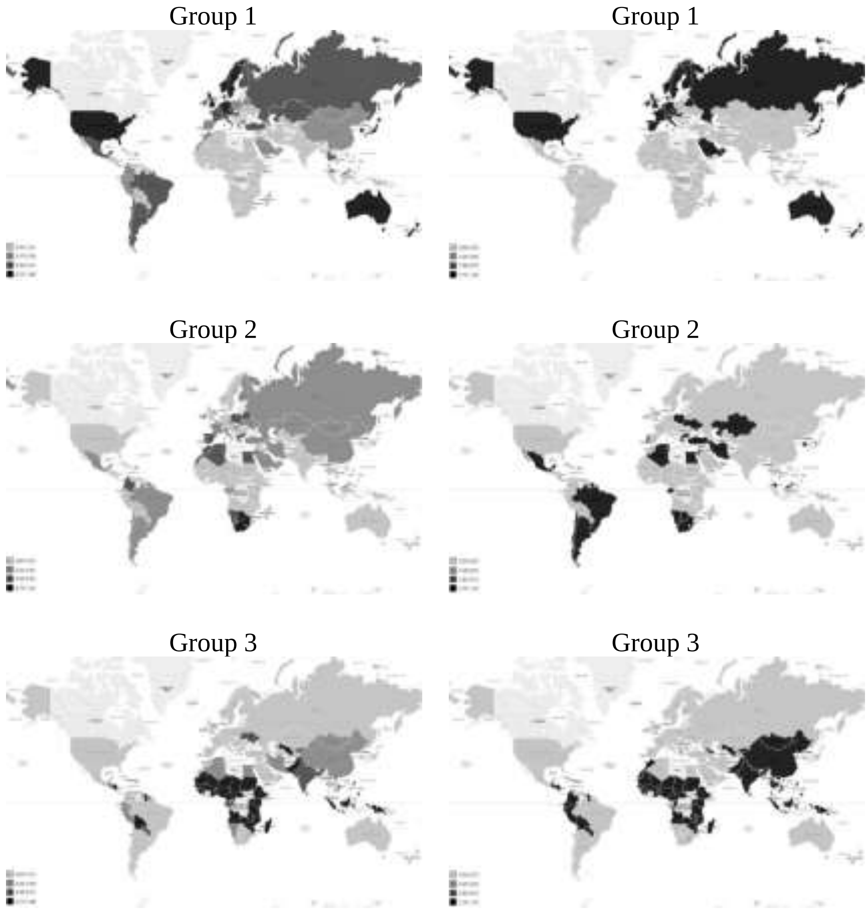


Figure 4. Prior probability $Pr(S_i = 2|z_i)$ as a function of unemployment rate, posterior probability $Pr(S_i = 2|z_i, y_i)$ and unemployment rate in ascending order

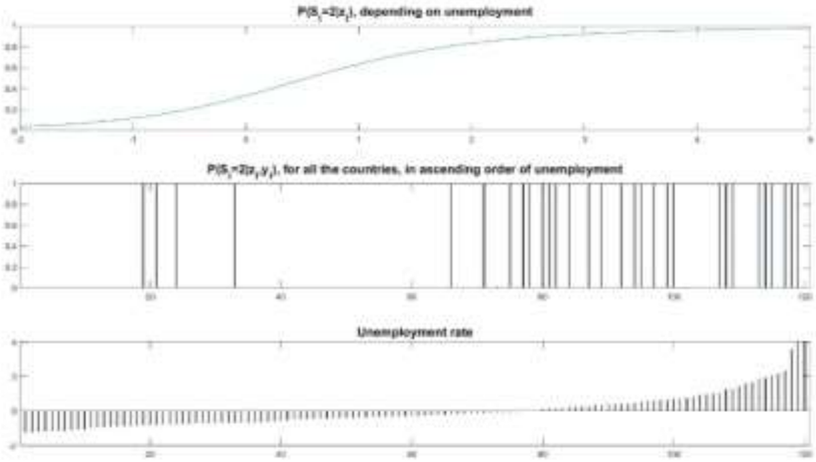
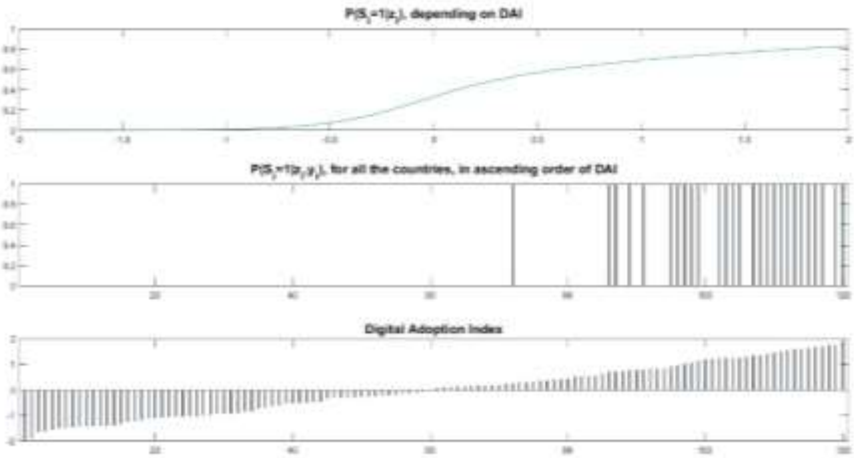


Figure 5. Prior probability $Pr(S_i = 1|z_i)$ as a function of DAI, posterior probability $Pr(S_i = 1|z_i, y_i)$ and DAI in ascending order



Appendix

Table A1. List of countries and variables values

COUNTRY	CODE	GDP/SE	U	INDUSTRY	LAMRIG	DAI
Angola	AGO	24.50	5.25	55.67	2.42	0.33
Albania	ALB	36.86	16.58	21.99	1.42	0.58
Argentina	ARG	198.99	10.96	26.50	1.55	0.66
Armenia	ARM	45.96	12.36	25.83	1.77	0.61
Australia	AUS	459.13	6.57	25.25	0.98	0.70
Austria	AUT	752.78	4.86	27.10	1.52	0.84
Azerbaijan	AZE	27.61	6.60	47.63	1.72	0.57
Burundi	BDI	2.37	1.59	15.32	1.81	0.25
Belgium	BEL	720.37	7.78	22.17	1.57	0.77
Benin	BEN	7.36	1.33	16.82	1.81	0.22
Burkina Faso	BFA	4.52	3.35	22.44	1.60	0.23
Bangladesh	BGD	11.06	3.65	24.29	1.90	0.34
Bulgaria	BGR	283.49	11.31	24.97	1.73	0.60
Bahrain	BHR	2578.20	1.12	43.11	1.20	0.77
Belarus	BLR	622.95	9.00	35.22	2.47	0.56
Bolivia	BOL	21.67	2.72	27.48	1.86	0.46
Brazil	BRA	89.96	8.57	23.63	2.37	0.67
Botswana	BWA	148.44	19.47	40.53	1.16	0.47
Central African Republic	CAF	2.93	5.65	22.95	1.76	0.14
Switzerland	CHE	701.45	3.90	26.33	1.26	0.81
Chile	CHL	163.01	7.79	33.61	1.48	0.74
China	CHN	22.34	3.94	44.62	1.65	0.54
Cameroon	CMR	9.27	5.46	27.04	1.89	0.28
Republic of the Congo	COG	19.23	20.11	54.73	1.70	0.30
Colombia	COL	51.58	11.28	29.39	1.89	0.62
Comoros	COM	18.96	5.97	11.61	2.30	0.24
Costa Rica	CRI	137.83	6.79	23.80	2.16	0.63
Czech Republic	CZE	414.74	5.56	33.71	1.52	0.71
Germany	DEU	886.82	7.27	27.84	2.15	0.82
Denmark	DNK	1084.61	6.15	21.61	1.72	0.78
Dominican Republic	DOM	67.37	6.32	30.55	1.51	0.48
Algeria	DZA	121.04	18.29	37.97	0.75	0.40
Ecuador	ECU	49.98	4.20	31.70	1.91	0.55
Egypt	EGY	84.69	10.23	33.60	1.68	0.52
Spain	ESP	471.99	17.14	24.67	2.46	0.75
Ethiopia	ETH	2.86	2.77	12.67	1.39	0.25
Finland	FIN	667.82	10.17	27.35	2.21	0.80
France	FRA	832.68	9.78	19.87	2.23	0.75
Gabon	GAB	171.84	18.70	51.55	1.41	0.36
United Kingdom	GBR	615.60	6.46	21.16	0.86	0.75
Georgia	GEO	29.71	13.32	21.27	1.77	0.58
Ghana	GHA	11.24	6.26	24.98	1.13	0.42
Guinea	GIN	6.05	4.68	30.34	1.55	0.21
Gambia	GMB	10.02	9.23	14.51	1.29	0.34
Greece	GRC	207.16	13.64	16.87	1.56	0.59
Guatemala	GTM	41.54	2.79	23.72	1.41	0.48

Table A1. *Continued*

COUNTRY	CODE	GDP/SE	U	INDUSTRY	LAMRIG	DAI
Guyana	GUY	73.14	12.10	22.78	1.27	0.34
Honduras	HND	23.98	4.45	27.69	1.01	0.42
Haiti	HTI	11.29	11.76	26.13	1.17	0.25
Hungary	HUN	433.43	7.94	26.15	1.66	0.66
Indonesia	IDN	28.57	5.25	43.24	1.61	0.42
India	IND	12.87	5.55	28.10	1.38	0.48
Ireland	IRL	675.97	9.29	30.39	0.95	0.65
Islamic Republic of Iran	IRN	95.35	11.25	40.86	1.94	0.46
Italy	ITA	417.85	9.97	23.55	1.96	0.75
Jamaica	JAM	61.28	13.38	21.48	1.16	0.47
Jordan	JOR	318.84	14.79	24.62	1.56	0.54
Japan	JPN	531.85	3.83	30.06	0.50	0.83
Kazakhstan	KAZ	108.19	7.29	34.80	2.08	0.65
Kenya	KEN	13.59	3.09	16.99	1.25	0.43
Kyrgyzstan	KGZ	22.33	7.34	24.19	1.92	0.46
Korea, Republic of	KOR	188.16	3.36	34.45	1.38	0.85
Lebanon	LBN	147.67	8.53	18.03	1.20	0.55
Sri Lanka	LKA	49.67	7.69	27.79	1.61	0.45
Lesotho	LSO	10.97	30.80	32.84	1.29	0.28
Luxembourg	LUX	2649.66	4.07	14.01	2.00	0.85
Morocco	MAR	33.33	11.08	25.97	1.31	0.54
Madagascar	MDG	3.87	3.73	19.30	1.99	0.24
Mexico	MEX	126.08	4.02	32.14	2.01	0.57
North Macedonia	MKD	157.68	30.69	23.47	1.65	0.54
Mali	MLI	6.48	6.64	20.03	1.70	0.30
Mongolia	MNG	33.00	6.01	30.55	1.39	0.53
Mozambique	MOZ	2.21	3.04	18.01	2.21	0.27
Mauritania	MRT	32.24	9.94	30.22	1.82	0.32
Mauritius	MUS	174.59	8.32	23.78	1.21	0.58
Malawi	MWI	5.03	5.80	17.26	1.75	0.25
Malaysia	MYS	171.33	3.32	42.48	0.85	0.67
Namibia	NAM	85.79	21.00	26.15	1.06	0.38
Niger	NER	2.93	1.42	20.87	1.66	0.16
Nigeria	NGA	15.82	4.53	28.11	1.27	0.39
Nicaragua	NIC	25.18	6.26	22.12	0.82	0.42
Netherlands	NLD	718.54	5.08	21.10	2.16	0.83
Norway	NOR	1484.82	4.09	32.79	2.07	0.79
Nepal	NPL	5.83	2.02	16.65	1.90	0.33
New Zealand	NZL	392.08	6.07	23.09	0.49	0.69
Oman	OMN	1454.48	3.79	55.44	1.30	0.65
Pakistan	PAK	19.70	1.30	20.14	1.15	0.38
Panama	PAN	134.82	3.58	21.73	2.42	0.56
Peru	PER	31.12	4.17	31.43	1.65	0.54
Philippines	PHL	32.27	3.48	33.38	1.64	0.47
Papua New Guinea	PNG	11.93	2.55	34.23	1.01	0.32
Poland	POL	202.44	11.70	29.27	2.25	0.67
Portugal	PRT	277.40	7.92	21.57	2.45	0.76
Paraguay	PRY	46.49	5.43	35.19	1.71	0.50
Russian Federation	RUS	1023.61	7.43	32.82	2.25	0.72

Table A1. *Continued*

COUNTRY	CODE	GDP/SE	U	INDUSTRY	LAMRIG	DAI
Rwanda	RWA	3.42	0.87	17.32	1.77	0.42
Saudi Arabia	SAU	2304.87	5.68	53.52	1.02	0.67
Sudan	SDN	34.61	15.86	18.33	1.67	0.29
Senegal	SEN	14.33	6.84	23.52	1.66	0.34
Singapore	SGP	847.97	3.99	28.64	0.86	0.87
Sierra Leone	SLE	4.44	3.89	17.04	1.81	0.25
El Salvador	SLV	45.94	6.12	25.64	1.77	0.49
Suriname	SUR	258.69	10.10	29.41	0.85	0.46
Sweden	SWE	844.30	7.26	24.34	2.33	0.82
Chad	TCD	4.40	0.89	14.21	1.83	0.20
Togo	TGO	6.28	3.44	18.27	1.73	0.23
Thailand	THA	39.70	1.32	37.20	1.77	0.59
Trinidad and Tobago	TTO	227.75	9.18	47.84	0.58	0.55
Tunisia	TUN	107.38	14.97	27.23	1.72	0.54
Turkey	TUR	143.46	9.30	27.84	1.72	0.61
Tanzania	TZA	4.29	2.97	21.21	1.63	0.32
Uganda	UGA	5.43	2.39	21.15	1.71	0.31
Ukraine	UKR	177.22	7.73	30.41	2.23	0.49
Uruguay	URY	138.18	9.79	24.10	1.27	0.74
United States	USA	1496.20	5.85	20.31	0.65	0.73
Uzbekistan	UZB	22.84	7.07	24.81	1.55	0.36
Vietnam	VNM	11.58	1.90	33.85	1.75	0.49
South Africa	ZAF	268.84	28.02	27.15	1.16	0.61
Zambia	ZMB	9.06	13.18	31.89	1.23	0.32
Zimbabwe	ZWE	12.64	5.17	25.76	0.86	0.32

Part IV: Concluding remarks

Chapter 8: Conclusions and future research

This dissertation explored empirically the drivers and inhibitors of decision to become self-employed and its dynamics at the macro level, by using different strategies, observational units and econometric approaches.

After an empirical application of business cycle dating methods in the EU-28, the first part looks at the extent to which the new forms of employment and the employment intensity of growth in the post-Great recession era are modifying the traditional counter-cyclicality of self-employment and at the same time the persistence into self-employment. Two works included in this first part addressed these issues.

The first one explored whether the self-employment dynamics after the last recession pre-COVID was similar to the previous ones, by using long time series from the UK. We applied time series techniques for checking the macrodynamics of opportunity and necessity self-employment during the business cycle, circumventing the lack of necessity and opportunity long time series, separating the evolution of self-employment into two relationships: one related to labor market performance –as the push theory states– and a second hypothesis depending on the opportunities for profit –pull hypothesis–. By using the business confidence index and the unemployment rate as indicators of these two dimensions, we provided evidence on: (1) turning points dating of self-employment rate time series to establish a self-employment cycle; (2) the characteristics of the cycle phases; (3) an analysis of the synchronization between the self-employment cycle and the cycles of unemployment and business confidence; and (4) a non-linear causality analysis between these sets of variables. In some extent these results qualified the previous ones and open a new domain in this kind of literature: the search of leading indicators for monitoring and forecasting the self-employment evolution during the business cycle. Furthermore, the analysis of the self-employment dynamics and co-movements in a cross-country framework may be included in a future research agenda.

The second one addressed the persistence in self-employment and the cyclical effects in a single framework. Firstly, we reported evidence of unit roots and secondly, we estimated an unobserved components model for testing the existence of hysteresis in the self-employment rate in the United Kingdom. The results provided robust evidence of hysteresis in entrepreneurship. These results indicate that policies to promote entrepreneurship and self-employment income support schemes have long-term effects in the UK. In any case, further research is needed to determine whether it is different national and institutional conditions, or structural changes which lead to different findings.

The third part of this dissertation focused on the determinants of self-employment and the productivity of self-employed workers across countries.

The first work included in this part, provided empirical evidence on the drivers of self-employment in a new harmonized and much larger dataset than in the available empirical literature, including 117 countries observed 15 periods and a set of 21 potential entrepreneurship determinants. As usual in prior related literature, joint to our focus variable –the economic development proxied by GDP per capita– a large battery of control variables is also included –e.g., GDP components, institutions, human capital, openness, and technological progress, among others–. To circumvent problems associated to model uncertainty we adopted a Bayesian model averaging approach for panel. Our results provide a new explanation of the cross-country differences in the level of self-employment. We show that the unemployment rate, the frictions in the labor market and the stage of economic development are strong determinants of self-employment across the 117 countries included in our sample. Other potential drivers are not significantly correlated with self-employment.

The second paper of this second part applied the same approach, focusing on the effects of the greater or lesser employment protection legislation stringency in conjunction with compliance/enforcement. We provided empirical support to the following hypothesis: employment protection legislation can either boost or contract the self-employment rate depending on the degree of practical compliance with employment legislation. Our results indicate that the relationship between entrepreneurship and labor market rigidity might be affected by the rule of law, i.e., on the degree of compliance of the employment protection laws, at least for solo self-employed workers. This result can help us to understand the existence of mixed evidence and controversies on the relationship between the role of labor market institutions as an inhibitor or driver factor of entrepreneurship.

The last work reexamined the diversity in the level and dynamics of the self-employment rate across countries, in terms of productivity. To this end we applied a non-conventional approach based in a Bayesian clustering which allows to reveal, not only homogeneous groups in terms of the national entrepreneurship productivity, but also the factors that rule the transition from a group to a more productive one. By using a new and more complete dataset that covers a wide range of countries –including less developed, developing and developed countries–, our results point to the existence of three groups in terms of the entrepreneurship productivity. There are many parallels between these groups and the so-called factor- efficiency- and innovation-driven economies. The main contributions of this paper were the identification of groups of countries on the basis of the productivity of their self-employment sectors, the determinants of the membership to a particular group of countries, and more importantly, how different factors affect the probability of transition between groups. Taken together, these results should guide the shift towards policy for entrepreneurial economy, taking the quality of self-employment as a focal point.

Limitations and further extensions

This dissertation has explored new strategies for studying the self-employment macro-dynamics. In particular, we provided frameworks for dating and studying the characteristics of self-employment cycles, for analyzing causality relationships between the entrepreneurship cycle and the business cycle/unemployment cycle, and for exploring the hysteresis phenomenon in self-employment.

Future work could include the fruitful application of the methodologies used to a broader range of countries, looking for common and idiosyncratic underlaying factors. In addition, it is a fact that we cannot rule that our results could be biased depending on the relative weight of different types of self-employed workers in the national entrepreneurship composition, i.e., different sources of heterogeneity into self-employment. For this reason, we should also seek the differences by decomposing the aggregate self-employment rate into different types –i.e., between genuine and non-genuine or necessity/opportunity entrepreneurs, among others– in order to determine whether the observed dynamics is given due to sample composition issues and/or non-consideration of heterogeneity.

On the other hand, and in any of the exercises, including the cross-country analyses in the second part of this thesis, we have faced a trade-off in which we have had to sacrifice observation units or time dimension depending on the availability of the indicators used either as focus variable or as controls, and in which we have even conditioned the very operationalization of the concept of entrepreneurship. Therefore, we are aware that it is necessary to apply these analyses to different samples with alternative indicators that allow us to test the robustness of our results or to qualify them. Likewise, the analysis should be extended to the analysis of other drivers, for which the evidence is mixed, and their interactions: trade openness or the determinants of market power (brands and patents) are two candidates in this regard.

We are aware of the usefulness of the data-driven classifications implemented in this thesis as a basis for contrasting theoretical models on the dimensions that define an entrepreneurial economy and on how to design strategies that foster the transition from a managed economy to a knowledge-based entrepreneurial economy, and move to the group of economies that lead international growth. However, we believe that our analysis is a starting point that should be extended in at least two directions: the first is related to the quality of the indicators used to capture the dimensions that define the differences between the model of the entrepreneurial/innovation, the managed/efficiency and the factor-driven economy; and the second is related to the inclusion of other proxies of self-employment.

Focusing on the first aspect, the use of variables traditionally used at the macro-level to capture dimensions such as education or innovation is increasingly questionable. Indicators of investment effort (spending on education or R&D over GDP) or performance (educational attainment, patents, brands) are not very appropriate in this context. The processes of technological and/or commercial leadership in today's world are largely linked to leadership in the development of digitalization and the STEM world. In other words, it is the weight of these competencies in educational attainment and the fact that the holders of these competencies become entrepreneurs, that are determining factors of market power and of being closer to becoming an entrepreneurial knowledge-based economy.

The search for and use of more precise indicators on the availability of these competencies, probably in multilevel analysis, may shed new light on these conjectures.