Entrepreneurship and business cycles: Global evidence

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15 February 2025

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Abstract

This study examines the interplay between business cycles and entrepreneurship using data from 172 countries spanning 1990 to 2022. We employ the State Space model, panel vector autoregressive models, and the Granger non-causality tests and unravel three key insights. First, entrepreneurship exerts hysteresis, albeit with weak persistence. Second, entrepreneurship exhibits a countercyclical relationship with business cycles measured by both output and unemployment cycles, suggesting that high unemployment during global recessions may push individuals to start new businesses. These countercyclical results remain robust to structural breaks across different sub-sample periods. Third, entrepreneurship acts as a lagging indicator of business cycles, meaning changes in output and unemployment precede changes in entrepreneurial activity. Further analysis indicates that these findings are primarily driven by upper-middle and high-income countries. We conclude by discussing the policy implications of these results and outlining promising directions for future research.

Keywords: business cycles, entrepreneurship, self-employment, unemployment, economic growth

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1. Introduction

Amidst the intertwined global economic and financial crises and their resulting recessions, economists and policymakers have increasingly focused on understanding the role of entrepreneurship in either stimulating recoveries or stabilising economies (Audretsch et al., 2007; Carmona et al., 2012; Fritsch et al., 2015). This resurgence of interest stems from substantial evidence linking entrepreneurship to job creation and economic growth (Audretsch & Acs, 1994; Audretsch & Keilbach, 2008; Faria et al., 2010), which governments worldwide view as a critical solution to unemployment challenges. For instance, a World Bank report on Micro, Small and Medium Enterprises (MSMEs) (2019) revealed that about 322 million formal MSMEs employed 72 per cent of private sector workers (705 million people). Furthermore, entrepreneurship fosters market competition (Aghion & Howitt, 1992), which in turn spurs technical innovations that contribute to long-term economic growth (van Stel et al., 2005; Audretsch & Keilbach, 2008).

These important roles emphasize the centrality of entrepreneurship in economic policy. For decades, governments and international development agencies have implemented strategies to encourage the unemployed to venture into entrepreneurship (Congregado, Golpe, & Carmona, 2010; Klapper et al., 2014). The success of such policies is often measured by the ability of individuals to sustain self-employment over the long term or evolve into job creators. However, a significant challenge lies in the timing of these interventions. Policies are frequently introduced during economic crises, yet research indicates that individuals transitioning from unemployment to entrepreneurship during downturns face lower survival rates (Millán et al., 2014). Only a small fraction become job creators, and an even smaller proportion remain self-employed once the economy recovers (Millán et al., 2012). Consequently, understanding how entrepreneurship responds to or causes business cycles is crucial for designing effective policies that foster job creation or mitigate the adverse effects of economic fluctuations.

Building on foundational studies by Koellinger and Thurik (2012), Klapper et al. (2014), and Parker et al. (2012a, 2012b), this study explores the intricate relationship between entrepreneurship and business cycles. Specifically, we address key questions: whether macroeconomic shocks have transitory or permanent effects on the natural rate of entrepreneurship, the debate surrounding the procyclicality or countercyclicality of entrepreneurial activity, and whether entrepreneurship serves as a lagging or leading indicator of business cycles. Our research contributes to this discourse by analyzing the global economy and selected economic and geographic units for more than 30 years. Unlike previous studies, which often focused on single-country analyses of entrepreneurship time series, this study employs a comprehensive panel dataset over an extended period. Additionally, it incorporates the possibility of structural breaks, examining their impact on results across different sub-periods. Unlike Congregado et al. (2012a) and Tubadji etal (2016), we also test the hysteresis of entrepreneurship with global data for the first time.

Extant literature presents mixed and often complex evidence on the relationship between entrepreneurship and business cycles (Schumpeter, 1942; Francois & Lloyd-Ellis, 2003; Rampini, 2004; Congregado et al., 2012a; Klapper et al., 2014) as well as unemployment rates (Ghatak et al., 2007; Faria et al., 2010). Scholars have long debated whether individuals are more likely to become entrepreneurs during economic booms or recessions, and whether high (or low) unemployment rates push (or pull) people into starting new businesses (Congregado et al., 2012b). Additionally, studies highlight the potentially procyclical nature of entrepreneurship (Koellinger & Thurik, 2012; Aubry et al., 2015) and explore whether new business creation acts as a lagging or leading indicator of macroeconomic fluctuations (Parker et al., 2012b; Sanchis Llopis et al., 2015). These discussions underscore the nuanced and multifaceted dynamics between entrepreneurship and economic cycles.

To contribute to this debate, we first examine the long-term evolution of entrepreneurship, as its effects on economic growth and job creation often manifest over a decade (Carree & Thurik, 2008; Fritsch & Mueller, 2008). A critical question is how economic or policy shocks affect the natural rate of entrepreneurship over time. While much of the background is influenced by insiders-outsider dynamics in labour market literature (Blanchard & Summers, 1986; Jaeger & Parkinson, 1994), studies addressing this question evaluate whether entrepreneurship follows a trend-stationary or non-stationary path (Parker et al., 2012a) If trend-stationary, shocks are assumed to have temporary or transitory effects, with rates of entrepreneurship eventually reverting to their long-run natural rate. Conversely, a non-stationary trend implies that shocks can have permanent effects, (i.e. hysteresis), where shocks permanently alter the natural rate of entrepreneurship (Congregado et al., 2012a; Tubadji et al., 2016). This is closely tied to the "state dependence" property of entrepreneurship, which posits that current self-employment is a strong predictor of future self-employment (Henley, 2004; Fritsch & Mueller, 2007). Both outcomes have varying effects on entrepreneurship and consequently, economic policy. In their empirical analysis, Congregado et al. (2012a) and Tubadji et al., (2016) found evidence of hysteresis in Spain but not for USA, while Parker et al. (2012a) found that entrepreneurship exhibited persistence. To this end, we explore whether economic shocks have transitory or permanent effects on entrepreneurship.

Next, we explore the entrepreneurship-business cycle nexus. Early theoretical frameworks by Schumpeter (1942), Shleifer (1986), Bernanke and Gertler (1989) lean toward procyclicality. For instance, Schumpeter’s concept of "creative destruction" views entrepreneurship as episodic innovation-driven disruptions that generate macroeconomic fluctuations, resulting in a procyclical relationship (Schumpeter, 1942). Shleifer (1986) emphasizes the simultaneous implementation of inventions, boosting labour demand and output during booms. Bernanke and Gertler (1989) highlight the role of entrepreneurs' balance sheets, enabling them to secure loans during expansions for investments that further fuel growth.

In contrast, the contemporary line of literature proposes the countercyclical nature of entrepreneurship. For instance, Francois and Lloyd-Ellis (2003) critique Shleifer's assumptions, proposing that entrepreneurs can produce and store output during recessions and market it during expansions, leading to countercyclical entry. Similarly, the "recession push" hypothesis (Ghatak et al., 2007) suggests that high unemployment and lower wages during downturns push individuals into entrepreneurship, supporting countercyclicality (Thurik et al., 2008). Recessions often reduce labour costs, rents, and opportunity costs, encouraging necessity-driven entrepreneurship (Fairlie, 2011; Congregado et al., 2012b). Thus, we examine whether the relationship between entrepreneurial activities and business cycles is procyclical or countercyclical.

Theories also diverge on whether entrepreneurship lags, leads, or is contemporaneous with business cycles. Shleifer's model suggests contemporaneity with booms, while Francois and Lloyd-Ellis (2003) argue it leads the business cycles. Bernanke and Gertler (1989) posit that the business cycles lead entrepreneurship, which then perpetuates economic conditions. Rampini (2004) views entrepreneurship as a lagging indicator, while Ghatak et al. (2007) propose bidirectional causality. Empirical studies further complicate the picture, with Caballero and Hammour (1994) and Carmona et al. (2012) finding contemporaneous adjustment to GDP, and Parker et al. (2012b) identifying bidirectional causality. Based on this, we examine whether entrepreneurial activities are leading or lagging indicators of business cycles.

While theoretical predictions vary widely, empirical literature mirrors this complexity, producing mixed and debated results. Studies have extensively examined how entrepreneurship affects economic growth and business cycles (Fritsch & Mueller, 2004; van Stel et al., 2005; Wennekers et al., 2005; Aubry et al., 2015), but research on the reverse causation remains underexplored (Audretsch & Acs, 1994).

The remaining sections are organised in the following order. Section 2 outlines our empirical specifications and data. Section 3 presents results and a litany of other relevant tests, while section 4 concludes the study and outlines promising areas for future studies.

2. Methodology and data

2.1 Empirical specification

This study employs several statistical and econometric procedures, including correlation analysis, panel unit root tests, the panel vector autoregressive (PVAR) model, and the new Granger non-causality tests to investigate the business cycles-entrepreneurship nexus. Previous studies typically analysed the data to capture either global or national trends between the variables. The former explores possible global trends in entrepreneurial activities and how they interact with business cycles, while the latter considers the relationship at national levels. According to Koellinger and Thurik (2012), the two approaches are likely to arrive at different results if entrepreneurial activities are influenced by different factors at the global and national levels. Therefore, the analysis in this study closely reflects global business cycle fluctuations rather than national ones.

Many empirical studies equate a unit root process with hysteresis (Blanchard & Summers, 1986; Jaeger & Parkinson, 1994; Iversen et al., 2008; Parker et al., 2012a) or more formally, we hypothesise that hysteresis in entrepreneurship occurs if the panel series has a unit root. To verify this hypothesis with our data, we use a host of standard panel unit root tests, including Levin et al. (2002) and Im et al. (2003). To control for heterogeneity and cross-sectional dependence (CSD), we also employ Pesaran's (2007) test. Since Jaeger and Parkinson (1994) suggested that the existence of unit root was a necessary but insufficient condition for hysteresis, we further check for robustness by following the procedure in Congregado et al. (2012a). Firstly, we assume that entrepreneurship (S_t) is the sum of its non-stationary natural rate (S_t^N) and the stationary cyclical components (S_t^C), and $S_t = S_t^N + S_t^C$. If we define S_t^N as a random walk and include a term that captures the potential hysteresis effect, we have Eq. (1):

$$S_t^N = \alpha + S_{t-1}^N + \lambda S_{t-1}^C + \eta_t^N \qquad (1)$$

We finalise the specification with the cyclical component of entrepreneurship by writing it as a stationary ARMA(1,1) process with a trend.

$$S_t^C = \alpha + \beta_1 S_{t-1}^C + \beta_2 S_{t-2}^C + \eta_t^C \qquad (2)$$

$$\eta_t^N \sim NID(0, \sigma_t^N),\ \eta_t^C \sim NID(0, \sigma_t^C)$$

Where α is the trend parameter, λ measures the percentage increase in self-employment given a percent increase in the cyclical component of the self-employment rate. In this case, hysteresis occurs when $\lambda > 0$ and the coefficient is statistically significant (Jaeger & Parkinson, 1994). Alternatively, deviations of entrepreneurship from its natural rate will induce permanent shifts in entrepreneurship when λ is significantly different from zero. We estimate Eqs. (1)-(2) with a linear state-space model by maximum likelihood using the Kalman filter.

Next, we turn to correlation analysis by following Burns and Mitchell (1946) and Parker et al. (2012b) to explore the bivariate relationship between business cycles and entrepreneurship, interpreted in the literature as co-movements. This procedure provides early insights on whether entrepreneurship is procyclical or countercyclical and whether it is a *lagging* or *leading* indicator of business cycles, depending on the *sign* and *magnitudes* of the correlation coefficients. Accordingly, a high correlation value at $t + k$ (or $t - k$) suggests that entrepreneurship is either lagging or leading the cycle by k years. However, if the cross-correlation coefficient is highest at $k = 0$, there is a contemporaneous relationship (Parker et al., 2012b).

Further, we study the relationship using the panel vector autoregressive (PVAR) model (Holtz-Eakin et al., 1988; Love & Zicchino,2006; Abrigo & Love, 2016). Reasons for our choice of PVAR include: (i) it helps us to explore the endogenous relationship between our core variables, especially through its impulse response functions (IRF); (ii) the direction of the relationship between business cycles and entrepreneurial activities is identified through granger causality, which helps us to establish possible bidirectional causalities; and (iii) it accounts for unobserved cross-country heterogeneity and removes biased estimations from cross-sectional regressions by accounting for country-fixed effects. For these reasons, previous studies within a similar framework also considered the same technique (see, for example, Congregado et al., 2010; Parker et al., 2012; Koellinger and Thurik, 2012; Klapper et al., 2014 and Fritsch et al. 2014).

To operationalise our variables, we specify the following model from Abrigo and Love (2016) and Yang et al. (2023):

$$Y_{i,t} = \sum_{j=1}^{p} A_{j,j-q}\, Y_{i,t-q} + v_t + \theta_i + e_{i,t} \qquad (3)$$

$$i \in \{1, 2, \dots N(N = 5504)\},\ t \in \{1, 2, \dots T_i(T = 32)\}$$

Where $Y_{i,t}$ denotes the vector of endogenous variables, including self-employment (S), real output (Y), and unemployment (U) cycles, $\sum_{j=1}^{p} A_{j,j-q}$ are kxk matrices of lagged coefficients that also show the cross-effects of the qth lag of the dependent variable on their current observations, v is a time effect vector; θ_i and $\epsilon_{i,t}$ are the $1xk$ vector of panel-specific fixed effects and the idiosyncratic error, respectively; where $E(e_{i,t}) = 0$, $E\left(e_{i,t}'e_{i,t}\right) = \sum e$, and $E\left(e_{i,t}'e_{i,t}\right) = 0\ \forall t > s$.

In a VAR system, all variables are often treated as endogenous, although identifying restrictions can be imposed to separate the effects of exogenous shocks on the system (Abrigo and Love, 2016). The PVAR system used in this study assumes that the panel is homogenous. Its parameters can either be estimated by fixed effects or by OLS. However, the presence of the lagged dependent variables on the R.H.S. of the system introduces bias (Nickell, 1981), even when N gets larger, and Judson & Owen (1999) have found the bias to be significant even when $T = 30$. Also, estimating Eq. (3) by OLS can lead to bias in the estimates due to country and time effects (θ_i, v_t). To address the bias, a common approach is to transform the model, via the first difference approach, and eliminate the fixed effects before employing the GMM with lagged variables as instruments and forward orthogonal deviations to avoid data loss using the following procedure (Arellano & Bover, 1995): $\forall y_{i,t} \epsilon Y_{i,t}$,

$$y_{i,t}^* = \left(y_{i,t} - \overline{y}_{i,t}\right)\sqrt{\frac{T_{i,t}}{T_{i,t}+1}} \text{ .... (4)}$$

Where $T_{i,t}$ in Eq. (2) is the number of future observations for the panel i at time t, and $\overline{y}_{i,t}$ is the average of all those observations. Based on Eq. (3), we can develop the following systems of linear equations for the PVAR system, starting with self-employment as the dependent variable:

$$\Delta L(S)_{i,t} = \sum_{j=1}^{p} \beta_{1j}\Delta L(S)_{i,t-q} + \sum_{j=1}^{p} \beta_{2j}\Delta L(Y)_{i,t-q} + \sum_{j=1}^{p} \beta_{3j}\Delta L(U)_{i,t-q} + v_t + \theta_i + e_{i,t} \text{ ... (5)}$$

when output is the dependent variable:

$$\Delta L(Y)_{i,t} = \sum_{j=1}^{p} \beta_{1j} \Delta L(Y)_{i,t-q} + \sum_{j=1}^{p} \beta_{2j} \Delta L(S)_{i,t-q} + \sum_{j=1}^{p} \beta_{3j} \Delta L(U)_{i,t-q} + v_t + \theta_i + e_{i,t} \qquad (6)$$

and when unemployment is the dependent variable:

$$\Delta L(U)_{i,t} = \sum_{j=1}^{p} \beta_{1j} \Delta L(U)_{i,t-q} + \sum_{j=1}^{p} \beta_{2j} \Delta L(Y)_{i,t-q} + \sum_{j=1}^{p} \beta_{3j} \Delta L(S)_{i,t-q} + v_t + \theta_i + e_{i,t} \qquad (7)$$

The setup in Eqs. (3) to (4) enable us to study the forecast error variance decomposition of how shocks affect different variables in the system over 10 years by implementing the PVAR programme by Abrigo and Love (2016). As part of the programme, the Granger causality test is often implemented directly to determine if past values of $x_{i,t}$ "Granger-causes" $y_{i,t}$ (Granger 1969). However, this procedure only establishes the existence of causality without identifying how the factors drive the relationship.

To gain further insights on the predictive causality and feedback between variables in the system over the short run, we perform Granger noncausality tests by following Xiao et al. (2023).

$$S_{i,t} = \phi_{0,i} + \sum_{p=1}^{p} \phi_{p,i} S_{i,t-p} + \sum_{p=1}^{p} \beta_{1,p,i} Y_{i,t-p} + \sum_{p=1}^{p} \beta_{2,p,i} U_{i,t-p} + \epsilon_{i,t} \,..(8)$$

For $i = 1, \ldots, N(= 172)$, and $t = P + 1, \ldots T(= 32)$.

$S_{i,t}$, $Y_{i,t}$, and $U_{i,t}$ are as previously defined.

The procedure in Eq. (6) is based on the method of testing the null hypothesis of no Granger causality developed by Juodis et al. (2021). Unlike the one implemented in Abrigo and Love (2016), this procedure is valid in models with both homogenous and heterogeneous coefficients. Heterogeneity is an important feature that typifies the kind of data we are analysing in this study, which Holtz-Eakin et al.'s (1988) process only weakly accounts for. The method also makes use of the half-panel jackknife (HPJ) procedure in correcting for the Nickel bias of the pooled estimator, which is effective with a large number of panel units, moderate time dimensions, and heterogeneous nuisance parameters. Using the Bayesian information criterion (BIC), it allows for manual or automatic lag-length selection (p) in Eq. (8), cross-sectional dependence and heteroskedasticity in the idiosyncratic errors. Our findings in Table 1 revealed the prevalence of CD and heteroscedasticity, which should be considered in the analysis.

The first advantage of the Granger causality test over Holtz-Eakin et al.'s (1988) procedure is that the GMM approach in the latter leads to instrument proliferation even when T is moderately large, which potentially renders the results highly inaccurate. Additionally, results in the former may not even be asymptotically valid when feedback based on past own values is heterogeneous. Although Dumitrescu and Hurlin's (2012) Granger causality test does account for heterogeneous slopes, the test statistics are only theoretically justified when N is sufficiently large and T is small, making the approach susceptible to substantial size distortions (Xiao et al., 2023). Finally, Monte Carlo experiments by Juodis et al. (2021) revealed that their Granger noncausality test had a power superiority over the Dumitrescu and Hurlin (2012) procedure.

We implement this procedure to investigate the type of temporal relationship between entrepreneurial activities and business cycles (output and unemployment). During the analysis, we tested whether output and unemployment cycles Granger-caused self-employment within a multivariate framework. We also considered univariate tests by modelling self-employment as a function of output and unemployment cycles, separately. We also extend the analyses into sub-samples of LICs, LMICs, UMICs, and HICs.

2.2 Data

We construct a global panel dataset spanning 172 countries and a period of 31 years (1991-2022) to provide comprehensive insights on the interplay between business cycles and entrepreneurship. The present dataset is the most comprehensive of all previous studies, covering major events such as the Asian financial crisis in 1998, the 2008 global financial crisis, and recently, the COVID-19 pandemic. The panel was sorted by year and countries dropped if they had missing observations for more than four continuous years. The final number of countries retained for the analysis is 172 of which 21 were LICs, 47 were LMICs, 46 were UMICs, and 58 were HICs. The full sample had 5,504 observations with 672 in LICs, 1,504 in LMICs, 1,472 in UMICs, and 1,856 in HICs.

A major bone of contention in the literature is how to qualify and quantify entrepreneurship. As a multidimensional concept, it assumes several roles and activities, including risk taking, arbitrage, and innovation (Iversen et al., 2008), which are difficult to measure with a single variable. The three most common measures in cross-country studies include: (i) self-employment rates (Faria et al., 2010; Parker et al., 2012b), the number of newly registered businesses (Fritsch et al., 2014), and entry density or the number of newly registered businesses per 1, 000 people aged 15–64 per year (Klapper et al., 2014). Although none of these is a perfect measure of entrepreneurship, we utilise self-employment rates ($S_{i,t}$) as our key measure in this study. Our choice is based on its extensive use in empirical studies, data availability, and ease of comparing self-employment between countries over time. Additionally, it has the advantage of inclusiveness and convenience (Parker et al., 2012b), and by being owners of their businesses, the self-employed closely mirror key features that define entrepreneurship and the entrepreneurship culture of different countries in our sample (Iversen et al., 2008). However, a pitfall of the index is that it also includes several smaller, informal, less innovative ventures, and long-established businesses. Therefore, self-employment under-sampled dynamic entrepreneurs (Parker et al., 2012b).

Based on previous studies by Koellinger and Thurik (2012) and Fritsch et al. (2014) that defined business cycles as a series of deviations from long-term trends, we measure business cycles with cyclical components of Real output ($Y_{i,t}$) and unemployment rates ($U_{i,t}$). There is a vast theoretical literature that links business cycles (measured with growth or unemployment) and entrepreneurship (Rampini, 2004; Ghatak et al., 2007). Employing both measures gives us further insights about the data, and it is consistent with previous studies by Koellinger and Thurik (2012), Parker et al. (2012b), and Aubry et al. (2015). GDP results are based on real output at constant prices (2015 US dollars)[1]. Data on self-employment, GDP, and unemployment is collected from the World Development Indicators.

Following conventional literature (Carmona et al., 2012; Aubry et al., 2015; Fritsch et al., 2015), we decompose all three variables into trends and cycles using the Hodrick-Prescott filter (Hodrick & Prescott, 1997), hereafter referred to as the HP filter. Given the panel nature and annual observations of the data, the smoothing parameter (λ) of the filter, which penalises acceleration in the trend relative to the business cycle component, is specified as 100. Detrending the data with a λ value of 6.25 as suggested by Ravn and Uhlig (2002) yielded similar results, suggesting that it was not sensitive to the method of detrending. Before implementing the HP filter, we used the Inverse Hyperbolic Sine Transformation to log-transform our data[2] because it can handle transformations with negative and zero values.

[1] We also experimented with output at current prices and found no difference in the overall conclusions about the trajectory of business cycles.

[2] $\bar{x} = arcsinh(q) = \ln(q + \sqrt{q^2 + 1})$

3. Results

3.1 Summary Statistics

Table 1 summarises the descriptive statistics for the logs of self-employment, output, and unemployment cycles. The minimum and maximum values indicate the minimum contractions (recessions) and maximum expansions (booms) in the global economy. For instance, self-employment was approximately 37.4% below its trend, which represents a significant downturn. Similarly, the maximum value of 0.264 represents the highest point at which self-employment reached 26.4% above the trend. Despite these fluctuations, the standard deviation of 0.032 suggest that the overall deviation of the cyclical component of self-employment from its trend was modest at approximately 3.2%.

The short-run fluctuations are more conspicuous in output cycles, reaching 60.9% below trend and 66.5% above trend or during expansionary periods. However, the fluctuations of output cycles remain modest in terms of the standard deviation, which is 5.5%. The largest fluctuations are uncovered with unemployment cycles, which reached 122% lower than the trend rate and 81.9% above the trend. Overall, its standard deviation shows that the percentage of volatility around the trend for the unemployment cycle in the global economy of 13.2%.

We perform a series of diagnostics to determine the underlying characteristics of the data. First, we test for cross-sectional dependence (CSD) using Pesaran and Frees tests, which reject the null of CSD at the 1% level. We attribute this correlation of residuals across countries to the spillover effect of business cycles, since the global economy is highly integrated through international trade in goods and services and supply chain networks. There is also evidence of heteroskedasticity and autocorrelation. PVAR robustly addresses these challenges. Finally, results from the Kao and Pedroni tests support the existence of long-run relationship between the variables. Therefore, our data is suitable for further analysis in this study.

<<Insert Table 1: Summary statistics and preliminary diagnostics >>

3.2 Results of panel unit root and ARMA (1,1) State Space model

Next, we turn to panel unit root and stationarity tests to verify the presence of hysteresis. The methods determine whether shocks have transitory or permanent effects on the natural rate of entrepreneurship. According to the Harris-Tzavalis, Breitung, and Im et al.'s (2003) results in Table 2, global entrepreneurship follows a unit root process, and therefore, fail to reject the null of hysteresis. However, this conclusion appears inconsistent under the Levin et al. (2002) and Hadri tests, including Pesaran's (2007) procedure that controls for heterogeneity and CSD. While the former rejects the null of hysteresis at all conventional levels, the latter tips towards transitory effects of shocks on the natural rate of entrepreneurship at the 1% level.

<<Insert Table 2: Panel unit root tests>>

We present results from the State Space model in Table 3. Since State Space models are traditionally designed for time series analysis and initial attempts to estimate the models at country levels and average the outcomes to arrive at the final verdict about hysteresis resulted in many countries not converging, we collapsed the data (stack) into a single time series and assumed that it has a common dynamic structure. This procedure essentially ignores potential heterogeneity across countries, but since our objective is to capture the global dynamic process of entrepreneurship, we find this a plausible strategy to circumvent the challenge.

We experimented with several forms of the models and the best one was ARMA (1,1) with trend. This was because it produced the lowest Akaike Information Criterion (AIC) and the best autocorrelation function (ACF). The coefficient of λ (0.170) is positive, albeit small but statistically significant. It implies that a 1% increase in the cyclical component of entrepreneurship leads to a permanent increase in its natural rate by 0.170%, although with weak persistence. Further scrutiny of the half-life showed that shocks to the growth of entrepreneurship fade away after 0.58 years ($ln(0.5/ln(0.170))$). The trend parameter shows that entrepreneurship slightly drifts downward per year by −0.0023%. Figure 1 shows this evolution, where the natural rate of entrepreneurship follows the actual rate quite closely.

<<Insert Table 3: State-space model results >>

<<Insert Figure 1: State-space model results >>

To get a better picture of the business cycles-entrepreneurship nexus over time, we collapsed the cross-country observations after detrending the original data to arrive at a time series of the world economy from 1991 to 2022. Figure 1 plots the decomposed cyclical components of output and unemployment cycles against self-employment cycles. The figure shows considerable short-run fluctuations in the variables around a stable mean value of zero. Points below the origin correspond to recessionary periods, while those above correspond to periods of economic growth. Upon examining Figure 1, it is observed that the cycles of self-employment and output exhibit an inverse relationship in panel (a), suggesting the potential countercyclicality of entrepreneurship. Figure 1(b) seem to portray a direct linear link with unemployment, also pointing to a potentially countercyclical relationship.

<<Insert Figure 2: Cyclical components of self-employment, GDP, and unemployment rates (HP filtered data with λ=100): 1991—2022 >>

To gain more insights from the graphical analysis, we turn to correlation and perform the analysis between the multiple HP filtered series at four lags and leads and present the results in Table 4. We note that the correlation coefficients are infinitesimally close to zero, indicating extremely weak linear relationships. Considering the co-movements between entrepreneurship and output in the first row, the coefficients indicate that entrepreneurship is countercyclical with respect to output cycles. The negative correlation coefficients at the first three lags imply that entrepreneurship decreases when output is high or increases when it is low. The lead analysis shows that the countercyclicality persists for the first two leads before reversing at the third and fourth leads. Therefore, entrepreneurship becomes procyclical at longer horizons. Regarding unemployment cycles in row 2, the results follow a similar pattern with entrepreneurship shifting from a countercyclical to a procyclical relationship over longer horizons with unemployment cycles. Finally, the correlation coefficients are highest at $k = 0$, suggesting a contemporaneous relationship between entrepreneurship and business cycles. Since the time period is long (1991-2022), it is possible that the series undergo structural breaks, and consequently, shifts in the relationships. To establish more conclusive results, we turn to PVAR estimates and Granger causality tests in the next section, and also explore the possibility of structural breaks subsequently.

<<Insert Table 4 Correlation between self-employment, output, and unemployment cycle (Hodrick-Prescott filter)>>

3.3 Panel vector autoregressive (PVAR) results

Given that the HP filtered series are stationary, we explore the joint relationships between entrepreneurship, output, and unemployment cycles within the panel autoregressive context with two lags and present results in Table 5. Beginning from column (1), where self-employment is the dependent variable, we uncover mixed results over different periods. The previous period self-employment and output cycles have significant effects on current self-employment cycles. The negative and significant effect in the first lag reinforces our previous conclusion about a possible *countercyclical* relationship between entrepreneurship and output cycles, although the sign turns positive and the error margin increases to 10% at the second lag ($Y_{(t-2)} = 0.016$). In column (2), where output is the dependent variable, the previous period output cycle is a significant determinant of current output, while unemployment is also significant at the second lag. In column (3), previous output and unemployment are significant determinants of current unemployment. Therefore, the results show that there is a unidirectional relationship running from output to self-employment and unemployment cycles. Entrepreneurship is also a *lagging indicator* since it appears to be reacting to changes in previous business cycles without predicting them.

<<insert Table 5 Results of PVAR>>

The PVAR results in Table 3 are predicated on the ability to choose an optimal lag order for the analysis. Whereas including more than the required lags can lead to model overparameterization and corresponding inefficient estimates, retaining less than the required lags could also bias the results due to omitted variables and make the model unable to fully capture the system's dynamics. We followed the criteria suggested by Andrew and Lu (2001) when choosing the optimal moments and lag order by considering the Bayesian Information Criterion (MBIC), Akaike information criterion (MAIC), and the Hannan and Quinn Information Criterion (MQIC) and chose the lags that minimised all three IC. The procedure relies on Hansen's J-statistic of over-identifying restrictions in GMM to identify consistent moments and lag order, and also reports CD and various MMSC if the model is overidentified.

Table 6 reports the optimal lag order selection from the first to third PVAR model using the first three lags of endogenous variables as instruments. In the third PVAR, the model is just identified and only the CD is estimated. Based on the three criteria above, the second-order PVAR model is optimal because it minimises MBIC, MAIC, and MQIC. The second-order PVAR models also fail to reject Hansen's overidentification restriction at the 1% alpha level, indicating that the model is correctly specified.

<<Insert Table 6 Selection order criteria: 1995 - 2022>>

Additionally, we checked the stability of the PVAR estimates by calculating the moduli of eigenvalues of the fitted model. Theoretically, the PVAR system is considered stable if the moduli of the companion matrix are less than one. The analysis led us to conclude that the system was stable, since the moduli of all eigenvalues were entirely less than 1. To strengthen our conclusion, we present the graph of the stability test in Figure 1, showing the roots of the companion matrix inside the circle. Therefore, the PVAR model satisfies the stability condition of all eigenvalues, which is also consistent with results from the Granger causality Wald test that we present subsequently.

<<**insert Figure 3 Variable Stability>>**

3.3.1 Impulse Response Function (IRF)

To circumvent the challenge of potentially ascribing wrong interpretations to results in Table 3, we utilise the impulse Response Function (IRF) and forecast-error variance decomposition (FEVD) to shed light on how shocks affect the system's dynamics over time[3].

The IRF plots show the responses in self-employment, output, and unemployment cycles to shocks in other variables in the system. Figure 3 graphs IRF for each of the variables. The solid lines of each plot are orthogonalized IRF for the corresponding variable for a ten-year period and

[3] According to Abrigo and Love (2016), moment coefficients of the PVAR model in reduced form cannot be interpreted as causality unless identifying restrictions on estimated parameters are applied.

the shaded areas indicate the 95% confidence interval, which is generated from 200 Monte Carlo simulations from the fitted PVAR model. In row 1, the middle graph shows that an unemployment shock causes an increase in self-employment from year 1 to year 3, before it starts declining in year 4 through to the rest of the years. Similarly, an unemployment shock reduces output from year 1 to year 2, rising from years 2 to 5 before the downward spiral continues through the remaining years. The bottom-left graph shows that an output shock led to a continuous increase in unemployment up to year 5, before stabilising for the remaining years.

Regarding the effects of output shocks on self-employment in row 3, the bottom-middle graph shows that an output shock causes an initial decrease in self-employment during the first year, before it turns on an upward trajectory from years 2 to the 7^{th} year. Overall, these results further confirm the countercyclical nature of self-employment with respect to output cycles in the bottom middle graph, and its countercyclicality in the top middle graph.

<<Insert Figure 4 Graphs of orthogonalized IRFs>>

3.3.2 Forecast-error variance decomposition (FEVD)

PVAR assumes that variables ordered earlier have a contemporaneous effect on those following, while variables appearing later affect earlier ones with a lag of one period. In other words, variables appearing earlier are more exogenous, while subsequent ones are more endogenous. Our ordering aligns with theoretical foundations and results of the Granger-causality test in Table 1A (see the Appendix), stressing the importance of fundamental shocks that impact current and future self-employment, output, and unemployment cycles. According to our PVAR model's performance, the variables are ordered as follows: output, self-employment, and unemployment. We complement the preceding analysis from IRF by presenting FEVD that show the cumulative contribution of one co-variate on other variables. Table 7 shows that output shocks explain about 0.080% of self-employment fluctuations in period 10. Similarly, self-employment shocks accounts for around a 2.93% of the output and 0.364% of unemployment fluctuations in period 10. Finally, an unemployment shock explains about 0.524% of self-employment and 10.556% of the fluctuations in output cycles by the 10^{TH} year. A detailed analysis of the 10-year period reveals that unemployment shocks have a stronger influence on entrepreneurship relative to output shocks.

<<insert Table 7 Forecast-error variance decomposition>>

3.4 Granger non-causality tests

This last set of results explores the type of temporal relationship between entrepreneurship, output, and unemployment cycles and determines whether there are bidirectional causalities between entrepreneurship and business cycles. Table 8 presents the Granger noncausality test results. Self-employment, output and unemployment are the dependent variables in columns (1), (2) and (3), respectively. We can see that the null hypothesis that output and unemployment do not Granger-cause self-employment is rejected in column (1) at the 1% level of significance. This is revealed by the p-value of the Wald test of the Half-Panel Jackknife Statistic. Additionally, HPJ bias-corrected pooled estimates are reported, and the regression coefficients reveal that the test outcome is driven by both output cycles and unemployment cycles. In this case, a percent increase in previous output is associated with a decrease in current self-employment by 0.034%, while a percent increase in previous unemployment also predicts a current increase in self-employment by 0.013%. The negative and positive coefficients of output and unemployment cycles further support the countercyclicality of entrepreneurship documented in the preceding analyses. However, the coefficient of self-employment is insignificant in columns (2) and (3). Since self-employment reacts to changes in previous output and unemployment, but does not predict future output and unemployment cycles, we conclude that entrepreneurship is a *lagging indicator* of output and unemployment cycles. In column (2), we fail to reject the null hypothesis that unemployment and self-employment do not Granger-cause output cycles, and in column (3), we reject the null hypothesis that output and self-employment do not Granger-cause unemployment cycles at the 1% level of significance. The latter results in the unemployment equation are again driven by output cycles. Throughout the analysis, our modelling allowed for a maximum of four possible lags of the dependent and independent variables. Based on the BIC for the full sample in Table 5, the optimal number of lags equals 1.

<<Insert Table 8 Granger noncausality tests: self-employment, output, and unemployment in the global economy>>

4. Robustness check

To further explore our data, we split the sample into four groups following the World Bank classification by income level, constituting HICs, UMICs, LMICs, and LICs. Table 9 presents the complete results by sub-samples. Again, we allowed for a maximum of four lags for all variables in the modelling. In HICs, we rejected the null hypothesis that output and unemployment cycles do not Granger cause self-employment at the 1% level in column (1) and further uncovered from the regression coefficients that the results were driven by output cycles. Again, the coefficient of $Y_{(t-1)}$ of -0.097 supports our initial findings of a countercyclical relationship, and that entrepreneurship is a lagging indicator.

In LICs and LMICs, we fail to reject the null hypothesis that output and unemployment cycles do not Granger-cause self-employment. However, column (4) shows that unemployment cycles are positively associated with self-employment and the coefficient is significant at the 10% level. This relationship is consistent with the *countercyclicality* of entrepreneurship and unemployment observed earlier in the analysis. Finally, output and unemployment cycles Granger cause self-employment in UMICs, and once again, the relationship is driven by output cycles. The results remain consistent with previous findings, especially in column (12) where output cycles are the main driver of the Granger causality test results in its unemployment model.

<<insert Table 9 Granger noncausality tests: self-employment, output, and unemployment in different sub-samples >>

The preceding analysis show that entrepreneurship has a countercyclical relationship with business cycles. However, Parker et al. (2012a) found that such results could be sensitive to multiple structural breaks. In line with their procedure, we applied the Bai & Perron (1998) tests for structural breaks and detected three breakpoints with output cycles (2006 (I), 2012(II), 2018(III)), but no breaks with the unemployment cycles (See Appendix Table 2A). Given the existence of structural breaks in the entrepreneurship-output nexus, it behoves to re-estimate separate VAR models for the four sub-periods identified by the tests over which cyclical relationships could possibly vary (1991(II)-2005(IV); 2006(I)-2012(I); 2012(II)-2018(II); and 2018(III)-2022(III)). However, we were unable to proceed with the PVAR analyses due to the limited number of years over the included sub-periods.

Since conclusions from correlation analysis were mostly consistent with those from the PVAR, we re-estimated bivariate correlations between entrepreneurship and output cycles with four lags and leads (see Burns and Mitchell (1946) and Parker et al., (2012b)), and summarised the results in Table 7. Our findings were generally congruent with the hypothesis that entrepreneurship maybe sensitive to structural breaks. In sub-period 1(1991(II)-2005(IV), entrepreneurship is countercyclical but the relationship changes to procyclical over a longer horizon. In sub-period II (2006(I)-2012(I), the relationship is countercyclical. In Sub-period III (2012(II)-2018(II), entrepreneurship is also countercyclical. In Sub-period 1V (2018(III)-

2022(III)), however, entrepreneurship is procyclical during the early phase of the cycle. In a nutshell, our results show that entrepreneurship acts as a stabiliser during recessions, increasing when output is low, but aligning with output growth over a longer period.

<<Insert Table 10 Bivariate correlation between entrepreneurship and business cycles at different sub-periods>>

5. Discussion of results

The recent wave of overlapping global economic crises has prompted researchers to re-examine the role of entrepreneurship in addressing unemployment during recessions (Stel et al., 2005; Wennekers et al., 2010). However, the precise nature of this relationship on a global scale remains contested. This study employs a range of econometric methods to explore three key questions: (1) whether economic shocks have transitory or permanent effects on entrepreneurship, (2) whether the relationship between business cycles and entrepreneurship is countercyclical or procyclical, and (3) whether entrepreneurship acts as a lagging or leading indicator of business cycles.

Regarding the first question, the study finds that shocks have permanent effects on entrepreneurship. Therefore, we failed to reject the null of hysteresis. The results are robust to different stationary tests, including the Harris-Travis, Breitung, Im et al. (2003), Fisher-type ADF, Hadri LM approaches, and the ARMA (1 1) State Space model. Therefore, the most robust results support hysteresis of entrepreneurship in the global economy with weak persistence, since shocks may permanently adjust its natural rate. Previous studies by Parker and Robson (2004), Henley (2004), Fritsch & Mueller (2007) found that entrepreneurship followed a unit root process. While Parker et al. (2012a) rejected the null of hysteresis while finding entrepreneurship exhibited persistent effects, our findings align more closely with Congregado et al. (2012a) and Tubadji et al. (2016), who also found that shocks triggered permanent changes in the natural rate of entrepreneurship.

Our results also support the concept of "state dependence" in self-employment (Henley, 2004), which posits that current self-employment status is the best predictor of future self-employment. This suggests that shocks lead to permanent adjustments in entrepreneurship. For instance, if a recession augments the natural rate of entrepreneurship (e.g., necessity-driven startups), the level stays elevated post-shock, supporting our hypothesis of hysteresis. Since most entrepreneurs face sunk cost, Dixit and Pindyck (1994) explained how shocks—such as the financial crisis or the COVID-19 affect investment under uncertainty. Accordingly, shocks reduce access to finance, increasing exits or deterring entries into markets. Firms that survive may hoard capital after the shocks while new startups face stronger barriers at entry, which permanently reduces the rate of entrepreneurship and creates a new trajectory. Conversely, innovations or post-shock stimulus packages may also permanently increase the natural rate of entrepreneurship.

Drawing inspiration from the insider-outsider dynamics in labour market literature (Blanchard & Summers, 1986), recessions may push individuals to start new businesses out of necessity, but once established, they may never return to wage-paying jobs when economies fully recover, leading to a permanent change in the natural rate of entrepreneurship. Conversely, major shocks may also discourage opportunity entrepreneurs, increasing risk aversion and downshifting the natural rate.

Hysteresis in global entrepreneurship has two key policy implications. First, public policy measures aimed at promoting entrepreneurship—such as incentives, grants, training programs, and regulatory changes—may permanently boost self-employment, creating a lasting impact on its natural rate. Secondly, policymakers must be proactive in mitigating the negative effects of shocks (pandemics, financial crisis) as they can change the trajectory of the natural rate of entrepreneurship by downshifting it (trend = -0.0000231). Some proactive measures may include tax relief policies during recessions or the issuance of emergency credits. These can preserve opportunity entrepreneurship, curb necessity-driven entrepreneurship, and stabilise its natural rate. However, these effects may vary across countries, necessitating targeted policies based on their specific experiences.

For the second research question, the study finds strong evidence that entrepreneurship is countercyclical with output and unemployment cycles. This conclusion is consistent across graphical and correlation analyses, PVAR results, and Granger non-causality tests. In addition to estimating the Granger non-causality tests within a multivariate framework, we further explored causalities for each variable separately within a univariate framework and found that the conclusions remained the same. First, regarding the entrepreneurship-the business cycle nexus, our finding of countercyclicality is consistent with Francois and Lloyd-Ellis's (2003) model which argued that the ability to store output implied that entrepreneurs could produce during recessions and sell during expansionary periods, a separation that incentivises entrepreneurs to enter the market during recessions to take advantage of the reduced cost. Additionally, entrepreneurship in the global economy may be driven by opportunities that arise during recessions rather than solely by growth prospects during expansions.

In contrast, Rampini's (2004) model posits that entrepreneurship is procyclical, rising with economic growth as agents become more willing to take risks. However, empirical evidence challenges this view. High startup failure rates (Hamilton, 2000) and the limited role of risk-return profiles in private enterprise investments (Moskovitz and Vissing-Jørgensen, 2002) suggest that entrepreneurship is not always a rational investment choice, weakening the case for procyclicality.

Second, regarding the entrepreneurship- unemployment nexus, our countercyclical finding suggests that during economic downturns, rising unemployment often forces individuals into self-employment, perhaps out of *necessity*, thereby expanding the pool of entrepreneurs. Conversely, during recoveries, improved labour market conditions—such as increased demand for labour and higher wages—reduce the need for entrepreneurship, leading to the exit of marginal entrepreneurs (Faria et al., 2010; Thurik et al., 2008; Congregado et al., 2012a; Fritsch et al., 2015).

Monetary policy further reinforces this dynamic. During economic booms, the rising cost of capital discourages entrepreneurship, prompting exits from self-employment. In contrast, during recessions, lower capital costs encourage entries into self-employment, aligning with the countercyclical nature of entrepreneurship. These patterns are consistent with the "recession push" and "prosperity pull" effects (Ghatak et al., 2007; Congregado et al., 2012b). Román et al. (2013) highlight that countercyclical startup incentives may facilitate transitions from unemployment to self-employment, though they often favour necessity-driven entrepreneurship over serial entrepreneurship, which tends to decline during recoveries. These findings underscore the importance of tailored entrepreneurship support programs that adapt to different phases of the business cycle to mitigate the adverse effects of recessions.

Regarding our third question—whether entrepreneurship is a lagging or leading indicator of business cycles—the evidence overwhelmingly supports the view that global entrepreneurship cycles respond to business cycle fluctuations rather than causing them. This indicates a unidirectional relationship, with entrepreneurship acting as a lagging indicator of global business cycles. Consequently, proactive policy measures are essential for economic stabilization. Policymakers should prioritise countercyclical monetary and fiscal policies to stabilize output and unemployment, which in turn can foster entrepreneurial activity. Additionally, supporting entrepreneurs through targeted initiatives, such as job creation and training programs during recessions, can help mitigate unemployment and equip individuals to seize business opportunities during economic recoveries.

6. Concluding remarks

This study addresses the critical relationship between entrepreneurship and business cycles—a topic of growing importance as policymakers increasingly view self-employment as a potential solution to global unemployment. By exploring how business cycles influence and are influenced by self-employment, we provide valuable insights into this complex nexus. Our study reveal evidence of hysteresis in entrepreneurship, showing that shocks permanently adjust the natural rate of entrepreneurship, albeit with weak persistence. If a recession boosts entrepreneurship (e.g., necessity-driven startups), however, the new equilibrium level remains permanent post-shock. This underscores the importance of proactive policies in mitigating the negative effects of shocks (pandemics, financial crisis) as further analysis showed they can downshift the natural rate of entrepreneurship. Additionally, the countercyclical relationship between entrepreneurship and business cycles highlights the need for targeted support during recessions to harness the potential of necessity-driven entrepreneurship. Finally, our results confirm that entrepreneurship acts as a lagging indicator of global business cycles, emphasizing the need for proactive policy measures to stabilize economies and foster entrepreneurial activity.

We argue that policymakers should prioritize targeted interventions (subsidies and other incentives) during downturns to help transition necessity-driven entrepreneurs into sustainable self-employment (Millán et al., 2014). Building a resilient entrepreneurial ecosystem capable of weathering business cycles through innovation and economic diversification should also be a key policy goal. Moreover, long-term, sustainable support programs are essential to enable entrepreneurs to thrive across all phases of the business cycle.

While this study provides valuable insights, its limitations offer avenues for further exploration. First, caution is warranted when generalizing global findings to specific countries, as national policies and institutions shape business cycles and entrepreneurship in diverse ways. Much of the existing literature focuses on developed economies (e.g., mostly the U.S., Germany, the U.K., and Spain), leaving a gap in understanding how these dynamics play out in other regions. Future research should examine the differential effects of business cycles across diverse economic contexts.

Second, our reliance on self-employment rates as a measure of entrepreneurship may obscure important distinctions between employers (those who hire workers) and own-account entrepreneurs (those who work independently). These two groups likely respond differently to business cycles. For instance, employers may benefit from economies of scale during expansions, potentially drawing own-account workers into paid employment, while own-account entrepreneurs may be more vulnerable during downturns (Congregado et al., 2012a). Given that most self-employed individuals start without employees (Congregado et al., 2010), future studies should explore how business cycles affect these distinct categories of entrepreneurs.

Finally, a micro-level analysis of entrepreneurship over business cycles would provide deeper insights. Future research could focus on the entry, exit, and survival rates of entrepreneurs across different phases of the business cycle. Utilizing microdata would enable a more nuanced understanding of how various types of entrepreneurships—such as innovative, high-growth ventures versus necessity-driven startups—behave during economic fluctuations. This could inform policies aimed at fostering high-potential entrepreneurship and mitigating the challenges faced by vulnerable entrepreneurs during downturns.

References

Abrigo, M. R., & Love, I. (2016). Estimation of panel vector autoregression in Stata. *The Stata Journal*, *16*(3), 778-804. https://doi.org/10.1177/1536867X1601600314

Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica, 60*(2), 323-351. https://doi.org/10.2307/2951599

Aubry, M., Bonnet, J., & Renou-Maissant, P. (2015). Entrepreneurship and the business cycle: the "Schumpeter" effect versus the "refugee" effect—a French appraisal based on regional data. *The Annals of Regional Science*, *54*, 23-55. https://doi.org/10.1007/s00168-014-0645-x

Audretsch, D. B., & Acs, Z. J. (1994). New-firm startups, technology, and macroeconomic fluctuations. *Small Business Economics*, *6*, 439-449. https://doi.org/10.1007/BF01064858

Audretsch, D. B., & Keilbach, M. (2008). Resolving the knowledge paradox: knowledge-spillover entrepreneurship and economic growth. *Research Policy*, *37*(10), 1697-1705. https://doi.org/10.1016/j.respol.2008.08.008

Audretsch, D. B., Grilo, I., & Thurik, A. R. (Eds.). (2007). *Handbook of research on entrepreneurship policy*. Edward Elgar Publishing.

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 47-78. https://doi.org/10.2307/2998540

Blanchard, O. J., & Summers, L. H. (1986). Hysteresis and the European unemployment problem. *NBER Macroeconomics Annual*, *1*, 15-78. https://doi.org/10.1086/654013

Burke, A., & van Stel, A. (2014). Entry and exit in disequilibrium. *Journal of Business Venturing, 29*(1), 174–192. https://doi.org/10.1016/j.jbusvent.2013.02.004

Burns, A. F., & Mitchell, W. C. (1946). The basic measures of cyclical behavior. In *Measuring business cycles* (pp. 115-202). NBER.

Caballero, R. J., & Hammour, M. L. (1994). The cleansing effect of recessions. *American Economic Review, 84*(5): 1350–1368.

Campbell, J. R. (1998). Entry, exit, embodied technology, and business cycles. *Review of Economic Dynamics*, *1*(2), 371-408. https://doi.org/10.1006/redy.1998.0009

Carmona, M., Congregado, E., & Golpe, A. A. (2012). Comovement between self-employment and macroeconomic variables: evidence from Spain. *Sage Open*, *2*(2), 2158244012448665. https://doi.org/10.1177/2158244012448665

Carree, M. A., & Thurik, A. R. (2008). The lag structure of the impact of business ownership on economic performance in OECD countries. *Small Business Economics*, *30*, 101-110. https://doi.org/10.1007/s11187-006-9007-0

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. https://doi.org/10.1016/j.jpolmod.2010.09.001

Congregado, E., Golpe, A. A., & Parker, S. C. (2012a). The dynamics of entrepreneurship: hysteresis, business cycles and government policy. *Empirical Economics*, *43*, 1239-1261. https://doi.org/10.1007/s00181-011-0516-6

Congregado, E., Golpe, A., & Van Stel, A. (2012b). The 'recession-push' hypothesis reconsidered. *International Entrepreneurship and Management Journal*, *8*, 325-342. https://doi.org/10.1007/s11365-011-0176-1

Dixit, A. K., & Pindyck, R. S. (1994). Investment under uncertainty. Princeton University Press.

Francois, P., & Lloyd-Ellis, H. (2003). Animal spirits through creative destruction. *American Economic Review, 93*(3), 530–550. https://doi.org/10.1257/000282803322156972

Fritsch, M., & Mueller, P. (2004). Effects of new business formation on regional development over time. *Regional Studies*, *38*(8), 961-975. https://doi.org/10.1080/0034340042000280965

Fritsch, M., & Mueller, P. (2007). The persistence of regional new business formation-activity over time– assessing the potential of policy promotion programs. *Journal of Evolutionary Economics*, *17*, 299-315. https://doi.org/10.1007/s00191-007-0056-6

Fritsch, M., & Mueller, P. (2008). The effect of new business formation on regional development over time: the case of Germany. *Small Business Economics*, *30*, 15-29. https://doi.org/10.1007/s11187-007-9067-9

Fritsch, M., Kritikos, A., & Pijnenburg, K. (2015). Business cycles, unemployment and entrepreneurial entry—evidence from Germany. *International Entrepreneurship and Management Journal*, *11*, 267-286. https://doi.org/10.1007/s11365-014-0326-3

Ghatak, M., Morelli, M., & Sjöström, T. (2007). Entrepreneurial talent, occupational choice, and trickle up policies. *Journal of Economic Theory*, *137*(1), 27-48. https://doi.org/10.1016/j.jet.2006.02.007

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424-438. https://doi.org/10.2307/1912791

Hamilton, B. H. (2000). Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy*, *108*(3), 604-631. https://doi.org/10.1086/262131 Henley, A. (2004). Self-employment status: the role of state dependence and initial circumstances. *Small Bus Econ, 22*, 67–82. https://doi.org/10.1023/B:SBEJ.0000011573.84746.04

Hodrick, R. J., & Prescott, E. C. (1997). Postwar US business cycles: an empirical investigation. *Journal of Money, Credit, and Banking*, *29*(1), 1-16. https://doi.org/10.2307/2953682

Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica: Journal of the Econometric Society*, 1371-1395. https://doi.org/10.2307/1913103

Iversen, J., Jørgensen, R., & Malchow-Møller, N. (2007). Defining and measuring entrepreneurship. *Foundations and Trends® in Entrepreneurship*, *4*(1), 1-63. http://dx.doi.org/10.1561/0300000020

Jaeger, A., & Parkinson, M. (1994). Some evidence on hysteresis in unemployment rates. *European Economic Review*, *38*(2), 329-342. https://doi.org/10.1016/0014-2921(94)90061-2

Judson, R. A., & Owen, A. L. (1999). Estimating dynamic panel data models: a guide for macroeconomists. *Economics Letters*, *65*(1), 9-15. https://doi.org/10.1016/S0165-1765(99)00130-5

Klapper, L., Love, I., & Randall, D. (2015). New firm registration and the business cycle. *International Entrepreneurship and Management Journal*, *11*, 287-306. https://doi.org/10.1007/s11365-014-0345-0

Koellinger, P. D., & Roy Thurik, A. (2012). Entrepreneurship and the business cycle. *Review of Economics and Statistics*, *94*(4), 1143-1156. https://doi.org/10.1162/REST_a_00224

Kuznets, S. (1940). Schumpeter's business cycles. *The American Economic Review, 30*(2), 257-271. https://www.jstor.org/stable/1807049

Love, I., & Zicchino, L. (2006). Financial development and dynamic investment behavior: Evidence from panel VAR. *Quarterly Review of Economics and Finance, 46*, 190–210. https://doi.org/10.1016/j.qref.2005.11.007

Millán, J. M., Congregado, E., & Román, C. (2014). Persistence in entrepreneurship and its implications for the European entrepreneurial promotion policy. *Journal of Policy Modeling, 36*(1), 83–106

Millán, J.M., Congregado, E. & Román, C. (2012). Determinants of self-employment survival in Europe. *Small Business Economics, 38*, 231–258. https://doi.org/10.1007/s11187-010-9260-0

Moskowitz, T. J., & Vissing-Jørgensen, A. (2002). The returns to entrepreneurial investment: A private equity premium puzzle? *American Economic Review*, *92*(4), 745-778. https://doi.org/10.1257/00028280260344452

Parker, S. C. (2012). Theories of entrepreneurship, innovation and the business cycle. *Journal of Economic Surveys*, *26*(3), 377-394. https://doi.org/10.1111/j.1467-6419.2012.00728.x

Parker, S. C., & Robson, M. T. (2004). Explaining international variations in self-employment: Evidence from a panel of OECD countries. *Southern Economic Journal, 71*(2), 287-301. https://doi.org/10.1002/j.2325-8012.2004.tb00640.x

Parker, S. C., Congregado, E., & Golpe, A. A. (2012a). Testing for hysteresis in entrepreneurship in 23 OECD countries. *Applied Economics Letters*, *19*(1), 61-66. https://doi.org/10.1080/13504851.2011.566175

Parker, S. C., Congregado, E., & Golpe, A. A. (2012b). 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. https://doi.org/10.1177/0266242612437560

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, *22*(2), 265-312. https://doi.org/10.1002/jae.951

Rampini, A. A. (2004). Entrepreneurial activity, risk, and the business cycle. *Journal of Monetary Economics, 51*(), 555–573. https://doi.org/10.1016/j.jmoneco.2003.06.003

Ravn, M. O., & Uhlig, H. (2002). On adjusting the Hodrick-Prescott filter for the frequency of observations. *Review of Economics and Statistics*, *84*(2), 371-376.

Robson, M. T. (1998). Self-employment in the UK regions. *Applied Economics*, *30*(3), 313-322. https://doi.org/10.1080/000368498325831

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. https://doi.org/10.1016/j.jbusvent.2012.01.004

Sanchis Llopis, J. A., Millán, J. M., Baptista, R., Burke, A., Parker, S. C., & Thurik, R. (2015). Good times, bad times: entrepreneurship and the business cycle. *International Entrepreneurship and Management Journal*, *11*, 243-251. https://doi.org/10.1007/s11365-015-0361-8

Schumpeter, J.A. (1942). Capitalism, Socialism and Democracy. NY: Harper

Shleifer, A. (1986). Implementation cycles. *Journal of Political Economy, 94*(6), 1163–1190. https://doi.org/10.1086/261428

Thurik, A. R., Carree, M. A., Van Stel, A., & Audretsch, D. B. (2008). Does self-employment reduce unemployment. *Journal of Business Venturing, 23*(6), 673-686. https://doi.org/10.1016/j.jbusvent.2008.01.007

Tubadji, A., Nijkamp, P., & Angelis, V. (2016). Cultural hysteresis, entrepreneurship and economic crisis: An analysis of buffers to unemployment after economic shocks. *Cambridge Journal of Regions, Economy and Society*, *9*(1), 103-136. https://doi.org/10.1093/cjres/rsv035

van Stel, A, Carree, M., & Thurik, R. (2005). The effect of entrepreneurial activity on national economic growth. *Small Business Economics, 24*, 311-321. https://doi.org/10.1007/s11187-005-1996-6

Wennekers, S., van Wennekers, A., Thurik, R., & Reynolds, P. (2005). Nascent entrepreneurship and the level of economic development. *Small Business Economics*, *24*, 293-309. https://doi.org/10.1007/s11187-005-1994-8

Yang, R., An, X., Chen, Y., & Yang, X. (2023). The knowledge analysis of panel vector autoregression: A systematic review. *SAGE Open*, *13*(4), https://doi.org/10.1177/21582440231215991

List of Tables

Table 1 Summary statistics and preliminary diagnostics

Descriptive Statistics			
Variable	Self-employment cycle	Output cycle	Unemployment cycle
Obs	5504	5504	5504
Mean	7.06e-12	9.31e-12	-1.35e-11
Std. Dev.	0.032	0.055	0.132
Min	-0.374	-0.609	-1.223
Max	0.264	0.665	0.819
Cross-sectional dependence		**Heteroskedasticity test**	
Pesaran's test of CD	4.566***		
Average absolute value of the off-diagonal elements	0.214	Breusch-Pagan LM test of independence	33454.142***
Frees' test of CD	8.093***	Modified Wald test for groupwise heteroskedasticity	3788970.070***
Serial correlation			
	F (1, 171) = 101.862***		
Kao Test	**Cointegration Test**	**Pedroni Test**	
Modified Dickey–Fuller	-45.920***	Modified Phillips–Perron	-8.019***
Dickey–Fuller	-28.152***	Phillips–Perron	-18.159***
Augmented Dickey–Fuller	-24.979***	Augmented Dickey–Fuller	-20.728***
Unadjusted modified Dickey–Fuller	-50.558***		
Unadjusted Dickey–Fuller	-28.773***		

***Significance at 1% level

Table 2 Panel unit root tests

Method	Statistic
Levin–Lin–Chu	-5.631***
Harris-Tzavalis	0.862
Breitung	2.292
Im–Pesaran–Shin	1.951
Fisher-type	-1.421
Hadri LM test	120.704***
Pesaran (2007)	-4.433 ***

Table 3 State-space model

S_t^N	(1)
S_t^C (λ)	0.1697***
u2. L1	1(constrained)
Constant (α)	-0.0000231***
e.u1(η_t^N)	1(constrained)
e.u1 (η_t^N)	-1***
D.S_t^Nu1	1(constrained)
var(u1)	0.722***
Mean dependent var	4.167
Prob > chi2	0.000
SD dependent var	0.863
Chi-square	4786248.190
Akaike crit. (AIC)	13841.573

*** *p<.01,* ** *p<.05,* * *p<.1*

Table 4 Correlation between self-employment, output, and unemployment cycle (Hodrick-Prescott filter)

Lags in years	$t-4$	$t-3$	$t-2$	$t-1$	$\boldsymbol{t}$	$t+1$	$t+2$	$t+3$	$t+4$
					Global economy				
Output	0.007	-0.034**	-0.089***	-0.154***	-0.173***	-0.091***	-0.014	0.033**	0.065***
Unemployment	0.015	0.042***	0.086***	0.137***	0.152***	0.069***	-0.024*	-0.069***	-0.093***

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Table 5 Results of PVAR

Variables	(1) S	(2) Y	(3) U
$Y_{(t-1)}$	-0.034**	0.679***	-0.138*
	(0.016)	(0.130)	(0.081)
$Y_{(t-2)}$	0.016*	-0.059	0.204***
	(0.009)	(0.055)	(0.056)
$U_{(t-1)}$	0.011	-0.010	0.718***
	(0.011)	(0.018)	(0.064)
$U_{(t-2)}$	-0.001	0.018**	-0.163***
	(0.006)	(0.008)	(0.031)
$S_{(t-1)}$	0.640***	-0.040	0.102
	(0.117)	(0.045)	(0.151)
$S_{(t-2)}$	-0.048	0.020	-0.077
	(0.039)	(0.022)	(0.085)
Observations	4,988	4,988	4,988

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: Panel VAR model is estimated by GMM. Panel and time-fixed effects are removed by outlier test prior proceed to estimation. Heteroskedasticity adjusted t-statistics are in parentheses.

Table 6 Selection order criteria: 1995 - 2022

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.681	96.975	0.000	-55.660	60.975	20.018
2	0.717	12.876	**0.168**	-63.441	-5.124	-25.602
3	0.647	.	.	.	.	.

Table 7 Forecast-error variance decomposition

Response variable and Forecast horizon		Impulse variable		
Output		Output	Self-employment	Unemployment
	0	0	0	0
	1	1	0	0
	2	0.999146	0.000502	0.000353
	3	0.998909	0.000725	0.000366
	4	0.998376	0.000785	0.000839
	5	0.997834	0.000798	0.001368
	6	0.997512	0.0008	0.001687
	7	0.997371	0.000801	0.001828
	8	0.997319	0.000802	0.001879
	9	0.997301	0.000802	0.001897
	10	0.997296	0.000802	0.001902
Self-employment				
	0	0	0	0
	1	0.01265	0.98735	0
	2	0.02182	0.977179	0.001001
	3	0.026497	0.971143	0.00236
	4	0.028429	0.9684	0.003172
	5	0.029082	0.96742	0.003498
	6	0.029268	0.967132	0.0036
	7	0.029314	0.967059	0.003627
	8	0.029324	0.967042	0.003634
	9	0.029326	0.967038	0.003636
	10	0.029327	0.967037	0.003637
Unemployment				
	0	0	0	0
	1	0.088277	0.002913	0.90881
	2	0.105559	0.004738	0.889704
	3	0.104071	0.005214	0.890715
	4	0.103042	0.005243	0.891716
	5	0.103909	0.005233	0.890858
	6	0.104833	0.005238	0.889929
	7	0.105304	0.005245	0.889452
	8	0.105482	0.005248	0.889271
	9	0.10554	0.005249	0.889212
	10	0.105557	0.005249	0.889194

Table 8 Granger noncausality tests: self-employment, output, and unemployment in the global economy

Variables	(1) S	(2) Y	(3) U
$Y_{(t-1)}$	-0.034***		-0.161***
	(0.010)		(0.052)
$U_{(t-1)}$	0.013***	-0.005	
	(0.005)	(0.006)	
$S_{(t-1)}$		-0.002	-0.099
		(0.022)	(0.099)
Observations	172	172	172
HPJ Wald test	26.4346	0.7808	9.7814
P value	0.0000	0.6768	0.0075

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9 Granger noncausality tests: self-employment, output, and unemployment in different sub-samples

	High income countries			Low-income countries		
	(1)	(2)	(3)	**(4)**	(5)	(6)
Variables	**S**	Y	U	**S**	Y	U
$Y_{(t-1)}$	-0.097***		-0.516*	-0.000		-0.019
	(0.037)		(0.273)	(0.011)		(0.043)
$Y_{(t-2)}$			0.321			
			(0.251)			
$S_{(t-1)}$		0.010	0.066		0.376	0.244
		(0.030)	(0.124)		(0.494)	(0.731)
$S_{(t-2)}$			-0.143			
			(0.117)			
$U_{(t-1)}$	0.011	-0.010		0.011*	-0.034	
	(0.008)	(0.010)		(0.006)	(0.029)	
Observations	58	58	58	21	21	21
HPJ Wald test	21.8941	1.0185	9.6661	3.3071	1.4836	0.603
P value	0.0000	0.6010	0.0464	0.1914	0.4762	0.740
	Lower middle-income countries			Upper middle-income countries		
	(7)	(8)	(9)	(10)	(11)	(12)
$Y_{(t-1)}$	-0.011		-0.061	-0.024*		-0.158**
	(0.010)		(0.079)	(0.013)		(0.080)
$U_{(t-1)}$	-0.003	0.014		0.004	0.015	
	(0.009)	(0.013)		(0.011)	(0.010)	
$S_{(t-1)}$		-0.065	0.334		-0.022	-0.135
		(0.062)	(0.210)		(0.030)	(0.133)
Observations	47	47	47	46	46	46
HPJ Wald test	1.3330	2.0149	3.1440	6.3259	2.8668	4.3542
P value	0.5135	0.3652	0.2076	0.0423	0.2385	0.1134

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10 Bivariate correlation between entrepreneurship and business cycles at different sub-periods

$t-4$	$t-3$	$t-2$	$t-1$	$t+1$	$t+2$	$t+3$	$t+4$
Output cycles							
Sub-period 1 (Countercyclical→Procyclical) 1991(II)-2005(IV)							
-0.013	-0.058***	-0.111***	-0.167***	-0.085***	-0.003	0.059***	0.099***
Sub-period II (Countercyclical) 2006(I)-2012(I)							
-0.001	-0.056*	-0.117***	-0.179***	-0.080***	-0.018	0.001	0.043
Sub-period III (Countercyclical) 2012(II)-2018(II)							
0.033	-0.012	-0.053*	-0.127***	-0.129***	-0.019	0.013	0.017
Sub-period 1V (Procyclical) 2018(III)-2022(III))							
-0.060*	0.002	0.077**	0.082**	-0.055	0.036	-0.001	-0.037

LIST OF FIGURES

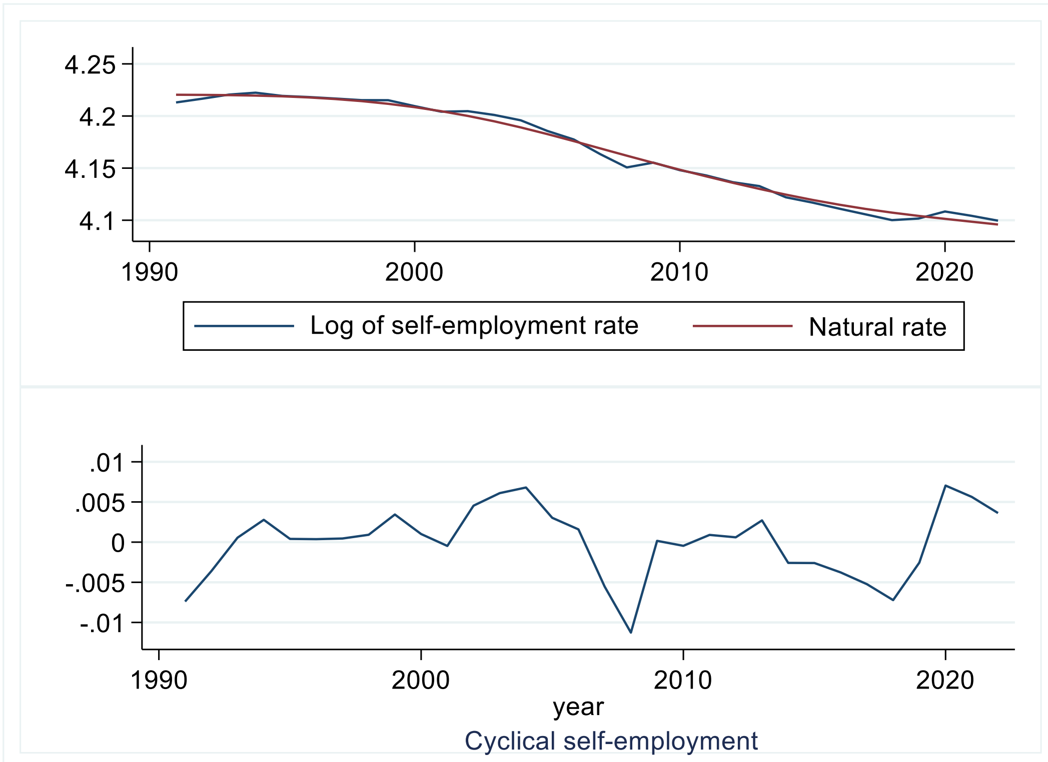

Figure 1 Actual, natural, and cyclical entrepreneurship rates

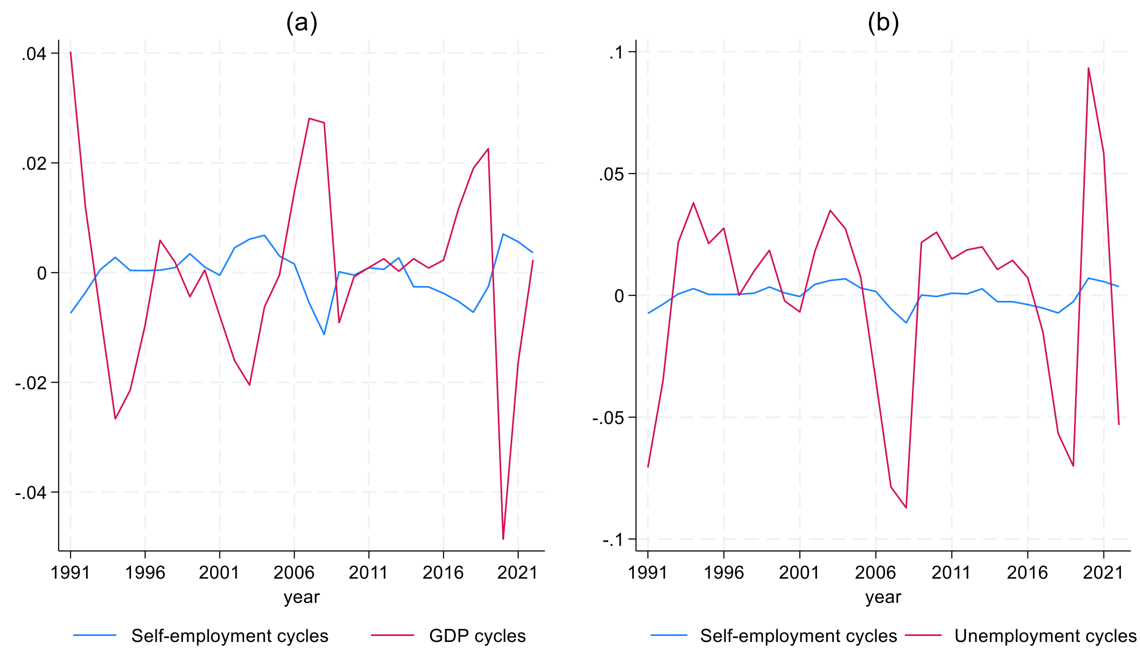

Figure 2. Cyclical components of self-employment, GDP, and unemployment rates (HP filtered data with λ=100): 1991—2022

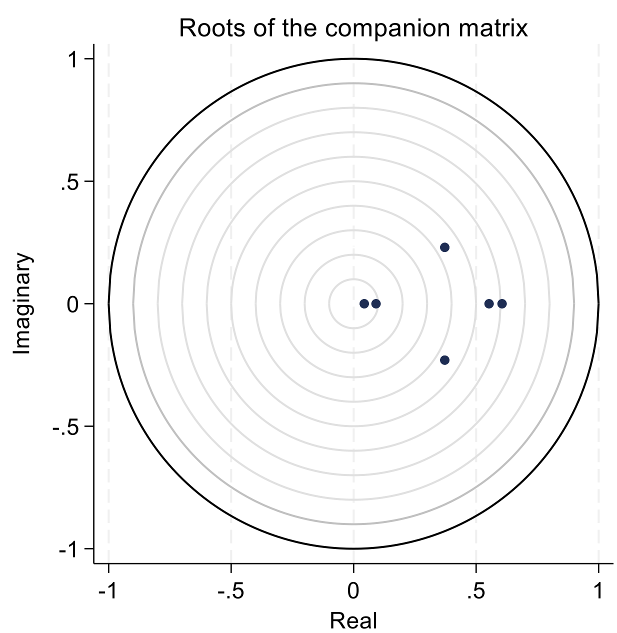

Figure 3 Variable Stability

Notes: Impulse responses in the full sample. Error is 5% on each side generated by Monte-Carlo with 200 reps.

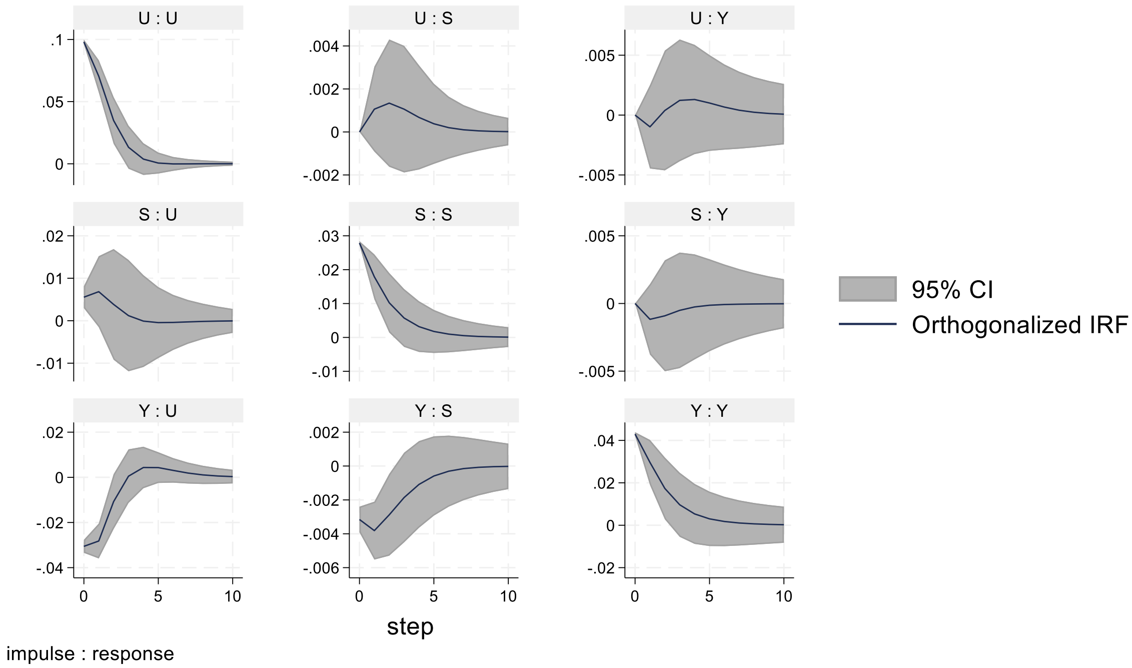

Figure 4 Graphs of orthogonalized IRFs