Economic cycles and self-employment: Synthetic Cohort Analysis for Greater Santiago*

Ciclos económicos y trabajo independiente: análisis de cohortes sintéticos para el Gran Santiago

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Abstract

Economic cycles affect both unemployment and the composition of employment, which can have an impact on the well-being of individuals if these changes in composition are involuntary or involve a decrease in the quality of employment. In this article, we study the relationship between economic cycles and self-employment, distinguishing between employers and own-account workers, through a synthetic cohort methodology using data for Chile. The results suggest that the proportion of employers is procyclical and that of own-account workers is countercyclical. This suggests that own-account employment is a refuge in times of crisis from the shortage of wage-based employment. This highlights the importance of designing public policies that would improve the conditions of self-employed workers.

Key words: *Self-employment, employer, own-account.*

JEL Classification: *J08, J38, J39.*

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Resumen

Los ciclos económicos afectan tanto el desempleo como la composición del empleo, lo que puede tener impactos en el bienestar de los individuos si es que los cambios en la composición son involuntarios o implican disminuir la calidad del empleo. El objetivo de este artículo consiste en analizar la relación entre los ciclos económicos y el empleo independiente, distinguiendo entre empleadores y trabajadores por cuenta propia, utilizando la metodología de cohortes sintéticos para una muestra de 53 años del Gran Santiago. Los resultados revelan que la proporción de empleadores es procíclica y la de trabajadores por cuenta propia es contracíclica. Esto puede interpretarse como que el trabajo por cuenta propia sirve como refugio en las épocas de crisis ante la escasez de trabajo dependiente. Esto resalta la importancia de diseñar políticas públicas que mejoren las condiciones de los trabajadores independientes.

Palabras clave: *Trabajo independiente, empleador, cuenta propia.*

Clasificación JEL: *J08, J38, J39.*

1. Introduction

There is a debate about the relationship between the occupational category (wage-based versus self-employment), its quality and the well-being of individuals. In developed countries, self-employed workers report being more satisfied with their work and life than employees, partly because they enjoy more autonomy (Blanchflower, 2000; Benz and Frey, 2008). However, in Latin American countries this correlation is negative, as, in many of these nations, self-employment is of lower quality since it has fewer guarantees and benefits (Graham and Felton, 2006). Furthermore, this relationship is heterogenous because of the differences between being an own-account worker and an employer (Aguilar *et al.*, 2013).

Booms and economic crises lead to important changes in employment and occupational categories. On the one hand, there is a movement between employment and unemployment, and on the other hand, there are changes in the composition of employment. For example, during the Subprime crisis, unemployment increased by 1.9 percentage points between 2008 and 2009, and the share of self-employment went from 26.8% in October 2008 to 28.4% in December 2009.[1]

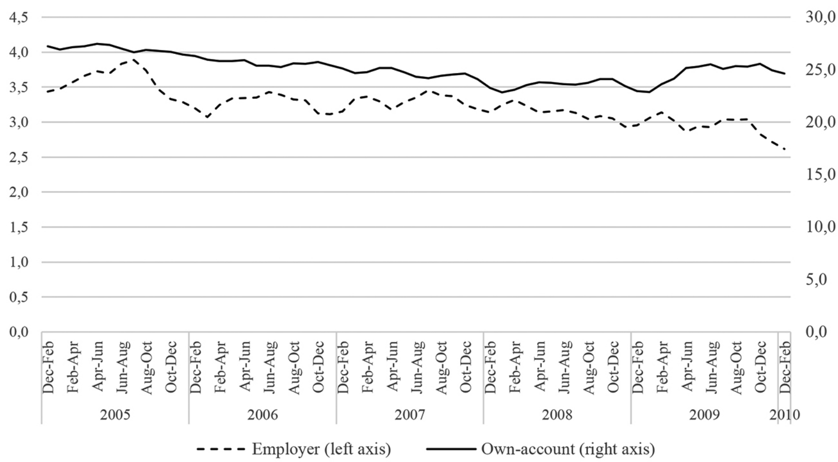
[1] For these calculations, the data from the National Statistics Institute (INE) was used. In addition, wage-based and self-employed workers were considered employed, excluding unpaid family members and service personnel.

In particular, the proportion of employers fell by 0.2 percentage points and that of own-account workers increased by 1.8 percentage points. This trend is illustrated in Figure 1.

These changes induced by economic cycles affect the well-being of individuals, beyond the unemployment situation, if the decision to be self-employed is not voluntary or the quality of this work is lower. Therefore, understanding the relationship between the economic cycle and the composition of employment is relevant, since it can help to design stabilizing public policies that minimize involuntary job changes and improve individuals' options to have good quality jobs, regardless of their occupational category.

In this article, we explore the relationship between the economic cycle and occupational category over 53 years, using the University of Chile Employment and Unemployment Survey (EUS) for Greater Santiago.[2] In particular, the relationship between business cycles and the probability of being self-employed is analyzed, either as an employer or as own-account worker. An employer is defined as a person who has at least one worker he is in charge of, and an own-account worker is defined as a person who does not have workers depending on him. This distinction is relevant because it allows us to clarify whether self-employment serves as a source of entrepreneurship opportunities or if it is a job that functions as a refuge from the shortage of wage-based employment.

FIGURE 1
EMPLOYERS AND OWN-ACCOUNT WORKERS
AS A SHARE OF TOTAL EMPLOYMENT (%)



2 Greater Santiago accounts for roughly 30% of Chile's population, and 40% of the GDP.

Most of the existing research has been aimed at studying the determinants of self-employment, mainly focused on individual characteristics such as gender, age, schooling, risk aversion and months of previous unemployment (Blanchflower, 2000; Simoes *et al.*, 2015). In the case of Chile, the evidence suggests that being male, being older and having low schooling levels increases the probability of becoming self-employed (Cea *et al.*, 2009). In addition, self-employment is associated with worse working conditions and vulnerable or informal employment (Puentes *et al.*, 2007). Furthermore, the estimation is that a third of self-employed workers do so because they cannot find wage-based work (Contreras *et al.*, 2017).

Conversely, this paper contributes to the incipient literature that focuses on the role of external factors, such as business cycles, in self-employment. Most of this research has found that self-employment in developing countries is related to informal work and, as such, tends to be countercyclical, that is to say, in times of crisis, informal employment grows as a refuge against the scarcity of wage-based employment generated by the short-term rigidities of the formal labor market (Loayza and Rigolini, 2011; Gunther and Launov, 2012; Fernández and Meza, 2015). There is also evidence for this behavior in the US during the Great Recession (Fossen, F. M., 2020). However, sometimes informal employment behaves procyclically, because of the changes in relative demand and productivity shocks in the non-tradable sector (Fiess *et al.*, 2010). Svaleryd, H. (2015) highlights the importance to distinguish between high and low human capital to establish the effect of the business cycle on self-employment, establishing that workers with low human capital are more likely to be pushed into self-employment (refuge effect). In the Chilean case, the scant evidence available suggests that there is no relationship between business cycles and long-term self-employment (Puentes *et al.*, 2007).

This article contributes to the existing discussion on whether self-employment corresponds to a refuge or entrepreneurial work. In particular, it highlights the importance to distinguish between the type of self-employment (employer or own-account worker), given the different effects observed for each one. Second, it provides long-term evidence for a developing economy, regarding the role of macroeconomic factors in the decision of becoming a self-employed worker. Third, the study shows the effect of macroeconomic cycles on the composition of employment, beyond the traditional approach of studying its effects on unemployment. In this way, it contributes to a global vision of the effect of the environment on employment.

To explore the relationship between economic cycles and occupational category of the labor force, a synthetic panel methodology is used, which allows to characterize employment behavior during the life cycle.[3] This methodology assumes that individuals born around the same cohort have similar characteristics,

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3 Other authors who have used the synthetic panel methodology for employment and income distribution studies in Chile are Contreras *et al.* (2005) and Sapelli (2011).

with the objective of grouping them by year and cohort, creating “cells” which are representative of these individuals. Using grouped information at the cohort level for each year, a fixed effect model is estimated that captures the effect of economic activity on the probability per cohort of being an employer and own-account worker. Three business cycle measures are used, namely the Gross Domestic Product (GDP) growth rate, the unemployment rate, and the GDP gap (defined as the difference between actual and trend output).

The results suggest that a one percentage point increase in the GDP gap is associated with and increase in the probability of being an employer by 0.06 percentage points and decreases the probability of being an own-account worker by 0.13 percentage points. From this result, it can be interpreted that the probability of being an employer is procyclical and the probability of being an own-account worker is countercyclical, which suggests that own-account employment is a source of refuge in the face of labor shortages.

To understand what mechanisms could be behind this result, the authors studied the heterogeneity of the estimates based on schooling, for which the model is estimated by separating the sample into two groups: individuals with more than twelve years of schooling and individuals with less than twelve years of schooling. The results suggest that business cycles increase the proportion of employers with more than twelve years of schooling. On the other hand, no heterogeneous effects by schooling can be seen for own-account workers.

Given the time series nature of the observations by cohort, it is necessary to address the possible persistence over time of the variables that make up the panel. To incorporate the dynamic nature of the variables, the lag of the dependent variable is included in the model and is estimated using the Arellano and Bond methodology (1991). The main results are maintained.

Additionally, an analysis has been done to establish whether the economic cycles are related to the incomes of the self-employed, and to the educational levels of these groups. The results indicate that business cycles do not affect relative earnings between groups of employers and own-account workers with respect to the rest. On the other hand, there is no consistent relationship between the educational composition of these groups and the economic cycle.

This article is structured as follows. Section 2 describes the data used in this study. Section 3 contains the methodological strategy. Section 4 presents the results, and finally, section 5 concludes.

2. Data

This paper used the data from the Employment and Unemployment Survey of the University of Chile (EUS); it should be noted that this survey has characterized the labor market in Santiago de Chile since 1957. This survey (quarterly) collects information on the employment situation of all household members. The data obtained from this survey is comparable over time, since in each survey the basic questions related to employment have remained constant.

This study used the survey corresponding to the month of June of each year for the 1965-2017 period containing a sample of 2,900 households on average for each year.[4] A subsample of men of working age (between 18 and 64 years) who are employed is used. Women are excluded from the analysis, as their labor force participation, which averages 48% for the period, 38 percentage points lower than for men, induces a potential selection bias, which is difficult to control for given the limited availability of observable variables in the EUS dataset. The survey allows us to make distinctions by type of worker, wage-based and self-employed (own-account or employer), which makes it especially useful for this research.

The following macroeconomic variables are used to measure economic cycles: unemployment rate, the real GDP growth rate and the GDP gap (with respect to trend GDP). The unemployment rate is calculated from the survey data for each year, for the entire workforce. On the other hand, GDP growth corresponds to the one reported by the Central Bank of Chile, in percentage points compared to the previous year. Finally, the GDP gap corresponds to the difference between actual GDP and trend GDP, measured in percentage points, published by the Advisory Committee on Trend GDP.[5]

2.1. Description of the sample

A first approach to understanding the relationship between business cycles and the occupational category is to analyze the composition of employment over time. Figure 2 presents the composition of employment growth by occupational category. We can see that, especially from the 1990s, it is recurrent to observe periods in which growth (decrease) in wage-based employment is reversed by the fall (increase) in self-employment. The clearest example of this behavior is seen in years such as 2002 and 2014, when wage-based employment fell, but total employment remained almost unchanged due to the growth of self-employment. Therefore, this figure illustrates the importance of distinguishing between waged-based and self-employment.

The behavior of the incidence of self- employment over time is illustrated by four-year periods in Figure 3. We can observe a level of male self-employment of around 24%, nearly a third of which corresponds to employers. The highest level of self- employment is observed for the 1986-1989period, where 25.5% of the employed male population between the ages of 18 and 64 worked as self-employed. Subsequently, this level began to fall during the 2006-2009 period, reaching 20.5% for the 2010-2013 period. In the last period analyzed, there was a significant recovery in self-employment in Greater Santiago, mainly driven by own-account workers.

4 Noteworthy is the fact that there is systematized information available for the 1957 to 1964 period (June of each year). However, the years from 1957 to 1964 are not considered because there is no consistent information for the schooling variable.

5 This Committee is convened by the Budget Office.

FIGURE 2
COMPOSITION OF EMPLOYMENT GROWTH BY OCCUPATIONAL CATEGORY
(THOUSANDS)

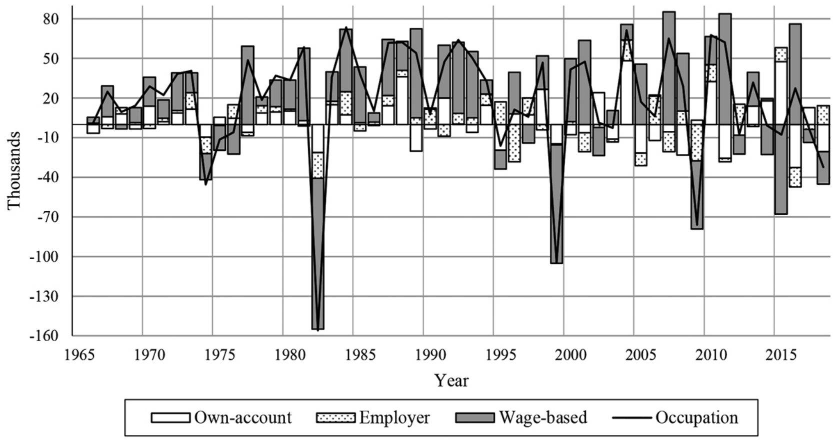
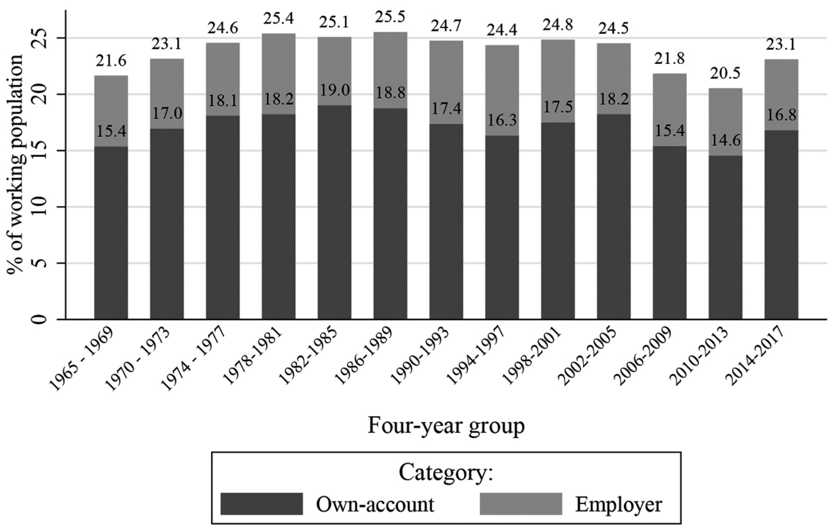


FIGURE 3
INCIDENCE OF SELF-EMPLOYMENT BY FOUR-YEAR GROUPS
(% OF WORKING POPULATION)



Although self-employment maintains low volatility using these four-year averages, there is high dispersion of its composition in the short term. Figure 4 shows the proportion of employers and own-account workers with respect to the total number of employed workers per year. It can be observed that there is high volatility of self-employment per year, for both employers and own-account workers. This result suggests that there are short-term variables that affect the incidence of self-employment, both for own-account workers and employers.

It is also relevant to know the relative position in terms of income by occupational category. Figure 5 shows the difference in the logarithm of labor income between employers and the rest of the workers; and own-account workers and

FIGURE 4
ANNUAL INCIDENCE OF SELF-EMPLOYMENT (% OF WORKING POPULATION)

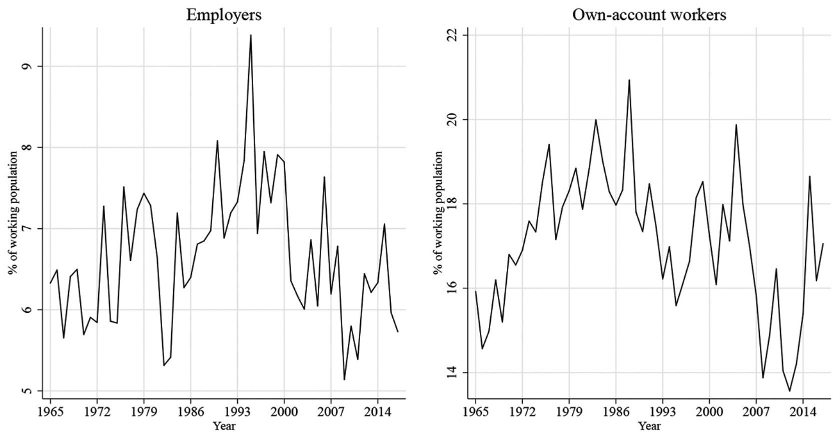


FIGURE 5
RELATIVE INCOME OVER TIME (DIFFERENCE OF NATURAL LOGARITHMS)

the rest of the workers. Therefore, the ordinate measures the percentage difference in income. From this figure it follows that employers have more income than the rest of the workers, for all years, while own-account workers have lower income for the entire analyzed period.

A deterioration in the relative incomes of both occupational categories has also been observed during the last 50 years. Employers have tended to converge with the rest of the workers, reducing their relative advantage from 130 to 70%, while the situation of own-account workers has become more precarious, with earnings of around 50% less than the rest of the workers.

In summary, there are differences in behavior between employers and own-account workers, which justifies a separate analysis of these occupational categories. While own-account workers account for a large proportion of self-employment, they have lower incomes in relation to the income of employers and dependent workers. In turn, the high volatility per year of self- employment and the increase in self-employment compared to decreases in salaried employment, suggests that there is a relationship between self-employment and the economic cycle.

2.2. Description of the synthetic panel cohorts

Construction of a synthetic cohort dataset consists of grouping observations in the cells of individuals born around the same year, who thus have the same age in any given year. The panel is constructed by calculating the average of the relevant variables for each cohort-year cell.

In this case, a synthetic panel of 20 cohorts is built in five-year windows. In particular, there are individuals born between 1900 and 1999, which we observe as participating in the labor market between 1965 and 2017. The greatest number of observations is found in the cohorts that were born in the 1945-1949 and 1950-1954 periods, since all of their labor history is observable (see Table 1). For the first generation (1900-1904), only four observations are available, as this cohort was retiring at the time when the survey began. For the last generation (1995-1999), there are only five observations since this cohort is just beginning its labor history.

To analyze the aggregate behavior of self-employment, we can observe the evolution of the proportion of employers and own-account workers with respect to the total number of employed, by age bracket and cohort. Figure 5 shows the incidence of employers and own-account workers of five of the cohorts from the year 1965 to 2017. We can see that consistent with the existing evidence, the incidence increases with age for both groups (Simoes *et al.*, 2015; Cea *et al.*, 2009). Particularly, a higher proportion of own-account workers is observed than employers for all ages. We can also see that the oldest cohorts are already older at the beginning of the series, so there are no observations about their employment status when they were younger. The opposite is true for the younger cohorts. For the rest of the cohorts, information on their complete labor history is available.

TABLE 1
NUMBER OF OBSERVATIONS PER COHORT IN THE SYNTHETIC COHORT

Cohort	Number of observations
1900-1904	4
1905-1909	9
1910-1914	14
1915-1919	19
1920-1924	24
1925-1929	29
1930-1934	34
1935-1939	39
1940-1944	44
1945-1949	49
1950-1954	50
1955-1959	45
1960-1964	40
1965-1969	35
1970-1974	30
1975-1979	25
1980-1984	20
1985-1989	15
1990-1994	10
1995-1999	5
Total	540

Note: Each observation represents a group of individuals born around the same time window, and thus have the same age in any given year. A five years window is used.

As discussed above, the existence of unobserved determinants of labor force participation induce a potential bias in estimations, especially for the case of women. Thus, women are excluded from the main analysis, given their lower labor force participation. Regardless, Figure 6 is separated between men and women to illustrate the different dynamics of self-employment across these groups. Similar trends are observed between men and women, although more volatility and lower levels of incidence are observed for women.

Table 2 presents a characterization of the control variables by cohort. In the first panel, the individual variables are characterized and in the second panel it is the macroeconomic variables. It can be seen that, by cohort, the average age is 41 years, the average schooling is ten years, and there is an average of 1.5 children per household (children under 6, and children between 7 and 18 years). Regarding the macro variables, the average GDP growth in the analyzed period is 4.1%, with an average GDP gap of -1.1% and an average unemployment rate of 10%.

FIGURE 6
COMPOSITION OF EMPLOYMENT BY AGE GROUPS FOR FIVE COHORTS
(% OF WORKING POPULATION)

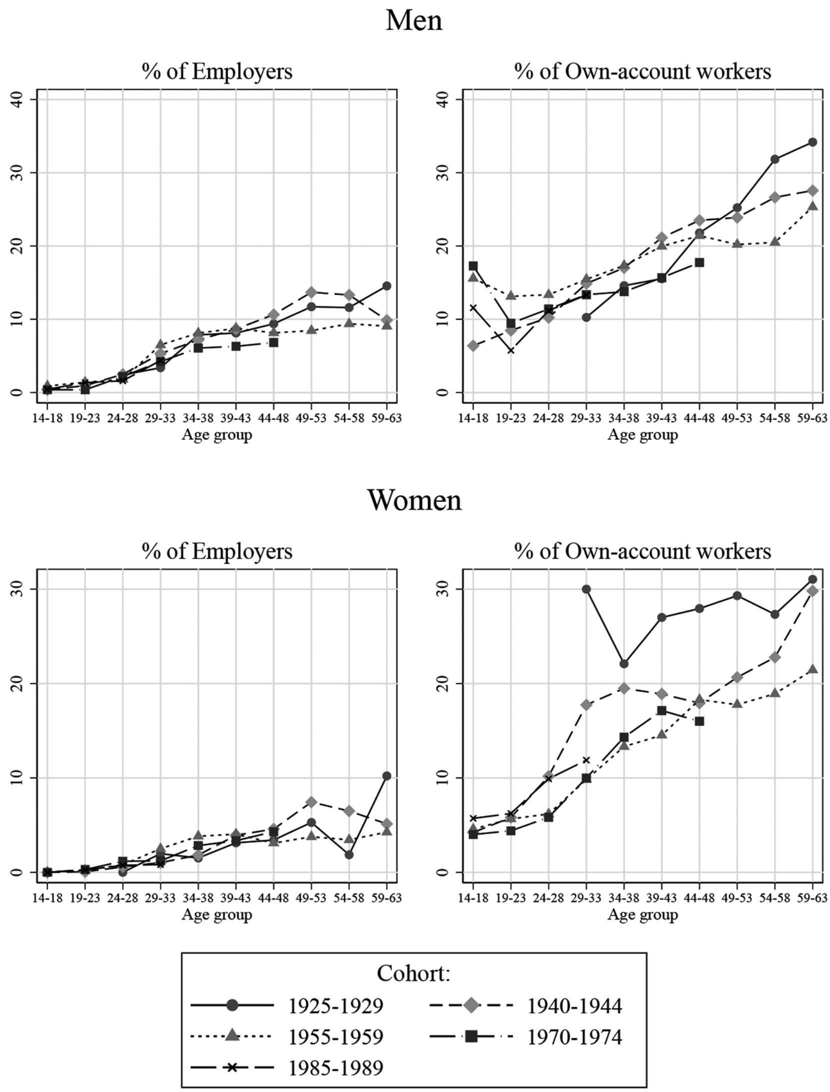


TABLE 2
DESCRIPTIVE STATISTICS FOR CONTROL VARIABLES

Variable	Description	Mean	Standard deviation	Min.	Max.	N
Children younger than 6	Number of children in the household younger than 6, as an average for the working population of cohort i in year t.	0.5	0.3	0.0	1.6	540
Children between 7-18	Number of children in the household between 7 and 18 years of age, as an average for the working population of cohort i in year t.	1.0	0.6	0.1	3.5	540
Age	Average age for the working population of cohort i in year t.	41.0	14.3	18.0	64.0	540
Years of schooling	Average years of schooling for cohort i in year t.	10.2	1.8	6.1	14.2	540
GDP growth	Percentage of GDP growth in year t with respect to the previous year.	4.1	4.7	-12.9	11.2	53
GDP gap	Difference between actual GDP and trend GDP in year t, as percentage of trend GDP in year t.	-1.1	5.0	-16.2	11.3	53
Unemployment rate	Unemployed in year t, as percentage of total workforce in year t.	10.4	4.9	3.1	26.0	53

3. Methodology

As indicated in the previous section, a synthetic panel of 20 cohorts was constructed in five-year windows. The main advantage of using this type of data structure is that, assuming that individuals born in the same time window have similar characteristics, individuals can be averaged in the same observation per year. This aggregation allows to study the behavior of individual cohorts throughout the income life cycle, controlling, in turn, the heterogeneity observed between the different generational cohorts. This heterogeneity is determined by the characteristics of each generation. Furthermore, the construction of these cohorts allows for the usage of a large panel dataset, both in terms of observations and length of time, which is unusual for a developing country.

Using this synthetic panel, a fixed-effects model is estimated, which is controlled by shared characteristics of each cohort. Thus, the estimated coefficient for the variables of interest in the model will correspond to an effect shared by all cohorts throughout the 53 years contained in the sample. Finally, by taking the average values of each variable in each cell, volatility decreases at the level of an individual, allowing for more efficient estimates in a context in which control variables are limited.

However, this methodology limits the predictive capacity at the level of an individual, since the coefficients found will only be applicable to averages for each cell. On the other hand, the estimates could be biased in finite samples, as we have different individuals representing the same cohort in different years (Devereux, 2007).

From this data structure, the following fixed effects model per cohort is estimated by ordinary least squares:

$$Self_{it} = X_{it}\beta + \delta act_t + c_i + \epsilon_{it} \tag{1}$$

where $Self_{it}$ corresponds to self- employment of cohort i in period t, measured as the percentage of total employment in its two forms: employers (self-employed who have at least one worker depending from them) and own-account workers (self-employed who do not have workers depending on them).

Furthermore, we can assume that each individual chooses to work as self-employed with a probability $Self_{it}$, defined by her own characteristics and economic activity according to equation (1). Given a large number of observations, the proportion of self-employed workers will be equal to this probability. Thus, we will interpret the coefficients as changes in probabilities, although the dependent variables are defined as rates.

The vector of control variables X_{it} corresponds to averages per cell of the following variables: number of children in the household under the age of six, number of children in the household between the ages of 7 and 18, age, age squared and years of schooling. In turn, act_t corresponds to the macroeconomic variables mentioned above, and c_i is the cohort effect, which determines the entry into self-employment of individuals who were born around the same year, which are independent of time. Finally, ϵ_{it} is the error term.

The inclusion of the fixed effect by cohort allows to mitigate the bias in the estimation by including the characteristics of each generation, such as willingness to engage in entrepreneurship, risk aversion, entry costs for each occupational position, preferences for types of employment, educational quality, among others. Given the use of these fixed effects, standard errors are estimated using clusters at the cohort level.

Additionally, the robustness of the results is analyzed, incorporating into the estimation the existence of persistence in the dependent variable, given the time series nature of the observations by cohort. Assuming persistence of one period, a model is proposed where the dependent variable is generated by an AR(1) process.

$$Self_{it} = \alpha Self_{i,t-1} + X_{it}\beta + \delta act_t + c_i + \epsilon_{it} \tag{2}$$

with $|\alpha| < 1$. If parameter α is non-zero, equation (1) will produce biased estimates since it would ignore the dynamic nature of the dependent variable. Given the bias induced by the inclusion of the lag of the dependent variable in a panel data model, the estimation proposed by Arellano and Bond (1991) is implemented.

4. Results

4.1. Cohort level estimation

Table 3 presents the results of estimating Equation (1) where the observation unit is the cohort per year and includes fixed effects per synthetic cohort. We can see that both the GDP growth rate and the GDP gap are positively correlated with the proportion of employers. Also, a higher unemployment rate decreases the proportion of employers. This suggests a pro-cyclical behavior of employers. Furthermore, it can be seen that the magnitudes (in absolute value) are greater than those obtained in the estimates made previously with observations at the level of an individual.

In particular, a one percentage point increase in GDP growth produces a 0.1 percentage point increase in employers as a proportion of employed population, an effect that is reduced to about half if the GDP gap is used. On the other hand, increases of one percentage point in the unemployment rate produce a 0.04 percentage point reduction f in the percentage of employers, although this effect is significant only at 10%.

Additionally, we can observe that the greater the GDP gap, the lower the proportion of own-account workers. Similarly, the greater the unemployment, the greater the proportion of own-account workers. These results suggest countercyclical behavior by own-account workers. Specifically, an increase of one percentage point in the unemployment rate causes a 0.26 percentage

TABLE 3
FIXED EFFECTS ESTIMATION FOR SYNTHETIC COHORT PANEL

	(1)	(2)	(3)	(4)	(5)	(6)
	% of employers			% of own-account		
Children younger than 6	-3.320*** (-6.06)	-3.241*** (-5.54)	-3.576*** (-6.19)	-9.246*** (-9.03)	-9.530*** (-9.57)	-7.986*** (-8.58)
Children between 7-18	0.252 (0.60)	0.217 (0.49)	0.157 (0.34)	-1.330 (-1.41)	-1.356 (-1.46)	-1.050 (-1.25)
Age	9.340*** (2.99)	10.03*** (3.20)	10.31*** (3.29)	2.957 (0.58)	3.713 (0.74)	3.978 (0.76)
Age squared	-0.114** (-2.81)	-0.123*** (-3.04)	-0.128*** (-3.16)	-0.0344 (-0.51)	-0.0450 (-0.68)	-0.0428 (-0.63)
Years of schooling	1.530*** (5.13)	1.536*** (4.85)	1.606*** (5.04)	0.634 (1.44)	0.744* (1.78)	0.548 (1.52)
Economic activity:						
–GDP growth	0.110*** (3.91)			-0.0238 (-0.82)		
–GDP gap		0.0628** (2.50)			-0.132*** (-3.72)	
–Unemployment rate			-0.0403* (-1.73)			0.260*** (5.81)
Observations	540	540	540	540	540	540
R-squared	0.522	0.512	0.508	0.408	0.420	0.450

Note: Columns (1) to (3) use the percentage of employers in each period as a dependent variable. Columns (4) to (6) use the percentage of own-account workers in each period as a dependent variable. Standard errors are shown in parentheses, using clusters at the cohort level. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

point increase in own-account workers. On the other hand, an increase of one percentage point in the GDP gap leads to a 0.13 percentage point reduction of own-account workers.

The number of children under the age of 6 shows large negative coefficients for all equations. This is especially true for own-account workers, where an additional child under 6 in the household reduces occupation in this category by 8 to 9.6 percentage points (it is important to note, however, that the average number of children under 6 is 0.5 for the complete sample). This provides evidence for the additional risk associated with self-employment in terms of social protection or job stability, suggesting that the presence of children in the household induces the search for wage-based employment.

The rest of the control variables are highly correlated with the percentage of employers and to a low degree with the proportion of own-account workers (the effects are not statistically significant). In particular, the greater the number of years of average schooling in the cohort, the greater the probability of being an employer, since the human capital acquired allows them to have a greater probability of being entrepreneurs. Conversely, increased human capital does not increase the probability of being an own-account worker. Similarly, we can see that the average age of the cohort has a large positive and concave relationship with the probability of being an employer, reaching its maximum at 41 years.

Thus, these results provide evidence in favor of the procyclicality of the employer category, and own-account as a countercyclical job. This can be understood as that the entrepreneur does it as of his own volition, while the own-account worker takes it as a refuge job, in other words, such workers must move to this type of employment because of the relative shortage of formal jobs.

4.2. Heterogeneous effects

One problem that affects the type of estimates presented is the heterogeneity detected for self-employed workers, even when disaggregated by employer and own-account worker. For example, within the own-account worker group there are professionals who practice their profession through consulting, while within the employers´ group there could be low-skilled small businesses. In both examples, the relationship between the business cycle and the probability of being an employer and own-account worker may be opposite to that found in the estimation of the main equation.

Additionally, the presence of heterogeneous effects of economic activity will determine which types of individuals benefit from economic growth. For example, if higher growth makes all workers more likely to be employers, regardless of their schooling, then economic activity does not cause greater inequality among workers. Conversely, if growth only creates more opportunities for qualified employers, then economic activity will tend to increase inequality.

To capture this heterogeneity, the sample is divided into two groups: workers with more than twelve years of schooling (who have higher education) and workers with twelve or fewer than years of schooling (complete secondary education or lower). From this limited sample at the individual level, the synthetic panel was generated using the previously described methodology.

Tables 4 and 5 show the results of these estimates for employers and own-account workers, respectively. In the case of employers, we can see that the effect is only maintained at its level of significance for those with less schooling, where higher coefficients are observed than those observed in the estimates of Table 3. At the same time, for workers with more than twelve years of schooling, we can observe parameters similar in magnitude to the estimates in Table 3, but they lose their significance.

TABLE 4
FIXED-EFFECTS ESTIMATION FOR THE PERCENTAGE
OF EMPLOYERS BY SCHOOLING LEVEL

	(1)	(2)	(3)	(4)	(5)	(6)
	More than 12 years of schooling			Less than 12 years of schooling		
Children younger than 6	-7.140***	-7.185***	-7.122***	-0.886*	-0.770	-1.174**
	(-3.92)	(-3.96)	(-4.27)	(-1.89)	(-1.54)	(-2.40)
Children between 7-18	-1.055	-1.110	-1.110	0.244	0.245	0.106
	(-1.15)	(-1.20)	(-1.21)	(0.92)	(0.92)	(0.40)
Age	23.51***	24.91***	25.74***	3.091	3.068	3.569
	(4.70)	(5.12)	(5.35)	(0.81)	(0.79)	(0.94)
Age squared	-0.298***	-0.317***	-0.328***	-0.0292	-0.0289	-0.0368
	(-4.50)	(-4.93)	(-5.17)	(-0.59)	(-0.58)	(-0.75)
Years of schooling	3.305***	3.381***	3.391***	0.457	0.407	0.411
	(6.24)	(6.62)	(7.20)	(0.89)	(0.77)	(0.79)
Economic activity:						
–GDP growth	0.179*			0.0557***		
	(1.94)			(3.09)		
–GDP gap		0.0706			0.0687***	
		(1.19)			(2.95)	
–Unemployment rate			0.0496			-0.0718***
			(0.68)			(-4.92)
Observations	540	540	540	540	540	540
R-squared	0.353	0.341	0.340	0.246	0.250	0.250

Note: The dependent variable is the percentage of employers in each cell. In columns (1) to (3) the panel is constructed using only individuals with 12 or more years of schooling. In columns (4) to (6) the panel is constructed using only individuals with less than 12 years of schooling. Standard errors are shown in parentheses, using clusters at the cohort level. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

These results indicate that only for those with higher education the acquisition of an additional year of schooling is relevant. This could be evidence that only higher education can create the necessary skills to lead an enterprise of a sufficient scale to hire workers (leadership, contact networks, financial education, etc.), and that secondary education lacks training in relation to these capacities. In the case of workers with fewer years of schooling, it seems that they do not have the necessary entrepreneurial skills, and the level at which they access jobs as employers is mainly determined by economic activity. This result is consistent with previous research documenting high volatility in the employment situation of the population with fewer years of schooling and resources (Contreras *et al.*, 2008).

TABLE 5
FIXED-EFFECTS ESTIMATION FOR THE PERCENTAGE OF OWN-ACCOUNT WORKERS BY SCHOOLING LEVEL

	(1)	(2)	(3)	(4)	(5)	(6)
	More than 12 years of schooling			Less than 12 years of schooling		
Children younger than 6	-6.799**	-6.900**	-5.914**	-8.912***	-9.079***	-7.751***
	(-2.43)	(-2.46)	(-2.47)	(-5.41)	(-5.47)	(-5.41)
Children between 7-18	-1.933	-1.955	-1.748	-1.732**	-1.800**	-1.349*
	(-1.60)	(-1.61)	(-1.45)	(-2.13)	(-2.22)	(-1.82)
Age	-2.013	-1.649	-2.273	19.35**	20.38**	20.29**
	(-0.35)	(-0.28)	(-0.38)	(2.23)	(2.33)	(2.29)
Age squared	0.0361	0.0314	0.0429	-0.238**	-0.252**	-0.246**
	(0.48)	(0.41)	(0.55)	(-2.12)	(-2.23)	(-2.14)
Years of schooling	0.506	0.525	0.351	-1.395	-1.221	-0.875
	(0.26)	(0.28)	(0.20)	(-0.97)	(-0.86)	(-0.63)
Economic activity:						
–GDP growth	-0.0322			0.0128		
	(-0.29)			(0.27)		
–GDP gap		-0.0674			-0.0874**	
		(-1.02)			(-2.29)	
–Unemployment rate			0.207*			0.304***
			(1.91)			(5.63)
Observations	540	540	540	540	540	540
R-squared	0.200	0.201	0.216	0.320	0.323	0.348

Note: The dependent variable is the percentage of own-account workers in each cell. In columns (1) to (3) the panel is constructed using only individuals with 12 or more years of schooling. In columns (4) to (6) the panel is constructed using only individuals with less than 12 years of schooling. Standard errors are shown in parentheses, using clusters at the cohort level. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

In the case of own-account workers, a similar situation is observed. The positive effect of the unemployment rate on own-account employment found in the main regression remains significant for low-schooling individuals and marginally significant for high-schooling individuals. At the same time. GDP growth is not significant for any of the schooling brackets, while the GDP gap has a negative and significant effect only for own-account workers with low schooling.

The results observed for this exercise indicate that workers with less education are more sensitive to changes in the levels of growth and unemployment, since the category they are in will be determined by their environment, and to a lesser extent by their characteristics. This is because jobs accessible to people with less education tend to be more precarious and, therefore, are more sensitive to cycles. On the contrary, workers with higher education can remain in their occupational position, regardless of economic activity, in line with the results obtained in the previous section.

Finally, we can observe that the rest of the controls have significance levels that depend both on the occupational category (own-account or employer) and on their level of education (over or under twelve years). In the case of employers, the number of children in the household, age and schooling have statistically significant effects for highly educated workers. Quite the opposite happens in the case of own-account workers whereby these variables are significant only for individuals with low education. This indicates that for individuals with higher education, it is their endowments that define the decision to be an employer or not, without being affected by the economic cycle. In contrast, for individuals with low education, both individual endowments and the economic cycle affect the probability of being an own account worker.

4.3. Robustness Analysis

Given the time series nature of the observations by cohort, it is necessary to address the possible persistence over time of the variables that make up the panel. To incorporate the dynamic nature of the variables, the lag of the dependent variable is included in the estimate, as indicated in equation 2. This specification can be controlled for persistence in the dependent variable. The estimation is made using the consistent generalized method of moments estimator derived by Arellano and Bond (1991), and robust standard errors adjusting for clusters on cohorts.

The estimation results are presented in Table 6. First, the lag of the dependent variable is only significant for the estimates of the percentage of own-account workers, which suggests that this variable contains a greater degree of persistence. Secondly, we can see that the coefficients of the variables of interest differ their magnitudes slightly. Third, significance levels increase in four out of six coefficients. In fact, the effect of the GDP growth rate on the proportion of own-account workers becomes significant. Lastly, tests for autocorrelation in the first-differenced errors cannot reject the null hypothesis of no second-order serial correlation, supporting the consistency of the estimates. In sum, the robustness analysis carried out confirms the findings presented above.

TABLE 6
ARELLANO-BOND ESTIMATION

	(1)	(2)	(3)	(4)	(5)	(6)
	% of employers			% of own-account		
Lagged % of employers	0.119 (1.11)	0.121 (1.13)	0.139 (1.27)			
Lagged % of own-account				0.212*** (3.99)	0.199*** (3.83)	0.171*** (3.13)
Children younger than 6	-2.946*** (-3.54)	-2.932*** (-3.45)	-3.268*** (-3.88)	-6.945*** (-5.99)	-7.460*** (-6.87)	-6.801*** (-6.57)
Children between 7-18	0.0526 (0.13)	0.0259 (0.06)	-0.0959 (-0.22)	-1.685** (-2.17)	-1.733** (-2.28)	-1.452** (-2.03)
Age	6.868** (2.37)	7.700*** (2.65)	7.216** (2.48)	-2.331 (-0.53)	-2.183 (-0.49)	-0.520 (-0.11)
Age squared	-0.0835** (-2.21)	-0.0946** (-2.49)	-0.0901** (-2.39)	0.0316 (0.55)	0.0290 (0.50)	0.0119 (0.20)
Years of schooling	1.461*** (3.21)	1.462*** (3.09)	1.525*** (3.21)	0.853*** (3.42)	0.956*** (4.14)	0.874*** (3.90)
Economic activity:						
–GDP growth	0.115*** (3.82)			-0.0552** (-2.15)		
–GDP gap		0.0646*** (2.83)			-0.122*** (-4.34)	
–Unemployment rate			-0.0599*** (-3.14)			0.211*** (5.32)
Arellano-Bond test for zero autocorrelation in first-differenced errors:						
–First order	-2.9255**	-2.956**	-3.0126**	-3.4983***	-3.4763***	-3.4933***
–Second order	-1.625	-1.5351	-1.4266	-1.2208	-1.2768	-1.4506
Observations	500	500	500	500	500	500

Note: Columns (1) to (3) use the percentage of employers in each period as the dependent variable. Columns (4) to (6) use the percentage of own-account workers in each period as the dependent variable. Standard errors are shown in parentheses, using clusters at the cohort level. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Rows "Arellano Bond autocorrelation test" show z-statistics for respective tests in which the null hypothesis corresponds to zero autocorrelation in the first-differenced errors.

4.4. Additional results

The results found suggest that there is a relationship between business cycles and the incidence of self-employment (differentiated for employers and own-account workers). This section explores whether these cycles also affect the position of these groups in the income distribution, and the composition in terms of years of schooling. For example, in the face of an economic crisis, the earnings of own-account workers could decrease due to a contraction in demand. Furthermore, as a result of an increase in the supply of own-account workers (as a consequence of a crisis), there could be a downward pressure in this group's income. Similarly, an economic crisis could induce the composition of own-account workers in terms of years of schooling to be lower.

To examine the relationship between workers' earnings and business cycles, a relative measure of income is defined as the distance (measured in terms of standard deviations) between the income per cohort / year of each type of self-employed worker (employer and own-account) and the income of the rest of the working population. With this, equation 1 is estimated now using the relative income of employers and own-account workers as the dependent variable. Likewise, control variables are expressed in relative terms (for example, difference in schooling between employers and non-employers measured in years, age difference between own-account and non-own account workers measured in years, and so on).

Table 7 shows the results of these estimates. It can be appreciated that the economic cycle variables are not correlated with the relative earnings of self-employed workers. This suggests that the economic cycle only affects the employment situation of the self-employed through its composition, as described in previous sections. One possible explanation for these results is that the changes in the relative position of the independent in terms of labor income are due to variables other than those captured by economic activity. On the other hand, since the survey focuses on the employment situation of individuals, the information on income levels could be measured with error.

It should be noted, however, that these results do not constitute evidence for a causal relationship between economic activity and income for self-employed workers. This is because income levels are affected by the entrance and departure of the population to and from the self-employed workforce. Rather, estimates in this case should be interpreted as correlations, providing evidence as to whether changes in relative income are expected for the self-employed workforce, when economic activity increases.

To examine the relationship between the composition of self-employed workers in terms of years of schooling and business cycles, the schooling of employers and own-account workers is defined as a dependent variable, measured in number of years of average difference from the rest of the workers for each cohort. Table 8 presents the results of the estimates considering these dependent variables. The relevant coefficients indicate, therefore, in how many

TABLE 7
FIXED-EFFECTS ESTIMATION OF RELATIVE INCOME FOR SELF-EMPLOYED WORKERS

	(1)	(2)	(3)	(4)	(5)	(6)
	Employers' relative income			Own-account workers' relative income		
Children younger than 6	0.507	0.515	0.510	0.00700	0.00241	0.00863
	(1.19)	(1.23)	(1.20)	(0.07)	(0.02)	(0.09)
Children between 7-18	-0.151	-0.141	-0.129	-0.0635	-0.0641	-0.0644
	(-0.86)	(-0.81)	(-0.72)	(-1.34)	(-1.36)	(-1.33)
Age	0.0152	0.00995	0.0274	0.167**	0.167**	0.166**
	(0.09)	(0.06)	(0.17)	(2.29)	(2.28)	(2.28)
Years of schooling	0.324***	0.321***	0.314***	0.110***	0.110***	0.110***
	(4.51)	(4.59)	(4.46)	(7.00)	(7.02)	(7.15)
Economic activity:						
–GDP growth	-0.00203			-0.00220		
	(-0.12)			(-1.43)		
–GDP gap		-0.0133			-0.00165	
		(-0.86)			(-1.04)	
–Unemployment rate			0.0215			-0.000721
			(1.30)			(-0.45)
Observations	497	497	497	539	539	539
R-squared	0.121	0.123	0.126	0.212	0.212	0.211

Note: Columns (1) to (3) use relative income for employers in each cell as a dependent variable. Columns (4) to (6) use relative income for own-account workers in each cell as a dependent variable. Relative income is defined as the distance, measured in standard deviations, between labor income of each self-employed worker and the rest of the working population. Standard errors are shown in parentheses, using clusters at the cohort level. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

years the relative education of the self-employed increases when economic activity increases.

The results indicate that the activity does not seem to significantly affect the schooling of the self-employed, except in the case of the unemployment rate on the relative schooling of employers (which is significant only at 10%), which indicates that the increase in one percentage point of unemployment translates into an increase in the average relative education of employers of 0.04 years in

TABLE 8
FIXED-EFFECTS ESTIMATION OF RELATIVE YEARS OF SCHOOLING FOR SELF-EMPLOYED WORKERS

	(1)	(2)	(3)	(4)	(5)	(6)
	Employers' relative schooling			Own- account workers' relative schooling		
Children younger than 6	-0.788 (-1.57)	-0.773 (-1.53)	-0.765 (-1.50)	-0.816* (-1.84)	-0.846* (-1.86)	-0.814 (-1.68)
Children between 7-18	-0.121 (-0.55)	-0.0981 (-0.44)	-0.0646 (-0.29)	-0.392* (-1.76)	-0.390* (-1.77)	-0.398* (-1.88)
Age	0.240 (1.27)	0.240 (1.24)	0.267 (1.46)	-0.397*** (-3.24)	-0.394*** (-3.10)	-0.402*** (-3.34)
Economic activity						
–GDP growth	0.0105 (0.62)			-0.00815 (-0.56)		
–GDP gap		-0.0165 (-1.25)			-0.0114 (-1.28)	
–Unemployment rate			0.0418* (2.08)			-0.00144 (-0.08)
Observations	497	497	497	539	539	539
R-squared	0.028	0.030	0.045	0.046	0.048	0.045

Note: Columns (1) to (3) use relative schooling for employers in each cell as a dependent variable. Columns (4) to (6) use relative schooling for own-account workers in each cell as a dependent variable. Relative schooling is defined as the distance, measured in years, between years of schooling of each self-employed worker and the rest of the working population. Standard errors are shown in parentheses, using clusters at the cohort level. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

relation to non-employers. This result indicates that, in times of higher unemployment, employers with a higher level of schooling are more likely to remain in their occupational position, a relationship that is not observed in the case of own-account workers.

5. Conclusion

This paper analyzes the relationship between business cycles and the probability of being self-employed (separating employers and own-account workers) using the University of Chile Employment and Unemployment Survey for Greater Santiago for more than 50 years.

The differentiation between employer and own-account worker was made to distinguish whether self-employment is used as a source of entrepreneurial opportunities or refuge from the shortage of wage-based employment.

Using the synthetic panel methodology, a significant correlation is found between economic activity and the probability of being an employer and an own-account worker. This correlation is particularly positive when considering the probability of being an employer and negative when considering the probability of being an own-account worker. This result is relevant since it contributes to the incipient literature on the role of external factors on self-employment. Especially, the fact that the business cycle heterogeneously affects employers and own-account workers is in line with the literature that seeks to analyze the transmission mechanisms of the effect of the business cycle on employment (Loayza and Rigolini, 2011; Gunther and Launov, 2012; Fernández and Meza, 2015).

The results presented here contrast with those obtained by Puentes et. al. (2007), which do not find a relation between business cycles and self-employment. The difference could be explained by the usage of a wider time period in this paper, along with the inclusion of direct measures of economic activity.

There are limitations in the implemented methodology that could affect the interpretation of the results. For example, using the synthetic panel methodology, movements from one job category to another are measured in aggregates and not by individual. Therefore, all the interpretations of the coefficients are at the level of the cohort average and are not particular to the individuals in the sample. In particular, the effect of the business cycle may affect the aggregate differently than it would affect individuals. Additionally, the current analysis does not consider the effect of the individual's employment history on their probability of changing from one job category to another. For example, the probability that a formal employee will remain in his category if he has already been in it for a long period of time is not considered.

Additionally, it is important to note that these results may not correspond to a causal relationship between economic activity and self-employment. For example, flexibility induced by labor regulation may affect both self-employment and growth simultaneously. Other unobserved variables, such as changes in cultural attitude towards self-employment, could lead to increases in self-employment, and in turn, drive economic activity.

Furthermore, it is not clear whether the results can be extrapolated to other areas with different socioeconomic, territorial and productive characteristics, given that EUS covers only the urban area of the Greater Santiago.

The results suggest that there is a segment of the population that requires special attention in the presence of economic cycles. This segment corresponds to individuals who, due to the economic cycle, are forced to access more vulnerable and informal jobs. Therefore, the formulation of public policies must consider that, although these individuals may be employed, they lack a number of social benefits that diminish their wellbeing.

In the case of Chile, in recent years public policies have been formulated which try to improve the conditions of self-employment. An example of this are the laws that incorporate self-employed workers into social protection regimes.[6] These laws require independent workers to contribute to the social security system, offering them the benefits of healthcare insurance coverage, occupational accident insurance and pension contributions, among others. This way, the continuous provision of social benefits to all types of workers is guaranteed.

Furthermore, the recent pandemic caused by the novel Coronavirus has highlighted the importance of self-employment in the recovery of the labor market. More recent reports of the results of the EUS show that self-employment accounts for more than 70% of total growth in employment for the March 2020 – March 2021 period (see Centro de Microdatos, 2021), during a time of economic downturn.

Future research should model employment dynamics using individuals' employment history. In turn, it should be analyzed which characteristics of the workers make them more exposed to economic cycles. These analyses would permit to understand better how to focus public policies aimed at minimizing the impact of economic cycles on employment.

References

Aguilar, A. C., Muñoz, T. M. G., and Moro-Egido, A. I. (2013). "Heterogeneous self-employment and satisfaction in Latin America". *Journal of Economic Psychology*, 39, 44-61.

Arellano, M. and Bond, S. (1991). "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations". *Review of Economic Studies*, 58 (2):277.

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

Barrero, A. Fuentes, M. and Mena J. (2018). "Formalidad y brechas de ingresos en el mercado laboral chileno", *Economía Chilena*, Volumen 21, Nº 2.

Benz, M. and Frey, B. (2008). "The value of doing what you like: Evidence from the self-employed in 23 countries". *Journal of Economic Behavior & Organization*, 68(3-4), 445-455.

Cea, S., Contreras, M., Martínez, C and Puentes, E. (2009). Trabajadores por Cuenta Propia: ¿Quiénes Son? ¿De Dónde Vienen? ¿Para Dónde Van? Documentos de Trabajo del Departamento de Economía de la Universidad de Chile, SDT 308, Diciembre.

Centro de Microdatos, Universidad de Chile (2021). Encuesta de Ocupación y Desocupación en el Gran Santiago, junio 2021. https://

[6] Laws No. 20,255 and 21,133.

b6323ffa-7fb7-4415-b07a-a0afa49c7f3f.filesusr.com/ugd/fc7a5e_81fcf43ceadf422082a46ef913153c3f.pdf?index=true

Contreras, D., Puentes, E., and Bravo, D. (2005). "Female labour force participation in greater Santiago, Chile: 1957-1997. A synthetic cohort analysis". *Journal of International Development*, 17(2), 169-186.

Contreras, D., Gilmore, R., and Puentes, E. (2017). "Self-Employment and Queues for Wage work: Evidence from Chile". *Journal of International Development*, 29(4), 473-499.

Devereux, P. J. (2007). "Small-sample bias in synthetic cohort models of labor supply". *Journal of Applied Econometrics*, 22(4), 839-848.

Earle, J. S., and 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.

Fernández, A. and Meza, F. (2015). "Informal employment and business cycles in emerging economies: The case of Mexico". *Review of Economic Dynamics*, 18(2), 381-405.

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

Graham, C., and Felton, A. (2006). "Inequality and happiness: insights from Latin America". *The Journal of Economic Inequality*, 4(1), 107-122.

Günther, I. and Launov, A. (2012). "Informal employment in developing countries: Opportunity or last resort?". *Journal of Development Economics*, 97(1), 88-98.

Loayza, N. and Rigolini, J. (2011). "Informal Employment: Safety Net or Growth Engine?". *World Development*, 39(9), 1503-1515.

Neilson, C., Contreras, D., Cooper, R., and Hermann, J. (2008). "The Dynamics of Poverty in Chile". *Journal of Latin American Studies*, 40(2), 251-273.

Fiess, N., Fugazza, M. and Maloney, W. (2010) "Informal self-employment and macroeconomic fluctuations". *Journal of Development Economics*, 91(2), 211-226.

Pérez, J. (2019). Trabajo independiente en el Gran Santiago, Chile: 1965-2017, un Análisis de Cohortes Sintéticos. Thesis to be eligible for the Master's degree en Economic Analysis, Universidad de Chile.

Puentes, E., Contreras, D., and Sanhueza, C. (2007). "Self-employment in Chile, long run trends and education and age structure changes". *Estudios de Economía*, 34(2), 203-247.

Sapelli, C. (2011). "A cohort analysis of the income distribution in Chile". *Estudios de Economía*, 38(1), 223-242.

Simoes, N., Crespo, N. and Moreira, S. B. (2016). "Individual determinants of self-employment entry: What do we really know?". *Journal of Economic Surveys*, 30: 783-806.

Svaleryd, H. (2015). "Self-employment and the local business cycle". *Small Business Economics*, 44(1), 55-70.