Applied Research in Quality of Life
https://doi.org/10.1007/s11482-021-09941-7

Would you Value a few More Hours of work? Underemployment and Subjective Well-Being Across Chilean Workers

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Received: 27 July 2020 / Accepted: 16 March 2021 / Published online: 08 April 2021

Abstract

Underemployment has gained attention in recent years because of its effects on health and well-being (life satisfaction), it is a widespread phenomenon in the labor force that affects not only workers, but also households, companies and governments. This paper explores the relationship between underemployment and subjective well-being for a representative sample of Chilean workers using an ordered probit model. Also, by using different underemployment definitions and a latent class ordered probit model we analyze the observed and unobserved heterogeneity in this relationship. Finally, we assess the monetary valuation of well-being costs by estimating the amount of money that a worker is willing to accept in order to bear the potential negative effects of underemployment on well-being. Our results find a negative relationship between underemployment and subjective well-being, as the average worker is willing to accept an increase of CLP$64,009 (roughly 30.5% of the minimum wage) in her/his monthly wage for being underemployed. If we take into account the observed and unobserved heterogeneity, our results identify a group that is not sensitive to underemployment, while others are willing to accept an increase of CLP$146,622 in her/his monthly wage for being underemployed. Our work highlights the importance of well-being in the workplace and has implications for labor flexibility legislation and the empowerment of workers. Heterogeneous responses to underemployment imply that one-size-fits-all policies to regulate working hours might not suffice.

Keywords Underemployment · Subjective well-being · Unobserved heterogeneity · Willingness to accept

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Introduction

In almost every country in the modern era, economic turmoil is often associated with unemployment, informality, discouragement from work and underemployment. Underemployment (UND) happens when workers carry out an activity that is less productive than what they could achieve in their full potential (Greenwood 1999). This concept is studied in two different ways, one is the time-related underemployment due to insufficient work hours, and the other one is about precarious employment conditions in the workplace, which is also subdivided in underemployment by competencies and underemployment by income, which is measured by the number of workers who want to improve their current work situation (García-Ubaque et al. 2012).

This phenomenon has gained attention in the empirical literature because of the effects underemployment has on workers' health and well-being (Bunting 2011; Hilbrecht et al. 2017; Esenaliev and Ferguson 2019; Lepinteur 2019; Mousteri et al. 2020). There has been an increasing number of articles in the empirical literature that study the relationship between underemployment and subjective well-being of workers (Friedland and Price 2003; Wilkins 2007; Angrave and Charlwood 2015; Bell and Blanchflower 2019). Fewer attempts to explain this relationship have used theoretical insights (Angrave and Charlwood 2015). Wunder and Heineck (2013) use life satisfaction measures to approximate workers' utility and explain how working time mismatches affect welfare. Nevertheless, there is still a gap to fill with regards to the economic valuation of underemployment in developing and recently developed countries with more informal economies (Esenaliev and Ferguson 2019), therefore, we propose to study the case of Chile and its particular labor market.

Our analysis focuses on the Chilean case due to its high wage inequities, relatively high female participation, socioeconomic segregation, partial formality and rigid workdays (Gatica et al. 2005; Albagli 2005). Although Chile is a recently developed country that belongs to the OECD, it is still far from achieving labor standards and providing formal safety nets similar to those seen in richer countries (Carrillo et al. 2018). A sizable part of the labor market is still informal, and Chile is ranked as the OECD country with the fourth-highest rate of involuntary workday arrangements by 2017 (Páez and Sáez 2018). Moreover, its underemployment rates were the fourth among Latin American countries by 2013 (ILO 2017) and the precariousness of its health system also differs from richer countries belonging to the OECD (Goic 2015). These differences make Chile an interesting case to motivate our study, as we are able to test at least how contractual rigidity and informality are related to subjective well-being. Similarly, the high underemployment rate in Chile makes the analysis more relevant, since it matters more for overall life satisfaction, and helps us to identify the point estimates and WTA with more accuracy.

This paper attempts to provide evidence on the empirical association between underemployment (due to insufficient work hours) and the subjective well-being of a representative sample of Chilean workers. By doing this, we will be able to assess the monetary valuation of such well-being costs by assessing the amount of money that a worker should be willing to accept to bear the potential negative effects of underemployment on well-being. To quantify these costs, our key dependent variable is subjective well-being (SWB), defined as the assessment made by a person, according to their own criteria, of the physical, emotional and social state in which they are at a given time (Vinaccia and Orozco 2005). The idea is to estimate the minimum amount that a worker is willing to accept (WTA) in order to maintain the same level of subjective well-being after being underemployed, which is a frequently used method to measure the monetary valuation that individuals give to certain attributes that do not have a market price (Clark and Oswald 2002). This methodology is especially attractive for policymakers who are interested in quantifying (at least roughly) the value of some resources or situations that do not involve monetary transactions (Sarrias 2019; Sarrias and Jara 2020).

By doing this, we will be able to provide some evidence and test a common hypothesis in the literature that affirms that underemployed workers are more likely to have low levels of subjective health and well-being (Angrave and Charlwood 2015). However, the results we might get from such an estimation of WTA values may differ across workers because of observed and unobserved heterogeneity on their underemployment circumstances, which may result in different valuations across the sample. An important limitation of most empirical research on this matter is that it focuses on the average effect of the variables on SWB (Binder and Coad 2015), therefore, in most cases they do not take into account heterogeneity. Studying observed and unobserved heterogeneity across workers allows us to go further than just an average WTA and calculate the variability that exists within the sample, leaving out the assumption that the entire sample is part of the same population (Wang and Hanges 2011).We are able to explain part of this variation (the observed part) by differences in working arrangements, as well as the type of job contracts they have. In the case of unobserved heterogeneity, according to Hess (2014) the main explanation of the existence of unobserved factors are the idiosyncratic differences in preferences across individuals. At the same time, unobserved heterogeneity may affect how individuals answer subjective measures, which may be also a source of bias in the results and the WTA estimation (Palomino and Sarrias 2019).

To accomplish our objectives, we use the Chilean cross-sectional National Socioeconomic Characterization Survey (CASEN) for 2013, which contains information on socioeconomic and socio-demographic characteristics of households, their work environment, as well as subjective well-being measures. Our results suggest that a negative relationship is indeed found, and the average value of the WTA is around CLP$64,009 monthly wage for the whole sample (roughly USD$122 at the time, and 30.5% of the minimum wage). After heterogeneity is taken into account, we identify two distinct classes in most of our specifications, one with a higher WTA than the whole sample (class 2), and another without significant underemployment effects.

The rest of the paper is organized as follows, in "Literature Review" we review relevant studies related to underemployment, subjective well-being and the relationship between them. In "Data" we present the data we use and some descriptive statistics to highlight how subjective well-being is distributed across workers. In "Empirical Strategy" we present the empirical-econometric strategy used to compute the valuation. In "Results" we present the empirical results. Finally, in "Conclusions" we discuss our findings, propose the policy implications regarding our results and conclude.

Literature Review

Underemployment is a highly studied topic in the economics literature. It happens when workers find themselves in a job that is less productive than what they are able to produce (Greenwood 1999). The concept is divided into two categories: time-related underemployment due to insufficient hours of work and workers in inadequate employment situations.

More specifically, Greenwood (1999) states that workers in time-related underemployment due to insufficient hours of work are those willing to work more hours than they actually do, and were available to do so in a given period of time. On the other hand, workers in inadequate employment situations might want to change their current job status for a variety of reasons related to their well-being and capacities (Greenwood 1999). This kind of underemployment can be further divided into two, the first one is due to competence mismatches among workers possessing a higher level of skill than the job demands (Scurry and Blenkinsopp 2011), the second one is due to income or earnings and relate to workers earning at least 20% less in their current job than the previous one (Zvonkovic 1988; Feldman 1996). Even though our empirical strategy does not deal directly with this category of underemployment, our conclusions apply to the broad definition of this concept.

In the literature, underemployment has gained attention because its effects on health and well-being have been extensively documented (Friedland and Price 2003; Bunting 2011; Angrave and Charlwood 2015; Esenaliev and Ferguson 2019; Lepinteur 2019; Mousteri et al. 2020). It is well known that individuals' subjective well-being depends on many factors, but job and labor market status are often the main determinants of life satisfaction, happiness and health for workers (Radcliff 2005; Taht et al. 2019). For instance, underemployment generates inefficiency due to under-utilization of the workforce and lower worker's welfare (Rodríguez et al. 2016), increased alcohol consumption and depression, lower levels of health and well-being (Friedland and Price 2003), and negative mental health consequences (Mousteri et al. 2020; Caceres and Caceres 2015).

From a theoretical perspective, there are fewer articles that tackle how underemployment affects individual or collective choices. We briefly review these theories in order to understand the mechanisms that may explain how underemployment affects subjective well-being. Nevertheless, the empirical strategy in this document cannot really distinguish between them. One insight used by Angrave and Charlwood (2015) is the person-environment fit theory (P-E fit). This theory is based on how employee needs, preferences, and job characteristics fit and balance together. According to Kristof-Brown et al. (2005), this theory predicts that workers' performance and well-being will be higher where P-E fit exists. In cases where a misfit happens between preferences and job characteristics, an unmet need (in this case more working hours) becomes a source of stress for the worker, causing a reduction in SWB (Feldman 1996; Friedland and Price 2003).

Another theory is proposed by Wunder and Heineck (2013), in which each worker has her/his own wage-hour preferences. If they receive job offers with fixed wage-hour combinations, but are unable to reveal their own preferred time workload for a given offer, then a working time mismatch emerges (Altonji and Paxson 1988).

According to Wunder and Heineck (2013), a working time mismatch leads to lower utility (well-being) for workers, compared to those who are adequately matched for their own preferred and actual hours of work. In summary, both theories (Wunder and Heineck 2013; Angrave and Charlwood 2015) reach the same conclusion about the association between underemployment and lower levels of subjective well-being. Even though this discussion would be irrelevant in the absence of transaction costs, it broadly affects the policy recommendations we propose at the end of this article.

On the empirical side, there is a growing body of literature that studies the relationship between underemployment and workers' subjective well-being. To mention some examples, Angrave and Charlwood (2015), Kamerāde and Richardson (2018), and Bell and Blanchflower (2019) find that over-employment and underemployment are associated with lower subjective well-being in the UK. Also for this country, Mousteri et al. (2020) find that there exists an important negative impact of underemployment on workers' mental health, but this impact is reversible when workers switch from underemployment to a full-time job. Heyes et al. (2017) analyze the consequences of underemployment on the subjective well-being of UK employees, and assess how the Great Recession affected this relation. The authors find that those who are underemployed experience lower levels of well-being compared to those who are more adequately employed, and also suggest that economic conditions like the Great Recession do have implications on both well-being and its relation with underemployment. For the United States, Friedland and Price (2003) reach similar conclusions. Finally, Wooden et al. (2009) finds that it is not the number of hours worked that matters for subjective well-being, but working time mismatch for Australian workers. There is still a void in the empirical literature that studies this relationship for developing countries (Esenaliev and Ferguson 2019), justifying the need to pursue our research objectives.

In Chile, to the best of our knowledge, the relationship between UND and SWB is not well documented, however some research indicates that Chile suffers high underemployment rates by insufficient hours of work, around 20% in 2013 (Bravo 2016). By 2013, Chile featured among the highest OECD and Latin American countries in terms of underemployment rates (ILO 2017; Páez and Sáez 2018). According to Kremerman et al. (2017), more than 40% of Chilean workers experienced underemployment in 2016. Jaar et al. (2016) note that the reasons for such high underemployment rates might be the high heterogeneity and segmentation levels found in the Chilean labor market, with some characteristics typically found both in poorer and richer countries.

Data

We use the Chilean National Socioeconomic Characterization Survey (CASEN by its initials in Spanish) developed by the Ministry of Social Development (MDS) to describe the socioeconomic situation of the Chilean population in detail. This is Chile's largest and most updated source of data on various social and economic indicators, including poverty, labor market, health, among others (Boncompte and Paredes 2019). The analysis is carried out for the year 2013 because this is the last wave that includes the subjective well-being (SWB) question. The initial sample consists of 218,491 individuals in 2013, from which we excluded non-worker respondents, individuals younger than 18 and older than 65. We also exclude those workers who do not report SWB or wage, and those that do not identify themselves in any economic sector or specific occupation. All these filters give us a final sample of 29,568 workers.[1]

Our dependent variable is the SWB of workers, which is obtained from the question *"All things considered, how satisfied are you with your life right now?"*, the range of response options goes from 1 "completely unsatisfied" to 10 "completely satisfied". Due to the small amount of people reporting their SWB levels in the first four categories, we opt to re-scale the dependent variable to 7 categories grouping the options 1 to 4 as completely unsatisfied.[2]

According to Sumner (1996) the variable represents individuals' well-being as a complete assessment of their life, providing many advantages for our empirical analysis. In the economics literature this variable is used as a proxy for individual utility, happiness and life satisfaction (Frey and Stutzer 2002). Similarly, it allows us to measure the impact of other variables on a measure of welfare by estimating a happiness equation (Powdthavee 2010). Finally, according to Sandvik et al. (1993) this self-reported measure converges to other types of assessment of well-being, including multi-item measures.

Figure 1 shows the relative frequencies for the SWB variable. Almost a quarter (24.83%) of the surveyed workers report complete satisfaction with their life and approximately 6% of the individuals in our sample are completely unsatisfied. The quantitative average of SWB is 4.67 (Table 1), meaning that most workers in the sample are satisfied with their lives. Chile was ranked sixth among the happiest Latin American countries between 2006 and 2016, and seventh between 2017 and 2019 (Rojas 2018; Helliwell et al. 2020).

Our key independent variable of interest is underemployment status, in this case the analysis is focused in the category defined by insufficient work hours. These workers are those that were willing and available to work more hours. This variable is obtained from the question *"Are you willing to work more hours a week?"*, and is a dummy variable that takes the value of one if the worker is willing to work more hours in the week. We later address potential limitations of this binary response through observed heterogeneity interactions, such as formality arrangements and work hours.

To control for individual socioeconomic characteristics, we use a number of control variables that are common in the literature of SWB (Wooden et al. 2009; Palomino and Sarrias 2019). These variables include measures of age, the quadratic

[1] The large reduction in the sample is due to the fact that we dropped 129,792 non-workers respondents, 3,881 individuals with an age less than 18 or more than 65, 55,098 individuals that do not report SWB, wage or underemployment, and 152 individuals with no information in other variables used in the estimations.

[2] As we can see in Fig. 1, these four categories (now grouped in category 1) represent only 6% of total responses. This collapse might lead to missing information and less efficient estimators (Greene and Hensher 2010). However, as indicated by Murad et al. (2003) this is a common practice to obtain better asymptotic approximation in maximum likelihood estimation.

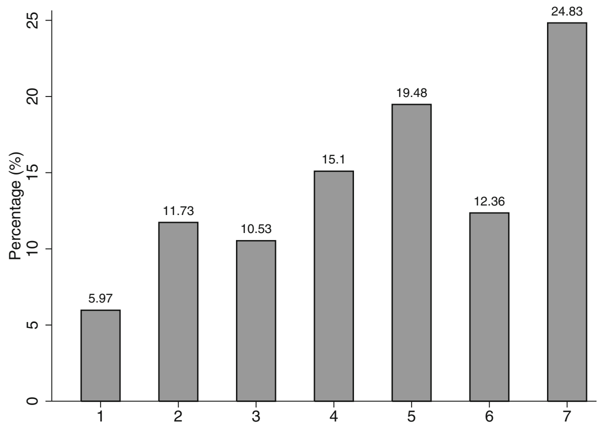

Fig. 1 Distribution of SWB (Life satisfaction). Source: Own elaboration using CASEN 2013

term of age, gender (a dummy variable with 1 for females and zero otherwise), monthly labour wage,[3] couple status (a dummy with 1 for workers with a couple and zero otherwise), the number of children between 0 and 6 years old in the household, the number of children between 7 and 17, schooling years, worker's occupation (classified as high, medium or low skill), the economic sector of the worker (divided in primary, secondary and tertiary), and hours of work. Since SWB is affected both by individual properties and social environments (Neira et al. 2018a), we include a dummy variable for urban areas and each one of the Chilean administrative regions. Most of these variables are routinely included as controls in regression models explaining subjective measures of well-being, mainly because they are determinants of life satisfaction and are considered confounders affecting also underemployment (Clark et al. 2001; Ferrer-i Carbonell and Frijters 2004; Carroll 2007; Shields et al. 2009). For example, research evidence suggests that individuals with a couple are in average more satisfied with their lives than single people (Wooden et al. 2009).

Table 1 reports the summary statistics of the variables included in the study (first two columns). We note that a significant amount of workers in our sample are underemployed (39%). This rate positions Chile as the fourth Latin American country in terms of underemployment (ILO 2017). This rate of underemployment in not only high, but it has also been increasing. While other Latin American countries[4] experienced reductions in their underemployment numbers between 2001 and 2009, Chile's rate increased by more than 3 percentage points in the same period (Caceres and Caceres 2015).

The average age in our sample is approximately 41 years and females account for 54% of it. The mean monthly labor wage was CLP$401,476 (Chilean pesos, roughly

[3] This variable is important to capture our WTA value, yet it is important to address its potential endogeneity. Therefore, we test our regressions with and without it in order to check the consistency of our model, as can be seen in Table 7.

[4] Argentina, Brazil, Colombia, Ecuador, Peru and Uruguay.

Table 1 Summary Statistics and Test for mean differences by underemployment (UND)

	Mean	SD	UND = 0	UND = 1	P-value
Underemployment (UND)	0.39	0.49			
Life Satisfaction (SWB) (1-7)	4.67	1.89	4.72	4.58	0.0000
Age	41.05	11.75	41.41	40.48	0.0000
Gender (1=Female, 0=Male)	0.54	0.50	0.56	0.51	0.0000
Wage	401,476	496,943	424,667	364,849	0.0000
Couple(1=Couple, 0=Single)	0.57	0.49	0.59	0.55	0.0000
# of Children 0-6 years	0.37	0.63	0.37	0.37	0.5802
# of Children 7-17 years	0.59	0.79	0.58	0.60	0.0056
Schooling in years	11.76	3.76	11.85	11.63	0.0000
Hours of work	42.07	15.09	43.34	40.08	0.0000
High Skill Occupation	0.23	0.42	0.25	0.22	0.0000
Medium Skill Occupation	0.34	0.47	0.34	0.33	0.0181
Low Skill Occupation	0.43	0.50	0.41	0.46	0.0000
Primary sector	0.10	0.28	0.01	0.01	0.5127
Secondary sector	0.37	0.48	0.03	0.03	0.0025
Tertiary sector	0.53	0.50	0.97	0.96	0.0027
Urban zone	0.85	0.36	0.85	0.85	0.3247
Administrative regions					
Tarapaca	0.04	0.20	0.05	0.03	0.0000
Antofagasta	0.04	0.19	0.03	0.04	0.0000
Atacama	0.04	0.19	0.04	0.03	0.0164
Coquimbo	0.04	0.21	0.05	0.03	0.0000
Valparaiso	0.10	0.30	0.10	0.08	0.0000
O'higgins	0.08	0.28	0.08	0.09	0.0120
Maule	0.07	0.25	0.06	0.07	0.0004
Bio Bio	0.13	0.33	0.13	0.13	0.2732
La Araucania	0.07	0.25	0.07	0.08	0.0006
Los Lagos	0.05	0.23	0.05	0.06	0.0007
Aysen	0.03	0.18	0.03	0.04	0.1209
Magallanes	0.03	0.18	0.04	0.03	0.0000
Metropolitana Santiago	0.19	0.39	0.19	0.19	0.9241
Los Rios	0.05	0.21	0.04	0.05	0.0017
Arica y Paranicota	0.04	0.19	0.03	0.04	0.0000
Number of observations	29,568		18,107	11,461	

Sample used in the estimations (CASEN)

equivalent to USD$ 767 at the time). 43% of the workers in the sample declare to be single. As expected, the division between high (23%), medium (34%) and low (43%) skill workers is skewed towards the last group. In terms of location, workers that live in urban areas account for 85% of the sample, and 19% of them live in the Metropolitan region of Santiago (Chile's capital and largest city).

Similarly, Table 1 shows the results of the mean differences tests between underemployed and fully employed workers (final three columns). These results are consistent with those found by Friedland and Price (2003) and Bell and Blanchflower (2019) where underemployed workers report lower levels of health and SWB. Similarly, there are significant differences between both groups of workers in human capital, since the underemployed have a lower number of years of schooling on average and mostly occupy low-skilled jobs. In addition, underemployed workers obtain lower wages than fully employed workers, and the lower earnings hold even after controlling for hours of work.

Empirical Strategy

The first part of this section is devoted to outline the Ordered probit model (OPM) we use to estimate the relationship between underemployment and subjective well-being in Chile and the willingness to accept (WTA) calculations to understand the magnitude of that value. In the second subsection, we take into account the observed and unobserved heterogeneity across workers and use the Latent class ordered probit model (LC-OPM) to compute how the WTA changes for that case.

Ordered Probit Model (OPM)

Probit and multilevel models are the most commonly used approaches in empirical studies about subjective well-being (SWB) (Neira et al. 2018b). Since SWB is an ordered variable, we use an ordered probit model (OPM). This model can be used in a similar way as the standard probit model to capture the individual's choice of outcomes driven by latent utility (McKelvey and Zavoina 1975).

Since we cannot observe the SWB of workers as a continuous variable, we assume that the true latent SWB of worker k depends on her/his underemployment status (u_k), the logarithm of monthly labour wage (y_k), a vector of socio-demographic characteristics (x_k) and a stochastic error term (ε_k).[5] This latent SWB can be stated as:

$$SWB_k^* = \beta u_k + \alpha log(y_k) + x_k'\gamma + \varepsilon_k, \tag{1}$$

Where SWB_k^* is an unobserved (latent) continuous variable, that ranges from $-\infty$ to $+\infty$. We can see this latent function as a way to operationalize the indirect utility function that gives workers the maximum utility according with those characteristics (Van Praag and Baarsma 2005). We do not observe this latent measure SWB_k^* directly, but instead a discrete variable with categories that represent the workers'

[5] It is common to include the logarithm of income in the subjective well-being research, as in Palomino and Sarrias (2019), this allows us to introduce heterogeneity in the WTA value, implying that richer individuals should have higher compensations, as their marginal utility of income is lower.

subjective well-being. We can then link the discrete category variable with the continuous latent one (SWB_k^*) using theoretical thresholds, and through this, generate the category variable (SWB_k).[6]

A growing body of empirical research uses the SWB measure to compute the compensating variation (CV), allowing us to calculate the monetary value of a change in a specific variable that affects individual welfare (Sarrias 2019). This method, first proposed by Ciriacy-Wantrup (1947), allows us to use survey questions and calculate how much are workers willing to pay or accept for an improvement in their utility (Mitchell and Carson 2013).

With these estimated parameters we can compute the willingness to accept (WTA) at the average monthly labour wage $\bar{y}$ by totally differentiating Eq. 1 in equilibrium, setting $\partial SWB_k^* = \partial x_k' = 0$ and leaving all the other variables constant, in the form:

$$WTA = \frac{\partial Log(y_k)}{\partial u_k} = -\frac{\beta \bar{y}}{\alpha} \tag{2}$$

We expect $\beta < 0$ and $\alpha > 0$, so that the average WTA for all workers in the sample is positive. Greene et al. (2014) point out that other unobserved factors may influence how workers answer the questions about their SWB. This serves as a strong motivation to use a model that allows for heterogeneity, and also interact our model with observable characteristics.

Observed and Unobserved Heterogeneity

One limitation of the previous model is the assumption that the parameters k, β, α and γ are assumed fixed across workers, implying they have homogeneous underlying preferences, which is not entirely realistic (Sarrias 2016). According to Boxall and Adamowicz (2002) consumer preferences are characterized by observed and unobserved heterogeneity. An important consequence of not taking this into account is that the estimation of the WTA will be just an average or mean of all workers. Also, assuming that workers' preferences and the thresholds when answering the SWB question in the surveys are the same for all workers is very restrictive. According to Schneider et al. (2012) and Williams (2016) there is a problem known as reporting heterogeneity, which means that the threshold points k are not the same across workers and tend to vary, generating an estimation problem.

We use two strategies to take heterogeneity into account. Firstly, we estimate the previous model using interactions between the underemployment variable and observable characteristics, such as working hours, type of contract, and work schedule arrangements. This will help us to understand how observable features might be influencing the effect of underemployment on SWB.

Secondly, we tackle the unobservables using latent class (LC) discrete choice models, a commonly used method for understanding the structure of heterogeneity (Keane and Wasi 2013). The approach assumes a discrete distribution and

[6] We do not develop the complete explanation of the OPM since is standard in the literature, see Palomino and Sarrias (2019) for more details.

captures preference heterogeneity by classifying workers in distinct classes (Boxall and Adamowicz 2002; Greene and Hensher 2003; Sarrias and Daziano 2017). The main objective of the Latent class ordered probit model (LC-OPM) is to account for unobserved heterogeneity across workers that influence SWB effects of underemployment, going further than just an average WTA and consider the variability that exists in workers preferences and thresholds. This method endogenously generates population sub-groups to account for such differences (Clark et al. 2005).

To implement this, Eq. 1 needs to be modified to let the parameters vary across workers:

$$SWB_k^* = \beta_k u_k + \alpha_k Log(y_k) + x_k'\gamma_k + \varepsilon_k, \tag{3}$$

Where the parameters β_k, α_k and γ_k capture the unobserved heterogeneity across worker's preferences.

To capture heterogeneity in the thresholds we allow μ to vary for each worker:

$$SWB_k = j \longleftrightarrow \mu_{j-1,k} < SWB_k^* \leq \mu_{j,k} \quad j = 1, ..., 7 \tag{4}$$

The LC-OPM follows the assumption that the population consists of groups of individuals called classes, formed by a finite number or workers (Q). Each class has a set of common parameters $\theta = (k_q, \beta_q, \alpha_q, \gamma_q)$ (fixed parameters within a class), but they differ between groups (heterogeneity across classes). Following Greene and Hensher (2010) we are able to get closer to know to which class each worker belongs to, assuming that θ_k varies following the non-parametric distribution of the form:

$$g(\theta_k|\delta_q) = \begin{cases} \theta_1 & \text{with probability } \pi_{k1}(\delta_1) \\ \theta_2 & \text{with probability } \pi_{k2}(\delta_2) \\ . & . \\ . & . \\ . & . \\ \theta_Q & \text{with probability } \pi_{kQ}(\delta_Q) \end{cases} \tag{5}$$

Where a worker k belongs to class q with probability π_{kq}, such that $\sum_{q=1}^{Q} \pi_{kq} = 1$ and $\pi_{kq} > 0$, δ_q is a set of parameters that allows us to determine the class probability assignment (Palomino and Sarrias 2019).

Finally, we assume that the formulation of π_{kq} follows the semi-parametric formula of a multinomial logit model, specified as follows:

$$\pi_{kq}(\delta_q) = \frac{exp(z_k'\delta_q)}{\sum_{q=1}^{Q} exp(z_k'\delta_q)}; \quad q = 1, ..., Q, \quad \delta_1 = 0 \tag{6}$$

Where z_k is a vector of socioeconomic and sociodemographic characteristics of workers that determine the assignment to each one of the classes. The variables included in this vector seek to describe different behaviors between groups and classify them accordingly (Palomino and Sarrias 2019). Since our interest is the relation between UND and SWB, we choose specific variables intended to capture groups of individuals with different propensities to be underemployed.

An important disadvantage of this approach is that the researcher chooses the number of classes (Boxall and Adamowicz 2002). The empirical literature using latent class models affirms that a greater number of classes generates an improvement in the goodness of fit of the model, but the number of parameters also grow, making the interpretation of results more difficult (Hess 2014). Also, the greater number of classes may generate loss of significance in the parameters, problems in the estimation process and classes representing a small proportion of the sample (Palomino and Sarrias 2019).

As we did with the standard ordered probit model, we can use the parameters and compute the WTA by totally differentiating Eq. 3. In this case we can account for the unobserved heterogeneity of workers computing a different WTA for each class:

$$WTA_q = \frac{\partial Log(y_k)}{\partial u_k} = -\frac{\beta_q \bar{y}}{\alpha_q} \tag{7}$$

Results

We divide this section in three parts. The first one presents the results associated with the relationship between SWB and underemployment using the standard OPM. We address the observed and unobserved heterogeneity afterwards and present the results using the LC-OPM, as well as the interaction with observable characteristics. In both sections we show the results for WTA values.[7]

General Relationship Between SWB and Underemployment: OPM

In this subsection we present the marginal effects (ME) of our ordered probit model, so they can be interpreted as the effect of a variable in the probability to experience each level of SWB. It is important to note that we present the ME as the estimation result of the relationship between SWB-UND, as these values were used to compute the WTAs. Table 6 in the Appendix reports the marginal effects of each answer of the SWB, going from 1 (completely unsatisfied) to 7 (completely satisfied), evaluated at the mean of each variable.[8] The standard errors for each marginal effect were calculated using the delta method. Figure 2 shows the marginal effects of answer 7 (completely satisfied) on the SWB scale.[9] For this category, results behave according to the expected signs. Conditional on the controls described in "Data", underemployment reduces the probability of reporting the highest level of life satisfaction.

The remaining control variables also show the expected signs. While the number of children between 0 and 6 years old, primary sector, hours of work and living in an

[7] We also tried a specification of all the following estimations with linear income instead of its logarithm. Although the magnitude of the estimates change, the confidence intervals for the WTA values suggest that the difference between both specifications is not statistically significant.

[8] In order to avoid convergence issues of the models in the search of maximum likelihood estimate, we re-scaled some of the variables in all estimations, as in Palomino and Sarrias (2019). This can be seen in the variable names in Fig. 2, and Tables 5, 6 and 7.

[9] For reasons of clarity, the marginal effects of the quadratic term of age and the administrative regions were excluded from the graphs, but they are included in the estimation.

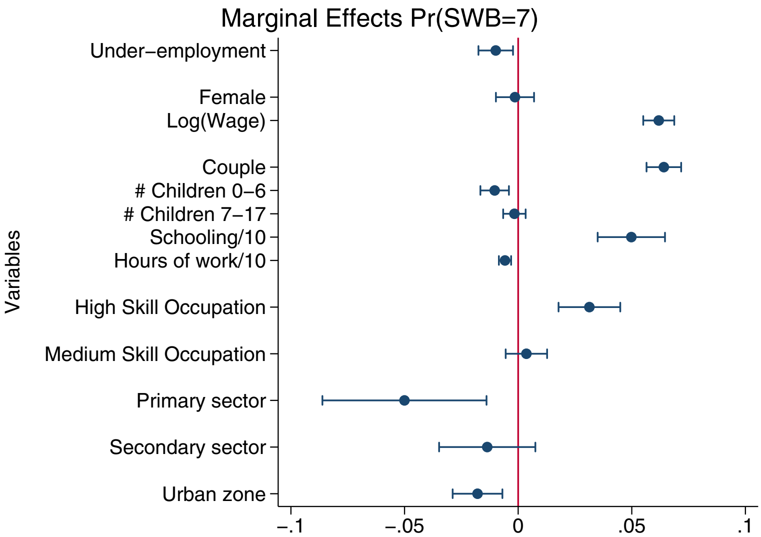

Fig. 2 Marginal effects ordered probit model (SWB=7). Age, quadratic term of age and dummy variables for administrative regions added as controls. Source: Own elaboration using CASEN 2013

urban place display a significant negative association with the subjective well being, wage, being in a couple, years of schooling, and being in a high skilled occupation show a positive correlation with SWB.[10]

Using the parameters of column (1) of Table 5 and Eq. 2 we compute the WTA for the whole sample. Table 2 shows the 90%, 95% and 99% confidence intervals of the WTA for underemployment in Chilean pesos (CLP) and in American dollars (USD). On average, the WTA is CLP\$64,009 (roughly USD\$122 at the time, and 30.5% of the minimum wage) for being underemployed. This means that, on average, each worker is willing to accept an increase of CLP\$64,009 in her/his monthly labour wage for being in underemployment.

In summary, the results confirm that holding all other variables constant, workers report significantly lower subjective well-being when they face underemployment. This WTA is an average value for the complete sample, but as mentioned, the estimation may differ by worker because of observed and unobserved heterogeneity. Therefore, in the following sub-sections we interact the underemployment variable with observable characteristics, and then use the LC-OPM model to compute a WTA for each class, allowing us to capture part of the unobserved heterogeneity in the sample.

[10]We can also use these results to interpret some examples of the average partial effects. For instance, if the worker is underemployed the probability of being completely satisfied with life decreases by 1.0 percentage points. Similarly, if the worker has a couple the probability of being completely satisfied with life increases by 6.4 percentage points.

Table 2 WTA for underemployment

	WTA	90% CI	95% CI	99% CI
CLP $	64009.02	[21724 ; 106294]	[13623 ; 114395]	[-2209 ; 130228]
USD $	122.21	[41 ; 203]	[26 ; 218]	[-4 ; 249]

WTA and 99%, 95% and 90% confidence intervals for underemployment. Standard errors were computed using delta method. WTA converted to USD using observed conversion rate from 30/Dic/2013, $523.76 CLP/USD. Source: Own elaboration using CASEN 2013

Observed Heterogeneity in the Relationship Between SWB and Underemployment

Observed heterogeneity could be described in many forms, yet we focus our attention into variables that are directly tied to the type of contracts and the number of total working hours. For the latter, we simply divide the sample into quartiles[11], according to the distribution of working hours. With regards to the type of contracts, we consider both if workers had a formal job contract, or whether the hiring arrangements are part-time (a relatively recent addition in the Chilean labor legislation), full-time, or explicitly extended schedule arrangements (contractual overtime).

Table 3 shows that these groups have indeed different average values for SWB, not only in terms of working hours (particularly between the first two quartiles), but also in terms of contract and working day arrangements. Most of these mean differences between groups are high, showing that, on average, workers with full-time formal jobs seem to report higher levels of subjective well-being.

Figures 3 and 4 show how our WTA estimations change whenever observed heterogeneity is taken into account.[12] In contrast with the first estimation, the first quartile is the only one that remains statistically significant, showing that workers that are currently working less than 39 hours per week are willing to accept approximately CLP$162,307[13] in order to work more hours. For people working more than 40 hours, the coefficients are not statistically significant.

When we take into account the observed heterogeneity by contract, we find important differences. Workers with formal contracts do not show a statistically significant WTA for underemployment, while workers with no contract are willing to accept approximately CLP$73,045. When analyzing the heterogeneity by working schedule arrangements, on the other hand, the results do not show a statistically significant differences in their WTA (See Fig. 6 in the Appendix).

[11] The third quartile includes the largest share of the sample, as most workers are hired for exactly 45 hours per week in formal full-time jobs.

[12] To compute the WTA for the different groups of individuals we interact UND with the categorical variables representing the observed heterogeneity dimensions. In non-linear models like the OPM, we follow Ai and Norton (2003), Norton et al. (2004), and Karaca-Mandic et al. (2012) to compute the correct marginal effects of the interaction terms. However, our focus is on the marginal effect of each category in order to compute the WTAs.

[13] As a reference, the Chilean minimum wage in 2013 was CLP$210,000 (USD$404)

Table 3 Summary Statistics, observed heterogeneity

	Avg.Hours	Avg.SWB
Q1(less than 39 weekly hours of work)	19.4	4.57
Q2(between 40 and 44 weekly hours of work)	41.7	4.89
Q3(between 45 and 48 weekly hours of work)	45.4	4.64
Q4(more than 49 weekly hours of work)	64.1	4.67
Formal contract	Share	
With contract	85.3%	4.73
Without contract	14.7%	4.28
Schedule arrangement		
Full working day	84.0%	4.68
Part-time working day	11.5%	4.50
Extended working day	4.5%	4.75

Sample used in the estimations (CASEN)

Unobserved Heterogeneity in the Relation SWB and Underemployment: LC-OPM

In this stage we present the results of our estimations using a latent class ordered probit model (LC-OPM) to address unobserved heterogeneity. This procedure allows

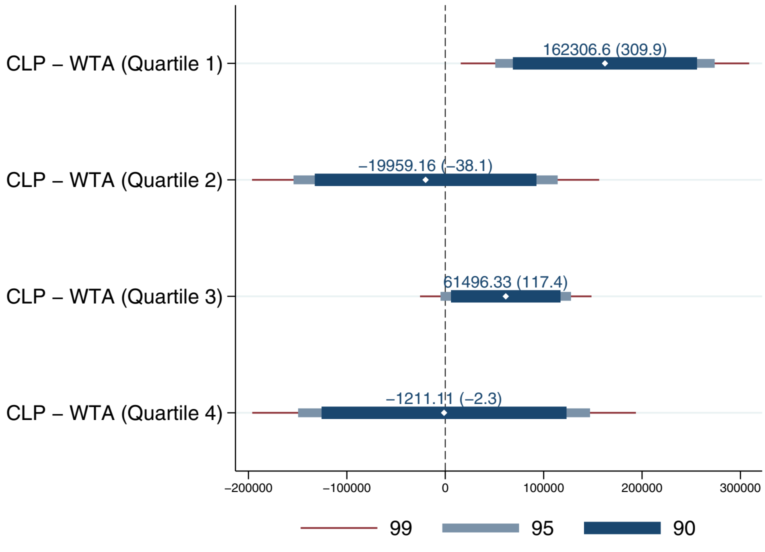

Fig. 3 WTA for underemployment by hours of work. WTA and 99%, 95% and 90% confidence intervals for underemployment. Standard errors were computed using delta method. USD WTA values in parentheses. WTA converted to USD using observed conversion rate from 30/Dic/2013, $523.76 CLP/USD. Source: Own elaboration using CASEN 2013

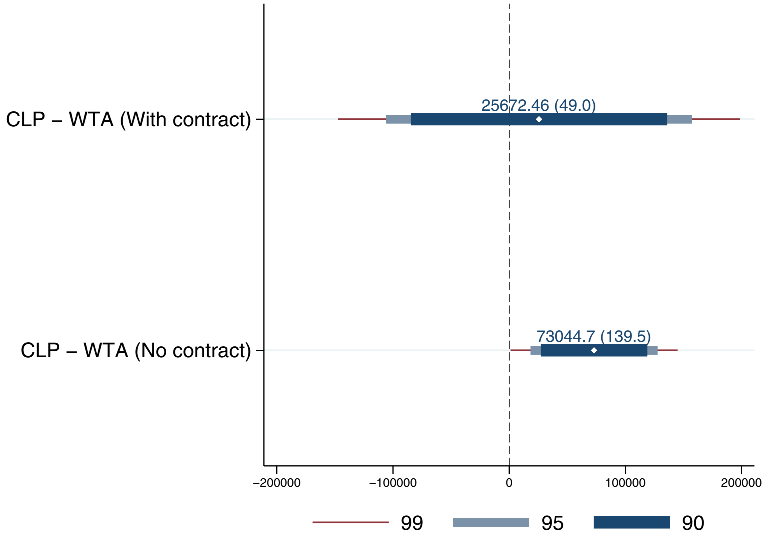

Fig. 4 WTA for underemployment by contract. WTA and 99%, 95% and 90% confidence intervals for underemployment. Standard errors were computed using delta method. USD WTA values in parentheses. WTA converted to USD using observed conversion rate from 30/Dic/2013, $523.76 CLP/USD. Source: Own elaboration using CASEN 2013

us to analyze how unobserved factors may influence how workers answer the question of SWB, as well as letting us take into account the heterogeneity in the WTA for being underemployed. Controlling for heterogeneity reduces many potential biases caused by its omission (Williams 2016). This approach also has the advantage of being less arbitrary than the observed heterogeneity analysis.

As mentioned in "Observed and Unobserved Heterogeneity", in this model we have to determine the number of classes (Q) beforehand (Boxall and Adamowicz 2002). Generally, the most used criterion for the selection of the number of classes is estimating the model using a differing number of classes and compare the Akaike information criterion (AIC) (Hess and Daly 2014; Sarrias and Daziano 2018). Nevertheless, as mentioned in "Observed and Unobserved Heterogeneity", parameters grow as the number of classes increases, jeopardizing convergence and interpretability (Hess and Daly 2014). A second problem is that classes themselves might end up representing a small proportion of the sample (Palomino and Sarrias 2019).

Through a combination of AIC, the number of parameters and shares of individuals in each class, we end up considering 2, 3 and 4 classes (Romero-Espinosa et al. 2020). Table 4 shows these comparisons. Although the AIC is minimized when Q = 4, the models presented problems to converge and the proportions of individuals are small in some classes. For example, when Q = 3 the proportion of individuals in each class is 60.63%, 1.20% and 38.17%, respectively. Due to the problems of choosing a large number of classes mentioned above, we decided to estimate the LC-OPM with

Table 4 Selection of the number of classes (Q)

Q	AIC	Parameters	Shares			
1			1	2	3	4
2	107730.1	98	40.29%	59.71%		
3	107579.1	155	60.63%	1.20%	38.17%	
4	107574.9	215	40.99%	18.13%	8.55%	32.33%

Source: Own elaboration using CASEN 2013

Q = 2. This approach has the advantage of representing an important proportion of the sample, the first class is the smallest with 40.29% of the sample, and the second class is the remaining 59.71% .

Table 5 shows the results for the OPM and the LC-OPM that accounts for unobserved heterogeneity, this table allows us to analyze the differences between classes. This table shows the coefficients rather than the ME for clearer comparison, as Palomino and Sarrias (2019). The estimated coefficient for UND is negative and significant for class 2, but shows no significance for class 1, meaning that the magnitude and significance of the coefficient in the OPM model is mostly driven by class 2. That is, only for the 59.71% of workers potentially experiencing underemployment this could be detrimental to their satisfaction with life, while for workers in class 1 (40.29%) underemployment would not affect their SWB. A similar pattern is found for the coefficients of number of children between 0 and 7 years old, and residence in urban areas. On the contrary, class 1 drives the significance of the coefficients found in the standard OPM for the primary sector. Finally, as expected, the logarithm wage coefficient is positive and significant for both classes, as well as the couple variable, years of schooling and high skill occupation. From these findings we can derive an important first conclusion, if one focuses only on the average effect, we would be leaving behind hidden patterns and relevant information.

To further understand this unobserved heterogeneity we can analyze the class assignment variables and obtain some insights on why individuals are more likely to belong to one class or another. For the first group, the class probability assignment variables are set as the baseline (normalized to zero), for class 2 the assignment is a function of socioeconomic and socio-demographic variables.[14] Since our interest is the relationship between SWB and underemployment, the variables included in this vector z_k are intended to capture groups of individuals with different propensities to be in underemployment, also these variables are those that show some interesting results in the OPM. For example, underemployment and part-time work happen

[14] Note that any single class can be set as baseline.

Table 5 Ordered Probit and Latent Class Ordered Probit Model

	(1) OPM: β/SE	(2) Class 1: β/SE	(3) Class 2: β/SE
Constant		2.887*	–2.776***
		(1.560)	(0.328)
Underemployment (UND)	–0.032***	0.048	–0.116***
	(0.012)	(0.030)	(0.022)
Age / 10	–0.273***	–0.561***	–0.147**
	(0.039)	(0.102)	(0.067)
$(\text{Age} / 10)^2$	0.026***	0.056***	0.003
	(0.039)	(0.011)	(0.008)
Female	–0.004	0.006	–0.009
	(0.014)	(0.048)	(0.027)
Log(Wage)	0.204***	0.163***	0.317***
	(0.011)	(0.028)	(0.022)
Couple	0.214***	0.186***	0.241***
	(0.013)	(0.046)	(0.027)
# of Children 0-6 years	–0.034***	–0.055*	–0.101***
	(0.010)	(0.032)	(0.021)
# of Children 7-17 years	–0.005	0.015	–0.027**
	(0.008)	(0.018)	(0.014)
Schooling in years / 10	0.164***	0.306***	0.611***
	(0.025)	(0.078)	(0.066)
Hours of work / 10	–0.019***	–0.021**	–0.025***
	(0.004)	(0.009)	(0.008)
High Skill Occupation	0.101***	0.478**	0.163***
	(0.022)	(0.202)	(0.044)
Medium Skill Occupation	0.011	0.089	0.118***
	(0.015)	(0.055)	(0.033)
Primary sector	–0.177**	–0.303**	–0.200
	(0.070)	(0.137)	(0.207)
Secondary sector	–0.045	–0.109	–0.055
	(0.036)	(0.107)	(0.078)
Urban	–0.058***	0.126**	–0.093**
	(0.018)	(0.050)	(0.044)
Region Dummies	Yes	Yes	Yes
Class probability assignment variables			
Constant			–0.422
			(0.356)
Age / 10			–0.113***
			(0.038)

Table 5 (continued)

	(1) OPM: β/SE	(2) Class 1: β/SE	(3) Class 2: β/SE
Female			0.011
			(0.086)
Couple			–0.138
			(0.086)
# of Children 0-6 years			–0.121**
			(0.060)
Schooling in years / 10			0.875***
			(0.152)
High Skill Occupation			0.506***
			(0.182)
Medium Skill Occupation			0.282***
			(0.100)
Primary sector			–0.192
			(0.447)
Secondary sector			–0.096
			(0.232)
Urban			0.330***
			(0.113)
Regions Dummies	Yes	Yes	Yes
Observations	29568	11912	17656
% of the sample	100%	40.29%	59.71%
AIC	108818.956	107730.1	

Thresholds not reported. Standard errors in parentheses - ME: SE computed using Delta Method
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

more frequently among women than men (Kjeldstad and Nymoen 2009; Kamerāde and Richardson 2018).

Since only class 2 shows a significant negative relationship between UND and SWB, we expect workers in this class to be more sensitive to underemployment. The bottom part of Table 5 shows the coefficients for the variables included in the class-assignment equation.[15] These results show that younger workers, with more

[15] It is important to note that only the coefficients associated to class 2 are shown. They should be interpreted in relation to class 1, because the first class coefficients have been normalized to zero.

schooling, high and medium skill occupations (compared to low skill occupations), and people living in urban areas are more likely to belong to class two, which is the class most affected by underemployment.

Similarly to the previous subsection, by using the parameters of columns (2) and (3) Table 5 and Eq. 7 we can compute the WTA for both classes. Figure 5 shows the 90%, 95% and 99% confidence interval of the WTA for underemployment, computed for the whole sample, class 1 and class 2. As expected, using the LC-OPM to compute the WTA allows us to get some insights of the unobserved heterogeneity across workers.

In Fig. 5 we show that WTA is not significant for class 1, while for class 2 it is significant at the 95% level and larger than that computed with the standard OPM. On average, for workers in class 2, the WTA is CLP$146,622 (roughly USD$280 at the time) for being underemployed. This means that the average worker in this class is willing to accept an increase of this amount in her/his monthly labour wage for being in such situation, a surprisingly similar magnitude to the one we found using the observed heterogeneity analysis for the workers in the first quartile of working hours.

In summary, our results suggest that being underemployed affects negatively the SWB of workers, but not necessarily for the whole sample. It seems to affect mostly workers that already work less than 39 hours or no dot have contract jobs. The latent-class models tell us that one of the groups (59.71% of the sample), a group that we

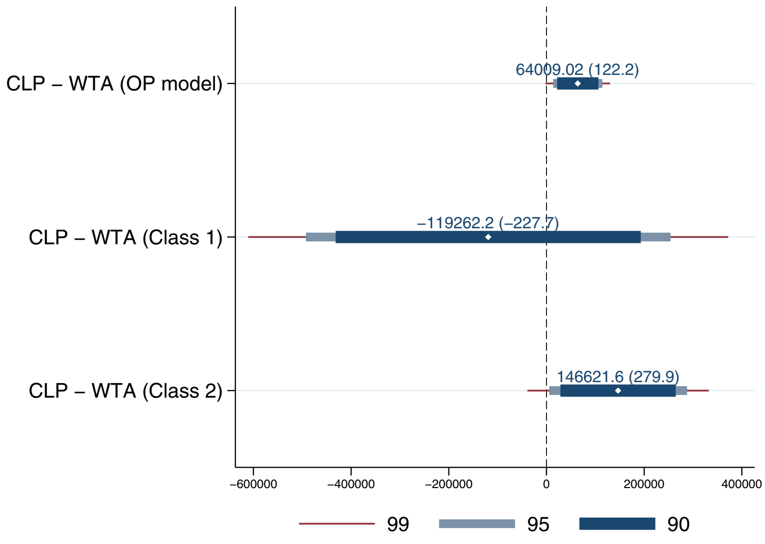

Fig. 5 WTA for underemployment. WTA and 99%, 95% and 90% confidence intervals for underemployment. Standard errors were computed using delta method. USD WTA values in parentheses. WTA converted to USD using observed conversion rate from 30/Dic/2013, $523.76 CLP/USD. Source: Own elaboration using CASEN 2013

can broadly characterize as older, more educated, living in urban areas, and working in high skill occupations would be affected.

It is important to note that the WTAs we obtain in this subsection are much higher than the WTA for the complete sample computed with the standard OPM, giving support to the fact that focusing only on the average value and not taking into account the unobserved heterogeneity could lead to biased results.

Conclusions

In this paper we provide evidence on the empirical association of underemployment due to insufficient hours of work and subjective well-being of Chilean workers, and by doing this, we are able to assess the monetary valuation of such well-being costs by calculating the amount of money that a worker is willing to accept in order to bear the potential negative effects of underemployment on well-being. Similarly, we find that our results and the WTA estimation may differ by worker because of unobserved and observed heterogeneity on underemployment status, which results in different valuations across workers. Therefore, as our second objective we to control for both types of heterogeneity across workers using a latent class discrete choice model, as well as interactions with observable categories.

Our main findings seem to confirm that, on average, underemployed workers are more likely to have low levels of subjective well-being (SWB). With respect to the willingness to accept (WTA), on average it is CLP$64,009 for being underemployed, meaning that a worker should be willing to accept an increase of CLP$64,009 (USD$122) in her/his monthly labour wage for bearing that situation.

When taking into account the observed and unobserved heterogeneity, our results confirm the existence of heterogeneous preferences with respect to the effect of underemployment on SWB. Using two different approaches, we identify that some workers are more sensitive to underemployment, while others do not seem to be sensitive to the effects of underemployment in their SWB. Following this, the class that presents a significant WTA (class 2) has a higher value than the average value of the WTA calculated using the whole sample. These results highlight the fact that it is necessary to use models that take into account individual heterogeneity when analyzing the effects of a variable on SWB and when computing the WTA. A model that does not take into account this underlying heterogeneity would lead us to inappropriate results and generalizations about the effects.

Overall, these results are important for several reasons. Firstly, there is an increasing interest by researchers in many academic disciplines to assess, and study the relationships affecting individuals' health and well-being, as well as the factors and circumstances influencing it. Based on this, we contribute with our results to document the relationship for the Chilean case, showing that a fraction of underemployed workers present lower levels of SWB, and some are willing to accept an important part of their income to bear this situation. Second, studies focused on Latin America about the relationship between underemployment and subjective well-being are scarce, and this piece of research aims to enrich and broaden our knowledge related to diverse labor markets, this is important for the literature, as most studies have been made in rich countries with more formal and secure labor markets.

Finally, it is important to highlight that our findings are not only valuable for scholars but also for policymakers, both in countries with precarious labor markets, as well as places that may experience increased economic turmoil or recessions in the near future. According to Mousteri et al. (2020) the negative effects of underemployment are reversible when workers transition from hours-underemployment to full-time positions. In this regard, policymakers could face stark choices in times of crisis, as tackling the precariousness in labor markets is proving extremely relevant to societies. Labor market interventions targeted at improving workers' safety nets, formality and reaching their full potential would not only improve overall working conditions and boost local economies, but also show effects in well-being that are also valuable for societies as a whole. Our results help to quantify such welfare effects, both as a rough estimation of the hidden costs of underemployment, and as a policy guide to prevent labor market mismatches in the first place. The monetary values we obtain for compensation are intended to guide policymakers to design schemes that facilitate the relocation of to better and more productive employment opportunities whenever mismatches do have effects on individuals' well-being.

Our conclusions do not advocate for labor flexibilization schemes that disproportionately benefit employers[16], nor to rigidize labor legislation further as a policy recommendation. In that sense, policies that empower workers to choose their preferred workload and schedules could be better for their well being than labor flexibilization policies that are just suited to benefit the interests of employers. Pursuing better matches as a policy recommendation is also consistent with theoretical findings on this area (Angrave and Charlwood 2015; Wunder and Heineck 2013)

We would also like to acknowledge some limitations of this study. Although we are able to identify time-related underemployed workers due to insufficient hours of work, data constraints did not allow us to explore other definitions of this variable, future research in this area would benefit greatly from specific surveys covering employment details such as underemployment by income or competences, as well as subjective well-being indicators. This work focuses on the role of heterogeneity and the WTA computation, however causality is still an issue that is not easily addressed in the empirical literature of subjective well-being, as many variables may present reverse causality issues with well-being indicators. For example, workers with low levels of SWB may still want to spend more time at work or end up in poor quality jobs. Finally, we just scratched the surface on spatial issues that might be influencing our results, such as sorting, spatial autocorrelation, regional differences in income, economic structure and human capital. In-depth interdisciplinary research about the intrinsic causes and motivations behind underemployment would greatly contribute to advance our understanding of the labor force's well being and build better working environments.

[16] Such as easy contract terminations, lack of severance pay, unilateral working hours adjustments and random schedule assignments.

Appendix: Additional Tables and Figures

Table 6 Ordered Probit Model: SWB - Marginal Effects Pr(SWB = 1,2,3,4,5,6,7)

	(1) ME/SE	(2) ME/SE	(3) ME/SE	(4) ME/SE	(5) ME/SE	(6) ME/SE	(7) ME/SE
Underemployment (UND)	0.004**	0.005**	0.003**	0.002**	–0.001**	–0.002**	–0.010**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.004)
Age / 10	0.007***	0.009***	0.005***	0.003***	–0.001***	–0.004***	–0.018***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Female	0.001	0.001	0.000	0.000	–0.000	–0.000	–0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.004)
Log(Wage)	–0.023***	–0.030***	–0.017***	–0.011***	0.005***	0.014***	0.062***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.003)
Couple	–0.025***	-0.031***	–0.017***	-0.011***	0.006***	0.015***	0.064***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
# of Children 0-6 years	0.004***	0.005***	0.003***	0.002***	–0.001***	–0.002***	–0.010***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.003)
# of Children 7-17 years	0.001	0.001	0.000	0.000	–0.000	–0.000	–0.002
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)
Schooling in years / 10	–0.019***	–0.024***	–0.013***	–0.009***	0.004***	0.011***	0.050***
	(0.003)	(0.004)	(0.002)	(0.001)	(0.001)	(0.002)	(0.008)
Hours of work / 10	0.002***	0.003***	0.002***	0.001***	–0.000***	–0.001***	–0.006***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
High Skill Occupation	–0.011***	–0.015***	-0.008***	–0.006***	0.002***	0.007***	0.031***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.000)	(0.001)	(0.007)
Medium Skill Occupation	–0.001	–0.002	–0.001	–0.001	0.000	0.001	0.004
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.005)
Primary sector	0.023**	0.026**	0.014***	0.007***	–0.007*	–0.013**	–0.050***
	(0.010)	(0.011)	(0.005)	(0.002)	(0.004)	(0.006)	(0.018)
Secondary sector	0.005	0.007	0.004	0.002	–0.001	–0.003	–0.014
	(0.005)	(0.005)	(0.003)	(0.002)	(0.001)	(0.003)	(0.011)
Urban	0.006***	0.008***	0.005***	0.003***	–0.001***	–0.004***	–0.018***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.000)	(0.001)	(0.006)
Region Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29568	29568	29568	29568	29568	29568	29568

Standard errors in parentheses - ME: SE computed using Delta Method. Quadratic term of age added as control

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 Ordered Probit Model: SWB - Marginal Effects Pr(SWB =7) with and without wage

	(1) ME/SE	(2) ME/SE
Underemployment (UND)	–0.010**	–0.015***
	(0.004)	(0.004)
Age / 10	–0.018***	–0.014***
	(0.002)	(0.002)
Female	–0.001	–0.025***
	(0.004)	(0.004)
Log(Wage)	0.062***	
	(0.003)	
Couple	0.064***	0.069***
	(0.004)	(0.004)
# of Children 0-6 years	–0.010***	–0.010***
	(0.003)	(0.003)
# of Children 7-17 years	–0.002	–0.003
	(0.003)	(0.003)
Schooling in years / 10	0.050***	0.091***
	(0.008)	(0.007)
Hours of work / 10	–0.006***	0.001
	(0.001)	(0.001)
High Skill Occupation	0.031***	0.072***
	(0.007)	(0.007)
Medium Skill Occupation	0.004	0.008*
	(0.005)	(0.005)
Primary sector	–0.050***	–0.052***
	(0.018)	(0.019)
Secondary sector	-0.014	-0.011
	(0.011)	(0.011)
Urban	–0.018***	–0.014**
	(0.006)	(0.006)
Region Dummies	Yes	Yes
Observations	29568	29568

Standard errors in parentheses - ME: SE computed using Delta Method. Quadratic term of age added as control

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

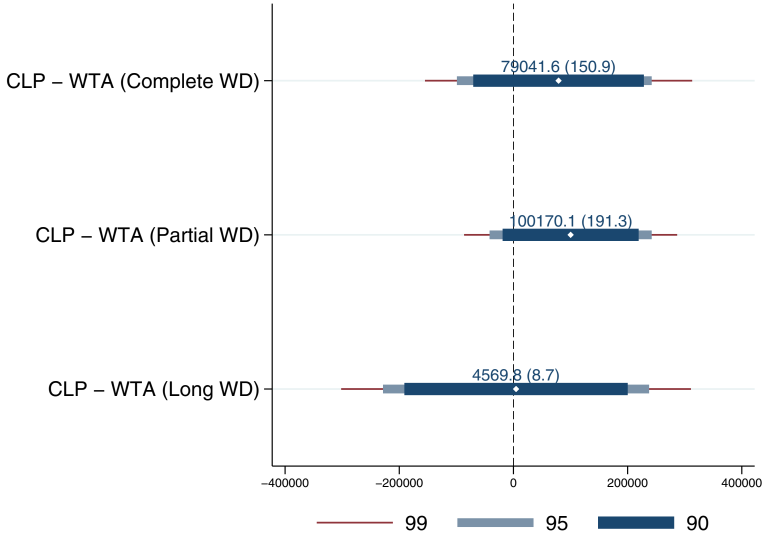

Fig. 6 WTA for underemployment by Working day type. WTA and 99%, 95% and 90% confidence intervals for underemployment. Standard errors were computed using delta method. USD WTA values in parentheses. WTA converted to USD using observed conversion rate from 30/Dic/2013, $523.76 CLP/USD. Source: Own elaboration using CASEN 2013

Funding This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Declarations

Conflict of Interests The authors declare that they have no conflict of interest.

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