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ABSTRACT

While studies using pre-2000 data for Chile implied that technological change drives the skill premium evolution, post-2000 data suggests that the supply of skilled labour expansion has reduced this premium. In contrast, literature shows a consistent link between technology and the growing demand for skilled labour, despite educational improvements, leading to skill premium increases. We examine these interactions under the race between education and technology model (RBET) for Chile between 1980 and 2018 considering the inconsistent findings (e.g., negative elasticities) reported by past studies. We also find inconsistencies using cointegration techniques. Alternatively, we apply an Unobserved Component Model using a Bayesian estimation that enforces the required economic and theoretical conditions. We find that, before the 2000s, the technological change dominated. However, in the 2000s, the demand was surpassed by educational supply increases, reducing the premium. The estimated elasticity of substitution between skilled and unskilled labour is 6.5, implying that both are more substitutable than commonly thought.

1. Introduction

In recent economic discourse, the dynamics of the skill premium, i.e., the skilled labour wages relative to unskilled labour or the wage gap between tertiary-educated workers and those with less education, have garnered considerable attention. In this regard, some have emphasised the pivotal role the skill premium plays in Latin American economies, notably in Chile (see, e.g., Acosta et al., 2019; Guerra-Salas, 2018; Parro and Reyes, 2017). The Chilean economy offers a compelling case study for several reasons: its distinct economic transitions over the last four decades, marked by significant reforms and trade liberalisations, and its shift in labour dynamics from physically intensive sectors to knowledge-based ones (see Gallego, 2012). Furthermore, the evolution of Chile's educational sector has considerably impacted the availability of skilled labour, influencing the trajectory of the skill premium (Murakami and Nomura, 2020; Parro and Reyes, 2017). These simultaneous shifts in skilled labour supply and demand factors implicitly refer to *a race between education and technology* (the RBET model henceforth) (Acemoglu and Autor, 2011; Autor et al., 2020; Goldin and Katz, 2008; Katz and Murphy, 1992; Tinbergen, 1972, 1974). The RBET model is also known as the skill-biased technological change model or the supply-demand framework and, the literature generally uses these different names to refer to the same model. While the empirical applications of this model, as seen in early works by Acemoglu (2002), Johnson (1997), and Katz and Murphy (1992), and more recently, Mallick and Sousa (2017) and Zhang et al. (2018) offer vital insights, there remain considerable challenges in its empirical verification. These challenges, which usually receive less attention, stem from

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methodological difficulties, data limitations, and, in certain instances such as Chile, results that confront theoretical expectations (Murakami, 2014; Robbins, 1994b). In this regard, it becomes imperative to recognise these empirical difficulties while simultaneously offering alternative approaches and appreciating the nuances offered by the Chilean context.

In Chile, like most Latin American countries, the skill premium has been suggested as the main force driving the observed rise and fall of income inequality in recent decades (Acosta et al., 2019; Guerra-Salas, 2018; Parro and Reyes, 2017). In this regard, there is a widespread agreement about the inverted U-shaped pattern shown by the skill premium evolution during the last five decades in Chile. It grew considerably since the mid-1970s, peaked in 1987, then held steady over the 1990s, and it has been declining since the 2000s (Gallego, 2012; Murakami, 2014; Murakami and Nomura, 2020; Parro and Reyes, 2017).

A distinction between the pre-2000 and post-2000 periods provides insights on the rise and fall of the skill premium. Most of the major economic reforms that feature the Chilean economy occurred before the 2000s, with trade liberalisation as the most relevant (Beyer et al., 1999). This openness allowed the absorption of foreign technologies, most of them biased toward skilled labour, leading to higher demand for skilled labour and increasing the skill premium (Gallego, 2012). At the same time, economic development from physically intensive sectors, i.e. agriculture and manufacturing, moving to less physically demanding and more knowledge intensive sectors such as services, also led to higher demand for better-educated workers before the 2000s (Buera and Kaboski, 2012). In the post-2000 period, the skill premium decline has been linked to the increasing availability of skilled workers due to the expansion of tertiary education (Murakami and Nomura, 2020; Parro and Reyes, 2017). This expansion, which was fuelled by critical educational reforms in the 1980s and 1990s (Schneider, 2013; Valiente et al., 2020), has resulted in fewer returns to tertiary education (Murakami and Nomura, 2020). In a context of increased relative demand for skilled workers arising from a skill-biased technological change (SBTC), the skill premium should respond to changes in the relative supply of better-educated workers. Thus, it should rise if the supply of skilled workers does not compensate for technology's demand for skilled labour growth. Alternatively, if the supply rises faster than the demand, the skill premium should decrease. As introduced, the RBET model offers a theoretical framework to give insights on these simultaneous shifts in supply and demand for skilled labour.

The idea behind the RBET model was initially introduced by Tinbergen (1972), (1974). There is ample empirical evidence supporting its main predictions with pioneering applications such as Acemoglu (2002), Johnson (1997), Katz and Murphy (1992), Levy and Murnane (1996), among others. Similarly, recent literature has also shown a consistent link between technology and the growing demand for skilled labour, leading to skill premium improvements. Zhang et al. (2018) evidenced that the spread of technology, especially computerisation, tends to widen the wage gap between low and high-skilled workers. Also, using data from US manufacturing, Mallick and Sousa (2017) present evidence on how technology has become more favourable to skilled labour since the 1980s, where the productivity differentials between skilled and unskilled labour contribute to the increased demand for the former workers, as they are not perfect substitutes. Similar findings have been recently founded for, mostly, high-income economies (Buera et al., 2022; Yeo et al., 2023).

Conceptually, the RBET framework relies on a production function with a Constant Elasticity of Substitution (CES), where skilled and unskilled labour are imperfect substitutes. The elasticity of substitution between both kinds of labour plays a pivotal role since whether its value approaches zero, one or positive infinity dictates the RBET framework's predictions (see section 2). For example, elasticities greater than one would imply that skilled and unskilled are substitutes. In addition, the elasticity will show the strength of the influence of both the SBTC and the relative supply of skilled labour on the skill premium. Therefore, several interpretations and assumptions rely on the empirical estimation of the elasticity of substitution.

Regarding the implementation required to test the RBET model empirically, it relies on specifications proposed in the most prominent studies in this literature (Acemoglu, 2002; Acemoglu and Autor, 2011; Katz and Murphy, 1992). Typically, we can obtain the skill premium and the relative supply by using observed wages and skilled and unskilled labour quantities, respectively. In the case of the SBTC term, since we do not directly observe this component, a standard procedure is to use linear trends to capture its dynamics (Acemoglu, 2002; Acemoglu and Autor, 2011; Katz and Murphy, 1992). However, as introduced, researchers have warned that the RBET estimation is difficult, beset by numerous methodological and data problems (Acosta et al., 2019; Borjas et al., 2012; Fernández and Messina, 2018; Varella, 2008b). In the case of Chile, some produced theoretically unfeasible results due to the appearance of a positive sign for the coefficient representing the relative supply of skilled labour (Murakami, 2014; Robbins, 1994b). This coefficient is theoretically impossible because a positive sign runs counter to the expected negative relationship between the skill premium and the relative supply of skilled workers. A positive coefficient also leads to negative estimates for the elasticity of substitution between skilled and unskilled labour (see Eq. 2.9 related statements). Therefore, empirical implementation of the RBET model can be problematic (Acosta et al., 2019) and, it is proper to emphasise alternative ways of implementing and empirically testing the RBET predictions.

The empirical testing of the RBET framework for Chile is sparse and inconclusive. On the one hand, some studies analysing data in the pre-2000 period support the RBET model by documenting an SBTC effect leading to the increasing skill premium and elasticities of substitution between skilled and unskilled labour between one and two (Beyer et al., 1999; Gallego, 2012; Robbins, 1994a). Given the increasing pattern in the skill premium, this evidence shows that increases in the relative supply of skilled workers did not compensate for the growth in technology's demand for skilled labour. Therefore, within the RBET model, the SBTC appears to be the *winner* or the dominant factor. In contrast, some analysing the pre-2000 period or extending data beyond 2000 cite the appearance of "improbable estimation results" leading to negative elasticities, or elasticities beyond the *consensus*, i.e., the range [1,3], as a reason to reject the RBET model for Chile (Murakami, 2014; Robbins, 1994b; Sánchez-Páramo and Schady, 2003). Some researchers, such as Cantore et al. (2017) and Johnson (1997), proposed the notion of a so-called *consensus* based on the estimates observed in the most prominent papers of this literature (Acemoglu, 2002; Goldin and Katz, 2009; Katz and Murphy, 1992).

On the other hand, Robbins (1994b) and Murakami (2014) conclude that the relative supply changes in some of their models could not explain the skill premium for 1975–1992 and 1974–2007, respectively. In both cases, the rejection of the RBET predictions was due to the appearance of a positive sign for the coefficient representing the relative supply of skilled labour. Robbins (1994b) and Murakami (2014) suggested that the differences in quality education between traditional and private universities, whose creation and development were fuelled by major educational reforms in the 1980s and 1990s (Valiente et al., 2020), as a possible reason. However, studies applying cohort analyses reported that the quality between these higher education institutions did not influence the skill premium (Gallego, 2012; Gindling and Robbins, 2001). Despite the challenges and complexities surrounding the estimation of the elasticity of substitution, these issues have received less attention.

The empirical issues encountered when estimating the elasticity of substitution have not been a central issue within much of the literature. One reason for this lack of interest might be that most research focuses on high-income countries (e.g., the US) where the skill premium has continued to show a long-run increasing pattern (Autor et al., 2020; Buera et al., 2022; Mallick and Sousa, 2017). In contrast, as noted above, the skill premium in Latin American countries like Chile has shown an inverted U-shaped pattern in recent decades. In this context, researchers warned that evaluating skill premium drivers in a context of changing patterns is difficult, and it risks imposing incorrect interpretations or assumptions (Acosta et al., 2019; Havranek et al., 2020; Varella, 2008b). Additionally, the elasticity estimation is complicated by alternative potential modelling approaches and data structures, among other issues, affecting the evaluation of this important indicator in several studies at the country level (Acemoglu and Autor, 2011; Acosta et al., 2019; Blankenau and Cassou, 2011; Borjas et al., 2012). In this regard, some suggested that the obtention of negative elasticities might arise from imprecision in data or the use of inappropriate methods (Blankenau and Cassou, 2011; Havranek et al., 2020).

In the case of elasticities between skilled and unskilled labour for Chile that were outside the *consensus* range [1,3], Sánchez-Páramo and Schady (2003) estimated elasticities around 10 for 1970–1999, arguing that such values were imprecise and improbable without questioning the *consensus* range since the RBET conceptualisation does not consider an upper threshold for elasticities. However, elasticities around four are frequent in the RBET or SBTC literature, while around five or six are less frequent (Havranek et al., 2020). In Latin American countries, empirical estimates suggested elasticities around three and four (Acosta et al., 2019; Manacorda et al., 2010) and 11 for the important maquiladora industry in Mexico (Varella and Ibarra-Salazar, 2013). Also, researchers have reported higher elasticity values after extending the analysis period using the same data (Acemoglu and Autor, 2011; Blankenau and Cassou, 2011; Varella, 2008a, 2011). These examples suggest that no upper threshold for reporting positive estimates should exist. Also, publication biases have been suggested since most published estimates adhere to the *consensus* range (Havranek et al., 2020). Thus, it seems that the evidence favouring the rejection of the RBET framework for Chile has relied on theoretically unfeasible results or the appearance of elasticity values lying outside the *consensus* range. More generally, studies using Chilean data that reported "refutational" results or larger elasticities of substitution do not refer to any imprecision in data or flaws in methods (Murakami, 2014; Sánchez-Páramo and Schady, 2003). Some of these results could be due to the application of cointegration techniques (e.g., Murakami, 2014), which require a variety of ancillary assumptions that may lead to a rejection of expected theoretical relationships (Guisan, 2001; Moosa, 2017) or unfeasible results (Gianfreda et al., 2023).

As this brief overview illustrates, Chile provides a good case for investigating estimation issues when testing the RBET model in countries where the skill premium shows a changing pattern. Hence, this study aims to test the RBET model empirically for Chile using data from 1980 to 2018. We apply (among other methods) cointegration techniques within a Vector Error Correction Model, VECM. Researchers have previously reported that both the skill premium and the relative supply for Chile are not trend-stationary variables, i.e., there are unit roots in the autoregressive representation of the data even when deterministic trends are accounted for (Beyer et al., 1999; Gallego, 2012; Murakami, 2014). Some have warned that using linear time trends is insufficient and that the potential existence of unit roots in the data necessitates accounting for non-stationarity. However, the testing of stationarity or presence of unit roots has often been ignored in this literature (Varella, 2008b). A VECM allows us to analyse non-stationary variables, in a way which will not lead to inferring spurious relationships as might be obtained using standard regression estimation. Besides, VECMs remain restrictive with respect to the treatment of non-stationarity and can be sensitive to auxiliary assumptions about the treatment of lags. From the perspective of the RBET model, our VECM yields the "wrong" sign for the coefficient representing the relative supply of skilled labour; this was similar to the experience of Murakami (2014) and Robbins (1994b). Therefore, we apply an Unobserved Component Model, UCM, estimated using a Bayesian approach as an alternative strategy (UCM-Bayesian henceforth).

Some advantages of our UCM-Bayesian strategy are its flexibility, allowing the model components to vary over time and the direct estimation of elasticity of substitution. With VECM, this elasticity is obtained as a reciprocal, the usual procedure in this literature. Some suggest that the computation of the elasticity as a reciprocal might be inaccurate since small differences in the relative supply coefficients can lead to large variations in elasticity estimations (Behar, 2009; Havranek et al., 2020). In this sense, the computation of direct estimates would be appropriate. Bayesian estimation also allows us to include the expected value for the elasticity of substitution according to the *consensus* range and past studies for Chile (Beyer et al., 1999; Gallego, 2012) and for other countries in the region (Manacorda et al., 2010) as *priors*.

Our UCM-Bayesian results give empirical support for the RBET model. We found that both forces, demand and supply factors, play a role in explaining the evolution of the skill premium in Chile between 1980 and 2018. In the context of the race between technology and education, in the pre-2000 period, the relative demand attributable to SBTC with its rapid acceleration contributing to a high skill premium is suggested as the dominant factor. However, in the post-2000 span, the demand factor started to be surpassed by strong increases in the relative supply, suggesting education as the new winner, inducing a declining trend in the skill premium. Furthermore, our estimate for the elasticity of substitution is greater than one: this is 6.5, which would imply that both kinds of workers are imperfect substitutes but more substitutable than commonly thought, given the past estimates for this parameter.

The paper will proceed by first outlining the RBET model in Section 2, followed by its empirical implementation in Section 3. Section 4 will discuss the data, before outlining the empirical strategies that we employ in Section 5. Section 6 gives and discusses the results, and Section 7 concludes. The dataset and additional material for replication purposes is available in Campos-González and Balcombe (2023).

2. The RBET conceptualisation and estimation

Conceptually, we follow Acemoglu (2002), Goldin and Katz (2008, 2009), and Katz and Murphy (1992) in modelling the evolution of the skill premium as a race between SBTC and the relative supply of skilled labour. The form of the CES function with skilled and unskilled quantities modelled with factor-specific productivities is:

$$Q=\left[(A_S S)^{\rho}+(A_U U)^{\rho}\right]^{1/\rho} \tag{2.1}$$

where Q is aggregated output, S and U are quantities of skilled and unskilled workers, respectively, A_S is the factor augmenting technology for the skilled and A_U is the factor augmenting technology for the unskilled. The term ρ, with $\rho \leq 1$, is the substitution parameter and, it is related to σ_{SU}, the aggregate elasticity of substitution between skilled and unskilled workers (formally, $\sigma_{SU} \equiv 1/(1-\rho), \rho \in (-\infty, 1)$. The value of σ_{SU} shows how changes in either technology (given by A_S and A_U) or supplies (S and U) affect demand and wages. There are three special cases for σ_{SU} given that $\rho \in (-\infty, 1)$ (Acemoglu, 2002). First, when $\sigma_{SU} \to 0$ (or $\rho \to -\infty$), skilled and unskilled workers will be perfect complements and they are used in fixed proportions (output function is Leontief). Second, when $\sigma_{SU} \to 1$ (or $\rho \to 0$), the output function tends to be Cobb Douglas, and thirdly, when $\sigma_{SU} \to \infty$ (or $\rho \to 1$), both kinds of workers are perfect substitutes.

The skill premium configuration assumes competitive labour markets with many firms and factors paid at the marginal product value. From Eq. (2.1), the wage for skilled labour, w_S, is

$$w_S=\frac{\partial Q}{\partial S}=A_S^{\rho}\left[A_U^{\rho}(S/U)^{-\rho}+A_S^{\rho}\right]^{(1-\rho)/\rho} \tag{2.2}$$

and, for unskilled, w_U,

$$w_U=\frac{\partial Q}{\partial U}=A_U^{\rho}\left[A_U^{\rho}+A_S^{\rho}(S/U)^{\rho}\right]^{(1-\rho)/\rho} \tag{2.3}$$

To set the skill premium, ω, as the ratio between the skilled and unskilled wages, Eqs. (2.2)and (2.3) are combined, and the elasticity reordered, as follows:

$$\omega = \frac{w_S}{w_U} = \left(\frac{A_S}{A_U}\right)^{\rho}\left(\frac{S}{U}\right)^{-(1-\rho)} = \left(\frac{A_S}{A_U}\right)^{(\sigma_{SU}-1)/\sigma_{SU}}\left(\frac{S}{U}\right)^{-1/\sigma_{SU}} \tag{2.4}$$

Rewriting Eq. (2.4) by taking logs of both sides yields

$$\ln \omega = \left(\frac{\sigma_{SU}-1}{\sigma_{SU}}\right)\ln\left(\frac{A_S}{A_U}\right) - \frac{1}{\sigma_{SU}}\ln\left(\frac{S}{U}\right) \tag{2.5}$$

Eq. (2.5) links the skill premium defined as log wage differentials between skilled and unskilled wages, *ln* ω, to the SBTC term represented by $ln\left(\frac{A_S}{A_U}\right)$ and to the relative supply of skills, $ln\left(\frac{S}{U}\right)$.

The representation in Eq. (2.5) shows that the association between the skill premium, SBTC and the relative supply of skilled labour can be expressed as a simple log-linear relationship. Therefore, we can summarise the expected primary outcomes in terms of the interactions between these variables (Acemoglu and Autor, 2011).

Formally, to evaluate how the skill premium responds to SBTC, we differentiate Eq. (2.5) as follows:

$$\frac{\partial \ln \omega}{\partial \ln(A_S/A_U)} = \frac{\sigma_{SU}-1}{\sigma_{SU}} \tag{2.6}$$

Given the values of elasticity of substitution σ_{SU} presented above, a value of $\sigma_{SU} > 1$, i.e., skilled and unskilled labour are imperfect substitutes, in Eq. (2.6) implies that relative improvements in the SBTC term increase the skill premium. Hence, we expect skilled workers to become relatively more productive due to technological improvements. Conversely, if $\sigma_{SU} < 1$, i.e., skilled and unskilled groups are gross complements, then we expect an increase in the SBTC term to shift the relative demand curve inward and reduce the skill premium.

Regarding the effect of the provision of skills on the skill premium, the differentiation of Eq. (2.5) to the relative supply factor $ln\left(\frac{S}{U}\right)$ yields

$$\frac{\partial \ln \omega}{\partial \ln\left(\frac{S}{U}\right)} = -\frac{1}{\sigma_{SU}} < 0 \tag{2.7}$$

Eq. (2.7) implies that, for a given *skill bias of technology* captured here by the SBTC term, an increase in the relative supply of skills $ln\left(\frac{S}{U}\right)$ reduces the skill premium. Therefore, there is an inverse relationship between both variables. In other words, the higher availability of skilled workers might lead to relatively lower wages for this kind of labour. Therefore, the elasticity of substitution rules these interactions and establishes the level of substitution or complementarity between skilled and unskilled labour.

Now we show how the RBET model represented by Eq. (2.5) can be applied to the data. As introduced, the skill premium and the relative supply can be quantified by using observed wages and quantities of skilled and unskilled labour, but the SBTC term, $\left(\frac{\sigma_{SU}-1}{\sigma_{SU}}\right)\ln\left(\frac{A_S}{A_U}\right)$, is not directly observed. However, it has been assumed that the SBTC dynamics can be captured by a linear trend in the most prominent studies in this literature (Acemoglu, 2002; Acemoglu and Autor, 2011) as follows:

$$\left(\frac{\sigma_{SU}-1}{\sigma_{SU}}\right)\ln\left(\frac{A_S}{A_U}\right) = \beta_0 + \beta_1 t \tag{2.8}$$

Then, the SBTC dynamics formalised in Eq. (2.8) are substituted into Eq. (2.5) and adding time subscripts to the components, except for σ_{SU} which is assumed fixed, and a parameter β_2 standing for $\left(\frac{1}{\sigma_{SU}}\right)$ to be estimated, yields

$$\ln \omega_t = \beta_0 + \beta_1 t - \beta_2 \ln\left(\frac{S}{U}\right)_t \tag{2.9}$$

where β_0 and β_1 are as in Eq. (2.8). There is a SBTC effect if $\beta_1 > 0$ (see Eq. 2.6 related statements). Also, we see that $-\beta_2 = -\left(\frac{1}{\sigma_{SU}}\right)$. Then, the estimated $-\beta_2$ must be inverted and multiplied by -1 to compute the elasticity of substitution.

3. Empirical models

We estimate a base and an extended model. Recapitulating from the RBET model specified in Eq. (2.9), we specify our empirical base model as

$$\ln \omega_t = \beta_0 + \beta_1 t - \beta_2 \ln\left(\frac{S}{U}\right)_t + \beta_3 Ch98_t + e_t \tag{3.1}$$

where ω_t is the skill premium at time *t*, β_0 and β_1 represent the trend component that acts as a proxy for the SBTC, and $\left(\frac{S}{U}\right)_t$ is the skilled labour supply relative to unskilled at time *t*. *Ch*98 is a dummy variable for methodological change in our data source related to educational attainment (1 = March 1998 and onwards, 0 = before March 1998) (see section 4 for details). Our extended model includes variables related to institutional controls as follows:

$$\ln \omega_t = \beta_0 + \beta_1 t - \beta_2 \ln\left(\frac{S}{U}\right)_t + \beta_3 Ch98_t + \beta_4 Unem_t - \beta_5 MinW_t + e_t \tag{3.2}$$

where $Unem_t$ is the unemployment rate in time *t* and $MinW_t$ is the minimum wage in time *t*. In the case of Chile, unemployment rates and minimum wages are considered labour market conditions that might also affect the evolution of the skill premium as reported in previous studies for the Chilean case (Gallego, 2012; Gindling and Robbins, 2001; Murakami, 2014). Besides, in the case of the unemployment rate, theoretical approaches such as the Added-Worker Effect (AWE), the Discouraged-Worker Effect (DWE) and, more recently, the Entitled-Worker Effect (EWE) (Martín-Román, 2022) predict changes in the context of cyclical movements of the aggregate labour supply during economic downturns, which are often accompanied by changes in the unemployment rate.[1]

We model a positive relationship between the skill premium and unemployment, i.e., a higher unemployment rate leading to an increase in wage differential, suggesting, on the one hand, that a disproportionately high number of unskilled workers are represented among the unemployed.[2] Consequently, their wages would probably fall more rapidly than the wages of the skilled labourers, leading to a greater skill premium (Gindling and Robbins, 2001). On the other hand, if unemployment affects predominantly skilled labour, a negative relationship between unemployment and the skill premium might occur. Thus, our results will provide additional insights on the influence of this variable on the skill premium.

Regarding labour policies to establish minimum wages, it is assumed that these interventions affect the wages of unskilled labour. Therefore, without changes in skilled labour wages, the increases in minimum

[1] As detailed by Martín-Román (2022), the AWE predicts that individuals not participating in the workforce may enter the labour market to supplement household income, leading to an increase in the labour participation rate and a decrease in the unemployment rate. The DWE predicts that some workers may become discouraged and stop looking for work, leading to a decrease in the labour participation rate and an increase in the unemployment rate. Conversely, the EWE is related to the unemployment rate because it arises from the existence of unemployment benefits, which can affect the behaviour of workers and potentially impact the unemployment rate. We appreciate the suggestion of the EM reviewers to include these theories relating to the skill premium and the rate of unemployment.

[2] According to available data for 2010–2018 from the Chilean National Statistics Agency (*Instituto Nacional de Estadísticas*, INE, in Spanish), unskilled labour represents, on average, over 63% of unemployed workers (INE, 2023).

wages might lead to a decline in the skill premium. Previous studies show evidence of this inverse relationship like Murakami (2014), although from models reporting "estimation difficulties". Others reported no statistically significant estimates (Gallego, 2012; Gindling and Robbins, 2001). Therefore, in our extended model, we expect a negative and significant coefficient standing for the expected inverse relationship between the skill premium and minimum wages.

4. Data and estimation of variables

We use data from the Employment and Unemployment Survey for Greater Santiago (in Spanish, *Encuesta de Ocupación y Desempleo del Gran Santiago* or EOD) carried out by the University of Chile since 1956 (University of Chile, 2020). We use biannual data (March and June), which has been available since 1980, for 1980–2018 i.e., 78 time periods. Each biannual survey covers about 3000 households and interviews all household members (about 10,000 individuals). The survey is considered a good representation of the Chilean labour market (Gallego, 2012; Robbins, 1994c). The EOD has practically applied the same questionnaire from its creation, which reinforces the comparability of its data. This feature has been helpful for the design and evaluation of labour policies. Also, the EOD has been widely used in studies examining wage differentials and their drivers in Chile (see e.g., Beyer et al., 1999; Gallego, 2012; Gindling and Robbins, 2001; Murakami, 2014; Robbins, 1994b).

Regarding the method of constructing estimates of the skill premium and the relative supply of skilled workers, we closely follow the strategies of Autor et al. (2008), Card and Lemieux (2001), and Ciccone and Peri (2005), among others. Other researchers also have applied these strategies to Chile (see e.g., Beyer et al., 1999; Gallego, 2012; Murakami, 2014). In particular, we have adopted the definitions and thresholds of Murakami (2014) for our computation of skilled and unskilled labour variables.

To compute the skill premium, we define skilled labour as suitable for college or post-secondary graduates and unskilled labour as suitable for graduates of high school or secondary education or those whose education has not reached these levels. We focus on monthly earnings according to the EOD, and our group of interest is restricted to salaried and full-time (more than 30 hours a week) male workers aged 14–65 years. We exclude women because of potential sample selection biases generated by changes in their labour participation (Beyer et al., 1999; Card and Lemieux, 2001; Gallego, 2012; Murakami, 2014; Rothwell, 2012). Our estimation follows a three-steps process. First, we construct education by experience subgroups to adjust for compositional changes. Second, we regress the monthly log earnings for each of the 78 time periods on the usual determinants of wages (e.g., education level, experience). Thirdly, we compute the predicted log wages difference between the college graduates (our skilled group) and high school graduates (our unskilled group) as our proxy for the skill premium. We detail these steps in Supplementary Material (see Appendix A Supplementary material section A.1.).

Similarly, in the computation of the relative supply, we consider skilled labourers as equivalent to college graduates and unskilled labourers as equivalent to high school graduates, as in previous studies (Card and Lemieux, 2001; Ciccone and Peri, 2005; Gallego, 2012; Murakami, 2014). Therefore, we define our relative supply measure as the ratio of monthly hours worked by the former to the latter. This estimation is based on Card and Lemieux (2001), Ciccone and Peri (2005) and Murakami (2014). Since the RBET model assumes only two production factors, skilled and unskilled labour, we classify all workers into categories of college graduates and high school graduate equivalents. We detail the construction of these categories in Supplementary Material (see Appendix A Supplementary material section A.1.).

Regarding our control variable $Ch98$ stated in Eqs. (3.1) and (3.2) it is a dummy variable for methodological change related to educational attainment (1 = March 1998 and onwards, 0 = before March 1998). This change in data categorisation consisted of splitting secondary education into regular secondary education and vocational secondary education from March 1998 and onwards. In the case of our institutional control variables stated in our extended empirical model in Eq. (3.2), the unemployment rate and minimum wages are obtained from Banco Central de Chile (2020) and Biblioteca del Congreso Nacional (2020), respectively. Minimum wages are expressed in December 2018 real value using the *Unidad de Fomento*[3] as a deflator. Supplementary material shows both variables time series (see Appendix A Supplementary material section A.2.).

5. Empirical strategies

This section introduces our methods, VECM and UCM-Bayesian, to test empirically the models represented in Eqs. (3.1) and (3.2).

5.1. VECM

We follow the standard steps for our VECM estimation (see e.g., Cryer and Chan, 2008; Lutkepohl, 2005). Firstly, we need to assess stationarity or trend stationarity in the data-generating process in order to specify the VECM specification correctly. We conduct stationarity testing on each variable individually, applying the Augmented Dickey-Fuller (ADF) and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests (Dickey and Fuller, 1979; Kwiatkowski et al., 1992). While the null hypothesis of ADF is the existence of a unit root, which implies a non-stationary series, in KPSS, the null is the presence of stationarity.[4] Secondly, we select and estimate the best unrestricted VAR model for our dependent variable in terms of lag order by applying the Schwarz Bayesian criterion, BIC, and Hannan-Quinn criterion, HQC, which lead to consistent estimates of the optimal lag order (Neusser, 2016). If the variables are non-stationary, we assess if both variables are cointegrated following the Johansen (1995) approach. In this research, we specified the Johansen's case 4, "unrestricted constant + restricted trend", which considers that the cointegration equation includes a trend, but the first difference of the series does not. The assumption of the trend being restricted to the cointegrated system comes from our empirical model specification (see section 3), where we include a trend parameter as a proxy for the SBTC effect. We test cointegration by applying the maximum eigenvalue and the "trace" tests (Johansen, 1995). Finally, we specify and estimate our VECM using the selected parameters in previous steps. Particularly, Engle and Granger (1987) show that cointegrated variables can be represented by error correction models, ECM. Thus, we can specify the ECM equation on the skill premium, ω, as follows:

$$\Delta \ln \omega_t = a + \alpha(ect_{t-1}) + \sum_{i=1}^{p-1} \rho_i \Delta \ln \omega_{t-i} + \sum_{i=1}^{p-1} \gamma_i \Delta \ln \left(\frac{S}{U}\right)_{t-i} + \varepsilon_t \tag{5.1}$$

where $\Delta \ln \omega_{t-i}$ and $\Delta \ln \left(\frac{S}{U}\right)_{t-i}$ are the differences that capture short-run variations in the skill premium, $\ln \omega$, and the relative supply of skilled labour, $\ln\left(\frac{S}{U}\right)$, respectively. a, ρ, γ, α coefficients to be estimated and ε_t is white noise. In this specification ect_{t-1} (the "error correction term) is the deviation from equilibrium defined by the long-run relationship if the skill premium and the relative supply of skilled labour are cointegrated. Therefore, our base empirical model from Eq. (3.1) is implemented using a VECM structure estimated using the Johansen procedure with the error correction term

[3] The *Unidad de Fomento* (UF) is a Chilean unit of account. The exchange rate between the UF and the Chilean peso is constantly adjusted for inflation.

[4] Neusser (2016) noted that this hypothesis swap allows complementarity between both tests since each test has its weaknesses and strengths. For example, the ADF test has good size properties but low power, while the KPSS test has higher power but may exhibit size distortions.

$$ect_{t-1} = \ln \omega_{t-1} - \beta_o - \beta_1 t + \beta_2 \ln \left(\frac{S}{U}\right)_{t-1} - \beta_3 Ch98_{t-1} \tag{5.2}$$

Eq. (5.2) assumes that there is a long run equilibrium for wages at time t of the form

$$\beta_o + \beta_1 t - \beta_2 \ln \left(\frac{S}{U}\right)_{t-1} + \beta_3 Ch98_{t-1} \tag{5.3}$$

Thus, Eq. (5.3) reflects our base empirical model in Eq. (3.1). We expect that β_2 coefficient in Eq. (5.3) to be negative and significant as evidence for an inverse relationship between the skill premium and the relative supply of skilled labour, as posited by the RBET model. Besides, a negative β_2 coefficient allow us to compute a positive elasticity as discussed earlier. The same procedures apply to our extended empirical model from Eq. (3.2). All procedures detailed in this section are estimated using the statistical software Gretl (Baiocchi and Distaso, 2003; Cottrell and Lucchetti, 2021).

5.2. The UCM-Bayesian

Our UCM formalisation follows the notation and descriptions given mainly by Pelagatti (2016) and Durbin and Koopman (2012). Then, we shall present the main Bayesian estimation features and our empirical models under UCM-Bayesian specifications following Koop (2003) and Gelman et al. (2020), among others.

The UCM, also known as structural time series models, is the basic structure used to represent a time series. It is specified directly in terms of its components of interest (e.g., trend, seasonal and error components) plus additional relevant terms (e.g., a regressor). The main UCM feature is that the model components are modelled as stochastic processes. We specified the trend as Local Linear Trend, LLT, which can be interpreted as a linear trend with intercept and slope evolve synchronised over time as random walks (Pelagatti, 2016). In this regard, the LLT specification is defined by two state equations modelling the level and the slope, as follow:

$$\mu_t = \mu_{t-1} + \nu_{t-1} + \eta_t \tag{5.4}$$

$$\nu_t = \nu_{t-1} + \zeta_t \tag{5.5}$$

where μ_t represents the stochastic level of the trend at t, and ν_t *is* the stochastic slope of the trend (or the increment of level between t and $t+1$). The terms η_t and ζ_t are independent white noise sequences. The initial conditions for level and slope, μ_0 and ν_0, respectively, are usually unknown. Therefore, our UCM specification is a system compounds by an observation equation and two additional state equations modelling the level and the slope.

We estimate our UCM using a Bayesian approach. Koop (2003) cover in detail this approach focusing on time series analysis. We show the specification of our base and extended empirical models from Eq. (3.1) and Eq. (3.2), respectively, under UCM. Remarkably, the Bayesian estimation allows us to specify the parameter standing for the elasticity of substitution between skilled and unskilled labour, σ_{SU}, directly in our UCM specification. Recalling our empirical models in section 3 and considering that the $-\beta_2$ parameter in these models supplies an estimate of $-\left(\frac{1}{\sigma_{SU}}\right)$, our UCM specification for our base empirical model represented by Eq. (3.1) is:

$$\ln \omega_t = \mu_t - \frac{\ln \left(\frac{S}{U}\right)_t}{\sigma_{SU}} + \alpha Ch98_t + \gamma S_t + \varepsilon_t \tag{5.6}$$

$$\mu_t = \mu_{t-1} + \nu_{t-1} + \eta_t \tag{5.7}$$

$$\nu_t = \nu_{t-1} + \zeta_t \tag{5.8}$$

and the extended model represented by Eq. (3.2),

$$\ln \omega_t = \mu_t - \frac{\ln \left(\frac{S}{U}\right)_t}{\sigma_{SU}} + \alpha Ch98_t + \gamma S_t + \epsilon Unem_t - \delta MinW_t + \varepsilon_t \tag{5.9}$$

$$\mu_t = \mu_{t-1} + \nu_{t-1} + \eta_t \tag{5.10}$$

$$\nu_t = \nu_{t-1} + \zeta_t \tag{5.11}$$

where ω_t is the skill premium at time t, μ_t is the trend component or the level of the series at time t, and $\left(\frac{S}{U}\right)_t$ is the skilled labour supply relative to unskilled at time t. σ_{SU} is the parameter to be estimated standing for the elasticity of substitution between skilled and unskilled labour. $Ch98_t$, $Unem_t$ and $MinW_t$ are as in Eqs. (3.1) and (3.2). Unlike the VECM, there is no lag controlling seasonality[5]; therefore, we include a seasonal dummy, S, which controls for seasonality given the biannual data (1 = March; 0 = June). ν_t is the slope and ε_t, η_t and ζ_t are independent white noise sequences. As σ_{SU}, the parameters α, γ, ϵ, and δ also be estimated.

Recalling our Bayesian estimation, it evaluates probability models where conditional probability distributions characterise all variables and unknown parameters. Therefore, to express our empirical UCM base model specified by Eqs. (5.6), (5.7) and (5.8) as a probability model, they must be expressed in terms of observations and unknown parameters regarding the proper probability distributions. Since the model is a linear regression where the residuals are assumed to follow a Normal distribution, then the UCM base model can be written as the next group of equations (same for the extended model):

$$ln\ \omega_t \sim N\left(\mu_t - \frac{\ln \left(\frac{S}{U}\right)_t}{\sigma_{SU}} + \alpha Ch98_t + \gamma S_t, \sigma_\varepsilon^2\right) \tag{5.12}$$

$$\mu_t \sim N\left(\mu_{t-1} + \upsilon_{t-1}, \sigma_\eta^2\right) \tag{5.13}$$

$$\upsilon_t \sim N\left(\upsilon_{t-1}, \sigma_\zeta^2\right) \tag{5.14}$$

where σ_{SU}, α and γ are component parameters and σ_ε^2, σ_η^2 and σ_ζ^2 are the variance parameters for white noise innovations. From the Bayesian point of view, our parameters are seen as random variables which have associated prior probability distributions, and we will update these distributions as we observe data. In this regard, we condition all the parameters specified by Eqs. (5.12), (5.13) and, (5.14) belonging to $\mathbb{R}$ with some precision. For our elasticity of substitution parameter, σ_{su}, the prior distribution represents our beliefs about the possible values that the parameter can take. We incorporate current beliefs about the elasticity of substitution using a Normal distribution with a parameter sampling space in the range [0.01, 10]. For Chile, past studies reported values in the *consensus* range [1,3] (Gallego, 2012) and values around 10 (Sánchez-Páramo and Schady, 2003). Also, since we use Stan (Stan Development Team, 2019) as software to estimate our UCM-Bayesian models (additional details below), this tool defines the Normal on the standard deviation, σ, instead the variance, σ^2. Therefore, the prior probability distribution for our elasticity of substitution parameter, σ_{su}, is defined on the standard deviation (see Eq. 5.15 below).

In the case of the white noise parameters, σ_ε^2, σ_η^2 and σ_ζ^2, the prior distributions are Cauchy and conditioned with a lower threshold of 0.01 without an upper threshold. The use of a Cauchy with centre zero (mean) and scale (standard deviation) equalling ten implies also the use

[5] Despite there being no consensus on this issue, literature covers the modelling of seasonality using lagged variables in VAR models (see e.g., Enders, 2015; Lutkepohl, 2005). Some applied this procedure to capture potential seasonality and to reduce the number of parameters to be estimated as compared to seasonal dummies (see e.g., Campbell and Diebold, 2005; Liu et al., 2016; Motegi and Sadahiro, 2018).

of relatively noninformative prior distribution (Gelman, 2006; Gelman et al., 2008). We use the same specification for α and γ. For the state equations of μ_t, Eq. (5.13), and υ_t, Eq. (5.14), it is suggested the use of hierarchical priors (Koop, 2003). Moreover, we specify noninformative uniform priors for μ_0 and υ_0, i.e., the prior distributions are Uniform, U, to give same probability to all the possible values since we cannot properly specify our prior knowledge of these parameters. The *priors'* distributions are (where [,] denotes the prior range of the distribution):

$$\begin{aligned}
\sigma_{su} &\sim N(0.1, 3)\ [0.01, 10] \\
\sigma_{\varepsilon}^2 &\sim Cauchy(0, 10)[0.01, \infty] \\
\sigma_{\eta}^2 &\sim Cauchy(0, 10)\ [0.01, \infty] \\
\sigma_{\zeta}^2 &\sim Cauchy(0, 10)\ [0.01, \infty] \\
\alpha &\sim Cauchy(0, 10) \\
\gamma &\sim Cauchy(0, 10) \\
\mu_0 &\sim U(0, 1) \\
\nu_0 &\sim U(0, 1)
\end{aligned} \tag{5.15}$$

The Bayesian formulation of our UCM probability model specified in Eqs. (5.12)(5.13) and (5.14) plus the specified priors in Eq. (5.15), consists of the *Likelihood* function $p(y|\mu,\sigma_{su},\alpha,\gamma,\sigma_{\varepsilon}^2)$, the *Prior* distributions given to μ, σ_{su}, α, γ, and σ_{ε}^2, and the *Posterior* distribution $p(\mu,\sigma_{su},\alpha,\gamma,\sigma_{\varepsilon}^2|y)$. A particular parameter from the *posterior* is approximated numerically by simulating draws to evaluate the *function of interest* at the random sample (e.g., the mean, the variance).

The sampling method used in our procedure relies on Monte Carlo Markov Chains, MCMC, techniques. Particularly, the MCMC estimation of parameters uses the Hamiltonian Monte Carlo algorithm, HMC. As stated earlier, we use Stan as a computational tool based on the probabilistic programming language to define a log density function conditioned on data to estimate our UCM-Bayesian models (Gelman et al., 2020). Specifically, we use rStan (Stan Development Team, 2019), the Stan interface for R (RStudio Team, 2020). With rStan we fit the UCM-Bayesian model in and generate MCMC posteriors draws for each specified parameter (e.g., the parameters stated in Equations 5.12, 5.13 and 5.14). In Supplementary materials (see Appendix A Supplementary material section A.3.), we show the Stan code that represents our base model specification. The rStan output computes summary statistics, estimates and diagnostic indicators such as $\widehat{R}$ statistic[6] to measure if the MCMC samples have converged to the *posterior* and evaluate that the posterior draws are distributed in a stationary manner.

6. Results

6.1. The skill premium and the relative supply over 1980–2018

This section outlines the results from estimating the skill premium and the relative supply of skilled labour following the strategies detailed in section 4. Fig. 1 displays the evolution of our measures for both variables over 1980–2018. The skill premium shows an inverted U-shaped pattern, growing up to the late 1980s and then reducing after the 1990s, although with fluctuations. On average, the skill premium increased from 1.27 in the 1980s to 1.34 in the 1990s. In turn, in the 2000s, it decreased to 1.29 and, in the 2010–2018 span, to 1.06. This pattern over time, i.e., an increase followed by a decrease of the skill premium, is consistent with previous works (Gallego, 2012; Murakami, 2014; Parro and Reyes, 2017). As a labour outcome that reflects the relative price of skills, these results imply both a rise and fall in demand for qualified workers during recent decades. On the one hand, Beyer et al. (1999), Gallego (2012), and Robbins (1994a) suggested that the increase in the relative demand for skilled labour in the 1980s and 1990s is related mainly to trade liberalisation implemented in Chile in the pre-2000 period. One of the implications of this trade openness was the absorption of foreign technologies biased towards skilled labour, suggesting an SBTC effect leading to the increasing skill premium.

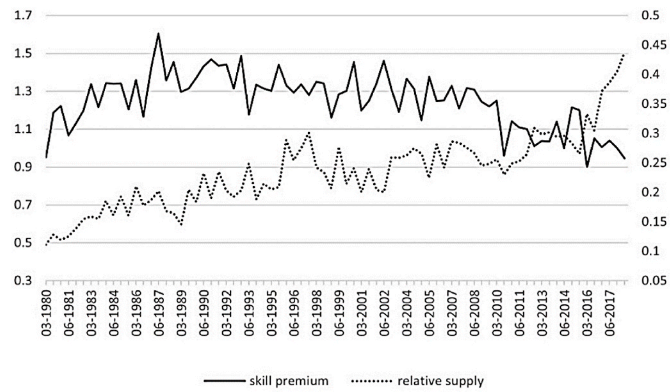

Fig. 1. Evolution of the skill premium and the relative supply (secondary axis), 1980–2018.

On the other hand, since Chile had already implemented these structural reforms, the significant increase in educational attainment in recent decades has been considered one of the critical forces behind the skill premium fall (Azevedo et al., 2013; Murakami and Nomura, 2020). In this regard, for countries like Chile, which recently became a high-income economy[7], this lower premium for skills might affect current economic status since the demand for skilled labour is an essential feature of their economic development (Gallego, 2012). Furthermore, it should be noted that the post-2000 skill premium decline may be attributed not only to improvements in the educational attainment of the workforce but also to other demand-side factors, such as changes in the demand for less-skilled workers due to structural changes or a commodities boom. In the 2000s, in most Latin American countries, this decline was partly driven by an expansion in the relative demand for less-skilled workers, mainly due to the expansion of the low-skilled intensive sector, e.g. services (Guerra-Salas, 2018). In Chile, the commodity price boom observed in the 2000s (in particular, copper) increased unskilled workers' wages (Pellandra, 2015). The role of these other factors in explaining the skill premium decline represents an opportunity for future research.

The relative supply of skilled labour shows an increasing pattern over the sample period, as shown in Fig. 1 (secondary axis), with fluctuations as conspicuous as those in the skill premium but ending at a hugely different point. On average, this ratio grew from 0.16 in the 1980s to 0.22 and 0.24 in the 1990s and 2000s, respectively. In the span 2010–2018 it reached 0.30. These findings also are consistent with past studies (Gallego, 2012; Murakami, 2014; Murakami and Nomura, 2020; Parro and Reyes, 2017). Furthermore, the official statistics report that enrolment in tertiary education sextupled between 1984 and 2018 (INE, 2017; MINEDUC, 2020). This evolution reflects the gradual increase of skilled labour in the labour market and the exit of the older and less educated cohorts (Parro and Reyes, 2017). Additionally, beyond the

[6] The $\widehat{R}$ diagnostic is known as the potential scale reduction factor. It compares the variation between the MCMC posterior samples or chains to the variation within the chains. It is expected $\widehat{R} < 1.1$ for all parameters as an indicator of convergence, i.e., if all chains converged on the same sampling region with similar behaviour, then the variance between them should be approximately equal to the average variance within chains (Gelman et al., 2020; Muth et al., 2018).

[7] The World Bank classifies countries into four income groups—low, lower-middle, upper-middle, and high-income countries using thresholds based on Gross National Income (GNI) per capita in current USD Income. Chile in 2012 was assigned to the high-income category since its GNI per capita has been higher than USD$12,615 since that year (World Bank, 2023).

endogenous response of agents to the increase in returns to education in the 1980s and 1990s, the changes in educational attainments were also fuelled by educational reforms designed to expand and diversify the Chilean tertiary educational system (Gallego, 2012; Murakami and Nomura, 2020; Parro and Reyes, 2017). Thus, the relative supply of skilled labour is suggested as a critical driver pushing the skill premium down in recent decades. In this regard, we found evidence of this relationship within the RBET model along with the effect of SBTC, as discussed below.

6.2. VECM estimation

Firstly, Table 1 displays the ADF results individually on the skill premium, the relative supply, the minimum wage, and the unemployment rate. ADF test results show the presence of unit roots at levels for all variables. For example, the results for the skill premium at levels without and with time trend indicate the presence of unit roots in this variable since we cannot reject the null hypothesis of unit roots at the 1% significance level.

Secondly, in Table 2, we present the results for the KPSS test, which shows that the null hypothesis of stationarity is rejected for all variables. To illustrate, the skill premium at levels without and with time trend shows that this variable is non-stationary since we reject the null hypothesis of stationarity at the 1% significance level. Therefore, based on our ADF and KPSS, there are unit roots in all variables, which implies all series are non-stationary, and their order of integration is $I(1)$.

Thirdly, Table 3 shows the results for optimal lag order estimation regarding the proper model specification for the VAR specification. Our results show that the optimal number of lags to include is two, based on the minimised values of the BIC and HQC information criteria.

Fourthly, Table 4 shows the results of the Johansen Cointegration tests. The null hypothesis of cointegration rank = 0 is rejected for both the trace and the max eigenvalue value at 5% significance level (in favour of the rank being greater than 0). However, rank = 1 is not rejected (in favour of the rank being greater than 1); therefore, there is evidence that the series are cointegrated.

Since the cointegration rank testing results from Table 4 suggest that the skill premium and the relative supply are cointegrated, we present the findings related to the coefficients that rule the cointegration relationship between both variables. In this regard, Table 5 displays the VECM estimation results, both cointegration vector coefficients and the VECM equation coefficients, with the skill premium as the target variable. Residuals diagnostic testing and other robustness analysis for our VECM estimation can be found in Supplementary material (see Appendix A Supplementary material section A.4.).

Table 2
KPSS test results.

Variable		Case	Lags	t-critical 1%	t-statistics
Level	Log Skill Premium	No trend	2	0.731	1.229*
	Log Relative Supply		1		3.158*
	Log Minimum wage		2		2.587*
	Log Unemployment rate		0		1.983*
	Log Skill Premium	Trend	2	0.215	0.468*
	Log Relative Supply		1		0.251*
	Log Minimum wage		4		0.277*
	Log Unemployment rate		0		0.531*
First difference	Log Skill Premium	No trend	1	0.731	0.188
	Log Relative Supply		0		0.028
	Log Minimum wage		1		0.323
	Log Unemployment rate		0		0.047
	Log Skill Premium	Trend	1	0.215	0.026
	Log Relative Supply		0		0.027
	Log Minimum wage		1		0.279*
	Log Unemployment rate		0		0.048

Note: Lag order selection as in the ADF test (see Table 1). (*), (**) and (***) denotes a rejection of the null of stationarity at 1%, 5% and 10% significance level, respectively.

Table 3
Optimal lag order for the VAR using the BIC and HQC information criteria.

VAR system	lags	BIC		HQC	
With constant and trend	1	−3.075567		−3.225291	
	2	−3.232868	*	−3.457454	*
	3	−3.086778		−3.386226	
	4	−2.928868		−3.303177	

Note: Results estimated from VAR systems of order 1 to max. lag order 4. (Log Skill premium and Log Relative Supply as endogenous variables. The results, including control variables, are the same) The asterisks indicate the best (that is, minimised) values for the respective information criteria. BIC and HQC are sensible to choose maximum lag order; therefore, this testing was also performed using 6 and 8 lags with the same results in terms of optimal lag order for all cases/models (with constant, without trend and with constant and trend).

From the VECM estimation procedure developed in section 5.1, the estimated coefficients for the cointegration vector (upper rows in Table 5) expressed as the ect_{t-1} for the base model (see Eq. 5.2) yield (noting that here and in the results in Table 5 the constant term has been assumed into the drift component of the VECM, i.e., the Johansen's Case 4):

Table 1
ADF test results.

Variable		Case	Lags	t-critical 1%	t-statistics
Level	Log Skill Premium	with Constant	2	−3.520	−1.011
	Log Relative Supply		1	−3.519	−1.248
	Log Minimum wage		2	−3.520	−0.960
	Log Unemployment rate		0	−3.517	−2.000
	Log Skill Premium	with Constant and Trend	2	−4.085	−2.511
	Log Relative Supply		1	−4.083	−2.973
	Log Minimum wage		4	−4.087	−2.414
	Log Unemployment rate		0	−4.079	−2.343
First difference	Log Skill Premium	with Constant	1	−3.518	−11.209*
	Log Relative Supply		0	−3.517	−17.187*
	Log Minimum wage		1	−3.518	−3.490**
	Log Unemployment rate		0	−3.517	−9.425*
	Log Skill Premium	with Constant and Trend	1	−4.083	−11.427*
	Log Relative Supply		0	−4.079	−17.067*
	Log Minimum wage		1	−4.083	−3.507**
	Log Unemployment rate		0	−4.079	−9.365*

Note: Lag order selection using criterion BIC (max was 4). (*), (**) and (***) denotes a rejection of null of presence unit roots at 1%, 5% and 10% significance level, respectively.

$$ect_{t-1} = 1.0000\ln\,\omega_{t-1} + 0.0095t - 0.4139\ln\left(\frac{S}{U}\right)_{t-1} - 0.0815Ch98_{t-1} \tag{6.1}$$

Reordering Eq. (6.1) on the skill premium implies a sign for the relative supply, $\ln\left(\frac{S}{U}\right)$, that is inconsistent with the negative coefficient established by the RBET model. Consequently, the computation of the elasticity of substitution as the reciprocal of this positive coefficient, multiplied by -1, yields a negative elasticity: $-(1/0.4139) = -2.42$ (see Eq. 2.9 related statements). Similar results are obtained for the extended model.

As discussed earlier, past studies like Murakami (2014) and Robbins (1994b) also estimated positive coefficients for the relative supply of skilled labour in some models, concluding that this variable did not contribute to the skill premium. For example, Murakami obtained positive coefficients in some specifications using cointegration techniques (Murakami, 2014, p. 93). More generally, researchers have warned about some limitations of cointegration approaches to testing causal relationships in Economics and Econometrics (Guisan, 2001; Moosa, 2017) since it is generally a high dimensional model, and the cointegration approach entails imposing many auxiliary assumptions in terms of how we specify trends and lags. To illustrate, VECM assumes only linear trends within the cointegration equation and statistically significant lags are required (Von Brasch, 2016), and, recent research has addressed some difficulties such as noise in the data, that in the case of ADF and Johansen's tests, can lead to unreliable results (Gianfreda et al., 2023). Researchers have also warned of estimation and data difficulties when the skill premium evolution changes (Acosta et al., 2019). As also discussed earlier, our data show an inverted U-shaped pattern for the skill premium through time. Most of the studies using data until 2000 obtained results as expected, i.e., the negative coefficient for the relative supply (Beyer et al., 1999; Gallego, 2012). By contrast, Murakami (2014) extended the period until 2007, where we can observe an incipient decline in the skill premium. As discussed earlier, standard cointegration might not be well equipped to model these changing patterns, particularly in the sense that they generally employ only linear trends within the cointegrating equation.

6.3. UCM-Bayesian estimation

Table 6 shows the mean, standard deviation, and confidence intervals that summarise the *posterior* distribution for all parameters given our observed data, chosen priors distributions, and assumed data-generating process in our base and extended models. In particular, the 2.5% confidence interval, CI, and 97.5% CI show the bounds of the 95% central interval of the *posterior* probability distribution for a given parameter. Also, we display the $\widehat{R}$ statistic results, which shows $\widehat{R} < 1.1$ for all variables, implying that the MCMC samples have converged to the posterior (see footnote 6). More details on parameters convergence diagnostics and posterior full distribution plots are in Supplementary Material (see see Appendix A Supplementary material section A.5.).

Our results support the empirical evidence for the RBET model for Chile. We found that demand and supply factors explain the evolution of the skill premium during 1980–2018. Our estimate of the elasticity of substitution between skilled and unskilled labour implies that both kinds of workers are imperfect substitutes. Our direct estimate for the elasticity of substitution, σ_{su}, i.e., our point estimate or the mean of the *posterior* distribution, is 6.51 with 95% *posterior* confidence intervals CI $=$ [3.97, 7.50]. Similar results are obtained in our extended model. In Fig. 2, we can visualise the *posterior* distribution of σ_{SU} for both models. The plots show that the probability mass for the elasticity of the substitution parameter is away from the bounds imposed in our parameter and *priors* modelling, suggesting that our results are not entirely driven by the constraints imposed on the parameters.

Our result for the elasticity of substitution between skilled and unskilled labour is close to estimates from countries in the same region and to the few studies for Chile. For example, elasticities out of the *consensus* were reported for pools of Latin American countries with estimates between three and four (Acosta et al., 2019; Manacorda et al., 2010) and values above 10 for the crucial maquiladora industry in Mexico (Varella and Ibarra-Salazar, 2013). For Chile, Sánchez-Páramo and Schady (2003) estimated values around 10, although they reported them as

Table 4
Johansen Cointegration statistical tests results.

Rank	Eigenvalue	Trace test	p-value	Lmax test	p-value
$r = 0$ (None)	0.23767	29.463	0.0151**	20.625	0.0299**
$r = 1$ (At most 1)	0.10978	8.8381	0.1957	8.8381	0.1956

Notes: Number of equations = 2; Lag order = 2; Estimation period: 2:1–39:2 (T = 76); Johansen approach's Case 4: Restricted trend, unrestricted constant.[8] (*), (**) and (***) denote a rejection of null (= 0 or $r = 1$) at 1%, 5% and 10% significance level, respectively.

Table 5
VECM estimations results for the empirical base and extended models.

Base model, Eq. (3.1)	$\ln\omega_t = \beta_0 + \beta_1 t - \beta_2\ln\left(\frac{S}{U}\right)_t + \beta_3 Ch98_t + e_t$	
Extended model, Eq. (3.2)	$\ln\omega_t = \beta_0 + \beta_1 t - \beta_2\ln\left(\frac{S}{U}\right)_t + \beta_3 Ch98_t + \beta_4 Unem_t - \beta_5 MinW_t + e_t$	
Estimated coefficients	**Base model**	**Extended model**
Cointegration vector		
$\ln\omega_{t-1}$ (Skill premium)	1.0000	1.0000
	(0.0000)	(0.0000)
t (Trend)	0.0095574	0.011545
	(0.071423)	(0.0026041)
$\ln(S/U)_{t-1}$ (Relative supply)	−0.41398	−0.50134
	(0.16574)	(0.17140)
$Ch98_{t-1}$ (Change year 98)	−0.081560	−0.13380
	(0.0025162)	(0.076770)
$Unem_{t-1}$ (Unemployment)		0.17358
		(0.11089)
$MinW_{t-1}$ (Minimum wage)		0.030110
		(0.28368)
VECM equation ($\Delta\ln\omega_t$ as target variable)		
Constant	0.62033*	0.67643*
	(0.13080)	(0.13778)
$\Delta\ln\omega_{t-1}$	0.24901**	−0.28248*
	(0.09898)	(0.09501)
$\Delta\ln(S/U)_{t-1}$	−0.21019*	−0.21504*
	(0.07114)	(0.07096)
ect_{t-1}	−0.530232*	−0.501203*
	(0.111274)	(0.101650)
R^2	0.43	0.45

Note: VECM estimated with cointegration rank = 1, lag order = 2 and, Johansen's Case 4: restricted trend, unrestricted constant. Data are of biannual frequency (March and June) from 1980 to 2018. Standard errors in parentheses (). *, ** and *** denote a rejection of the null hypothesis of zero coefficients at 1%, 5% and 10% significance levels, respectively. We explore different specifications of our VECM approach, such as additional lags, but the results remain unchanged. Also, as a robustness check suggested by EM reviewers, we split the sample period into two sub-periods (one up to about 2000 and from then onwards). However, VECM results remain similar the whole period, particularly the wrong sign for the relative supply. This analysis and other robustness test (e.g., residual normality) can be found in the Supplementary material (see see Appendix A Supplementary material section A.4).

[8] The modelling has included the presence of trends at level data and in the cointegrating equations. This research specifies the case of "unrestricted constant and restricted trend" or Case 4, which considers that the cointegration equation includes a trend, but the first difference of the series does not. Also, Cases 2 and 3 were analysed for "restricted constant" and "unrestricted constant", respectively, with similar results.

Table 6
Posterior summary statistics of UCM-Bayesian estimation.

	Base model (see Eqs. 5.12, 5.13 and 5.14. Priors in 5.15)					Extended model				
	$ln\ \omega_t \sim N\left(\mu_t - \frac{\ln\left(\frac{S}{U}\right)_t}{\sigma_{SU}} + \alpha Ch98_t + \gamma S_t, \sigma_\varepsilon^2\right)$ $\mu_t \sim N(\mu_{t-1} + \upsilon_{t-1}, \sigma_\eta^2)$ $\upsilon_t \sim N(\upsilon_{t-1}, \sigma_\varsigma^2)$					$ln\ \omega_t \sim N\left(\mu_t - \frac{\ln\left(\frac{S}{U}\right)_t}{\sigma_{SU}} + \alpha Ch98_t + \gamma S_t + \delta Unem_t - \epsilon MinW_t, \sigma_\varepsilon^2\right)$ $\mu_t \sim N(\mu_{t-1} + \upsilon_{t-1}, \sigma_\eta^2)$ $\upsilon_t \sim N(\upsilon_{t-1}, \sigma_\varsigma^2)$				
Parameters	mean	St dev	2.5% CI	97.5% CI	$\widehat{R}$	mean	St dev	2.5% CI	97.5% CI	$\widehat{R}$
Elasticity (σ_{SU})	6.51	1.42	3.97	7.50	1.00	6.54	1.42	3.98	7.52	1.00
Ch98 (α)	−2.09	5.79	−13.3	1.52	1.00	−2.53	5.78	−14.1	1.15	1.00
Seasonality (γ)	0.74	1.71	−2.63	1.89	1.00	0.65	1.69	−2.63	1.79	1.00
Unemployment (δ)						0.01	0.05	−0.10	0.04	1.01
Minimum wage (ϵ)						−0.07	0.11	−0.15	0.14	1.00
σ_η^2	1.66	0.97	0.37	2.23	1.01	1.66	1.06	0.24	2.30	1.02
σ_ς^2	0.41	0.21	0.12	0.51	1.01	0.40	0.23	0.09	0.51	1.03
σ_ε^2	7.56	0.71	6.29	8.01	1.00	7.62	0.73	6.30	8.09	1.00
μ_0	−3.15	5.79	−15.1	0.87	1.00	−15.2	18.3	−51.4	−3.32	1.00
υ_0	2.49	1.35	0.20	3.31	1.00	2.55	1.35	0.19	3.29	1.00
μ_1	−3.17	5.48	−14.43	6.96	1.00	−15.28	18.25	−51.05	20.70	1.00
…	…	…	…	…	…	…	…	…	…	…
μ_{76}	9.24	7.47	4.35	24.69	1.00	20.58	18.11	−16.38	54.65	1.01
υ_1	2.49	1.27	1.62	5.27	1.00	2.55	1.28	0.25	5.44	1.00
…	…	…	…	…	…	…	…	…	…	…
υ_{76}	−0.46	1.18	−2.81	0.22	1.00	−0.27	1.22	−2.78	2.15	1.00

Notes: 1) To conserve space, note that in the case of the trend term level and trend term slope equations, μ and υ, we only display parameters for the initial conditions and the first (e.g., μ_1) and last estimates (e.g., μ_{76}).
2) Data are of biannual frequency (March and June) from 1980 to 2018.
3) The inference for the Stan model consisted of 12 chains, each with iter = 25000; warm-up = 20000; thin = 5; post-warm-up draws per chain = 1000, total post-warmup draws = 12000). Glossary from Stan Manual (Stan Development Team, 2019): iter specifies the number of iterations for each chain (including warm-up), warm-up specifies the number of warm-up (also known as burn-in) iterations per chain to discard non-representative samples produced by early stages of the sampling process, thin specifies the period for saving samples i.e., how often we store our post-warm-up iterations (thin = 5 implies to store every fifth).

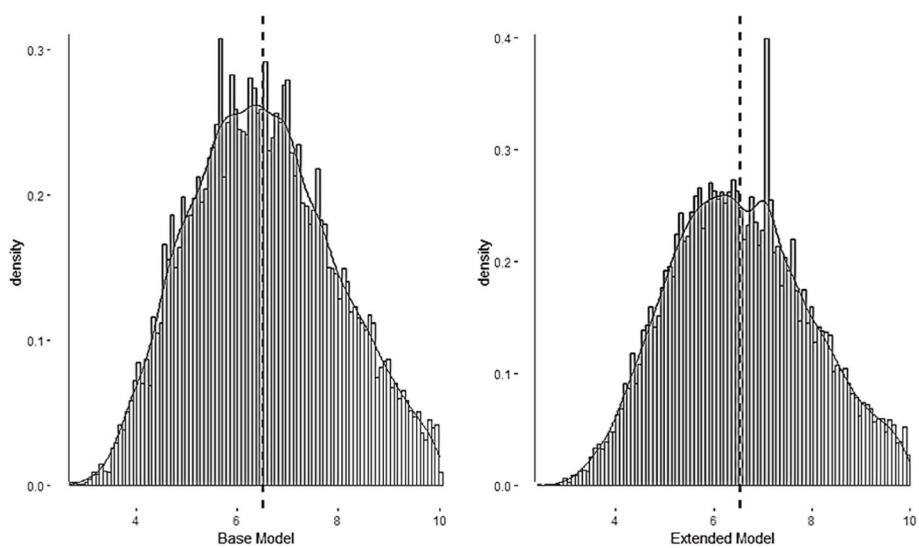

Fig. 2. *Posterior* distribution of the elasticity of substitution parameter, σ_{SU}, for the base (left side) and extended models. The dashed line shows the point estimate of the *posterior* mean.

"implausible", and Gallego (2012) estimated values between one and two. The distance between our values and Gallego's estimates might partly be explained by data granularity and the features of the period analysed. For instance, it has been suggested that higher than annual data granularity (in our case, it is bi-annual) might expand the elasticity, which can be due to measurement error associated with a higher frequency of data (Havranek et al., 2020). Higher elasticities (e.g., four and above) were also linked to periods that witnessed a more rapid SBTC, but the evidence is inconclusive since values between one and two have featured in periods of slow SBTC growth (Acemoglu, 1998; Katz and Murphy, 1992). The relative demand estimated by Gallego (2012) showed an increasing pattern within the analysed period (1965–2000) but an elasticity in the range [1,2]. In this regard, more research is needed to evaluate how the elasticity value responds to the analysis of sub-periods (e.g., decades).

The interpretation of larger elasticities is scarce in the RBET literature, but some implications emerge. Firstly, the possibility of switching between skilled and unskilled workers is higher. Therefore, our results suggest that skilled and unskilled labour are more substitutable than Gallego (2012) reported for Chile (elasticity of substitution between one and two). A larger elasticity might also suggest that the impact on the skill premium for an observed relative supply time series will be more negligible than relative demand or SBTC (Katz and Murphy, 1992; Varella and Ibarra-Salazar, 2013). However, since the 2000s, the SBTC effect has not been enough to compensate for the rapid growth in the relative supply of skills, resulting in the observed decline in the skill premium. As discussed earlier, the relative supply not only increased due to the endogenous response of agents but also was fuelled by policies promoting educational expansion (Gallego, 2012; Murakami and Nomura, 2020; Parro and Reyes, 2017; Schneider, 2013; Valiente et al., 2020). In this regard, larger elasticities might co-occur with non-negligible impacts from the supply factor. Also, larger elasticities might imply that the market size of skilled workers drives the design and implementation of skill-biased technologies (Acemoglu, 2002). In this regard, examining the RBET model under a specification that assumes endogeneity between the skill premium and the SBTC parameter may be an attractive topic for future research.

In terms of the RBET model conceptualisation and predictions, this non-zero value of the elasticity shows that changes in the relative supply of skilled workers contributed to the evolution of the skill premium during 1980–2018 and satisfies the inverse relationship between both variables as specified in our empirical models following the conceptual statements related to Eq. (2.7). Furthermore, our estimated elasticity implies that both groups of workers are gross and imperfect substitutes: that is, the relative availabilities of each labour are not related to changes in wages. Therefore, we reject the idea of perfect substitution between skilled and unskilled labour. This result is consistent with past studies for Chile (Beyer et al., 1999; Gallego, 2012) but disagree with other studies due to “improbable estimation results” (Murakami, 2014; Robbins, 1994b).

Related to our estimates for the time trend parameter μ that stands for the SBTC in the RBET model, Table 6 displays the results for its initial conditions μ_0 and υ_0 and first and last datapoints, but we evaluate the results visually, using the posterior mean for these parameters' series over time. Fig. 3 displays the trend level (and the skill premium) and the trend slope in the left-hand and right-hand plots, respectively. Our estimates for the trend level show an upward movement until the first half of the 2000s. Then, we see an enormous decline towards the beginning of the 2010s. Since this parameter captures the increases in the relative demand for skilled labour coming from technology, we can assume that the SBTC effect drove the skill premium intensively between 1980 and the first half of the 2000s. In most of the rest period, the trend displays a downward pattern suggesting a lesser importance of the SBTC. These patterns reflect the positive and negative slopes of the trend during the upward and downward periods, respectively, as seen in the right-hand plot in Fig. 3.

In the context of the race between both forces, our results suggest that deciding on a given *winner* or dominant factor will depend on the analysed period. Before 2000, the dominant factor was the relative demand attributable to SBTC. Conversely, after 2000, this demand decreased, surpassed by the workforce's increases in educational attainment, mainly promoted by government policy. Thus, it seems that the relative supply of skilled labour has grown fast enough to meet the increased relative demand attributable to SBTC and thus to induce a declining trend in the skill premium as posited in our RBET conceptualisation (see Eqs. 2.6) and 2.7 related statements). Hence, in the post-2000 period, the new dominant factor is education. This story, with technology as an early dominant contributor to the skill premium increase, which then is moderated and reversed by the relative supply of skilled labour, coincides with Parro and Reyes (2017), who used a measure of hourly wage inequality to analyse the rise and fall in income inequality between 1990 and 2011. Thus, our study contributes to the evidence for the wage differential drivers under the RBET model.

Regarding our extended model, unemployment and minimum wages show results as expected. Despite a near-zero magnitude, the former is positive, showing that changes in the unemployment rate can explain the evolution of the skill premium. This result suggests that most of the unemployed are unskilled workers. Past studies also reported a positive but statistically no significant relationship between the skill premium and unemployment (Gindling and Robbins, 2001; Murakami, 2014). Thus, the small influence captured by our estimation might not have been captured with past estimation methods. Regarding minimum wage, our results show a negative impact on the skill premium evolution. Since this kind of labour policy mainly affects unskilled labour, it is expected to decrease the gap between skilled and unskilled workers' wages, a point that has been discussed earlier in the statements related to Eq. (3.2). In this sense, our result coincides with findings from Murakami (2014), who reported evidence about this inverse relationship between minimum wages and the skill premium (although this evidence comes from models yielding unfeasible results as in our VECM implementation). Other studies have reported similar findings, but they were not statistically significant (Gallego, 2012; Gindling and Robbins, 2001).

7. Conclusion

The RBET model offers a coherent theoretical framework to analyse

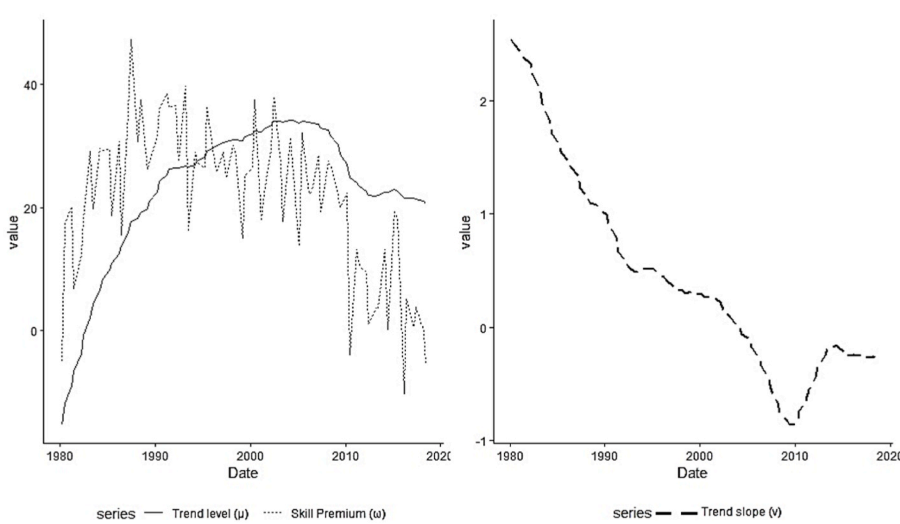

Fig. 3. The skill premium and the trend level (left side), and the trend slope (right side).

how the skill premium responds to demand and supply factors. However, its implementation has challenged researchers, possibly due to the nature of the trends in the data, particularly in Latin American countries. Since some researchers have abandoned or rejected the RBET model due to difficulties in its implementation when using linear models and results such as computation of negative elasticities, the UCM-Bayesian approach offers a way to tackle these issues principally due to its more flexible treatment of trends and the estimation of the elasticity directly and not its reciprocal. It is important to note that large elasticities outside what we have termed the *consensus* range do not imply that the RBET model is invalid, as positive elasticities have no upper limit. While obtaining exceptionally large elasticities may raise questions about just how powerful the RBET framework is, at the very least, researchers should entertain the idea that large elasticities may also validly reflect that the skill premium is quite insensitive to the relative increases in skilled to unskilled labour. This aspect would help to explain why models that contain simple linear trends sometimes lead to the implausible conclusion that the decreases in the relative supply of skilled workers to unskilled workers decrease the skill premium.

This study of the Chilean labour market during 1980–2018 can help us understand the implicit race between technology and education over time. Most of the previous research analysed the period before the 2000s, which witnessed an important growth in the relative demand for skilled labour resulting in an upward pattern in the skill premium. In contrast, after 2000, this wage differential declined, and researchers testing the RBET model under this changing pattern reported theoretically unfeasible results using cointegration techniques. Our cointegration results also yielded unfeasible results, while our alternative UCM-Bayesian strategy has allowed us to estimate results consistent with the RBET model. In this regard, we gave empirical evidence for the relationships posited by the RBET model for Chile using bi-annual data from 1980 to 2018. We have shown that either the relative demand or the relative supply influences the skill premium evolution. Our direct estimate for the elasticity of substitution between skilled and unskilled labour is 6.5, showing that these forms of labour are imperfect substitutes. Previous research falling within the *consensus* range has generated elasticities between one and two. Therefore, our larger estimate suggests that skilled and unskilled labour are more substitutable than commonly thought.

From the perspective of the race between technology and education over time, our findings suggest that in the 1980s and 1990s, the dominant factor was the relative demand attributable to SBTC, given its contribution to the skill premium. In this period, the growth of the relative supply of skilled labour was starting, fuelled mainly by policies focussed on the expansion of tertiary education. Consequently, this factor was not capable of counterbalancing the SBTC effect. However, in the 2000s and 2010s, the vigorous educational expansion increased the supply factor, which grew rapidly to meet the increasing demand attributable to SBTC. As a result, the provision of skills is winning the race, suggesting that this factor has been driving the skill premium decline in recent decades.

Our findings could indirectly supply some policy implications since this phenomenon might be a case where the lack of mechanisms for coordinating the supply of skills with the labour markets' needs has been underestimated, given Chile's inability to absorb skilled labour in its workforce. First, investments in higher education are essential to achieve a reasonable income distribution in countries like Chile, where these investments have been essential for the expected transfer of knowledge and skills to jobs, resulting in a boost to Chile's economic development. (Schneider, 2013; Valiente et al., 2020). However, these investments, apparently, do not consider the economy's capacity to absorb the observed greater availability of better-educated workers. This greater availability resulted from significant enrolment in tertiary education. For example, in 1984, the 18–24 age group enrolled in tertiary education grew from 11% of this age group (189,151 enrolments) to above 67% of this age group (above 1.2 million enrolments) in 2018 (INE, 2017; MINEDUC, 2020). In this sense, Chile does not have institutional mechanisms for creating relationships between firms and education suppliers. Recent strategies such as the development of the National Qualification Framework (Cruz Fuentes et al., 2020; Sevilla and Farías, 2020) and the Job Prospection Policy Committee (in Spanish *Comisión asesora ministerial de Prospección Laboral*) are addressing these issues.

Second, some suggested that the Chilean labour market compounds by a huge proportion of jobs linked to low levels of skills and technology; therefore, it might not require intensive use of skills provided by better-educated workers resulting in high rates of overqualification and over skilling (Sevilla and Farías, 2020). In this regard, our findings on the higher substitutability between skilled and unskilled workers than previously reported are also in line with the lower demand for skilled labour observed in recent decades, and it might imply that technologies are not suitable for Chilean skilled labour. As Gallego (2012) reported, most technologies biased toward skilled labour came from abroad. In this sense, technology might be being underexploited due to a lack of proper skills or workers in STEM fields. For example, only 3% of students in tertiary education graduate with degrees in ICT, and only 1% with degrees in natural sciences, mathematics, and statistics, placing Chile in the lowest positions of all OECD countries (OECD, 2018). Therefore, policies to correct the mismatch between the supply and demand related to skills, the development of regulations such as intellectual property rights (Acemoglu, 2003), technological re-training or promoting technologies better suited to Chilean skilled labour, and the improving of graduating rates of fields of study like ICT and STEM may be required.

Finally, policy implications also arise due to the unemployment rate and minimum wage as labour market conditions and institutions driving the skill premium. Regarding unemployment, as suggested by Porras-Arena and Martín-Román (2023), Chile exhibits one of the highest Okun's coefficients of the Latin American countries. This condition entails that output growth impacts strongly on unemployment, which in turn, and according to our results, influences the skill premium. Thus, the solid unemployment-output relationship implies that policies that tend to stimulate economic activity also stimulate the skill premium evolution. Regarding minimum wages, our results support the expected inverse relationship between minimum wages and the skill premium. However, minimum wage policies have been debated regarding their impact on income inequality indicators such as the skill premium with supporting (see e.g., Alinaghi et al., 2020) and contrasting (see e.g., Foster et al., 2019) evidence. Overall, the impact of this kind of policy is complex and varies depending on the context and parameters of the analysis (Atkinson et al., 2017).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

See Campos-González, J., Balcombe, K., 2023. *Data and materials for 'The race between education and technology in Chile and its impact on the skill premium'* [dataset]. Mendeley Data. https://doi.org/10.17632/8424ky469w.1.

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Appendix A. Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.econmod.2023.106616.

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