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ARTÍCULOS

Departamento de Economía

The quantum harmonic oscillator expected shortfall model*

El modelo de déficit esperado basado en el oscilador armónico cuántico

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Abstract

This paper presents a new Expected Shortfall (ES) model based on the Quantum Harmonic Oscillator (QHO). It is used to estimate market risk in banks and other financial institutions according to Basel III standard. Predictions of the model agree with the empirical data which displays deviations from normality. Using backtesting, it is shown that the model can be reliably used to assess market risk.

Key words: *Expected Shortfall; market risk; Basel III standard; stock returns; S&P index.*

JEL Classification: *G24, C22, C52, C53.*

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Resumen

Este documento presenta un nuevo modelo de déficit esperado basado en el oscilador armónico cuántico para la estimación de riesgo de bancos e instituciones financieras conforme al estándar de Basilea III. Las predicciones del modelo son consitentes con los datos del mercado accionario que presentan desvíos de normalidad. Utilizando "backtesting", se muestral que el el modelo es fiable para la evaluación del riesgo de mercado.

Palabras clave: *Déficit esperado; riesgo de mercado; Basilea III; retorno accionario; S&P.*

Clasificación JEL: *G24, C22, C52, C53.*

1. Introduction

Back in the 1960s, Mandelbrot (1963, 1972) and Fama (1965) showed that the series of daily returns of securities have a distribution that deviates from the normal distribution and from the identical and independent distribution assumption. Fama (1965) assumed that the distribution of price change is approximately Gaussian or normal, which was confirmed by observations. It was found that extreme tails of empirical distributions are higher than those of normal distribution, and four parameter Paretian distribution was introduced to describe data. Blattnerg and Gonedes (1977) showed that returns distributions are characterized by fat tails. They considered another family of symmetric distributions that can consider fat tails. It was Student or t distribution, and authors concluded that Student model has greater descriptive validity then the normal distribution. Kan and Zhou (2017) also presented similar findings using multivariate t distribution with 7 degrees of freedom to model stock returns. They point out that due to the presence of fat tails, the assumption of normality must be rejected. Empirical evidence of non-Gaussian properties of stock market return distribution led to the development of a lot of theoretical models on this subject. From the econophysics point of view, the Brownian movement of the classical particles was used to model the stock returns in the first place (Dragulescu and Yakovenko, 2002; Roumen, 2013; Reddy and Clinton, 2016; Agustini *et al*. 2018). Change of the stock price return is modelled as position change of random displacement of classical Brownian particle in these papers. The main problem with this model is that lead to Gaussian-type processes (Madan and Seneta 1990). Traditional economic models were developed to better describe the stock return distributions (Linden, 2001; Dragulescu and Yakovenko, 2002). On the other side, the real data and empirical stock return distributions show deviations from Gaussian type distributions since Probability Density Function - PDF tails decay slower than log-normal Gaussian type (Şener *et. al*. 2012; Zikovic and Filer, 2013; Rossignolo, *et. al*. 2012, 2013, Radivojevic *et al*. 2016b, 2017a, 2020; Doncic *et al*. 2022). Fat tails which include negative skewness on one side and positive excess kurtosis on the other side of the center of distribution are the most common types of deviations from Gaussian type distribution (Ahn *et al*. 2017).

In the market models based on statistical physics, which try to make the analogy of the stock market behavior with microsystems in physics, an important role found quantum mechanics (QM), which naturally inherent statistical fluctuations via uncertainty principle (Ataullah *et al*. 2009). The main problem in QM is that the potential that describes the interaction of the physical system (which is used to describe market) with the environment is generally unknown. To use QM models to describe the stock market return distributions, the appropriate potential is needed (Zhang and Huang, 2010; Haijun and Guobiao, 2015; Wróblewski, 2017). The main principle is to make an analogy between some QM system, e.g. quantum particle (or systems of particles) and stock price return. In Schrodinger's nonrelativistic QM of closed systems, the particle is described with wave functions of particle state. Physically meaning has a square of the amplitude of wave function, which should describe the PDF of stock market returns. This is the merging point of stock market returns and the QM system: there is a need for QM system with wave function, which square can describe PDF of stock market returns. Closed quantum systems with time independent potentials lead to stationary states, so some perturbation potential needs to be introduced to enable time evolution and nonstationary.

It is interesting to note that stock return distributions of stable markets tend to have Gaussian properties. In general, all markets tend to reach an equilibrium state (Balvers *et al*. 2000), and settle to some form of Gaussian-like distributions shape (Ahn *et al*. 2017). Fat tails are one of the most common deviations. Stock market returns tend to settle in some equilibrium or near-equilibrium state, which can be described as a true or local minimum of the potential energy in the physics analogy. A market can be described as some sort of physical system which is in equilibrium or near equilibrium with its surrounding. Quantum mechanical systems which are isolated can be described with the Schrodinger equation in which the parameter that need to be known is its potential energy or potential. Since the potential is unknown, some reasonable guesses need to be introduced and substantiated with some real physical assumptions (Zhang and Huang, 2010). Stock markets returns in general tend to long-run equilibrium, where returns dissipate around some mean value. It implies that a

QHO can be used to describe these oscillations, which fluctuate over time, so first order perturbation theory needs to be introduced. Hence, the aim of this study is to take advantage of this opportunity.

Among the first was Bachelier (1900), who described the financial assets price movement using a random walk model, and introduced the concept of Brownian motion, which is a type of random process that has played a fundamental role in the development of modern mathematical finance. From the point of view of the current paper, random processes in economics can be transformed into the form of Schrodinger equation (Wroblewski, 2017; Ahn *et al*, 2017; Vukovic *et al*, 2015), which is a fundamental equation in Quantum physics. For instance, the famous Black-Scholes equation which gives a model to pricing theory is an instance of Schrodinger equation (Vukovic et al, 2015; Contreras et al, 2010). It was shown by Vukovic et al, 2015, that starting from Black Scholes equation, using mathematical transformations, one can get to the exact form of Schrodinger equation. Phenomena that have the same or similar mathematical foundations in different disciplines, will have same or similar physical behavior.

Important property of QHO is that like every bounded quantum system it has eigenstates and discrete spectrum of energies. Hence QM oscillator can be described with one of eigenstates or superposition of eigenstates. This practically means that QHO can be described as linear combinations of eigenstates. Like classical Brownian particle, QHO in ground state is described with Gaussian distribution. Since stock markets show deviations from Gaussian (negative skewness and positive excess kurtosis) classical Brownian particle is not quite suitable for describing it. On the other hand these deviations can be very well described with higher states of QHO. Eigenstates of QHO are Hermitian polynomials, which can be even or odd. Even states lead to more symmetric distributions and can contribute to the fat tail and lead to higher kurtosis. Odd states lead to distributions with a larger skewness, (Ahn *et al*, 2017).

The paper is organized as follows: Section 1 contains the introduction. The following section gives an overview of the most significant empirical research in the area of ES models. Section 3 presents the theoretical basis of the possibility of applying QHO for predicting the movement of stock market returns. In Section 4 presented results of applying QHO. In Section 5, the backtesting results are presented, analyzed, and discussed. Section 6 summarizes the conclusions.

2. Literature Review

There is an abundance of papers in literature dealing with the improvements of the applicability of different market risk models according to Basel Commitment rules. All those papers can be classified into two groups. The first group consists of the papers which try to improve applicability of different ES models. In this group of papers researchers use a traditional technique for predicting behavior patterns of assets in financial markets, following known distributions. Such papers were presented by Barone-Adesi and Giannopoulos (2001), Pascual *et al*. (2006), Chen *et al*. (2011), Brandolini and Colucci (2012), (2012), Alemany et al (2012), Bee (2012), Radivojevic *et al*. (2016, 2017, 2020) etc. The second group includes the papers which try to improve the applicability of completely different models for prediction stock returns. Those papers are based on artificial intelligence, data mining, machine learning, and similar concepts for assessing risks to which participants in financial markets are exposed. Such papers were presented by Scaillet (2003 and 2004), Fermanian and Scaillet (2005), Atsalakis and Valavanis (2009), Thomaidis and Dounias (2012), Aguilar-Rivera et al. (2015), Cavalcante *et al*. (2016), Chong et al. (2017) Xing *et al*. (2018), Hiransha *et al*. (2018), Fischer and Krauss (2018), Rundo *et al*. (2019), Nti *et al*. (2019), Shah *et al*. (2019), Sezer *et al*. (2020), Doncic *et al*. (2022) etc.

From the second group of papers, one can single out papers that focus on opportunities of applying solutions from physics. Such papers were presented by Meng *et al*. (2016), Agustini *et al*. (2018), Maruddani and Trimono (2018) etc. Inspired by a series of studies that successfully used concepts and tools from quantum mechanics to options pricing (Ye and Huang, 2008; Baaquie, 2009; Bagarello, 2009; Zhang and Huang, 2010; Pedram, 2012 and Cotfas, 2013), Agustini et al. (2018) were use Geometric Brownian Motion model for stock prices prediction. Like them, Maruddani and Trimono (2018) used multidimensional Geometric Brownian Motion model to describe stochastic process of stock price movements. However, despite of the mathematical success of quantum-mechanics models for financial instruments, only few studies have been tried to exploit quantum statistical dynamics relying on open-system concepts yet (Meng et al. 2016). The justification for applying solutions from QM can be found in empirical findings that point to the unsustainability of the efficient market hypothesis. Empirical findings such as non-Markovian memory (Wan and Zhang, 2008) and fat-tail deviation (Wan and Zhang, 2008, Radivojevic *et al*. 2020) suggest that the stock market does not satisfy the classical Brownian motion model (Ye and Huang, 2008). And Meng, *et al*. (2015) were among the first to point out the possibility of describing dynamical problems in the stock market using a wave function. In this context, Meng *et al*. (2016) were among the first authors who presented the idea of the possibility of applying the Brownian motion quantum oscillator model. They showed that the movement of financial asset returns can be described by the Markovian Klein-Kramers equation. However, they focused only on predicting the movement of stock prices, without considering the possibility of applying the model for assessing market risk. Original idea from QM, that the more we learn of the coordinate the less we know the momentum (and vice versa) (Cohen-Tannoudji *et al*. 1992), can be applied to stocks because the more we know the stock price the less information we can use to estimate the trend of it (Meng *et al*. 2016).

In QM this is the Heisenberg uncertainty principle, which states that one cannot with certainty know position of particle and its momentum or speed. This principle has its analogy in the economy. As Ye *et al*, 2008 stated if all the people know the price value, even though the price has deviated, it will turn back to the value swiftly and never start to fluctuate again. In this sense, precise knowledge of stock price will harden estimates of its change (see Ye et al, 2008 for details).

3. The Theoretical Basis Of The Possibility Of Applying QHO For Predicting The Movement Of Stock Market Returnsw

In case of harmonic potential QM solutions of the stationary Schrodinger equation are already known and are

$$\psi_n(x) = \left(\frac{m\omega}{\pi\hbar}\right)^{1/4} \frac{1}{\sqrt{2^n n!}} H_n\left(\sqrt{\frac{m\omega}{\hbar}}x\right) e^{-\frac{m\omega}{2\hbar}x^2}, \tag{1}$$

where $H_n\left(\sqrt{\frac{m\omega}{\hbar}}x\right)$ are Hermite polynomials. Expression in equation 1 can be simplified by introducing dimensionless variable $\xi = \sqrt{\frac{m\omega}{\hbar}}x$. In physics, x is the coordinate of the observed particle. This physical quantity has its analogy in the stock market model $x \equiv \ln s$, which is logarithmic stock price return, where s is stock price (Meng *et al*, 2016). Parameter m is the mass, while ω is the angular velocity of the quantum particle, $\hbar = 1.05457 J \cdot s$ is reduced Planck constant and $n = 0,1,2,...$ is positive integer number. Angular velocity is related to the energy of the quantum particle as

$$E_n = \left(n + \frac{1}{2}\right)\hbar\omega. \tag{2}$$

According to Ye and Huang, 2008 and Meng et al 2015 and 2016 mass of particle correspond to inertia of the stock, energy of the particle corresponds to trading volume of the stock, while $\psi_n(x)$, which is called wave function, has special properties. As it was stated earlier in the text, the wave function doesn't have physical meaning in physics, but its square of amplitude represents the probability density of finding a particle with coordinate *x*. Square of amplitude of the particle corresponds to the probability density distribution of the stock price (Ye and Huang, 2008 and Meng *et al* 2015; Meng *et al* 2016).

General solution of stationary Schrodinger equation for the potential of the harmonic oscillator can be constructed in form of infinite expansion over Hermite polynomials or to be more precise over eigenstate wave functions given by equation 1:

$$\psi(x) = \sum_{n=0}^{\infty} c_n \psi_n(x). \tag{3}$$

Expansion coefficients have important physical implications: its square gives the probability that the system can be found *n*-th state.

Since stock returns change over time, we need to introduce some small potential, which acts as a perturbation on our quantum system and changes states over time. If the perturbation is small, we could expect that eigen states are not changed due to the influence of small potential, and in first-order perturbation theory we could expect that the state of the system can be described as

$$\Psi(x,t) = \sum_{n=1}^{k} c_n(t) \psi_n(x) e^{-i\frac{E_n}{\hbar}t}. \tag{4}$$

Perturbation leaves eigen states unchanged, but consequently, expansion coefficients are time dependent.

Let us assume that stock return distribution can be described as the probability distribution function of the QHO. Many authors use QHO to model stock return distributions (Tingting and Yu, 2017; Jaroonchokanan and Suwannay, 2018). Since the market has a tendency toward an equilibrium state (Menga *et al*. 2016), with some amount of fluctuations, it is quite reasonable to assume that model of QHO is mostly in the ground state, which has Gaussian shape properties, with additional impurities of excited states, which lead to the fat tails and non-Gaussian properties. Some form of the superposition state could be a real representation of the market model (Menga *et al*. 2016). General state function can be represented as

$$\psi(x) = \sum_{n=1}^{k} c_n(t) \psi_n(x), \tag{5}$$

where expansion is limited to some k-th excited state.

Let us further build our model. We can take stock returns of some real markets for three years period, represented by 750 daily stock price returns. Our goal is to use the first two-year period to build the QHO model and predict stock returns of the third year.

4. Model Estimation

At start, we take the first year of stock returns to construct initial PDE of the real market. This function needs to be fitted with the square of the QHO superposition state function in the form

$$\psi(x) = \sum_{n=0}^{9} c_n(0)\psi_n(x) \tag{6}$$

In the expansion series, let us assume the first ten members (greater members are neglectable small, which will be seen in result part of the paper).

It is important to notice that the PDE of the stock return should be fitted with the square of the function in explicit form

$$\psi(\xi) = \sum_{n=0}^{9} c_n(0)\left(\frac{m\omega}{\pi\hbar}\right)^{1/4} \frac{1}{\sqrt{2^n n!}} H_n(\xi) e^{-\xi^2/2} \tag{7}$$

In our QHO model all parameters are uncertain, i.e. mass m and angular frequency ω.

These parameters should be extracted from the data of the real market. To do so, let us first introduce function

$$f(x) = \left(\sum_{n=0}^{9} a_n H_n(x)\right)^2 e^{-\kappa^2 x^2} \tag{8}$$

which will be used to fit stock market PDE. This is necessary, since it is important to find an appropriate function which can have enough degrees of freedom, so the iteration procedure of finding fitting coefficients can lead to minimal residuals. Finding the best fit is procedure to find ten coefficients and an additional κ unknown coefficient which is in correlation with all ai coefficients. Linear regression procedure of finding best parameters starting from best guess initial values of coefficients, lead to great accuracy of fit. Here, the fitting procedure was done not over the variable x, but instead, independent variables are Hermite polynomials $H_n(x)$. This complicates the procedure a bit since function $f(x)$ need to be minimized over terms of Hermite polynomials.

To perform fit over Hermite polynomials as independent variables, a least-square fit method was used. This method is based on minimizing χ^2 function, or minimising expression $\sum r_i^2$, where r_i are residual, or differences between original data point and its fitted value. In order to perform a such fit, initial values of the fitting parameters need to be set. The parameters can be arbitrary, or based on the intuitive knowledge of the fitting curve. Here, we can make assumption that ground level of the QHO is dominant and have contribution about 90% (initial guess), which will give expansion coefficient of the ground level $\sqrt{0.9} \approx 0.95$. Excited states of the QHO are abundant with less probability, and expansion coefficients in equation 3 to 7 need to fulfill constraint $\sum c_i^2 = 1$. Mathematica Wolfram provide fitting algorithm (Wolfram, 2022) used to perform fitting over Hermite polynomials in the above described way. Fitting procedure is based on minimising χ^2 function over paremeters c_i.

Afterwards, it is necessary to relate a_n fit coefficients in eq(8) with c_n coefficients in eq (7). To do so, in function $f(x)$, Hermite polynomials need to be factored, in form $H_n(\kappa x)$ due to correspondence with eq(7). $\kappa = \sqrt{\frac{m\omega}{\hbar}}$ is determined from fit, and κ can be trivially factored in form $H_n(\kappa^{-1}\kappa x)$. If we introduce $\gamma = \kappa^{-1}$, we can transform term $H_n(\gamma\kappa x)$ to $a_n H_n(x)$ as following

(9) $$\begin{gathered}\sum_{n=0}^{9} a_n H_n(x) = \\ \sum_{n=0}^{9} a_n \sum_{i=0}^{Floor[n/2]} \gamma^{n-2i} (\gamma-1)^i \binom{n}{2i} \frac{(2i)!}{i!} H_{n-2i}(\kappa x) = \\ \sum_{n=0}^{9} A_n H_n(\kappa x)\end{gathered}.$$

Now we can expand right side of equation (9) and collect coefficients A_n beside $H_n(\kappa x)$ members. Finally, our state expansion coefficients are

(10) $$c_n = A_n \left(\frac{\xi^2}{\pi}\right)^{-\frac{1}{4}} \sqrt{2^n n!}\,.$$

Now our state can be expressed in terms of known coefficients

(11) $$\psi(x) = \sum_{n=0}^{9} c_n \left(\frac{\kappa^2}{\pi}\right)^{\frac{1}{4}} \frac{1}{\sqrt{2^n n!}} H_n(\kappa x) e^{-\frac{\kappa^2 x^2}{2}}.$$

Following the above procedure, PDF from stock return empirical data can be created, and fitted with Hermite polynomials.

To build a predictive stock return model, the first year period, i.e. the first 250 data points from the stock return values, are used to generate PDF which represents the initial state of our QHO. The natural states of the real model are not stationary and are changing over time. To explain non-stationarity, perturbation is introduced, resulting in the time-dependent wave function given by eq(4). To obtain time dependence of expansion coefficients in eq(4) second year period of stock return data is used. The initial state of QHO is created from 250 data from the first-year period, while the next state is created using data from the 2nd to the 251st day. In this way, the window consisted of 250 data points representing one state is created, and this window is moved forward for one day. By continuing procedure of fitting PDF with QHO, wave functions and time expansion of coefficients in eq(4) can be found, using the method of rolling window. At this point, it is necessary to state that the mass of the QHO is one parameter introduced in fitting equations. By finding the best fit, this parameter changes in rolling windows since it is not fixed. To fix the mass of the QHO, second-year data of stock return distributions were used and fitted using the rolling window method. Afterwards, the most probable mass is extracted as a parameter. Now fitting procedure must be repeated for all second-year stock return data to obtain new fitting coefficients, which correspond to the fixed mass of the QHO. At the end of this procedure, coefficient of expansion in eq(4) are known.

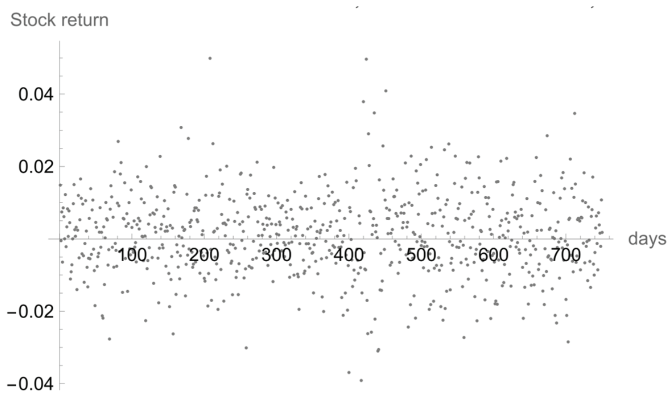
If we can assume that time evolution of expansion coefficients, $c_n(t)$, are due to some weak perturbation, it is reasonable to suggest that this evolution can be extrapolated to a future time. Uncertainty of prediction increases over time, but for us, it is important to find PDF for the following day, related to the present one. It is enough to use a two-year period (500 data points) to predict one day after two-year period (501 data point). For the following day (502 data point) we do not need to predict expected stock returns from the first 500 data points. Instead, we can use 501. data point and repeat procedure with building PDF, fitting empirical data and predict outcome for just next day. This repeating procedure can lead us through the whole third year, and predictions of the model can be compared with real data. It is important to note that this model is probabilistic, and by predicting time series coefficients, $c_n(t)$, for the following day, we are predicting tomorrows wave function, $\psi(x)$, of QHO. This information does not give us data values that will occur the following day, but rather PDF of the following day ($\mathrm{PDF} = |\psi(\mathrm{x})|^2$).

5. The Results Of QHO Model Application

To verify presented model, we need to start with real data of the stock return. These data are presented on the Fig 1 for the three years period. The data used were the daily logarithmic returns of the Standard and Poor stock index, which was used in Christoffersen (2011) for VaR estimates. The returns were collected for the period between January 2st, 1997 to December 30th, 1999. These empirical data are starting point of building model, following Methodology procedure.

FIGURE 1

STOCK RETURN VALUES FOR THREE YEAR PERIOD – 750 DATA POINTS FOR THE S&P INDEX FOR THE PERIOD BETWEEN JANUARY 2ND, 1997 TO DECEMBER 30TH, 1999



The first year of the three-year period is used to build a PDF of the stock return. In this function, all information about the behavior of the stock market is hidden and needs to be extracted. PDF is created by discretizing stock return values and counting the number of data that falls into the correspondent bin. To have proper distribution properties (i.e. Probability Density Function), distribution needs to be normalized to the unit. Connection with QHO is that PDF generated from real data gives probabilities of measuring QHO with a given x coordinate. On the other side, this PDF of QHO is equal to the square of the quantum wave function which describes a state of QHO. QHO is described with real functions and written in the general form given by eq (7) and can be used to fit empirical PDF. The result within the range of empirical data is shown in Fig 2 for one 250 days period. Figure 2 included a fit with Gausian and Pareto type IV function. Gaussian function describes the random walk of Brownian particles, while general Pareto distribution – GDP is used to approximate asymptotic distributions of extreme values.

From Figure 2 the QHO function can more realistically describe empirical data. Figure 3 shows residuals in the fit procedure for three mentioned functions. QHO fits data better compared to Gaussian and GPD distribution (Pearson N., 2002). One of the reasons is in the fact that QHO has greater degrees of freedom, and odd members in the expansion can consider skewness, while even one capture kurtosis. In this way, any arbitrary function can be fitted. If not with given degrees of freedom, then with more degrees of freedom, which can be easily added. Reason for this lies in the fact that the QHO function is a kind of expansion in series, but not over the variable, but over Hermite polynomials that depend on the variable.

FIGURE 2

DOTS-EMPIRICAL PDF OF STOCK RETURNS FOR ONE YEAR PERIOD; DASHED LINE – GAUSSIAN FIT; DOTTED LINE – PARETO TYPE IV DISTRIBUTION FIT; FULL LINE – FITTED FUNCTION OVER THE SUPERPOSITION STATE OF QHO

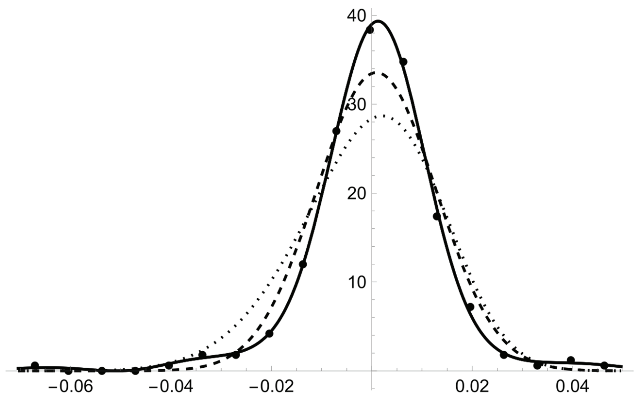
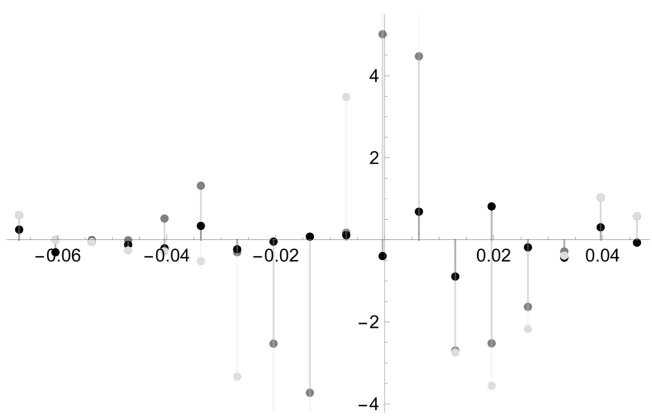


FIGURE 3

GRAY DOTS – RESIDUAL FROM GAUSSIAN FIT; LIGHT GRAY DOTS – RESIDUALS FROM PARETO FIT; BLACK DOTS – RESIDUALS FROM QHO FIT.



It is interesting to note that fitted QHO function does not diverge in the region out of the fitted data (fitting function is defined in the region $(-\infty,+\infty)$) and the norm of the fitted function given at Fig 2 is

$$\int_{-\infty}^{+\infty} \left|\psi\left(x\right)\right|^{2} dx = 0.991002 \tag{12}$$

The function has a norm, which is less than one per cent smaller than the unit, which leads us to the conclusion that the superposition state of QHO is natural state of stock return. This is the case with all 250 PDF functions generated from a two-year period of stock returns. A number of iterations and precision goal of the fitting procedure are set in a way, that norm of all functions needs to be in the range of one per cent around the unit. Values of the coefficients of the fitted wave functions from Fig 2 – initial state, and their squares, are given in Table 1.

TABLE 1
FITTING COEFFICIENTS AND ITS SQUARES FOR THE EMPIRICAL PDF OF FIRST YEAR PERIOD OF STOCK RETURNS

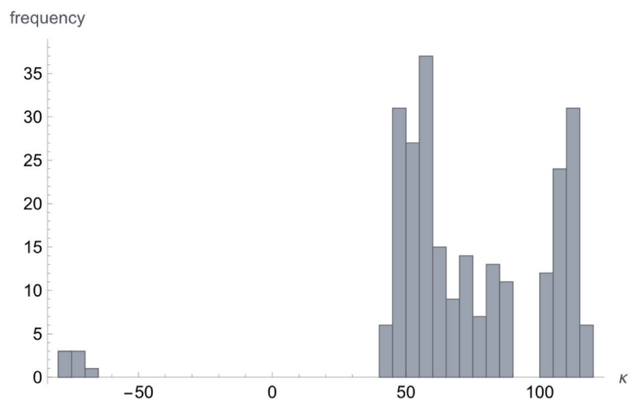
C_0	0.984902	C_0^2	0.970032
C_1	0.0603988	C_1^2	0.00364801
C_2	0.125271	C_2^2	0.0156929
C_3	-0.0135641	C_3^2	0.000183984
C_4	0.0268013	C_4^2	0.000718308
C_5	0.00142965	C_5^2	$2.0439 \cdot 10^{-6}$
C_6	0.0274061	C_6^2	0.000751093
C_7	0.0012143	C_7^2	$1.47453 \cdot 10^{-6}$
C_8	$-2.2201 \cdot 10^{-6}$	C_8^2	$4.92883 \cdot 10^{-12}$
C_9	$-8.63369 \cdot 10^{-8}$	C_9^2	$7.45406 \cdot 10^{-15}$

Looking at the values given in Table 1, QHO is in a superposition state, where the most probable is the ground state. Excited states give a smaller contribution to the overall wave function. This fact has physical implications. Ground state of QHO has Gaussian shape, and the tendency to Gaussian-like stock returns of the markets is conserved. Excited states are odd and even and each gives contributions to different properties of stock markets return (skewness and kurtosis). Going further to higher excited states will give even smaller contributions and can be neglected.

Following the fitting procedure of rolling window for the second year of stock returns wave functions which represent the state for every day are obtained. These functions still have no significant physical meaning, since they present only the mathematical best fit of the data. As the fitting parameter in every fit, the quantity $\kappa = \sqrt{\frac{m\omega}{\hbar}}$ of the oscillator arises, and it has different values in each fit iteration. For the harmonic oscillator, this value needs to be constant. Idea is to find the best fit in each iteration and then choose the most probable one. Figure 4 gives the histogram of the occurrence of the values of κ . The most probable value is 49.684 m^{-1}, and this value is fixed as the parameter of the oscillator. At the first look at the Fig. 4 some paradox fact arise - the negative value of parameter κ . One need to keep in mind that these values still have no physical meaning, rather than pure mathematical products of the criteria for the best fit. Another thing that can be noticed is that histogram has two modal properties. Again, this is pure mathematical property of accumulating possible values around the two values. The presented model does not include two coupled oscillators, nor the changeable mass of the oscillator. Hence, the most probable value has been chosen. Also, the occurrence of negative mass has no physical implications and needs to be rejected.

FIGURE 4

HISTOGRAM DISTRIBUTIONS OF OCURRENCE OF DIFFERENT VALUES OF CONSTANT κ



At this point with the fixed mass of the oscillator, the fitting procedure can be repeated from the beginning, while this time parameter κ is no more changeable. Finding best fits leads us to different values of expansion coefficients in eq. (6). For the second-year window of data, 250 values of expansion coefficients are obtained. Their values are presented in Figure 5.

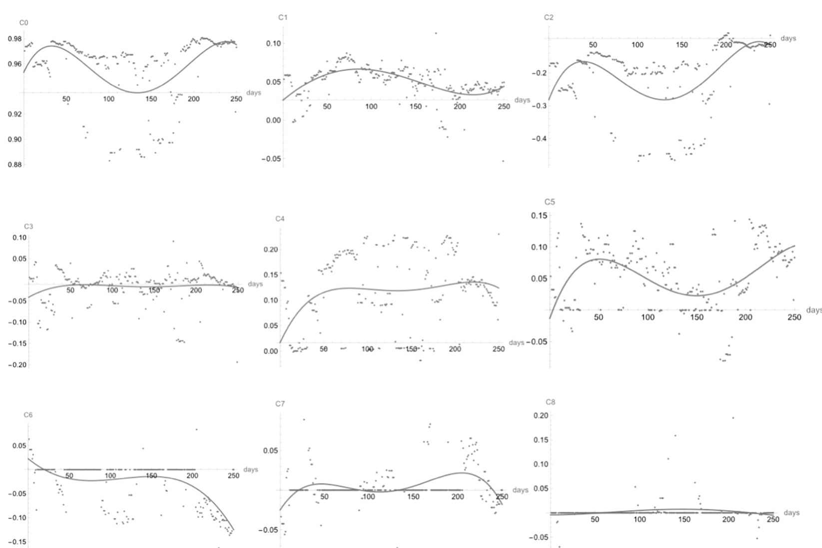
The perturbating potential is unknown, and possible form of time-dependent function that expansion coefficients should have been undetermined. This led us to use polynomial series expansion and assume that power series consisting of a few first members will be a good approximation of general function. Each expansion coefficient is now fitted with a time-dependent function in the form of

$$C_n(t) = A + Bt + Ct^2 + Dt^3 + Et^4 \tag{13}$$

Fitting functions for each expanding coefficient $C_n(t)$ are presented in Fig 5 for rolling windows of the second year of stock returns. These functions are then used to calculate the expanding coefficients off the first day of the third year period of the stock returns, which is at this point an unknown variable. This enables us to write down wave function for the unknown tomorrow data, determine PDF and predict tomorrow's outcome with a certain probability. Predictions can be extrapolated to a future period, greater than one day, but uncertainty can be large. Instead, we can wait for the empirical value for the next day and repeat the above procedure to obtain the wave function for the following day. Since empirical data in our model are known for a whole three-year period, we iteratively repeated the procedure to predict outcomes for the whole third year.

FIGURE 5

TIME EVOLUTION OF EXPANSION COEFFICIENTS FOR THE SECOND YEAR PERIOD OF STOCK RETURNS



To validate our model, predicted mean values of expected stock rerun with limits of one standard deviation are presented in Fig 6 and compared with empirical data. To calculate the standard deviation

$$\sigma = \sqrt{\langle x^2 \rangle - \langle x^2 \rangle}\,, \tag{14}$$

mean, $\langle x \rangle$ and mean square values, $\langle x^2 \rangle$ need to be calculated

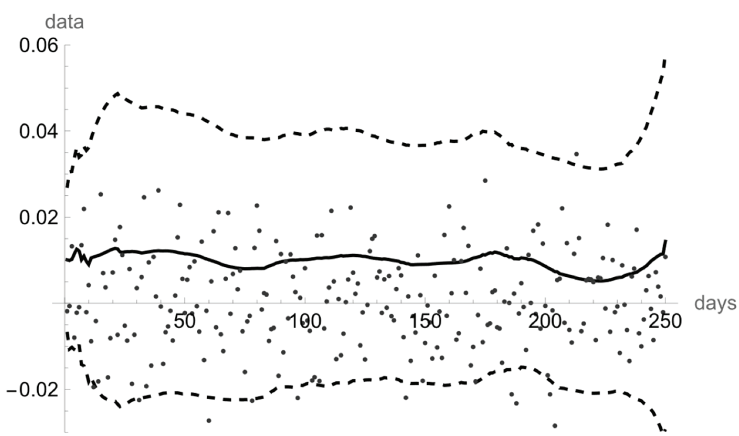
$$\langle x \rangle = \int_{-\infty}^{+\infty} \psi^* x \psi \, dx\,, \text{ and } \langle x^2 \rangle = \int_{-\infty}^{+\infty} \psi^* x^2 \psi \, dx\,, \tag{15}$$

where asterix refer to complex conjugation. These operations doesn't change real functions.

Since PDF distributions are roughly Gaussian shape distributions, the interval of one standard deviation covers approximately 68% of the whole range. It is expected that two-thirds of the whole data fall into the presented region in Fig 6. Newer the less only 4% of data is outside of the region. Sock return distributions for data used in the presented model have negative skewness and fat left tail and distributions are asymmetric around the mean value. This is the reason why more data are below the mean curve in Fig 6.

FIGURE 6

STOCK RETURN DATA IN THIRD YEAR – DOTS; PREDICTED MEAN – FULL LINE; STANDARD DEVIATION INTERVAL AROUND MEAN – DASHED LINE; FOR THE PERIOD BETWEEN JANUARY 2ND, 1997 TO DECEMBER 30TH, 1999



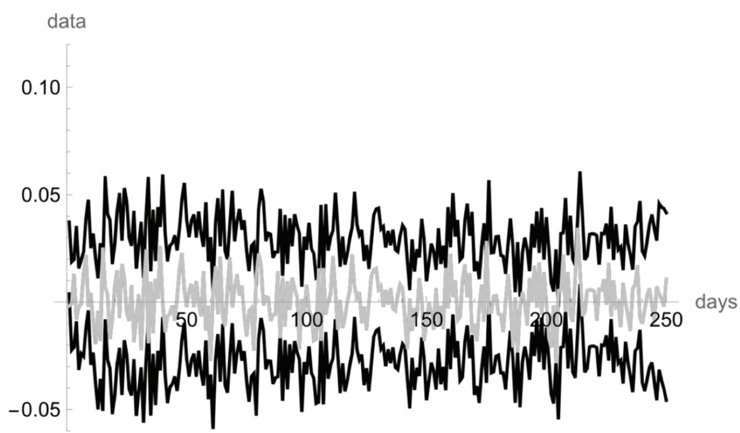
A powerful tool in Quantum Mechanics are selection rules that can be derived from wave functions, determine possible transitions between quantum states and give transition probabilities. This could limit the possible outcomes and better predict tomorrow's stock returns. For the derivation of selection rules, an exact form of perturbation potential is needed. At this point, the best-predicted value of tomorrow's outcome can be obtained using the traditional formula

$$P_{t+1} = P_t \pm \mu \cdot \sigma \tag{16}$$

where P_{t+1} is tomorrow's stock return, P_t is stock return at present day μ is the quantile that gives confidence interval (taken to be unit) and σ is the standard deviation calculated using the predicted wave function for tomorrow outcome. Eq (16) has great importance, since implies that tomorrow's outcome is directly related to today's stock return values. On Figure 7 are presented predicted outcomes given with full line, while empirical tomorrow's outcome is plotted with gray line. It is of great importance to notice that outcomes do not falls out of the predicted interval.

FIGURE 7

PREDICTED OUTCOME OF STOCK RETURN – FULL BLACK LINE; EMPIRICAL STOCK RETURN – FULL GRAY LINE; FOR THE PERIOD BETWEEN JANUARY 2ND, 1997 TO DECEMBER 30TH, 1999

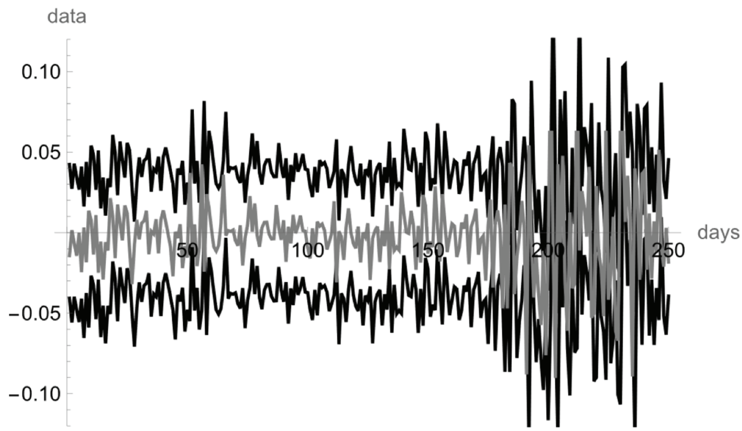


6. Backtesting Model According to Basel III Standards

The obtained data were used to estimate the Expected Shortfalls (ES) according to Basel III standards (Bank for International Settlements, 2013). More precisely, the ES are calculated for the one-day-ahead horizon for the period from January 1st, 1998, to January 1st, 1999, according to the Basel III standard, and for the period from January 1st, 2008 to January 1st, 2009, which was during an economic crisis, Figure 8.

FIGURE 8

PREDICTED OUTCOME OF STOCK RETURN – FULL BLACK LINE; EMPIRICAL STOCK RETURN – FULL GRAY LINE, FOR THE CRISIS PERIOD FROM JANUARY 1ST, 2008 TO JANUARY 1ST, 2009



The ES estimates were made for the confidence levels of 97.5%. Since VaR does not fulfil all the characteristics of coherent risk measures, the Basel Committee has proposed fundamental changes in the regulatory treatment of financial institutions' trading book positions (Kellner and Rösch, 2016). Among other things, the replacement of 99% VaR with the 97.5% expected shortfall (ES) for the quantification of market risk is recommended (Radivojevic *et al.*, 2019; Doncic *et al.*, 2022). The rest of the observations were used as the resample observations needed for the ES starting values. At the same time, to answer the question of whether the model contributes to the improvement of risk assessment, i.e., whether the model gives better results compared to traditional risk models, the performance of the model was compared with the performance of three ES models: GARCH models under the assumption that innovations follow the Student's T, GED and Skewness GED distributions. Models were chosen given in the mind results of studies conducted by Radivojevic *et al*. (2015) and Rossignolo *et al*. (2013, 2012). The maximum likelihood of the estimated parameters of the GARCH models are given in Table 2. More precisely, in the first part of the table, the estimated parameters of the GARCH models for the period January 1st, 1998, to January 1st, 1999, are given, while in the second part of the Table 2 the estimated parameters of the GARCH models during the period of the economic crisis in 2008 are given.

TABLE 2

THE ESTIMATES OF THE PARAMETERS OF APPROPRIATE GARCH(1,1) MODEL DURING REGULAR MARKET CONDITIONS

Type of GARCH model	GARCH(1,1) with Student's t	GARCH(1,1) with GED	GARCH(1,1) with Skewness GED
	0.066 (0.004)	0.082 (0.001)	0.081 (0.003)
	0.873 (0.000)	0.851 (0.000)	0.860 (0.000)
	0.000 (0.023)	0.000 (0.025)	0.000 (0.027)
			-0.113 (0.045)
η	7.754 (0.000)	1.479 (0.000)	1.515 (0.000)
Log- likelihood	2322.90	2318.08	2320.70
During conditions of the crisis			
Type of GARCH model	GARCH(1,1) with Student's t	GARCH(1,1) with GED	GARCH(1,1) with Skewness GED
	0.114 (0.000)	0.107 (0.000)	0.105 (0.000)
	0.899 (0.000)	0.895 (0.000)	0.895 (0.000)
	0.000 (0.226)	0.000 (0.137)	0.000 (0.133)
			-0.116 (0.240)
η	4.610 (0.000)	1.166 (0.000)	1.180 (0.000)
Log- likelihood	2378.93	2381.70	2385.40

Notes: p-values are given in parentheses

Presented models did not produce any ES breaks, which implies that the models potentially can be reliably used to assess market risk according to the requirements of the Basel III standard. However, this conclusion can only be made based on backtesting. Unlike VaR backtesting, ES backtesting is significantly more complex (Doncic *et al.* 2022). This is the reason why the Basel III standard is not the prescribed manner of backtesting the validity of ES assessments. For that purpose, the in this paper we used two tests Berkowitz's test (LRB) (2001) and Acerbi and Szekely's (2014) first method (Z1). Berkowitz (2001) presented a test based on the Levy Rosenblatt transformation that can be mathematically presented as follows:

$$LR_B = 2\left[\ln L\left(\mu = \mu_{ML}, \sigma^2 = \sigma_{ML}\right) - \ln L\left(\mu = 0, \sigma^2 = 1\right)\right]., \tag{17}$$

where LR_B is the Berkowitz's likelihood ratio. Berkowitz's ES back test is the test that tests a joint hypothesis of zero mean (μ) and unit variance (σ^2), while ($\hat{\mu}_{ML}$) and ($\hat{\sigma}_{ML}$) are (μ) and (σ^2) estimates obtained using maximum likelihood.

The LR_B test is asymptotically distributed as $\chi 2$ with two degrees of freedom. Berkowitz's test compares the shape of the forecasted tail of density to the observed tail. Any observations that did not fall within the tail were truncated, noting that the threshold was defined as follows: $TH = max\left\{ES_1, ES_2, \ldots ES_t\right\}$. Since the Berkowitz test validity is disputed in the case of a relatively small number of exceedances, one of the authors in (Radivojevic *et al.* 2019) proposed the use of bootstrap simulation, where F is the unknown distribution of the estimator θ^k. Thus, Berkowitz's ES backtesting based on bootstrap simulation as presented (Radivojevic *et al.*, 2019) was used in the paper. In fact, the estimation of the unknown density F of our ES estimates was used by repeating the simulations by the appropriate models several times[1]. The number of bootstrap repetitions is determined according to the Andrews and Buchinsky procedure (Andrews and Buchinsky, 1997). Determining the bootstrap repetitions number is particularly important in this case because the sample of the breaks utilized in obtaining a single ES estimate is a small fraction of the number of draws. The procedure for calculating the p-value is then continued by analogy, as previously described. The results are given in Table 3.

Given the limitations of Berkowitz's test, Acerbi and Szekely's first method was also used to test the model's validity. Acerbi and Szekely defined the null hypothesis: $H_0 : P_t^{[a]} = F_t^{[a]}$ for $\forall(t)$ against the alternatives $H_1 : \widehat{ES_{\alpha,t}}\left(X\right) \geq ES_{\alpha.t}\left(X\right) for \forall\left(t\right) and > for\, some\left(t\right) \quad \widehat{VaR_{\alpha,t}}\left(X\right) \geq VaR_{\alpha.t}\left(X\right)$

[1] According to the bootstrap method (Efron and Tibshirani, 1993), we generated multiple new samples from the data sample and calculated the value of the estimator θ^k in each sample. The size of the data-sample, of the exceedances, is known as it is a direct function of the number of trials in the bootstrap simulation and the probability level used in defining the ES. We have chosen a level of error PDB equal to 10% and a confidence level equal to 95%, the initial value of bootstrap repetitions, initial excess kurtosis of the sample of ES repetitions set to zero.

$for \forall(t)$ wherein Ft is the realized distribution of returns, $P_t^{[a]}$ is the conditional distribution tail of the distribution of P_t below the quantile α. We can write this as $P_t^{[a]}(x) = \min(1, P_t(x)/a)$.

$\widehat{ES_{\alpha,t}}(X)$ and $\widehat{VaR_{\alpha,t}}(X)$ are the sample ES and VaR from the realized returns. Under the null hypothesis, the realized tail is assumed to be the same as the predicted tail of the return distribution. The alternative hypothesis rejects the ES without rejecting VaR. To test the null hypothesis, Acerbi and Szekely defined the following test statistics:

$$Z_1(\boldsymbol{X}) = \frac{\sum_t^T (X_t I_t / ES_{a,t})}{N_t} + 1 \tag{18}$$

where **X** denotes the vector of realized returns ($X_1, X_2, \ldots, X_T$), I_t – the indicator function $I_t = 1_{(R_T < VaR_a(R))}$ that indicates the backtesting exceedance of VaR for the realized return X_t in the period *t*, and $N_T = \sum_{t=1}^T I_t$ is the number of the exceedances.

The simulations from the distribution under H0 were used to test for significance in the above method. More precisely, we followed the steps below:

1) simulate X_t^i from P_t for all *t* and *i* = 1,2…, M; where M is a suitably large number of scenarios.

2) for every *i*, compute $Z^i = Z(X^i)$,i.e., compute the value of Z_1 using the simulations from the first step;

3) estimate the *p*-value as $p = \sum_{i=1}^{M} \frac{Z^i < Z(x)}{M}$, where *Z*(x) is the observed value on Z_1.

4) we conducted the test for a confidence level of 95%.

The results of this test are shown in Table 3.

TABLE 3

BACKTESTING RESULTS DURING REGULAR MARKET CONDITIONS

	QHO	GARCH(1,1) with Student's t	GARCH(1,1) with GED	GARCH(1,1) with Skewness GED
LR_B	0.123	0.210	0.119	0.301
Z_1	0.144	0.172	0.144	0.106
RMSE	0.038	0.052	0.046	0.042
Backtesting results during conditions of the crisis				
	QHO	GARCH(1,1) with Student's t	GARCH(1,1) with GED	GARCH(1,1) with Skewness GED
LR_B	0.154	0.056	0.211	0.177
Z_1	0.122	0.098	0.381	0.428
RMSE	0.075	0.156	0.107	0.082

The p-values were obtained by applying 10.000 simulations. The test was conducted for a confidence level of 95%. According to the results shown in Table 3, it can be concluded that all models successfully passed both tests. Interestingly, no cluster of ES breaks was recorded in any simulations. To answer the question of whether the model contributes to improving the risk assessment, the root mean-squared error ($RMSE = \sqrt{\frac{\sum_{i=1}^{255}\left|R_i^2 - ES_i^2\right|}{255}}$) was used to compare the model performances with the performances of selected models. RMSE results are given also in Table 3. Based on the RMSE results, it can be clearly seen that the model generates smaller deviations, which means smaller capital burdens for banks. Hence, it can be concluded that the model contributes to the improvement of the traditional ES model. These results were obtained under regular market conditions. In the conditions of the crisis, the results are shown in the second part of Table 3. The results, also show that the model generates better risk assessments. This means that the model contributes to the improvement of traditional models and conditions of high volatility. A comparison of models has been also performed in the context of the RMSE of the first four moments of the distribution. The results are given in Table 4 . The results show that the model produces better risk estimates in all four moments of the distribution compared to traditional models. According to Radivojevic et al. (2019), it is clear that in the case of the GARCH model, the assumption of innovations distribution is more important than model specification. In other words, the assumption that is more compatible with real conditions leads to a better-performing model. Since the Student t distribution has a higher degree of freedom parameter than the GED distribution, it was expected to better capture the kurtosis of the return's distribution, especially in crisis conditions, which means that the GARCH(1,1)-Student t model is better equipped to handle extreme events in the data. On the other hand, the GED distribution is better suited for modeling skewness because it has a flexible shape that can be skewed in either direction. This is because the Student t distribution has a symmetric shape, whereas the GED distribution allows for skewness. In situations where the data exhibits skewness, the GARCH(1,1)-GED model may provide better estimates of the dispersion of stock returns. However, theoretical distributions are not fully able to capture empirical phenomena. As the number of extreme cases increases, different variants of Garch models produce larger deviations. They are less able to predict the probability of extreme returns occurring, as well as the magnitude of these deviations. However, it is characteristic of the used variants of the Garch model that it is not possible to make a universal conclusion about which variant is better from the aspect of smaller deviation in moments of the distribution. It is evident that their performance weakens in crisis conditions, but a general conclusion cannot be drawn about whose performance will weaken the most. On the other hand, in the case of the QHO model, the finding showed that it better captures the occurrence of extreme outliers, as well as the probability of their occurrence. This is from reasons because the quantum oscillator provides information about the current trend and momentum of the security.

TABLE 4

THE RESULTS OF COMPARISON OF MODELS IN TERMS OF THE RMSE OF THE FIRST FOUR MOMENTS OF THE DISTRIBUTION

	QHO	S&P Garch(1,1)-student t	S&P Garch(1,1)-GED	S&P Garch(1,1)-Skewed GED
Mean	5.25E-05	1.89E-04	5.47E-05	1.30E-04
Standard Deviation	0.007	0.004	0.011	0.011
Kurtosis	1.104	1.652	1.726	2.080
Skewness	0.801	0.914	0.906	0.924
Conditions of crisis				
	QHO	S&P Garch(1,1)-student t	S&P Garch(1,1)-GED	S&P Garch(1,1)-Skewed GED
Mean	5.37E-05	1.99E-04	5.50E-05	1.40E-04
Standard Deviation	0.011	0.011	0.011	0.011
Kurtosis	1.297	1.865	1.977	2.291
Skewness	0.920	0.921	0.947	0.929

7. Conclusion

First order of time dependent perturbation theory is applied on QHO model of stock market returns for the market with non-Gaussian properties. Semiempirical approach is introduced, since perturbating potential is unknown, to obtain series of time dependent coefficients of QHO wave functions. Fitting procedure over Hermitian polynomial as the independent variables is introduced and enables good fit of empirical data within all second year period of stock returns. In summary, this method enables prediction of tomorrow's outcomes of stock return. Real tomorrow's outcomes show no fallout from predicted ranges within confidence interval of one standard deviation.

In the context of meeting the model validation rules defined by the Basel III standard, the model was tested using Berkowitz's ES backtesting based on bootstrap simulation and Acerbi and Szekely's first method. The model provided satisfactory results. As not only the number of exceedances but also the size of the loss is relevant for the bank, it is important to allow for this criterion when comparing the models. Unfortunately, due to the scope of the work, no such comparison was made with other ES models. For the results to be comparable, for this reason, the data used by Christoffersen were taken.

Model presented in the present paper uses Harmonic oscillator potential, which tends to return the position of the particle towards equilibrium state. In economic terms this implies that stock-markets have the ability of self-correction of stock market returns toward equilibrium. At first glance, it seems that the model can be applied onto markets which are autocorrelated. This would be true for the classical model of the harmonic oscillator, where simple random movement around equilibrium position is described. Considering QHO, this problem is removed, since arbitrary deviation from equilibrium state can be described, even oscilations around new equilibrium state. This can be done by taking into account superposition quantum states, where displacements from equilibrium, which corresponds to pure ground state of QHO can be described with higher quantum states of the particle. Higher QM states are described with higher members of the wave function, i.e. higher orders of Hermite polynomial members in equation 3. For very unstable markets, where stock returns have a long-term tendency of increasing or decreasing, higher order polynomial members will have greater contribution, and larger values of coefficients in Table 1. From a theoretical point of view any stock return distribution can be expanded over infinite numbers of Hermite polynomial members. The only practical question is how fast convergence will occur, and after which order of member series infinite expansion can be truncated. For the crisis period, it was shown that taking into account the first 10 members, stock returns can be well modeled.

Further validation of presented model requires its application on developed and undeveloped markets, so that its general applicability can be verified. It is also important to compare time series of expansion coefficients with the same obtained using different markets in order to check if there is some universal pattern. This will imply that there is some common perturbating potential that can be applied on various stock markets.

The existence of agents whit heterogeneous beliefs and behavioral rules, which may change over time due to social interaction and evolutionary selection, points to the need to respect the views of Dieci and Xe (2018) and Adam *et al*. (2016). The consequence is that their expectations may be different than what would be expected under the assumption of a rational investor. This have to be considered when determining the factors that affect the volatility of returns. For this reason, future research into the application of the quantum oscillator should include how to incorporate these factors into the model.

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Much ado about nothing: A failed case for banning combustion vehicles*

Mucho ruido y pocas nueces: el fallido caso de la prohibición de los vehículos de combustión

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Abstract

The Balearic Islands (Spain) passed a regional law in 2019 banning the registration of diesel and petrol vehicles from 1 January 2025 and 1 January 2035, respectively. This law was heavily criticised before and during its implementation and was finally abolished after six months. This paper analyses the effect of this law on the registrations of both types of vehicles, as well as the registration of non-polluting vehicles. Both the synthetic control method and the difference-in-difference estimator show that the ban had no impact on any type of vehicle, not even on those that are non-polluting. Although the Balearic Islands' regional government sought to pioneer implementation of this policy, the incorrect specification of the law, the uncertainty surrounding its approval and its short-term effects and may have reduced its effectiveness.

Key words: *Combustion vehicles; Climate change; Synthetic control method.*

JEL Classification: *L90; Q40; Q58.*

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Resumen

El Gobierno de las Islas Baleares (España) aprobó una Ley regional en 2019 por que la impedía las matriculaciones de vehículos diésel y de gasolina desde el 01 de enero de 2025 y 2035, respectivamente. Esta Ley fue duramente criticada antes y durante su implementación y, finalmente, abolida tras seis meses de vigencia. Este artículo analiza los efectos de esta Ley en las matriculaciones de ambos tipos de vehículos, así como de otros menos contaminantes. Tanto el método de control sintético como el de diferencia-en-diferencias muestran que la prohibición no tuvo impacto en las ventas de ningún tipo de vehículo. Aunque el gobierno regional de las Islas Baleares intentó ser pionero en la aplicación de esta política, la incorrecta especificación de la Ley, la incertidumbre que rodeó su aprobación y sus efectos a corto plazo pueden haber reducido su eficacia.

Palabras clave: *Vehículos de combustión; Cambio climático; Método de control sintético.*

Clasificación JEL: *L90; Q40; Q58.*

1. Introduction

Road transport contributed to almost 21% of total EU emissions of carbon dioxide (2016), the main greenhouse gas, as well as to air pollution in cities and associated health issues. Thus, reducing transport needs, promoting public transport, and moving away from fossil fuels are examples of policies that should be implemented to reduce both emissions and pollution. In this context, it is relevant to evaluate which public policies can be most successfully implemented. In particular, one question to ask if it is a good strategy to ban combustion vehicles, and how consumers will adapt? The main objective of this paper is to assess econometrically the causal effects of a ban on the registration of combustion vehicles in a region. The results will indicate how (not) to define the political economy of climate change.

Following the EU's environmental objectives and the 2015 Paris Agreement on Climate Change (which acknowledges the importance of commitment at all levels of government and for all relevant actors), and given its special vulnerability to climate change as an island territory, the Spanish regional government of the Balearic Islands approved Law 10/2019, of 22 February, on climate change and energy transition.[1]

[1] The text, in Spanish, can be found here: https://www.boe.es/boe/dias/2019/04/13/pdfs/BOE-

It should be noticed that in Spain, as Pérez (2013) explains, the Constitution considers that the national government and the autonomous communities share responsibility for environmental policy. Basic legislation and general rules are designed at the national level, while their development and concrete implementation is a competence of the region to the extent defined in its corresponding Statute of Autonomy.[2]

In this context, the aim of the 2019 Balearic law was to help address climate change by adopting specific mitigation policies and move towards a sustainable, decarbonised, efficient and renewable model. Thus, the Balearic Islands aimed to have an emission-free vehicle fleet by 2050.

To achieve this objective, one of the new law's key measures was to ban diesel vehicles in the Islands from 1 January 2025, and of petrol vehicles from 1 January 2035. Unlike other more common policies that, for example, incentivise (through subsidies or tax rebates) the purchase of less polluting vehicles or restrict the circulation of only the most polluting, this was considered a very radical measure, as it directly banned the circulation of all polluting vehicles. As expected, the change was heavily criticised by both manufacturers and the national government and, in fact, the government threatened to appeal against the law to the Constitutional Court.[3]

From an economic point of view, two clear criticisms quickly emerged. First, the law could have pre-emptive effects. While it was passed in February 2019 and implemented in May 2019, the draft law was presented in August 2018, and had been under discussion since February 2018.[4] In addition to this uncertainty, the law was stalled in November 2019 until the national level climate change law was implemented.[5] This timing is relevant, and will be considered in detail in our econometric analysis later. Although the autonomous community of the Balearic Islands may be a pioneer in the implementation of this policy, the uncertainty surrounding its approval may have detracted from its effectiveness. Secondly, the law had a clear limitation: it established that 'although the circulation of combustion vehicles after the deadlines was prohibited', there were exceptions 'for reasons of public service' or 'for vehicles registered prior to these dates'. Implementation deficiencies in the measure, coupled with uncertainty about a possible reversal by the courts, suggests that it is unlikely to have generated any effect on the purchase of vehicles, at least

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2 Jaria-Manzano and Cocciolo (2020) review the competences of the Autonomous Community of Balearic Islands in relation to climate change.

3 https://www.diariodemallorca.es/mallorca/2019/07/20/balears-topa-sanchez-2857885.html

4 http://partidoequo.es/presentada-la-ley-de-cambio-climatico-de-illes-balears/

5 https://www.abc.es/sociedad/abci-baleares-paraliza-veto-diesel-previsto-para-2025-201911191407_ noticia.html

in the short term.

The main objective of this paper is to analyse whether the ban on the registration of polluting vehicles affected both the purchase of diesel and petrol vehicles and the purchase of non-polluting vehicles. Our main contribution lies in both the type of policy considered for evaluation and its focus on the short-term and anticipatory effects under uncertainty. To this end, vehicle registrations in 50 Spanish provinces (excluding Ceuta and Melilla) have been collected for the period 2011-2019. The synthetic control method has been applied to obtain a control group for the treated unit. Our results show that implementation of the policy had no impact on diesel and petrol vehicle registrations, and neither did it increase the purchase of non-polluting vehicles. Furthermore, we show that the announcement of the policy did not produce significant anticipation effects either.

Following this introduction, the next section summarizes the literature on measures taken to restrict the circulation of polluting vehicles. Then, the data and the empirical strategy are presented, followed by the results obtained. The study concludes with some policy recommendations.

2. Literature Review

As explained, pollution, mainly in large cities, is a serious problem that significantly affects the health of people living in those areas. Road traffic is one of the main generators of pollution, for which there have been various measures introduced with the aim of reducing pollution levels and improving air quality. These measures can be divided into two broad groups: those that seek to restrict the movement of vehicles via quantities, and those that seek to do so via prices.

Regarding the restrictive measures to the movement of vehicles via quantities, one of the most frequently implemented measures is the restriction of driving depending on the vehicle registration number. In these types of restrictions, the vehicles cannot circulate on certain days, depending on the last number of the registration car. Despite the fact that these types of restrictions have recently been implemented in European cities such as Madrid and Lyon (usually only on days when certain levels of contamination are exceeded), they are more widely implemented in Latin America, where it is sometimes permanent.

The policy implemented in Mexico City in 1989 called “Hoy No Circula” stands out. As Fageda and Flores-Fillol (2018) point out, drivers cannot circulate one day per week depending on the number in which their registration number ends. This restriction covers the entire metropolitan area between 5 in the morning and 10 at night. The result of the program is analysed by Davis

(2008) who does not find any type of impact on air quality levels. In fact, the author does not find any decrease in fuel consumption, nor any significant increase in the use of public transport. In fact, what you see is a significant increase in the number of vehicles. Later Gallego et al (2013) show how in the short term (one month after program implementation) carbon monoxide levels decreased between 5 and 13%, while in the long term they increased, to around 11%. This result is due to the fact that a proportion of citizens (especially middle and high income) acquire a second vehicle to travel; which in some cases is even more polluting. Hence, as Fageda and Flores-Fillol (2018) point out, these types of measures are traditionally inefficient, ineffective in the long term, and regressive, since low-income people have difficulty avoiding the restriction. Similar results are found in Santiago, Chile, where De Grange and Troncoso (2011), show very insignificant reductions in the flow of cars (just 5%) in times of emergency, and not significant in normal periods. It should be noted that the efficiency of some of these quantitative measures depends on their good design. There are examples where the setting of more restrictive emission standards has led to the manufacture of more efficient vehicles (Voltes-Dorta et al., 2013), or restrictions on the circulation of polluting vehicles has led to people substituting their polluted car for a more efficient one (Barahona et al., 2002).

In fact, articles that analyse implementation of the measure in Beijing (China) show significant reductions in pollution levels. Thus, Viard and Fu (2015) detail how the levels of particulate matter 10 micrometers or less in diameter (PM10) decreased in this city by between 18 and 21% thanks to the restriction of circulation. Gu et al (2017) show that pollution reduction is due to the transfer of movements from private vehicles to public transport and not to a reduction in the number of movements. In addition, they observe how this substitution does not occur in high-income families with more than one private vehicle, nor on short trips, where it is possible to violate the regulation with low risk of being detected.

The latter outcome does not coincide with Zhang et al (2019) who show how Chinese cities that have implemented restrictions by registration do not generate a significant increase in public transport. Only cities that combine this type of restriction with other driving restriction programs generate increases in the demand for public transport (between 20 and 30%).

Low Emission Zones (LEZ) is one of the restrictions via quantity. There are many European cities that have implemented these types of restrictions, where entry to a certain geographical area is limited to vehicles that do not meet certain pollution standards. We can see how various cities in Germany, Italy and Greece, or large cities like Lisbon, London and Paris have implemented these types of restrictions. In Asia it is also a relatively popular measure in cities such as Beijing, Tokyo, Shanghai and Hong Kong.

As Fageda and Flores-Fillol (2018) indicate, the most analyzed case is Germany, due to it being implemented earlier, since its legislation dates back to 2007. In this country, it is allowed to define a geographical area as LEZ, and limit access to vehicles with a certain badge, since they are classified according to three types of colors: green, yellow and red (the most polluting ones do not have a label). This restriction was significantly extended by Germany, with 48 LEZ's involving 76 cities, in 2018.

Malina and Scheffer (2015) analyze the impact of this measure on PM10 levels. The result shows that it effectively manages to significantly reduce the levels of this type of pollutant. In fact, the impact is greater as the program is more restrictive, when access by fewer polluting vehicles is allowed. On average, this type of restriction managed to reduce PM10 levels by 13%. This result is similar to that found by Wolf (2014), on average. However, this paper also observes how the impact of this type of measure is not significant in small cities and reaches levels of reduction of 15% in large cities such as Berlin. Another interesting result of this paper is that it does not find any increase in pollution in the areas bordering the LEZ.

In Portugal we can also observe empirical papers that analyze the impact on air quality of these types of restrictions. Thus, Dias et al (2016) note how LEZ implementation in the city of Coimbra generated a significant decrease in the levels of PM10 and NO_2 emitted by vehicles, specifically at 63 and 52% respectively. However, the impact on the city's air quality is very small as emissions from other activities increased and the air quality worsened. These results are similar to those found by Santos et al (2019) for the city of Lisbon. In this case, the authors find decreases of 30.5% in PM10 and 9.4% in NO_2, within zone 1 (basically the historic center of the city), while for zone 2 (the rest of the city) the decreases are 22.5% and 12.9% for both types of pollutants. This result occurs despite the fact that the restriction is stricter in zone 1, where Euro-3 criteria are required to access, than in zone 2, where access with Euro-2 technology is allowed. On the other hand, the article does not find any type of effect on PM2.5, nor on NOx, an outcome that leads the authors to conclude that the criteria for access to the LEZ should be tightened.

As we have seen in previous papers, in general the implementation of the LEZ causes a significant decrease in pollution in the short term. However, as Fageda and Flores-Fillol (2018) point out, these measures may cease to be efficient in the medium and long term as more drivers replace their old vehicle and can access the LEZ. As traffic (and sometimes congestion) increases, pollution levels rise again. In addition, it can be considered a regressive measure, since it is the high-income drivers who have the least difficulty changing cars and getting around the restriction.

Precisely to facilitate the renewal of the car park in many countries, public aid programs have been implemented. In these initiatives, owners receive a subsidy by replacing their old vehicles for a new, less polluting one. These types of programs, known as "Cash for Clunkers", have generated a great deal of controversy about their efficiency in reducing pollution levels, especially if we consider the possible rebound effect (because cars consume less fuel, drivers tend to perform a greater number of displacements, which is why they end up generating more contamination). While some studies show that this type of program would generate a significant decrease in pollution levels by replacing polluting vehicles with more efficient ones (Diamond, 2009; Beresteanu and Li, 2011; or Gallagher and Muehlegger, 2011), others show that in the medium term, they do not have a significant impact on the composition of the vehicle fleet, so contamination levels would not be affected (Huang, 2010; Mian and Sufi, 2010; or Li et al., 2013).

The key, as shown by Adda and Cooper (2000) in the case of France, is that drivers strategically postpone or advance the purchase of the new vehicle to be eligible for the plan, causing a decrease in car sales before and after its application. Therefore, in the medium term the number of new lesser polluting vehicles is the same, and the impact on air quality is near to zero. Licandro and Sampayo (2006) find a similar result for the case of Spain. In fact, Lenski et al (2013) show how the value of tons of CO_2 saved (90 million dollars) plus the increase in consumer surplus (about 2 billion) was less than the cost of the program in the United States (3 billion dollars), meaning that the program would generate social welfare losses.

Spain has a long tradition of applying this type of initiative, called Renove or PIVE plans, with controversial results. Thus, Cantos-Sánchez et al (2018) observe that the PIVE plan increases the probability of buying a vehicle, although in a very limited way, of about 10,400 vehicles. Laborda and Moral (2019), for their part, found a greater impact of the PIVE program, estimating an increase of 676,463 vehicles from 2012 to 2016. The authors find this result after applying duration models, where the scrapping rate depends on the age of the vehicle, as well as other factors related to the business cycle, as well as the transport sector. This increase in sales would have generated savings of 6.03 tons of CO_2. On the contrary, Jiménez et al (2016) found no impact on sales, but on prices. Manufacturers take advantage of the plan to increase prices and grab a portion of the program grant. This fact means that the program is not efficient in reducing CO_2 levels, unless there had been a 30% increase in the demand for new vehicles, which did not happen.

As a whole, restrictive measures via quantities, as already indicated by Fageda and Flores-Fillol (2018), can be effective in the short term to reduce pollution, but they are ineffective, inefficient and even regressive in the medium and long term. However, in our case the measure supposes the total prohibition of circulation by any internal combustion vehicle, so the impact on air quality is supposed to be positive. What has not been previously analysed is how drivers react to these types of restrictions on the vehicle fleet. One possibility is that they change their internal combustion vehicles for less-polluting vehicles (hybrids) or non-polluting vehicles (mainly electric and hydrogen vehicles), although there is also the possibility that they will not change their vehicle and decide to move to public transport at the time of application of the program.

Compared to these measures via quantities, there are measures via prices; basically the application of entrance tolls to cities. In contrast to the above, it allows access for those consumers with a greater willingness to pay, making it efficient. By reducing the number of vehicles, it facilitates the reduction of pollution, and is therefore an effective measure; and to the extent that the toll price is low, it is not regressive. There is considerable empirical evidence on the operation of this type of measure. In Singapore, the speed of circulation increased from 19 to 36 kilometers per hour (Phang and Toh, 1997), as the number of vehicles decreased, both during rush hour (45%) and with respect to the entry of automobiles into the city (70%) (Willoughby, 2000). In the case of London, there is consensus on the effectiveness of the toll, although different studies vary in calculating the social benefit generated by it (Prud'homme and Bocarejo, 2005; and Mackie, 2005). Eliasson (2009) finds a similar result for the application of the Stockholm toll, which generates an increase in social welfare. In the case of Milan, Rotaris et al. (2010) and Percoco (2013) show that the access toll reduces pollution levels, generating an increase in social welfare; which is a similar result to that found in Gothenburg (Andersson and Nässén (2016); and Börjesson et al. (2016).

An alternative to the congestion toll is to modify the registration tax. Various international experiences have shown how linking the registration tax with the car's level of pollution significantly influences the type of vehicle purchased, especially in Europe. Zimmermannova (2012) already showed through correlations how this type of measure had generated an increase in the number of new vehicles instead of second-hand vehicles, which are more polluting, in the Czech Republic. This fact led to a decrease in the emissions generated by the vehicles. These results have been confirmed in different European countries through different econometric models. In Ireland, a 13% decrease in vehicle emission levels is observed (Rogan et al. 2011); in the Netherlands the decrease is 11% in CO2 levels (Kok, 2015); and in Norway 4.3% (Ciccone, 2018). Klier and Linn (2015) carry out a joint analysis for France, Germany and Sweden, observing a decrease in the number of registered vehicles, and especially in the case of France a change towards more environmentally efficient vehicles.

This result is partly explained by the reduction in the number of registered vehicles (Klier and Linn, 2015), by the substitution in the purchase of more polluting vehicles for others that generate fewer emissions (Ciccone, 2018), and by the increase in market share of diesel vehicles (Rogan et al 2011; and Ciccone, 2018). This effect seems to be greater in company vehicles compared to private consumer vehicles, as shown by Kok (2015) in the case of the Netherlands. Despite the fact that this measure has been shown to be effective in reducing pollution levels from new vehicles, the cost can be high, as shown by Rogan et al., (2011). The introduction of a lower registration tax for the most environmentally efficient vehicles caused a decrease of 33% in Ireland, approximately 166 million euros.

Another possible price measure is to increase fuel prices by increasing taxes. It should be noted that Spain is one of the EU countries with the lowest fuel taxes, only above the eastern countries (Romania, Poland, Lithuania, Hungary, Estonia and Bulgaria) and Luxembourg. The other 20 countries have higher diesel taxes.[6]

As mentioned, the main purpose of this paper is to analyze the effect of a measure via quantities such as forbidding the registration (nor circulation) of internal combustion vehicles in the Balearic Islands. To our knowledge, this is the first time that the effectiveness of this type of measure has been assessed, although, as we have seen in this section, these types of measures via quantities have not had a high degree of effectiveness in modifying vehicle fleet composition and in significantly reducing pollution levels.

3. Database And Empirical Strategy

We have collected data from three different sources. First, the database is composed by registrations by type of vehicle (diesel, gasoline and non-polluting cars[7]) at province level, from January 2011 to January 2020. A total of 50 Spanish provinces, excluding Ceuta and Melilla, compose the sample. The data has been obtained from the statistic portal of the Spanish General Directorate of Traffic. On the other hand, control variables such as the Gross Domestic Product per capita by province and petrol prices have been obtained from the National Statistics Office (INE) and from the Ministry of Industry, Trade and Tourism (Spanish Government), respectively.

Figure 1 depicts the evolution of vehicle registrations by type of vehicle

6 Data obtained from the Oil Bulletin of the European Commission in July of 2020 (https://ec.europa.eu/energy/data-analysis/weekly-oil-bulletin_en?redir=1).

7 This category encompasses electric and hydrogen vehicles (the latter shows very low cases). Hybrid cars, those that combine combustion and other type of engine, are not considered in this study due to the low share and the presence of zero monthly registrations.

separately, for the case of the Balearic Islands and the average of the other Spanish provinces. While the data for the Balearic Islands shows seasonality and ups and downs, computing the average for several observations (provinces) smoothens the series. The average monthly registrations of diesel vehicles in Balearic are 1,518 (1,236 for the remaining provinces), and 2,658 for gasoline vehicles (1,027 for the other provinces). However, for the case of the electric and hydrogen vehicles average monthly registrations in the Balearic Islands totals approximately 19 vehicles (16 for the rest of the provinces). Figure 1 shows that the registrations of electric and hydrogen vehicles have increased since mid 2016-beginning of 2017 in the Balearic Islands and, on average, in the remaining provinces included in the sample.[8]

The main takeaway from this figure is that the other Spanish provinces may not be an appropriate natural control group for the behavior of vehicle registrations in the Balearic Islands to apply the difference-in-differences estimator. Moreover, a deeper analysis of vehicle registrations by provinces reveals great differences in the number and the behavior of registrations across provinces.[9]

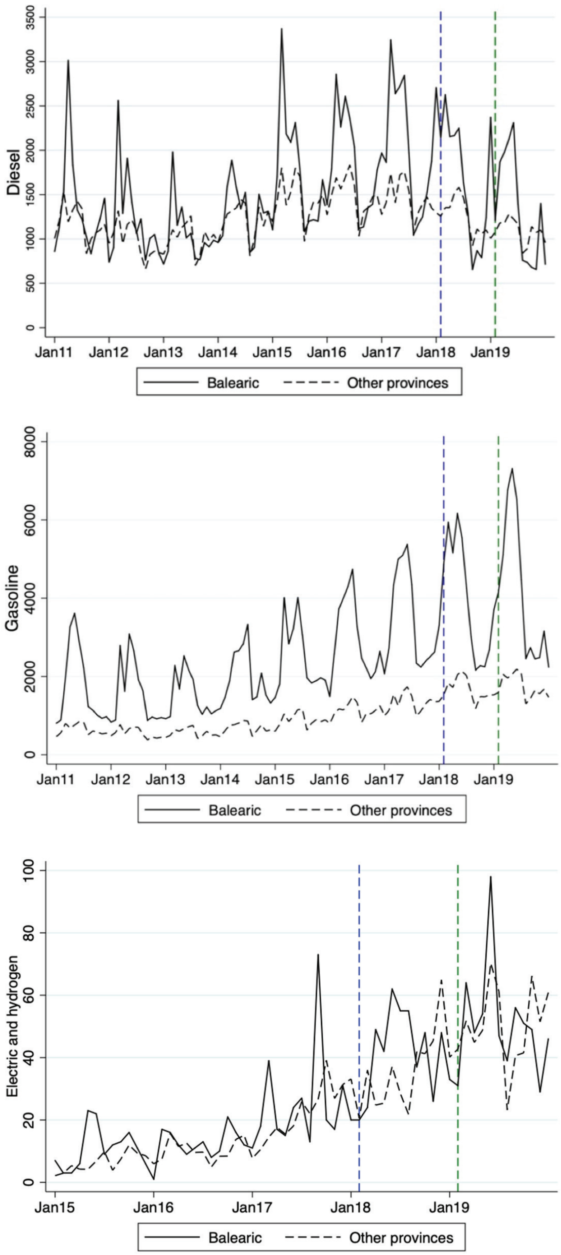
Therefore, we need to look for a control group that approximates vehicle registration of the treated unit before estimating the regression. In order to do so, we have applied the the synthetic control method[10], following Abadie and Gardeazabal (2003). This methodology allows us to approach this problem by comparing the Balearic Islands during the treatment period with a synthetic region, i.e., a weighted combination of other Spanish regions chosen to resemble the characteristics of the treated region (Balearic Islands) in the period previous to the shock (before the Law was implemented). This idea was developed by Abadie and Gardeazabal (2003), who create a vector of weights (a combination of control provinces), which specifically best resemble the treated before the treatment takes place and developed by Abadie et al (2010).

8 We do not consider registrations of these types of vehicles between 2011-2014 due to more than 65% of provincial data being zero (i.e. there were no registrations of electric and hydrogen vehicles).

9 Graphical analysis by provinces is available upon request to authors. They have not been included for simplicity.

10 It should be noted that the matching estimator has also been applied to obtain the control group. However, the optimally selected provinces do not properly replicate the behavior of vehicles registrations in the Balearic Islands.

FIGURE 1
REGISTRATIONS BY TYPE OF VEHICLE. BALEARIC VS. OTHER PROVINCES (AVERAGE)



Source: Own elaboration.

Notes: Blue dashed line: February 2018, when the Law was announced; Green dashed line: February 2019, when the Law was passed.

In our case, the synthetic control method considers not only monthly registrations but also the average monthly rate of registrations, the quarterly rate of registrations, the gross domestic product per capita and the average hydrocarbon price. All of them are predictors in our model. The synthetic control method provides a control unit much more similar to the Balearics than the average of all other Spanish regions.

The synthetic control method has been applied separately for each type of vehicle. Moreover, we have distinguished between *two different* treatment periods. Taking into account the process of discussion and passing of the law (see Introduction section), we have considered three different stages: *stage 0* refers to the control period, before the law was discussed/presented, from January 2011 to January 2018[11]; *stage 1* refers to the period between the discussion and presentation of the law but before its passing, from February 2018 to January 2019; and *stage 2* considers the period when the law was passed and implemented, from February 2019 to November 2019. As noted, the law was passed in February 2019 but came into force in May 2019. Given that the period between the approval of the law and its implementation is short, we have considered both treatments together.

We have applied the synthetic control method and estimated regressions considering stage 2 as the treatment period first (it starts in February 2019 and lasts until November 2019), and then used stage 1 as the initial treatment period (it starts in February 2018 and lasts until November 2019). This strategy allows us to estimate the policy's potential anticipation effects.

TABLE 1

AVERAGE REGISTRATIONS (AND VARIATION RATE)

	Diesel			**Gasoline**			**Electric and hydrogen**		
	St. 0	St. 1	St. 2	St. 0	St. 1	St. 2	St. 0	St. 1	St. 2
Treated (Baleares)	1240	1682	1374	1716	4003	4329	7	42	51
Variation rate St 0		36%	-25%		133%	19%		500%	129%
Variation rate St t-1			-18%			8%			21%
Synthetic control (Announcement)	1249	1296	1218	1665	4267	4626	14	90	97
Variation rate St 0		4%	-6%		156%	22%		543%	50%
Variation rate St t-1			-6%			8%			8%
Synthetic control (Law was passed)	1566	1626	1539	2644	7584	8202	13	96	110
Variation rate St 0		4%	-6%		187%	23%		638%	108%
Variation rate St t-1			-5%			8%			15%

Source: Own elaboration.

Notes: St. 0: Stage 0 (before). St. 1: Stage 1, announcement. St. 2: Stage 2 (Law was passed).

11 Excepting electric and hydrogen vehicles, which was between January 2015 to January 2018.

Table 1 summarizes the average registrations, and its variation rates, by vehicle type, distinguishing between the Balearics and observations of the synthetic control. It can be seen that the registration of diesel vehicles increased by 36% in the Balearic Islands in stage 1 with respect to stage 0, while they decreased in the second stage in comparison with the stage of reference. Registrations of the remaining vehicles increased in the Balearic Islands during the analyzed stages. However, these figures should be compared with vehicle registrations in the synthetic control group, which follow the same pattern, although the quantities of variation are slightly different.

4. Results

Figures 2 to 4 depict the behavior of the different types of vehicles for the province of the Balearics and for the synthetic province. All these figures separately represent the two treatments or starting points considered: the month in which the policy was announced (February 2018) and the month in which the policy was passed (February 2019). Especially in the cases of diesel and gasoline vehicles, it can be seen how the control group now behaves similarly to the treated unit, in comparison with the raw data (previous Figure 1).

For each analysis (by type of cars, announcement and passing Law), the synthetic method uses different unit weights among control regions, in order to create the synthetic Balearic Islands. All are included in Table 2.

TABLE 2

REGIONS AND WEIGHTS CONSIDERED BY SYNTHETIC

	Diesel	**Gasoline**	**Electric and hydrogen**
Announcement	Málaga (38.1%), Castellón (31.1%), Alicante (20.1%) and Ourense (10.7%)	Málaga (57.7%) and Alicante (42.3%)	Cádiz (0,2%), Girona (9,7%), Madrid (3,8%), Cuenca (6,3%), Alicante (43,5%), Álava (32%), Bizkaia (2,1%) and Gipuzkoa (2,4%)
Law	Málaga (50.6%), Castellón (36.7%) and Alicante (12.7%)	Málaga (53.7%) and Alicante (46.3%)	Cádiz (1,2%), Girona (18,5%), Tarragona (29,8%), A Coruña (47,5%) and Madrid (3%)

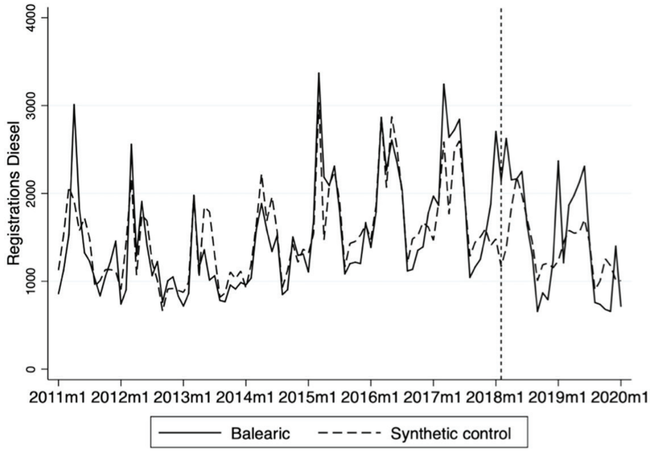
Source: Own elaboration from synthetic control estimations described in Figures 2 to 4.

At this time, it should be highlighted that considering two different starting points affects the control group used in the estimation. This is a relevant question for the emerging electric and hydrogen vehicles market, but not for the combustion vehicle, which is a mature market. In fact, as Figure 1 shows, non-polluting vehicle registrations did not take off until mid-2016, two years before the law was announced.

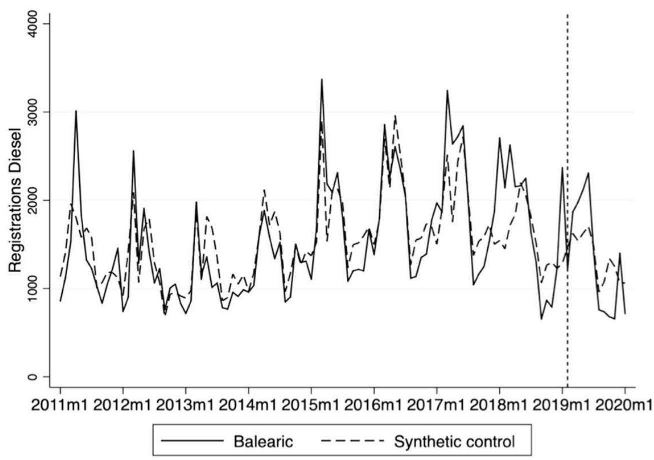
FIGURE 2

DIESEL. SYNTHETIC CONTROL

A: STARTING POINT: FEBRUARY 2018 (ANNOUNCEMENT)



B: STARTING POINT: FEBRUARY 2019 (LAW)

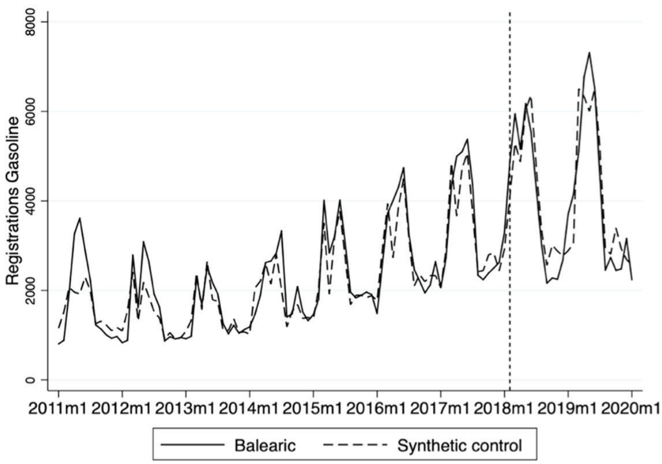


Source: Own elaboration.

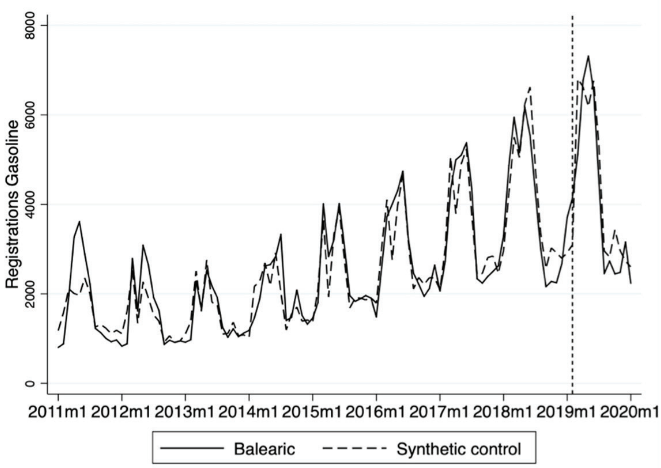
FIGURE 3

GASOLINE. SYNTHETIC CONTROL

A: STARTING POINT: FEBRUARY 2018 (ANNOUNCEMENT)



B: STARTING POINT: FEBRUARY 2019 (LAW)

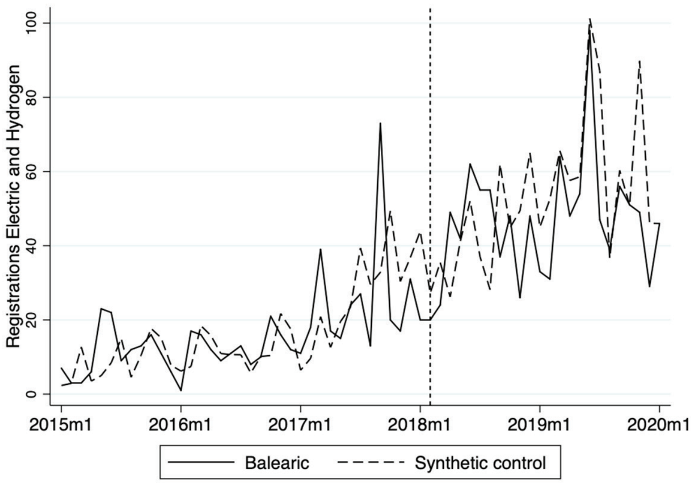


Source: Own elaboration.

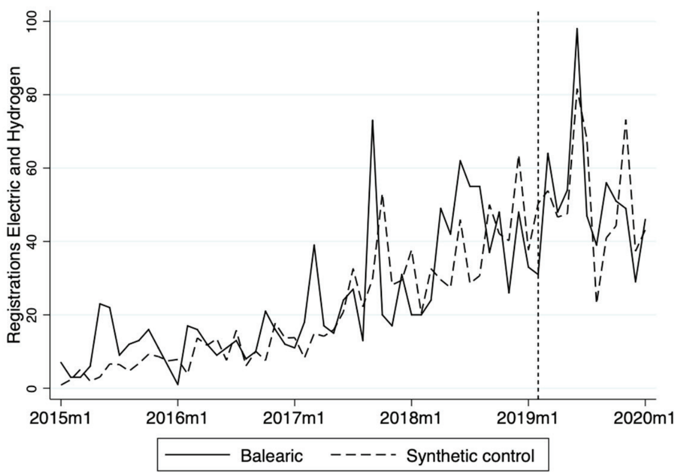
FIGURE 4

ELECTRIC AND HYDROGEN. SYNTHETIC CONTROL

A: STARTING POINT: FEBRUARY 2018 (ANNOUNCEMENT)



B: STARTING POINT: FEBRUARY 2019 (LAW)



Source: Own elaboration.

These figures show how policy has changed registrations in diesel, petrol and electric and hydrogen cars. As can be seen, no relevant or notable increase or decrease has been found. In order to quantify the impact of the policy, a difference-in-difference analysis (hereinafter DiD) has been implemented using the synthetic province as a control group. In each type of vehicle, we consider only two types of observations in all periods: registrations of vehicles in the Balearic Islands versus the synthetic control group. And we also consider the treatments of the announcement of the law and the passing of the law, respectively.

Specifically, the Ordinary Least Squares method was applied in order to estimate these causal effect, robust to heteroscedasticity, following equation (1):

$$R_{it} = \beta_0 + \beta_1 \text{Treated}(\text{Balearic})_i + \beta_2 \text{Stage2}(\text{After Law was passed})_{it} + \beta_3 \text{DiD}_{it} + \alpha_i + u_{it} \quad (1)$$

where R_{it} is the number of registrations of the region's vehicles (*i*, Balearic vs. synthetic group) at month (*t*); $\text{Treated}(\text{Balearic})_i$ takes value 1 if the region (*i*) is the Balearic Islands and 0 otherwise (synthetic control countries); $\text{Stage2}(\text{After Law was passed})_{it}$ takes value 1 for the months in which the policy was passed in the Balearic Islands and 0 in other cases; DiD_{it} is the interaction of both previous binary variables, so it takes value 1 for the Balearic Islands after the Law was passed, and 0 in all other cases. This represents the average effect of this policy. Finally α_i represents individual fixed effects (month and year effects); and u_{it} is the error term. In order to estimate potential different effects due to the Law being announced or once the Law was passed, we split both Stage and DiD into two variables. Stage 1 was the announcement while Stage 2 was the passing of the Law.

TABLE 3

DIFFERENCE IN DIFFERENCE ESTIMATIONS. REGISTRATIONS. STARTING POINT: FEBRUARY 2019 (LAW WAS PASSED)

	Diesel	**Gasoline**	**Electric and hydrogen**
Treated(Balearic)	-0.0471*	-0.0019	0.5447***
	(0.03)	(0.02)	(0.10)
Stage 2(after Law was passed)	-0.4859***	-0.2023	-0.5044
	(0.15)	(0.13)	(0.41)
DiD Stage 2	-0.0761	-0.0719	0.0491
	(0.09)	(0.07)	(0.23)
Month effect	Yes	Yes	Yes
Year effect	Yes	Yes	Yes
Observations	214	214	118
R^2	0.76	0.92	0.78

Standard errors in parentheses. Endogenous variables are measured in natural logarithms.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 and Table 4 summarize the results of the difference-in-differences estimator. They show that the law's implementation had no impact on the registrations of diesel, gasoline vehicles or electric and hydrogen (Table 3). The same conclusion is obtained when the announcement of the law is considered as a starting point (Table 4). Additionally, we can rule out the existence of anticipation effects.

The policy has not had an effect during the period of the data. But specifically it had two main results: first, both synthetic and DiD shows that the policy has not been effective at discouraging the purchase of polluting vehicles; second, it has not incentivized the acquisition of non-polluting vehicles.

Uncertainty around the passing of the law (there were many discussions during the draft process) together with the fact that it is not clear in the law whether any diesel or gasoline vehicle can circulate, or whether the vehicles already registered could circulate ("prohibition of circulation except for reasons of public service or previous establishment in the autonomous community"), could explain these results.

Table 4 shows that the coefficient of the difference-in-difference estimator is not significant for these types of vehicles in stage 1 (announcement of the policy). Regarding the electric and hydrogen vehicles, no significant impact of the law's implementation has been found.

TABLE 4

DIFFERENCE IN DIFFERENCE ESTIMATIONS. REGISTRATIONS. STARTING POINT: FEBRUARY 2018 (ANNOUNCEMENT)

	Diesel	**Gasoline**	**Electric and hydrogen**
Treated (Balearic)	-0.0371	0.0248	0.0182
	(0.03)	(0.02)	(0.10)
Stage 1 (Law announcement)	-0.6793***	-0.2439*	-0.7965***
	(0.15)	(0.13)	(0.38)
Stage 2 (after Law was passed)	-1.1998***	-0.5122***	-1.4407**
	(0.22)	(0.19)	(0.59)
DiD Stage 1	0.1148	-0.0628	-0.0609
	(0.08)	(0.07)	(0.20)
DiD Stage 2	-0.0483	-0.0758	-0.2263
	(0.08)	(0.07)	(0.22)
Month effect	Yes	Yes	Yes
Year effect	Yes	Yes	Yes
Observations	214	214	118
R^2	0.79	0.92	0.81

Standard errors in parentheses. Endogenous variables are measured in natural logarithms.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These results are related to and may also be explained by the findings obtained by Rubio et al. (2020), who surveyed 2,290 participants in Spain to analyse their support for three potential policies to combat climate change, which included prohibiting the use of polluting light-duty vehicles from 2029. The results show that only 27% of the directly affected respondents (those who have a vehicle) and 35.7% of the non-directly affected respondents would support this policy. Moreover, the authors analyse which of the five considered factors could explain support from respondents, namely: i) perceived effectiveness of the policy; ii) self-perceived individual responsibility to act against climate change; iii) self-perceived capacity to change own behavior; iv) resistance to change; and v) the distance with which the effects of climate change are perceived.

5. Policy Recommendations And Conclusions

Climate change has become one of the leading economic problems at global level. Road transport is among the most polluting sectors, and for this reason different countries have implemented measures to reduce pollution by internal combustion vehicles. Despite the existence of empirical evidence in favor of the implementation of measures via prices (mainly the introduction of toll access to the main cities), many countries continue implementing measures via quantities.

This paper analyses the introduction of one of these measures via quantities, specifically the prohibition of diesel and gasoline registration vehicles in the Balearic Islands from 2025 and 2035 respectively, and its impact on the registration of new vehicles today. However, a weakness of the law is that it prohibited the registration from the indicated date, but not the circulation of vehicles of these types registered in advance. This fact generated significant rejection by vehicle manufacturers, which included a legal appeal to the European courts.[12] In addition, the central government of Spain considered that the measure exceeded regional powers and warned the Balearic Islands' government if it did not withdraw the measure, it would appeal to the Constitutional Court.[13] This paper is about the very short-term effects of the policy taking into account the fact that by the very nature of the policy short-term effects can be modest.

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12 https://www.abc.es/motor/economia/abci-fabricantes-coches-denuncian-gobierno-balear-ante-bruselas-plan-para-vetar-motores-combustion-201901161044_noticia.html#vca=mod-sugeridos-p1&vmc=relacionados&vso=los-fabricantes-de-coches-denuncian-al-gobierno-balear-ante-bruselas-por-su-plan-para-vetar-los-motores-de-combustion&vli=noticia.foto.sociedad&ref=

13 https://www.abc.es/sociedad/abci-baleares-paraliza-veto-diesel-previsto-para-2025-201911191407_noticia.html

This opposition by both agents is still surprising when economic rationality indicates that these types of measures are not specific to significantly modify the fleet of vehicles, and therefore the levels of pollution emitted by them. The results obtained in this paper confirm this result, showing how the measure did not generate any significant change in the vehicle fleet: neither a significant decrease in the registration of gasoline and diesel vehicles, nor an increase in the registration of non-polluting vehicles. Allowing the circulation of previously registered diesel and gasoline vehicles beyond 2025 and 2035 meant that drivers had no incentive to change their vehicle for a non-polluting one before then. The approval of these types of measures is completely ineffective unless the circulation of previously registered vehicles is also prohibited and the entry into force date is close. The possible reversion of the policy and the short-term horizon of the data may also explain why we do not find a relevant effect. A better design and implementation of these types of regulatory measures would improve its efficiency significantly.

An alternative to quantity measures, even when implemented efficiently, are price measures. The price mechanism is tremendously powerful to efficiently modify the individual decisions, so introducing access tolls to main cities, increasing registration taxes on the most polluting vehicles and/or significantly increasing fuel taxes, could significantly help to modify the vehicle fleet, by encouraging the introduction of non-polluting vehicles. Furthermore, this type of measure generates additional resources for the public sector, which can be used to increase investment in public transport, which is key to reducing the number of vehicles in circulation.

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Policy response to COVID-19 shock: measuring policy impacts on lending interest rates with granular data*

Respuesta de política ante el shock de COVID-19: medición del impacto sobre las tasas de interés activas con datos granulares

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Abstract

As a response to the COVID-19 shock, the Uruguayan government expanded an existing public credit guarantee and introduced deductions in local currency reserve requirements. Policies of the same nature were also implemented by several governments throughout the world. This paper contributes to the financial additionality literature and the literature on the bank lending view of the monetary policy by analyzing the impact of this type of policies on loans' interest rate spread over the interbank rate. Using a very detailed database on loan contracts, we estimate a dynamic panel model to analyze the effects of policy responses to the COVID-19 shock over loan interest rates. We find that the PCG policy had a relatively higher effect on loans' interest rates in comparison to the reserve requirements policy.

Key words: *banks, COVID-19, PCG, reserve requirements, interest rate caps.*

JEL Classification: *G21, E65.*

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Resumen

Como respuesta al shock de COVID-19, el gobierno uruguayo extendió una garantía de crédito público existente e introdujo deducciones en los requisitos de reserva en moneda nacional. Este artículo contribuye a la literatura sobre adicionalidad financiera y la literatura sobre el canal crediticio de la política monetaria. A partir de datos detallados de contratos de préstamos, estimamos un modelo de panel dinámico para analizar los efectos de las respuestas de política al shock de COVID-19 sobre las tasas de interés de los préstamos. Encontramos que la política de garantías públicas de crédito tuvo un efecto relativamente mayor sobre las tasas de interés de los préstamos en comparación con la política de deducción de requisitos de reserva.

Palabras clave: *bancos, COVID-19, PCG, requisitos de reserva, topes de tasas de interés.*

Clasificación JEL: *G21, E65.*

1. Introduction

Following the COVID-19 shock, several governments around the globe implemented a set of policies in order to cope with the contraction in the supply of credit. Uruguay was no exception; among other policy measures, between March and April 2020 the Uruguayan Government expanded an existing public credit guarantee and introduced deductions in local currency reserve requirements.

Regarding the first policy measure, public credit guarantees were one of the most popular policy actions implemented throughout the world in support of micro-, small and medium-sized firms (MSMEs from now on) during the pandemic and the associated lockdowns. Loans backed with a public guarantee offer risk mitigation to lenders by taking a share of the lenders' losses in case of default. According to the financial additionality hypothesis (Uesugi et al. (2010), de Blasio et al. (2018)), public credit guarantees (PCG from now on) allow targeted firms to experience an increase in their credit supply and/or an improvement in their borrowing terms. For example, previous studies from Ciani et al. (2020), Calcagnini et al. (2012), and d'Ignazio and Menon (2013) find that guaranteed firms were benefited from a reduction in interest rates charged in their term loans. In addition, as was the case in other economies, the PCG policy included interest rates ceilings in order to prevent banks' predatory practices and also to facilitate cheap credit to firms suffering the impact of the pandemic. As has been analysed by the literature, although interest rate caps can make credit more accessible and protect borrowers from exorbitant rates, they may also include side-effects in the form of credit rationing or higher non-interest fees and commissions (Ferrari et al. (2018), Freixas and Rochet (2008)). Regarding the former, the policy implemented in Uruguay also applied a significant reduction in the fees that banks could charge for this type of loans.

In addition, Uruguay's policy toolkit also included deductions in banks' reserve requirements associated to their local currency operations. Specifically, the deductions were conditional on the increase in the supply of loans in this currency. As the literature has shown, this type of monetary policy instrument may have an impact on economic activity through changes on banks' lending behavior (Bernanke and Blinder (1988), Kashyap and Stein (2000), Dassatti Camors et al. (2019)). For example, if the funds that are not subject to reserve requirements are also not covered by deposit insurance, banks will face an adverse selection problem that will disable their ability to fully substitute one unit of insured funds with one unit of non-reservable funds, hence, their lending behavior can be affected. Although other countries also applied reductions in their reserve requirements during the pandemic,[1] the usage of these type of instruments has a long history in the region (Cordella et al. (2014), Tovar Mora et al. (2012), Federico et al. (2014)).

Both measures intended to enhance firms' liquidity, one in a more general manner, and the other one targeting a specific segment of the corporate sector. In addition, the interest rate cap on loans backed by public guarantees reflects the intention of the policymaker of keeping the costs of PCG loans low. As a result, if the cap set were not binding, banks could have incentives to charge higher rates which could have rationed firms targeted by the policy. Regarding the other policy, according to the well known Monti-Klein model (Freixas and Rochet (2008)) of bank competition, reserve requirements' deductions could also translate into lower loan interest rates by reducing banks' cost of funding.

Our focus in this paper is to analyse the impact of these policies on loan's interest rates. Specifically, a relevant question is whether under a credit crunch situation it is better to release reserve requirements conditional on the growth in the supply of credit or to grant PCG loans with interest rate caps. In Uruguay, lending interest rates fell during 2020 and the first half of 2021; this fall may be explained, among other things, by a combination of domestic factors associated with an expansionary monetary policy (with an instrument change implemented in September 2020), the release of reserve requirements, and the PCG policy.

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[1] During the pandemic, reserve requirements were also reduced in the United States, China, Indonesia, The Philippines and Brazil.

Applying panel data regression methods with a detailed database for 11 commercial banks from April 2020 to April 2021, this paper contributes to the financial additionality literature and the literature on the bank lending view of the monetary policy by analysing the impact of this type of policies on loans' interest rate.

The rest of the paper is structured as follows. Section 2 introduces the main features of the policy response to the COVID-19 shock. Section 3 describes our dataset and the main figures. Section 4 describes the empirical strategy and Section 5 shows the results of the estimations. Finally, Section 6 concludes.

2. Policy Framework

One of the main policies implemented by the Uruguayan government during the pandemic was the expansion of an existing PCG mechanism in April 2020. Specifically, some of the restrictions of the original mechanism were softened with the aim of reaching the more affected firms and also providing good incentives to lenders in order to avoid inefficient allocations and opportunistic behaviors.

In particular, the possible destinations of guaranteed loans now included the restructure of past loans and the extension of their maturities, in addition to the already existing possible uses as working or investment capital. The coverage of the guarantee increased to a level of up to 80% of the loan (before it was 60%) and could cover up to 50% of the credit balance of a firm restructuring previous loans. The maximum loan amount that could be covered was UI 1.200.000 (approximately US dollar 150.000),[2] and the loan could be granted either in national currency (Uruguayan pesos or UI) or in US dollar. The maturity of the amortizing loan could vary from a minimum of 3 months to a maximum of 3 years, including a grace period of up to 6 months. In addition, the fees charged to banks decreased considerably and varied according to the currency of the loan (annual fee of 0.6% for a guarantee in domestic currency, and 0.8% in US dollar). Finally, the interest rate of guaranteed loans were now subject to caps.[3]

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2 UI stands for "Unidad Indexada"; it is a unit of value that adjusts according to inflation measured by the Consumer Price Index.

3 For loans in Uruguayan Pesos the cap was ITLUP 4y node + 450 basic points: 17.22% as of April, 2020. The *ITLUP Curve* is a spot yield curve of Uruguayan Securities with sovereign risk issued in current national currency (Uruguayan pesos). For loans in UI the cap was CUI 4y node + 250 basic points: 5.65% as of April, 2020. The *CUI Curve* is the spot curve of Uruguayan sovereign securities issued in national currency indexed to inflation. For loans in US Dollar, the cap was CUD 4y node + 250 basic points: 5.24% as of April, 2020. The *CUD Curve* is the spot yield curve of Uruguayan sovereign securities issued in US Dollar.

While the decision-making on borrower eligibility and credit risk was fully devoted to the lender, there were still a series of pre-established requirements. Firstly, the eligible firm needed to be formally established, with payment capacity and up to date with tax obligations. Secondly, the firms' annual sales must be below UI 75.000.000 (approximately 8 million US dollar). Thirdly, if the firm had already an active loan in February 2020, it must be less than 59 days past due in the payment of its loans as of February 29, 2020. Fourthly, the firm must have a relatively good rating (i.e. "2B" or better[4]) in the credit registry as of February 2020. If it had a lower rating, it would still be eligible as long as one of the following conditions were met: (i) its debt was lower than 100 US dollar or its equivalent in Uruguayan pesos as of February 2020, (ii) the firm had improved its rating and at the time of receiving the guarantee it was at least 2B.

On the other hand, regarding the reserve requirements deductions, although this type of policy was already implemented in the past, it had a novel feature since the deductions were conditional on the increase in the stock of credit granted in local currency (Uruguayan pesos and UI) between February and June 2020. In addition, the increase in the supply of credit admitted for applying the deductions had a limit defined by a weighted sum of liabilities according to their maturities.[5]

The magnitude of both policies was significant. As a result of the PCG policy, the total loans granted as of April 2021 reached a level of USD 724 million. Before the pandemic the total stock of credit with a PCG was approximately USD 45 million, and the accumulated guaranteed credit between 2009 and 2019 reached USD 538 million. As can be seen, the total amount of guaranteed credit up to April 2021 was almost one and a half times the accumulated guaranteed credit in the previous ten years. In addition, these credits represented, on average, 3,4% of the amount of the new loans granted by the banking system per month (10% if we consider loans to MSMEs), and only 37% of these loans were granted in local currency. On the other hand, in the second half of 2020, total reserve requirements deductions reached USD 167 million per month, arising to USD 204 million during 2021. These values represent, on average, 60% of the total monthly supply of credit in local currency.

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4 See Appendix A.1

5 Specifically, the weights were the following: 7% of liabilities with a maturity of less than 30 days, 5% of liabilities with a maturity between 30 and 90 days, 5% of liabilities with a maturity between 91 and 180 days, 3% of liabilities with a maturity between 181 and 367 days.

3. Data And Descriptive Statistics

3.1 Data

We exploit three databases from the Central Bank of Uruguay in its role as banking regulator and supervisor. All datasets cover the period from April 2020 to April 2021 and are available on a monthly basis.

The first database contains monthly detailed information on new loan contracts granted to firms, including variables such as the type of loan-product, the currency in which it was granted, the maturity, the interest rate and the amount of the loan, the economic sector to which the firm belongs, the size of the firm and the banking institution that granted the loan. This data is complemented with a second database with monthly information on the loan contracts guaranteed with PCG Funds, including the same variables as the previous dataset, as well as new variables associated with these type of loan contracts, such as: the period of grace, the frequency of amortization, the credit rating of the firm as of February 2020 and the current credit rating, the percentage covered by the PCG guarantee, the type of PCG Fund,[6] and the destination of the loan (working capital, investment capital, restructured debt).

We also have monthly balance sheet and income statement information from all the banking institutions operating in the Uruguayan financial system during the period considered, which we also complement with detailed information on reserve requirements deductions applied to the banks that satisfied the conditions imposed by the policy design.

After combining all datasets, we start with 910,965 observations, from which we exclude loan contracts associated to credit card debt and to operations from the Public Sector or from foreign borrowers. We then have 656,606 observations which we collapse by creating an id given by the combination of the following variables: banking institution, currency of the loan, type of loan, the industry of destination of the loan, the firm size and the maturity of the loan. The justification for this level of analysis is twofold: first, we do not have information at the firm level; second, working at the industry level would lead to results that are too aggregated. To cope with this challenge, we decided to have a unit of analysis that identifies different type of loan contracts, where the type of contract is not only given by the accounting code but also by the

6 Initially, when the policy was created in 2009, the funds were targeted for the MSME segment of the corporate sector. During the pandemic, new specific funds were created. The first and most important fund was denominated “PCG Emergency”, since it targeted all micro, small and medium-sized firms that were being affected by the COVID-19 shock. Later on, in November 2020, a new fund (“PCG Corporate”) was created in order to target big firms (not included in the first fund during the pandemic). Finally, a “PCG Tourism” fund was created with the objective of maintaining the operative of firms in the tourism industry during the summer season.

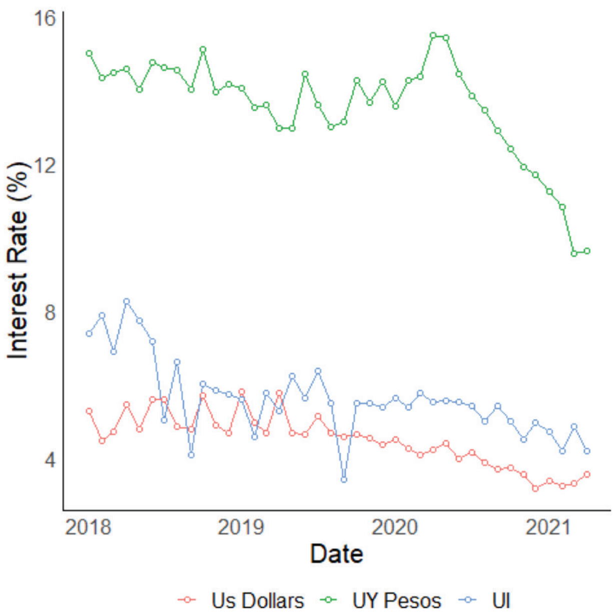
maturity and the currency of the loan operation. In order to reach a unit that uniquely identifies each of these operations, we collapse the loan amount at the id level. After this, we finish with a total of 23,844 observations that include specific loan contract data for the period between April 2020 and April 2021.[7]

3.2 Descriptive Statistics

We compute monthly interest rates at the bank level and for the aggregate of the banking system as a weighted average where the weights are given by the capital of each loan operation. This methodology was also applied for obtaining the monthly average rates of the PCG operations by bank.

FIGURE 1

BANKS' LOAN INTEREST RATE (JAN/2018 - APR/2021)



As can be observed in Fig 1, interest rates experienced a clear decrease from March 2020 onward. As we have already mentioned, this fall may be explained by a combination of factors associated to the change in monetary policy, the release of reserve requirements and the PCG policy of credit guarantees. The objective of this document is to understand how much of the effect on loan interest rates may be explained by the last two factors.

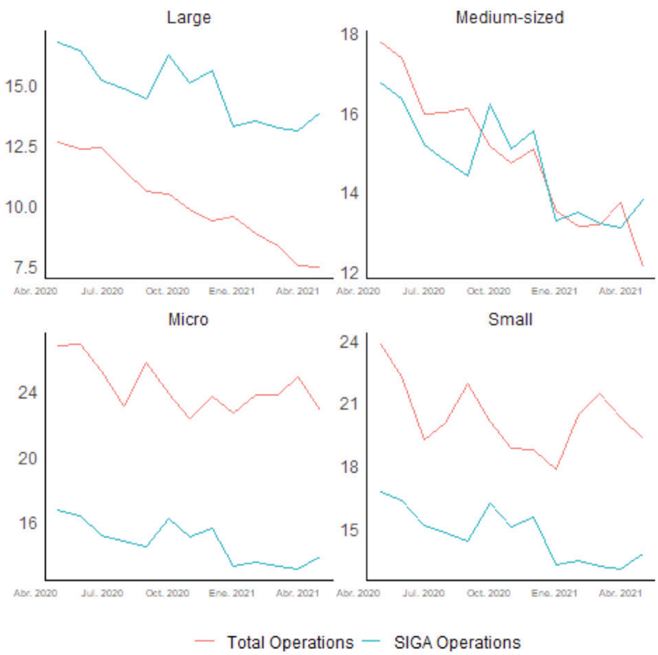
7 We have an unbalanced panel, with 13 months and more than 400 individuals appearing in all periods.

Like most countries, Uruguay maintained an expansionary monetary policy stance during 2020. In September 2020, it changed its monetary policy instrument from money aggregates to interest rate, setting the interest rate at 4.5%, a level that was maintained until August 2021 with an inflation above 8%.

In 2020, the evolution of credit to the non-financial sector showed different performances in domestic and foreign currencies. In the former case, it increased in real terms by 3.4%, while in foreign currency it fell by 1.8%.

FIGURE 2

AVERAGE INTEREST RATES VERSUS PCG RATES IN LOCAL CURRENCY



When comparing loan interest rates charged by the banking system according to firms' size with the rate charged in PCG loans (Fig 2), we observe that the latter is lower than the average loan rate for micro and small firms. In contrast, the PCG interest rate is higher than the average rate charged to large firms. The same pattern is observed in loan contracts denominated in foreign currency. Although large firms are not included in the most important portion of the supply of loans backed with public guarantees, the comparison is relevant. Large firms have more credit history than MSMEs and are more likely to offer collateral/personal guarantees to the bank. In that sense, large firms obtain lower interest rates due to a higher repayment probability and a smaller expected loss given default. Although the PCG policy improves MSMEs credit profile by providing a high-quality guarantee, these firms still are charged higher interest rates when compared to those paid by large firms.

When focusing on loan operations in local currency (Table 1), the average lending interest rate in the whole period is 19.2%, while the PCG interest rate is 14.7% and the mean of the spread between lending interest rate and interbank call rate is 14.3%. In addition, the rate cap associated to PCG operations is binding in 28% of these loan contracts and PCG operations represent, on average, only 4% of the total amount of new loans granted each month –considering loan operations from MSME firms, these ratio rises to 8.5%–. In addition, during the second half of 2020, total reserve requirements deductions reached USD 167 million per month, arising to USD 204 million during 2021. These values represent, on average, 60% of the total amount of credit (Table 1).

TABLE 1

DESCRIPTIVE STATISTICS - LOCAL CURRENCY

Variable	N	Mean	SD	Min	Max
Loan.Rate	9836	19.20	8.58	0.00	55.51
Siga.Rate	7779	14.69	1.98	5.50	17.22
Max.SigaRate	7779	16.09	1.18	14.41	17.22
Deposit.Rate	9722	5.27	1.95	2.90	10.52
Rate.Spread	9836	14.29	8.57	-6.75	50.52
Inflat.Expect.	9836	7.71	0.63	6.95	9.00
Binding	9836	0.28	0.45	0.00	1.00
SIGARatio	9836	0.04	0.05	0.00	0.18
ResReqRatio	9836	0.60	0.61	0.00	4.71
Act.Share	9836	0.14	0.09	0.00	0.35
Log(loan.amount)	9836	12.19	2.76	-4.61	20.79
Solvency Ratio	9836	1.62	0.34	1.14	3.09

When focusing on loan operations denominated in foreign currency, the cap rate associated to PCG operations is binding in 14% of these loan contracts (Table 2), the average lending interest rate in the whole period is 5.5%, while the PCG interest rate is 4.3%.

TABLE 2

DESCRIPTIVE STATISTICS - FOREIGN CURRENCY

Variable	N	Mean	SD	Min	Max
Loan.Rate	12199	5.45	1.95	0.00	12.35
Siga.Rate	10800	4.34	0.66	2.92	5.28
Max.SigaRate	10800	5.00	0.35	4.23	5.31
Deposit.Rate	12103	0.18	0.20	0.03	1.58
Rate.Spread	12199	4.48	1.94	-2.31	11.46
Binding	12199	0.14	0.35	0.00	1.00
SIGARatio	12199	0.03	0.03	0.00	0.14
Act.Share	12199	0.16	0.09	0.00	0.32
%USD.Deposits	12199	0.79	0.05	0.35	0.99
Country Risk	12199	177.63	48.80	125.00	44.19
Log(loan.amount)	12199	13.47	2.72	-0.86	20.64

4. Empirical Strategy

To analyse the impact of the policy response to the COVID-19 shock over banking loans' interest rates, we will use static and dynamic panel data models.

For the static models, the specification is the following:

$$lspread_{b.i,t} = \beta_1 lexpinfl_t + \beta_2 X_{b,i,t} + \beta_3 ResReqRatio_{b,t} + \beta_4 PCGRatio_{b,t} + \beta_5 Binding_{b,i,t} + \beta_6 PCGRatio_{b,t} * Binding_{b,i,t} + \beta_7 Z_{b,t} + \varepsilon_{b,i,t} \tag{1}$$

where $lspread_{b,i,t}$ is the logarithm of the spread between the local currency loan interest rate and the monthly average rate of interbank call operations of bank b and loan contract i between months t and $t-1$; $X_{b,i,t}$ are loan-contract variables, $lexpinfl_t$ is the logarithm of annual inflation expectations in month t; $ResReqRatio_{b,t}$ is the ratio between monthly reserve requirements deductions and the total amount of new loans granted for bank b in month t; $PCGRatio_{b,t}$ is the ratio between the amount of loans backed with PCG guarantees and the total amount of new loans granted for bank b in month t; $Binding_{b,i,t}$ is a dummy that takes the value of 1 when the PCG interest rate cap is binding for the loan contract i, granted by bank b at month t, 0 otherwise; and $Z_{b,t}$ are bank controls. Following Nikitin and Smith (2009) and Cottarelli and Kourelis (1994), we control for inflation expectations because, given that bank spreads are the difference between two nominal rates, if inflation shocks are not passed through to both rates equally fast, then spreads should reflect this. In addition, we also control for loan-contract and firm variables such as the logarithm of the loan amount and firms' size, while we also include bank controls such as the solvency ratio of bank b at month t.

Given the potential problems of endogeneity in equation (1), we will also use dynamic panel data models, starting from a pooled regression model (P. OLS) and a fixed effects model (FE) and later using the Generalized Method of Moments (GMM). Specifically, we will use the System GMM estimator developed by Arellano-Bover/Blundell-Bond for dynamic panel data (Arellano and Bover (1995), Blundell and Bond (1998)), which augmented the Arellano-Bond (Arellano and Bond (1991)) estimation by making the assumption that first differences of instrument variables are uncorrelated with the fixed effects. This estimator combines the first difference in equations with the equation in levels in which the variables are instrumented by their lags. This approach enables us to work with a dynamic panel with few time periods and with a sufficient number of individuals (small T, large N panel). Blundell and Bond (1998) add that Arellano- Bond estimation performs poorly when instrumenting variables are highly persistent. Some other characteristics of this estimator that make it suitable for this analysis are that the model may include: a dependent variable that depends on its own past realizations (inertial behavior), independent variables that are not strictly exogenous, fixed effects, heteroscedasticity and autocorrelation within individuals but not across them.

As is well known, the proliferation of instruments can cause an overidentification problem when the number of individuals is small in terms of the number of periods and instruments used, which can affect the efficiency of the system GMM estimator. We address this issue applying the two typically used approaches for reducing the number of instruments: curtailing and collapsing (Roodman (2009b), Kiviet (2020)). In addition, we run the specification tests proposed to deal with overidentification problems (Roodman (2009a)): the Sargan and Hansen tests. Finally, we apply the Arellano-Bond serial correlation test to ensure absence of higher-order serial correlation of the differenced error terms, this is crucial for the validity of the lagged values of the dependent variable as instruments and for the instruments of predetermined and endogenous covariates.

In all specifications, we clustered standard errors at the bank-industry level in order to account for potential correlation in the residuals.[8]

The general specification for the dynamic models is the following:

$$\begin{aligned} &lspread_{b.i,t} = \alpha lspread_{b.i,t-1} + \beta_1 lexpinfl_t + \beta_2 X_{b,i,t} + \beta_3 ResReqRatio_{b,t} + \\ &\beta_4 PCGRatio_{b,t} + \beta_5 Binding_{b,i,t} + \beta_6 PCGRatio_{b,t} * Binding_{b,i,t} + \beta_7 Z_{b,t} + \varepsilon_{b,i,t} \end{aligned} \tag{2}$$

We decided to exclude from the analysis the foreign currency model because interest rates in this case are mostly influenced by external conditions. In particular, the literature has shown that the pass-through from the reference rate is

[8] The are 78 clusters at the bank-industry level.

weaker for interest rates in foreign currency (Gianelli, 2010), and Lorenzo and Tolosa (2000) have shown that the spread in foreign currency has a stochastic nature. Additionally, under the pandemic context, with expansionary monetary policies around the world, banks were not able to find profitable investment options abroad and kept extremely liquid positions in foreign currency. Also, because of the pandemic, deposits in foreign currency grew faster during 2020, which probably affected the supply of credit in foreign currency. As a results, expansive policies such as deductions on reserve requirements were not necessary to impulse the supply of credit in this currency, and liquidity should not operate as a relevant constraint on credit pricing in foreign currency. On the other hand, despite the importance of foreign-currency loans over the total PCG operations (67%), the interest cap rate imposed on them was binding only for 14% of the cases.

5. Results

We start estimating equation (1), where the dependent variable is the logarithm of the spread between the loan interest rate in local currency of bank *b*, loan-contract *i* at month *t*, and the monthly average rate of interbank call operations. Our regressors of interest are $ResReqRatio_{b,t}$ and the interaction term between the $PCGRatio_{b,t}$ and the dummy variable that indicates whether the PCG rate cap is binding. The expected sign is negative for both coefficients and the intuition is the following. Given that the rates associated with PCG operations were lower than the average interest rate charged by banks (see Section 3), one could expect a downward effect on the interest rate charged by those banks with a relatively more active participation in the PCG scheme and when the PCG rate cap is binding, since those clients that do not have the PCG collateral could demand lower interest rates. Moreover, one could also expect an additional downward effect on the spread of loan rates given by the impact of the reserve requirements' deductions, since banks have more liquidity to offer new loans at a lower cost.

In general, the coefficients have the expected signs and the variables are significant (See Table 3). The results of the Hausman test indicate that the FE model is preferred to the RE to explain the policy response over the interest rate spread in local currency. However, as was expected, when performing complementary tests,[9] we reject the null hypothesis of no autocorrelation, which indicates the need for estimating dynamic panel models.

[9] Following Wursten (2018), we performed the Ionue-Solon test for serial autocorrelation, recommended when the panel is unbalanced and the panel dimension (N) is larger than time series dimension (T).

TABLE 3
ESTIMATES OF THE STATIC MODELS

	(1) OLS	(2) FE	(3) RE
IExplnfl $_{t}$	-0.005	0.061***	0.058***
	(0.009)	(0.005)	(0.005)
Loan Amount $_{b,i,t}$	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Res.Req. Ratio $_{b,t}$	-0.174***	-0.062***	-0.072***
	(0.009)	(0.007)	(0.006)
PCG Ratio $_{b,t}$	-0.804***	0.428***	0.309***
	(0.148)	(0.088)	(0.087)
Binding $_{b,i,t}$	0.183***	0.022***	0.026***
	(0.016)	(0.008)	(0.008)
Binding $_{b,I,t}$ ·PCG $_{b,t}$	-1.099***	-0.776***	-0.781***
	(0.236)	(0.115)	(0.115)
Observations	9,849	9,849	9,849
R-squared	0.141	0.072	
Adjusted R-squared	0.141	-0.0660	
Number of id		1,271	1,271

The results of the estimations of the first set of dynamic models are included in Table 4, where the first column shows the estimates of the Pooled OLS model and column 2 the results from estimating a FE dynamic panel model.

TABLE 4
ESTIMATES OF THE STATIC MODELS

	(1) OLS pooled	(2) FE
ISpread $_{b,i,t-1}$	0.841***	0.194***
	(0.026)	(0.045)
IExplnfl $_{t}$	-0.002	0.056**
	(0.010)	(0.010)
Loan Amount $_{b,i,t}$	-0.000**	-0.000***
	(0.000)	(0.000)
Res.Req. Ratio $_{b,t}$	-0.025***	-0.034***
	(0.008)	(0.009)
PCG Ratio $_{b,t}$	-0.287***	0.333
	(0.084)	(0.231)
Binding $_{b.i.t}$	0.070***	0.029**
	(0.018)	(0.012)
Binding $_{b.i.t}$ · PCG $_{b,t}$	-0.093	-0.623***
	(0.243)	(0.175)
Observations	7,553	7,431
CIuster	bank*industry	bank*industry
R-squared	0.790	0.887
r2	0.790	0.887
r2 a	0.790	0.873

Given the potential correlation between the independent variables and past events and the correlation between the error term and the lagged endogenous variable, these estimations deliver biased results. To deal with this, we perform estimations based on the Generalized Method of Moments (Table 5).

TABLE 5
ESTIMATES OF GMM MODELS

	(1) GMM Difference	(2) GMM system
ISpread $_{b,i,t-1}$	0.184***	0.326***
	(0.052)	(0.064)
IExpInfI $_{t}$	0.540***	0.386***
	(0.108)	(0.138)
Loan Amount $_{b,i,t}$	-0.030***	-0.028***
	(0.009)	(0.008)
Res.Req. Ratio $_{b,t}$	-0.003	-0.074***
	(0.015)	(0.023)
PCG Ratio $_{b,t}$	0.450***	0.243**
	(0.154)	(0.102)
Binding $_{b,i,t}$	0.068***	0.074***
	(0.021)	(0.026)
Binding $_{b,i,t}$ · PCG $_{b,t}$	-1.297 ***	-1.121**
	(0.441)	(0.516)
Observations	6,325	7,553
Cluster	bank*industry	bank*industry
Number of id	788	953
Wald Test p-value		0.000
AR(1)	0.00	0.000
AR(2)	0.88	0.798
Hansen Test p-value	0.10	0.124
Number of Instruments	54.00	61.000

Following Bond (2002), in order to evaluate the coefficients found in the Difference and System GMM models, it is possible to compare them to those found in Table 4, where the coefficients associated with the Pooled OLS and the FE model deliver the maximum and minimum values that these parameters could achieve. For the GMM Difference model, the lagged variable parameter was 0.184, while for the GMM System model the value found was 0.326.

Although the Difference GMM estimator assesses the autocorrelation problems that arise from first differentiation, the properties of this estimator are weak when variables are highly persistent over time. Simulations obtained by Blundell and Bond (1998) show that, in the context of persistent series, the finite sample bias for the Difference GMM estimator is at a level close to that of the Fixed Effect estimator. We obtained an estimate of 0.184 by the Difference GMM estimator, which was very close, and even lower, to the estimate obtained by Fixed Effects -0.194-.

In order to check for persistence, we performed Fisher-type unit root tests and conclude that we cannot reject the null hypothesis that all panels contain unit roots under the assumption of inverse normal distribution (Table 6). According to Choi (2001) simulations, considering the trade-off between sample size and test´s power, the inverse normal statistic outperforms other unit root tests developed for panel data analysis.

TABLE 6
RESULTS FROM UNIT-ROOT TEST

Fisher-type unit-root test for Ispread			
Based on augmented Dickey—Fuller tests			
HO: All panels contain unit roots			Number of panels = 1271
Ha: At least one panel is stationary			Avg. number of periods = 7.75
AR parameter: Panel-specific			Asymptotics: T -> Infinity
Panel means: Included			
Time trend: Not included			
Drift term: Not included			ADF regressions: 1 lag
	Statistic	p-value	
Inverse normal	z	3.2760	0.9995
P statistic requires number o panels to be finite.			
Other statistics are suitable for finite or infinite number of panels.			

In light of the above evidence, and considering also that we have a relatively small T and large N, we decided to choose our System GMM specification. The main results of our estimations are included in Table 7. The first model represents the reference model, which considers our main variables of interest (Res. Req. Ratio, PCG Ratio, binding and the interaction of the last two) and the lag of the dependent variable (lspread). Columns (2) to (5) show the results of gradually including independent variables at the macro, firm and bank level. Specifically, in column (3) we control for bank characteristics, such as solvency (Capital Adequacy Ratio, CAR), the situation of the institution in terms of liquid assets (30-day liquidity ratio), and its market power (Herfindahl–Hirschman index). In column (4) we include dummy variables associated to firms’ size, while in column (5) we include a dummy indicating if the banking institution is the state-owned bank, with the objective of analysing whether the fact of being a state-owned bank implied a different behavior in terms of credit pricing for PCG operations.

TABLE 7

ESTIMATES OF SYSTEM GMM MODELS

	(1) GM M System	(2) GMM System	(3) GMM System	(4) GMM System	(5) GMM System
Spread $_{b,i,t-1}$	0.358***	0.326***	0.477***	0.431***	0.212***
	(0.073)	(0.064)	(0.066)	(0.073)	(0.065)
lExplnfl $_{t}$		0.386***	0.263**	0.208*	0.487***
		(0.138)	(0.128)	(0.119)	(0.134)
Loan Amount $_{b,i,t}$		-0.028***	-0.038***	-0.034***	-0.032***
		(0.008)	(0.008)	(0.007)	(0.008)
Res.Req. Ratio $_{b, t}$	-0.066***	-0.074***	-0.069***	-0.073***	-0.036**
	(0.021)	(0.023)	(0.020)	(0.021)	(0.017)
PCG Ratio $_{b, t}$	-0.036	0.243**	-0.374**	-0.283*	-0.823***
	(0.168)	(0.102)	(0.165)	(0.163)	(0.273)
Binding $_{b, i, t}$	-0.003	0.074***	0.059***	0.057***	0.038**
	(0.056)	(0.026)	(0.020)	(0.019)	(0.018)
Binding $_{b, i, t}$ · PCG $_{b, t}$	0.665	-1.121**	-0.618*	-0.618*	-0.594
	(0.807)	(0.516)	(0.355)	(0.340)	(0.408)
State Bank $_{b, t}$					-0.794***
					(0.089)
State Bank $_{b,t}$ · PCG $_{b, t}$					2.475***
					(0.324)
Binding $_{b, i, t}$ · Stałe Bank $_{b,t}$					3.484***
					(0.996)
Binding $_{b, I, t}$ · Stałe Bank $_{b, t}$					-28.737***
· PCG $_{b, t}$					(8.032)
Medium Sized Firm $_{b, i, t}$				0.176***	0.252***
				(0.043)	(0.047)
Small Sized Firm $_{b, i, t}$				0.327***	0.448***
				(0.082)	(0.082)
Micro Sized Firm $_{b, i, t}$				0.297***	0.407***
				(0.068)	(0.067)
CAR $_{b,t}$			-0.193**	-0.142	0.454***
			(0.088)	(0.092)	(0.108)
Liq.Ratio $_{b, t}$			0.425**	0.151	0.272
			(0.215)	(0.243)	(0.273)
HHI $_{b, t}$			0.013***	0.012***	0.004**
			(0.002)	(0.002)	(0.002)
Observations	7,553	7,553	7,553	7,553	7,553
Cluster	bank*industry	bank*industry	bank*industry	bank*industry	bank*industry
Number of id	953	953	953	953	953
Waald Test p-value	0.000	0.000	0.000	0.000	0.000
AR(1)	0.000	0.000	0.000	0.000	0.000
AR(2)	0.957	0.798	0.795	0.787	0.544
Hansen p value	0.001	0.124	0.300	0.296	0.161
Number of Instruments	28.000	61.000	70.000	73.000	73.000

As can be observed in Table 7, the coefficient associated with the lag of the spread of the interest rate is positive and highly statistically significant, which means that its variations can be persistent over time.

In addition, the coefficients associated with the variables PCG and reserve requirements are statistically significant and the signs are the expected; we find that the PCG policy has a relatively higher effect on loans' interest rates in comparison to the reserve requirements policy. Specifically, although in the more general model the variable $PCGRatio_{b,t}$ has a positive coefficient, when we control for loan and bank characteristics the sign of the coefficient is always negative. In addition, the coefficient of the interaction term with the $Binding_{b,t}$ dummy variable is higher and negative, which means that when the cap established on PCG rates is binding, banks that granted loans under the public guarantees policy charged lower interest rates. This result also shows the effectiveness of the interest rate cap introduced in the PCG policy, since the cap level could not be binding. These results also hold for the most saturated specifications.

Given that we performed the two-step estimation (heteroscedastic weight matrix), we focus in the Hansen´s overidentification test, which shows that our overidentification restrictions are valid (Table 7). As for the Arellano-Bond test for serial correlation, we reject the null hypothesis of no autocorrelation of order 1 and cannot reject the hypothesis of no autocorrelation of order 2, which implies that there is evidence that the Arellano-Bond model assumptions are satisfied.

Finally, we defined dummy variables to identify heterogeneus effects over the interest rate charged by banks under the PCG and the Reserve Requirements policies. Specifically, we run specifications including a dummy indicating whether the bank was private or state-owned, a dummy indicating if the banking institution was significantly active in the supply of PCG loans, as well as a dummy indicating whether the loan was granted to an industry affected by the pandemic. We did not find heterogeneous behaviors in terms of the effect of the analysed policies over interest rates charged by banks.

6. Final remarks

Following the COVID-19 shock, several governments around the globe implemented a set of policies in order to cope with the contraction in the supply of credit. Uruguay was no exception; among other policy measures, between March and April 2020 the Uruguayan Government expanded an existing public credit guarantee and introduced deductions in local currency reserve requirements.

We analyse the impact of this type of policies on loans' interest rate spread over the interbank rate. Uruguay offers an ideal setup for this study since we have both type of policies implemented in conjunction with detailed data on loan contracts. We find that the PCG policy had a relatively higher effect on loans' interest rates in comparison to the reserve requirements policy.

The design of the PCG policy seems to have been adequate as the restriction of the maximum allowed interest rate was binding in one third of the local currency loan operations. As we have said before, during 2020 PCG operations represented only 8.5% of new loans granted to MSMEs per month. However, the results found in this research indicate that not only this 9% was favored by this policy, since its effect on the interest rate seems to have spread to the remaining lending operations.

Given the widespread application of the analysed policies around the world in the context of the pandemic, this study not only contributes with evidence on the performance of recent policies but also for policymakers' discussion on the design of policies as a quick response to a negative shock.

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Appendix

CREDIT RATINGS IN URUGUAY

According to Uruguayan regulation, borrowers are classified with a rating scale that reflects their payment capacity.[10]

Rating 1A: back-to-back loans, that is, loans fully covered by very liquid collaterals.

Rating 1C: borrowers with strong payment capacity (i.e. less than 10 days past due).

Rating 2A: borrowers with an adequate payment capacity (i.e. less than 30 days past due).

Rating 2B: borrowers with potential problems in their payment capacity (i.e. less than 60 days past due).

Rating 3: borrowers with a compromised payment capacity (i.e. less than 120 days past due).

Rating 4: borrowers with a very compromised payment capacity (i.e. less than 180 days past due).

Rating 5: unrecoverable borrowers (more than 180 days past due).

TABLE A1

DEFINITION OF THE VARIABLES

Loan-Contract Variables	
ISpread $_{b,i,t-l}$	Monthly average lending interest rate minus monthly average rate of interbank call operations
Loan Amount $_{b,i,t}$	Loan amount (in logs)
Res.Req. Ratio $_{b,t}$	Reserve requirements deductions to total loans granted by month
PCG Ratio $_{b,t}$	Ratio between the amount of loans backed with PCG guarantees and the total amount of new loans granted for bank b in month t
Binding $_{b,i,t}$	Dummy that takes the value of 1 when the max cap for the siga rate is binding
Bank Variables	
CAR $_{b,t}$	Capital adequacy ratio
HI-Il $_{b,t}$	Bank's market power in loan market (measured by the HH Index)
State Bank $_{b,t}$	Dummy that takes the value of 1 when the banking institution is the state-owned bank
Macroeconomic Variables	
IExplnf $_{t}$	Anual inflation expectations

[10] For more detail: Comunicación No 2019/001, Superintendencia de Servicios Financieros, BCU.

Exploring gender differences in labor markets from the perspective of the task based approach*

Explorando diferencias de género en los mercados laborales desde la perspectiva del enfoque basado en tareas

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Abstract

Using households survey microdata from Argentina, Brazil, Chile, Colombia, Mexico and Peru, we characterize changes in employment and wages between the mid-2000s and the late-2010s emphasizing the gender dimension from the viewpoint of the task-based approach. We employ surveys from PIAAC-OECD to study the task content of jobs and create an index of routine task content (RTC) of occupations. We document five facts: (i) The proportion of routine tasks is currently higher for women than for men. (ii) The employment structure is considerably more biased towards high-RTC jobs in Latin America than in OECD countries, for both genders. (iii) There was an increase in the employment participation of low-RTC jobs during the period under study, mainly driven by movements in the occupational structure of women, especially the young and middle-aged. (iv) Wage gains were relatively higher in high-RTC occupations, with this pattern more pronounced for men than for women. (v) While there was a modest reduction in the gender wage gap, the decline was stronger in computer-intensive occupations.

Key words: *Wages, Employment structure, Occupations, Tasks, RTC index, Gender, Latin America.*

JEL Classification: *J16, J21, J31, J62.*

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Resumen

Utilizando microdatos de encuestas de hogares de Argentina, Brasil, Chile, Colombia, México y Perú, caracterizamos los cambios en el empleo y los salarios entre mediados de la década de 2000 y finales de la década de 2010, enfatizando la dimensión de género desde la perspectiva del enfoque basado en tareas. Empleamos encuestas de PIAAC-OCDE para estudiar el contenido de tareas de los trabajos y crear un índice de contenido de tareas rutinarias (RTC) de las ocupaciones. Documentamos cinco hechos: (i) Actualmente, la proporción de tareas rutinarias es mayor para las mujeres que para los hombres. (ii) La estructura de empleo está considerablemente más sesgada hacia trabajos de alto RTC en América Latina que en los países de la OCDE, para ambos géneros. (iii) Hubo un aumento en la participación laboral de los puestos de bajo RTC durante el período de estudio, impulsado principalmente por movimientos en la estructura ocupacional de las mujeres, especialmente las jóvenes y de mediana edad. (iv) Las ganancias salariales fueron relativamente más altas en las ocupaciones de alto RTC, con este patrón más pronunciado para los hombres que para las mujeres. (v) Si bien hubo una reducción modesta en la brecha salarial de género, la disminución fue más fuerte en las ocupaciones con uso intensivo de computadoras.

Palabras clave: *salarios, estructura del empleo, ocupaciones, tareas, índice RTC, género, América Latina.*

Clasificación JEL: *J16, J21, J31, J62.*

1. Introduction

The confluence of the roles of men and women in society was a great advance of humanity in the 20th century (Goldin, 2014). However, to achieve gender equality in the labor market there must be changes in the way jobs are organized and remunerated in order to enhance time flexibility and alleviate women from the responsibilities associated with childcare and other unpaid domestic activities (Berniell et al., 2021; Pinto, 2022).

Latin America experienced modest gains in gender equality during the last two decades. Women's labor force participation has grown slowly, especially for married women in disadvantaged households (Gasparini and Marchionni, 2015), and the gender wage gap declined only modestly. The main goal of this paper is to explore gender differences in the evolution of key labor markets outcomes in Latin America between the mid-2000s and the late-2010s, a period of rapid technological change, from the perspective of the task-based approach (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011).

To this end we employ surveys from the Programme for the International Assessment of Adult Competencies (PIAAC) conducted by the OECD in several countries, including Chile, Ecuador, Mexico, and Peru, to study the task content of jobs and create our own version of the widely used routine task content (RTC) index. We merge the RTC index to employment and wages at the occupation level for different demographic groups in two time periods: the mid-2000s (2003-2005) and the late-2010s (2016-2018). This information is computed using household surveys microdata for the six largest economies of Latin America: Argentina, Brazil, Chile, Colombia, Mexico, and Peru.

The PIAAC includes several questions related to job tasks. We are interested in tasks related to the routine task content of each occupation. Tasks that demand creative thinking, problem solving and person abilities are flexible and more prone to be complementary with new technologies. Instead, tasks that are repetitive or follow a defined pattern are more likely to be codified and substitutable by automation technologies. We consider the main following tasks: (i) managing, supervising or instructing other workers; (ii) planning the activities of co-workers; (iii) confronting and solving complex problems; and (iv) writing articles or reports. All these tasks require a human input, can be performed both in manual and cognitive occupations, and are not codifiable. We document that workers performing these tasks have a higher probability of using a computer at work, which we interpret as partial evidence of complementarity between flexible tasks and technology use.

We find that women are less likely to perform each of the four flexible tasks frequently, even after controlling for individual differences in age, education, computer use at work, country and occupation, which suggests that the current division of tasks in the labor market is characterized by a larger fraction of routine tasks among women than men.[1] In this context, technologies that allow the automation of routine tasks (such as workplace computerization) may alter the task content of certain jobs and partially contribute to reduce the gender wage gap (Autor et al., 2003; Black and Spitz-Oener, 2010). We provide soft evidence of this hypothesis using an (static) instrumental variable approach.

We construct the RTC index at the two-digit occupation level (International Standard Classification of Occupations, version 08). The RTC index captures the fraction of workers in each occupation that do not perform any of the four flexible tasks frequently. The higher the RTC of an occupation the greater the chances of substitutability by automation technologies. Our RTC index is strongly correlated with the abstract, routine and manual task measures traditionally used in the literature (Autor et al., 2003; De La Rica et al., 2020).

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1 Similar findings are reported in Brussevich *et al*. (2018) and Egana-delSol *et al*. (2022). We comment on these papers later on.

We match the RTC index to employment and wages at the occupation level (computed from household surveys) and conduct pooled and country-specific regressions separately by gender, age group (16-24, 25-40, 41-65) and gender-age group cells. We find that between the mid-2000s and the late-2010s there was a relative increment in the employment participation of low-RTC jobs, which was mainly driven by shifts in the occupational structure of women. It was pervasive across all age groups, but the magnitude was stronger for the young and middle-aged women, which suggests than entry patterns of newer cohorts compared to older cohorts are changing towards low-RTC occupations. The largest shifts in the occupational structure of women took place in Peru, Brazil, Argentina and, to a lower extent, Chile. Mexico and Colombia exhibit different patterns.

Wage gains were relatively stronger in high-RTC occupations, and this pattern was more pronounced for men than women. The gender wage gap exhibits a small decline in Mexico, Brazil, Chile, and Argentina, and a modest rise in Colombia and Peru. However, there is a lot of heterogeneity across countries and occupations. We find that the decline in the gender wage gap concentrated in low-RTC jobs. Women relative wage gains materialized mainly in semi-routine occupations such as secretaries and other clerical work, and in flexible jobs such as managers, professionals, and associated occupations in business, science, engineering, health, legal and social fields. Given that most of these jobs are intensive in the use of computers, the finding is reinforced when we instrument the RTC index with computer use intensity. This finding suggests that technological change might partially help to reduce the gender wage gap, especially for women that are able to work in complement with computers and the new digital technologies of the 21st century.

Finally, when contrasting the occupational structure of Latin America with OECD countries, we find that there is a high correlation in the participation of women *within occupations*, which confirms that horizontal gender segregation is a pervasive feature of labor markets across economies with different degrees of development (Rubery and Fagan, 1993; Anker, 1998). In contrast, we document that the employment structure *across occupations* is considerably biased towards high-RTC jobs in Latin America, for both genders. Men in routine jobs work mainly in the primary, construction, manufacturing and transport sectors, and women are over-represented in routine service occupations such as sales, cleaners and helpers. This result warns about the potentially disruptive effect of the ongoing process of technological change on the structure of employment in the near future, especially for unskilled individuals performing routine jobs highly exposed to automation.

Related literature. This paper relates to several strands of the literature on labor economics, technological change and gender inequality. Technology has been one of the leading explanations for increasing inequality in the last decades and historically. The early literature on skilled-biased technological change assumes that technology is complementary with skilled labor, therefore positively affecting the relative demand and wages of skilled workers (Katz and Murphy, 1992; Bound and Johnson, 1992; Card and Lemieux, 2001). Recent theories argue that the complementarity or substitutability between technology and labor does not occur at the worker skill level but rather at the task level (Autor et al., 2003; Acemoglu and Autor, 2011). Unlike the early literature, these authors assume that computers and automation technologies are more likely to substitute routine tasks performed by workers in the middle of the skill distribution and to complement analytical and interactive tasks most frequently performed by skilled workers, and that they have no predictable impact on routine manual tasks most commonly carried out by unskilled workers. These assumptions lead to the polarization hypothesis, which was successful in rationalizing the changing pattern of labor markets in developed countries since the 1980s, as they characterize by employment and wage gains at both tails of the skill distribution, mainly in service occupations, at the expense of middle-skill workers mostly employed in manual, production and clerical jobs (Autor et al., 2003; Spitz-Oener, 2006; Goos and Manning, 2007; Autor and Dorn, 2013; Michaels et al., 2014; Goos et al., 2014).

However, the story seems to have been different in the developing world, where the evidence in favor of the polarization hypothesis is scant or non-existent (Maloney and Molina, 2016; Messina and Silva, 2017; Das and Hilgenstock, 2018). Developing lag behind high-income countries in many dimensions, being the most obvious income per capita, investment, education, health, infrastructure and institutional quality. The adoption of new technologies has not been the exception. For instance, PIAAC data suggests that on average 35 percent of workers under ages 16-65 report using a computer at work in Latin American countries, while this fraction is 62 percent in OECD members. Other automation technologies that have been expanding in recent decades are industrial robots. East Asian countries lead by far the ranking of robot adoption in manufacturing, followed by Germany, Japan, Sweden, Denmark, US, and many other European countries. Latin America (mainly Brazil and Mexico) occupy the last positions of the list of robot adopters. For example, in 2016 there were on average 74 industrial robots per 10,000 workers globally, and the ratio was close to 5 and 10 in Brazil and Mexico, respectively (data from the International Federation of Robotics). These simple statistics suggest that Latin America is still at an early stage of technology adoption, which might be one of the key reasons that explain the absence of labor market polarization.

Developed countries have also been experiencing a narrowing gap between men and women in labor force participation, paid hours of work, education and earnings (Goldin, 2014). The reduction in the gender wage gap is visible at least since the 1970s. The leading explanations point to supply side factors related to changes in education and experience that favored women relative to men, and a larger negative effect of de-unionization for men than women (Blau and Kahn 1997, 2003, 2006). Blau and Kahn (1997) argue that rising inequality delayed the progress of women in the labor market. On the demand-side, some authors argue that changes in product demand associated with rising import competition and large trade deficits in the 1980s were associated with a sharp decline in manufacturing employment and a shift towards sectors that are education and women-intensive such as professional and personal services (Murphy and Welch, 1991; Katz and Murphy, 1992). Welch (2000) attributes the closing of the gender wage gap to the expansion in the value of intellectual skills relative to physical skills (or ``brains relative to brawn'') given the assumption that women are more intensive in intellectual skills than men.

Other contributions argue that the adoption of computers is associated with changes in the nature and conditions of work in forms that benefit women over men. Weinberg (2000) presents decompositions of the growth in women employment and cross-industry-occupation regressions suggesting that rising computer adoption can account for over half of the growth in demand for labor of women. Bacolod and Blum (2010) argue that the large increase in the rewards of cognitive and people skills, with which women tend to be well endowed, and a reduction in the price of motor/manual skills account for up to 40 percent of the rising inequality and 20 percent of the closing gender wage gap. Borghans, ter Weel, and Weinberg (2014) argue that technological and organizational changes rise the importance of interactive/people skills in the workplace, affecting the labor-market outcomes of under-represented groups including women.

In the task-based approach of Autor et al. (2003) computers are substitutes for routine tasks. An implication of this assumption is that demographic groups who initially work in jobs with different routine task content will be affected differently by workplace computerization. The model predicts that groups with higher initial routine task intensity will experience faster computer adoption; and that they will face a stronger relative shift away from routine and towards non-routine tasks. Moreover, if one assumes that computer capital and labor are perfect substitutes in performing routine tasks, the declining price of computers translates into declining rewards for routine tasks. Their model also assumes that computers are a relative complement to non-routine analytical and interactive tasks so, computers increase the productivity of workers carrying out these tasks.

Based on this framework, Black and Spitz-Oener (2010) study the changing nature of tasks for men and women to explain the large decline in the gender wage gap in West Germany between 1979 and 1999, and find that relative task changes explains half of the observed convergence.[2] In particular, the authors show that women experienced a relative increase in non-routine analytical and interactive tasks, which were associated with higher skill levels. Most notably, they find that women routine task intensity in 1979 was much higher than men, that only women experienced a large relative decline in routine tasks, and that task changes were more pronounced in jobs that experienced greater workplace computerization.

We are aware of two papers in the literature conducting exercises comparable to ours. Using the PIAAC survey, Brussevich, Dabla-Norris, Kamunge, Karnane, Khalid, and Kochhar (2018) document that women on average perform more routine tasks than men and that horizontal gender segregation explains most of these differences. The authors estimate that women are at a higher risk of automation than men (11% versus 9%). Using data from the Skills Towards Employment and Productivity (STEP) survey, Egana-delSol, Bustelo, Ripani, Soler, and Viollaz (2022) show that men are more likely than women to perform tasks related to the "skills of the future": science, technology, engineering and mathematics, information and communication technology, solving problems and management, which poses women at a higher average risk of automation than men (21% versus 19%). Our main contribution compared to these papers is that our findings do not focus solely on computing differences in the routine task content of jobs across genders but also on the comparison of the evolution of the structure of employment and relative wages across occupations in Latin America over time.

The rest of the paper is organized as follows. Section 2 presents a detailed description of the data sources. Section 3 discusses the estimation strategy. All the empirical findings are explained in Section 4. Section 5 concludes. All tables and figures are included in the Appendix.

2. Data

2.1 The Task Content Of Occupations

To measure the task content of jobs we rely on skills surveys microdata from the Programme for the International Assessment of Adult Competencies

[2] In a previous contribution, Spitz-Oener (2006) document that computer adoption relates to a shift from routine manual and routine cognitive tasks toward analytical and interactive non-routine tasks at all levels of aggregation (aggregate, within industry, and within occupation). Other explanations potentially related to the observed changes in tasks are changes in the selection of workers into the labor market, shifts in product demand arising from growing international trade, or shifts in consumer preferences.

(PIAAC) conducted by the OECD in several countries since 2011.[3] The data set includes demographic variables such as age and gender, education level, occupation at the four-digit International Standard Classification of Occupations (ISCO version 08), use of computer at work, adults' competences in crucial information-processing skills such as literacy, numeracy and problem solving, and organizational abilities related to decision-making and teamwork like management and planning. We work at the two-digit level of the ISCO08 for a total of 40 occupations (see Table 1) to get a more precise statistical representation and minimize matching errors across household surveys.

We exploit information for 24 countries.[4] Most PIAAC data covers high-income countries that are members of the OECD. The majority of surveys were carried out in the first round of the programme (2011-2012). The second round (2014-2015) included upper-middle-income economies such as Chile and Turkey, and the most recent wave (2017) covered middle-income countries like Ecuador, Mexico and Peru. We count on information for four Latin American countries: Chile, Ecuador, Peru and Mexico.[5] For simplicity we refer to the remaining 20 countries as high-income countries or simply OECD.

The sample represents individuals between 16 and 65 years old. We count on 71,107 observations which, using national-representative person weights, represent around 310 million workers. Of this total, 13,157 observations correspond to the four Latin American countries (representing about 67 million workers). Performing a separate analysis for each country proves challenging because sample size is relatively small, so in most of the work carried out with PIAAC data we broadly separate across Latin America and high-income countries.

The PIAAC survey includes several questions related to job tasks. We are interested in tasks that allow to define the routine task content (RTC) of each occupation. Tasks that require creative thinking, problem solving and person abilities are flexible and more prone to be complementary with new technologies, whereas activities that are repetitive or follow a defined pattern are more prone to be codified and replaced by automation technologies. We consider the main following questions/tasks: Do you manage or supervise other people? Do you plan activities of other workers? Are you confronted with complex problems? Do you write articles or reports? These tasks are not codifiable, require a

3 These data are publicly available at https://www.oecd.org/skills/piaac/

4 Although there is data for more countries (35 in total) in 11 of them there is no information on key variables such as occupations classified under the ISCO08. We work with Belgium, Chile, Czech Republic, Denmark, Ecuador, France, Greece, Israel, Italy, Japan, Kazakhstan, Lithuania, Mexico, Netherlands, Peru, Poland, Republic of Korea, Russian Federation, Slovakia, Slovenia, Spain, Sweden, Turkey, United Kingdom.

5 Notably, three out of these four countries were not included in Brussevich *et al.* (2018). This is important for our purposes because we construct an RTC index that is specific for Latin America.

human input and can be performed both in manual and cognitive occupations. Importantly, they are unambiguously related to the job performed and not to characteristics of the working environment, and present a high variability of responses across individuals. These are the main reasons to justify the validity of our index. For each individual in the survey we define a flexibility index F. The index is a dummy variable that is equal to one when the individual replies that he performs at least one of the four tasks often or very often.[6] F has an intuitive interpretation as it represents the percentage of individuals that perform at least one of the main four flexible tasks frequently. See Appendix for more details on PIAAC data.

For robustness we define an additional flexibility index. Flexibility index F_2 takes values between 0 and 1 and captures the percentage of flexible tasks that the individual performs. The index can take values of 0, 1/4, 2/4, 3/4, 4/4 according to how many flexible tasks the worker performs.

Table 2 presents the percentage of workers performing each flexible task, using a computer at work, and the average value of flexibility indexes across all countries and separately for Latin America and high-income countries. It shows that 12 percent of workers report supervising others, 27 percent planning, 31 percent solving problems, and 30 percent producing written output. There is a lower fraction of workers performing these tasks in LAC than in HIC, with differences ranging from 1 p.p. for supervising to 4 p.p. for planning. The F index says that 54 percent of workers in Latin America perform at least one flexible task compared to 59 percent in high-income countries. The F_2 index, which takes into account the intensity of the tasks performed, goes in the same line but has not an intuitive interpretation as F.

Notably, the use of a computer at work is considerably lower in Latin America than high-income countries (35 percent and 62 percent, respectively). A simple regression analysis using these data suggests that differences in formal education and occupational structure between both groups of countries explain less than half of the lag in computer use, while gender and age structure do not seem to play a critical role.[7]

The relatively low use of computers in Latin America may be one of the explanations for the absence of labor market polarization (Maloney and Molina 2016; Messina, Pica and Oviedo 2017; Das and Hilgenstock 2018; Gasparini et al. 2020). It seems that there is much more room for technology adoption in Latin America than it is currently observed. Whether tasks are indeed automatized or not will depend on many inter-related factors such as the price and

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6 Individuals respond with a number between 1 and 5 meaning: 1=never; 2=less than once a month; 3= less than once a week; 4=at least once a week; 5=every day. Our main definition considers replies of 4 and 5 to mean often. Results are very similar when we include option 3.

7 These results are beyond the scope of this paper but are available upon request.

availability of new technologies (and labor), network and capital infrastructure, stock of human capital, credit constraints, government policies, labor market and trade policy regulations and, more broadly, state of the art technology and production methods.

2.2 The RTC Index

For each individual in the PIAAC survey we know the occupation according to the ISCO 08 classification. We use the information related to job tasks to define a routine task content index (RTC_1) at the occupation level, which represents the percentage of workers in each occupation that do not perform any of the four flexible activities often.

That is, for occupation i , the index is defined as

$$RTC_{1,i} = 1 - \frac{1}{n_i}\sum_h F_{1,h} \tag{1}$$

where h are individuals and n is the number of individuals in occupation i . The index captures the percentage of individuals within an occupation that mostly perform routine tasks. A similar approach is used by Autor, Levy, and Murnane (2003) and Autor, Katz, and Kearney (2006, 2008). We analogously define a routine task content index RTC_2 , by computing weighted averages of the individual level flexibility index F_2 .[8]

The lower the RTC of an occupation the higher the possibilities of complementarity with new technologies. The higher the RTC of an occupation the lower the chances of complementarity with new technologies or the higher the chances of substitutability by labor-saving automation technologies. This is not a one-to-one mapping and is not deterministic but provides a clear ranking of occupations that is useful to characterize the temporal evolution and the current state of the labor market structure and the associated wage distribution, enabling international comparability. To construct these indexes we pull together the 24 countries with complete information from the PIAAC surveys to have a more representative sample of workers for each occupation. If we construct the RTC index separately for Latin America and high-income countries the ranking of occupations is very similar (the Pearson rank correlation coefficient is 0.93 and statistically significant at the 99% confidence interval) and all of our results remain valid.

Table 1 presents the complete list of occupations at the 2-digit ISCO08 ordered from the lowest to the highest RTC index. Most of the ranking of occupations is explained by the average education of workers in each occupation

8 We proceed in a similar manner to compute the abstract, routine and manual task measures from De La Rica et al. (2020); mentioned at the end of this section.

(the pairwise correlation coefficient between the RTC index and education is -0.9). However, it is worth noting that the relation is far from being linear (see Figure 1). The RTC index is around 0.58 for individuals with up to 8 years of formal education. Then this trend decreases gently for individuals with up to 12 years of education and sharply decrease thereafter, reaching a minimum around 0.25 for the most educated individuals. Table 1 also shows the percentage of workers in each occupation that report to be using a computer at work. We classify occupations in three groups taking into account the nature of occupations: (1) Flexible occupations (RTC index ranging from 0.09 to 0.29); (2) Semi-routine occupations (0.36 to 0.58); and (3) Routine occupations (0.66 to 0.78). The first group contains skilled jobs related to professional occupations such as managers, engineers, professors, doctors, lawyers, accountants, which generally perform tasks that involve highly cognitive skills (such as creative thinking and problem solving) and interpersonal abilities (managing, planning, organizing) and, in most cases, demand several years of formal education. The majority of workers in these jobs perform flexible tasks and have the adaptability required to benefit from technological change and work in complement with computers and other recent technologies. Indeed, computer use is very high within this group (86 percent).

The second group encompasses middle-skill occupations related to the provision of services such as nursery, personal care, personal services, security, electricians, repairers, customer services, sales, secretariat. It also include middle skill jobs in manufacturing, construction and transport such as welders, mechanics, builders, machine operators, assemblers, drivers. Most tasks in these jobs require job-specific knowledge, practical experience and, in the case of services, interpersonal abilities. Computer use in this group is medium (0.44) and exhibits a high variability across occupations (being very high for clerical jobs and very low for crafts, drivers, assemblers and builders, which use other tools as complements for their work). Health and personal care jobs seem hardly automatable. The same for jobs related to repairs, electricity and building. There is some room for automation of tasks related to customer services and sales through digital sales platforms, programming, new software. While jobs that are physical, repetitive and risky are prone to be codified and substitutable by machines and robots. In fact, the literature points to many of these occupations as the ones displaced by the automation process that has occurred in developed countries in recent decades, especially in industry and manufacturing (Autor and Dorn 2013; Goos et al. 2014).

The third group contains unskilled occupations in agriculture, industry or services such as day laborers, elementary workers, assistants, street sellers, cleaners and helpers. Most of these jobs involve manual tasks related to essential activities such as cropping and farming, food preparation, cleaning, and community tasks that are physically intensive and repetitive. Computer use in this group is very low (0.13). In Latin America, these jobs are generally precarious, informal and poorly paid. Although they have a high RTC, the actual risk of automation seems to be moderate because wages are low and a large fraction of individuals in this group are family workers in the primary sector.[9]

For robustness, we follow the approach of De La Rica, Gortazar, and Lewandowski (2020) and compute abstract, routine and manual task measures that are consistent with the previous literature on this topic (Autor et al., 2003; Autor and Handel, 2013). The PIAAC questions used to construct these measures are reported in the Appendix (see Table 3). We find that there is a strong correlation between our measure of RTC and those of abstract and routine task content traditionally used in the literature (see Table 4 and Figure 2). The pairwise correlation coefficients are 0.93 and 0.90, respectively. Our index of RTC also presents a very high correlattion with the RTC index 2 (0.95), the one that takes into account tasks intensity. The RTC index also correlates positively with the index of manual tasks (0.66), which highlights that persons conducting manual tasks are more prone to be substitutable by automation technologies. Importantly, all our regressions are robust to the use of these alternative indexes. For briefness, all of these tables will be presented in a separate appendix of the paper.

2.3 Labor Market Statistics At The Occupation Level

We employ microdata from household surveys for Argentina (*Encuesta Permanente de Hogares*, EPH), Brazil (*Pesquisa Nacional por Amostra de Domicílios*, PNAD), Chile (*Encuesta de Caracterización Socioeconómica Nacional*, CASEN), Colombia *(Encuesta Nacional de Hogares*, ENAHO), Mexico (*Encuesta Nacional de Ingresos y Gastos de los Hogares*, ENIGH) and Peru (*Gran Encuesta Integrada de Hogares*, GEIH) since the early 2000s. We define two periods: mid-2000s (generally 2003-2005) and late-2010s (generally 2016-2018). In most countries we pull together three years of data in each period to increase the precision of our estimates.[10] Household surveys come from the SEDLAC database and have individual information on wages, gender, age, household composition, education, occupation, informality condition, which

[9] The agricultural revolution has occurred many decades ago with the advent of technical advances and mechanization such as seeders and harvesters, crop rotation and, more recently, genetic improvement of seeds, new tillage and storage methods. Recently, the region has experienced a strong advance of the agricultural frontier that was fostered mainly by the boom in commodity prices.

[10] The only exceptions are Chile and Mexico. The CASEN is quite big and generally conducted every three years: we use 2003 and 2017. The ENIGH is conducted every two years: we use 2004, 2006 and 2016, 2018.

we standardize over time and across countries.[11] The data set is a repeated cross-section. We restrict the sample to individuals under ages 16-65.

The period under study begins in this date for various reasons: to avoid the confusing effect of the macroeconomic crises that hit Latin America around the 2000s, to use recent surveys of higher quality and comparability, and to focus on a period of rapid technological change.

In the following exercises the unit of analysis is the occupation, as we match the RTC index computed from PIAAC to labor market statistics for each occupation. We will perform a separate analysis for each country and always use occupation weights to obtain estimates that are representative of the working population in each country. Additionally, we will run separate regressions by gender, age groups (16-24; 25-40; 41-65) and gender-age group's cells.

Table 5 presents the median wage across occupations, the gender wage gap (defined as the median women wage divided by the median men wage in each occupation), the employment share of each occupation, and the women participation in each occupation (women *participation*). Levels are the simple average across Latin America in the most recent years of our sample (late-2010s) and the average change during the period under study (mid-2000s to late-2010s). In all cases we use person weights that vary by country and year (i.e. weights are survey-specific).[12] And employment statistics are computed using the number of hours worked by each worker as reported in the survey.[13]

Descriptive statistics uncover several facts. The majority of workers in Latin America belong to the group of semi-routine occupations (53.9 percent on average), which a priori is the most exposed to automation technologies. This holds also if we separate workers by gender, but it is somewhat more accentuated for men than women (55.7 percent of working men belong to this group while this fraction is 51.3 for women). Salespersons and cashiers is the occupation that employs most workers in Latin American countries (12.5 percent on average across countries). This occupation is more relevant for women than men: 17.9 percent of employed women are salespersons. Other occupations in this group that are relevant for women are personal services (7.5 percent), general clerks and secretaries (4.7 percent), personal care (4.5 percent) and food processing, woodworking, textile and other craft workers (3.5 percent). The second occupation that employs the most workers in this group is drivers and mobile plant operators (7.8 percent on average) and, since these are jobs mainly carried out by men (the share of men is 97.2 percent) this job represents

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11 For more details visit http://www.cedlas.econo.unlp.edu.ar/wp/en/estadisticas/sedlac/

12 We have also computed these statistics separately for each country but tables are not included in the paper to save space (they are available upon request). We will refer to specific country statistics when appropriate.

13 All of our estimates are robust to weight all employed individuals equally, irrespective of the number of hours worked.

12.4 percent of men employment. Other occupations in this group that employ a good fraction of men are sales (9 percent) and building and related trades (8.3 percent). The participation of semi-routine occupations increased in Latin America during the period under study (on average by 3.3 p.p.). There is some heterogeneity across occupations within this group. For instance, there are three occupations that exhibit a decreasing participation in all countries: metal, machinery and related trades workers (-0.5 p.p. on average), handicraft and printing workers (-0.5 p.p.) and food processing, woodworking, textile and other craft workers (-0.8 p.p.). These are occupations that could have been replaced by labor-saving automation technologies. However, the decline in the share of such occupations seems small compared to what has had occurred in developed countries.[14] On the other side, two occupations present a growing trend in all countries: personal services (1.3 p.p. on average) and drivers and mobile plant operators (0.9 p.p.).

Routine occupations represent around a quarter of employment in Latin America in the late-2010s. The participation of this group in total employment is very similar for both genders in all countries except Argentina.[15] There is a large reduction in the employment participation of routine occupations during the period under study (-5.2 p.p. on average). The decrease was generalized across all countries in the sample, across all occupations within this group, and across both genders, except for laborers in mining/construction/manufacturing (which grew on average by 1.1 p.p.). For women, the most important occupation in this group is cleaners and helpers (9.8 percent). The employment share of this job diminishes by 1.6 p.p. For men, agricultural workers and laborers together add to 11.8 percent and exhibit a decline of 2.9 p.p.

The fraction of workers employed in flexible occupations is on average 21 percent. It is lower in Colombia, Mexico and Peru (around 17-18 percent), larger in Argentina and Brazil (about 22 percent) and considerably higher in Chile (29 percent). The fraction of workers employed in this group increased moderately during the period under study (1.7 p.p.). If we separate employment by gender, this group is more relevant for the employment of women than men in all countries (24 percent versus 19.1 percent) and the gap increased in all countries during the period under study (except in Chile).[16] For men, the most important occupations in this group are associate professionals in

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14 Assemblers is another occupation commonly displaced by automation. However, its participation has changed little in Latin America.

15 In Argentina 17.8 percent of women are employed in routine occupations and this fraction is 12.5 percent for men. The gap was even larger in the mid-2000s.

16 Chile exhibits the highest fraction of workers employed in this group and this holds for both women and men (which represent 35.5 percent and 24.8 percent of employment for each gender, respectively.). The fraction of men employed in flexible occupations increased by 3.4 p.p. and that of women diminished by 0.4 p.p. during the period under study.

science and engineering (2.7 percent), associate professionals in business (2.6 percent) and production managers (1.9 percent). For women: teaching professionals (5.8 percent), associate professionals in business (4.1 percent) and health professionals (2.6 percent). Notably, production managers exhibit a decreasing participation in all countries (on average -1.1 p.p.). In line with the growing trend of college and university graduates, most professional and associated occupations present a growing trend in all countries, specially in science and engineering (around 1 p.p., including both professionals and associates), health (1 p.p.), legal/social/cultural (0.6 p.p.), business (0.3 p.p.) and teaching (0.2 p.p.).

The participation of women in each occupation in the late-2010s is on average 44.6 percent in flexible occupations, 37.2 percent in semi-routine occupations, and 39.5 percent in routine occupations. There is an increase in women participation in most occupations, which is in line with a growing trend in female LFP. In the first group, the jobs with the largest fraction of women are health and teaching professionals (61.7 percent and 69.2 percent, respectively). Health professionals exhibit a rise in women participation of 10 p.p. Managerial occupations in production, administrative, and services have on average a women participation of 32.3, 42.8 and 38.7 percent, respectively. Women gain participation in managerial positions in administrative and commerce (the average rise across countries was 15.7 percent) and production and specialized services (6.4 percent) and this holds for all countries. Although there is a growing trend in the women share in professional occupations in science and engineering (6.9 percent) they are still very under-represented in this group: representing 25.5 percent of employment for professionals and 15.7 percent for associates. The situation is similar in ICT occupations: the participation of is 18.9 percent for professionals and 13.1 percent for technicians.

For semi-routine occupations, jobs with the largest women participation are personal care (85.8 percent on average), associate professionals in health (72.9 percent), general clerks (71.9 percent) and customer service clerks (64.3 percent). The first three categories present a decreasing trend in the women participation during the period under study, which works in the direction of balancing the disparity in gender composition. On the other side, some occupations in this group are almost entirely dominated by men: building and related trades, electricians and repairers, metal and machinery workers, assemblers, protective service workers and drivers and mobile plant operators. This fact holds in all countries and presents minor changes during the period under study.

For routine occupations, the participation of women increased by 2.5 percent. The share of women is largest for cleaners and helpers (78.3 percent) and food preparation assistants (65.3 percent) and presents little changes during the period under study. On the contrary, the participation of women is very low in agricultural jobs, laborers and elementary occupations (below 25 percent). Three occupations in this group exhibit a growing trend in the participation of women in all countries: street sales/service workers (6.6 p.p.), agricultural laborers (4.2 p.p.) and industry laborers (4.1 p.p.).

Median wages are on average higher for flexible occupations and lower for routine jobs (the pairwise correlation coefficient between the RTC index and median wage at the occupation level is -0.83 and it is statistically significant at the 99% confidence level). Highest paid occupations are administrative and commercial managers (9 USD per hour at PPP 2011 on average), science and engineering professionals (8.6 USD), and public administration officials (8.5 USD). The lowest paid occupations (below 3 USD per hour) are all categories in the group of routine occupations, and workers in handicraft and printing, crafts, and personal services. Hourly wages in flexible occupations are highest in Chile and Argentina (on average 8.5 and 7.9 USD, respectively), followed by Brazil (6.8 USD), Colombia (5.5 USD), Mexico (5.2 USD) and Peru (4.5 USD). The ranking is similar for semi-routine and routine occupations, but wage differences across countries are lower in these groups than in the flexible category. The percentage change in median wages during the early 2000s and the late 2010s is on average higher for occupations with high-RTC and lower for flexible occupations, and this holds for all countries in our sample. This is in line with the decreasing trend in income inequality that have occurred in Latin America in the 2000s and 2010s. Messina et al. (2016) suggest that currency appreciation triggered by the commodity boom increased the relative demand for workers in the non-traded sector, which reduced returns to education and compressed the wage distribution. There was also a general expansion of minimum wages that mostly benefited low-wage workers. Technological change should have moved relative wages in the opposite direction. If the technology channel had dominated the others, we should have observed larger relative wage gains for flexible occupations (as they use technology more intensively) and lower for routine occupations (which are less complementary or even substitutable by ongoing automation).

Finally, in most occupations the median wage of women is lower than the median wage of men (i.e. gender wage gap coefficient is lower than 1). It is on average 11 percent lower for flexible occupations, 12 percent for semi-routine and 11 percent for routine jobs. In the first group, the gender wage gap is largest for ICT technicians (-20 percent), health professionals (-18 percent), and business professionals and associates (-17/18 percent). In the second group, the wage gender gap is very large for plant and machine operators (-41 percent), handicraft and printing workers (-39 percent), crafts (-24 percent) and sales workers (-23 percent). In the third group, this gap is larger for subsistence workers in the primary sector (-36 percent) and for agricultural workers and laborers (-21 percent). Gender differences in median wages across occupations in the late 2010s are lowest in Colombia (-7 percent) and Argentina (-8 percent), somewhat higher in Brazil and Chile (-10.3 and -11 percent, respectively) and largest in Mexico and Peru (around -21 percent). Notably, although there is a lot of heterogeneity across occupations within countries, the average gender wage gap decreased for flexible occupations (-5 p.p.) and this holds for all countries. On average, the largest reduction in the gender wage gap occurred in managerial occupations (-13 p.p. for production and administrative managers, and -9 p.p. for services managers), science and engineering professionals (-12 p.p.) and health professionals (-12 p.p.). These occupations are intensive in skills and technology use. Within the semi-routine group, three occupations present a reduction in the gender wage gap in most countries: general clerks (3.2 p.p. on average), customer service clerks (4.2 p.p. on average) and sales workers (3.7 p.p.). All of these jobs are relatively intensive in the use of computers.

3. Methods

3.1 Estimates Of Gender Differences In Job Tasks And Occupational Structure

We begin documenting gender differences in job tasks. To do that we run simple regressions using microdata from the PIAAC surveys. We run the following regression:

$$Task_{ijc} = \beta_0 + \beta_1\, Women_{ijc} + X_{ijc}\text{'}\beta + \mu_{jc} + \varepsilon_{ijc} \tag{2}$$

where i, j and c index individuals, occupations and countries, respectively. $Task_{ijc}$ is a binary variable that takes the value 1 if the person reports performing the corresponding flexible task often, or 0 otherwise. We consider the main four flexible tasks discussed in the previous section (supervising, planning, solving problems, producing written output) and the flexibility indexes F and F_2. X_{ijc} is a vector of control variables including age, education and computer use at work. μ_{jc} are country-occupation fixed effects and ε_{ijc} is a mean-zero disturbance. We run this regression by OLS pooling the four countries of Latin American.

We also study the non-parametric relation between age and tasks by conducting local polynomial regressions for each flexible task on age, separately by gender.

Secondly, we document gender differences in the employment structure across occupations between Latin America and high-income countries and relate it to our index of routine task content of each occupation. This second analysis is entirely graphical and, like the first exercise, it is conducted using the microdata from the PIAAC surveys.

3.2 Estimates Of Changes In Employment Structure And Relative Wages

We exploit the information from household surveys of six Latin American countries to study the relation between changes in employment composition, relative wages and the gender wage gap, and the RTC index.

To study the changes in the employment structure, we estimate the following regression:

$$\Delta_{t,t+1}\frac{L_{jc}}{L_c} = \beta_0 + \beta RTC_j + \mu_c + \varepsilon_{jc} \tag{3}$$

where L_{jc} is total employment in occupation j and country c (in year t or $t+1$) and L_c is total employment in country c (in year t or $t+1$). Dependent variable is the change in the employment share of each occupation between the mid-2000s and the late-2010s. We always use the hours worked by each worker to compute total employment. The regressor is the RTC index. We run separate regressions for each country and a common (main) regression (pooling the six countries) that controls for country fixed effects and clusters standard errors at the country level. We compute the participation of each occupation in total employment for individuals aged 16-65 using the reported hours of work, separately by gender, age (16-24; 25-40; 41-65) and gender-age groups cells. First we run regressions by OLS. Then, we run regressions by 2SLS using computer use as an instrument for the RTC index.

To study changes in relative wages and gender wage gaps, we estimate the following regression:

$$\Delta_{t,t+1}W_{jc} = \beta_0 + \beta_1 RTC_j + \mu_c + \varepsilon_{jc} \tag{4}$$

where W_{jc} is the change in the log median wage of occupation j in country c. Additionally, we use the change in the gender wage gap as dependent variable. As before, we run OLS regressions with the RTC index as explanatory variable and 2SLS regressions instrumenting this variable with computer use.

Identification. The idea is to predict the variation of the RTC index that is explained by computer use in each occupation, to proxy for the complementarity between flexible tasks and computer use at work. The identification assumption is that computer use affects employment and wages only through the task content of jobs. This assumption would be problematic if computers affect productivity through mechanisms not related to the task content of jobs (e.g. gender norms or stereotypes).

We exploit the fact that there is a strong negative and statistically significant correlation between the RTC index and computer use across occupations (Figure 3). The Pearson rank correlation coefficient is -0.85 and it is statistically significant at the 99% confidence interval, and the pairwise correlation coefficient is -0.89. This means that workers in occupations with low-RTC (high-RTC) are more (less) prone to use a computer at work. We exploit this correlation to instrument the RTC index with computer use across occupations. The idea is simple. We use the variation in task content across occupations that is explained by differential use of computers at work. These variables are in levels, fixed over time, and only exhibit variation across occupations. They do not vary across countries or over time. What varies in these dimensions are labor market variables that we compute using information from households surveys: wages, gender wage gaps, employment structure across occupations, women participation. We acknowledge that these estimates are not entirely causal, but they allow us to characterize the evolution of the employment structure across occupations and relative wages in a comparable manner for the six largest Latin American economies over the last two decades.

4. Results

4.1 Gender Differences In Job Tasks

Results in this section highlight that women are less likely to perform each of the flexible tasks frequently, even after controlling for individual differences in age, education, computer use at work, country and occupation, which suggests that the current division of tasks in the labor market is characterized by assigning a greater fraction of routine tasks to women than men.

Table 6 presents the estimated coefficients for women and computer use at work, obtained from running regression equation (2). Panels correspond to each flexible task and the F indexes, and columns represent different specifications. All columns control for age and education groups. Estimates in column 1 suggest that women are on average less likely to perform all of these flexible tasks than men within the same occupation. Differential probabilities range from 2 p.p. for writing to 5.9 p.p. for solving problems. Column 2 controls for computer use at work, which is positive and statistically significant, in line with the idea that computers and flexible tasks are complementary, which is the result that we exploit in our identification strategy. Column 3 includes the interaction of country and occupation fixed effects to control for differences in the structure of occupations across countries. All coefficients remain statistically significant and present little changes. Point estimates suggest that women in Latin America exhibit on average lower probabilities than comparable men of solving problems (-5.5 p.p.), planning (-4.1 p.p.), writing output (-2.9 p.p.) and supervising others (-1.9 p.p.) at work.[17]

Non-parametric relation between age and tasks by gender

We conduct local polynomial regressions for each flexible task on age, separately by gender, and plot this correlation in Panel A of Figure 4. In Panel B we employ the F index. Besides the small sample size of the PIAAC survey, we find that women are less likely to perform all of these flexible tasks than men across the entire age distribution, but this pattern is less pronounced for the youngest cohorts, in line with the idea that youngest cohorts of women are moving towards more flexible (or less-RTC) occupations. As flexible tasks correlate with skills and there is a general trend towards increasing education over time in most countries, the cohort of older workers has on average lower skills and is less prone to perform all of these flexible tasks frequently than the cohort of young and middle-age workers.

We observe an asymmetric inverted U-shape for all flexible tasks and for both genders. The probabilities of performing planning and supervising are initially increasing on age (more rapidly for men), peak around age 30-35 and decrease thereafter. These are activities that reflect changes in the career paths of individuals, as they correlate with experience and job tenure, and they work in the direction of increasing job flexibility over time for a given individual. In the same tone, the chances of solving problems and producing written output grow on age for the youngest (again, faster for men), peak at about age 25-30 and steadily decrease for older cohorts. These activities relate more to individual skills and human capital and need not change much along the career path, thus peaking earlier than planning and supervising. The group of youngest workers (age 16-24) represents early entrants in the labor market and has a lower level of education than individuals who have finished higher education and then join the labor market (presumably around age 25-30). The youngest tend to be employed in repetitive occupations demanding low-skills, while those with tertiary education in occupations demanding cognitive skills and non-routine tasks.

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17 Estimated coefficients for unskilled workers are negative and statistically significant at the 99\% level in all panels across the three specifications, which suggests that workers with secondary education (or below) are less prone to perform flexible tasks than workers with tertiary education: -7.5 p.p. for solving problems, -5.8 p.p. for writing output, -5.2 p.p. for planning and -2.3 p.p. for supervising. Not shown for briefness and available upon request.

The probability of performing at least one flexible task is lower for women than men, and the difference becomes statistically significant around age 25-30. At least two facts explain this pattern. First, men have a higher participation in professional and associated occupations than women and thus exhibit a higher change of performing flexible tasks when they join the labor market after finishing tertiary education (horizontal gender segregation). Secondly, motherhood might play a role in shaping women's career paths reducing the chance of reaching a managerial or top-rank positions (vertical gender segregation).

From now on and up to the following section, we make a comparison between Latin American and high-income countries. Figure 5 plots the probabilities of performing each of the four main flexible tasks frequently across cohorts by gender in high-income countries. It is worth mentioning that these countries have an older population and a higher fraction of skilled workers than Latin America. Additionally, there are more observations for HIC, which increases the statistical power and precision of the estimates considerably. The asymmetric inverted U-shape is much more clear in high-income countries than Latin America (especially for planning and supervising). The probability of performing these tasks is initially increasing on age but more rapidly in high-income than Latin America (in both cases faster for men) and peaks some years later in high-income than Latin America. The gender gap in flexible tasks for younger versus older cohorts seems to have decreased more rapidly in high-income economies than in Latin America, presumably due to women's earlier educational improvements in HIC.

4.2 Gender Differences In Occupational Structure

In this section we compare the occupational structure of Latin America and high-income countries and relate it to the routine task content of each occupation. Results in the current section might be read with caution because the PIAAC samples are small. In all cases, we use person weights to emulate the occupational structure of each country.

That women and men occupy different jobs (horizontal gender segregation) is an stylized fact for almost all countries in the world (Anker, 1998). Men and women also face different career paths within the same occupation (vertical segregation). Both factors seem to explain the gender wage gap, while differences in promotion and access to managerial positions is generally considered as the main cause of gender inequality (Ponthieux and Meurs, 2015). More generally, the causes are biological, historical, cultural and social.

Figure 6 relates differences in occupational structure across Latin America and high-income countries to the routine task content of each occupation, as defined by the RTC index. The vertical axis represents the difference in the employment share of each occupation between Latin America and high-income countries. Positive (negative) values are occupations employing more (less) workers in Latin America than in HIC. The size of each bubble is the employment share of each occupation in Latin America. The relation is quite clear: employment in Latin America is significantly more (less) concentrated in occupations with high (low) RTC than in high-income countries. Part of this difference is explained by the existing educational and technological gaps between these regions. But the relation holds even after controlling for differences in computer use at the occupation level, education, and age. For instance, occupations that exhibit a high routine task content and employ a large fraction of workers in Latin America are salespersons, cleaners and helpers, crafts, food preparation assistants, unskilled laborers. All these workers together represent about 15 percentage points more employment in Latin America than in high-income countries (17.5 percent of total employment in high-income versus 32.5 percent in Latin America).

To take into account horizontal segregation, Panel B of Figure 7 presents the same comparative relation but separately for men and women. The share of each occupation calculates over the total employment of each gender. The same pattern emerges: a larger fraction of both men and women in Latin America works in occupations with high-RTC. Men in routine jobs work mainly in the primary and industry sectors, presumably performing physical and repetitive manual tasks, and women tend to be employed in service occupations like sales, cleaners and helpers and food preparation assistants. A notable exception is textile manufacturing, which employs a larger fraction of women than men.

Figure 7 (upper graph in panel A) shows that there is a high correlation in the share of women in each occupation between Latin America and high-income countries. So, horizontal gender segregation is a pervasive characteristic of the labor market in both sets of economies. Lower graph in panel B-left shows that the share of women in each occupation in Latin America is not related to the RTC index. While the graph in panel B-right shows that differences in the share of women in each occupation across Latin America and high-income is slightly negative, but this relation is weak and not statistically significant.

Overall, the main message of this section is that the occupational structure of Latin America is considerably biased towards occupations with high routine task content compared to high-income countries, and this holds for both genders.

4.3 Changes In The Employment Structure

In this section we present the results of running equation regression (3), that relates changes in employment composition across occupations and the RTC index. Results are in Table 7. The main finding is that on average there is a relative increase (decrease) of the employment participation of women in occupations with low (high) routine task content. Estimated coefficients present a negative sign for women across all age groups and the magnitude is decreasing on age, which suggests that differences across cohorts are larger in the younger cohorts than in the older cohorts, which is presumably explained by different entry patterns of the youngest generations. The largest shifts in the women occupational structure happen in Peru, Brazil, Argentina and to a lower extent, Chile. Colombia and Mexico present different patterns. The main coefficient for Colombia is negative and it is driven by movements in the employment structure of men towards occupations with low RTC, while the employment structure of women moves in the opposite direction (but coefficients are not statistically significant and standard errors are relatively large). In Mexico, the main coefficient is positive and statistically significant and driven by a relative movement of the employment structure of men towards jobs with high RTC (especially for middle and old-age workers).

These results are reinforced by 2SLS regressions (Table 8). First-stage regressions satisfy by large the weak IV test, as there is a high correlation between the RTC index and computer use (Figure 3). Results show that there is an increase in the magnitude and precision of estimated coefficients, which may be partly explained by the fact that these estimates give less weight to routine occupations in the primary sector (that practically do not use computers) that are mostly carried out by men. In contrast, they give more weight to semi-routine occupations such as secretaries and related clerical jobs that are mostly performed by women, and also to managerial, professional and associated occupations that are intensive in the use of computers and present a relative increase in the employment share of women during the period under study.

We also run similar regressions for the change in the women participation in each occupation. Naturally, in this case we do not separate our estimates by gender because men and women shares are complements. Still, we compute separate estimates by age groups. Tables 9 and 10 present these results. We find that on average the relative rise in women participation is higher for flexible occupations and lower for routine jobs. This result is especially pronounced in Argentina but it also holds for the group of old-age workers in Mexico and Peru.

4.4 Changes In Relative Wages And Gender Wage Gaps

In this section we present the results of running equation regression (3), that relates changes in wages and the gender wage gap across occupations and the RTC index. Results are in Table 11. We find that on average wage gains were relatively higher for routine occupations, and this was much more pronounced for men than women, especially in the middle and senior groups. The estimated coefficient is positive but not statistically significant for women in Chile, Colombia and Mexico. Senior workers in Peru represent an exception (the estimated coefficient is higher for women than men). In contrast, the estimated coefficient for the RTC index is on average higher for women than men in the group of young workers, especially in Argentina, Mexico and Chile.

Results from the 2SLS regressions confirm these findings (Table 12). The magnitude of estimated coefficients for the RTC index slightly increases compared to OLS coefficients, suggesting that different factors related to the routine task content of jobs and their rewards (other than the predictability of the RTC given by computer use) work in the direction of biasing estimated coefficients towards zero.

Finally, Table 13 presents the results of these regressions using the gender wage gap as dependent variable. In line with the above results, in particular, that men exhibit a higher gradient of wage changes on the RTC index than women, we find that the reduction in the gender wage gap was higher for flexible occupations. This was especially pronounced for senior workers in Brazil, Colombia and Argentina, and for middle-age workers in Chile. Results from the 2SLS regressions confirm this finding, and reinforce the idea that relative wage gains for women were more pronounced for workers under ages 41-65. Again, these results are driven by Brazil, Colombia and, to a lower degree, by Argentina and Mexico.

The case by case analysis suggests that reductions in the gender wage gap occurred mainly in semi-routine occupations such as secretaries and related clerical jobs, and also in flexible occupations such as managers, professionals and associated occupations in business, science/engineering, health, and legal and social fields. All of these jobs are relatively intensive in the use of computers. In this context, it seems that technological change could help, at least partially, to reduce the gender wage gap within occupations, especially for educated women that are able to work in complement with computers and the new digital technologies of the 21st century.

4.5 Robustness Exercises

For robustness, we have run the 2SLS regressions using different indexes of

RTC in the right hand side of equations (3) and (4). These indexes are: the RTC index 2 (which is based on the flexibility index 2), and the abstract, routine, and manual task measures from Autor et al. (2003) and De La Rica et al. (2020). Remember that there is a strong correlation our preferred definition of the RTC index and these different measures (see Table 4 and Figure 2).

It is impressive that all of our results remain virtually unchanged when using any of these alternative indexes. For briefness, all of these tables are included in a separate appendix of the paper.

5. Conclusion

In this paper we empirically characterize the recent changes in employment and wages across occupations in Latin America, with a particular focus on the gender dimension from the perspective of the task based approach. We exploit microdata from household surveys for the six largest economies of the region: Argentina, Brazil, Chile, Colombia, Mexico and Peru, around the mid-2000s (2003-2005) and the late-2010s (2016-2018). The data were previously homogenized following the SEDLAC protocol in order to maximize international and intertemporal comparability.

We also employ recent surveys from PIAAC-OECD to study the task content of jobs and create an index of routine task content (RTC) of occupations. Our RTC index has an intuitive interpretation: the fraction of workers in each occupation that do not perform any flexible tasks frequently. Seen otherwise, the RTC index captures the fraction of workers that mostly perform routine tasks. Flexible tasks are (i) managing, supervising or instructing other workers, (ii) planning the activities of co-workers, (iii) confronting and solving complex problems, and (iv) writing articles or reports. All of these tasks require a human input, can be performed both in manual and cognitive occupations, are not codifiable and present a high variability of responses across workers. We show that workers performing these tasks exhibit a higher probability of using a computer at work, which we interpret as partial evidence of complementarity between flexible tasks and technology use, and we exploit this correlation to implement an instrumental variable approach.

We document five facts:

(i) During the period under study there was a relative increase in the employment participation of flexible occupations that was mainly driven by movements in the occupational structure of women, especially the young and middle-aged.

(ii) Wage increments were relatively higher for routine occupations, and this pattern was more pronounced for men than women.

(iii) Women are less likely to perform each of the four flexible tasks frequently, even after controlling for individual differences in age, education, computer use at work, country and occupation, which suggests that the current division of tasks in the labor market assigns a greater fraction of routine tasks to women than men.

(iv) Although there was a modest reduction in the gender wage gap, the decline was stronger for flexible occupations like managers, professionals and clerical jobs. This result is reinforced when we predict the variation in routine task content across occupations with the use of computers at work. We interpret this finding as soft evidence of the idea that technologies that allow the automation of routine tasks (such as workplace computerization) may alter the task content of some occupations and partially contribute to reduce the gender wage gap (Black and Spitz-Oener, 2010).

(v) The employment structure is considerably more biased towards routine jobs in Latin America than in OECD countries for both genders. Men in routine jobs work mainly in the primary, construction, manufacturing and transport sectors, and women are over-represented in routine service occupations such as sales, cleaners and helpers.

The last point warns about the potentially disruptive effects of future automation on the structure of employment, especially for unskilled individuals performing routine jobs that do not use specific machinery for their work.

Our findings reflect that the largest Latin American economies, at their current stage of development, do not exhibit the polarization patterns documented in developed economies. However, we do find evidence in line with the idea that computer use may help to achieve a reduction in the gender wage gap, which is in line with previous findings for developed nations.

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APPENDIX

The PIAAC are the Survey of Adult Skills conducted in several countries by the OECD as part of the Programme for the International Assessment of Adult Competencies. The surveys are publicly available at the OECD-PIAAC website https://www.oecd.org/skills/piaac/.

We base our index definition on the following questions:

- The Supervision task dummy is based on the following two questions. Do you manage or supervise other employees? (Possible answers: 1, 2) (d--q08a). How often does your job usually involve instructing, training or teaching people, individually or in groups? (Possible answers: 1, 2, 3, 4, 5) (f--q02b). The Supervision dummy is defined as positive when the first answer is equal to one, or the second answer is equal to 4 or 5.
- The Planning task dummy is based on the following question. How often does your job usually involve planning the activities of others? (Possible answers: 1, 2, 3, 4, 5) (f--q03b). The Planning dummy is defined as positive when the answer is equal to 4 or 5.
- The Problem solving task dummy is based on the following question. How often are you confronted with more complex problems that take at least 30 minutes to find a good solution? The 30 minutes only refers to the time needed to think of a solution, not the time needed to carry it out. (Possible answers: 1, 2, 3, 4, 5) (f--q05b). The Problem solving dummy is defined as positive when the answer is equal to 4 or 5.
- The Written output task dummy is based on the following two questions. In your job, how often do you write reports? (Possible answers: 1, 2, 3, 4, 5) (g--q02c). In your job, how often do you write articles for newspapers, magazines or newsletters? (Possible answers: 1, 2, 3, 4, 5) (g--q02b). The written output dummy is defined as positive when at least one of the two answers is equal to 4 or 5.

The aggregate routine tasks content index RTC is based on these four dummies. As a previous step to the aggregation across individuals we compute the individual level index F.

SEDLAC DATABASE DETAILS

SEDLAC is a database of socio-economic statistics constructed using official household surveys microdata from Latin American and the Caribbean countries. It is developed by CEDLAS at Universidad Nacional de La Plata and The World Bank's LAC poverty group (LCSPP).[18] We use the SEDLAC

[18] http://www.cedlas.econo.unlp.edu.ar/wp/en/estadisticas/sedlac/

database to obtain information for wages and employment at the occupation level (at the 2-digit of the ISCO08) for all workers in each job and separately by gender, age group, and gender-age group combinations in Argentina, Brazil, Chile, Colombia, Mexico and Peru in two periods of time: the mid-2000s (circa 2003-2005) and the late-2010s (circa 2016-2018). We use person level weights to obtain estimates that are representative of the labor market at the national level.

TABLE A.1

ROUTINE TASK CONTENT (RTC) INDEX AND COMPUTER USE ACROSS OCCUPATIONS

	ISCO08 (2-digits)	RTC index	Computer use
Highly flexible occupations		0.22	0.86
Managers: Production	13	0.09	0.91
Managers: Administrative	12	0.11	0.95
Managers: Services	14	0.16	0.81
Professionals: ICT	25	0.19	1.00
Public administration officials	11	0.19	0.82
Professionals: Business and administration	24	0.20	0.99
Professionals: Science and engineering	21	0.21	0.91
Associate Prof: Science and engineering	31	0.21	0.74
Professionals: Health	22	0.25	0.79
Professionals: Legal, social, cultural	26	0.25	0.85
Associate Prof: Business and administration	33	0.26	0.91
Associate Prof: Legal, social, cultural	34	0.28	0.81
Professionals: Teaching	23	0.29	0.81
Technicians: ICT	35	0.29	0.96
Fairly routine occupations		0.50	0.44
Workers: Protective service	54	0.36	0.43
Workers: Electrical and electronic trades	74	0.36	0.55
Clerks: Numerical/Material recording	43	0.38	0.82
Workers: Personal care	53	0.38	0.46
Associate Prof: Health	32	0.38	0.77
Clerks: Other	44	0.40	0.82
Clerks: Customer service	42	0.40	0.88
Workers: Metal and machinery	72	0.42	0.40

Workers: Handicraft and printing	73	0.47	0.45
Clerks: General, Keyboard, Secretaries	41	0.47	0.96
Workers: Building and related trades	71	0.50	0.21
Workers: Sales and cashiers	52	0.51	0.51
Plant and machine operators	81	0.52	0.33
Workers: Forestry, Fishery, Hunting	62	0.54	0.16
Assemblers	82	0.57	0.35
Workers: Crafts (Food, Wood, Garment, others)	75	0.58	0.24
Workers: Personal services	51	0.58	0.28
Drivers and mobile plant operators	83	0.58	0.23
Highly routine occupations		0.71	0.13
Workers: Agriculture	61	0.66	0.17
Elementary workers	96	0.66	0.29
Laborers: Mining, construction, manuf., transport	93	0.67	0.24
Food preparation assistants	94	0.70	0.09
Street sales and service workers	95	0.70	0.07
Workers: Subsistence primary sector	63	0.74	0.02
Laborers: Agriculture, forestry, fishing	92	0.77	0.06
Cleaners and helpers	91	0.78	0.06

Notes: Data from PIAAC pooled surveys for 24 countries. Sample represents employed individuals between 16 and 65 years old that can be matched to an ISCO 08 occupation. Routine task content (RTC) index is the fraction of workers in each occupation that do not perform any flexible task frequently. Flexible tasks are managing, planning, writing, and solving problems. Computer use is the fraction of workers in each occupation that report using a computer at work. Occupations are ranked from lowest to highest RTC index.

TABLE A.2

FLEXIBLE TASKS, F INDEX AND COMPUTER USE

	All countries (1)	Latin America (2)	High-income (3)
Supervising	0.12	0.11	0.12
Planning	0.27	0.24	0.28
Solving problems	0.31	0.29	0.32
Written output	0.30	0.28	0.30
Using computer	0.56	0.35	0.62
F	0.58	0.54	0.59
F2	0.77	0.76	0.78
Observations	71107	57950	13157

Notes: Data from PIAAC pooled surveys for 24 countries. Sample represents individuals between 16 and 65 years old. Table shows the percentage of workers that that respond "yes" to performing each flexible tasks often (Supervising, Planning, Solving problems, Producing written output), the fraction of workers using a computer at work, the average flexibility index across individuals (F), and the number of observations, separately for Latin America (Chile, Ecuador, Peru and Mexico) and OECD countries. Calculations are based on employed individuals that can be matched to an ISCO 08 occupation.

TABLE A.3
TASK FRAMEWORK WITH PIAAC DATA
(DE LA RICA, GORTAZAR, AND LEWANDOWSKI, 2020)

Task index	PIAAC questionnaire item	Item no.
Abstract tasks	Face complex problems (< 30 mins)	f_q05b
	Use more advanced math or statistics, or use regression techniques	g_q03h
	Read articles in professional journals or scholarly publications	g_q01d
	Planning the activities of others	f_q03b
	Persuading/influencing people	f_q04a
Routine tasks	Planning your own activities (inverse)	f_q03a
	Organising your own time (inverse)	f_q03c
	Instructing, training or teaching people, individually or in groups (inverse)	f_q02b
	Making speeches or giving presentations (inverse)	f_q02c
	Advising people (inverse)	f_q02e
Manual tasks	Working physically for a long period	f_q06b
	Using skill or accuracy with hands or fingers	f_q06c

Notes: To ensure the reliability of the statistical constructs, all questions provide the same time answers: (i) every day; (ii) at least once a week but not every day; (iii) less than once a week; (iv) less than once a month; (v) never. Source: this table is taken from De La Rica, Gortazar, and Lewandowski (2020).

TABLE A.4

CORRELATION COEFFICIENTS BETWEEN RTC INDEXES

	RTC index	RTC index 2	Abstract	Routine	Manual
RTC index	1				
RTC index 2	0.948	1			
Abstract	-0.924	-0.937	1		
Routine	0.904	0.855	-0.942	1	
Manual	0.658	0.699	-0.746	0.623	1

Notes: This table presents the pairwise correlation coefficients across different RTC indexes used throughout the paper.

TABLE A.5

WAGES AND EMPLOYMENT STRUCTURE BY GENDER IN LATIN AMERICA: LEVELS (LATE-2010S) AND CHANGES (EARLY-2000S TO LATE-2010S)

	Employment structure (LAC6)								Wages (LAC6)			
	All		Males		Females		Female intensity		Median Wage		Gender wage gap	
	Level	Change	Level	Change	Level	Change	Level	Change	Level	Change	Level	Change
Highly flexible occupations	21.0	1.7	19.1	1.3	24.0	1.9	44.6	3.5	6.4	19.9	0.89	0.05
Managers: Production	1.8	-1.1	1.9	-1.4	1.5	-0.6	32.3	6.4	7.9	27.2	1.05	0.13
Managers: Administrative	1.0	0.3	1.0	0.3	1.0	0.3	42.8	15.7	9.0	12.5	0.92	0.13
Managers: Services	1.7	-0.2	1.6	-0.1	1.8	-0.4	38.7	-0.9	5.1	17.4	0.90	0.09
Professionals: ICT	0.5	0.2	0.6	0.3	0.2	0.0	18.9	-4.2	8.2	4.1	0.94	-0.06
Public administration officials	0.2	0.0	0.3	0.0	0.1	0.0	29.7	2.0	8.5	19.0	0.86	-0.39
Professionals: Business	1.4	0.4	1.3	0.4	1.7	0.5	47.2	4.9	7.5	20.9	0.83	0.05
Professionals: Science and engineering	1.2	0.3	1.5	0.4	0.8	0.4	25.5	6.9	8.6	3.7	0.90	0.12
Associate Prof: Science and engineering	2.0	0.7	2.7	1.0	0.8	0.3	15.7	0.4	4.9	24.9	0.89	0.08
Professionals: Health	1.6	0.5	1.0	0.1	2.6	0.9	61.7	10.0	8.2	1.8	0.82	0.12
Professionals: Legal, social, cultural	1.4	0.2	1.1	0.1	1.7	0.3	45.6	4.8	7.2	20.9	1.01	0.00
Associate Prof: Business	3.2	-0.1	2.6	-0.2	4.1	-0.1	50.0	6.2	5.1	27.4	0.84	0.06

Associate Prof: Legal, social, cultural	1.3	0.4	1.0	0.3	1.9	0.5	45.3	-2.7	4.3	24.7	0.90	0.06
Professionals: Teaching	3.2	0.2	1.6	0.1	5.8	0.0	69.2	1.1	7.2	20.8	0.87	0.00
Technicians: ICT	0.5	0.0	0.8	0.1	0.2	0.0	13.1	-0.7	4.4	24.1	0.80	-0.06
Fairly routine occupations	53.9	3.3	55.7	3.3	51.3	3.8	37.2	1.4	3.2	37.0	0.88	0.00
Workers: Protective service	2.6	0.4	3.7	0.4	0.8	0.4	11.8	5.9	3.7	33.2	1.11	-0.09
Workers: Electrical and electronic trades	0.8	-0.1	1.3	-0.1	0.0	0.0	1.7	-0.4	3.7	36.8	0.93	0.16
Clerks: Data	2.0	0.0	1.9	0.1	2.1	-0.3	37.7	-4.7	3.9	20.1	1.00	0.03
Workers: Personal care	1.9	0.3	0.2	0.1	4.5	0.3	85.8	-2.5	2.8	48.6	0.84	0.12
Associate Prof: Health	1.4	0.5	0.6	0.3	2.5	0.7	72.9	-2.7	4.2	16.9	0.91	0.00
Clerks: Other	0.8	-0.2	0.7	-0.3	1.0	0.1	43.6	12.2	4.2	40.8	0.89	-0.11
Clerks: Customer service	1.5	0.1	0.8	-0.1	2.6	0.1	64.3	6.1	3.3	27.3	0.90	0.04
Workers: Metal and machinery	2.4	-0.5	3.9	-0.5	0.1	-0.1	2.4	-0.6	3.6	40.9	0.94	0.05
Workers: Handicraft and printing	1.2	-0.5	1.4	-0.6	1.0	-0.3	30.0	4.5	2.4	25.9	0.61	-0.03
Clerks: General	2.8	0.8	1.7	0.7	4.7	0.8	71.9	-6.0	4.1	28.5	0.87	0.03
Workers: Building and related trades	5.1	0.2	8.3	0.7	0.2	0.1	1.4	0.5	3.4	49.9	0.98	0.09
Workers: Sales	12.5	0.9	9.0	0.6	17.9	1.1	55.7	3.5	2.7	38.1	0.77	0.04
Plant and machine operators	2.2	0.0	2.5	0.1	1.7	-0.1	31.7	1.9	3.2	32.3	0.59	-0.02

Workers: Forestry, Fishery, Hunting	0.3	-0.1	0.5	-0.1	0.1	0.0	6.9	2.6	2.9	47.3	0.90	0.04
Assemblers	0.5	0.1	0.6	0.1	0.4	0.1	13.9	1.3	3.6	31.3	0.91	0.16
Workers: Crafts	3.1	-0.8	2.8	-0.6	3.5	-1.2	43.1	-0.1	2.7	37.4	0.76	-0.02
Workers: Personal service	5.0	1.3	3.5	0.8	7.5	1.9	55.7	3.4	2.9	41.1	0.89	0.01
Drivers and mobile plant operators	7.8	0.9	12.4	1.8	0.6	0.2	2.8	1.0	3.4	38.1	0.99	-0.14
Highly routine occupations	25.3	-5.2	25.6	-4.7	24.9	-5.8	39.5	2.5	2.5	49.0	0.87	-0.02
Workers: Agriculture	4.4	-0.9	6.1	-1.4	1.8	0.0	15.4	0.8	2.4	56.3	0.79	0.04
Elementary workers	1.9	-1.2	2.3	-1.3	1.2	-0.8	24.1	-1.1	2.9	37.1	0.94	-0.06
Laborers: Mining, construction, manuf., transport	4.5	1.1	6.4	1.6	1.5	0.7	15.9	4.1	2.6	43.2	0.91	-0.06
Food preparation assistants	1.6	-0.5	0.6	-0.1	3.1	-1.0	65.3	2.0	2.6	46.0	0.90	0.01
Street sales and service workers	2.3	-1.0	1.8	-1.1	3.2	-1.0	46.9	6.0	2.3	36.2	0.87	-0.08
Workers: Subsistence primary sector	0.7	-1.2	0.9	-1.1	0.4	-1.3	18.4	-3.1	1.3	92.8	0.64	-0.18
Laborers: Agriculture, forestry, fishing	5.0	-1.3	5.7	-1.5	3.8	-0.7	23.5	4.2	2.5	57.2	0.79	-0.12
Cleaners and helpers	4.9	-0.3	1.7	0.1	9.8	-1.6	78.3	-1.4	2.6	47.8	0.87	0.05

Notes: Statistics computed using household survey data from Argentina, Brazil, Chile, Colombia, Mexico and Peru. In all cases we present the simple average across countries using person weights that are survey-specific. The level of median wages is expressed in constant USD at PPP 2011.

TABLE A.6

DIFFERENTIAL PROBABILITIES OF PERFORMING FLEXIBLE TASKS IN LATIN AMERICA

	(1)	(2)	(3)
Supervising			
Women	–0.020**	–0.018+	–0.019+
	(0.010)	(0.010)	(0.010)
Computer		0.093***	0.094***
		(0.015)	(0.015)
Planning			
Women	–0.047***	–0.047***	–0.041***
	(0.014)	(0.014)	(0.014)
Computer		0.145***	0.146***
		(0.019)	(0.019)
Solving problems			
Women	–0.059***	–0.056***	–0.055***
	(0.015)	(0.015)	(0.015)
Computer		0.096***	0.098***
		(0.019)	(0.019)
Written output			
Women	–0.030**	–0.025+	–0.029**
	(0.014)	(0.014)	(0.014)
Computer		0.205***	0.205***
		(0.019)	(0.019)
Flexibility index F			
Women	–0.064***	–0.058***	–0.060***
	(0.015)	(0.014)	(0.015)
Computer		0.194***	0.195***
		(0.018)	(0.018)
Flexibility index F2			
Women	–0.038***	–0.036***	–0.039***
	(0.012)	(0.012)	(0.012)
Computer		0.096***	0.098***
		(0.013)	(0.013)
Obs.	13157	13157	13157
Occupation FE	Yes	Yes	-
Country FE	Yes	Yes	-
Country x Occ. FE	-	-	Yes

Notes: Data from PIAAC pooled surveys for Chile, Ecuador, Mexico and Peru. Sample represents employed individuals between 16 and 65 years old, whose occupations can be matched to the ISCO 08 classification. All columns control for age and education. Robust standard errors in parenthesis.

TABLE A.7

CHANGE IN THE EMPLOYMENT SHARE OF EACH OCCUPATION (MID-2000S TO LATE-2010S). OLS

	Age 16-65			Age 16-24			Age 25-40			Age 41-65		
	All	Males	Females	All	Males	Females	All	Males	Females	All	Males	Females
Argentina												
RTC index	-0.008	0.005	-0.055***	-0.020	-0.007	-0.114**	-0.009	0.005	-0.065**	0.004	0.008	-0.035***
	(0.006)	(0.008)	(0.013)	(0.012)	(0.011)	(0.048)	(0.009)	(0.009)	(0.028)	(0.006)	(0.008)	(0.008)
Brazil												
RTC index	-0.017	-0.005	-0.065*	-0.038	-0.023	-0.126	-0.023	-0.008	-0.096*	-0.002	0.005	-0.031
	(0.024)	(0.028)	(0.033)	(0.031)	(0.025)	(0.083)	(0.025)	(0.027)	(0.054)	(0.037)	(0.036)	(0.033)
Chile												
RTC index	-0.011	-0.011	-0.050	0.001	-0.006	-0.069	-0.037***	-0.031**	-0.090	0.013	0.005	-0.025
	(0.011)	(0.011)	(0.043)	(0.022)	(0.021)	(0.063)	(0.013)	(0.013)	(0.068)	(0.017)	(0.012)	(0.045)
Colombia												
RTC index	-0.026	-0.045	0.020	-0.064	-0.105	0.100	-0.025	-0.053	0.024	-0.013	-0.026	-0.007
	(0.020)	(0.035)	(0.029)	(0.059)	(0.073)	(0.089)	(0.019)	(0.034)	(0.033)	(0.014)	(0.021)	(0.016)
Mexico												
RTC index	0.028*	0.039*	0.025	0.030	0.031	0.005	0.028*	0.043*	0.020	0.026	0.048**	0.034
	(0.014)	(0.021)	(0.020)	(0.046)	(0.051)	(0.012)	(0.015)	(0.024)	(0.014)	(0.016)	(0.021)	(0.039)
Peru												
RTC index	-0.071**	-0.064**	-0.106***	-0.232***	-0.156	-0.211***	-0.052***	-0.061**	-0.065**	-0.052**	-0.027	-0.087*
	(0.028)	(0.029)	(0.030)	(0.077)	(0.096)	(0.075)	(0.019)	(0.026)	(0.030)	(0.021)	(0.032)	(0.044)
LAC6												
RTC index	-0.016	-0.012	-0.040*	-0.050	-0.041	-0.070	-0.019	-0.017	-0.050*	-0.002	0.003	-0.025
	(0.012)	(0.014)	(0.018)	(0.034)	(0.027)	(0.040)	(0.011)	(0.016)	(0.022)	(0.010)	(0.011)	(0.014)
Obs.	238	238	236	232	230	216	237	237	234	237	237	232
R-squared	0.068	0.036	0.130	0.123	0.061	0.082	0.076	0.041	0.149	0.046	0.031	0.083

Notes: Regressions run at the occupation level. Employment share of each occupation computed using total hours worked. Regressions are weighted by the employment share of each occupation in the mid-2000s. Standard errors are heteroscedasticity-consistent. Last panel pools the six countries, controls for country fixed effects and clusters standard errors at the country level.

TABLE A.8

CHANGE IN THE EMPLOYMENT SHARE OF EACH OCCUPATION (MID-2000S TO LATE-2010S). 2SLS

	Age 16-65			Age 16-24			Age 25-40			Age 41-65		
	All	Males	Females	All	Males	Females	All	Males	Females	All	Males	Females
Argentina												
RTC index	-0.014	0.010	-0.071***	0.003	0.028	-0.130***	-0.015	0.013	-0.083***	-0.011	-0.002	-0.053**
	(0.014)	(0.014)	(0.022)	(0.025)	(0.029)	(0.050)	(0.016)	(0.014)	(0.030)	(0.015)	(0.014)	(0.025)
Brazil												
RTC index	-0.028	-0.015	-0.072**	-0.058	-0.049*	-0.131	-0.034	-0.021	-0.102**	-0.017	-0.004	-0.047
	(0.026)	(0.028)	(0.034)	(0.044)	(0.028)	(0.082)	(0.025)	(0.027)	(0.052)	(0.038)	(0.034)	(0.038)
Chile												
RTC index	-0.016*	-0.010	-0.055	0.006	-0.003	-0.062	-0.043***	-0.037***	-0.092	0.006	0.007	-0.041
	(0.009)	(0.011)	(0.039)	(0.023)	(0.018)	(0.069)	(0.012)	(0.012)	(0.067)	(0.016)	(0.012)	(0.036)
Colombia												
RTC index	-0.025	-0.030	-0.000	-0.063	-0.077	0.026	-0.025	-0.041	-0.002	-0.010	-0.012	-0.004
	(0.020)	(0.033)	(0.020)	(0.049)	(0.067)	(0.039)	(0.019)	(0.033)	(0.020)	(0.015)	(0.023)	(0.020)
Mexico												
RTC index	0.023*	0.032*	0.025	0.021	0.025	-0.002	0.019	0.029	0.020	0.023	0.044**	0.036
	(0.014)	(0.019)	(0.022)	(0.047)	(0.048)	(0.016)	(0.015)	(0.023)	(0.015)	(0.016)	(0.018)	(0.039)
Peru												
RTC index	-0.065**	-0.052	-0.107***	-0.233***	-0.135	-0.245***	-0.041*	-0.052	-0.058*	-0.051**	-0.022	-0.080*
	(0.027)	(0.032)	(0.030)	(0.072)	(0.089)	(0.093)	(0.023)	(0.032)	(0.032)	(0.024)	(0.037)	(0.043)
LAC6												
RTC index	-0.020**	-0.010	-0.049***	-0.052	-0.034	-0.091***	-0.024***	-0.018	-0.058***	-0.009	0.002	-0.033**
	(0.010)	(0.010)	(0.017)	(0.032)	(0.022)	(0.033)	(0.009)	(0.012)	(0.019)	(0.008)	(0.008)	(0.014)
Obs.	238	238	236	232	230	216	237	237	234	237	237	232
R-squared	0.065	0.036	0.125	0.123	0.060	0.076	0.074	0.041	0.147	0.039	0.031	0.079
KP F-stat	1353	737.9	1125	875.8	723.3	1269	974.7	732	1259	1316	732.1	1256

Notes: Regressions run at the occupation level. RTC index instrumented with the percentage of workers using computer in each occupation. Employment share of each occupation computed using total hours worked. Regressions are weighted by the employment share of each occupation in the mid-2000s. Last panel pools the six countries, controls for country fixed effects and clusters standard errors at the country level.

TABLE A.9

CHANGE IN THE PARTICIPATION OF WOMEN IN EACH OCCUPATION (MID-2000S TO LATE-2010S). OLS

	All	Age 16-24	Age 25-40	Age 41-65
Argentina				
RTC index	-0.114***	-0.275*	-0.131***	-0.091***
	(0.027)	(0.155)	(0.047)	(0.026)
Brazil				
RTC index	-0.052	-0.123	-0.039	-0.119
	(0.075)	(0.173)	(0.065)	(0.103)
Chile				
RTC index	0.062	0.052	0.070	0.041
	(0.062)	(0.213)	(0.095)	(0.047)
Colombia				
RTC index	-0.025	0.010	-0.022	-0.038
	(0.049)	(0.048)	(0.058)	(0.052)
Mexico				
RTC index	-0.068	0.038	-0.057	-0.131**
	(0.040)	(0.086)	(0.043)	(0.049)
Peru				
RTC index	-0.008	-0.021	-0.008	-0.117
	(0.030)	(0.070)	(0.053)	(0.077)
LAC6				
RTC index	-0.032	-0.048	-0.028	-0.073*
	(0.026)	(0.048)	(0.027)	(0.030)
Obs.	236	217	235	232
R-squared	0.109	0.127	0.065	0.126

Notes: Regressions run at the occupation level. The participation of women is computed using total hours worked by women over total hours worked by men in each occupation. Regressions are weighted by the employment share of each occupation in the mid-2000s. Standard errors are heteroscedasticity-consistent. Last panel pools the six countries, controls for country fixed effects and clusters standard errors at the country level.

TABLE A.10
CHANGE IN THE PARTICIPATION OF WOMEN IN EACH OCCUPATION (MID-2000S TO LATE-2010S). 2SLS

	All	Age 16-24	Age 25-40	Age 41-65
Argentina				
RTC index	-0.098***	-0.334**	-0.106*	-0.074**
	(0.033)	(0.149)	(0.056)	(0.030)
Brazil				
RTC index	-0.019	-0.018	-0.005	-0.126
	(0.103)	(0.200)	(0.094)	(0.114)
Chile				
RTC index	0.026	0.067	0.036	-0.013
	(0.066)	(0.207)	(0.095)	(0.049)
Colombia				
RTC index	-0.030	0.004	-0.016	-0.056
	(0.054)	(0.052)	(0.064)	(0.054)
Mexico				
RTC index	-0.058	0.064	-0.043	-0.136**
	(0.072)	(0.132)	(0.079)	(0.067)
Peru				
RTC index	-0.017	-0.004	0.004	-0.132*
	(0.035)	(0.081)	(0.056)	(0.074)
LAC6				
RTC index	-0.030*	-0.029	-0.018	-0.088***
	(0.016)	(0.049)	(0.017)	(0.020)
Obs.	236	217	235	232
R-squared	0.109	0.126	0.064	0.124
KP F-stat	1352	834.4	974.2	1342

Notes: Regressions run at the occupation level. RTC index instrumented with the percentage of workers using computer in each occupation. The participation of women is computed using total hours worked by women over total hours worked by men in each occupation. Regressions are weighted by the employment share of each occupation in the mid-2000s. Last panel pools the six countries, controls for country fixed effects and clusters standard errors at the country level.

TABLE A.11

CHANGE IN LOG MEDIAN WAGE OF OCCUPATIONS (MID-2000S TO LATE-2010S). OLS

	Age 16-65			Age 16-24			Age 25-40			Age 41-65		
	All	Males	Females	All	Males	Females	All	Males	Females	All	Males	Females
Argentina												
RTC index	0.433***	0.457***	0.409***	0.361*	0.148	0.498*	0.359***	0.281***	0.419***	0.440***	0.476***	0.318***
	(0.052)	(0.079)	(0.078)	(0.185)	(0.165)	(0.284)	(0.076)	(0.101)	(0.109)	(0.068)	(0.083)	(0.043)
Brazil												
RTC index	0.453***	0.491***	0.340**	0.345**	0.373***	0.420**	0.396***	0.377**	0.382***	0.500***	0.625***	0.420**
	(0.106)	(0.108)	(0.138)	(0.134)	(0.122)	(0.190)	(0.125)	(0.142)	(0.120)	(0.132)	(0.139)	(0.170)
Chile												
RTC index	0.301**	0.446***	0.201	0.255***	0.193	0.245	0.334**	0.461***	0.179	0.407***	0.495***	0.316**
	(0.122)	(0.107)	(0.137)	(0.092)	(0.122)	(0.151)	(0.130)	(0.134)	(0.159)	(0.142)	(0.100)	(0.147)
Colombia												
RTC index	0.380***	0.502***	0.125	0.501***	0.476***	0.352***	0.379***	0.440***	0.240*	0.311**	0.535***	-0.006
	(0.126)	(0.111)	(0.133)	(0.118)	(0.103)	(0.126)	(0.105)	(0.120)	(0.124)	(0.153)	(0.152)	(0.199)
Mexico												
RTC index	0.322**	0.362**	0.292	0.463*	0.270	0.439	0.314**	0.364**	0.361**	0.328**	0.341**	0.368***
	(0.132)	(0.140)	(0.178)	(0.235)	(0.241)	(0.273)	(0.116)	(0.148)	(0.169)	(0.133)	(0.129)	(0.122)
Peru												
RTC index	0.394***	0.374***	0.516***	0.236***	0.357**	0.177	0.351***	0.348***	0.415**	0.323*	0.374**	0.666**
	(0.112)	(0.111)	(0.180)	(0.072)	(0.150)	(0.119)	(0.102)	(0.101)	(0.157)	(0.176)	(0.142)	(0.245)
LAC6												
RTC index	0.380***	0.442***	0.306***	0.361***	0.307***	0.356***	0.357***	0.382***	0.325***	0.392***	0.481***	0.343***
	(0.027)	(0.024)	(0.053)	(0.045)	(0.051)	(0.049)	(0.013)	(0.026)	(0.045)	(0.033)	(0.045)	(0.078)
Obs.	238	238	236	232	230	214	237	237	234	237	237	232
R-squared	0.651	0.676	0.544	0.606	0.433	0.510	0.641	0.637	0.555	0.575	0.608	0.418

Notes: Regressions run at the occupation level. Wages measured in constant 2011 USD (PPP). Regressions are weighted by the employment share of each occupation in the mid-2000s. Standard errors are heteroscedasticity-consistent. Last panel pools the six countries, controls for country fixed effects and clusters standard errors at the country level.

TABLE A.12

CHANGE IN LOG MEDIAN WAGE OF OCCUPATIONS (MID-2000S TO LATE-2010S). 2SLS

	Age 16-65			Age 16-24			Age 25-40			Age 41-65		
	All	Males	Females	All	Males	Females	All	Males	Females	All	Males	Females
Argentina												
RTC index	0.436***	0.484***	0.358***	0.375*	0.176	0.597**	0.409***	0.371***	0.339**	0.436***	0.509***	0.282***
	(0.057)	(0.081)	(0.105)	(0.212)	(0.185)	(0.260)	(0.079)	(0.111)	(0.147)	(0.066)	(0.081)	(0.042)
Brazil												
RTC index	0.568***	0.657***	0.406***	0.514***	0.529***	0.484***	0.504***	0.555***	0.457***	0.616***	0.827***	0.534***
	(0.117)	(0.139)	(0.118)	(0.150)	(0.159)	(0.181)	(0.135)	(0.172)	(0.105)	(0.146)	(0.198)	(0.159)
Chile												
RTC index	0.377***	0.539***	0.236**	0.295***	0.232*	0.289**	0.433***	0.579***	0.272**	0.525***	0.646***	0.387***
	(0.124)	(0.120)	(0.117)	(0.086)	(0.121)	(0.115)	(0.128)	(0.142)	(0.134)	(0.152)	(0.133)	(0.127)
Colombia												
RTC index	0.415***	0.555***	0.141	0.539***	0.548***	0.373***	0.441***	0.497***	0.297***	0.352**	0.580***	0.061
	(0.112)	(0.094)	(0.121)	(0.119)	(0.114)	(0.124)	(0.089)	(0.095)	(0.106)	(0.145)	(0.130)	(0.200)
Mexico												
RTC index	0.359***	0.373**	0.415***	0.580**	0.257	0.635**	0.359***	0.358**	0.516***	0.341***	0.355***	0.435***
	(0.127)	(0.145)	(0.157)	(0.261)	(0.254)	(0.276)	(0.112)	(0.149)	(0.165)	(0.131)	(0.136)	(0.133)
Peru												
RTC index	0.413***	0.393***	0.527***	0.226***	0.363**	0.216*	0.385***	0.393***	0.414***	0.310*	0.365**	0.682***
	(0.119)	(0.126)	(0.178)	(0.067)	(0.163)	(0.112)	(0.110)	(0.121)	(0.158)	(0.175)	(0.152)	(0.230)
LAC6												
RTC index	0.431***	0.507***	0.343***	0.424***	0.359***	0.430***	0.425***	0.466***	0.380***	0.443***	0.559***	0.402***
	(0.031)	(0.041)	(0.048)	(0.053)	(0.061)	(0.060)	(0.020)	(0.037)	(0.036)	(0.048)	(0.070)	(0.072)
Obs.	238	238	236	232	230	214	237	237	234	237	237	232
R-squared	0.648	0.672	0.542	0.603	0.431	0.507	0.636	0.630	0.552	0.572	0.603	0.414
KP F-stat	1353	737.9	1125	875.8	723.3	1269	974.7	732	1259	1316	732.1	1256

Notes: Regressions run at the occupation level. RTC index instrumented with the percentage of workers using computer in each occupation. Wages measured in constant 2011 USD (PPP). Regressions are weighted by the employment share of each occupation in the mid-2000s. Last panel pools the six countries, controls for country fixed effects and clusters standard errors at the country level.

TABLE A.13

CHANGE IN THE GENDER WAGE GAP (MID-2000S TO LATE-2010S). OLS

	All	Age 16-24	Age 25-40	Age 41-65
Argentina				
RTC index	-0.079	-0.070	-0.014	-0.158*
	(0.139)	(0.272)	(0.158)	(0.082)
Brazil				
RTC index	-0.230*	-0.114	-0.131	-0.364**
	(0.121)	(0.140)	(0.085)	(0.158)
Chile				
RTC index	-0.115	-0.409	-0.211*	0.032
	(0.113)	(0.439)	(0.110)	(0.176)
Colombia				
RTC index	-0.109	-0.009	0.048	-0.222**
	(0.080)	(0.221)	(0.085)	(0.094)
Mexico				
RTC index	-0.225	0.167	-0.134	-0.188
	(0.209)	(0.420)	(0.178)	(0.286)
Peru				
RTC index	0.014	-0.094	-0.029	0.185
	(0.153)	(0.123)	(0.161)	(0.211)
LAC6				
RTC index	-0.131**	-0.100	-0.084*	-0.135
	(0.036)	(0.081)	(0.041)	(0.078)
Obs.	236	212	235	232
R-squared	0.079	0.007	0.049	0.046

Notes: Regressions run at the occupation level. Gender wage gap is the ratio of the median wage of men over the median wage of women in each occupation. Regressions are weighted by the employment share of each occupation in the mid-2000s. Standard errors are heteroscedasticity-consistent. Last panel pools the six countries, controls for country fixed effects and clusters standard errors at the country level.

TABLE A.14

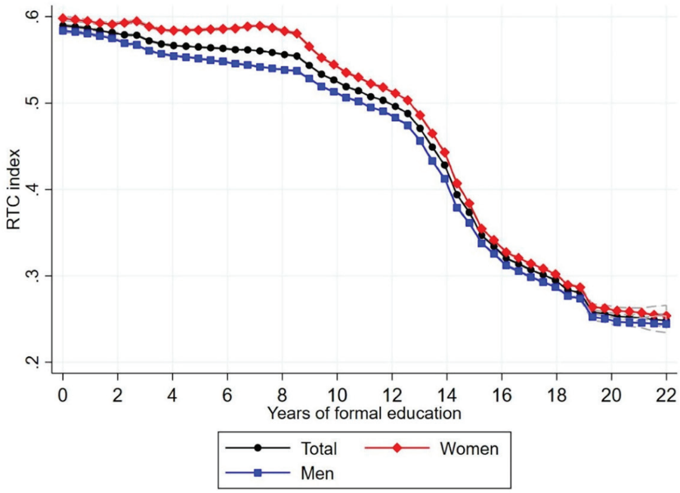
CHANGE IN THE GENDER WAGE GAP (MID-2000S TO LATE-2010S). 2SLS

	All	Age 16-24	Age 25-40	Age 41-65
Argentina				
RTC index	-0.021	0.179	0.083	-0.110
	(0.134)	(0.277)	(0.172)	(0.078)
Brazil				
RTC index	-0.250**	-0.123	-0.123	-0.413**
	(0.119)	(0.129)	(0.089)	(0.163)
Chile				
RTC index	-0.078	-0.372	-0.093	0.001
	(0.149)	(0.497)	(0.158)	(0.200)
Colombia				
RTC index	-0.177*	0.016	-0.035	-0.270***
	(0.092)	(0.198)	(0.092)	(0.103)
Mexico				
RTC index	-0.035	0.481	0.107	-0.192
	(0.256)	(0.460)	(0.271)	(0.280)
Peru				
RTC index	-0.094	-0.051	-0.140	0.009
	(0.170)	(0.135)	(0.180)	(0.203)
LAC6				
RTC index	-0.114***	-0.004	-0.038	-0.172***
	(0.035)	(0.107)	(0.038)	(0.066)
Obs.	236	212	235	232
R-squared	0.079	0.005	0.047	0.045
KP F-stat	1352	841.3	974.2	1342

Notes: Regressions run at the occupation level. RTC index instrumented with the percentage of workers using computer in each occupation. Gender wage gap is the ratio of the median wage of men over the median wage of women in each occupation. Regressions are weighted by the employment share of each occupation in the mid-2000s. Last panel pools the six countries, controls for country fixed effects and clusters standard errors at the country level.

FIGURE A.1

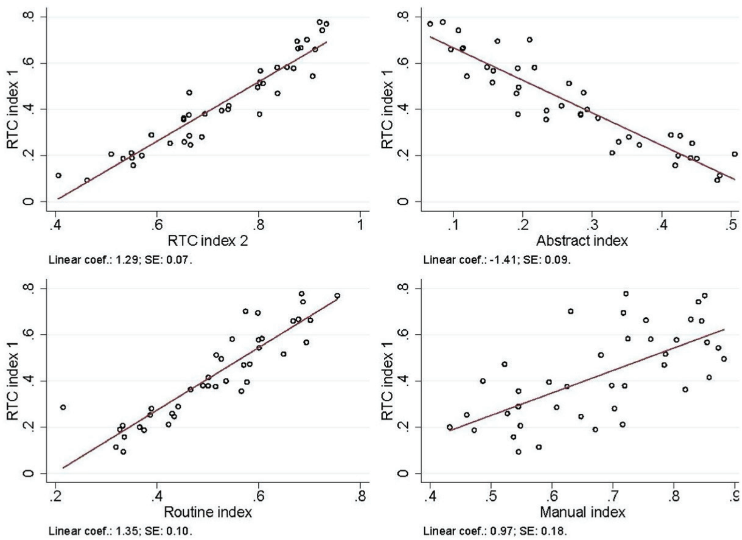
NON-LINEAR RELATION BETWEEN THE RTC INDEX AND EDUCATION



Notes: Data from pooled household surveys for Argentina, Brazil, Chile, Ecuador, Peru and Mexico around the late-2010s. Local polynomial regressions of years of formal education, separately by gender. Dependent variable is the RTC index. The RTC index captures the fraction of workers that mostly perform routine tasks in each occupation. Kernel bandwidth equal to 1. Dotted lines represent 99% confidence intervals (almost invisible given the very large sample size).

FIGURE A.2

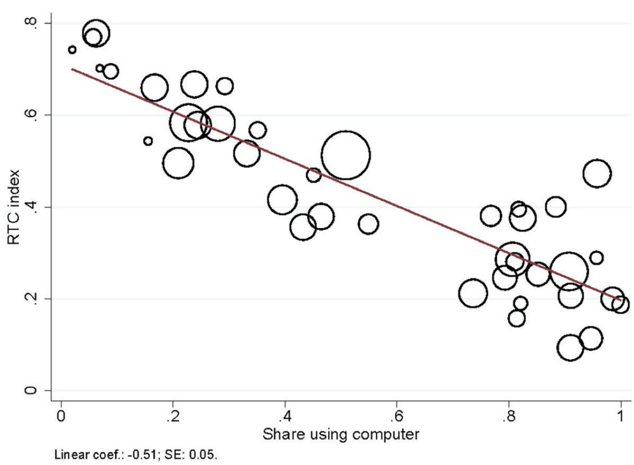
CORRELATION BETWEEN RTC INDEXES



Notes: Data from PIAAC pooled surveys for 24 countries. Occupations classified at the 2-digit ISCO08 level (N=40). Each occupation is weighted by its share in total employment (bubbles size).

FIGURE A.3

CORRELATION BETWEEN RTC AND COMPUTER USE

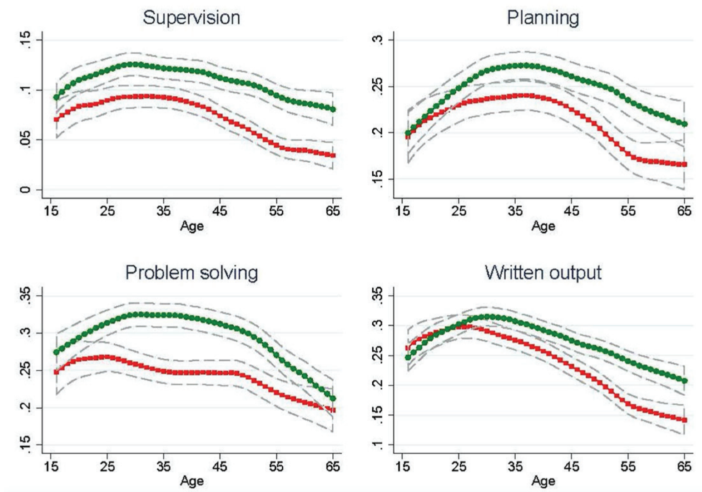


Notes: Data from PIAAC pooled surveys for 24 countries. Occupations classified at the 2-digit ISCO08 level (N=40). Each occupation is weighted by its share in total employment (bubbles size).

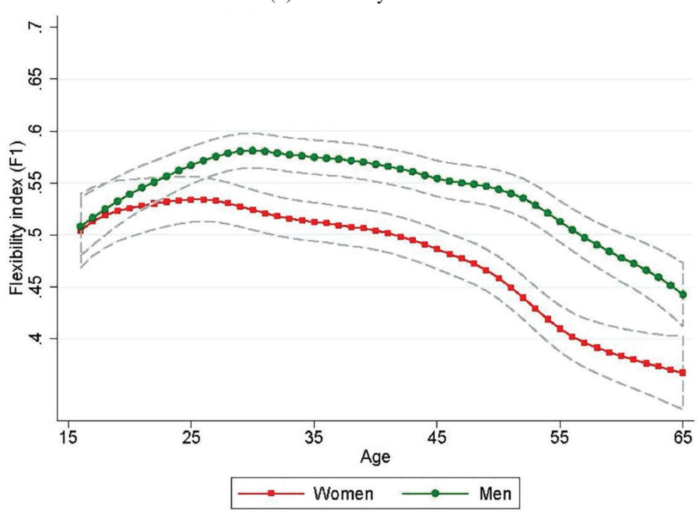
FIGURE A.4

PROBABILITY OF PERFORMING FLEXIBLE TASKS ACROSS COHORTS BY GENDER IN LATIN AMERICA

(a) Flexible tasks



(b) Flexibility index *F*

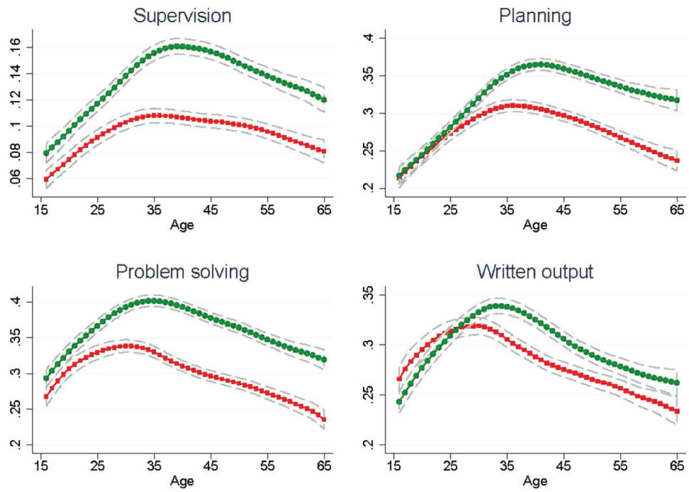


Notes: Data from PIAAC pooled surveys for Chile, Ecuador, Peru and Mexico. Local polynomial regressions of each flexible task on age, separately by gender. Dependent variable in the bottom panel is the flexibility index F. The index is a dummy variable that is equal to one when the individual replies that he performs at least one of the four tasks often or very often. Kernel bandwidth equal to 5. Dotted lines represent 95\% confidence intervals.

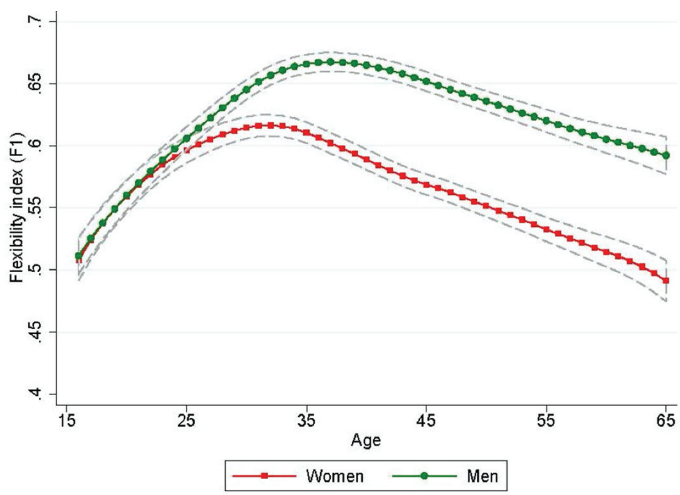
FIGURE A.5

PROBABILITY OF PERFORMING FLEXIBLE TASKS ACROSS COHORTS BY GENDER IN OECD MEMBERS

(a) Flexible tasks



(b) Flexibility index *F*

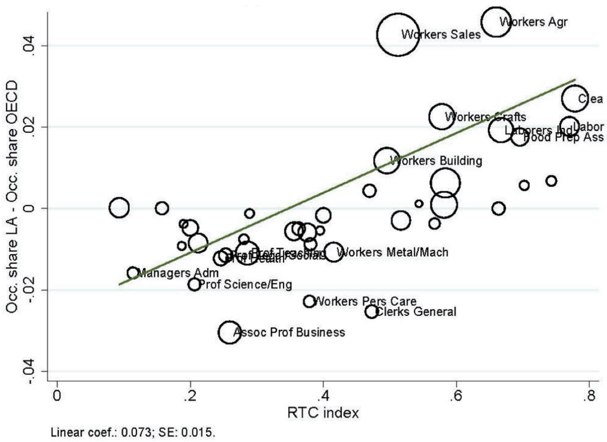


Notes: Data from PIAAC pooled surveys for 20 OECD countries. Local polynomial regressions of each flexible task on age, separately by gender. Dependent variable in the bottom panel is the flexibility index \$F\$. The index is a dummy variable that is equal to one when the individual replies that he performs at least one of the four tasks often or very often. Kernel bandwidth equal to 5. Dotted lines represent 95\% confidence intervals.

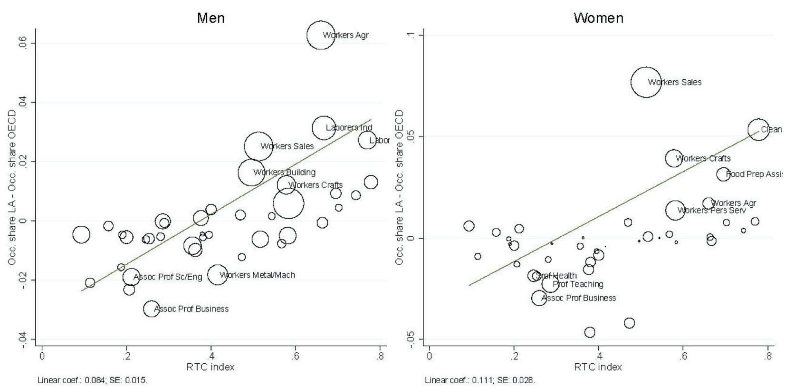
FIGURE A.6

DIFFERENCES IN EMPLOYMENT ACROSS OCCUPATIONS AND RTC

(a) All workers



(b) By gender

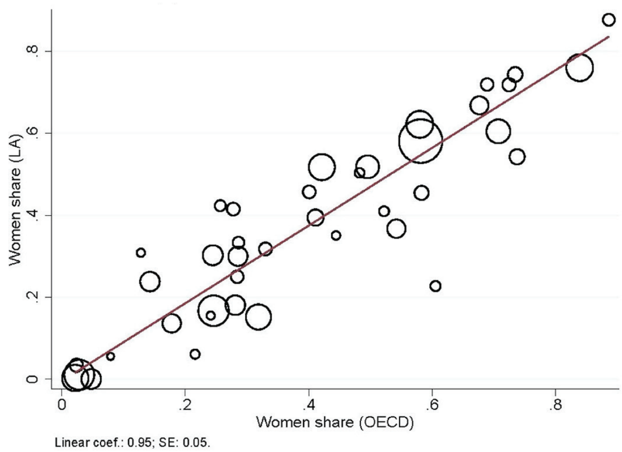


Notes: Data from pooled skills surveys (Programme for the International Assessment of Adult Competencies-PIAAC) conducted by the OECD since 2011. Occupations classified at the 2-digit ISCO08 level (N=40). Panel A depicts the relation between the difference in employment share of each occupation across Latin America (LA) and OECD countries and the RTC index. Weights (bubble size) represent occupation shares in employment in LA. Labels for occupations with employment share above 2.5 percent (which is the equally distributed fraction across 40 occupations) and an absolute difference in employment shares above 1 p.p. In Panel B occupation shares are gender-specific. Weights represent occupation shares for each gender in LA. Labels for occupations with gender-employment share above 2.5 percent and absolute differences in gender-employment shares above 1 p.p.

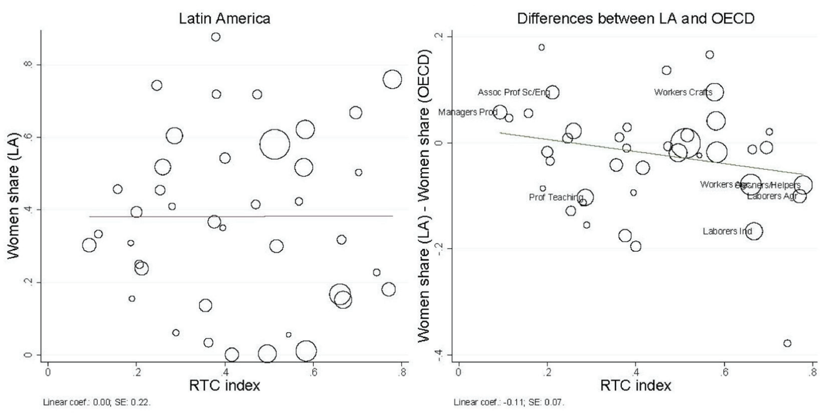
FIGURE A.7

DIFFERENCES IN THE SHARE OF WOMEN WITHIN OCCUPATION AND RTC

(a) Share of woman in LA and OECD



(b) Share of woman in each occupation and RTC



Notes: Data from pooled skills surveys (Programme for the International Assessment of Adult Competencies-PIAAC) conducted by the OECD since 2011. Occupations classified at the 2-digit ISCO08 level (N=40). Panel A plots the relation between the employment share of women in each occupation across Latin America (LA) and OECD countries. Weights (bubble size) represent employment share of each occupation in LA. Panel B (left) plots the relation between employment share of women and the RTC index. Panel B (right) plots the relation between the difference in the employment share of women across LA and OECD and the RTC index. Labels for occupations with employment share above 2.5 percent and absolute differences in employment shares of women above 5 p.p.

Efectos de la innovación sobre el empleo: México y Ecuador*

The effect of innovation on employment: Mexico and Ecuador

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Resumen

Este trabajo aporta evidencia del efecto de la innovación sobre el empleo en dos países donde tal impacto no ha sido analizado previamente: México y Ecuador. Siguiendo el método propuesto por Harrison et al. (2014) encontramos que la introducción de nuevos productos en el mercado afecta positivamente el empleo en México y Ecuador. En cambio, la innovación de proceso tiende a destruir empleo en México, pero no en el caso de Ecuador. Se observa que el resultado positivo de la innovación de producto es mayor que la pérdida de empleo causada por la innovación de proceso.

Palabras claves: *Innovación de producto y proceso; demanda de empleo; productividad laboral.*

Clasificación JEL: *D2, J23, L1, E31.*

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Abstract

This work provides evidence of the effect of innovation on employment in two countries where this impact has not been previously analysed: Mexico and Ecuador. Following the method proposed by Harrison et al. (2014), we find that introducing new products in the market positively affects employment in Mexico and Ecuador. While process innovation tends to destroy jobs in Mexico, it has no effect in the case of Ecuador. The positive impact of product innovation is observed to be greater than the loss of employment caused by process innovation.

Key words: *Product and process innovation; labor demand; labor productivity.*

JEL Classification: *D2; J23; L1; E31.*

1. Introducción

La discusión sobre los efectos de la innovación en el bienestar social en términos de desempleo se ha caracterizado frecuentemente por fuertes contradicciones; históricamente, el movimiento laboral suele subrayar los efectos negativos en el empleo en términos de calidad y cantidad, mientras que los empresarios destacan los beneficios del cambio tecnológico en cuanto a eficiencia, productividad y competitividad, pues confían en los mecanismos de compensación, suponen que el mercado laboral absorberá –en el mediano y largo plazo– a los trabajadores desempleados en nuevas actividades o en las tradicionales que han sido estimuladas por la demanda.

Actualmente, la robótica, automatización e inteligencia artificial han generado un fuerte debate sobre los efectos que tienen sobre el empleo porque implican un efecto drástico en la productividad del trabajo generando un efecto negativo en la demanda de empleo.[1] McKinsey (2017) analizó los efectos de la automatización en el mercado laboral global en 54 países y argumentó que los porcentajes de empleo que podrían ser destruidos debido a la nueva revolución tecnológica son del 40-50%. Para el caso de México, el estudio estima que el 52% del empleo puede ser reemplazado por robots, es decir, 25 millones de trabajadores (en el sector industrial 64%). Estas estimaciones colocan la relación entre el empleo y la innovación en el centro de la discusión política y pública. La intensidad y ritmo de la "robotización" dependen de la disponibilidad de la

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1 Dorn (2016); McKinsey (2017); Arntz *et al*. (2016); Acemoglu *et al*. (2017).

nueva tecnología, y de factores que influyen en las capacidades de absorción[2] (Arntz *et al.*, 2016). Según Dorn (2016), el pesimismo reflejado en el informe de McKinsey se basa en una visión intuitiva y profundamente equivocada del mercado laboral en el sentido de que existe una cantidad fija de trabajo, que puede ser realizada por humanos o por máquinas. Esta hipótesis, conocida por los economistas como el "lump of labor fallacy" o "falacia de una masa fija de trabajo" (Walker, 2007; Schloss, 1891), donde el uso cada vez mayor de máquinas en el proceso de producción reduce necesariamente el trabajo total, o la demanda general de mano de obra disponible para los seres humanos. Varios economistas[3] critican esta falacia y sostienen que el mercado laboral es dinámico y elástico, y se centran en las formas de creación de nuevos empleos.

En este contexto, el objetivo de este trabajo es aportar nueva evidencia empírica de los efectos de la innovación sobre el empleo en el sector manufacturero de dos países en vías de desarrollo que no han sido analizados previamente: México y Ecuador. El análisis se ha llevado a cabo utilizando el enfoque propuesto por Harrison *et al.* (2014), ya que este permite contrastar diferentes mecanismos de compensación presentes en la teoría de innovación y empleo. Los datos utilizados se han obtenido de las encuestas de innovación de cada país.[4]

Las secciones que componen el estudio contienen: breve revisión de las principales teorías que estudian la relación entre innovación y empleo; síntesis de la evidencia empírica actual explicando los modelos econométricos usados y de los resultados obtenidos. Seguidas por los modelos desarrollados para México y Ecuador; y en la última, se integran las conclusiones obtenidas analizadas críticamente con respecto a las limitaciones de la evidencia empírica existente e indicando futuras líneas de investigación.

2. Revisión De La Literatura: Los Modelos Econométricos

2.1 Modelos basados en el esfuerzo o "input" innovador

Se han revisado para este trabajo 44 estudios microeconómicos –son los trabajos empíricos detectados en la literatura– que analizan el efecto de la innovación sobre el empleo con base en los datos a nivel de empresa. Los trabajos empíricos detectados se dividen en dos grandes grupos. El primero incorpora los modelos econométricos que analizan los efectos de la innovación

[2] Entre otros, la capacidad técnica de las empresas, la disponibilidad o la falta de capital humano calificado, la regulación y tolerancia social.

[3] Véase entre otros Vivarelli (2007, 2014); Pianta (2003, 2012); Harrison *et al.*, (2014); Dorn (2016).

[4] En el caso de México INEGI: ESIDET-MBN (2010-2011) y en el caso de Ecuador ACTI (2009-2011).

empresarial mediante un indicador del esfuerzo o input innovador, básicamente, el gasto en I+D o en innovación. Este conjunto de estudios –aplicando un amplio y heterogéneo conjunto de modelos econométricos– reflejan en general un impacto positivo de la actividad innovadora sobre el empleo.[5] Son pocos los que no confirman del todo el efecto positivo del gasto en I+D; Matuzeviciute *et al*. (2017), Vivarelli *et al*. (1996) y Brouwer *et al*. (1993). Al parecer las conclusiones opuestas a la mayoría de los estudios están relacionadas con la especialización sectorial; principalmente en el sector servicios o en los sectores de bajo nivel innovador el efecto resulta no significante o negativo. Un segundo tipo de trabajos conceptualiza la innovación mediante los resultados obtenidos en términos de la introducción de innovaciones de producto o de proceso; la gran mayoría de éstos han utilizado el modelo desarrollado por Harrison et al. (2014). Para un mejor entendimiento de los resultados de dichos estudios se explican en detalle las especificaciones del modelo y la interpretación concreta de cada uno de los parámetros en las dos siguientes subsecciones.

2.2 Modelos basados en el "output" innovador: innovación de producto y de proceso

El modelo de Harrison *et al*. (2014) estima los efectos de la innovación mediante los resultados obtenidos en términos de la introducción de innovaciones de producto o de proceso. Respecto a la innovación de producto, distingue inicialmente dos tipos de productos: 1) la empresa elabora productos viejos o marginalmente modificados (Viejos productos) y 2) productos nuevos o significativamente mejorados (Nuevos productos). Se analiza a la empresa en dos períodos que se expresan con t=1 y t=2, donde se puede introducir un nuevo producto entre los dos años. La producción de viejos y nuevos productos en el año t se denota con Y_{1t} y Y_{2t}, respectivamente. En el año t=1 todos los productos son por definición viejos, ya que Y_{21} es siempre igual a cero. Si la empresa no introduce ningún producto nuevo entre los dos años, Y_{22} es igual a cero. En el modelo se asume que la producción tecnológica de viejos y nuevos productos presenta rendimientos constantes a escala en capital, trabajo e insumos intermedios. Además, la función de producción puede enunciarse como dos funciones de producción separables e idénticas con parámetros θ tipo neutral-Hicks.[6]

$$(1) \qquad Y_{it} = \theta_{it} F\left(K_{it}, L_{it}, M_{it}\right) e^{\eta + \omega_{it}}$$

---

5 Se han detectado 5 estudios que aplican una variable input innovador destacando el trabajo de Van Reenen (1997) o Bogliacino *et al*.- (2012, 2014)

6 Cuando se dice que el parámetro θ es tipo neutral de Hicks significa que ante la introducción de un cambio tecnológico y/o innovación, la razón entre capital y trabajo no varía, es constante.

donde K es el capital, L es el trabajo, M son los insumos intermedios y η es el efecto fijo no observado de la idiosincrasia de la firma. Dicha variable representa todos los factores no observables que permiten que una empresa sea más, o menos productiva que el resto de las empresas promedio usando la misma tecnología, θ representa el valor de la productividad de la empresa promedio; por ejemplo, la habilidad superior del manejo de la innovación, la capacidad de absorción más alta, y una organización más eficiente. ω_{it} son *los shocks* de productos y productividad en un tiempo específico $E(\omega_{it})=0$. El coeficiente anterior contiene todos los cambios –no observables– que podrían ocurrir en la función de producción que no están asociados con el desarrollo de las innovaciones tecnológicas; éstos se denominan "no tecnológicos", por ejemplo, la inversión en capital, los cambios en la organización del trabajo e industria (Harrison *et al*., 2014).

En el modelo de Harrison *et al*. (2014) se asume que la empresa invierte en I+D para generar innovación de producto y proceso, y por ende puede influir en la eficiencia de la producción de viejos y nuevos productos. El interés principal del análisis es estimar el cambio en la eficiencia de la producción de viejos productos θ_{12}/θ_{11}, también como la eficiencia relativa θ_{22}/θ_{11} de viejos y nuevos productos.

Asimismo, se asume que el empleo y otras decisiones de insumos se hacen a través de la minimización de costes tomando en cuenta los efectos de productividad individual η y los shocks de productividad ω. Dada la tecnología, la función de costes toma la forma:

$$C(w_{it},Y_{it},\theta_{it})=c(w_{it})\frac{Y_{it}}{\theta_{it}e^{\eta+\omega_{it}}}+F_i \tag{2}$$

donde el coste marginal $\dfrac{c(w)}{\theta_{it}e^{\eta+\omega_{it}}}$ es una función de un vector de precios w, y F es el coste fijo. De acuerdo con el Lemma de Shephard, la demanda de trabajo para productos viejos se escribe para t=1,2.

$$L_{1t}=c_{wL}(w_{1t})\frac{Y_{1t}}{\theta_{1t}e^{\eta+\omega_{1t}}} \tag{3}$$

y para productos nuevos

$$L_{22}=\begin{cases} c_{wL}(w_{22})\dfrac{Y_{22}}{\theta_{22}e^{\eta+\omega_{22}}} & si\, Y_{22}>0 \\ 0 & en\, cualquier\, otro\, caso \end{cases} \tag{4}$$

donde $c_{wL}(.)$ representa la derivada del c(.) con respecto al salario. Se asume que $c_{wL}(w_{11})=c_{wL}(w_{12})=c_{wL}(w_{22})$; es decir, el precio de los insumos permanece constante en dos años y es igual para nuevos y viejos productos.

Se descompone el crecimiento del empleo en dos años t=1 y t=2, tomando en cuenta los productos nuevos y viejos:

$$\frac{\Delta L}{L}=\frac{L_{12}+L_{22}-L_{11}}{L_{11}}=\frac{L_{12}-L_{11}}{L_{11}}+\frac{L_{22}}{L_{11}}\simeq \ln\frac{L_{12}}{L_{11}}+\frac{L_{22}}{L_{11}} \tag{5}$$

Por definición la tasa de crecimiento de nuevos productos se define como L_{22}/L_{11}. Despejando y aplicando logaritmos, se obtiene:

$$\cong -(\ln\theta_{12}-\ln\theta_{11})+\left(\ln Y_{12}-\ln Y_{11}\right)+\frac{\theta_{11}}{\theta_{22}}\frac{Y_{22}}{Y_{11}}-(\omega_{12}-\omega_{11}) \tag{6}$$

De acuerdo con Harrison *et al*. (2014), la ecuación anterior representa el crecimiento del empleo en cuatro elementos: primero, el cambio en la eficiencia en el proceso de producción para viejos productos; segundo, el cambio en la demanda de los productos viejos en el tiempo; tercero, la expansión en la producción atribuida a la demanda de nuevos productos; cuarto, el impacto de los shocks de productividad. La ecuación (6) se puede representar de forma econométrica:

$$l=\alpha_0+\alpha_1 d+y_1+\beta y_2+u \tag{7}$$

donde l es la tasa de crecimiento del empleo en el periodo (entre t=1 y t=2), y_1 e y_2 corresponden a las tasas de crecimiento de la producción de nuevos y viejos productos $\left(\ln Y_{12}-\ln Y_{11}\right)$ y Y_{22}/Y_{11}, respectivamente. $u = -(\omega_{12}-\omega_{11})+\xi$ es una perturbación aleatoria donde ξ representa diversos errores (no correlacionados). α_0 es el crecimiento de la eficiencia promedio en la producción de viejos productos. d es la variable que recoge la información sobre si ha implementado un proceso de innovación específico no asociado con alguna innovación de producto (α_1 captura dicho efecto). β sería la eficiencia relativa de la relación de nuevos y viejos productos Harrison *et al*. (2014).

De la expresión anterior puede observarse que el coeficiente de y_1 es 1 por lo que se puede despejar de lado derecho.

$$l-y_1=\alpha_0+\alpha_1 d+\beta y_2+u \tag{8}$$

Con la ecuación (8) surgen otros tipos de dificultades. En primer lugar, ya que la producción real no es observada, ésta se sustituye por el crecimiento de las ventas, que sí son observables. En segundo lugar, no se dispone de los precios a nivel empresa para deflactar las ventas nominales. Como solución al problema anterior, se denomina $g_1=\frac{P_{12}Y_{12}-P_{11}Y_{11}}{P_{11}Y_{11}}$ a la tasa de crecimiento nominal de ventas de viejos productos, la cual se puede escribir como $g_1 = y_1 + \pi_1$ donde $\pi_1 = \frac{P_{12} - P_{11}}{P_{11}}$ es la tasa de crecimiento de productos viejos. De igual manera, pero tomando en cuenta que $Y_{21} = 0$, se define $g_2 = \frac{P_{22}Y_{22}}{P_{11}Y_{11}}$ como la tasa de crecimiento nominal de las ventas debido a nuevos productos. $g_2 = y_2(1+\pi_2) = y_2 + y_2\pi_2$, donde $\pi_2 = \frac{P_{22} - P_{11}}{P_{11}}$ es la diferencia proporcional de los precios de nuevos productos con respecto a los viejos productos. Al sustituir g_1 y g_2 por y_1 e y_2, se obtiene:

(9) $$l - g_1 = \alpha_0 + \alpha_1 d + \beta g_2 + v$$

donde la nueva perturbación no observable ahora es: $v = -\pi_1 - \beta\pi_2 g_2 + u$. En el caso donde la media de π_1 es distinta de cero, el modelo incluirá $-E(\pi_1)$ en el intercepto y $-(\pi_1 - E(\pi_1))$ en la perturbación.

Para estimar la ecuación (9) se deben tener en cuenta dos problemas adicionales, g_2 (es decir, $y_2 + y_2\pi_2$) estará relacionado con el término de error ($-\pi_1 - \beta\pi_2 g_2 + u$). El término de error v incluye π_1 cuando no se puede controlar el cambio de los precios de viejos productos. En ausencia de la información del precio de las empresas, solo se puede identificar un efecto de innovación de proceso en el empleo neto (directo) de varios precios de compensación. Como solución a este problema en el análisis econométrico, se toma el precio del índice industrial π como proxy de π_1. Por lo tanto, la variable dependiente quedará de la siguiente forma $l - (g_1 - \pi)$. La ecuación (10) es la que se puede estimar empíricamente:

(10) $$l - (g_1 - \pi) = \alpha_0 + \alpha_1 d + \beta g_2 + v$$

Con base en la ecuación (10), Harrison *et al.* (2014) indican que la razón entre $\theta_{11} / \theta_{22}$ determina el impacto de la innovación de productos nuevos en el crecimiento del empleo, es decir, captura la eficiencia relativa en la producción de viejos y nuevos productos. Si la razón anterior es menor a la unidad, significa que los nuevos productos son elaborados más eficientemente que los viejos.

La estimación de la ecuación (10) se puede ver afectada por la presencia de endogeneidad en la variable incremento de ventas debido a nuevos productos (g_2). En forma general, tal problema se genera cuando la variable independiente se correlaciona con el término de error en una regresión. Uno de los métodos más habituales para solucionar la endogeneidad es el uso de las variables instrumentales (IV); las cuales, corregirían el modelo en relación con el posible sesgo generado por la variable explicativa endógena. Los instrumentos deben satisfacer los supuestos econométricos de exclusión e inclusión. Harrison *et al.* (2014) recomiendan algunas variables instrumentales, de las cuales destaca el incremento del rango de producción (bienes y servicios) como objetivo de la innovación; indican dos razones teóricas por las que es un buen instrumento: primera, es probable que aumentar la gama de bienes y productos esté correlacionada con la planificación (Innovación y desarrollo (I+D), diseño, exploración de marketing, etc.) y las expectativas de ventas; segunda, aumentar la gama de productos no implica necesariamente un cambio en los precios de los productos. Por lo tanto, parece poco probable que la importancia del rango de productos como objetivo de la innovación esté correlacionado con shocks de productividad no anticipados. Para mostrar la robustez del modelo se han utilizado otras variables instrumentales, cuyos objetivos son: aumento de la cuota de mercado y mejora de la calidad de los productos; y, por otro lado, la importancia de los clientes como fuente de información para la innovación.

2.3 La evidencia empírica en los modelos basados en el output innovador

Para el caso de Ecuador y México no se han detectado estudios previos que hayan aplicado el modelo desarrollado por Harrison *et al.* (2014); sin embargo, existe evidencia empírica sobre algunos países de América Latina (AL). Por lo que en esta sección se exponen brevemente las ventajas y desventajas del enfoque descrito y se presenta la evidencia encontrada para AL contenida en la Tabla 1.

En este marco, la "constante" del modelo indicaría el efecto sobre la necesidad de empleo para producir productos viejos. El signo esperado de su valor (α_1) sería negativo, ya que se espera un aumento de la productividad laboral debido a las mejoras en los procesos de producción con respecto a la elaboración de los productos viejos. Los resultados que muestran los estudios sobre países de AL son heterogéneos. Tres estudios encuentran el efecto esperado, pero en otros tal efecto resulta "no significativo" e incluso se ha detectado para Uruguay una disminución de la productividad.

El parámetro "*d*" de la ecuación (10) se interpreta como el efecto de la innovación de proceso no asociada con una innovación de producto. La evidencia para el caso de los países europeos desarrollados y los de AL respecto al parámetro "*d*" no son del todo concluyentes. En el caso europeo 9 estimaciones detectan el efecto esperado y en 16 sub-muestras no se encuentran efectos estadísticamente significativos. En el caso de AL se encuentran 3 signos negativos y 6 no significativos. Es decir, existen contradicciones sobre el hecho de que las empresas que solo realizan "innovación de proceso" reducen su demanda de empleo. Lo más destacable sería el caso de Costa Rica, ya que muestra un efecto positivo y significativo sobre la tasa de crecimiento del empleo contrario a la predicción de la teoría.

TABLA 1

REVISIÓN DE ESTUDIOS EMPÍRICOS A NIVEL EMPRESA. CASO LATINOAMERICANO

Autor	Crespi *et al.*				de Elejalde *et al.*	Aboal *et al.*	Alvarez *et al.*	Benavente *et al.*	Fioravante
Año de publicación	2012				2015	2015	2011	2008	2008
País	Argentina	Chile	Costa Rica	Uruguay	Argentina	Uruguay	Chile	Chile	Brasil
Período evaluado	1998-2001	1995-2007	2006-2007	1998-2009	1998-2001	1998-2009	1995-2007	1998-2001	2001-2003
Innovación de proceso	1.398	0.333	**18.413**	**-2.716**	1.252	-2.610	0.297	0.132	0.0012
Crecimiento de ventas debido a nuevos productos	**1.17**	**1.751**	**1.015**	**0.961**	**1.151**	**0.964**	**1.74**	**0.549**	**0.933**
Constante	-0.994	-2.016	**-12.16**	**1.402**		**1.544**	-1.989	**-0.419**	**-0.5613**
Inversión									-
Salario						-	-		
Propiedad extranjera	ns	ns	+	-	-	ns	ns		
Localización de la empresa	ns	ns	ns		ns		ns		

Fuente: Elaboración propia con los coeficientes de las estimaciones de cado uno de los estudios revisados.

Notas: [a] Los valores en negrita son estadísticamente significativos.

[b] ns=No significativo.

El efecto de la innovación de producto en el empleo se refleja con base en el parámetro β, que captura la eficiencia relativa de la producción de productos antiguos y nuevos (Harrison *et al*., 2014). Respecto a este indicador, se confirma el efecto positivo en todos los estudios europeos y latinoamericanos. Esto indica que el crecimiento de ventas debido a nuevos productos incide positivamente sobre el empleo; es decir, pese a las diferencias económicas y sociales entre países con un nivel de desarrollo muy diferente la innovación de producto genera empleo.

Pero la Beta refleja un segundo aspecto del efecto de la innovación de producto sobre el empleo, ya que mide de forma directa la diferencia de la productividad laboral entre los productos nuevos y viejos. En el caso de que el coeficiente Beta sea menor a la unidad, se dice que la producción de nuevos productos es más eficiente que la de los viejos. Mientras que un coeficiente mayor a uno implicaría lo contrario.

Al mismo tiempo que la interpretación es una gran ventaja limita la ampliación del modelo con otros aspectos que podrían influir sobre el empleo. Para asegurar la correcta interpretación de sus componentes, los estudios que pretenden usar este modelo deben seguir exactamente el modelo teórico-metodológico desarrollado por Harrison *et al*. (2014).

3. Innovación y Empleo en Ecuador y México

3.1 Fuentes de datos y estadísticos descriptivos contexto global

La base utilizada que permite llevar a cabo el análisis para el caso mexicano proviene de la "Encuesta Sobre Investigación y Desarrollo Tecnológico y Módulo sobre Actividades de Biotecnología y Nanotecnología" (ESIDET-MBN[7]) de 2012. Para llevar a cabo el análisis ecuatoriano se utiliza la base de datos que proviene de la Encuesta Nacional de Actividades de Innovación (ACTI[8]) para los años 2009-2011. La Tabla 2 muestra los estadísticos de las variables que se utilizaran en el modelo de Harrison *et al*. (2014) para el caso mexicano (columna 1) y ecuatoriano (columna 2). Puede observarse para ambos países que el empleo crece más en empresas innovadoras que en las no innovadoras, aunque para el caso de Ecuador, dicho efecto es más agudo cuando las empresas introducen un nuevo producto. Por otro lado, el crecimiento de las ventas es en ambos países mayor para las empresas que han introducido nuevos productos seguido por innovadores de procesos respecto a las no innovadoras.

7 https://www.inegi.org.mx/programas/esidet/2014/default.html

8 http://www.ecuadorencifras.gob.ec/encuesta-nacional-de-actividades-de-ciencia-tecnologia-e-innovacion-acti/

TABLA 2

ESTADÍSTICAS DESCRIPTIVAS EN PORCENTAJES: INNOVACIÓN DE PRODUCTO Y PROCESO, CRECIMIENTO DE LAS VENTAS Y EMPLEO. SECTOR MANUFACTURERO

País	**Número de Empresas (%)**		**Crecimiento del Empleo (%)**		**Crecimiento de las ventas (%)**		**Crecimiento de precios (%)**	
	México	Ecuador	México	Ecuador	México	Ecuador	México	Ecuador
Total empresas	100	100	3.2	14.56	10.9	42.57	7.0	12.9
No innovadoras	88.4	45.97	3.1	11.94	10.7	35.01	6.9	12.34
Únicamente innovadoras de proceso	1.4	32.99	5.7	16.4	22.4	47.28	7.0	13.64
Innovadoras de Producto	11.6	21.03	5.6	17.4	13.5	51.54	8.0	13.04
Únicamente innovadoras de producto	5.8	3.46	5.1	12.36			7.9	12.85
[Innovadoras de Producto y Proceso]	5.8	17.57	6.0	18.42			8.2	13.08
Productos viejos					4.8	16.7		
Productos nuevos					5.8	24.09		
Número de empresas	5,954	1,155						

Fuente: Elaboración propia con datos de ESIDET-MBN y ACTI.

3.2 Resultados del modelo para Ecuador y México

A continuación, se ofrecen los resultados –Tabla 3– para el caso de México y Ecuador.[9] Los resultados para el caso ecuatoriano de las estimaciones mediante MCO no confirman los efectos teóricamente esperados posiblemente debido a la presencia de endogeneidad en las estimaciones que provocarían coeficientes sesgados e inconsistentes, por lo que se aplica el método de variables instrumentales. La columna 2 muestra los resultados de las estimaciones utilizando el incremento de rango de bienes y servicios como variable instrumental. La variable "solo innovación de proceso" no tiene efecto significativo sobre la tasa de crecimiento del empleo. Mientras que el incremento de ventas, debido a nuevos productos, muestra un efecto positivo y estadísticamente significativo y cercano a uno. Por último, la constante del modelo, que recoge las variaciones en la eficiencia relativa, muestra un coeficiente negativo y significativo. Esto indica que en Ecuador se ha producido un incremento de la eficiencia en la producción de viejos productos –aumento de la productividad–. Estos resultados van en línea con los esperados.[10] Por otro lado, para probar la robustez del modelo se han utilizado dos instrumentos más, la importancia de la mejora de calidad de bienes y servicios como objetivo de la innovación –columna 3– y la intensidad del esfuerzo innovador[11] –columna 4– en forma de un rezago. Los resultados obtenidos no difieren de los estimados cuando se utiliza un solo instrumento, por lo que podemos concluir que, para Ecuador, la innovación de proceso no tiene efectos significativos sobre el empleo y que la innovación de producto tiene un efecto positivo.

Los efectos obtenidos para México, columnas 5-8 de la Tabla 3, muestran en la columna 5 los resultados para las estimaciones mediante MCO, se observa que la introducción de innovaciones de proceso tiene un efecto negativo y significativo sobre la tasa de crecimiento del empleo. Mientras que el crecimiento de ventas de nuevos productos presenta un efecto positivo y significativo sobre el empleo; la constante no es significativa, por lo que no se puede hacer inferencia sobre la eficiencia en la producción de viejos productos. Debido a la posibilidad de que los resultados tengan algún sesgo, se ha estimado un modelo con variables instrumentales –columna 6–. Los resultados no presentan diferencias significativas con respecto a las estimaciones por MCO. Al contrastar la posible presencia de endogeneidad se observa que no se puede

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9 Todas las estimaciones son controladas por variables dicotómicas sectoriales según el nivel tecnológico (alta-tecnología, mediana alta tecnología, mediana baja-tecnología y baja tecnología) para el caso de México e industriales (según CNAE a nivel de dos dígitos) para el caso de Ecuador.

10 Cabe mencionar que los supuestos de exclusión e inclusión se satisfacen (véase prueba de Sargan Test y First Stage al final de la Tabla 3).

11 Esta variable es la razón entre gasto en investigación y desarrollo (I+D) y ventas para el caso de México. Mientras que para Ecuador se utilizó el gasto en innovación total sobre las ventas.

TABLA 3

LOS EFECTOS DE LA INNOVACIÓN EN EL EMPLEO MANUFACTURERO

Variable dependiente: l-(g1-π)								
	Ecuador				**México**			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	MCO	vi[a]	vi[b]	vi[c]	MCO	vi[a]	vi[b]	vi[c]
Sólo proceso (d)	-0.238***	-0.017	-0.034	-0.047	-0.088**	-0.092**	-0.092**	-0.087**
	[0.078]	[0.081]	[0.078]	[0.079]	[0.0379]	[0.0392]	[0.0391]	[0.0382]
Ventas debidas a nuevos productos (g2)	0.137	0.956***	0.893***	0.846***	0.968***	0.911***	0.906***	0.986***
	[0.145]	[0.164]	[0.139]	[0.142]	[0.022]	[0.178]	[0.167]	[0.105]
Constante	0.050	-0.158**	-0.142**	-0.131**	-0.0011	0.0043	0.0047	-0.0028
	[0.050]	[0.075]	[0.062]	[0.060]	[0.014]	[0.022]	[0.021]	[0.016]
Prueba de Endogeneidad		17.590	24.681	21.542		0.104	0.142	0.033
P-value		0.000	0.000	0.000		0.748	0.707	0.8548
Prueba de Sargan		2.120	2.595	3.174		0.488	0.822	1.042
P-value		0.145	0.458	0.529		0.784	0.976	0.984
Prueba First-Stage		80.378	62.530	51.840		47.477	29.165	30.611
P-value		0.000	0.000	0.000		0.000	0.000	0.000
Observaciones	1,115	1,115	1,115	1,115	5,909	5,909	5,909	5,909
Dummies sectoriales	Sí	Sí	Sí	Sí	Sí	Sí	Sí	Sí
R^2	0.047	0.239	0.305	0.318	0.293	0.292	0.292	0.293

Fuente: Elaboración propia con datos de ESIDET-MBN y ACTI.

Notas: a = Incremento del rango de bienes y servicios.
b = Incremento del rango de bienes y servicios, mejorar la calidad de bienes y servicios.
c = Incremento del rango de bienes y servicios, mejorar la calidad de bienes y servicios, e intensidad de innovación.
d = Los errores estándar están en los corchetes.
e = *** p<0.01, ** p<0.05, * p<0.1

rechazar la hipótesis de que la variable "crecimiento de ventas debido a nuevos productos" es exógena. Es decir, en términos estadísticos no existe un problema de endogeneidad por lo que el modelo MCO no estaría sesgado y, por tanto, sus coeficientes son los que se deben interpretar.

3.3 Descomposición de los efectos como forma de estandarizar los valores de los parámetros

Una vez estimados los modelos econométricos –ecuación (9)– se realiza una descomposición de la tasa de crecimiento del empleo, siguiendo las indicaciones del trabajo de Harrison *et al*. (2014) mediante la ecuación (11).

(11)
$$l = \sum_j (\alpha_0 + \alpha_{0j}) ind_{ji} + \alpha_1 d + \left[1 - 1(g_2 > 0)\right](g_1 - \pi) + \dots$$
$$\dots + 1(g_2 > 0)\left(g_1 - \pi + \hat{\beta} g_2\right) + \hat{\varepsilon}_i$$

El primer elemento, $\sum_j (\alpha_0 + \alpha_{0j}) ind_{ji}$, captura el crecimiento de la tendencia de la productividad en la producción de viejos productos (nivel industria). El segundo término, $\hat{\alpha}_1 d$, toma en cuenta el efecto bruto de la innovación de proceso en el crecimiento del empleo. El tercer término, $\left[1 - 1(g_2 > 0)\right](g_1 - \pi)]$, es la tasa de crecimiento del empleo relacionado con el crecimiento de las ventas si la empresa no ha introducido ninguna innovación de producto (no innovador o solo innovador de proceso). Finalmente, $1(g_2 > 0)\left(g_1 - \pi + \hat{\beta} g_2\right)$, proporciona información sobre el crecimiento del empleo relacionado con las ventas netas de nuevos productos. $\hat{\varepsilon}_i$ es el residual con media cero. Con lo anterior, de acuerdo con Harrison *et al*. (2014), es posible analizar como los efectos contribuyen al crecimiento del empleo.

(12)
$$l = t + \hat{\alpha}_1 P_{PO} + P_{NI} g_{NI} + P_I g_I$$

l es el crecimiento promedio del empleo; t es el promedio ponderado de las tendencias industriales específicas; P_{PO}, P_{NI}, y P_I, son las muestras proporcionales de únicamente innovadores de proceso, no innovadores de producto e innovadores de producto, respectivamente; g_{NI} captura la tasa promedio de las ventas para no innovadores de producto $g_{NI} = \frac{1}{N_{NI}} \sum_{i \in NI} g_{1i}$, mientras que g_I es la tasa promedio de las ventas para innovadores de producto $g_I = \frac{1}{N_I} \sum_{i \in I} (g_{1i} + \beta g_{2i})$ (Harrison *et al*., 2014).

TABLA 4

CONTRIBUCIONES AL PROMEDIO DEL CRECIMIENTO DEL EMPLEO

	(1) México	**(2) Ecuador**
Crecimiento del empleo	3.20	14.57
Debido a la tendencia de la productividad de productos viejos	-4.00	-6.75
Debido al efecto bruto de innovación de proceso en viejos productos	0.00	-0.02
Debido a crecimiento de ventas en viejos productos para empresas no innovadoras de producto	6.90	16.25
No innovadoras	6.50	12.00
Únicamente innovación de proceso	0.30	4.24
Debido a crecimiento de ventas netas debido a empresas innovadoras	0.40	5.09
Crecimiento de ventas debido a viejos productos	-0.30	0.80
Crecimiento de ventas debido a nuevos productos	0.70	4.29

Fuente: Elaboración propia con datos de ESIDET-MBN y ACTI, con los resultados de las estimaciones de la Tabla 3.

En la Tabla 4 se observa la contribución de las variables en el crecimiento del empleo (basándose en la ecuación (12)). El valor correspondiente a cada concepto se lee como la aportación de cada una de estas en el crecimiento del empleo. El crecimiento de la productividad de los productos ya existentes es una fuente de reducción de empleo para un nivel de producción dado para ambos países (-4% en México y -6.75% en Ecuador), este es mayor en Ecuador que en México. El efecto en las empresas que únicamente realizan innovación de proceso es muy pequeño para México y Ecuador. De hecho, se puede decir que es casi nulo (véase Tabla 2). El crecimiento de ventas de viejos productos de empresas no innovadoras compensa el efecto negativo de la productividad. Se observa que en México esta variable aporta un 6.9% y en Ecuador un 16.25%. Esta variable es la que tiene un mayor aporte sobre el crecimiento del empleo. Finalmente, el crecimiento neto de las ventas de empresas innovadoras de producto es positivo en el crecimiento del empleo. Dicho efecto es más pequeño en México (0.40%) que en Ecuador (5.09%).

En el primer caso, se observa un efecto moderado del crecimiento de las ventas debido a nuevos productos (0.70), pero que compensa el efecto negativo del crecimiento de las ventas debido a viejos productos (-0.30). En el segundo caso, tanto el crecimiento de las ventas a causa de viejos y nuevos productos es positivo.

4. Conclusiones

Los resultados del análisis realizado, sobre el efecto de la innovación en el empleo con base en el modelo propuesto por Harrison *et al*. (2014), para México y Ecuador, muestran que la innovación de proceso tiene un efecto negativo (aunque muy pequeño) para el caso mexicano, obteniendo el efecto esperado y sugerido por el modelo de Harrison *et al*. (2014). Se muestra que dicha forma de innovar ahorra trabajo. Por otro lado, en Ecuador, esta variable no es estadísticamente significativa siendo resultados similares al caso de Argentina y Chile (Crespi *et al*., 2011). Para ello, se utilizaron los resultados que provienen de las encuestas de innovación de cada país.

Se debe recordar que los análisis se realizan a nivel micro estudiando el efecto de la innovación sobre la empresa que la realiza. Por lo que el efecto de la introducción de innovación de proceso tiene dos efectos o mecanismos de compensación contrapuestos. Por un lado, la pérdida de empleo debido a una mayor productividad, pero, dado a los menores costes podría aumentarse la demanda total por lo que se suavizaría la pérdida de empleo. Además, las empresas que introducen innovaciones de proceso podrían captar parte del mercado de los competidores nacionales o internacionales (*business stealing effect*). Por otro lado, el efecto del crecimiento de las ventas de nuevos productos sobre el empleo es positivo y estadísticamente significativo, tanto en las estimaciones con MCO, como con las de variables instrumentales. Es importante mencionar que el coeficiente de dicha variable es cercano a uno para el caso de los dos países. Por lo que no hay evidencia de que tanto en México y Ecuador los nuevos productos se produzcan de forma más eficiente que los viejos. El efecto positivo de las innovaciones de producto se ha detectado en todos los estudios revisados por lo que el resultado del análisis realizado está en concordancia con la evidencia empírica previa.

Con la realización de la descomposición del crecimiento del empleo en sus distintos componentes (3.3), se observa que el efecto bruto de la innovación de proceso ha sido prácticamente nulo en ambos países. Las estadísticas muestran que hay muy pocas empresas que solo introducen innovación de proceso. En el caso de las ventas de viejos productos se advierte que es la variable que aporta más al crecimiento del empleo, tanto para México como para Ecuador. La variable captura el efecto de la demanda, la cual, ha aumentado en ambos países. El crecimiento neto de las ventas de empresas innovadoras de producto aporta positivamente en el crecimiento del empleo. Específicamente, el crecimiento de las ventas debido a nuevos productos tiene gran peso en el crecimiento de la empresa. A pesar del bajo nivel de innovación en dichos países.

Resumiendo, no se encuentra evidencia contundente de que la innovación de proceso tenga un efecto negativo sobre el empleo para Ecuador, mientras que, para México, aunque negativo el efecto es muy pequeño. Mientras que la innovación de producto es una fuente generadora de empleo. Ambos resultados se confirman para el caso manufacturero de México y Ecuador. Por lo tanto, se puede afirmar que la innovación (producto y proceso) no necesariamente reduce el empleo para estos países en términos cuantitativos.

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Direct and Indirect Impacts of Oil Price Shocks on Ecuador's Economic Cycles (2000:01-2020:01)*

Impactos directos e indirectos de las perturbaciones del precio del petróleo en los ciclos económicos de Ecuador (2000:01-2020:01)

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Abstract

We analyse the non-linear relationship between oil price shocks and the real business cycle in Ecuador, a dollarized economy where oil exports are the country's main source of foreign exchange. We estimate several autoregressive Markov switching models for the period 2000:01-2020:01 to identify the differentiated impact of nominal oil price shocks on real GDP in expansion and slowdown regimes. We find evidence that oil price shocks have an asymmetric effect on Ecuador's economic growth, with a larger impact during slowdowns. They also affect all components of aggregate demand differently in each regime, with a larger impact on investment during expansions.

Key words: *Business cycle; Oil prices; Nonlinear models; Markov Regime-Switching Model; Ecuador.*

JEL Classification: *E32, Q02, F63, O11.*

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Resumen

En este trabajo se analiza la relación no lineal entre las perturbaciones del precio del petróleo y el ciclo económico real en Ecuador, una economía dolarizada en la que las exportaciones de petróleo son la principal fuente de divisas del país. Para ello se estiman varios modelos autorregresivos de conmutación de Markov para el período 2000:01-2020:01 con el fin de identificar el impacto diferenciado de las perturbaciones nominales del precio del petróleo sobre el PIB real en los regímenes de expansión y desaceleración económica. Los principales resultados muestras que las perturbaciones de los precios del petróleo tienen un efecto asimétrico en el crecimiento económico del país, con un impacto mayor durante períodos de desaceleración. También se observa que afectan a todos los componentes de la demanda agregada de forma diferente en cada régimen, con un mayor impacto en la inversión durante fases de expansión del ciclo económico.

Palabras clave: *Ciclo económico; precios del petróleo, modelos no lineales, modelo de cambio de régimen de Markov; Ecuador.*

Clasificación JEL: *E32, Q02, F63, O11.*

1. Introduction

For most developing countries, commodity trade remains the main source of foreign exchange (Bowman and Husain 2004). This structure prevails today in most Latin American countries, exposing them to exogenous price shock in primary products (Acosta 1998). Commodity price fluctuations have a significant impact on economic and social aggregates in developing countries and are responsible for deeper growth cycles.

In the case of Ecuador, it is a small oil exporter with no influence on international oil prices but whose dependence is seen as a major factor in the country's economic cycles (Martinez Valle 2008). The weight of the oil sector in the economy has been around 6% of GDP since 2000, reaching a peak of 14% in 2010-2011 (CepalSTAT[1]). Domestic prices of oil derivatives have been intervened since 1973, always below international prices, with a staggered upward trend that has occurred every few years until 2018, and on an annual basis thereafter. This feature has largely insulated Ecuadorian demand from

[1] CEPALSTAT Bases de Datos y Publicaciones Estadísticas (https://statistics.cepal.org/portal/cepalstat/index.html?lang=es)

short-term oil price shocks, creating certainty and controlling inflation. However, investment is still affected by the oil shock on imported raw materials and capital goods. At the same time, the government allocates a high share of public expenditure to fuel subsidies, fluctuating between 32.1% in 2007 and 8.4% in 2017. (Muñoz-Miño 2018). However, since 2000, Ecuador has adopted the US dollar as its national currency, thereby losing its exchange rate policy and restricting its monetary policy. This has made the country more vulnerable to external shocks (Córdova Zambrano 2016). The country is currently embarking on large-scale mineral production, which will increase its dependence on commodities.

Several authors have analysed the transmission mechanisms of oil price changes on real variables and, ultimately, on the business cycle. Kilian (2008) points out that high oil prices cause economic crises in developed countries, most of which are net importers of this commodity. The direct or indirect transmission channels, ultimately affect aggregate demand and supply, either through changes in relative prices or through increases in production costs and uncertainty (Gonzalez and Hernandez 2016). In the case of primary exporters such as Ecuador, where oil exports are an important source of revenue for the public budget, this relationship should be the opposite.

The methodological strategy of most studies analysing the relationship between oil price shocks and economic growth was based on the application of linear models. However, several scholars find that commodity price shocks have different effects on output depending the business cycle (Raymond and Rich 1997; Clements and Krolzig 2002; Cologni and Manera 2009; Bjørnland *et al*. 2018; Cross *et al*. 2021). All of them agree that these dynamics are best characterized by Markov switching models.

With these considerations in mind, the aim of this paper is twofold. First, we analyse the business cycles of the Ecuadorian economy during the period 2000 to 2020 (quarterly series).[2] Second, we study the impact of oil price shocks on the business cycle in Ecuador, taking into account the presence of asymmetries or non-linearities in their relationship. A Markov Regime-Switching Autoregressive (MSAR) model is used to identify the regime shifts between expansions and contractions and how oil price shocks may have contributed to them. Instead of considering growth rates of both variables, we use trend deviations of both series to ensure stationarity of the underlying series.

The rest of the paper is structured as follows. The next section reviews the relevant literature on business cycles and their relationship with commodity price shocks in developing countries, with a particular focus on oil price fluctu-

2 The sample period starts from 2000:01 due to the unavailability of previous data for quarterly GDP and its components at the Central Bank of Ecuador. The latest quarter analysed is 2020:01 in order to avoid the impact of COVID-19.

ations. This is followed by a description of the Markov switching (MS) model first applied by Hamilton (1989), which provides a better fit to time series with important structural changes. We then include in the MS model the impact of exogenous oil shocks on real GDP cycle, following Raymond and Rich (1997), Clements and Krolzig (2002), Holmes and Wang (2003), Cologni and Manera (2009) or Balcilar (2017). This is followed by a discussion of the different alternatives used with respect to the variables considered in the empirical analyses (nominal or real, in levels, differences or deviations from trend) and introduce the data sources. We then present the main results obtained for the Ecuadorian economy during the period 2000:01-2020:01 to reflect the expansionary and contractionary states of the country and its relationship with oil price shocks. The last section concludes.

2. Economic Effects of Oil Price Shocks

Following the oil shocks of the 1970s, a large literature on oil price shocks and their impact on macroeconomic aggregates emerged (Mork 1989), especially in the United States, a country with a significant and secular oil trade deficit. Most of them found an inverse relationship between oil price growth and output growth (Hamilton 1983, 1996b 2011; Mork 1989; Lee *et al.* 1995; Raymond and Rich 1997; Clements 2002; Kilian 2010 2014; Kilian and Vigfusson 2011 among others). Blanchard and Gali (2007), Peersman and Robays (2012), Calvacanti and Jalles (2013), Taghizadeh-Hesary et al. (2016), find the same result for net oil importers.

Most studies have focused on investigating the possible non-linear and asymmetric relationship between oil price shocks and economic growth. (Balcilar et al. 2017) and its transmission mechanism. Hamilton (1983) finds that major oil shocks (1973-1974, 1979, and 1980-1981) have been followed by major recessions in the US. Mork (1989) observes a negative effect on US output growth when oil prices rise and no correlation when oil prices fall. Hamilton (1996) obtains similar results. Raymond and Richard (1997) find that oil price shocks are responsible for shifts in the mean of some low-growth periods of output rather than the transition probabilities between growth states. Hamilton (2003) notes that oil price increases have a larger effect on GDP growth than oil price decreases. Cologni and Manera (2009) analyse the impact of seven different definitions of oil shocks (all in differences) on business cycle measured as the output growth. They find asymmetric effects of oil price shocks depending on the phase of the cycle for the G-7 countries and that their ability to explain recessionary episodes has declined over time due to improvements in energy efficiency and a better management of external supply and demand shocks by monetary authorities. Herrera *et al*. (2011) observe that the results are sensitive to the estimation period and the aggregation level. Non-linear models have stronger supports for samples up to 1973, but samples with data after 1973 became much weaker. On the other hand, Kilian (2008) finds no evidence of asymmetries in the response of US demand to increases and decreases in energy prices.

Other studies have focused on the transmission channel of oil price shocks to real GDP and other relevant macroeconomic variables. On demand-side Hamilton (1988), Bresnahan and Ramey (1993), Kilian (2008) consider that oil shocks negatively affect US real GDP through consumer spending and business investment. On the supply side, McCallum (1989) finds that oil price increases are a prominent disruptor for industries, that have to pay for imported raw materials, especially energy. Hamilton (1983), Davis (1985), Loungani (1986) and Mork (1989) find reallocation effects of energy price shocks on capital and labour across sectors. However, Barsky and Kilian (2004) argue that energy price shocks should not be considered as aggregate supply shocks because they cannot be interpreted as productivity shocks to real GDP.

Over the past decade, a growing number of studies have also focused on emerging markets. Lescaroux and Mignon (2008) examine three groups of countries: oil importers, oil exporters and OPEC oil producers for different periods. They find that oil prices have a causal effect on GDP for oil importers and OPEC countries, but not for other oil exporters. Berument *et al*. (2010), using a set of small oil exporters and importers in the Middle East and North Africa between 1952 and 2005, find that a shock in oil prices (demand or supply driven) has a positive and significant effect on the growth of net oil exporting economies. In the case of oil-importing economies, output is found to fall for positive oil supply shocks, but rise with positive demand shocks. Alley *et al*. (2014), find a positive impact in oil exporting countries such as Nigeria. However, these shocks create uncertainty and undermine effective fiscal management of oil revenues.

Ahmadia and Manera (2021) find that the impact of oil shocks on the output of oil exporters varies across countries and depends strongly on the underlying cause of the oil shocks (demand or supply driven), as well as the economic health of each country. They also find no evidence of an asymmetric response of output to oil price rises or falls. Babuga and Ahmad (2022), for net oil exporters in Sub-Saharan Africa, whose economies are largely dependent on oil revenues for saving, investment and economic diversification, find a non-linear, inverted U-shaped relationship between the increase in oil prices above a certain threshold and real GDP.

For Latin American countries, Perilla (2010) observes a positive relationship between oil price shocks and the growth of the Colombian economy (a net oil exporter) for the period 1990-2009. Gonzalez and Hernandez (2016) confirm this result for the period 1982-2013, that last 4 to 5 quarters after the shock. They suggest that private consumption serves as an indirect transmission channel of oil price shocks to GDP, especially in the period 2000-2013. Alarcón *et al.* (2016), find for Brazil, a net oil importer, a strong significant negative effect on economic growth over the period 1991:01-2014:01. For Colombia and Peru, the result is less significant perhaps due to domestic oil price controls that allow industries to be less sensitive by oil price shocks, in line with Blanchard and Gali (2007) and Uribe and Ulloa (2011). For Ecuador, Paladines (2017) and Paladines and Paladines (2017) and Peralta (2020), using annual data, find a positive impact of oil price shocks on output per capita in the following two years, before returning to the initial level.

3. Oil Shocks Effects On Economic Cycles: A Markov–Switching Analysis

The study of business cycles has increased significantly in developed countries, especially in the United States, thanks to the efforts of the National Bureau of Economic Research (NBER), which have abundant information on business cycles and their impact on the different economic variables, especially employment (Mejía-Reyes 2003). Time series analysis has shown that the regression parameters are not constant over time and that there are structural changes that divide the time series into different regimes with different dynamic patterns over time. Nelson and Plosser (1982), Neftci (1984), De Long and Summers (1984), Watson (1986), Hamilton (1989) are among the first to note the existence of nonlinearities or asymmetries in economic variables and business cycles.

Since Hamilton (1989), a growing number of researchers have analysed these asymmetries using Markov Switching regression (Filardo 1994, Durland and McCurdy 1994; Hansen 1996). For Latin America, we find Mejía-Reyes (2000), Salamanca Lugo (2012) or Bayancela (2016) for Ecuador.[3] However, these studies only consider univariate autoregressive models in which the business cycle is explained by GDP growth. As Blanchard and Quah (1989) point out, the analysis of GDP alone is not sufficient to characterise the effects of both supply and demand shocks (Kuan 2002).

[3] Mejía-Reyes (2000) uses multiple univariate Markov Switching autoregressive (MSAR) models in eight economies, finding asymmetries in their business cycles, with recessions being deeper in absolute terms, less persistent and more volatile than expansions. Salamanca Lugo (2012), uses a Markov-Switching vector autoregressive regression model (MSVAR), to analyse the presence of a common cycle between Colombia, Venezuela and Ecuador, in which the fluctuations of each economy are characterized by similar movements of productive activity, with marked asymmetries between expansion and contraction phases. Bayancela (2016), applies a Markov regime-switching model, to explain the economic cycles in Ecuador for the period 1997-2015.

Hamilton (1996) is the first to include a dynamic specification of Markov switching models that depend on a vector of observable exogenous variables. However, he does not analyse their impact on the variable of interest. Raymond and Rich (1997) use a generalised Markov switching model to examine the influence of net real oil price increases on post-war US business cycle fluctuations (GDP growth) and whether they help to predict transitions between periods of positive and negative growth. Clements and Krolzig (2002) use a cointegrated Markov-switching vector autoregressive model (MS-VAR) with three-states and note that business cycle asymmetries do not appear to be explained by oil prices. Cologni and Manera (2009) examine the impact of oil shocks on the G-7 business cycle and find an asymmetric effect of oil price growth on output growth using different MS-VAR models. They find that models with exogenous oil variables generally outperform the corresponding univariate specifications. Balcilar *et al*. (2017) use a Bayesian Markov switching vector autoregressive model and found that oil price shocks affect South African real output growth under the low growth regimes. Bjørnland et al. (2018) take a different approach to analysing the role of oil price volatility in US macroeconomic variables and monetary policy. Based on Liu, Waggoner, and Zha (2011) and Bianchi (2013) they use a New Keynesian Markov switching rational expectations model in a DSGE framework. They find that the decline in oil volatility since 1985 is the most important factor reducing macroeconomic variability in the US. Živkov and Đuraškovi (2023) use MS-GARCH models to investigate how oil price uncertainty affects real GDP and industrial production in eight Central and Eastern European countries (CEEC). They find that oil price uncertainty has a small effect on output in moderate market conditions in the selected countries. On the other hand, in periods of deep economic crisis, an increase in oil price uncertainty reduces output, thereby adding to recessionary pressures in the economy. Conversely, when the economy is in expansion, oil price uncertainty has no effect on output.

Regime switching models were introduced into the literature by Quandt (1972), who examined time series processes that can exhibit random structural changes in which the switching events are independent over time (Kuan 2002). Subsequently, Goldfeld and Quandt (1973), Miron *et al*. (1987), Hamilton (1989) proposed a Markov regime switching model to analyse the US business cycle where switching events depend on the immediate past state.

The Markov switching model contains multiple structures that can capture nonlinear dynamics and sudden changes in the variability of a stationary time series autoregression (Hamilton 1996).[4] A general extension of the Markov

[4] Markov switching models require stationary data with zero mean. If the series have a unit root, the switching intercept results in a deterministic trend with breaks in that series. One solution is to transform the by applying first differences (Kuan 2002).

switching vector autoregressions of order p and s regimes mean adjusted model [MSM(s)-VAR(p)] is presented in Krolzig (1998) and Clements and Krolzig (2002):

$$(1) \qquad y_t - \mu_{s_t} = \sum_{k=1}^{p} \alpha_{ks_t}(y_{t-k} - \mu_{s_{t-k}}) + \varepsilon_{s_t} \text{ ,}$$

where y_t is a stationary vector, $\varepsilon_{s_t} \approx i.i.d.N\left(0,\sigma_{s_t}^2\right)$ and all parameters (μ_{s_t} , $\alpha_{ks_t}, \sigma_{s_t}^2$) depend on the realised regime, a latent variable s_t which is called a regime or state. In this model, there is an immediate one-off jump in the process mean after a regime change (μ_1 in regime s_1 , jumps immediately to μ_2 when regime changes to s_2). Krolzig (1998) also presents a model with smooth adjustment of the mean after the transition from one regime to another. In this case we can use a model with a regime-dependent intercept [MSI(s)-VAR(p)]:

$$(2) \qquad y_t = v_{s_t} + \sum_{k=1}^{p} \alpha_{ks_t}(y_{t-k} - \mu_{s_{t-k}}) + \varepsilon_{s_t} \text{ ,}$$

The Markov switching models are defined by the transition probabilities that determine the persistence of each regime (Kuan 2002). If we consider only two regimes, s_t = i,j are the unobserved first-order Markovian state variables governing the transition between the two distributions of y_t which can be summarised in the following transition probability matrix (P):

$$(3) \qquad \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix},$$

where $p_{ij} \equiv \Pr ob[s_t = j \mid s_{t-1} = i]$ (i,j=0,1) denotes the transition probabilities from state $s_{t-1} = i$ to state $s_t = j$, that satisfies $p_{00} + p_{10} = 1$ and $p_{01} + p_{11} = 1$. For example, p_{11} is the probability of being in state 1 in period t if the economy was in state 1 in t-1. Clements and Krolzig (2002) and Cologni and Manera (2008) support Raymond and Rich (1997)'s assumption that transition probabilities are time-invariant, i.e., the likelihood of transitioning between different states remain constant over the entire time period under consideration. This assumption is based in the ergodic property of the MS model.[5]

Other MS models have focused on state dependence in the variance of the error term. The Markov switching autoregressive conditional heteroscedasticity (MSARCH) model and a Markov switching generalised autoregressive conditional heteroscedasticity (MS-GARCH) model allow these differenc-

5 Other authors have considered endogenous switching models where the probability of switching regime can vary over time depending of the state of the economy (Chang *et al*. 2017; Bazzi *et al*. 2017; Benigno *et al*. 2020; Hubrich and Waggoner 2021). However, these models assume endogeneity of the switching process where there are structural breaks (Bhar and Hamori 2007).

es to be analysed. The first one assumes a conditional mean of the residuals for each state and the conditional variance as a function of the lagged squared residuals ($\sigma_{s_t} = \alpha_{0t} + \alpha_{1t}\varepsilon^2_{t-1}$). Here conditional variance captures recent shocks through the squared residuals. The MS-GARCH model extends the previous one by including the lagged values of the conditional variance ($\sigma_{s_t} = \alpha_{0t} + \alpha_{1s_t}\varepsilon^2_{t-1} + \beta_{ts_t}\sigma_{t-1s_t}$). It additionally captures the persistence and asymmetry in the volatility of the residuals by combining recent shocks with past volatility, through the lagged conditional variance (Bauwens *et al*. 2018). When $\alpha_{1t} + \beta_{ts_t}$ is statistically significant there will be conditional heterocedasticity in the dispersion of the error term (Ardia *et al*. 2019).

4. Variable Specifications

The effect of oil price shocks on business cycles has been analyzed using different models and variable specifications. There is consensus in the literature on the use of GDP in real terms, but there are different criteria on whether to include nominal or real oil prices. Some authors use nominal prices (Hamilton 1983, 2008; Jimenez-Rodriguez 2009; Alquist *et al*. 2013; Abdulkareem and Abdulhakeem 2016; Balcilar *et al*. 2017; Karaki 2017; Majidli 2020; Dwipa and Wicaksono 2021, just to cite a few). Others use the real price of oil by deflating the nominal price with the US consumer price index (Mork 1989; Ferderer 1992; Hooker 1996; Raymond and Rich 1997; Clements and Krolik 2002; Holmes and Wang 2003; Kilian 2006; Cologne and Manera 2009; Berument *et al*. 2010; Cross *et al*. 2021). At this respect, Hamilton (1993:238) gives two reasons in favour of using nominal oil prices: "(1) the institutional argument is that nominal, not real oil prices track the historical petroleum shocks and are the exogenous variable belonging in a reduced-form regression, and (2) it is naive to assume that the expected change in the relative shadow price of oil equals the (possibly disequilibrium) market price divided by a contemporaneous price index". We ran all the models with both real and nominal oil prices. The results were similar, although the fit was lower in the second case.

Another issue is whether these variables should be included in levels or in differences (change in the natural logarithm). In order to represent the business cycle, most of the literature cited has used GDP growth rates, measured as the percentage change in real GDP from one period to another. Positive growth rates indicate economic expansion, while negative growth rates denote contraction. The first-differencing method eliminates the trend component, but it exacerbates the effect of high frequency noise (Stock and Watson 1999). Alternatively, the business cycles can be measured as deviations of actual GDP from its long-term trend. Positive deviations from the trend indicate above-average economic activity, while negative deviations suggest below-average activity. Various statistical techniques are used to estimate the trend component of GDP, such as moving averages, Hodrick-Prescott (HP) or Baxter King (BK) filters or other time-series decomposition methods (Baxter and King 1994; Hodrick and Prescott 1997; Stock and Watson 1999; Orphanides and Van Norden 2002). The Central Banks of Ecuador, Chile, Mexico or Brazil calculates business cycles using GDP trend deviations based on OECD (1987).[6] However, using GDP trend deviations alone does not assure stationarity of GDP (Stock and Watson 1999). We need to analyse the properties of the GDP series using unit root tests (Augmented Dickey-Fuller, Phillips-Perron). We will use this approach.

Another concern is to control for the seasonality of the series. Stock and Watson 1988; Finn 1991; Artis *et al*. 1997; Xiong 2015) provide evidence of quarterly GDP seasonality. In order to deseasonalise the quarterly series, structural time series models may be used when needed which include seasonal dummies in the regression (Baum 2006).

With respect to oil price shocks, most studies have used the growth rate (Hamilton 1983, 1996b, 2003; Gisser and Goodwin 1986; Mork 1989; Dotsey and Reid 1992; Hooker 1996; Kilian 2008; Lescaroux and Mignon 2008; Berument *et al*. 2010; Bergman 2019; Maheu *et al*. 2020). Hamilton (1996b) recommends to use an annual net oil price increase over the previous year. Raymond and Rich (1997) and Clements and Krolzig (2002) use the same variable. Just a few have estimated oil prices at levels (Huntington 2005; Gronwald 2008; Gozali 2010; ThankGod and Maxwell 2013). Hooker (1996) analyses oil prices in nominal log-differences and in real log-levels, however he gives three reasons for using levels: the price of oil appears to be bounded up and down. Carruth, Hooker and Oswald (1995) and Phelps (1994) have developed theoretical models which imply that firms' input prices are affected by the level rather than the first difference. Finally, the real price of oil is now roughly at the level of the 1950s and 1960s, which is consistent with stationarity. Since Markov switching models require stationary series, we will use trend deviations for all variables.

On the other hand, oil price shocks can be assumed a state-invariant covariate as in Raymond and Rich (1997), based on evidence from Hamilton (1983) and Cochrane (1994) that oil price changes are exogenous to the state of US economy. Clements and Krolzig (2002) use the same approach for a three-regime model. Others consider state dependent mean effects of oil price shocks (Mork 1989, Holmes and Wang 2003, Balcilar *et al*. 2017 or Živkov and Đurašković 2022). As in Cologni and Manera (2009) we will consider both

[6] Central Bank of Ecuador uses the HP filter (Erraez 2014).

cases using different MS-VAR models.

The next step is to determine whether AR(p) or MA(q) terms are needed to correct for any remaining autocorrelation in the series (Becketti 2020). We should follow the principle of parsimony suggested by Box and Jenkins (1976), which implies that the simpler model (with fewer parameters) should be chosen. There are different approaches for a correct modelling of time series. Box-Jenkins (1970) propose an iterative process that involves four stages: identification, estimation, diagnostic checking and forecasting of time series (Wabomba *et al.* 2016). The identification process includes the analysis of the Auto Correlation Function (ACF) (for MA) and Partial Auto Correlation Function (PACF) (for AR). They can be complemented with Akaike's (1974) information criterion (AIC) and Schwarz (1978) BIC, or the maximization of the mean log-likelihood. Muma and Karoki (2022) also propose to check autocorrelation with Ljung-Box Q-statistic, and Jarque-Bera (JB) test for normality of the residuals.

The analysis of Ecuador's business cycle begins testing Hamilton's (1989) MSI-AR model, a univariate autoregressive Markov Switching model for real GDP to a two-state process (expansion and slowdown), which permits for gradual adjustment of the series after the change in the state of the GDP cycle. Then we allow the AR coefficients (α_{ks_t}) and/or the variance ($\sigma^2_{s_t}$) to be function of each regime (MSIAH-AR model).[7]

Next, we add the non-linear effects of oil price shocks in the MS model. We will assume the exogeneity of oil prices with respect to Ecuadorian output, in line with Killian (2005, 2006), Raymond and Rich (1997), Clements and Krolzig (2002), Cologni and Manera (2009) or Berument *et al.* (2010). In order to deseasonalise the quarterly series, we included state dependent quarterly dummies. From equation (2) we obtain:

$$(4) \qquad y_t = v_{s_t} + \sum_{k=1}^{p} \alpha_{ks_t}(y_{t-k} - \mu_{s_{t-k}}) + \sum_{d=1}^{4} \gamma_{ds_t} + \sum_{m=1}^{q} \beta_{ms_t} w_{t-m} + \varepsilon_{s_t} \, {}^{8}$$

$$\varepsilon_{s_t} \sim \text{i.i.d. } N(0, \sigma^2_{s_t}) \text{ t=1,2,...T}$$

where (y_t) is the quarterly trend deviation of Ecuador's real GDP; (y_{t-j}) is the autoregressive term, whose coefficients can be assumed to be state-independent (α_k) or state-dependent (α_{ks_t}) of the latent variable s_t which in-

[7] The error terms will be heterocedastic if ($\sigma^2_{s_t}$) differ between regimes.

[8] The general model can be also expressed as follows for p=q:

$$(5) \qquad \begin{gathered} y_t = \mu_{s_t} + y_{t-1}\alpha_{s_t} + w_t\beta_{s_t} \\ + \sum_{k=1}^{P} \theta_{is_t}(y_{t-k} - \mu_{s_{t-k}} - y_{t-2k}\alpha_{s_{t-2k}} - w_{t-k}\beta_{ks_{t-1}}) + \varepsilon_{s_t} \\ \varepsilon_{s_t} \sim \text{i.i.d. } N(0, \sigma^2_{s_t}) \text{ t=1,2,...T} \end{gathered}$$

The state-dependent AR terms (θ_{is_t}), corresponds to the lagged value of the residuals, and represents a moving average process (the current value of y_t depends linearly on the current and past error terms). (tsmswitch.pdf (stata.com) dicates the unobservable regimes (“expansion” and “contraction”). v_{s_t} is the state dependent intercept and the exogenous variable and γ_{ds_t} is a vector of seasonal dummy variables where $\gamma_{ds_t} = 1$ if t is in quarter d and 0 otherwise. (w_{t-m}) corresponds to the quarterly trend deviation of nominal WTI prices, where the coefficient (β_m) will initially be assumed to be state invariant. This assumption is subsequently relaxed and considered to be state-dependent (β_{ms_t}), to check whether oil prices shocks have an asymmetric or non-linear effect on economic growth (i.e. they can have either a positive or negative effect on economic growth depending on the state of the economy). (y_t) follows a p-th and (w_{t-m}) follows a q-th order autoregressive process. (ε_{s_t}) corresponds to the normally distributed errors with zero mean and state-independent (σ^2) or state-dependent ($\sigma^2_{s_t}$) variance. The number of lags (p, q) included for each variable will be determined using information criterion and likelihood ratio (LR) tests (Cologni and Manera 2009). The optimal specification (with lower information criterion and LR ratio) will be presented in the tables below. Unlike Hamilton (1996), Raymond and Rich (1997) or Clements and Krolzig (2002), we will also test the effects of oil price declines on real GDP cycles, given its direct dependence on the oil-exporting Ecuadorian economy.

The estimation of the parameters was based on the resolution of the expectation maximisation (EM) algorithm developed by Dempster *et al.* (1977) to find maximum likelihood estimators in probabilistic models that depend on unobservable variables. In addition, the inference of the probability of occurrence of each regime was performed using nonlinear filters and smoothers proposed by Hamilton (1989).

Finally, we test for the presence of volatility clustering in the residuals of the selected MS-AR-X model by assuming that the variance of the error term follows an MS-ARCH or an MS-GARCH process. We check whether they differ across regimes due to the effect of the explanatory variable, the oil price shocks.

5. Data Sources And Empirical Results

We examine two quarterly time series for the period 2000:01-2022:04[9]: (1) GDP in constant 2007 dollars, obtained from the Central Bank of Ecuador; (2) West Texas Intermediate (WTI) oil prices in nominal terms obtained from the FRED economic data on the St. Louis FED, which serve as a proxy for the price of Ecuadorian crude oil on international markets. Figure 1 displays the time paths of these series in levels and tend deviations.

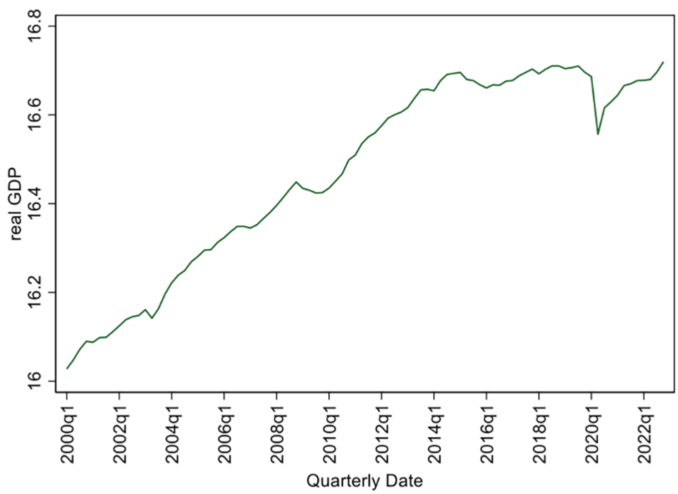
[9] Central Bank of Ecuador has historical series of quarterly GDP from 2000:01 to 2022:04.

FIGURE 1

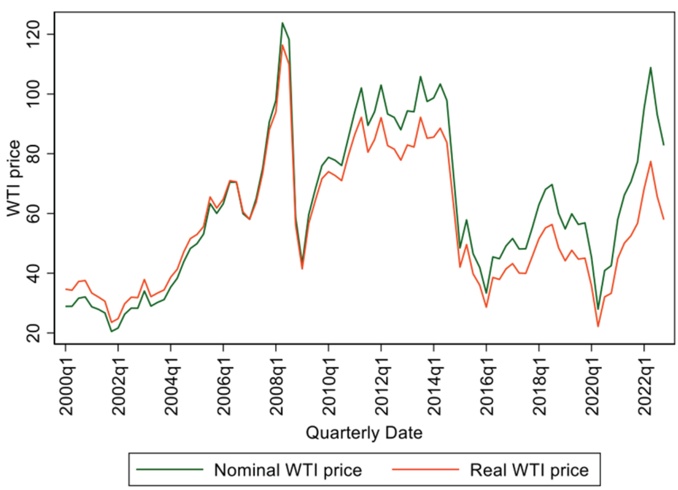
LEVELS AND DIFFERENCES OF QUARTERLY SERIES.

PERIOD 2000:01 TO 2022:04

A) Real GDP (US Dollar, 2007) (LOGS)

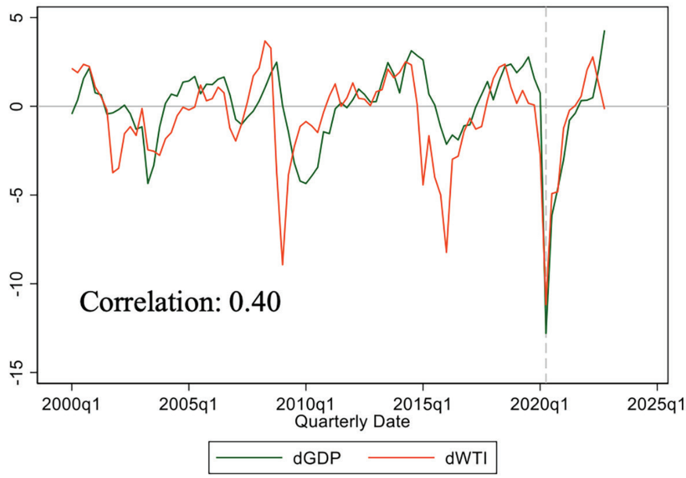


B) Nominal and Real (US Dollar, 2007) (LOGS)



The quarterly series of real GDP in logarithms (Figure 1a) are clearly non-stationary and could be characterized by a trend stationary process from 2000:01 to 2020:02. At this point Ecuador reaches its lowest real GDP growth

C) GDP and WTI Bussines Cycles (Trend Deviations)



Source: Central Bank of Ecuador for quarterly real GDP, FRED economic data from the St Louis FED for nominal and real oil prices.

of -12.8% (vertical dotted line) due to the Covid-19 pandemic, followed by a period of recovery. The quarterly series for nominal and real WTI in logarithms (Figure 1b) show a less clear pattern with significant fluctuations until 2015, when the price seems to stabilise. The nominal and real series also show similar trends, which start to diverge from 2009.01 onwards. We then present the trend deviation of both variables obtained after applying the Hodrick-Prescot filter, taking into account nominal oil prices. (Figure 1c). The series appear to be stationary with constant mean and variance. To guarantee stationarity of the underlying series, we conduct unit root tests (Augmented Dickey Fuller-ADF and Philip-Perron-PP). Table 1 confirms that the series are not stationary in levels but are stationary in trend deviations. Figure 1c also shows that both processes have a significant correlation (0.40), when the WTI price falls/rises, GDP also falls/rises, most often in the following quarter.

The next step is to examine the generating process of both series. The analysis of the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) indicate that trend deviations of the series are ARMA(2,2) (see Figure A1). Also the lower information criteria (AIC, AICC, BIC, HQIC) is found for two lags in both series (see Table A1). With regard to other statistics presented in Table A1, trend deviations for real GDP series (in logs) and nominal WTI prices appear to be normally distributed according to the Jarque-Bera Test. The Ljung-Box Q-test fails to reject the null hypothesis of a white nose, indicating that the series are not autocorrelated.

TABLE 1

UNIT ROOT TEST FOR STATIONARITY

			ADF		PP	
Variable			t-statistics	pvalue	t-statistics	pvalue
LnGDP	Level	Intercept	-2.193	0.2088	-2.434	0.1324
		Intercept, Trend	-0.305	0.9894	-0.694	0.9735
	Trend Deviation	Intercept	-3.486**	0.0083	-3.037*	0.0316
		Intercept, Trend	-3.444*	0.0458	-3.022*	0.0126
LnWTI	Level	Intercept	-2.037	0.2707	-2.076	0.2542
		Intercept, Trend	-1.966	0.6199	-2.116	0.5374
	Trend Deviation	Intercept	-3.907**	0.0020	-3.785**	0.0031
		Intercept, Trend	-3.880*	0.0129	-3.755*	0.0190

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Next, we test the Markov–Switching (MS) autoregressive time series models. We considered two regimes as proposed by Hamilton (1989), Raymond and Rich (1997), Cologni and Manera (2009), where the economy can be in a contraction state of the business cycle, represented by $s_t=1$, or in a phase of expansion, represented by $s_t=2$.[10] For both series, we applied a filtering process where factors such as seasonal patterns, outliers and trend, which may obscure the cyclical component of the series, are removed.

Table 2 presents the results of four MSAR models for the period 2000:01-2020:01 (quarterly series) in order to avoid the Covid-19 shock where the causes of the slowdown are linked to the pandemic and not so directly to changes in oil prices[11]. The standard deviations of the estimators are shown in parentheses. All MS test have been carried out with the EM algorithm.

The first column (1) replicates the Hamilton (1989) univariate two-state Markov switching model for GDP, taking into account two lags in the autoregressive term (MSI(2)-AR(2) model), as suggested by the PACF and the information criterion. This estimation is used as a benchmark for the rest of the models. We observe that output has two clearly distinct growth regimes, state 1 being the slowdown regime and state 2 being the expansion regime, with an

10 For Estimations and post-estimations of the Markov switching AR regression, the STATA *mswitch* package was used.

11 The fitted model would then have an inflated value of the variance for the stochastic level (Atkinson et al., 1997).

TABLE 2

EM ESTIMATORS FOR THE MARKOV REGIME-SWITCHING MODEL OF REAL GDP FOR ECUADOR, 2000:01-2020:01

	(1)	(2)	(3)	(4)
STATE INVARIANT				
AR_{t-1}	1.421*** (3.89)		0.787*** (6.20)	
AR_{t-2}	-0.702***		-0.0526 (-0.42)	
w_{t-1}			0.138** (2.93)	
w_{t-2}			0.237*** (4.79)	
STATE 1 (Slowdown)				
Average growth rate in recession state(μ_{s_1})	-0.267 (-0.72)	-0.246 (0.353)	-2.695*** (-5.36)	-0.802*** (0.140)
Decreasing oil price dummy				
AR_{1t-1}		1.261*** (0.106)		-1.341*** (0.0474)
AR_{1t-2}		-0.567*** (0.104)		
w_{t-1}				0.175** (0.0633)
w_{t-2}				0.973*** (0.0509)
STATE 2 (Expansion)				
Average growth rate in expansion state(μ_{s_2})	0.9753** (2.18)	0.756* (0.412)	0.183 (0.61)	0.699*** (0.0882)
Decreasing oil price dummy				
AR_{2t-1}		1.894*** (0.289)		0.673*** (0.0783)
AR_{2t-2}		-1.123*** (0.253)		
w_{t-1}				0.209*** (0.0415)
w_{t-2}				0.316*** (0.0231)

Standard Deviation (σ)	0.8626	0.83176	0.6314	
Standard Deviation State 1 (σ_1)				0.0961
Standard Deviation State 2 (σ_2)				0.5746
p_{11}	0.8179	0.7877	0.6633	0.5851
p_{21}	0.0569	0.0693	0.0282	0.0579
Log-Likelihood	-115.85	-114.37	-86.81	-69.74
AIC	3.2761	3.2898	2.5664	2.2499
HQIC	3.3625	3.4008	2.7125	2.4676
SBIC	3.4924	3.5679	2.9317	2.7937
Duration s_1	1.060	4.710	2.970	2.410
Duration s_2	5.493	14.43	35.388	17.263
Jarque-Bera test on residuals	2.771	2.829	74***	3974***
Ljung-Box Q-test on residuals	106.1417 (0.0000)	103.0371 (0.0000)	35.7911 (0.4785)	9.9041 (1.0000)
Skewness on residuals	-0.3765	-0.3774	-1.1627	-5.0164
Kurtosis on residuals	3.565	3.579	7.202	36.266
Obs.	75	75	77	79

Notes: Seasonal dummies are not presented in the table. Standard errors in parentheses * p<0.05, ** p<0.01, *** p<0.001. i=0,1

average growth rate of -0.27% and 0.97% respectively. The dynamics of real GDP series are captured by the autoregressive coefficients (AR_i). They are considered to be state-independent and indicate that shocks have a significant inertia in the next quarter, followed by an opposite effect. This means that there is a tendency to restore equilibrium. The estimated probability of remaining in state 1 in the next period, is 0.81 while the estimated probability of transitioning to state 2 is 0.19 (1-0.81). On the other hand, the probability of remaining in state 2 in the next period is 0.94 and to transition to state 1 is 0.06 (1-0.94). This implies that both states are highly persistent, although slightly higher for expansionary states. Finally, the average duration of state 1 $\left[(1-p_{11})^{-1}\right]$ is one quarter and for state 2 $\left[(1-p_{22})^{-1}\right]$ is 5.5 quarters.

The second column (2) shows an univariate MSIA(2)-AR(2) model where intercepts, and AR terms are allowed to vary across regimes. The fit of the model is similar to previous one (similar LL, AIC, HQIC and SIC). The mean growth in state 1 is -0.24% while for state 2 it is 0.76%. The slope estimates represented by the first-order autoregressive (AR_{is_t}). coefficients also differ across state, with higher values in expansions than in slowdowns, and with a positive impact in the first quarter followed by a shorter negative impact in the second quarter. The average duration of state 1 $\left[\left(1-p_{11}\right)^{-1}\right]$ is 1.14 quarters and that of state 2 $\left[\left(1-p_{22}\right)^{-1}\right]$ is 3.7 quarters, similar to those in the first model. In both cases, the residuals are normally distributed (we fail to reject the null hypothesis of the Jarque-Bera test), with skewness and kurtosis parameters close to zero. However, the Ljung-Box Q test for white noise in the residuals is rejected, suggesting that there is an autocorrelation problem in the error term.

We then include the nominal oil price shocks as an explanatory variable. The third column (3) presents the same specification as column (1) and includes two lags of nominal oil price deviations from trend as an exogenous state-invariant variable. This is the MSI(2)-AR(2)-X(2) model. The fit of the model improves with respect to the previous specifications (lower LL, AIC, HQIC and SIC). States 1 and 2 continue to represent the slowdown and expansion regimes, with an average growth rate of -2.7% and 0.18% respectively. The autoregressive coefficients (AR_i) have the same structural behaviour as in the previous cases, although only the first lag is statistically significant. With respect to nominal WTI price shocks, all coefficients are significant at 5%; an exogenous oil price shock has a direct effect on the business cycle of real GDP, which increases in the following quarter (0.14 and 0.23 respectively). The probability of remaining in the same state in the next quarter is higher in state 2 (0.97) than in state 1 (0.78). The average duration is also longer for state 2.

The fourth specification follows the structure of model (2) but includes oil price shocks as an exogenous state-dependent variable. After testing different specifications, the best fit was obtained with the model MSIAH(2)-AR(1)-X(2), where all parameters are allowed to be state-dependent. States 1 and 2 continue to represent contractionary and expansionary regimes (-0.8% and 0.7% respectively, both statistically significant). The autoregressive coefficients (AR_{is_t}) are significant at 99%, with a negative impact in state 1 (-1.3) and a positive impact in state 2 (0.7), implying that the lagged terms of y_t are better predictors in contractionary states than in expansionary states.

Oil price shocks also have a clearly asymmetric effect depending on the phase of the business cycle. In both states it has a positive and statistically significant effect on GDP, which increases in the second quarter after the shock. In expansionary states, this effect increases from 0.21 in the first quarter to 0.32 in the second one while in contractionary states the effect increases from 0,17 to 0.97. A 1% increase in the oil price has a cumulative positive effect on real GDP of 0.53% in slowdown states, while it reaches up to 1.14% over the following two quarters in expansionary states. The probabilities of remaining in states 1 and 2 are similar to models (1) and (2). Finally, the regime-dependent standard deviation of the residuals (σ_i) is much higher in state 2. This shows that expansions are more volatile than recessions suggesting the presence of a conditional heteroskedasticity process in the error terms.

With regard of the rest of the estimates, the probability of remaining in the same state in the next quarter is also lower in contraction states than in expansion states (0.79 and 0.96 respectively). The average duration of expansions is still higher than that of contractions (22.7 versus 4.9 quarters). The regime dependent standard deviation of the residuals (σ_i) is slightly higher in state 2.

Looking at the rest of the statistical properties of the estimated residuals for the oil price models (3 and 4), none of them are normally distributed according to the Jarque-Bera test, and although the skewness is close to zero (models 4 and 5), the kurtosis is significantly positive. This result together with the state-dependent variance, indicates that the residuals are not i.i.d. and that there may be a conditional heteroscedasticity process. However, Ljung-Box Q-tests for white noise in the residuals reject the null hypothesis of white noise, suggesting that the residuals are not autocorrelated. The former condition is necessary for conditional heteroscedasticity in regime-dependent variance MSAR models (Krolzig 1997). Later we test for the presence of ARCH and GARCH processes in the error terms.

To confirm the results of the MSIAH(2)-AR(2)-X(2) model (4), we compare the predicted values with the actual values of real GDP growth (Figure 2). We find that both series are very similar, which means that the predicted values account for a large part of the variation in the dependent variable. Next, we analyse the probability that the output process is in state 1 compared with the official data. Figure 3 compares the smooth and filtered predicted probabilities (Kim 1994) of being in state 1 with the Ecuadorian business cycles calculated by the CBE (shaded areas).

The MSIAH(2)-AR(2)-X(2) model appears to correctly predict the probability of being in contractionary (1) and expansionary (0) states in most periods. It also confirms that Ecuador is more likely to be in expansionary, durable and recurrent states than in contractionary states, in line with Balcilar *et al*. (2017) for South Africa. This result differs from those observed by Neftci (1982), Hamilton (1989) or Raymond and Rich (1997), who found for developed oil importing countries that growth periods are less durable and recurrent than recessionary periods. However, since 2013:04, the frequency of slowdowns has increased significantly in Ecuador.

We also include an impulse response (IRF) analysis under the linear VAR model, considering the whole period, and then we emulate an MS-IRF test using the series below trend for state 1 and the series above trend for state 2. Comparing the results for the aggregate model (VAR) with those for state 1

FIGURE 2

ACTUAL AND FITTED VALUES OF GDP TREND DEVIATIONS OF THE ECUADORIAN ECONOMY (2000:01-2020:1)

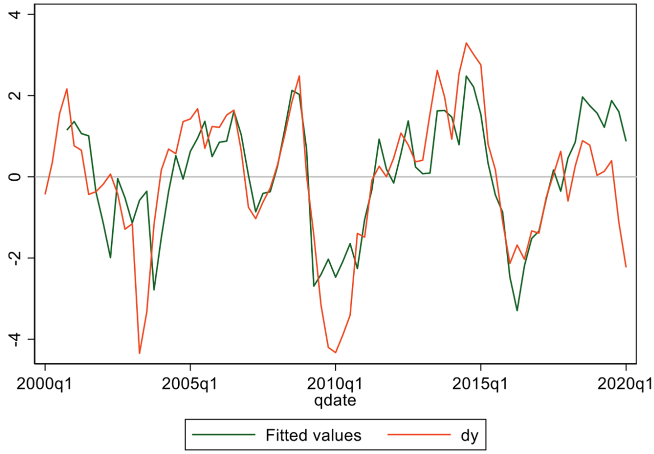
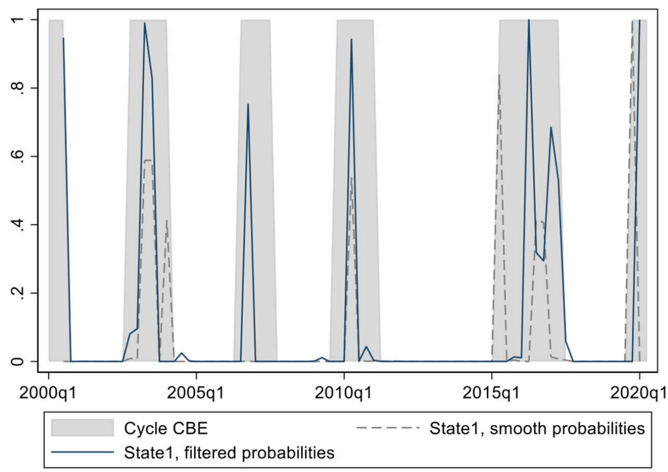


FIGURE 3

STATES OF THE ECUADORIAN ECONOMY OBTAINED WITH THE MARKOV REGIME SHIFT MODEL (2000:01-2020:01)

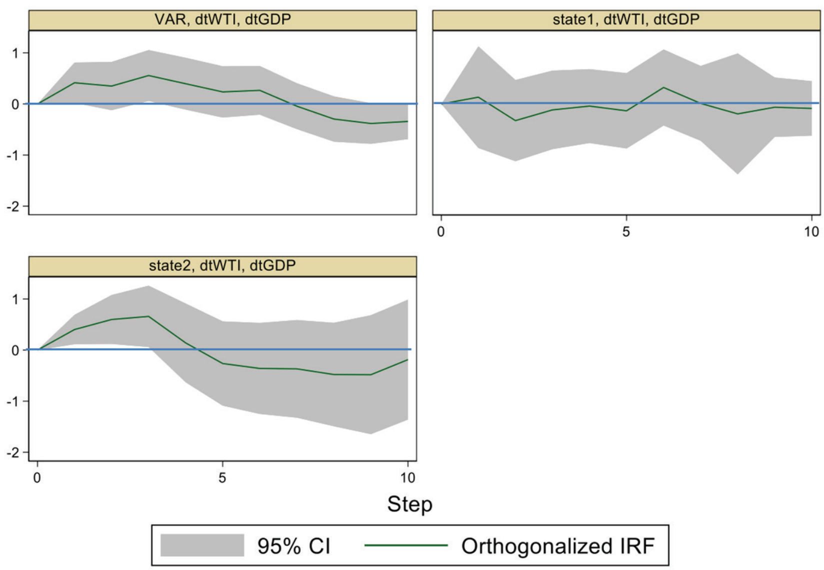


Notes: The shaded areas represent the periods of deceleration below trend calculated by the Central Bank of Ecuador. Filtered and smooth probabilities estimate the state in each period using previous and contemporaneous data in the first case and the smoothing algorithm in the second.

and 2, we observe the asymmetries in the impact of oil price shocks on the business cycle in Ecuador. In expansionary phases of the cycle (state 2), there is a higher positive effect in the first four quarters and then a negative effect in the following quarters. In contractionary phases (state 1), the effect is more discrete, with alternating periods of positive and negative impulses. The forecasting error variance decomposition (FEVD) gives us the total contribution of oil price shocks in explaining the forecast uncertainty of real GDP. In the case of the linear VAR model, we obtain a cumulative effect of 0.18% over 10 quarters. After decomposing the series, we find a deeper impact in expansionary states (0.64%) than in contractionary states (0.034%), which also confirms the asymmetric behaviour of oil price shocks over the GDP cycle.

FIGURE 4

IMPULSE RESPONSE OF REAL GDP TREND DEVIATION TO OIL PRICE SHOCKS IN LINEAR VAR AND MS-VAR MODELS (STATES 1 AND 2) (10 LAGS)



Graphs by irfname, impulse variable, and response variable.

To conclude this first exercise, we will analyse the conditional dependence of the error term obtained from our model (4). The residuals of the MSI-AH(2)-AR(2)-X(2) model were fitted with an MS-GARCH (1,1) model for each regime period[12], which allows us to estimate the conditional mean and variance parameters (Table 3).

TABLE 3
CONDITIONAL DEPENDENCE OF THE ERROR TERMS.
FITTED PARAMETERS

	Estimate	Std. Error	t value	Pr(>|t|)
α_{01}	2.7117	0.6268	4.3259	0.000
α_{11}	0.4236	0.0348	12.1608	0.000
β_1	0.3638	0.0159	22.9207	0.000
α_{02}	2.7119	0.6931	3.9126	0.000
α_{12}	0.4236	0.0362	11.7151	0.000
β_2	0.3638	0.0164	22.1326	<0.000

All coefficients are statistically significant, indicating that there are conditional variance effects. The conditional mean parameters (α_{0k}) and the conditional variance ARCH (α_{1k}) and GARCH parameters (β_k) are similar in the two regimes, implying that there are no statistically significant asymmetries across regimes with respect to the volatility process of the error terms. The conditional mean volatility is much higher than the conditional variance volatility, indicating that the mean of the residuals is highly volatile over the period analysed and that the variability around this mean is relatively stable. The ARCH term (α_{1k}) captures recent volatility via the squared residuals while (β_k) captures past volatility, through the lagged conditional variance. This second estimate is a bit higher. The persistence of volatility is also the same in both regimes ($\alpha_{1k} + \beta_k = 0.78$), showing that the positive oil shocks cause more volatility and vice versa in both regimes. However, further analysis should be carried out in this respect.

This analysis would be incomplete if we did not examine the indirect transmission channels of oil price shocks into GDP by recognising the deep interdependence between aggregate demand and aggregate supply. For simplicity, we

[12] We used *msgarch* package from *RStudio*.

focus on the impact of oil price changes on the main components of aggregate demand. We estimate the MSIAH(2)-AR(2)-X(2) (model 4), where the trend deviation of each component of demand is the dependent variable. In all cases, state 1 represents periods of contraction, while state 2 represents periods of expansion in demand aggregates (Table 4).

Nominal WTI price shocks show regime asymmetries in all components of aggregate demand. The effects are positive and larger in expansionary states (state 2). In the case of investment, an oil price shock has a strong positive and statistically significant effect in expansionary states (of investment) in the next quarter (3.157), followed by smaller effects in the following quarter (0.31). The cumulative effect over the two quarters is 3.4% for each 1% increase in oil prices. In the case of investment slowdowns, the effect of oil price shocks is smaller (a cumulative effect of 1.07%). These results demonstrate the pro-cyclical behaviour of Ecuadorian agents' investment decisions to international oil price shocks; when they rise, not only does the public sector have more revenue to invest, but the expectations of the private sector are higher, encouraging it to invest more. The opposite happens when oil prices fall, as the agents anticipate a crowding-out effect due to an increase in government borrowing to finance the public budget. This means that a rise in oil prices helps to restore the growth path of investment, but the opposite happens when oil prices fall, exposing the economy to a deeper cycle.

TABLE 4

EM ESTIMATORS FOR THE MARKOV REGIME-SWITCHING MODEL OF AGGREGATE DEMAND COMPONENTS FOR ECUADOR, 2000:01-2020:01

	Investment	**Openness**	**Public expenditure**	**Private consumption**
w_{t-1s_1}	0.574***	0.843***	0.234	-0.0606
	(0.170)	(0.0442)	(0.152)	(0.101)
w_{t-2s_1}	0.473***	0.0699*	0.877***	0.300**
	(0.107)	(0.0371)	(0.113)	(0.151)
Accumulated	1.047	0.9129	0.877	0.300
w_{t-1s_2}	3.157***	0.190**	0.509***	0.403***
	(0.109)	(0.0900)	(0.100)	(0.148)
w_{t-2s_2}	0.308*	0.989***	0.237**	0.202**
	(0.176)	(0.168)	(0.0779)	(0.0992)
Accumulated	3.465	1.179	0.746	0.605

Notes: Only the w_{t-m} effect is shown.

For openness, measured as the simple average of imports and exports, oil price shocks have a positive effect in both regimes. During cyclical slowdowns, the main effect is observed in the following quarter (0.84) and then declines to 0.07, with an aggregate effect of 1.18. In expansionary states, the main effect is observed in the second quarter with an aggregate effect of 0.91. For public expenditure, oil price shocks have a positive effect in both states (0.35 and 0.75 respectively). It increases in the second quarter in contractionary states, and decreases in expansionary states, confirming the pro-cyclical response of public policy to oil price shocks in expansionary states and the counter-cyclical response in slowing states. Private consumption seems to behave similarly, being positively affected by oil prices in both states.

6. Conclusions

This paper analyses the asymmetric effect of oil price shock on the business cycle of Ecuador, a highly oil-dependent and oil-exporting developing country since 1970. We applied a Markov switching autoregressive (MS-AR) regime model with two states, slowdown and expansion. We used two quarterly time series, real gross domestic product and the international price of WTI in nominal terms, during an observation period from 2000:01 to 2020:01, in order to avoid the effects of the COVID-19 pandemic on both series. Contrary to mainstream research that uses economic growth as a proxy for the business cycle, we use deviations from linear trend based on the methodology of the Central Bank of Ecuador (CBE) business cycle indicators, because although first differencing filters eliminate the trend component, they exacerbate the effect of high-frequency noise (Stock and Watson 1999). It also allows us to compare the results of our model with the Ecuadorian business cycles calculated by the CBE.

The oil price shocks are included as an exogenous variable (state-independent and state-dependent) in the Markov regime switching model with two lags. We find that exogenous oil price shocks have an asymmetric effect on Ecuador's business cycles: they have a more positive and persistent effect in expansions than in contractions; since GDP is in a slowdown process in contractionary states, an increase in oil prices would have a dampening effect but the opposite would occur when oil prices fall.

Using regime-dependent IRFs, we find that the cumulative impact of oil price shocks on real output is higher during expansions than in linear VAR models, and the opposite is true during slowdowns. The high aggregate impulse found between the two variables in expansionary states after 10 quarters (0.64) shows that Ecuador's economic specialisation in oil extraction has helped the country to generate further expansion thanks to oil price increases, but neither have oil price falls been determinants of contractions, as the aggregate impulse found in contractionary states is very low (0.034), perhaps as a result of the oil price controls that exist in the country.

We also observe that oil price volatility plays an important role in determining the volatility of GDP growth. However, we do not find asymmetries in the conditional variance of the error terms across regimes. Conditional mean volatility is higher than conditional variance volatility, the latter being similarly driven by recent volatility (via the squared residuals obtained from the ARCH model) and past volatility (via the lagged conditional variance obtained from the GARCH model). As in Abdulkareem and Abdulhakeem (2016) for Nigeria, the residuals show important persistence, with positive oil shocks causing more volatility and vice versa in both regimes.

The propagation mechanisms of oil price shocks on output have also been analysed through the components of aggregate demand (investment, private consumption, public spending and trade openness). We find that oil price shocks have significant and differentiated effects on these aggregates, demonstrating their indirect relationship with the business cycle and the importance of including them for a better understanding of the long-term evolution of the Ecuadorian economy. Oil price shocks have a strong effect in the same direction on the investment rate, which is higher in expansionary periods, demonstrating the procyclical behaviour of both variables. The same is true for the other components of demand, except for public spending, where the effect is higher in slowdown periods. This illustrates the complexity of the transmission mechanisms and the importance of a more detailed analysis of these variables.

These results suggest that Ecuador has a clear link with its natural resource specialisation, as Ocampo (2017) finds for South American countries. Exogenous (for the Ecuadorian economy) fluctuations in international oil prices have an important impact on its business cycle, especially in the case of slowdowns, exacerbating the fluctuations. This is a clear signal that the country should continue to seek new sources of income not linked to oil production and export. Public policies should strengthen and prolong the growth phases of the economy by stimulating private investment, reducing interest rates or raising total factor productivity, in order to insulate it from negative oil price shocks. However, oil revenues could continue to play an important role, especially in contractionary growth regimes, where the country has shown a weakness in its fiscal policy to stimulate growth through public spending (consumption and investment). So far, oil revenues have been used by the government to support economic growth through pro-cyclical and short-sighted fiscal policies, which have tended to exacerbate economic cycles. Instead, oil export revenues should be used to create stabilisation funds that allow fiscal policy to be counter-cyclical.

Further analysis should be done in relation to the conditional variance found in the MS-GARC models. We could also allow for time-varying probabilities using endogenous switching models along the lines of Chang et al. (2017), Bazzi et al. (2017), Benigno et al. (2020) or Hubrich and Waggoner (2021), where the probability of switching regimes may vary over time depending on the state of the economy. It would also be interesting to investigate the out-of-sample forecasting ability of the models.

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APPENDIX A1

FIGURE A1

ACF AND PACF OF THE ARIMA PROCESS FOR GDP TREND DEVIATIONS

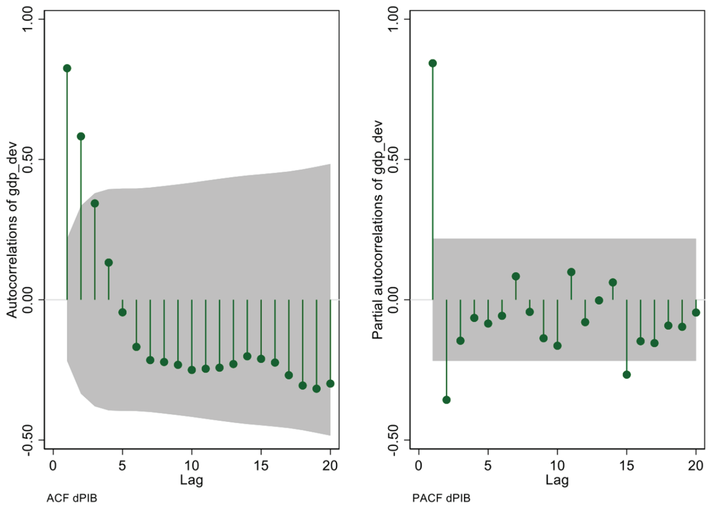

TABLE A1
LAG-ORDER SELECTION CRITERIA AND OTHER STATISTICS

	Lags	LR	AIC	HQIC	SBIC	J-B test	Skew	Kurtosis	Q-Test
dGDP	2	3.889	3.8901	3.9266	3.9814	5.828*	-0.633	3.351	261.92***
dWTI	2		-.3837	-.3720	-.354	34.66***	-1.180	5.166	194.79***

Notes: Likelihood ratio (LR), final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC). Only presented the Optimal lag. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Jarque-Bera normality test: Ho: normality. Ljung-Box Q-test: Ho: white noise (absence of autocorrelation).

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  Hirshleifer, J. (1958). "On the Theory of Optimal Investment Decisions", *Journal of Political Economy*, Vol. 56; 279-394.
  Judge, G., W. Griffiths, R. Carter, H. Lutkepohl and T. Lee. (1985). *The Theory and Practice of Econometrics.* 2nd edition. John Wiley.