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On the Shadow Economy in Latin America

Paulo Matos
CAEN/UFC
paulomatos@caen.ufc.br

Fernando Veiga
Central Bank of Brazil
fernando.veiga@bcb.gov.br

Abstract

We add to the discussion on the shadow economy in Latin America by applying multiple indicators and multiple causes (MIMIC) approach. We use an innovative and broad set of drivers and indicators aiming to measure shadow to GDP for 18 emerging countries during the period from 1990 to 2013. We are able to measure the liquidity elasticity of shadow, 0.12, and the investment elasticity of shadow, -0.19. We identify an upward trend for almost all Latin American countries with an average value of 35.6% of GDP. We may highlight Chile, Argentina and Costa Rica with lower ratios of shadow economy, while Panama, Bolivia, and Honduras have the highest levels of informality.

Keywords: Shadow economy; Cash circulation; Investments.

JEL Codes: C32, E26.

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1. Introduction

Tanzi (1982) defines shadow economy as the legal or illegal production of goods and services that cannot be included in official calculations of the Gross Domestic Product (GDP). This informal production is hidden from the public authorities to circumvent or dispense with regulation, taxation, government monitoring and to avoid the enforcement of labor regulations and compliance with administrative procedures.

Since the mid-twentieth century the literature is consensual on the relevance of measuring the size, identifying the drivers and the impacts of shadow economy. To exemplify some reasons, Schneider (1986) argues that those economic activities contribute to the aggregate value and thus they should be taken into account in calculating the national income. Schneider and Enste (2000) suggest that if they were reported to the government, they would be subject to taxation.

In short, theoretical contributions and empirical findings can be useful to policy makers who intend to draw policies able to reverse this situation and by allocating resources more efficiently in order to avoid tax evasion, lack of protection for workers and proliferation of criminal activities.

The dynamics of the shadow economy are simultaneously reflected in a set of indicators related to production and to the labor and money markets. Although it is not an all-inclusive indicator of the informal economy, the growth electrical energy consumption per capita is one of its main indicators.

According to data provided by the World Bank, the evolution of growth in electricity per capita consumption and per capita GDP from 1990 to 2013 suggests a downward trend of informality in the most developed countries, no significant change in the world and an upward trend in developing economies, such as Latin American and the Caribbean countries. Even more worrying, Hassan and Schneider (2016) find that eight of the Latin American and the Caribbean countries rank among the

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largest 20 largest informal economies in the world, expressed by shadow economy to GDP.

To summarize this empirical literature, the survey of Schneider and Enste (2000) compiles the results previously reported for various countries, classifying them by groups: developing countries, economies in transition, and members of the Organization for Economic Co-operation and Development (OECD). Almost two decades later, some of the most relevant findings reported in that survey remain according to Hassan and Schneider (2016).

For instance, they estimate a global average shadow economy of 33.8% of GDP (unweighted) from 1999 to 2013, while Latin American and Caribbean informal economies grew from 39.9% in 1999 to 45.1% of their GDP in 2013. Besides a growing trend, the average shadow economy on those countries is 42.4% of GDP. Moreover, Latin American countries such as Mexico, Colombia, Bolivia, and Haiti have historically been associated with corruption, particularly involving criminal organizations that impose their own law, undermining the legitimacy of the state. This evidence suggests that they require greater attention.

For this reason, we add to this issue by addressing the shadow economy and identifying its drivers in Latin America. We are aligned to Schneider (2002) and Ribeiro and Bugarin (2003) which also estimate shadow economy for Central and South American countries. However, here we take into account for a broader time series of an innovative set of drivers.

As usual, we propose using a set of causal variables commonly reported in this literature such as: tax burden, weight of the public sector as a proxy for regulatory intensity, economic openness, per capita GDP and unemployment rate. We also propose incorporating two additional explanatory variables still not addressed in studies about Latin America shadow economy: liquidity of the economy and investments.

The motivation is intuitive. A large money supply may lead families and companies to apply the surplus outside the official economy, while an increase of level of investment means improvement in the stage of development which keeps people in the official economy, on the other hand.

Methodologically, we follow the literature that has developed non-monetary methods to measure shadow economy. More specifically, we assume the shadow economy as a latent (non-observable) variable and to measure it we need to employ a set of multiple indicators and multiple causes (MIMIC) related to it. This approach was introduced by Frey and Weck-Hannemann (1984).

Finally, regarding the effects of the shadow economy, we follow the literature by measuring it through the rate of labor force participation and growth in electrical energy consumption, which is usual in physical entry modeling, but had not been used in MIMIC modeling for Latin America.

The remainder of this article is presented so that the next section presents the estimation technique, while in the third section we report our empirical exercise. Finally, the last section discusses the results and concludes with suggestions for future research.

2. Estimation technique

In addressing problems intrinsic to national accounting, Dornbusch and Fischer (2006) pose the following question: "how large is the underground economy, and how it can be measured?".

The answer that they themselves provide is that the nature of the subject makes estimation difficult and that the figures may vary widely. Some examples are: United States (between 3% and 33% of

GDP), Canada (between 4% and 22% of the national product), and Italy (between 8% and 33% of the national product). So, the literature is unanimous in stating that there is no ideal technique for measuring the informality, nor there is a best method.

The OECD classifies the approaches to estimating the shadow economy as direct (micro-models) and indirect (macro-models). Examples of direct methods include studies based on voluntary responses, tax audits, and other compliance-based methods. Indirect approaches include discrepancy, monetary, and physical input methods.

The physical input method, also known as the electrical energy consumption method, was developed in its most robust form by Kaufmann and Kaliberda (1996). They assume that the best physical indicator for measuring overall economic activity is the measurement of electrical energy consumption. Because its elasticity in relation to GDP is close to 1, electricity consumption can be used as a proxy for overall economic activity; by subtracting the official estimates of the GDP, one is left with an indicator of the shadow economy.

There are also techniques that dispense with the use of econometrics. For instance, the first study to measure the shadow economy using the approach of logic and fuzzy sets was conducted by Draeseke and Giles (2002), while Elgin and Öztunali (2012) used a dynamic general equilibrium (DGE) model, estimating the shadow economy of 161 countries through the solution of a mathematical problem of maximization.

In this context, Schneider and Enste (2000) consider the MIMIC model to be an additional type of approach. To summarize, the methods for measuring the shadow economy use one cause or indicator to note or register, respectively, all of the effects of the shadow economy which appear simultaneously in many markets, such as the production, labor, and money markets. Based on the statistical theory of latent (unobserved) variables, the MIMIC approach explicitly considers multiple causes of the existence and development of the informality, in addition to its multiple effects over time.

More specifically, this method is based on the statistical theory of latent variables, which considers various (observable) causes and indicators of the (unobservable) shadow economy. Developed by Jöreskog and Goldberger (1975), it is one of the models of the *Linear Interdependent Structural Relationships*. [1]

In the measurement model, the unobservable variable η determines a column vector of indicators $\boldsymbol{y}$ with p elements, which are observable variables that reflect shadow economy activities, subject to another column vector of p elements consisting of the random error terms $\boldsymbol{\varepsilon}$. η is a scalar, and $\boldsymbol{\lambda}$ is another column vector with p elements of parameters that relate $\boldsymbol{y}$ to η. Therefore, the measurement equation in reduced form is as follows:

$$\boldsymbol{y} = \boldsymbol{\lambda}\eta + \boldsymbol{\varepsilon} \tag{1}$$

The structural model determines the unobservable variable η by a column vector $\boldsymbol{x}$ of q elements of exogenous causes, which may be useful in predicting its movement and size, subject to an error

[1] See Schneider, Buehn and Montenegro (2010) for a didactic general structure of the MIMIC model.

term ς. $\boldsymbol{\gamma}'$ is a line vector of the structural parameters. Thus, the structural equation is given by:

$$\eta = \boldsymbol{\gamma}'\boldsymbol{x} + \varsigma \tag{2}$$

The MIMIC model's estimate, obtained by maximum likelihood, uses information of sample covariance to estimate the population parameters. Despite the critiques of the MIMIC approach, the literature considers it the most widely used model for the purpose of measuring the shadow economy. One of the primary advantages of MIMIC modeling is the ability to work with various types of variables, both causes and indicators, making it easier to obtain data for the research.

In the first application of the MIMIC method to estimate the informality, Frey and Weck-Hannemann (1984) reviewed data collected in 17 OECD countries.

3. Empirical Exercise

3.1 Database and descriptive statistics

Concerning the cross-section, there are 21 countries whose official languages derive from Latin. However, there are no data available for French Guiana and we have found significant gaps for Cuba and Haiti. Despite the existence of minor gaps with regards to other countries, the remaining 18 countries were chosen as the focus of this study.

In terms of sample size, our main limitation for the time series span used here regards the indicators. We follow Arby, Malik, and Hanif (2012) by using electricity per capita consumption and the labor force participation rate, an indicator widely used in these types of studies. Both series are available only from 1990 to 2013.

Regarding the drivers, the regulatory and tax burdens and the unemployment rate are factors traditionally considered in the related literature, such as Dell'Anno (2007) and Hassan and Schneider (2016). The weight of the public sector in the economy is taken as a proxy for the regulatory burden. Although rarely used in MIMIC modeling, the participation of gross capital formation is included in the present study because it is a variable related to a country's degree of economic development. High levels of this variable should lead to a smaller shadow economy. Another variable not commonly used is the degree of an economy's openness, which should be directly related to informal economic activity. Its influence has been analyzed by Schneider, Buehn, and Montenegro (2010). In addition, the macroeconomic variable of a country's money supply is examined, following Arby, Malik, and Hanif (2012).

We have extracted data used here from the World Bank Development Indicators. This source provides series of developmental and macroeconomic indicators compiled from officially recognized international sources. Table 1 reports statistics of the variables used here.

The average values of per capita GDP range from USD $3,500 in Nicaragua to USD $15,600 in Chile, values close to the average reported for Argentina and Venezuela (USD $15,500). We find the highest unemployment rate in the Dominican Republic, 16.1%, followed by Colombia, Argentina, Panama, and Venezuela, where rates are higher than 10%. Guatemala has the lowest unemployment rate (2.9%).

Money supply, proxy for the economy's liquidity, refers to money in circulation outside banks, short-term and long-term deposits, savings accounts, and residents' foreign currency reserves except for the central government, bank and traveler's checks, and other securities such as certificates of deposit and commercial promissory notes. The most liquid economies are Panama, Chile, and Brazil, with 65.9%, 61.2%, and 58.4%, respectively. Argentina and Ecuador, with averages close to 24% of GDP, have the least liquidity.

The heaviest tax burden was observed in Brazil, with 29.3% of GDP, far surpassing second-ranked Uruguay, with 23.0%, and Argentina, with 20.4%. The lightest burden was observed in Ecuador, with 11.3%. Data on the participation of the public sector in GDP, the participation of gross capital formation in GDP and the degree of openness of the economy from the Economic Commission for Latin America and the Caribbean (ECLAC).

With regards to the participation of the public sector in GDP, it first refers to the portion of GDP attributable to public spending, defense, social security payments, education, health, social services, and other community, social, and personal services. Brazil is the highest ranked, with expenses surpassing 27.5% of its GDP. Nicaragua and Peru follow, with 20.6% and 19.9%, respectively. Mexico commits only 11.6% of its GDP to public spending.

In terms of gross capital formation, Panama and the Dominican Republic have average investments of 34.5% and 27.8% of GDP, respectively, standing out as the largest in the region. Bolivia and El Salvador are the Latin American countries with the lowest levels of investment as a share of GDP, with approximately 16%.

Defined as the sum of exports and imports as a share of GDP, an economy's degree of openness denotes how prone the country is to trading with others, with a minimum of interference by the state. Brazil is the least open to international trade, whereas Panama is the most open. The average of this index varies between 21.9% and 144.5%.

3.2 MIMIC model: multiple causes and multiple indicators

As Giles (1999) warns, the MIMIC approach presupposes stationarity of the causal variables and indicators, in addition to their transformation as necessary. Table 2 reports the results for unit root tests applied with constant.

Given some rejections, for both testes using constant and also trend as a robustness check, we work with the first differences of the variables. It should be noted that regardless of the outcome of the unit root test, the LN variable (per capita GDP and electricity per capita consumption) would be transformed to its first derivative to capture the growth in both variables.

Concerning the specification of the MIMIC model, we first test a 7-1-2 MIMIC model (Figure 1), containing all seven drivers, shadow economy (ΔPE) as the latent variable, and two indicators.

The tax burden (ΔTB), the participation of the public sector in GDP (ΔRB), investment relative to GDP (ΔI), the economy's degree of openness (ΔEO), the unemployment rate (ΔUR), the natural logarithm of per capita GDP ($\Delta LnGDP$), and the money supply (ΔMS) are the determinants. The indicators are electricity per capita consumption ($\Delta LnEC$) and labor force participation (ΔLF). The model can be written using the following structural (3) and measuring (4) equations:

$$\Delta\eta = \gamma_1\Delta TB + \gamma_2\Delta RB + \gamma_3\Delta I + \gamma_4\Delta EO + \gamma_5\Delta UR + \gamma_6\Delta \mathrm{Ln}GDP + \gamma_7\Delta MS + \varsigma \tag{3}$$

$$\begin{cases} \Delta \mathrm{Ln}EC = \lambda_1\Delta\eta + \varepsilon_1 \\ \Delta LF = \lambda_2\Delta\eta + \varepsilon_2 \end{cases} \tag{4}$$

The parameters involved can be estimated using structural equation modeling (SEM) programs. The estimation's success depends on setting one of the two parameters $\boldsymbol{\lambda}$ at a number different from zero. According to Dell'Anno (2007), the choice may be limited to +1 or -1. The choice of the sign is very important because changing it inverts all of the coefficients γ_i to be estimated. Following Dell'Anno (2007), *reductio ad absurdum* was used to set the first parameter at λ_1+1; in other words, it is assumed that an increase in electricity consumption per capita will positively affect the growth of the shadow economy. As noted above, this is a foreseen theoretical hypothesis.

If the theory is correct, then setting it at -1 would result in the coefficients of $\Delta TB,\ \Delta RB, \Delta EO,$ and ΔUR, which we expect to be positive, to be estimated as negative. Setting λ_1, the maximum likelihood method is used to estimate the coefficients of the model (Table 3). In addition to the MIMIC 7-1-2 model, the coefficients were estimated for 6-1-2 and 5-1-2 models, removing the variables that were shown to be of least significance in the previous estimates. Based on the chi-square (p-value > 0.05), root mean square error of approximation (RMSEA) (approximately 0.05 with p-value > 0.05), and non-normed fit index (NNFI) (> 0.90) tests and because it showed significance of the greatest number of variables, the MIMIC 6-1-2c was chosen as the basis for calculating estimates of the informality in our sample.

This is however, a relative estimate: the value obtained does not reveal its size (as a % of GDP) but, rather, makes it possible to obtain it from past data. We proceed with what is called calibration, which is based on the results of previous studies. Following this literature, two steps are taken. First, a MIMIC index of the changes in shadow economy as a percentage of the GDP is calculated using structural equation (3), that is, by multiplying the coefficients of the significant causal variables of the MIMIC 6-1-2c model by the respective time series.

$$\Delta\tilde{\eta}_t = 0.0947\Delta RB_t - 0.1943\Delta I_t + 0.1738\Delta EO_t + 0.3524\Delta \mathrm{Ln}GDP_t + 0.1244\Delta MS_t \tag{5}$$

Considering that all of the variables are in first difference, the index also appears in first difference. It is necessary, in turn, to scale it in a $\tilde{\eta}_t$"level" MIMIC index showing the behavior of the shadow economy during the period of the series. The second step, is the calibration itself, which is performed by means of equation (6):

$$\hat{\eta}_t = (\tilde{\eta}_t/\tilde{\eta}_{2000})\eta^*_{2000} \tag{6}$$

In this equation $\tilde{\eta}_{2000}$ means the value of the MIMIC index in the base year 2000 η^*_{2000} is the average estimate for the year 2000 taken from previous studies. This year was chosen as the base year because there are at least two estimates of the shadow economy of each country available from which an average can be calculated.

The results for the estimates for the coefficients of the 6-1-2c MIMIC model are reported in Table 3. According to this table, the 6-1-2c MIMIC model shows that the development of the shadow economy is positively affected by the weight of the public sector, the degree of economic openness, per capita GDP, and the liquidity of the economy. Investment, on the other hand, has a negative effect on the shadow economy. Except for per capita GDP, for which the literature indicates an ambiguous effect, the signs obtained corroborate the literature.

Next, by substituting the temporal series $\Delta RB_t, \Delta I_t, \Delta EO_t, \Delta LnGDP_t,$ and ΔMS_t for each of the 18 Latin American countries concerned in equation (5), constructing a MIMIC index $\tilde{\eta}_t$ for each of them, and using the values of η^*_{2000} from Table 4 in equation (6), we obtain the estimate for the shadow economy.

The countries with the largest relative size of shadow economy are Panama, Bolivia, Honduras, and Peru. A second level of countries had informality equivalent to between 42% and 48% of their GDPs: Guatemala, Nicaragua, and Uruguay. The next category includes the largest number of countries: El Salvador, Ecuador, Brazil, Colombia, and Paraguay, each with informality equivalent to between 36% and 42% of their GDP. The penultimate category, composed of the Dominican Republic, Venezuela, and Mexico, have shadow values between 30% and 36% of their GDPs. Latin American countries with the smallest relative size of their informal markets in 2013 are Chile (22.1% of GDP), followed by Argentina (24.8% of GDP) and Costa Rica (27.2% of GDP).

On average (weighted by GDP), the Latin American countries showed growth in their informality levels during the period examined. From 1990 to 2013, there was 6.9% growth in the informality levels. Beginning in 1995, the trajectory was constantly growing. The benchmark coincides with the end of hyperinflation in several Latin American countries, suggesting that inflation does not favor growth in the shadow economy in this region. Regarding the degree of overall development between 1990 and 2013, it is noted that the majority of the countries experienced significant improvement in their GDP per capita, demonstrating the positive influence of this growth on the shadow economy.

In Figure 2 we plot our measure of the shadow economy to GDP trajectories during the period from 19990 to 2013 using the MIMIC 6-1-2c model. It enables us to compare our time-varying measure with the results obtained with the fuzzy methodology, as a kind of robustness check. We are able to evidence that the MIMIC 6-1-2c results show a smooth trajectory. One possible explanation for this fact is that the MIMIC method considers a single model for all 18 countries whereas other methods, as the fuzzy method, provide a model for each country, making it perhaps better at reflecting the reality of each. However, on average, the average sizes of the shadow economy do not differ much when we compare.

Our results also enable us to compare our trajectories with other previously reported in the literature. Even controlling by the methodology, there still remains a difference between our estimates and those reported in Hassan and Schneider (2016), given the differences in the set of variables besides the sample of countries. According to these researchers, between 1999 and 2013, the average weighted size of the shadow economy in Latina America increased from 34.7% to 38.3% of the size of GDP, while we find an increase from 33.1% to 35.6%. They found an informal market that averaged 35.7% of the size of the official economy during this period, whereas we found 34.6%.

These numbers indicate that considering the region as a whole, the two MIMIC models discussed provided similar results.

4. Conclusion

In a study on Latin America, Loayza (1996) argues that progress in market-oriented economic reforms in the early 90s can be seen as determinant able to reduce levels of informality in some economies, as Costa Rica, Argentina and Chile. However, although different studies provide a wide range of estimates, there is a common sense that the shadow economy in Latin America is higher than the levels observed in developed economies and it remains growing. This is a very worrying scenario since it suggests that we need to continue to make reforms in these economies.

In this context, our findings are important. First, we use the broadest span of countries and available time series. Second, we are the first to measure a direct relationship between usual drivers and more specifically, the monetary liquidity of the economy, the investments and their shadow economy as a ratio of the respective GDP. We are able to measure the liquidity elasticity of shadow, 0.12, and the investment elasticity of shadow, -0.19. These findings corroborate the intuitive pass-through suggests that a large money supply may lead families and companies to apply the surplus outside the official economy, while an increase of level of investment means improvement in the stage of development which keeps people in the official economy.

In practice, we claim that the reform in this region needs to incorporate public policies that are capable of promoting public and primarily private investment, as well as promoting the reduction of the level of cash circulation.

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Table 1. Summary statistics of the economic variables (average values from 1990 to 2013)

	Causes							Indicators	
Latin American country	Total tax burden on the GDP[a] (%)	Public sector participation in the GDP[b] (%)	Participation of gross capital formation in the GDP[c] (%)	Degree of openness of the economy[d] (%)	Unemployment rate as percent of total labor force[e] (%)	GDP based on per capita PPP[f] (Constant 2011 international US$)	Money supply in broad sense over GDP[g] (%)	Electricity consumption per capita[h] (kW)	Labor force participation, ages 15-64[i] (%)
Argentina	20.442	17.386	17.069	27.596	11.438	15,507.42	24.442	2,140.19	66.317
Bolivia	17.658	16.010	16.398	59.609	4.309	4,619.82	54.668	451.90	71.550
Brazil	29.269	27.513	18.488	21.901	7.621	12,051.11	58.355	1,902.23	72.762
Chile	19.387	14.065	23.531	62.183	7.138	15,615.80	61.223	2,605.57	61.008
Colombia	15.889	15.108	21.791	32.822	12.550	9,197.29	33.196	924.98	65.329
Costa Rica	19.223	16.457	19.334	74.761	5.958	10,569.99	38.884	1,577.29	64.917
El Salvador	13.272	14.092	16.175	64.250	7.187	6,475.14	45.336	662.63	63.792
Ecuador	11.343	13.471	22.993	52.145	6.021	8,354.80	24.773	794.03	69.450
Guatemala	12.000	12.154	17.577	64.135	2.865	6,084.13	33.121	391.41	66.354
Honduras	17.189	16.761	27.293	117.027	3.946	3,772.78	44.238	533.88	63.992
Mexico	16.902	11.617	23.542	51.691	3.896	14,462.16	33.663	1,672.18	62.492
Nicaragua	14.407	20.598	23.997	65.588	5.691	3,546.34	29.176	393.52	62.500
Panama	16.838	15.284	34.461	144.469	10.770	11,869.13	65.875	1,347.69	67.100
Paraguay	13.077	13.405	17.806	99.122	6.142	6,508.76	30.351	897.93	73.192
Peru	16.173	19.860	20.943	40.041	5.321	7,456.03	29.872	790.89	72.242
Dominican Republic	11.675	18.337	27.776	68.970	16.091	8,271.14	30.494	949.25	67.538
Uruguay	23.005	18.033	20.421	47.053	8.387	13,409.33	43.853	2,033.83	73.908
Venezuela	14.301	14.887	24.357	51.760	10.454	15,517.23	28.793	2,801.74	67.113

[a] Source: OECD (missing 1990 data for Nicaragua). [b] Source: Economic Commission for Latin America and the Caribbean (ECLAC) (missing 1990-1999 data for Guatemala and 2011-2013 data for Venezuela). [c] Source: ECLAC. [d] Source: ECLAC. [e] Source: World Bank (missing 1990 data for Bolivia, Guatemala, Mexico, Nicaragua, Panama, the Dominican Republic, and Uruguay). [f] Source: World Bank. [g] Source: World Bank (missing 2009-2013 data for Panama). [h] Source: World Bank. [i] Source: World Bank.

Table 2. Stationarity tests

Test	Causes							Indicators	
Type	Total tax burden on the GDP	Public sector participation in the GDP	Participation of gross capital formation in the GDP	Degree of economic openness	Unemployment rate as percent of total labor force	LN (GDP per capita based on PPP)	Money supply in broad sense over GDP	LN (Electricity consumption per capita)	Labor force participation, ages 15-64
ADF in level	0.1139	0.4052	0.0132**	0.5393	0.1195	0.9989	0.8012	0.9972	0.7432
PP in level	0.0166**	0.6277	0.0844	0.748	0.0289	0.1672	0.9647	0.2726	0.1952
ADF in 1st diff.	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
PP in 1st diff.	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***

Note: *, **, and *** indicate rejection of the non-stationarity hypothesis at levels of 10%, 5%, and 1%, respectively.

Figure 1. Structure of the full specification of MIMIC model

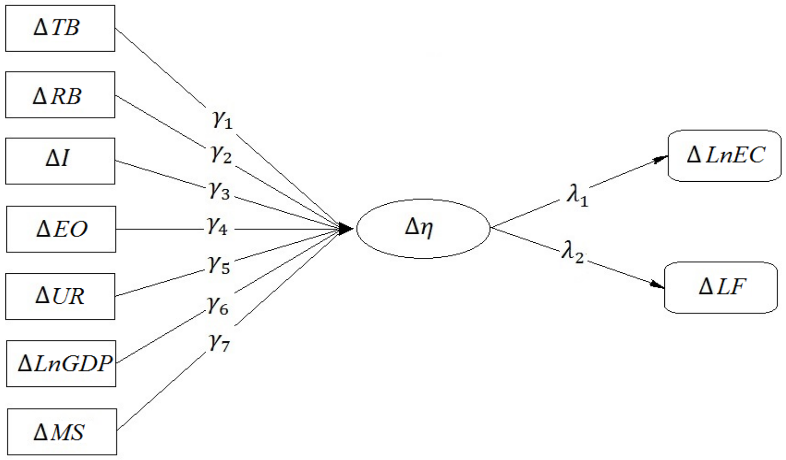

Table 3. Estimates of the coefficients of the proposed MIMIC models

Models	Causes							Indicators		Tests			
	Total tax burden on the GDP (ΔTB)	Public sector participation in the GDP (ΔRB)	Participation of gross capital formation in the GDP (ΔI)	Degree of economic openness (ΔEO)	Unemployment rate as percent of total labor force (ΔUR)	GDP per capita based on PPP (ΔLnGDP)	Money supply in broad sense over GDP (ΔMS)	Electricity consumption per capita (ΔLnEC)	Labor force participation, ages 15-64 (ΔLF)	χ^2 (p-value) [a]	RMSEA (p-value) [b]	AGFI [c]	NNFI [d]
MIMIC7-1-2	0.0264	0,0839	-0.1768***	0.1738***	0.1141**	0.4016***	0.1409***	+1	-0.1642	14.0351	0.0586	0.9415	0.8930
	[0.5366]	[1.5684]	[-2.9914]	[3.1012]	[2.1883]	[6.6685]	[2.9940]		[-1.1773]	(0.0292)	(0.3103)		
MIMIC6-1-2a	-	0,0859	-0.1747***	0.1767***	0.1114**	0.4051***	0.1411***	+1	-0.1774	12.8892	0.06361	0.9420	0.8938
		[1.6084]	[-2.9853]	[3.1672]	[2.1417]	[6.7722]	[3.0029]		[-1.2643]	(0.0244)	(0.2517)		
MIMIC6-1-2b	0.0283	-	-0.1210**	0.1371***	0.1192**	0.3600***	0.1353***	+1	-0.0748	12.4323	0.06081	0.9456	0.8812
	[0.5738]		[-2.0400]	[2.7457]	[2.2875]	[6.0110]	[2.8683]		[-0.5101]	(0.0293)	(0.2847)		
MIMIC6-1-2c	0.0163	0.0947*	-0.1943***	0.1738***	-	0.3524***	0.1244***	+1	-0.2690*	10.8454	0.0544	0.9516	0.9117
	[0.3387]	[1.8066]	[-3.3239]	[3.1434]		[6.1965]	[2.6846]		[-1.7697]	(0.0545)	(0.3726)		
MIMIC5-1-2a	-	0.0925*	-0.1883***	0.1739***	-	0.352***	0.1223***	+1	-0.2579*	9.9562	0.06132	0.9507	0.9067
		[1.7632]	[-3.2568]	[3.1549]		[6.2831]	[2.6406]		[-1.7108]	(0.0412)	(0.2879)		
MIMIC5-1-2b	0.0192	-	-0.1423**	0.1334***	-	0.3148***	0.1223***	+1	-0.1795	10.0631	0.0601	0.9516	0.8827
	[0.3927]		[-2.4172]	[2.6847]		[5.574]	[2.618]		[-1.1307]	(0.0394)	(0.2903)		
MIMIC5-1-2c	0.0190	0.1004*	-0.2026***	0.1738***	-	0.3398***	-	+1	-0.3343**	9.1537	0.0568	0.9550	0.9266
	[0.402]	[1.9535]	[-3.4561]	[3.1608]		[5.9626]			[-1.9935]	(0.0574)	(0.3422)		

Notes: *, **, and *** indicate that the estimated coefficients are significant at the level of 10%, 5%, and 1%, respectively. The *t* statistics are shown in brackets, and p-values are shown in parentheses. [a] Ratio of maximum likelihood chi-square indicates the discrepancy between the hypothetical model and the data (p-value > 0.05). [b] Root mean square error of approximation shows how well the model fits the matrix of covariance of the population, considering the number of degrees of freedom (close to 0.05: good; close to 0.08: moderate). [c] Adjusted goodness of fit index shows the comparison of the square residuals of the estimate with the real data, adjusted to the degrees of freedom (> 0.90). [d] Non-normed fit index shows how well the model fits compared to a baseline model, adjusted to the degrees of freedom (> 0.90).

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Table 4. Calculation of the average of previous estimates for the shadow economy in 2000 (η^*_{2000}) [a]

Source	Latin American country																	
	Arg	Bol	Bra	Chi	Col	Cos	Els	Ecu	Gua	Hon	Mex	Nic	Pan	Par	Per	Dom	Uru	Ven
1	-	-	-	-	-	-	-	-	-	49.6	-	-	64.1	-	-	-	-	-
2	-	68.1	-	20.3	41.3	27.0	47.1	-	51.9	-	31.8	46.9	65.1	29.2	60.3	-	-	35.1
3	21.7	31.6	33.9	24.8	38.5	27.6	30.9	46.4	32.3	-	30.0	34.3	-	33.9	30.1	34.9	33.8	34.2
4	27.8	72.3	39.4	18.2	32.5	26.1	45.4	35.1	54.0	57.3	31.1	47.9	-	43.3	57.3	37.4	50.8	29.9
Average	24.8	57.3	36.7	21.1	37.4	26.9	41.1	40.7	.46.1	53.4	31.0	43.0	64.6	35.5	49.2	36.1	42.3	33.1

[a] Results obtained from: (1) Schneider, Buehn, and Montenegro (2010); (2) Lesica (2011); (3) Alm and Embaye (2013); and (4) Hassan and Schneider (2016).

Figure 2. Growth of the shadow economy (% GDP) in Latin American countries (1990-2013)