THE IMPACT OF LOWERING THE PAYROLL TAX ON INFORMALITY IN COLOMBIA

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ABSTRACT

The Colombian government recently reformed the tax law by reducing payroll contributions from 29.5% to 16% and substituting them with a profit tax. The law was passed in December 2012, and two years later the informality rate in the 13 main metropolitan areas diminished from 56% to 51% in December 2014 (using the legal definition of informality). In the whole survey the reduction was a little less pronounced, going from 68% to 64%. This period was also characterized by high, yet also diminishing growth rates; changes in the tax rates, and increasing real minimum wages. It is of the most interest to know how much of this reduction was due to the tax reform. This paper performs this task using a Matching and Difference in Differences methodology. According to the results, the tax reform reduced the informality rate, of the workers affected by the reform in the 13 main metropolitan areas, between 4,3 and 6,8 p.p. which translated in a reduction of the informality rate between 2,0 and 3,1 p.p. given that the treated population was only 45% of the working population of the country in 2012. The impact over the whole survey was between 4,1 and 6,7 which translates into 1,2 to 2,2 p.p. impact on the informality rate of the whole country. Similar results were found using the firm definition of informality. The reform affected mostly salaried workers and employers, males between 25 and 50 years old and workers with low levels of education.

EL IMPACTO DE REDUCIR EL IMPUESTO A LA NÓMINA SOBRE LA INFORMALIDAD EN COLOMBIA

Fernández, C.
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RESUMEN

El gobierno colombiano reformó recientemente el código tributario, reduciendo las contribuciones sobre la nómina del 29,5% al 16%, y sustituyéndolas con un impuesto sobre los beneficios. La ley fue aprobada en diciembre de 2012, y dos años más tarde, la tasa de informalidad en las 13 principales áreas metropolitanas disminuyó del 56% al 51%, en diciembre de 2014 (usando la definición legal de la informalidad). En la encuesta, la reducción fue un poco menos pronunciada, pasando del 68% a 64%. Este período también se caracterizó por altas, y a la vez con tendencia a la baja, tasas de crecimiento, cambios en las tasas de impuestos, y aumento de los salarios mínimos reales. Es del mayor interés saber qué parte de esta reducción se debió a la reforma fiscal. En este trabajo se lleva a cabo esta tarea usando "matching", y un modelo de diferencias en diferencias. De acuerdo con los resultados, la reforma fiscal redujo la tasa de informalidad de los trabajadores afectados por la reforma en las 13 principales áreas metropolitanas, entre 4,3 y 6,8 P.P., lo que se tradujo en una reducción de la tasa de informalidad entre 2,0 y 3,1 P.P. dado que la población tratada fue de sólo el 45% de la población activa del país en 2012. El impacto sobre toda la encuesta fue de entre 4,1 y 6,7, lo que se traduce en 1,2 a 2,2 P.P. de impacto en la tasa de informalidad de todo el país. Resultados similares fueron encontrados utilizando la definición estricta de informalidad. La reforma afectó en su mayoría a trabajadores asalariados y empleadores varones entre 25 y 50 años de edad, y trabajadores con bajos niveles de educación.

The Impact of Lowering the Payroll Tax in Colombia

Cristina Fernandez
Leonardo Villar[1]

I.   Introduction

The Colombian government recently reformed the tax law by reducing payroll contributions from 29.5% to16% and substituting them with a profit tax. The law was passed in December 2012, and three years later the informality rate had diminished from 63% to 60% in December 2015 (GEIH[2]). In the 13 main metropolitan areas the reduction was a little more pronounced, going from 51% to 47% (Gran Encuesta Integrada de Hogares, GEIH). This period was also characterized by high, yet also diminishing growth rates; changes in the tax rates, and increasing real minimum wages. It is of the most interest to know how much of this reduction was due to the tax reform. This paper performs this task using a Matching and Difference in Differences methodology. According to the results, the tax reform reduced the informality rate, of the workers affected by the reform, in 7.7 p.p. Around 2 p.p of this reduction was made through the channel of formal workers earning less than a minimum wage that moved to be fully formal workers earning at least a minimum wage, and probably making pension and health contributions. The reform affected mostly salaried workers and employers, males between 25 and 50 years old and workers with high school studies.

The paper is structured as follows: Section 2 presents a literature review; Section 3 presents a short analysis of informality in Colombia; Section 4 presents the exercise of differences and differences and Section 5 presents the distributional impact of informality. Section 6 concludes.

II.   Literature review

The impact of lowering the payroll tax on informality, with few exceptions, has being focussed on emerging countries. The methods to estimate this impact includes General Equilibrium Models, cross country analysis, time series analysis and more recently, some authors have implemented a difference in difference estimations, as the one implemented in this paper.

Using theoretical models, Ulyssea and Reis (2006) found that the reduction of 12% on payroll taxes in Brazil would reduce informality on 5.5%. Similarly, Albrecht et al. (2009), also found that payroll taxes increase informality, particularly if firms are small and able to evade controls. The recent tax reform in Colombia has being estimated to increase of formal employment between 3.4 and 3.7%, and a decrease in informal employment between 2.9 and 3.4% (Anton, 2014).

With a cross-country methodology, Hazans (2011), found that European countries with higher payroll taxes show higher levels of informality and Lora and Fajardo (2012) found that payroll taxes increase informality if the workers do not perceive the direct benefits of these contributions, as is often the case in the region.

Using time series analysis, Kugler and Kugler (2009) surveyed a panel of Colombian firms and found that an increase of 10% in payroll tax was related to an increase in informal employment between 4% and 5%. Similarly, Mondragon et al. (2010) found, also for the case of Colombia, that an increase in 10% of payroll contributions was related to an increased probability of informality ranging between 5 and 8 percentage points.

The technique of differences in differences has been widely used in the labour market. One of the most known papers is (Card and Krueger, 1994) which analyses the impact of the increase in the minimum wage in New Jersey over employment in fast food restaurants. On informality, Bergolo and Cruces (2011) also applied a difference in differences technique to analyse the impact of an increase in coverage of health services to dependent children of private sector salaried workers over informality rates. The differences and differences and matching technique has been less used in the literature. One notable exception is the evaluation of training programs as in Blundell, Costa-Dias, Meghir and Van Reenen (2003) and Bergemann, Fitzenberger and Speckesse (2004. Another paper that should be mention is Encina (2013), who analysed the impact of the pension reform on the participation outcomes in Chile.

But probably the papers that resemble the most our estimations are Slonimczyk (2011) and Betcherman and Pages (2009). Slonimczyk (2011), using a difference in differences approach, found that a 17% reduction in payroll taxes in Russia in 2001 reduced the informality rate between 2.5% and 4%. Betcherman and Pages (2009), using a synthetic panel, found that a one percentage point decrease (increase) in the labor cost ratio (formal to informal) results in a 2.2 percentage point rise (fall) in the fraction of jobs that are registered.

Recently, the IDB commanded a series of studies (Steiner and Forero (2016), Kugler and Kugler, 2016; and Bernal, Eslava and Melendez, 2016) that used most of the reviewed techniques to estimate the impact of the reform and finding that the reform increased the absolute number of formal jobs in an amount between 200.000 and 800.000 employments (an increase of the number of formal jobs between 3.1% and 3.4% with respect to December 2012), and also increased the wages from 1.9% to 4.4%. According to the authors, most of the impact of the reform took place among small (less than 10 workers) and medium size enterprises (10 to 50 workers).

III.   Informality, payroll taxes and other variables affecting this relationship in the case of Colombia

This section explores the measurements, composition and recent behaviour of informality and payroll taxes in Colombia. It also reviews the behaviour of other variables mediating the relationship, as growth and the minimum wage. The next chapter tries to isolate the impact of payroll taxes on informality from this set of mediating variables.

Characteristics of the recent decrease of Informality in Colombia

The group of figures 1 shows four graphs that illustrate the composition and recent behaviour of informality in Colombia. The data used in this graphs, as well as in the majority of the ensuing analysis is from the *Gran Encuesta Integrada de Hogares* (GEIH). When needed, we also used the *Encuesta Continua de Hogares (Continuous Household Survey* (ECH, 2002-2006) Both surveys are provided by the Departamento Nacional de Estadística de Colombia (Dane).

Figure 1a shows the behaviour of the informality rate across the whole country and in the 13 main metropolitan areas. We used both aggregates across the analysis, but with an emphasis on the 13 main metropolitan areas, which is more representative and also the most commonly by the Colombian authorities; but when possible, we also presented the National and the dispersed areas aggregates[3]. According to this figure, around 60% of the working population in the country and 47% in the main 13 metropolitan areas is engaged in the informal sector. In this figure we can also appreciate that since 2002 informality has diminished in around 4 to 3 percentage points, depending on the aggregate.

Figure 1b shows that the recent declining trend is common across the different measurements of informality, despite of the wide range rates levels. Throughout this analysis we mostly applied the firm definition of informality, that includes workers employed in firms with no more than five employees; unpaid family helpers or housekeepers; self-employed with the exception of independent professionals and technicians; and business owners or firms with no more than five workers.[4] We were not able to compare the robustness of the exercise by using the legal definition of informality (which includes workers who do not make contributions to state health , pension schemes or either), since it was not possible to apply the differences in differences technique in this case, as we will explain later.

Figure 1c shows the behaviour of the total number of formal and informal employment. According to this graph the reduction of the informality rate in the last years was related to an increase in formal jobs rather than a substitution between informal and formal jobs. Between 2002 and 2004, about 530 thousand formal jobs were created, of which 90% were salaried. On the other hand, 51 thousand new self-employers[5] entered the occupied population and 21 thousand salaried informal jobs disappeared.

Figure 1d shows that the drop in informality rates was also more pronounced among the salaried workers and employers than among self-employment. These two groups also show wide differences in the informality rates: whereas, the informality rate among the salaried

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[3] The GEIH total aggregate covers 23 cities with rural areas, gathering information on more than 62 thousand households per quarter. The 13 metropolitan areas aggregate represents 60% of the total urban population according to the 2005 census, gathering information on more than 30 thousand households per quarter. The GEIH total sample includes not only the rural and the 13 metropolitan areas survey but also other urban areas.
[4] This criterion changed from 10 workers or less (ILO10) to 5 workers or less (ILO5) showing a higher correlation with other measures of informality (Bernal, 2009). Since 1999 the Delhi Group established the ILO5 as the standard measurement of informality (Central Statistical Organization, 1999).
[5] Defining self-employment as workers in unipersonal firms, and workers and employers as workers in firms with more than one worker.

workers is about 28% it amounts to about 76% among the informal self-employment. The self-employment in Colombia accounts for about 64% of the informal workers.

Figure 1. Recent behaviour of informality in Colombia

1.a Informality rates
Different aggregates

1.b Informality rates
Different measurements

1.c Number of jobs
Formal and informal workers*

1.d Informality rates
Self and salaried employment*
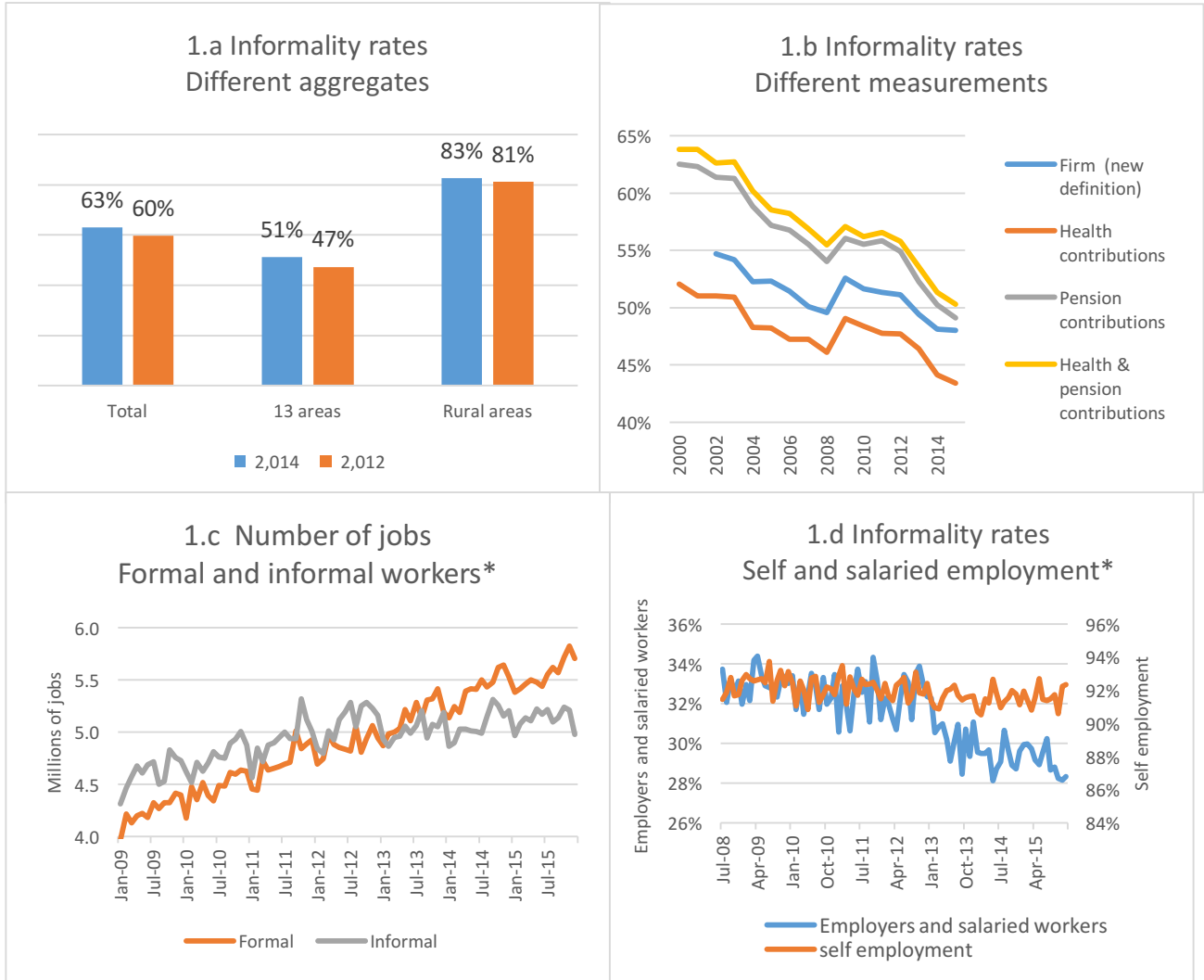
The payroll taxes in Colombia and the recent tax reform

As shown in Figure 2a, payroll taxes raised significantly during the nineties. Maloney (2004) and Perry (2007) argue that this increase is associated to the rapid increase of informality during the nineties. In 2013, Colombia showed one of the highest payroll taxes in Latin America, as shown in Figure 2b. In 2012, the Colombian government reformed the tax law (Ley 1607, 2012) by reducing payroll contributions from 29.5% to 16% over the wage. Despite of this fact, Colombia

continues to show a relatively high payroll tax rates at a global level and the minimum cost to hire a worker amounts to 1.5 times the minimum wage[6].

The reform only affects the payments made by the employers of workers that earn wages between one and ten times the minimum wage, and does not change the amount of taxes or contributions payable by the workers. From the fiscal point of view, the source of the contributions was substituted with a profit tax (CREE[7]) under the hypothesis that it is preferable to tax capital than to tax labour. As shown in Figure 2c passing and implementing the Law involved several milestones. Most of the discussions were held between October and November 2012, the Law was approved in December 2012, the waiver over SENA[8] and ICBF[9] contributions became effective in May 2013 and the reform was fully implemented on January 1st 2014, when the waiver over the health contributions became effective (8.5% of wages).
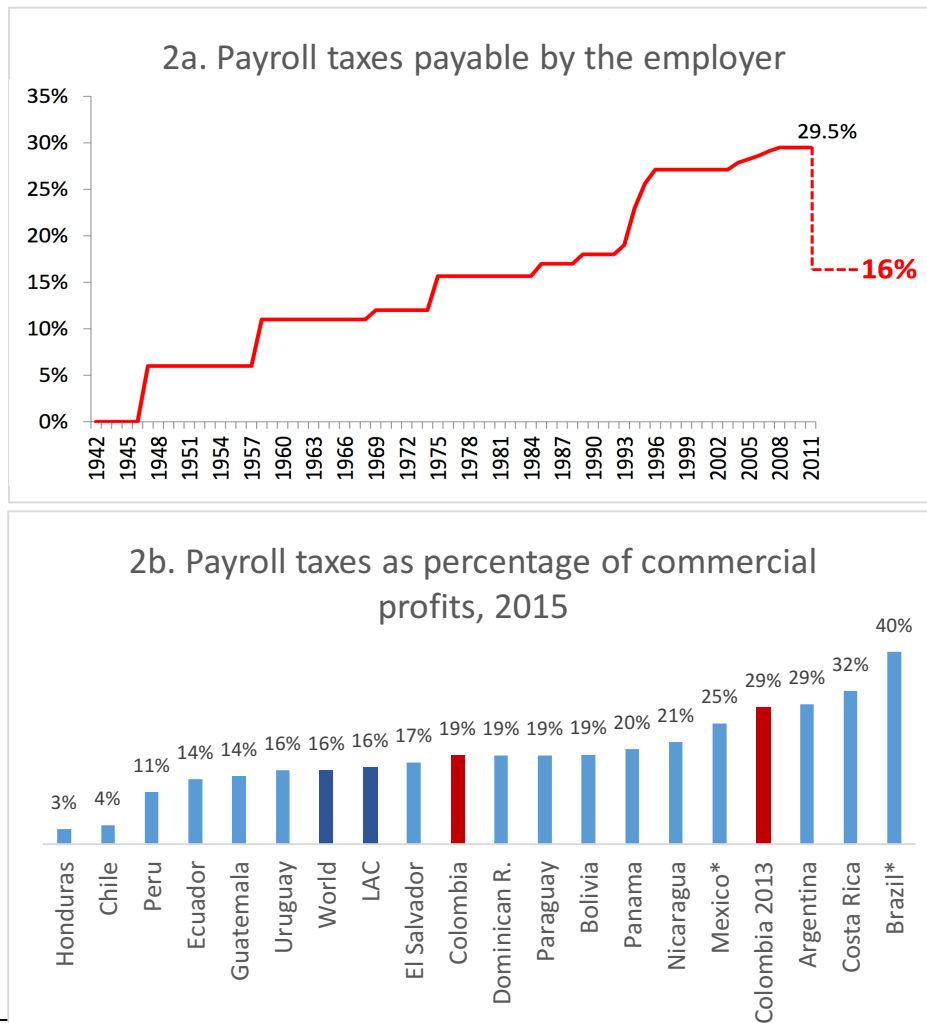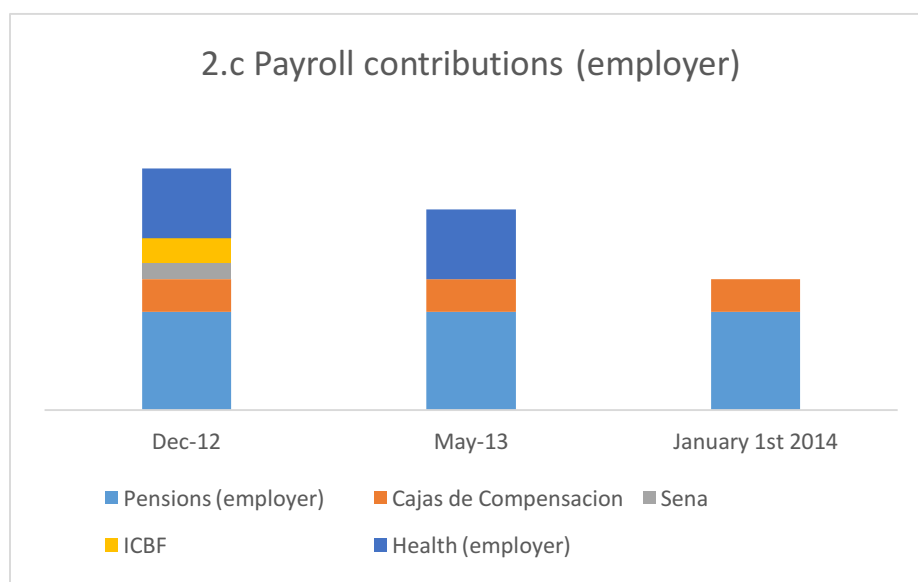

2a. Payroll taxes payable by the employer

2b. Payroll taxes as percentage of commercial profits, 2015

2.c Payroll contributions (employer)

| | Dec-12 | May-13 | January 1st 2014 |

Legend:
- Pensions (employer)
- Cajas de Compensacion
- Sena
- ICBF
- Health (employer)

Sources: Figure 2.a Santa Maria, Garcia and Mujica (2008), Figure 2.b World Bank and Figure 2c Own calculations.

Other variables impacting informality.

As we saw in the literature review, there is a close relationship between informality and payroll taxes that has being addressed through several methodologies. However, this relationship is often mediated by other variables. In the case of Colombia, we identified five main circumstances that might have also affected the informality results after the tax reform.

1. **A general change in taxes and in particular the creation of a profit tax (CREE) to substitute tax contributions as a fiscal source.** The spirit of this substitution was to tax the capital intensive firms instead of the labour intensive firms, but at the end the substitution was not perfect in the sense that the proceeds obtained by the government lowered in about 0.2% and 0.5% of the GDP, with respect to what was received in the past by the waived payroll taxes. However, some of this reduction would happen any way as a result of the lower economic growth. According to Forero and Steiner (2016), the impact would have been marginally higher (around 0.2 pp) using the VAT as as alternative income source rather than the CREE. Our claim is that the CREE affected the informality rate, in the same way that all the other dispositions of the tax reform, by an income, rather than a substitution effect.

2. **The post-reform period also coincided with high but diminishing economic growth rates.** Although the oil boom lasted until 2014, the proceeds of the oil boom as percentage of the GDP trend started to fall in 2012, and the output gap became negative in 2009 (given an increase in the potential GDP). In fact, the average real growth rate of the economy was 4.5% between 2007 and 2012, and 4.1% between 2013 and 2015. Given this behaviour of the economy, informality should have remained stable, or even diminished, since 2012. However, the relationship between informality and growth has change dramatically in the last years as we can appreciate in Table 1 and Figure 3. In

the main 13 metropolitan areas, the correlation coefficient of the formality rate[10] and the output gap is 0.74 at a 1% significance level, between 2002 and 2013, supporting the counter cyclicality hypothesis of informal employment in Colombia (Loayza & Rigolini, 2006; Tornarolli et al., 2014; and Fiess et al., 2008). The output gap from 2012 to 2015 was negative during this period, but formality increased (informality decreased) suggesting a change in behaviour. In fact, the correlation coefficient between formality and the output gap between 2002 and 2013 lowered to 0.42 when the last two years were included. This can probably be explained by the 2012 reduction in payroll tax. If we used the commodity exports over GDP trend as a proxy to the output gat (as suggested in Fernandez and Villar, 2016a) that might limit some endogeneity, the results are broadly comparable.

Table 1. Correlation between output gap and informality.

	Firm definition (2002-2015)	Firm definition (2002-2013)	Mondragón et al (1984-2006)
Output gap	0.46*	0.74**	0.74***
Commodities/ GDP trend	0.46*	0.63**	0.73***

Figure 3. Formal employment rate and the output gap/commodity exports over the GDP trend
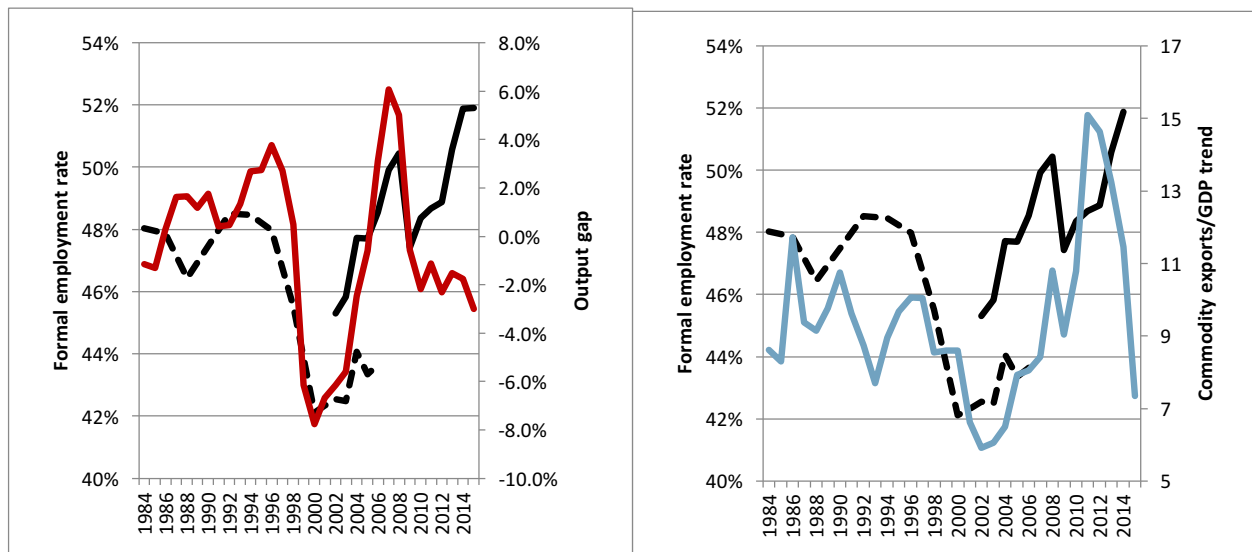
Source: Table 1: Own calculations using data from Fedesarrollo and the World bank

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[10] Defining the formality rate as one minus the informality rate. Note that the formality rate is calculated using two different ILO methodologies/series since one includes firms with less than 10 workers (ILO10, Mondragon et al, 2010), and the other includes firms with less than 5 workers (ILO5). We only performed this exercise using the aggregated 13 metropolitan area data since the wider sample suffered significant changes in the number of interviewed households.

3. **A simultaneous increase in the real minimum wage.** Figure 4 suggest a close relationship of informality and the minimum wage corrected or not by productivity[11]. However, during 2012 and 2014, the minimum wage corrected by productivity increased annually by 1.8% (in comparison with 1.1% between 2007 and 2011) and informality decreased. We claim, that this might be related to the recent reform. The impact of the minimum wage is rather difficult to isolate from the reform, but according to Forero and Steiner (2016) the impact of the reform would have been one percentage point larger if the minimum wage hadn't increased.

Figure 4. Informality rates and the minimum wage growth
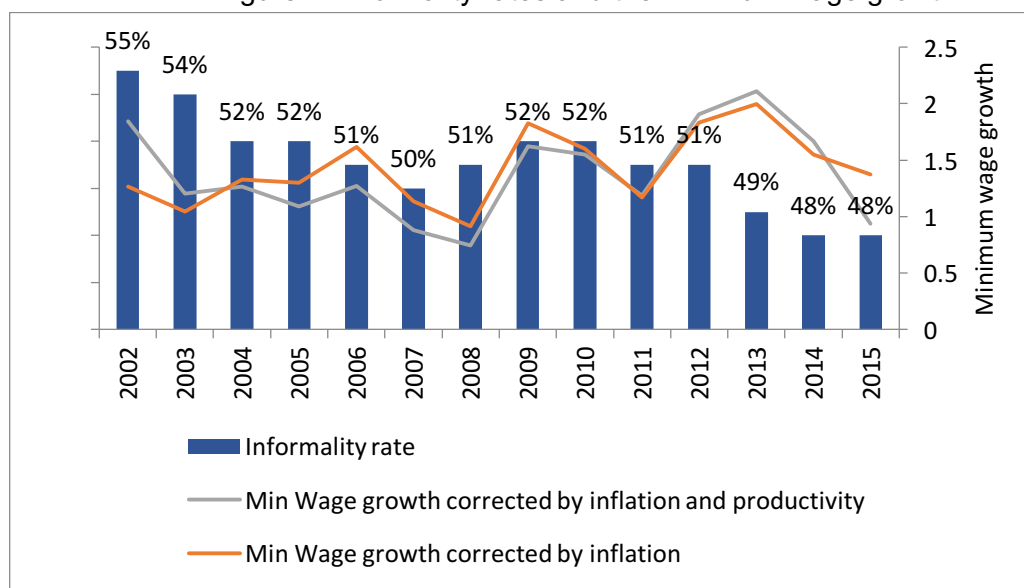
Source: Banco de la Republica, Fedesarrollo and GEIH.

4. **Changes in government employment.** The government employment was excluded from the reform and it might have change the behaviour of the informality rate since by the firm definition all government jobs are formal jobs. However, between 2012 and 2014 the participation of government employment over total employment diminished from 3.9% to 3.7%. This change is too small to have altered the informality results in a significant way.

5. **Anticipation of the reform.** Although the reform was approved on December 2012, it was widely discussed during the second semester of 2012, and the firms might have anticipated this policy reducing the impact after 2012. However, in the next section, we claimed that this was not apparently the case of this reform.

The next section implements a methodology to isolate the impact of the reform from growth, and other macroeconomic and regulatory conditions, by distinguishing the workers affected by the reform and the workers affected by a widely set of circumstances. In the case of the increase of

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[11] This positive relationship between informality and the minimum wage does not automatically imply the recommendation to reduce the minimum wage, since this reduction can negatively impact the income distribution.

the minimum wage, the impact is more difficult to be isolated, since it mostly affected the workers targeted by the reform.

IV.   *Applying a matching differences in differences approach*[12]

Applying a differences in difference approach

One of the most adequate methodologies for isolating the impact of growth over time is the Differences in Differences method, as in Card and Krueger (2006). The method involves dividing the population into two groups: one affected by the reform, the *treated* group, and the other unaffected by the reform, the *control* group. The change in probability of informality within the control group is then compared with the change observed in the probability of informality within the treatment group. By taking the difference between these changes –or the difference in differences- one isolates factors that affect both groups simultaneously, such as macroeconomic conditions, assuming that the impact on informality is evenly spread between both groups. This procedure is summarized in graph one. As Todd (1999) claims, the advantage of this methodology compared to a cross-section analysis is that it allows for time-invariant unobservable differences between the treatment and the control groups.

Diagram 1. Differences in Differences approach

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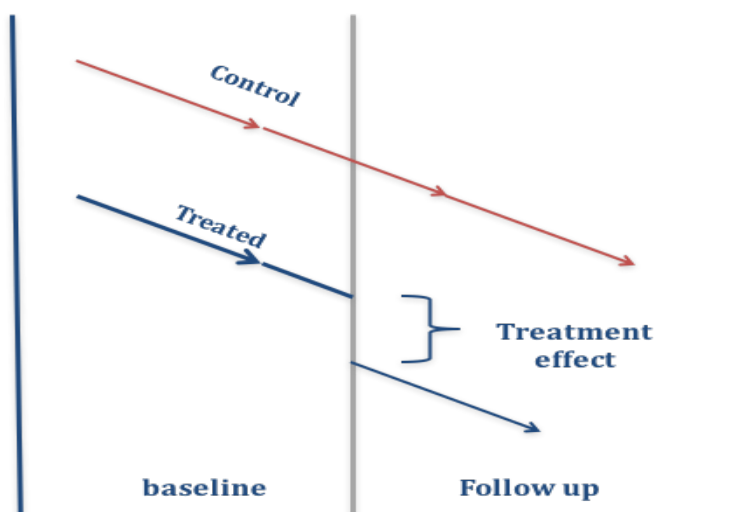
[12] This section is based on Fernandez et al (2016b).

As a first step, we performed this exercise for the case of Colombia, using the following equation and Ordinary Least Squares (OLS).

$$INF_{it} = \beta_0 + \beta_1 Year_t + \beta_2 Treated_i + \beta_3 (Treated_i \times Year_t) + \beta_4 X_{it} + u_{it}$$

where β_0 is the mean outcome of the control group at the baseline; $(\beta_0 + \beta_2)$ the mean outcome of the treated group at the baseline; β_2 the difference at the baseline; $(\beta_0 + \beta_1)$ the mean outcome of the control group at the follow up, $(\beta_0 + \beta_1 + \beta_2 + \beta_3)$ the mean outcome of the treated group at the follow up; $(\beta_2 + \beta_3)$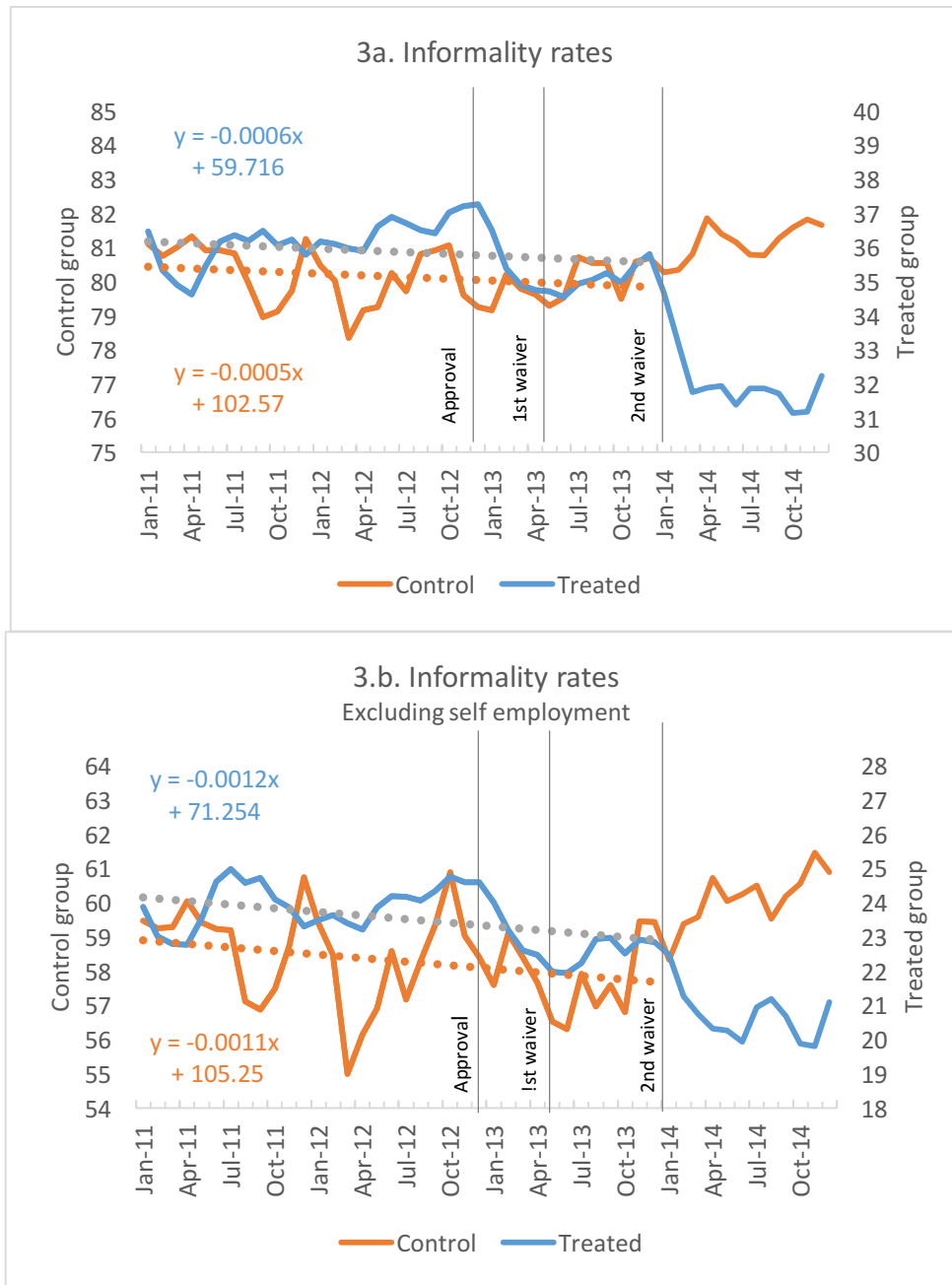 the difference at the follow up; β_3 the difference in difference estimator; X_{it} refers to the observable characteristics, Year is a dummy variable that takes the value of zero in the baseline period and a value of one in the period after the reform, and Treated is a dummy that takes the value of one if the individual is from the treatment group and zero if not.

The treatment group includes all workers that were directly impacted by the reduction in payroll taxes. According to the law, this includes workers that earn between one and 10 times the minimum wage excluding NGO workers. We also included those workers who reported an income close enough to the minimum wage or to ten times the minimum wage. In fact, we realised that a number of formal workers who probably earn the minimum wage rounded this figure up to the next ten thousand Colombian Pesos, and therefore we included them in the treatment group. The control group includes all other workers. We excluded from the exercise the government workers and those that did not reported a salary.

Figure 3a and 3b plots the informality rate for the treatment and control groups for the 13 metropolitan areas, before controlling by observable characteristics. As can be observed, although the reform was discussed in the second semester of 2012 and approved in December 2012, it only started to have an impact in January 2014 when it was fully implemented. After this period, the model confirms that workers affected by the reform, or the treatment group, were less likely to engage in the informal sector, while this was not the case for workers in the control group. The figures also indicate that relatively long-term moving averages should be considered in this type of analysis since the series demonstrates considerable volatility. Therefore, we defined our period of analysis from 2012, before the implementation of the reform, to 2014, after the implementation of the reform. We also estimated this series excluding self-employment because this category is not evenly distributed between the control and the treated groups but biased towards the control group, and they tend to show a different behaviour form the salaried workers. Therefore, from here on we tried to perform the exercises including and excluding self-employment.

3a. Informality rates

$y = -0.0006x + 59.716$

$y = -0.0005x + 102.57$

Approval

1st waiver

2nd waiver

Control — Treated

3.b. Informality rates
Excluding self employment

$y = -0.0012x + 71.254$

$y = -0.0011x + 105.25$

Approval

1st waiver

2nd waiver

Control — Treated

Source: GEIH. 1st waiver: reduction in Sena and ICBF contributions. 2nd waiver: reduction in Health contributions

The results of the OLS regression expanding the survey according to weights are showed on Table 2. The unweighted results are presented on Annex 1. The control variables were chosen according to Fernandez an Villar (2016b). Their impact on informality is the following:

- **Gender:** The base group are men, meaning that women are more likely to be informal than men. We separated the impact of women registered as spouses from women that are heads of the household, daughters, grandmothers etc., since both groups have different preferences for formality. We found that informality rates are higher for both

groups, disrespectfully of their preferences. However, in the 13 main metropolitan areas if we exclude self-employment, women tend to have slightly lower informality rates than men.

- **Age:** We included in the regression informal workers younger than 25 and older than 50, being the base group as workers between 24 and 45 years old. The younger group tends to show higher rates of informality, probably related to lack of experience, since they show preferences for formality in the survey. The second group also shows higher rates of informality but they seem to be more related to preferences.

- **Education:** This category is perhaps the one that has a wider impact over informality. The workers with primary education or less are much more likely to be informal than the workers with basic or secondary education, the base group. Similarly, workers with tertiary education are much less likely to be informal than the workers with lower education,

- **Diploma.** In the same sense, workers with high school or higher education diploma have a lower probability to be informal than those that do not have a diploma.

- **City:** Workers living in big city are more likely to be informal than those living in smaller cities, with exception of those who live in border cities where informality often comes in hand with smuggling.

- **Rural/urban:** Workers in the main Metropolitan areas tend to show lower informality rates than workers living in small cities, the base group. As expected, workers in rural areas are more likely to be informal.

- **Weights:** As suggested by Dugoff et al (2014) it is a good idea to include weights as a control variable to the difference in difference estimation since it can account for some variables that may capture relevant factors, such as where individuals live, their demographic characteristics and perhaps their availability to respond to surveys, that might intercede in the estimation of informality, but are burdensome to include in the estimations. However, the propensity score does not need to be weighted by weights, as Dugoff et al (2014) argue.

- **Months:** January, February and December were included in the regression to control for seasonality.

According to this setup, and the results that are summarized on Table 3, the control group showed an informality rate of 92% that increased to 93% in the next period; and the treated group reduced its informality rate from 59% to 55% and therefore. In other words, the difference between the control and the treated group in the baseline was -33 p.p and in the follow up -38 pp, meaning that the difference in difference estimator is -4.7, or that the impact of the tax reform on payroll contributions was statistically significant, having reduced informality in the workers included by the reform by 4.7 percentage points. Annex 2 shows the results for the unweighted sample.

Table 2. OLS estimation of difference on differences (weighted)

	Total			13 areas			Rural
	Total	Salaried and employers	Self-employment	Total	Salaried and employers	Self-employment	Total
Constant (B_0)	0.905*** [264.7]	0.740*** [137.1]	0.982*** [430.1]	0.883*** [221.0]	0.659*** [105.7]	0.976*** [310.3]	0.922*** [130.0]
Year (B_1)	0.014*** [6.8]	0.010* [2.2]	0.006*** [4.6]	0.017*** [5.0]	0.022** [3.2]	0.007** [2.9]	0.012*** [3.4]
Treated (B_2)	-0.330*** [-121.0]	-0.303*** [-76.0]	-0.023*** [-9.1]	-0.332*** [-94.8]	-0.288*** [-53.5]	-0.020*** [-5.7]	-0.282*** [-38.0]
Treated*year (B_3)	-0.047*** [-13.7]	-0.039*** [-7.3]	-0.011** [-3.1]	-0.048*** [-10.2]	-0.048*** [-6.1]	-0.014** [-2.8]	-0.038*** [-3.6]
Women (spouse)	0.024*** [9.4]	0.000 [0.1]	0.030*** [17.9]	0.043*** [12.5]	0.024*** [5.3]	0.048*** [15.3]	0.002 [0.4]
Women (other)	0.016*** [8.0]	-0.013*** [-4.5]	0.032*** [20.6]	0.027*** [9.8]	-0.003 [-0.8]	0.047*** [17.3]	-0.01 [-1.9]
Less than 25	-0.043*** [-16.5]	-0.004 [-1.2]	0.003 [1.5]	-0.054*** [-16.0]	0.005 [1.2]	-0.002 [-0.4]	-0.024*** [-4.0]
More than 50	0.073*** [33.9]	0.087*** [24.1]	-0.010*** [-6.7]	0.093*** [28.9]	0.090*** [18.3]	-0.017*** [-6.7]	0.042*** [10.3]
Primary (-)	0.029*** [10.7]	0.050*** [11.2]	0.009*** [8.3]	0.041*** [10.8]	0.045*** [7.3]	0.012*** [7.7]	0.041*** [6.9]
Tertiary (+)	-0.199*** [-73.7]	-0.125*** [-40.7]	-0.256*** [-57.9]	-0.193*** [-60.2]	-0.119*** [-34.3]	-0.287*** [-52.6]	-0.164*** [-12.4]
Diploma	-0.110*** [-37.8]	-0.106*** [-25.6]	-0.017*** [-10.6]	-0.131*** [-34.7]	-0.118*** [-23.4]	-0.022*** [-9.8]	-0.067*** [-8.3]
Big city	-0.058*** [-23.9]	-0.017*** [-5.5]	-0.007** [-3.2]	-0.065*** [-19.5]	-0.024*** [-6.3]	-0.002 [-0.6]	
Border city	0.049*** [18.2]	0.042*** [10.1]	0.006** [3.0]	0.047*** [17.4]	0.042*** [10.1]	0.005* [2.4]	
13 Metropolitan areas	-0.021*** [-9.0]	-0.065*** [-19.7]	-0.008*** [-4.4]				
Rural	0.012*** [4.3]	0.053*** [11.9]	0.007*** [5.7]				
Weights	0.023*** [7.1]	0.022*** [4.9]	0.001 [0.4]	0.019*** [4.4]	0.015** [2.8]	0.003 [0.7]	0.028*** [4.2]
January	-0.016*** [-4.9]	-0.021*** [-4.7]	0 [-0.2]	-0.011** [-2.7]	-0.009 [-1.7]	-0.006 [-1.3]	-0.027*** [-3.7]
February	0.010** [3.0]	0.010* [2.3]	0.001 [0.4]	-0.002 [-0.5]	-0.003 [-0.6]	-0.004 [-0.9]	0.027*** [4.2]
December	-0.000*** [-5.1]	0 [-1.5]	0 [-1.3]	0 [-0.2]	0 [0.6]	0 [-1.3]	-0.000*** [-8.6]
N	590201	343413	246788	289151	179957	109194	59089
F	7939.606	2876.119	442.083	5245.966	1203.339	375.783	405.083
df_m	18	18	18	16	16	16	14
df_r	590200	343412	246787	289150	179956	109193	59088
r2	0.33	0.25	0.20	0.30	0.17	0.22	0.20

Source: GEIH

Table 3. Difference in difference exercise extracted from the OLS coefficients

| | Coefficient | Total | | | 13 areas | | | Rural |
		Total	Salaried and employers	Self-employ-ment	Total	Salaried and employers	Self-Employ-ment	Total
Mean outcome of the control group at the baseline	B_0	92	75	98	89	66	98	93
Mean outcome of the treated group at the baseline	$B_0 + B_2$	59	45	96	56	38	96	65
Difference at the baseline	B_2	-33	-30	-2	-33	-29	-2	-28
Mean outcome of the control group at the follow up	$B_0 + B_1$	93	76	99	90	69	98	94
Mean outcome of the treated group at the follow up	$B_0 + B_1 + B_2 + B_3$	55	42	95	52	35	95	62
Difference at the follow up	$B_2 + B_3$	-38	-34	-3	-38	-34	-4	-32
Difference in difference	B_3	-4.7	-3.9	-1.1	-4.8	-4.7	-1.5	-3.8
% of treated on occupied		44%	55%	25%	57%	67%	36%	23%
Impact over total informality rate		-2.1	-2.1	-0.3	-2.8	-3.2	-0.5	-0.9

Source: GEIH

Considering that the treatment group in 2012 is only a percentage of the total occupied group, the impact of the reform after the first year of implementation was at least 2.1 p.p. assuming that all the workers that do not report income are in the treatment group. The impact is similar over the salaried workers (-2.1 p.p.). In the 13th metropolitan areas the impact over informality was stronger and the difference in difference estimators (-4.8 and -4.7p.p. including and excluding self-employment) results in a reduction in the total informality rate of 2.8 and 3.2 p.p. respectively. The impact over the self-employment group and rural groups is rather small and it is not going to be considered from here on.

Although the results are very plausible the methodology of the exercise has some limitations since it assumes common time effects across groups[13], and no changes to the composition of each group. These assumptions are less easy to control in absence of a panel structure (Blundell & Costa Dias, 2009). Therefore, we proceed to simulate a panel structure to partially reduce these limitations.

Applying a differences in differences and matching approach

The 'Matching Differences in Differences' (MDID) was initially developed by Heckman et al. (1997). The idea is to match the treatment individuals after the reform with treatment individuals before the reform and with the control individuals before and after the reform, and then compare the differences in informality rates between the treatment and control groups over time. By mixing the methodologies, Matching and Differences in Differences, we can control for differences in composition of the treated group before and after the treatment. Similarly, under this procedure, the assumption of common time effects on un-observables becomes common trend time effects on un-observables, and the linear assumption is no longer required (Blundell, 2009).

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[13]In fact, the model can control for non-observable individual specific effects and non-observable macroeconomic effects because they cancel one another out, but not for non-observable temporary individual specific effects.

The method used to perform this match in this paper is the kernel propensity score matching following Heckman, Ichimura, and Todd (1997, 1998), and Blundell and Costa Dias (2009). The steps of the model that we implement in this paper, following the Stata code designed by Villa (20166) and the paper that accompanies the code, are the following:

1. To selected the co-variables that might have an impact on the probability of either being treated or being informal, according to the previous section[14]. All these variables should affect both the treatment and the outcome variable, without predicting it perfectly and satisfy the requirement of being independent from the treatment, or the anticipation of it.
2. To estimate the propensity score, or the likelihood of being treated for all the four groups[15]. As shown by Rubin and Rosembaum (1983), matching on the propensity is score is equivalent to matching on co-variables, having the advantage or reducing the curse of dimensionality.
3. Depending on the researches preferences, the procedure can make use of all the p-score information available, or trim it to an area where there is available information for both the treated and the control groups (common support). We used common support in most of the estimation, since it reduces the chances of the kernel matching observations out of the common support area (Caliendo and Kopeinig, 2005). However, we did not used in the estimations with the total survey, since we were more interested in extrapolate these results. Nevertheless, results were very similar, with and without common support.
4. To estimate the kernel distance between the propensity score of each observation in the treated group after the reform and the propensity score of each observation of a range in the three other groups (the control groups before and after the reform and with the treated group before the reform) giving the highest weight to those with p-scores closest to the treated individual[16]. The treated group after the reform is assigned a value of 1.
5. The kernel weights are used to estimate the differences in differences equation as follows[17]:

$$\text{DID} = \{E(Y_{it=1}|D_{it=1} = 1, Z_i = 1, X_{it}) - w\,^c_{it=1} \times E(Y_{it=1}|D_{it=1} = 0, Z_i = 0, X_{it})\} -$$

$$w\,^t_{it=1} \{E(Y_{it=0}|D_{it=0} = 0, Z_i = 1, X_{it}) - w\,^c_{it=1} \times E(Y_{it=0}|D_{it=0} = 0, Z_i = 0, X_{it})\}$$

Where DID, is the difference in difference estimation; Y_{it} is the outcome; $D_{it=1}$ is the existence (1) or absence (0) of a treatment and Z_i is the group at which each observation belongs being Z_i =1; the treated group at the follow up and 0 any of the

three other groups; $w^{c}_{it=0}$, $w^{c}_{it=1}$ and $w^{t}_{it=0}$ are the kernel weights for the control in the baseline, the control group at the follow up, and the treatment at the follow up, respectively; X_{it}, the co-variables used in the exercise and $E(Y_{it}|D_{it}, Z_i)$ is the average outcome by group (On this case the probability of being informal conditional on the individual participation in the program, and on the group to which the individual belongs to).

Table 4 shows the results of applying the Matching and Difference in Difference methods between 2012, before the reform and 2014, after the reform. According to the results, informality rates among the treatment group reduced by 7.6 percentage points in the analysis period due to the reduction in payroll taxes or to a shock impacting the control but not the treatment group, such as the reduction in payroll taxes. Which means an impact over the total informality rate of -3.3 p.p., considering that the participation of the control group in the population is 44%. This impact is higher in the 13 metropolitan areas (-3.7 p.p) and among workers and employers (-3.7 overall and -4.5 in the 13 metropolitan areas). These outcomes are comparable to the OLS non weighted estimation of the Annex 1 and 2 and to what previous estimations predicted. In particular, an impact of 7.6% over the treatment group is equivalent to create 266.800 jobs in the formal sector, which is in the lower bound of the IADB estimation of the reform (between 200.000 and 800.000 formal jobs).

Table 4. DID matching results (baseline=2012, follow up=2014)

|	Total (1st semester)				13 areas			
	Total	Std. errors	Salaried and employers	Std. errors	Total	Std. errors	Salaried and employers	Std. errors
Mean outcome of the control group at the baseline	76%		58%		71.8%		53%	
Mean outcome of the treated group at the baseline	44%		30%		39.4%		25%	
Difference at the baseline	-31.5%***	0.002	-28.5%***	0.003	-32.4%***	0.002	-28.2%***	0.003
Mean outcome of the control group at the follow up	78%		60%		74.6%		57%	
Mean outcome of the treated group at the follow up	39%		25%		35.0%		21%	
Difference at the follow up	-39.1%***	0.002	-35.2%***	0.003	-39.6%***	0.002	-35.6%***	0.003
Difference in difference (p.p.)	-7.6***	0.003	-6.7***	0.005	-7.2%***	0.003	-7.4%***	0.004
% of treated on occupied population	44%		54%		51%		61%	
Impact over total informality rate (p.p.)	-3.3		-3.6		-3.7		-4.5	
Period of estimation	I sem		I sem		year		year	
R2					0.13		0.11	
Common support	No		Yes		Yes		Yes	
# observations	293,337		169,792		289,086		179,925	
Control at baseline	72985		28178		58539		22761	
Treatment at baseline	77769		59239		88119		68512	
Control at follow up	66718		22949		54431		66718	
Treatment at follow up	75865		59426		87997		75865	

Testing the results

In this section we will present only the tests related to the 13- Main Metropolitan Areas Survey, which is the most significant aggregate. In particular, we analyse five possible subjects that create bias and inconsistencies in the exercise[18]: common support, parallel trends, quality of the matching, and exogeneity of the treatment[19].

1. **Common support.** A key assumption of the Matching Differences in Differences procedure is the overlap of the region of common support between the treatment and the control group. It rules out the perfect predictability of the treatment, given that workers with same characteristics (X_{it}) might have a positive probability of being both participants and non-participants (Heckman, LaLonde, and Smith, 1999). In other words we need that $0 < P(D_{it} = 1|X_{it}) < 1$.

   In order to prove common support, a visual analysis is suggested by Caliendo et al (2005). Figure 4 shows that the p-score regions of the treated and the non-treated actually overlap, so overlap condition holds, and the concerns on perfect predictability of the treatment given the observables characteristics are ruled out[20]. According to Blundell (2009) in the MDID model the p-score distribution after the reform should be compared with with the three other control groups (treatment before the reform and control before and after the reform).

Figure 4a. P-score distribution
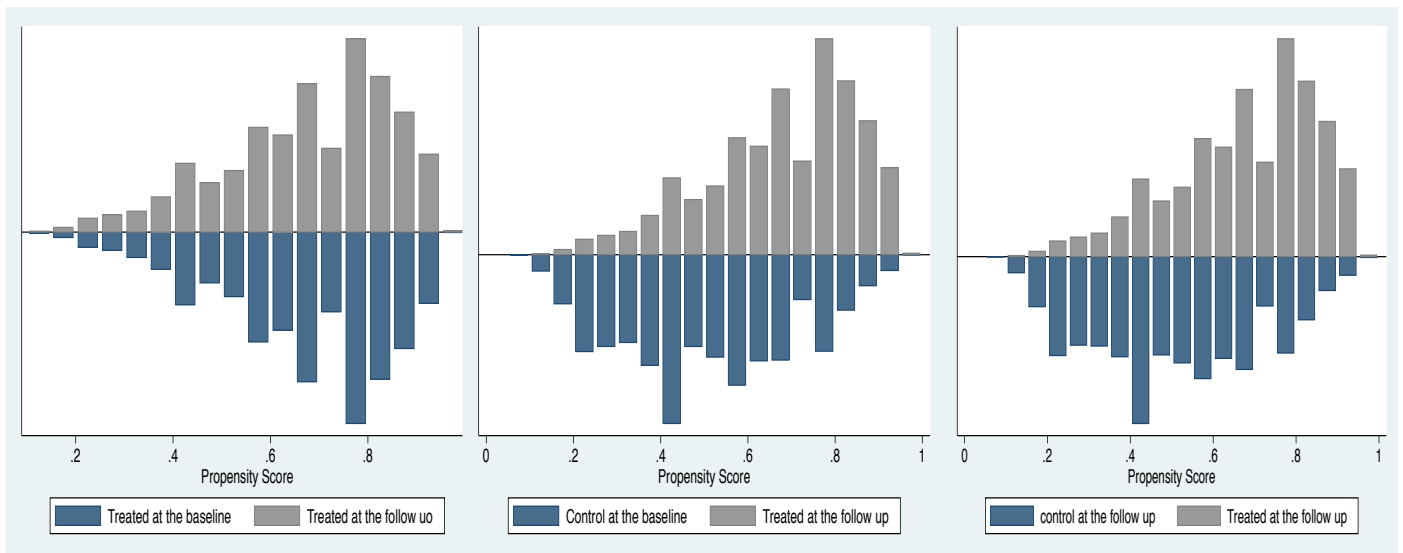
[18] See Blundell (2009) and Lechner (2011) on MDID assumptions.
[19] Another assumption of matching differences in differences is a Stable Unit Treatment Value. According to this specification, there are no relevant interactions between the members of the population. The SUTVA is violated if for example, in this case, the magnitude of the program generates spill-over effects that reduce the demand for labour in the non-treated group. A way to prove this situation is to observe the impact of the reform on the real wages of the non-treated group. We performed this exercise to a specific group, male 25 to 50 years old living in one of the three biggest cities, in order to avoid selection problems. We found that there is no significant increase in wages of the treated with respect to the no treated due to the reform. Therefore, we claim that the spillover-general equilibrium impact did not play a significant role in this case.

[20] The last two distributions are almost equal because the distribution does not change much across years

4b. P-score distribution excluding self-employment
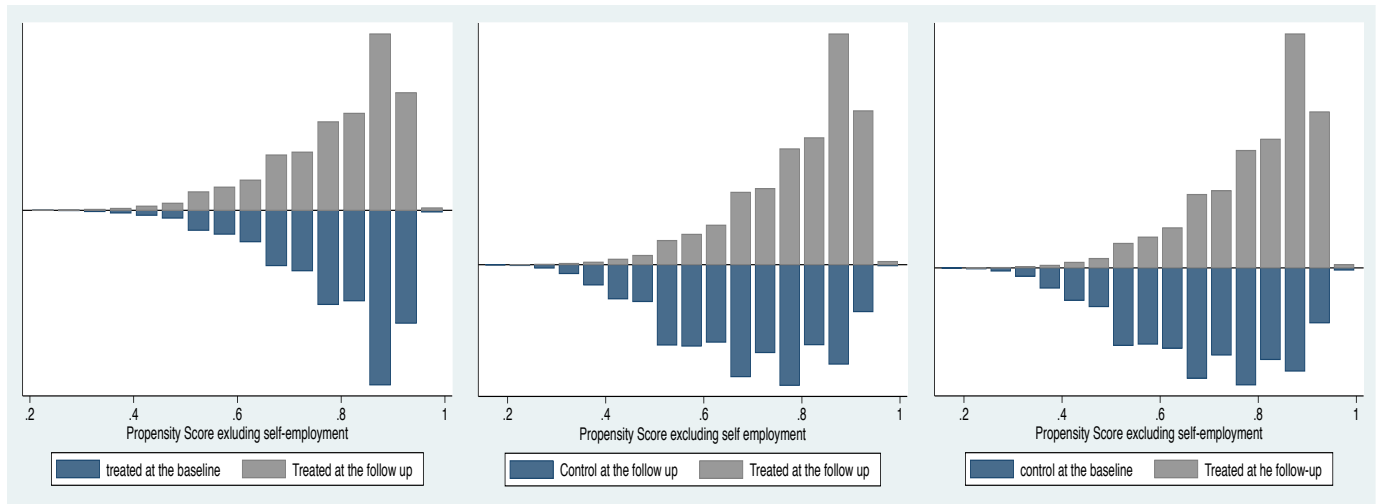
In order to verify the former result, we applied the difference and differences and matching exercises with and without common support, and the number of observations excluded was minimal (0.02%). The differences in the outcome were only reflected in minimal changes in the standard errors and no differences were observed in the coefficients.

2. **Parallel trends.** Another key assumption of the Matching Differences and Differences approach is parallel trends. This feature ensures that, in the post treatment period, the impact is caused by the reform and not by belonging to the treated or the control group. According to this assumption unobservable variables such as growth, should affect the outcome variable, informality, of treatment and control groups in a parallel (but not equal) way. In other words, if parallel trend holds and the treated have not been subjected to the treatment both populations would have experienced the same time trends conditional on X.

We implemented a Placebo Test to check the common trend assumption. For the Placebo Test, the Matching and Differences in Differences Methods are applied to any other year with similar external characteristics, faking the existence of a tax reform or a similar shock, with the expectation that the results will not be affected. We performed this exercise in relation to 2011/2012, and 2011/2013. We obtained no significant results in informality between the treatment and control groups between 2011/2013, as shown in Table 5. Although this test does not exclude the violation of the common trend assumption, it does suggest that growth or other unobserved variables did not impact informality in a differential manner[21]. Neither the results of the procedure over the 2012 and 2013 was significant

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[21]We had some concerns with the individuals who represent the formal workers in the control group in terms of the unobservable characteristics. This group includes some formal workers who earn more than 10 times the minimum wage, however most formal worker earn less than a minimum wage. This is not very common in a country like Colombia where the minimum wage prevails in the formal sector. Therefore, it might be the case of these workers having different unobservable characteristics when comparing them to the informal workers in the control group. However, as we are working with Differences in Differences this bias is netted

supporting the idea that the reform only generated an impact over the treated until it was fully implemented[22].

Table 5. Placebo Test. (Excluding self-employment)

	2012/2012				2013/2011			
	I sem	p-valule	II sem	p-valule	I sem	p-valule	II sem	p-valule
Mean outcome of the control group at the baseline	73	0.00	53	0.00	56	0.00	56	0.00
Mean outcome of the treated group at the baseline	40	0.00	25	0.00	25	0.00	26	0.00
Difference at the baseline	-33	0.00	-28	0.00	-31	0.00	-30	0.00
Mean outcome of the control group at the follow up	71	0.00	53	0.00	53	0.00	53	0.00
Mean outcome of the treated group at the follow up	39	0.00	24	0.00	24	0.00	24	0.00
Difference at the follow up	-32	0.00	-29	0.00	-29	0.00	-29	0.00
Difference in difference	0.1%	0.76	-0.7&	0.23	0.7%	0.28	1%	0.17

We also tested the hypothesis for multiple periods of pretreatment. For this purpose, we used the methodology suggested by Mora & Reggio (2014) to test the assumption of parallel trends:

$$E(Y_t|X,D) = \beta X_t + \delta + \sum_{\tau=t_2}^{T} \delta_\tau I_{\tau,t} + \gamma^D D + \gamma_p^D Post_t D + \gamma_1^D t D$$

where $I_{\tau,t}$ is a dummy variable for the period τ. The idea is to test for common pre-dynamics. For this purpose, we test the following hypothesis:

$$H_0: \gamma_\tau^P = 0 \ for \ all \ \tau \le t^*$$

where t* is the period where the treatment began. The results are shown in Table 6.

Thus, we don't reject the null hypothesis and conclude there are common pre-dynamics in both groups. This implies that the Parallel Paths assumption holds, so the results for the difference and difference estimators hold

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when subtracting the pre-reform results, unless these unobservable characteristics cause un-even changes in the rate of informality during the observed period. We did not find any reason for such an impact, as the placebo test confirms.
[22] It also indicates that there was no anticipation effect in terms or formal workers moving from the control to the treatment group in order to get advantage of the reform.

Table 6. Results for the Common Pre-treatment dynamics test.

Including self-employment	Output: *Informality*	Number of obs. = 304
	Sample Period: March 2009 – June 2015	H_0: Common Pre-dynamics = W =2.4903264
	Treatment Period: December 2013 – June 2015	p-value = 1
Excluding self-employment	Output: *Informality*	Number of obs. = 304
	Sample Period: March 2009 – June 2015	H_0: Common Pre-dynamics = W = 5.1173942
	Treatment Period: December 2013 – June 2015	p-value = 1

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3. **Quality of the matching.** In order to test the quality of the matching, we applied the criteria developed by Rosenbaum and Rubin (1985). We tested the quality of matching by using Rosenbaum and Rubin's (1985) rule of thumb according to which the standardised bias should be less than 5%. The standardized bias for the dummy co-variables was estimated as:

$$SB= 100 *(p_c - p_t) / [\{ p_t (1 - p_t) + p_c(1 - p_c)\} * 1/2]^{1/2},$$

where p_c is the proportion of each co-variable in the control group and p_t is the proportion of each co-variable in the treatment group. Tables 7a and 7b show that, after matching, all the control variables complied with this criterion with exception of the standardized bias in the exercise excluding self-employment. However, it should be taken into account that since we are working with standardized bias, the average bias in the p-score is actually what matters the most when using p-scores is -0.6.

Table 7a. Quality of the matching. Including self-employment

	Mean in treated	Mean in untreated	Std error		Mean in treated	Mean in untreated	Std error
Women (spouse)	0.12	0.12	0.4%	October	0.09	0.09	-0.1%
Women (other)	0.27	0.27	0.1%	November	0.09	0.09	0.1%
January	0.08	0.08	0.6%	December	0.08	0.08	0.0%
February	0.08	0.08	-0.8%	Less than 25	0.15	0.17	-6.4%
March	0.08	0.08	-0.3%	More than 55	0.29	0.3	-3.0%
April	0.08	0.08	0.0%	Primary (-)	0.15	0.15	0.9%
May	0.08	0.08	0.2%	High school (+)	0.39	0.4	-1.4%
June	0.08	0.08	0.0%	Diploma	0.7	0.71	-1.1%
July	0.08	0.08	-0.4%	Avgmin	1.59	1.59	0.6%
August	0.08	0.08	0.2%	Border city	0.09	0.09	-0.7%

Table 7b. Quality of the matching. Excluding self-employment

	Mean in treated	Mean in untreated	Std error		Mean in treated	Mean in untreated	Std error
Women (spouse)	0.13	0.14	-1.3%	October	0.09	0.09	0.2%
Women (other)	0.28	0.29	-1.2%	November	0.09	0.09	0.0%
January	0.08	0.08	0.9%	December	0.08	0.08	0.0%
February	0.08	0.08	-1.3%	Less than 25	0.17	0.19	-4.4%
March	0.08	0.08	-0.3%	More than 55	0.25	0.27	-4.8%
April	0.08	0.08	0.1%	Primary (-)	0.12	0.11	0.8%
May	0.09	0.09	0.1%	High school (+)	0.43	0.43	0.1%
June	0.08	0.08	-0.1%	Diploma	0.75	0.76	-1.8%
July	0.08	0.08	-0.2%	Avgmin	1.6	1.6	0.0%
August	0.08	0.08	0.0%	Border city	0.09	0.08	0.3%

4. **Exogeneity of the treatment. (Ashenfelter's dip).** A common critique to the difference in difference models with matching, and particularly over MDID with cross-section surveys, is to have a treated/no-treated variable endogenous to the policy implemented. This identification problem has been largely analysed by the literature (Abbring and Van den Berg (2003), Blundell (2009) and Lechner (2011) and is one of the downsides of using matching differences in differences that does not control for unobserved individual-specific shocks that influence the participation decision. A similar problem in another context might be easier to understand: A benefit program is implemented in two neighbouring towns and individuals migrate to the town where the program is implemented in order to get the benefits.

We don't have a panel to observe the number of workers that transit from control to treatment. The percentage of formal workers in the control group indeed diminished from 2012 to 2014 and this might be biasing our results. We have two caveats to the previous affirmation: First, if there is a bias, we can estimate it; and second, the direction of the bias goes in the same direction of the spirit of the tax reform.

Table 5 presents an estimate of the maximum bias of the exercise for the 13 Metropolitan areas excluding self-employed workers. According to the survey, the net number of formal workers that leaved the control group was 2258, and the net number of formal workers that leaved the control group was 3730 workers, then the maximum net number of switchers is 2258. We performed a simulation in which everything remains as in the baseline year, excepting the 2258 of formal workers that might have entered the treatment group to take advantage of the reform. According to the results, we claim that the tax reform diminished the informality rate of the treated in 7.4 p.p., of which 4.3 p.p. might be caused by formal workers entering the treatment group in order to obtain the benefits. Similarly, 2.2 of the 3.7 overall impact over the informality rate might have been affected by the formal switchers. (Note that the results are not obtained using matching but should approximate them). We understand that the composition of the groups in terms of socio-economic variables should not impact the results, since we are matching all four groups at the same time.

Table 8. Estimation of the bias caused by formal workers entering the treatment group to take advantage of the reform.

	13 areas (observed)				13 areas (simulation)			
	Total	Formal	Informal	Informality rate	Total	Formal	Informal	Informality rate
Control at baseline	58473	10710	47763	82%	58473	10710	47763	82%
Treatment at baseline	88142	53455	34687	39%	88142	53455	34687	39%
Control at follow up	54400	8452	45948	84%	56215	8452	47763	85%
Treatment at follow up	87997	57185	30811	35%	90400	55713	34687	38%
Net number of formals that leaved control	2258							
Net number of formals that entered treatment	3730							
Maximum net numbers of switchers	2258							
Difference in difference				-7.1%				-4.3%
% of treated on occupied (not weighted)				51%				51%
Impact over total informality rate (p.p.)				-3.6				-2.2

Our second claim is that the direction of the bias goes in the same direction of the spirit of the Law. In order to perform this analysis we divided the case of the lower threshold (one minimum wage) where formal workers that earned less than a minimum wage before the reform (for example if they work 90% of the time) move to a full time job in anticipation of the reform, given that the cost of being paid a full time job has been lowered; from the case of the upper threshold (10 minimum wages), where wages were reduced, or reported to be reduced, to less than 10 minimum wages in order to access to the benefit.

Whereas the impact on the upper threshold is undesirable, the impact on the lower threshold was not only positive but exactly the purpose of the reform: to reduce the labour cost, to make it more affordable to earn the minimum wage. It is, in a way, a channel through which the reform reduced informality. This a desirable result, since "quasi-formal workers" that work in the formal sector but earn less than a minimum wage moved to be fully formal and are likely contributing to health and pensions. This problem is very different from cases in which, for example, the individual does not accept a job in order to qualify to get an employment benefit or to what can happen in the upper limit of the Colombian reform (more the 10 minimum wages): workers reporting to earn less than 10 minimum wages to get access to the benefits.

According to the data, the endogeneity of the reform does not seem to be a problem at the upper bound. If we analyse only the impact restricting the reform to those individuals earning at least 10 minimum wages, the average increase in the treated group of the monthly sample would have actually decreased in 330 observations, overestimating the impact of the reform in a considerable amount. However, the number of the formal employment no treated did not increase. Therefore, we assume that there is no overestimation in this case.

In sum, we found that the informality rate of the treated group in comparison with the non-treated group decreased approximately 7.1 p.p. of which at most 4.3 p.p, was made effective

through the channel of formal workers earning less than a minimum wage that moved to be fully formal workers earning at least a minimum wage, probably making pension and health contributions. We understand that the composition of the groups should not have important implications in the method we used because we are matching all four groups at the same time. We also found that the change on the treated group was overestimated by the survey, meaning that if we get to use the matching differences in differences procedure using weights we will find a lower but more robust impact of the reform. Nevertheless, results at the upper bound should be taken with care since the amount of workers that report to earn more than 10 minimum wages is very small.

5. **Weights.** According to Dugoff (2014) estimations can incur in a considerable bias if the survey bias are not respected. However, there is not a clear procedure to include weights in this procedure. Dugoff (2014) suggests to include them in the estimation of the p-score, as we did in in the exercises described below. It is less clear how to include them in the second stage. One possibility is to multiply them by the kernel weights, but it might be necessary to standardize them first.

V.   *Impact of the Payroll Tax Reform on Income Distribution*

In order to be able to apply lessons from the Colombian case to other contexts and to analyse the impact of the reform on income distribution, we explored the characteristics of the workers most affected by the reform. We began by analysing the behaviour of the informality rate per income quintile for the first semester of 2012and the first semester of 2014. As shown in Graph 9, informality lowered during the period of analysis primarily amongst the middle-income quintile which includes minimum wage earners[23].When we performed the Differences in Differences exercise per socio-economic group, shown in Table 9, we also found that the workers with secondary education or less, benefited most from the reform. This can be explained by the fact that the reform removed a constraint that was bigger for minimum wage earners compared to workers receiving higher levels of income where wages are more flexible. The reform also benefited more males and adults 25-50.

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[23] Second or fourth quintile, depending whether we used the current or imputed income.
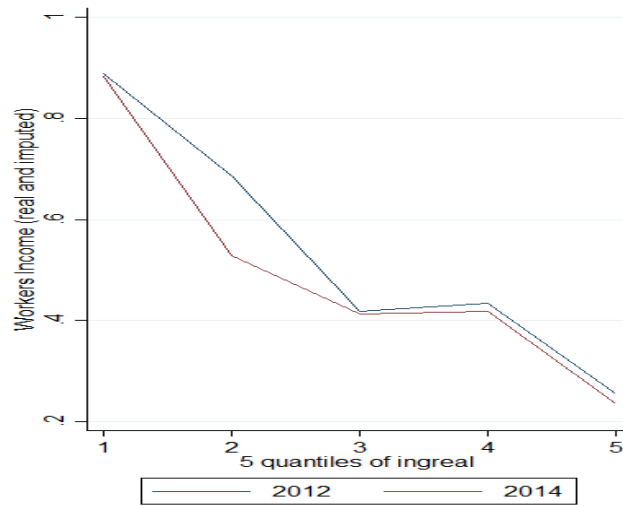
Graph 4. Lorenz curves before and after the reform

Table 9. Impact of the Tax Reform by population group.

		Baseline		Follow up		DID
	Outcome	Control	Treatment	Control	Treatment	
Low Educated (Primary or less)*	Informality $P > \|t\|P > \|t\|$	68% 0%	42% 0%	73% 0%	37% 0%	-10.2% 0%
High school*	Informality $P > \|t\|P > \|t\|$	56% 0%	25% 0%	66% 0%	22% 0%	-13% 0%
Tertiary education or higher*	Informality $P > \|t\|P > \|t\|$	36% 0%	14% 0%	35% 0%	13% 0%	-0.4% 0.78
Male 25-45 years	Informality $P > \|t\|P > \|t\|$	52% 0%	24% 0%	56% 0%	20% 0%	-8% 0%

Source: Own calculations, based on GEIH 2007-2015 *Male 25 – 45 years old.

VI.   Conclusions

The tax reform had a relatively significant impact on the informality rate of the treatment group after controlling for observable and some unobservable characteristics. This result reflects the most common findings in other studies. However, the reduction in informality seems to have been a one-off improvement and therefore new increases can be expected as a result of the current stage in the economic cycle. We also found that the payroll tax reform had the most impact on the middle-income population because workers in this group earn close to the minimum wage where the constraint was released.

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