

Minimum wages in formal and informal sectors: Evidence from the Colombian crisis

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Abstract

I estimate the effect of the minimum wage on formal wages, informal wages and employment in Colombia. I exploit an unexpected increase in the real minimum wage during the 1999 Colombian economic crisis to estimate short term effects of the minimum wage along the distribution of wages in both sectors. I find evidence of wage responses, with stronger incidence in the formal sector. Markets with a 10 % higher incidence of the minimum wage, measured by the number of workers affected, experienced wage increases of 4 % and 1.3 % in the formal and informal sector, respectively. I find negative employment effects on the informal sector, but no employment effects on the formal sector, and a lack

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of pass-through across sectors. My results suggest that minimum wages affect the informal labor market directly and not through the formal sector.

Keywords Minimum wage, wage distribution, informal labor markets.

JEL Codes J31, J38, J46

1 Introduction

The minimum wage is a common policy in developed and developing countries, and is conceived as a way to protect low skilled workers from earning below-subsistence wages and falling into poverty. Most of the literature about the impact of minimum wages focuses on the effects on a labor market where there is compliance with minimum wage regulation. We know less about the effects of the minimum wages in informal labor markets, understood as markets where labor regulations are not likely to be binding and compliance may be limited.

A common finding in the labor literature for developing countries is the incidence of the minimum wage in informal labor markets, ([Maloney and Mendez, 2004](#); [Gindling and Terrell, 2005](#); [Lemos, 2009](#); [Khamis, 2013](#)). This evidence shows that informal wage distributions have peaks at the minimum wage level. For formal markets in developing countries, the literature suggests that minimum wages affect the lower tail of the distribution of wages and reduce inequality ([Bosch and Manacorda, 2010](#)). We have less evidence about how these minimum wages impact informal wages. They may impact the informal market directly, by influencing contracts within the informal market, or indirectly, through interactions with the formal sector.

There is a theoretical basis for indirect effects. For example, in a segmented competitive labor market model, with a formal sector covered by regulations and a uncovered sector , theory suggests that a raise in the minimum wage would raise cov-

ered sector wages and decrease uncovered sector ones. Minimum wage regulation increases wages above the competitive level for workers in the lower part of the covered sector wage distribution, and leads some of them to be dismissed into the uncovered sector. These workers would enter the uncovered sector wage distribution at wages below the new minimum. In this model, in the spirit of [Harris and Todaro \(1970\)](#), there is pass-through from the formal to the informal sector.

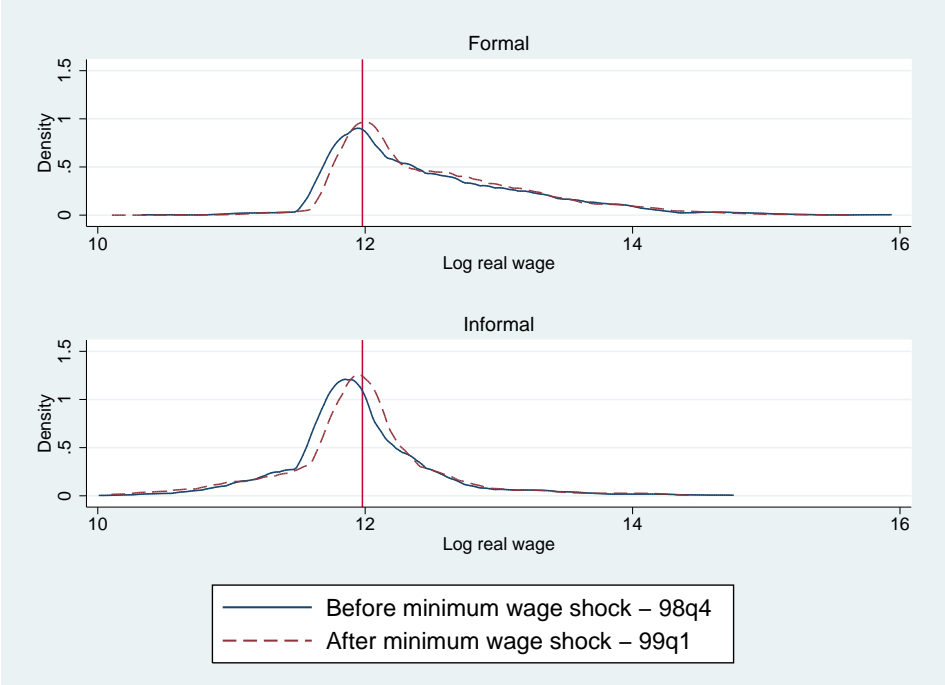
However, higher minimum wages may also have a direct impact in the informal labor market. If there is partial compliance, if the minimum wage is used as a benchmark for bargaining arrangements in the informal sector, or if it is used as a *numéraire* to set prices for informal prices, then higher minimum wages would affect the informal wage distribution directly.

In this paper, I estimate the effect of the minimum wage on the distribution of wages in formal and informal sectors in Colombia. The informal sector is characterized by workers that do not have access to health insurance. I exploit a inflation forecast error that followed the financial crisis of 1999, which led to a large unexpected increase in the real minimum wage. Colombian authorities increased the country-wide minimum wage in 16 % by the end of 1998, indexing the minimum wage to expected inflation in the upcoming year. However, due to the crisis, actual inflation was below expected and the minimum wage increased sharply that year.

Figure 1 shows the density of wages for the formal and informal sector in Colombia, before and after the minimum wage shock. Visual evidence suggests that both sectors react to the minimum wage shock, with the distribution shifting around the percentiles where the minimum wage binds. I estimate the effect of this unexpected shock on the marginal distributions of formal and informal wages, and address direct and indirect effects on the informal sector. I do this in three steps. First, I measure the incidence of the minimum wage by calculating the percentage of people that

earned wages close to the minimum right before the minimum wage shock. I calculate this incidence for different cities and industries, and for formal and informal sectors.

Figure 1: Density of monthly wages in formal and informal sector.



Vertical line at level of latter minimum wage. Source: ENH, author’s calculations.

Then, I compare wage distributions between markets with different incidence. To do this, I combine a unconditional quantile regression method, that allows me to estimate the impact on marginal distributions, with a difference in difference design. To address time-varying labor market differences between cities, I control for city specific trends and [Bartik \(1991\)](#) local labor demand shocks.

I find that in the quarter immediately following the minimum wage change, markets with higher incidence of the minimum wage had larger wages for formal and informal workers around the 30th and 50th percentiles of the wage distribution respectively, just where the minimum wage binds. The effects do not propagate to the rest of the distribution. For the formal sector, a 10 % higher incidence of the

minimum wage, measured by the fraction of workers affected by the increase, is associated with 4% higher wages around the minimum wage. When I compare these effects with the effects that would be obtained if all workers affected by the minimum wage received a wage increase, I find that the estimated effects are smaller than the counterfactuals for the lower tail of the distribution, but higher as I move towards the quantile where the minimum binds. This implies a low wage response for workers below the minimum wage, but a full response for workers earning it. These results are stable across several specifications and are robust to placebo tests. In the informal sector, wage responses are more limited and center around median wages, with wages about 1.3% higher in markets with 10 % larger incidence. These results are smaller and not as robust as the results for formal wages.

Inspired by the competitive model, I test for pass-through from the formal to the informal sector by looking at the effect of formal sector minimum wage incidence on informal wages, and estimate employment effects in both sectors. I find that these results can not be explained by pass-through from the formal sector, since markets with high minimum wage incidence in the formal sector do not show any wage response in the informal sector following the shock. When I turn to employment effects, I find small and insignificant effects on the formal sector, but some evidence of employment reductions in the informal sector. These results suggest that employment is more flexible in the informal sector. Together with the results for wages, these results imply limited pass-through from the formal to the informal sector following the minimum wage shock.

There are several theoretical explanations to account for minimum wage effects on the entire distribution of wages in developed countries ([Neumark and Wascher, 2008](#), chapter 4). Besides the competitive model, substitution from low skilled to high skilled labor could lead to wage gains for workers earning above the minimum

wage. If the minimum wage is used as a *numéraire* for setting other wages, then an increase on the minimum wage can lead to a shift in the whole distribution of wages. A large body of literature for developed countries estimates these impacts. In the US, these studies have followed different approaches, from decomposition approaches (DiNardo et al., 1996), quantile regressions (Lee, 1999; Autor et al., 2010) and panel data studies Neumark et al. (2004). This literature also examines the contributions of other factors to wage inequality, such as skill biased technological change (Card and DiNardo, 2002; Autor et al., 2008). In general, this literature finds a role of the decrease of the real value of the minimum wage on the increase in inequality in the US, but the magnitude of this effect is disputed.

In the presence of an informal sector not covered by the minimum wage, alternative models explain why the minimum wage can increase wages in both sectors and along the whole distribution. Effects in both sectors could happen, for example, if capital is reallocated into the informal sector increasing the marginal productivity of labor in that sector, or if the increase in wages in the covered sector raises the demands for goods produced in the uncovered sector (Khamis, 2013). The empirical literature for developing countries has tried to estimate impacts on the informal sector, guided by the competitive model and alternative models. The results are at odds with the competitive model and suggest alternative explanations. Gindling and Terrell (2005) find that the minimum wage reduced wage differentials in formal sectors and informal sectors with low minimum wage enforcement, but has no effect on the self employed. Lemos (2009) provide descriptive evidence showing responses of wage distributions to the minimum wage on the formal and informal sector. Khamis (2013) finds larger impacts of increases in the minimum wage in the informal sector when compared to the formal, using quasiexperimental variation of the minimum wage in Brazil and Argentina.

For Colombia, the evidence is limited. [Maloney and Mendez \(2004\)](#) argue that the minimum wage is binding and induces spikes in the distributions of both wages and income. Using time series methods, they find that the minimum wage increases real hourly wages through the conditional distribution of wages. The effects are large for those earning close to the minimum wage, but there are spill-over effects for the whole distribution. From the point of view of causal inference, the reliance on time series variation of the minimum wage is problematic, due to absence of clearly defined treated and control groups.¹ Their results have limited applicability to the effects on inequality, as effects on the conditional distribution do not translate equally to the marginal distribution.

[Arango and Pachón \(2007\)](#) using dynamic panel data methods, find that the minimum wage has negative but insignificant effects on family incomes for the tenth decile of the distribution of income, and positive and significant effects for higher deciles, leading to an increase in inequality as measured from deviations to the median. They do not address the impact on the informal sector, nor do they examine wages separately. This paper addresses the impact on both formal and informal wages.

Two other papers emphasize the impacts of the minimum wage on the informal sector [Mondragón et al. \(2010\)](#) use time and city variation in the median to minimum wage ratio, from 1984 to 2006, to estimate the impact on the probability of being informal. They find that a 10% increase in the minimum wage increases the probability of being informal in 1%. [Ruiz \(2010\)](#), using the same data and controlling for characteristics of the firms, finds that the minimum wage increases the probability of being informal and the income gap between formal and informal workers. Both of these

¹Also, as [Neumark and Wascher \(2008\)](#) point out, the use of lagged minimum wages implies that when the minimum wage increases, there are two treated groups: a group unaffected by the lagged effect of the minimum wage and another affected by it.

papers suggest the existence of pass-through from the formal to the informal sector. My paper suggests that while the minimum wage affects the informal market, this impact is due to within sector effects.

Beyond these differences, this paper contributes to the literature in several ways. First, I provide a methodology to estimate the effect of the minimum wage on unconditional wage distributions. This allows me to go beyond the descriptive evidence found in [Lemos \(2009\)](#) and [Khamis \(2013\)](#). Second, in contrast to the previous literature for Colombia and most of the minimum wage literature in the US, I examine a unexpected minimum wage shock instead of relying in time series variation with shocks that may be expected. This unexpected nature allows me to identify the minimum wage effect without confounding it with other expected end of year shocks. Finally, my paper casts doubt on the evidence of pass-through from the formal to the informal sector.

The rest of the paper is organized as follows. Section [2](#) provides some facts about the evolution of the minimum wage in Colombia, labor market regulations and the financial crisis of 1999. In section [3](#) I discuss my empirical strategy. I describe the data and provide some facts about the size of the sectors and the incidence of the minimum wage in section [4](#). The main results and robustness checks are presented in section [5](#). Finally, section [6](#) concludes. Two appendices provide details about data and variable construction and show additional estimation results.

2 The minimum wage in Colombia and the 1999 shock

In this section I provide basic facts about minimum wage legislation in Colombia, and explain the 1999 shock in the real minimum wage. I show that the financial crisis of 1999 produced a sharp, unexpected increase in the real minimum wage. I

use this shock to estimate the effects of higher minimum wage incidence on formal wages, informal wages and unemployment.

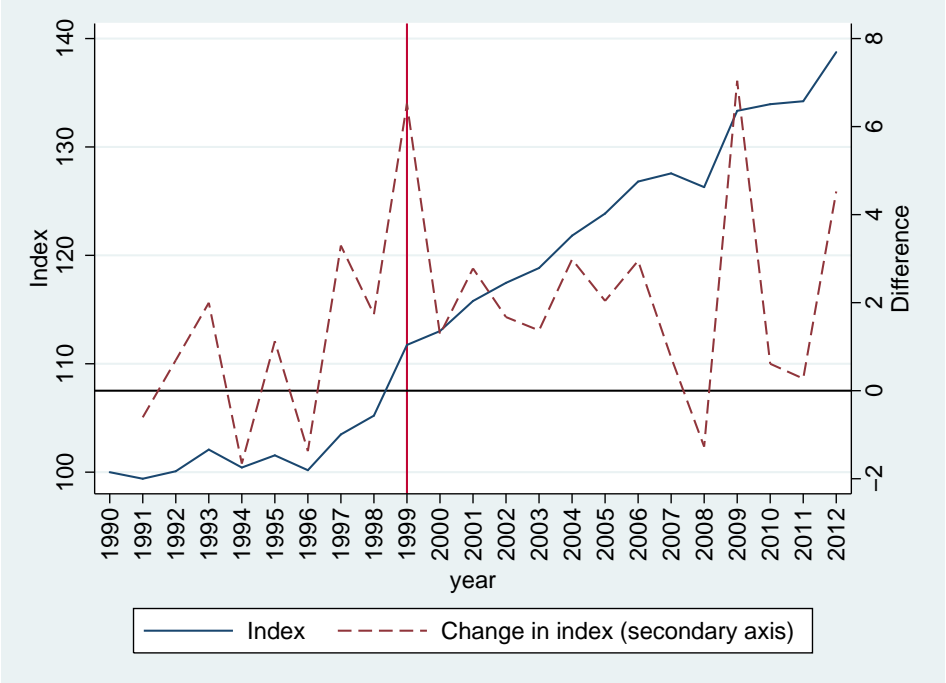
[Arango et al. \(2008b\)](#) summarizes the evolution of the minimum wage in Colombia and the changes in minimum wage legislation. Colombia started having minimum wage regulations in 1949, and had minimum wages that differed by firms and industries until 1983, where they were unified to a national minimum wage. After this and through 1991, the minimum wage was increased yearly according to realized inflation. In 1991, a new constitution was enacted and established minimum wage regulation should be linked to minimum living expenses and changes in labor productivity. In 1996, a commission to determine the minimum wage was established, and it has yearly discussed the adjustments to the minimum wage ever since. It is formed by representatives from the government, firms and unions. Every year, the commission negotiates a minimum wage increase for the next year. If the commission is unable to come to an agreement before December 15, the government sets the increase to the minimum wage before the end of the year. Up to 2014, there has never been agreement in the commission and the government has set the minimum wage increases.

Up to 1998, the government set the minimum wage according to several parameters: The inflation target for the following year, increases on labor productivity calculated by a productivity committee within the Ministry of Labor, GDP growth and the evolution of the consumer price index. From December of 1999, the Constitutional Court also required that minimum wage should not be below the inflation of the previous year, so the minimum wage has increased its real value from 2000 since increases always exceed inflation by a small margin.

Figure 2 shows the evolution of real minimum monthly wages from 1990. Over this period, the nominal minimum wage ranges from 88 current USD in 1990 to

123 USD at the end of the 2012. It shows that the real value of the minimum wage remained stable until 1996, when it started increasing steadily. There are two large yearly changes of the real minimum wage, in 1999 and 2009. These changes are due to misalignment between expected inflation during a financial crisis on 1999 and the global slowdown of 2009. I now focus on the first of this events.

Figure 2: Evolution of the Real Minimum Wage in Colombia. Index. 1990=100.



Source: Colombia’s Central Bank, Banco de la República. Author’s calculations.

The causes of the financial crisis of 1999 in Colombia have been widely studied (Parra and Salazar, 2000; Villar et al., 2005; Gomez-Gonzalez and Kiefer, 2006). Colombia experienced a credit boom in the 90’s as a consequence of financial liberalization in the early 1990s. A large expansion of the number of financial institutions and loans was accompanied by reductions in the quality of the loans. Also, monetary policy helped contribute to increases in interest rates. By 1999 a large capital reversion and a decrease in the terms of trade occurred. Sharp increases in non-performing loans forced the government to intervene and liquidate many of the in-

stitutions. GDP decreased in 1999 in about 4 %, but the crisis subsided in two years, and by 2001 GDP was back at its 1998 level.

By the last quarter of 1998 inflation was expected to be 16% for the upcoming year, and the minimum wage was increased accordingly. However, inflation in 1999 turned out to be only 9.25% due to the financial crisis, so the real minimum wage increased by 6.75 % by the end of 1999. For the first quarter of 1999, inflation was about 5 %, so the real minimum wage increase 11 % between 1998q4 and 1999q1. This change was, as usual, set by the government without agreement from the commission.

Due to the unexpected and external nature of the financial crisis, this shock is arguably more exogenous than other minimum wage increases analyzed for developing countries ([Lemos, 2009](#); [Khamis, 2013](#)). The change was nationwide and the posterior inflation misalignment was unexpected, so the shock was not likely to be driven by local labor market conditions. My minimum wage incidence measures are calculated for 1998q4, the quarter preceding the minimum wage shock.

3 Empirical strategy

In this section I describe the empirical strategy used to estimate wage effects through the distribution of formal and informal wages, and to estimate employment effects. To estimate wage effects, I combine a unconditional quantile regression method ([Firpo et al., 2009](#)) with a difference in difference specification to estimate a quantile difference in difference model. I explain how this methodology relates to well known methodologies to estimate distributional effects of the minimum wage ([DiNardo et al., 1996](#); [Lee, 1999](#); [Bosch and Manacorda, 2010](#)), and how I build a measure of the minimum wage incidence around the 1999 real minimum wage shock. To

estimate employment effects, I use a standard difference in difference specification, which I describe at the end of the section.

3.1 Effects on the wage distribution

3.1.1 Unconditional quantile regressions

My objective is to estimate the effect of the change in the minimum wage on the unconditional wage distributions for formal and informal sectors shown in figure 1. Assume that wages follow a structural model $W = h(X, \varepsilon)$, where X is a set of covariates which includes the minimum wage, ε is a unobservable term, and $h(\cdot, \cdot)$ is invertible in ε ². Start from writing the marginal distribution of wages W in either sector as a function of the conditional distribution of wages and the joint distribution of covariates.

$$F_W(w) = \int F_{W|X}(w|X = x)dF_X(x) \quad (1)$$

A standard approach would be to estimate a counterfactual distribution of wages given a new distribution of covariates $G_X(x)$ following a change in the minimum wage, assuming the conditional distribution $F_{W|X}$ remains constant:

$$G_W(w) = \int F_{W|X}(w|X = x)dG_X(x) \quad (2)$$

This is the approach used by [DiNardo et al. \(1996\)](#) to estimate the effects of minimum wages on inequality in the United States, and the basis of the methods of counterfactual wage decomposition ([Mata and Machado, 2005](#); [Chernozhukov et al., 2013](#)). Instead of estimating the entire counterfactual distribution $G_W(w)$, following

²This invertibility assumption is recurrent in the literature on distributional impact. See for example, [Athey and Imbens \(2006\)](#)

Firpo et al. (2009), I estimate the effect of a small change on the minimum wage, which induces a change in the distribution of covariates $F_X(x)$ to $G_X(x)$, on the quantiles of the counterfactual distribution $G_W(w)$. I refer to this as the *unconditional quantile effect*. I define this effect precisely and show how to estimate it below.

Let $Q_\tau(W) = Q_\tau(h(X, \varepsilon))$ denote the τ -th quantile of the distribution of wages, and $Q_\tau(W|X = x) = Q_\tau(h(X, \varepsilon)|X = x)$ be the conditional quantile given $X = x$. The *conditional quantile effect* (CQE) is the effect of a small change on covariates on the conditional quantile.

$$CQE(\tau, x) \equiv \frac{\partial Q_\tau(h(X, \varepsilon)|X = x)}{\partial x} \quad (3)$$

The *unconditional quantile effect* (UQE) is the weighted average of these conditional effects over the distribution of covariates, matching each conditional quantile to a quantile on the unconditional distribution:

$$\begin{aligned} UQE(\tau) &\equiv E[\omega_\tau(X) CQE(s(X), X)] \\ \omega_\tau(x) &\equiv \frac{f_{Y|X}(q_\tau|x)}{f_Y(q_\tau)} \\ s(x) &\equiv \{s : Q_s(W|X = x) = q_t\} \end{aligned} \quad (4)$$

The UQE can be seen as the marginal change in the marginal distribution of wages following a small change in the distribution of the covariates. Firpo et al. (2009) shows that the UQE can be rewritten as the average marginal effect from a binary response model on the probability of wages exceeding a particular value for the quantile.

$$UQE(\tau) = \frac{1}{f_W(q_\tau)} \int \frac{dPr[Y > q_\tau | X = x]}{dx} dF_X(x) \quad (5)$$

[Firpo et al. \(2009\)](#) propose to estimate the UQE estimating of the function $Pr[Y > q_\tau | X = x]$ by linear regression, and then rescaling the coefficients on the covariates by $\frac{1}{f_W(q_\tau)}$. This amounts to estimating a linear regression with the following dependent variable:

$$R\hat{I}F(W, \hat{q}_\tau) = \frac{I(W > \hat{q}_\tau)}{\hat{f}_W(q_\tau)} + \hat{q}_\tau - \frac{1 - \tau}{\hat{f}_W(q_\tau)} \quad (6)$$

where \hat{q}_τ and $\hat{f}_W(q_\tau)$ are estimates of the quantile and the density at the quantile, respectively. This methodology allows me to estimate the effect of a change in a covariate X on the quantiles of marginal distribution of wages. In the following section I explain how I combine this strategy with a differences in differences methodology to estimate the marginal effect of the minimum wage increase on these quantiles.

3.1.2 A difference in difference strategy

Previous attempts to estimate quantile difference in difference models, starting from [Meyer et al. \(1995\)](#), assume a linear specification for the conditional quantile function $Q_\tau(h(X, \varepsilon))$ in equation (3). Other papers that estimate the effect of minimum wages on inequality, such as [Lee \(1999\)](#), [Bosch and Manacorda \(2010\)](#) and [Autor et al. \(2015\)](#), also start from a linear model for conditional quantiles and assume they evolve in parallel across cities or industries. I depart from this assumption and assume a linear form of the function $E[Pr[Y > q_\tau | X = x]]$ in equation (5) directly. This allows me to estimate the UQE by linear regression and conduct inference using techniques available for OLS. OLS also provides the best linear approximation

to this expectation function.³

Let w_{icjt} be the wage of individual i in city c and industry j at time t . My simplest specification is a regression of the form

$$R\hat{I}F(w_{icjt}, \hat{q}_\tau) = \phi_c + \phi_t + \theta MW_{cj}1(t > 1998q4) + \delta X_{cjt} + \varepsilon_{cjt} \quad (7)$$

In this regression, ϕ_c and ϕ_t are city and time effects, MW_{cj} is a measure of the minimum wage shock incidence, $1(t > 1998q4)$ is a dummy variable equal to 1 after the minimum wage shock, X_{cjt} are covariates and ε_{cjt} is an error term.

Since there is not cross sectional variation in the nominal minimum wage, I measure the minimum wage incidence using a “fraction affected” variable, F_{cj} the proportion of workers earning between the old and the new real minimum wage. I count the number of workers that are between the old and the new minimum wage. If this percentage is larger for a particular city industry pair, this market should be more affected by the minimum wage increase. This variable has been used extensively in the minimum wage literature (Card, 1992; Stewart, 2002; Lemos, 2009; Khamis, 2013). I calculate this incidence for 1998q4, the quarter before the minimum wage changes.

$$F_{cj} = \frac{\#(mw_{98q4} < w_{icjt} < mw_{99q1})}{N_{cj,98q4}} \quad (8)$$

I provide details of the calculation of this variable in section A.3 of the appendix. I calculate this incidence for both formal and informal sectors. I also test other variables of incidence for robustness checks.

My identifying assumption is that the conditional probability of wages exceeding

³Firpo et al. (2009) also use this assumption when comparing conditional and unconditional quantile effects in their empirical application, and find that this estimator performs well and provides estimates close to fully nonparametric estimates.

a given value can be approximated by a linear function, and that this probability evolves in parallel across cities. This is unlikely if there are city specific trends in the wage distribution, or if there are city specific shocks that affect cities differentially according to the minimum wage incidence. Moreover, there maybe industry specific shocks that cause wage distributions to evolve differently across cities. I attempt to address these concerns using different specifications.

To address the existence of labor demand shocks that affect cities differently, I control for city level employment and Bartik shocks as covariates X in equation (7). Bartik shocks are intended to capture labor demand shocks that are external to each city. Details are provided in appendix A.3. I use either Bartik quantity or price shocks. To capture city specific trends in the distributions, I allow for a linear city specific trend, leading to a specification of the form:

$$R\hat{I}F(w_{icjt}, \hat{q}_\tau) = \phi_c + \phi_t + \Phi_c \times t + \theta MW_{cj}1(t > 1998q4) + \delta X_{cjt} + \varepsilon_{cjt} \quad (9)$$

For this specification, identification requires that any unobservables that evolve differently across cities are well approximated by a linear trend. In my last specification, I include city industry fixed effects, to control for permanent differences across city industry blocks. This is a standard difference in difference specification using the city industry blocks as treatment units:

$$R\hat{I}F(w_{icjt}, \hat{q}_\tau) = \phi_{cj} + \phi_t + \theta MW_{cj}1(t > 1998q4) + \delta X_{cjt} + \varepsilon_{cjt} \quad (10)$$

To conduct inference, I use the wild-bootstrap-t method of [Cameron et al. \(2008\)](#) and cluster by city, thus allowing for correlation of the error terms in equations (7), (9) and (10) across industries within each city. The bootstrap method is intended to

reduce over rejection, which is frequent in difference in difference studies (Bertrand et al., 2004), and to address the small number of clusters. I report parametric standard errors clustered by city, and p values and confidence intervals obtained through the bootstrap procedure. Note that since the p-values are obtained through the bootstrap, standard errors and p-values may point in different directions.

3.2 Effects on employment

I estimate effects on employment in both sectors using a differences in differences specification on data aggregated at the city industry level. The simplest specification includes city and time effects:

$$N_{cjt} = \phi_c + \phi_t + \theta MW_{cj} 1(t > 1998q4) + \delta X_{cjt} + \varepsilon_{cjt} \quad (11)$$

Here, N_{cjt} is a measure of employment or unemployment at the city industry level. A challenge in a industry level is to assign an industry to unemployed workers. I calculate unemployment rates at the industry level by assigning a unemployed worker to industry j if his previous job was in that industry or if he has looked for a job in this industry in the last quarter. For employment rates, I calculate the employment share in industry j for each city.

$$\begin{aligned} N_{cjt}^E &= \frac{O_{cjt}}{O_{ct} + U_{ct} + I_{ct}} \\ N_{cjt}^U &= \frac{U_{cjt}}{O_{cjt} + U_{cjt}} \end{aligned} \quad (12)$$

As an alternative employment variable, I use hours worked in the last week at the individual level. As in the previous section, I also try different specifications to

account for labor demand shocks, industry effects and city trends. I estimate the analogs of specifications (7), (9) and (10).

4 Data sources and descriptive statistics

My data comes from Colombia's National Household Survey (ENH) for the years 1996-2001. The ENH was a quarterly cross sectional survey used to calculate labor market indicators at a National and City Level. It is representative for the major metropolitan areas of the country. The survey collects data on wages, employment, demographic and labor market variables. I restrict my sample to occupied workers in the government and private sector, and exclude the self employed.

I classify workers who do not have health insurance provided by their employer as informal. There are other measures of informality available, but all of them capture the same dynamics and the health measure is available for most of the sample, as opposed to other measures. Appendix A.2 and Mondragón et al. (2010) provide details about how this measure compares to alternative measures.

Table 1 shows sample percentages by minimum wage incidence, formality, location and industry. This table shows several important facts about the extent of informality and the incidence of the minimum wage. First, it shows that the informal sector is large: about 22 % of workers in the pooled sample are informal according to my health insurance based measure. It also shows that the minimum wage is binding in both sectors, with about 9 % of workers earning around the minimum wage in either sector. While most formal workers earn above the minimum wage, most informal workers earn below it. Still, more than 40% of informal workers earn above the minimum wage. I also show that there is substantial spatial and industry heterogeneity in minimum wage incidence. In the largest cities in terms of number

of workers, they tend to earn above the minimum wage. Medellin, the city with the most minimum wage incidence, has about three times as many minimum wage workers as Bogota, the largest city. Construction and trade are the industries where most workers earn below or at the minimum wage, but there minimum wage workers are present in all industries, as opposed to the U.S., where they are mostly in the restaurant industry (Dube et al., 2010).

Table 1: Sample percentages by region, industry and informality relative to minimum wage

	Relative to Minimum wage							
	Below		At		Above		Total	
	Row %	Cell %	Row %	Cell %	Row %	Cell %	Row %	Cell %
Informality								
Formal	17.9	13.9	9.3	7.2	72.9	56.8	100.0	78.0
Informal	47.5	10.5	9.4	2.1	43.1	9.5	100.0	22.0
Total	24.4	24.4	9.3	9.3	66.3	66.3	100.0	100.0
City								
Barranquilla	23.9	2.2	8.2	0.8	67.9	6.4	100.0	9.4
Bogota	23.0	12.0	6.7	3.5	70.3	36.6	100.0	52.1
Bucaramanga	26.3	1.6	13.6	0.8	60.1	3.6	100.0	6.0
Cali	30.6	4.2	8.8	1.2	60.7	8.3	100.0	13.6
Manizales	21.5	0.6	15.1	0.4	63.4	1.7	100.0	2.6
Medellin	22.3	3.1	17.4	2.4	60.3	8.5	100.0	14.1
Pasto	32.8	0.7	8.4	0.2	58.7	1.3	100.0	2.3
Total	24.4	24.4	9.3	9.3	66.3	66.3	100.0	100.0
Industry								
Manufacturing	29.9	8.0	13.2	3.5	56.9	15.2	100.0	26.8
Construction	30.7	1.5	9.3	0.5	60.0	2.9	100.0	4.9
Trade, Restaurants, Hotels	32.6	6.6	12.4	2.5	55.0	11.2	100.0	20.3
Transport and Communications	19.5	1.2	7.2	0.4	73.3	4.4	100.0	6.0
Financial services	15.5	1.9	6.7	0.8	77.8	9.5	100.0	12.2
Social and Personal Services	17.3	5.2	5.2	1.6	77.5	23.1	100.0	29.9
Total	24.4	24.4	9.3	9.3	66.3	66.3	100.0	100.0
Sample size	34,142		14,940		83,409		132,491	

Source: ENH, author's calculations. Pooled data 1996q2-2001q4. All calculations based on real wages. "At minimum wage" includes workers whose real wage is within 3 p.p of the real minimum wage in their city. The sample is described in appendix A.2.

Appendix tables [B.1](#) and [B.2](#) provide additional facts about the incidence of minimum wages and informality. Most minimum wage workers are between 18 and 25 years of age, have between 6 and 11 years of schooling, and are on the private sector. Among those with less than 5 years of education, more than half earn at or below the minimum wage. Only 8% of government workers earn at or below the minimum wage, whereas 37 % of private sector workers are at or below the minimum wage in this pooled sample. Across all categories of age and schooling, most of the workers are in the formal sector, except for those below 18 years of age who are only 2 % of the sample. The incidence of informality is very low in the government sector, with only 4.3 % of government workers being classified as informal.

In table [2](#), I show the distribution of real wages along some demographic and labor market characteristics, including informality. Along with some interesting facts about the distribution of wages, this table shows that the minimum wage falls at around the 25th to 30th percentile of the distribution of formal wages, and slightly above the median of the distribution of informal wages. Wages are higher for males, older and more educated workers, and are higher in the government sector.

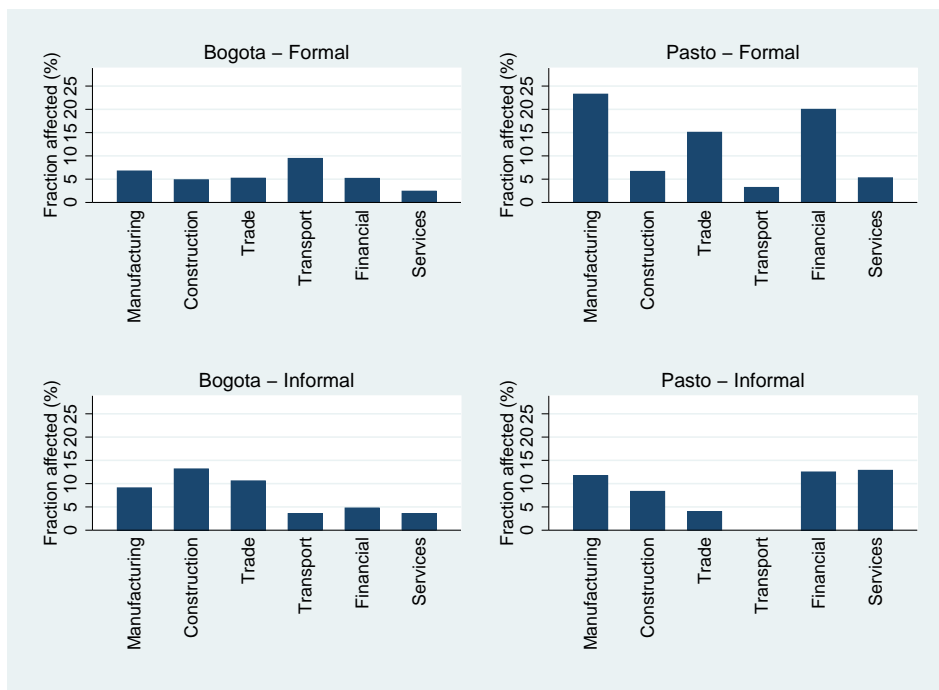
In figure [3](#), I show that there is substantial heterogeneity in the incidence of the minimum wage across locations and industries before the real shock of 1999. In the formal sector, the fractions of workers affected by the minimum wage shock are larger in the smallest city in the sample, Pasto, than in the largest city, Bogota. The difference can be as large as 15 p.p. for some sectors. In the informal sector, the differences across cities are less evident. Manufacturing and construction are the sectors with the largest incidence across cities and sectors. Appendix table [B.3](#) shows the full distribution of fraction affected across cities, sectors and industries.

Table 2: Distribution of real wages, by sample characteristics. Dollars of 1998.

	Mean	P10	P25	P50	P75	P90
Gender						
Male	176.9	64.9	72.9	100.5	178.7	351.5
Female	155.6	64.9	72.1	96.0	168.3	305.1
Total	166.8	64.9	72.4	98.1	175.7	324.8
Age						
12-17	63.5	22.6	37.7	62.0	72.5	91.4
18-25	108.1	60.2	69.2	79.5	116.9	177.2
26-50	185.4	66.8	75.4	114.3	199.7	365.7
51-65	231.8	66.3	77.3	126.3	255.2	496.0
Total	166.8	64.9	72.4	98.1	175.7	324.8
Years of schooling						
0-5	88.8	50.5	66.3	74.1	92.7	134.1
6-11	112.4	64.0	71.1	84.2	126.8	182.8
12-17	283.5	84.0	125.7	197.6	329.6	548.4
more than 17	496.3	96.1	223.1	378.8	623.9	990.0
Total	166.8	64.9	72.4	98.1	175.7	324.8
Sector						
Private	152.3	64.1	71.5	89.9	149.5	286.7
Government	257.3	83.4	125.0	188.1	300.8	482.4
Total	166.8	64.9	72.4	98.1	175.7	324.8
Relative to Minimum wage						
Below	60.9	37.3	58.3	66.1	70.2	72.9
At	74.5	69.7	71.5	74.1	77.6	79.5
Above	218.7	83.8	98.7	141.9	235.5	413.4
Total	166.8	64.9	72.4	98.1	175.7	324.8
Informality						
Formal	185.7	68.2	76.5	114.7	198.0	364.7
Informal	99.9	40.8	63.8	73.1	97.7	153.5
Total	166.8	64.9	72.4	98.1	175.7	324.8
Sample size	132,491					

Source: ENH, author's calculations. Pooled data 1996q2-2001q4. All calculations based on real wages for 1998, converted to us dollars using a 1 dollar = 2000 pesos exchange rate. "At minimum wage" includes workers whose real wage is within 3 p.p of the real minimum wage in their city. The sample is described in appendix A.2.

Figure 3: Variation in minimum wage incidence in 1998q4



Source: ENH, author’s calculations. Incidence is measured by “fraction affected”, the fraction of workers between the old and new minimum wage, defined in equation 8. The sample is described in appendix A.2.

5 Results

In this section I describe the main results of my analysis. I describe results on wages and employment on the formal and informal sectors.

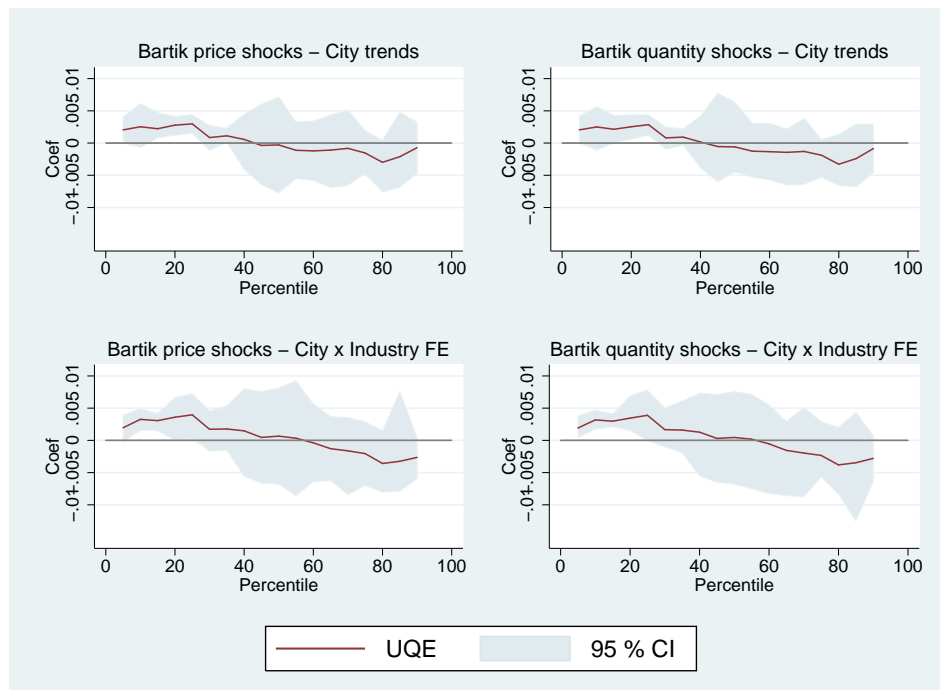
5.1 Effects on wages

5.1.1 Formal sector

Figure 4 shows estimated unconditional quantile effects for the formal wage distribution. For all specifications, I find evidence of increases in wages in the lower tail of the distribution, implying compression of the distribution. The results are fairly stable across specifications. Effects are found up to the 30th percentile of the distribution, where the minimum wage binds. For higher percentiles, the effects are not significant.

Table 3 shows these results for selected percentiles of the distribution. These are increases in log wages at each percentile when incidence is 1% larger in a city industry block. The real minimum wage increased by 9.75 % in the shock. Had incidence been 10 p.p higher across cities and industries, wages at the 5th percentile would have increased by about 2% in response to the minimum wage shock. These effects grow larger up to the 25th percentile of the distribution, where wages would increase about 4 % with a 10 p.p higher incidence. The increase in incidence from the market with the least minimum wage incidence (social services in Bogotá) to the market with the most incidence (construction in Manizales) is of about 32 p.p. My estimates imply that if all cities had this highest incidence, wages would grow around 12% for the quantiles of the wage distribution close and below the minimum wage.

Figure 4: Effects of minimum wage on the distribution of formal wages



Source: ENH, author's calculations. The sample is described in appendix A.2. The red line corresponds to the estimates of unconditional quantile effects for percentiles of the distribution of formal wages. Minimum wage incidence is measured by "fraction affected" defined in equation 8. Upper panels correspond to specifications 6, lower panels to specifications 9 and 10 of the text. Shaded areas are 95% confidence intervals obtained using a wild bootstrap-t procedure with 200 replications, clustered by city, where the null hypothesis is equality of the coefficient to 0. Full estimation results for selected quantiles are on table 3.

Table 3: Effect of minimum wage incidence on formal wage distribution.

	(1)	(2)	(3)	(4)	(5)	(6)
p5	0.0020** (0.0009) [0.040]	0.0019** (0.0008) [0.030]	0.0020** (0.0009) [0.030]	0.0021* (0.0009) [0.100]	0.0020** (0.0009) [0.045]	0.0019** (0.0008) [0.025]
p10	0.0033** (0.0006) [0.005]	0.0032*** (0.0006) [0.000]	0.0025 (0.0011) [0.109]	0.0025 (0.0012) [0.119]	0.0033** (0.0006) [0.005]	0.0032** (0.0006) [0.005]
p15	0.0031*** (0.0004) [0.000]	0.0030*** (0.0004) [0.000]	0.0022* (0.0008) [0.090]	0.0021* (0.0008) [0.060]	0.0031*** (0.0004) [0.000]	0.0030*** (0.0004) [0.000]
p20	0.0036*** (0.0008) [0.000]	0.0035** (0.0008) [0.020]	0.0028** (0.0005) [0.020]	0.0025** (0.0006) [0.030]	0.0036*** (0.0008) [0.000]	0.0035** (0.0008) [0.020]
p25	0.0040** (0.0011) [0.020]	0.0039** (0.0011) [0.010]	0.0030** (0.0005) [0.010]	0.0029** (0.0006) [0.020]	0.0040*** (0.0011) [0.000]	0.0039* (0.0011) [0.060]
p30	0.0017 (0.0012) [0.408]	0.0017 (0.0012) [0.348]	0.0009 (0.0007) [0.627]	0.0008 (0.0007) [0.343]	0.0017 (0.0012) [0.274]	0.0017 (0.0012) [0.398]
p50	0.0007 (0.0027) [0.915]	0.0005 (0.0026) [0.871]	-0.0003 (0.0020) [0.915]	-0.0006 (0.0018) [0.826]	0.0007 (0.0027) [0.866]	0.0005 (0.0026) [0.920]
p75	-0.0021 (0.0016) [0.159]	-0.0023 (0.0016) [0.308]	-0.0015 (0.0015) [0.289]	-0.0019 (0.0013) [0.279]	-0.0021 (0.0016) [0.348]	-0.0023 (0.0016) [0.269]
p90	-0.0026 (0.0011) [0.149]	-0.0028** (0.0012) [0.050]	-0.0007 (0.0015) [0.711]	-0.0009 (0.0015) [0.746]	-0.0026 (0.0011) [0.124]	-0.0028 (0.0012) [0.149]
Observations	101656	101656	101656	101656	101656	101656
City FE	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bartik price shocks	Yes		Yes		Yes	
Bartik quantity shocks		Yes		Yes		Yes
City specific trends			Yes	Yes		
City x industry FE					Yes	Yes

Source: Author's calculations. Each row of the table corresponds to the estimates of unconditional quantile effects for a quantile of the distribution of formal wages. Minimum wage incidence is measured by "fraction affected" defined in equation 8. Columns correspond to specifications on equations 6 - 10 of the text. The sample is described in appendix A.2. Standard errors clustered by city in parentheses. P-values in brackets. P-values are obtained with a wild bootstrap-t procedure with 200 replications, where the null hypothesis is equality of the coefficient to 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

To better assess the magnitude of these effects, I conduct two counterfactual exercises. First, I assume that after the minimum wage shock, all the workers between the old and the new minimum wage are paid the new minimum. I call this effect “partial pass-through”. I calculate the implied conditional quantile effect of equation (3) for each city and industry, and obtain the implied unconditional quantile effect averaging over the distribution of workers across cities using equation (4). I then scale these effects by the incidence in each market to obtain an implied coefficient. The results are shown in the first column of table 4.

Table 4: Counterfactual unconditional quantile effects under partial and full pass-through

Percentile	Market and passthrough			
	Formal - partial	Formal - full	Informal - partial	Informal - full
p5		0.0219		0.1186
p10		0.0113		0.0978
p15		0.0071		0.0984
p20	0.0055	0.0055		0.0737
p25	0.0032	0.0032		0.0654
p30	0.0008	0.0008		0.0403
p35				0.0212
p40				0.0151
p45				0.0109
p50				0.0082
p55			0.0066	0.0066
p60			0.0048	0.0048
p65			0.0024	0.0024

Source: Author’s calculations. Effects are the implied UQE under counterfactual effects of the minimum wage. “Full pass-through” assumes all workers below the new minimum are paid the minimum wage after the shock. “Partial pass-through” assumes all workers between the old and the new minimum wage are paid the minimum wage after the shock. Effects are calculated using equation 4.

A comparison of these implied coefficients with the coefficients of table 3 for percentiles 25 and 30 of the distribution shows that the implied coefficients are smaller than the estimated coefficients, with ratios ranging from 1 to 2 across specifications.

For percentile 20, the ratio is about 0.6. This shows that the estimates are large and beyond a mechanical effect of mere wage increase for the affected workers. Moreover, I find positive effects for lower percentiles, which are absent in this first counterfactual exercise.

I also calculate counterfactual effects if all workers below the minimum wage are brought to the new minimum. I call these effects “full pass-through”, and show them in the second column of table 4. Compared to the estimates in table 4, the counterfactual effects are larger. This implies that, while not all workers at these percentiles are brought to the minimum wage, there is partial incidence in this tail of the distribution. It could also imply that a fraction of workers at the lower tail of the distribution are being dismissed.

There are some caveats to these counterfactual exercises. First, the conditional quantile effects calculated ignore the effect of the other covariates. Higher incidence cities may also be experiencing worse labor market conditions which allow smaller wage responses. If this were the case, merely comparing the estimates to the counterfactual coefficients underestimates the actual incidence of the minimum wage. Second, they assume absence of an employment response. If, for example, all workers below the minimum wage were dismissed as a response to the shock, then the counterfactual estimates would be higher.

As robustness checks, I estimate effects using two alternative measures of incidence: a “fraction at” measure, which counts the number of people earning close to the minimum wage, and the minimum to median wage ratio by city and industry. Appendix section A.3 provides details about these variables. The results for “fraction at” are shown in figure C.1 and table C.1. The same pattern of effects emerges, with significant effects up to the 30th percentile of the distribution, stable across different specifications. The same pattern is apparent in figure C.2 and table C.2, where

I use the minimum to median wage ratio.

To check that my estimates are not simply capturing unobservables that vary with minimum wage incidence, I provide two pieces of evidence in the appendix. I reestimate the effects on the quarter previous to the minimum wage shock, from 1998q3 to 1998q4 ⁴. Figure C.3 and table C.3 show absence of significant effects or patterns in the quantile effects. I also show the evolution of the formal density of wages across quarters in figure C.4 as a nonparametric way of seeing if the distribution changes from quarter to quarter. Changes only appear after the minimum wage shock occurs, around the percentiles where the minimum binds. Taken together, these facts suggest that the effects I estimated are not due to unobservable differences across cities or time trends in the distribution of formal wages.

Overall, my results imply a positive and significant impact of the minimum wage shock on the distribution of formal wages, at quantiles below and around the minimum wage. A 10 p.p. higher minimum wage incidence across cities and industries would imply wage increases of about 2 % in the lower tail and of about 4 % in the percentiles where the minimum wage binds. I turn to the effect on the distribution of informal wages in the next section.

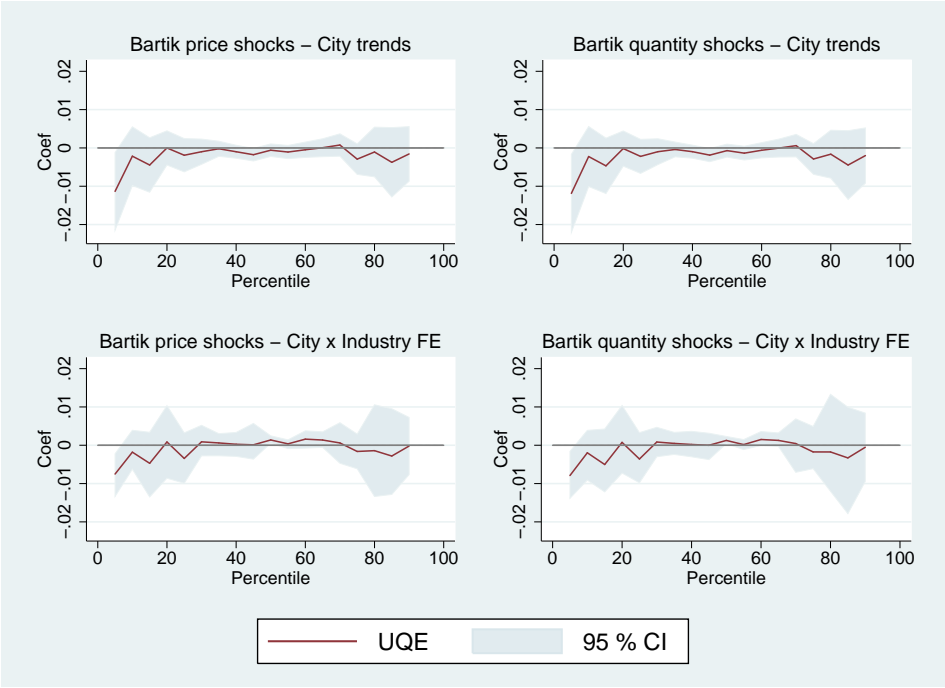
5.1.2 Informal sector

I follow the same strategy used in the previous section to estimate effects in the informal wage distribution. Figure 5 shows the estimated effects using “fraction affected” as the incidence variable. Unlike the effects for formal wages, these are mostly not significant. There is limited evidence of an increase in median wages, but it is not robust across all the specifications, as shown in table 5. A 10 p.p larger incidence of the minimum wage across cities and industries would imply 1.3% higher

⁴Since my incidence measure is based on real wages, which vary with inflation, I still have variation in the independent variable.

median wages according to the last specification. Comparing these estimates to the counterfactual estimates of the third and fourth columns of table 4 shows that the estimates are much lower. This casts doubt on the incidence of the minimum wage in the informal sector.

Figure 5: Effects of minimum wage on the distribution of informal wages



Source: ENH, author’s calculations. The sample is described in appendix A.2. The red line corresponds to the estimates of unconditional quantile effects for percentiles of the distribution of informal wages. Minimum wage incidence is measured by “fraction affected” defined in equation 8. Upper panels correspond to specifications 6, lower panels to specifications 9 and 10 of the text. Shaded areas are 95% confidence intervals obtained using a wild bootstrap-t procedure with 200 replications, clustered by city, where the null hypothesis is equality of the coefficient to 0. Full estimation results for selected quantiles are on table 5.

Estimates using “fraction at” as an incidence measure tell a different story. Estimates are about the same magnitude as those use “fraction affected”, but are significant and appear from the 40th to the 60th percentile, as shown in figure 6 and table 6. In figure C.5 and table C.4 of the appendix, I also show estimates using the minimum to median wage ratio. These are not significant, but this variable does not

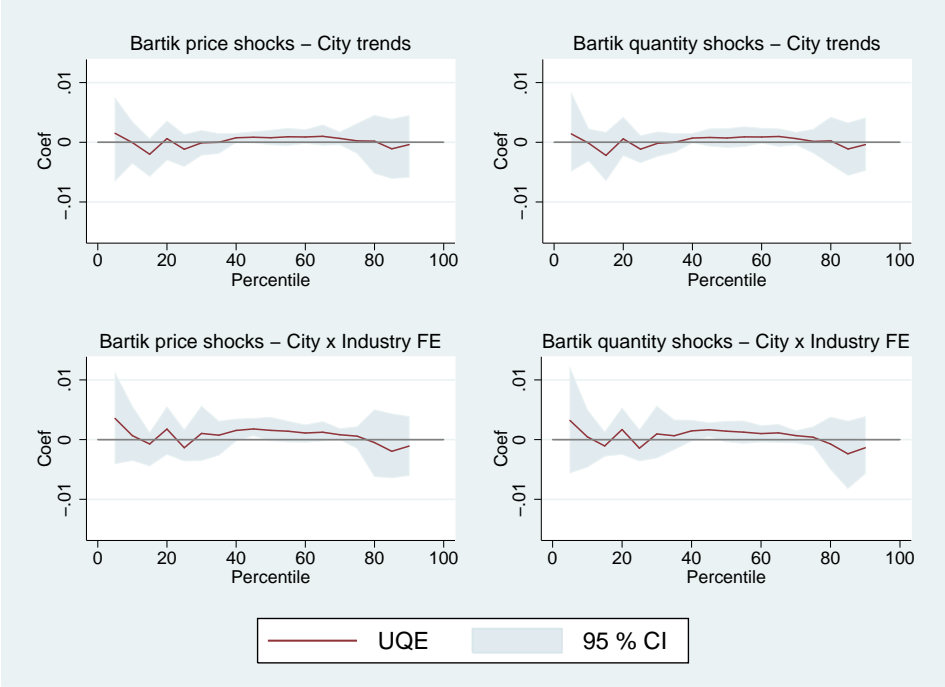
Table 5: Effect of minimum wage incidence on informal wage distribution.

	(1)	(2)	(3)	(4)	(5)	(6)
p30	0.0009 (0.0016) [0.627]	0.0008 (0.0016) [0.647]	-0.0010 (0.0016) [0.544]	-0.0010 (0.0017) [0.556]	0.0009 (0.0016) [0.622]	0.0008 (0.0016) [0.726]
p35	0.0006 (0.0012) [0.811]	0.0005 (0.0010) [0.836]	-0.0002 (0.0010) [0.827]	-0.0004 (0.0010) [0.677]	0.0006 (0.0012) [0.597]	0.0005 (0.0010) [0.677]
p40	0.0003 (0.0011) [0.816]	0.0002 (0.0010) [0.960]	-0.0010 (0.0008) [0.234]	-0.0010 (0.0008) [0.246]	0.0003 (0.0011) [0.995]	0.0002 (0.0010) [0.900]
p45	0.0001 (0.0008) [0.995]	-0.0000 (0.0007) [0.955]	-0.0018** (0.0008) [0.029]	-0.0019** (0.0008) [0.027]	0.0001 (0.0008) [0.925]	-0.0000 (0.0007) [0.940]
p50	0.0014** (0.0004) [0.040]	0.0013*** (0.0004) [0.000]	-0.0006 (0.0008) [0.463]	-0.0007 (0.0008) [0.403]	0.0014** (0.0004) [0.010]	0.0013*** (0.0004) [0.000]
p55	0.0004 (0.0005) [0.408]	0.0002 (0.0004) [0.463]	-0.0011 (0.0008) [0.209]	-0.0014 (0.0009) [0.126]	0.0004 (0.0005) [0.458]	0.0002 (0.0004) [0.582]
p60	0.0016 (0.0008) [0.179]	0.0015 (0.0008) [0.209]	-0.0005 (0.0010) [0.630]	-0.0006 (0.0010) [0.536]	0.0016 (0.0008) [0.159]	0.0015 (0.0008) [0.169]
p65	0.0014 (0.0008) [0.159]	0.0013 (0.0008) [0.199]	0.0001 (0.0012) [0.964]	-0.0000 (0.0012) [0.974]	0.0014 (0.0008) [0.294]	0.0013 (0.0008) [0.209]
p70	0.0006 (0.0018) [0.935]	0.0004 (0.0018) [0.746]	0.0008 (0.0014) [0.598]	0.0006 (0.0015) [0.681]	0.0006 (0.0018) [0.751]	0.0004 (0.0018) [0.831]
Observations	30835	30835	30835	30835	30835	30835
City FE	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bartik price shocks	Yes		Yes		Yes	
Bartik quantity shocks		Yes		Yes		Yes
City specific trends			Yes	Yes		
City x industry FE					Yes	Yes

Source: Author's calculations. Each row of the table corresponds to the estimates of unconditional quantile effects for a quantile of the distribution of formal wages. Minimum wage incidence is measured by "fraction affected" defined in equation 8. Columns correspond to specifications on equations 6 - 10 of the text. The sample is described in appendix A.2. Standard errors clustered by city in parentheses. P-values in brackets. P-values are obtained with a wild bootstrap-t procedure with 200 replications, where the null hypothesis is equality of the coefficient to 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

seem relevant for the informal market, because, since median wages are lower than in the formal market, it assumes that the incidence is higher in the informal market mechanically.

Figure 6: Effects of minimum wage on the distribution of informal wages. “Fraction at” as incidence measure



Source: ENH, author’s calculations. The sample is described in appendix A.2. The red line corresponds to the estimates of unconditional quantile effects for percentiles of the distribution of informal wages. Minimum wage incidence is measured by “fraction at” defined in equation A.1. Upper panels correspond to specifications 6, lower panels to specifications 9 and 10 of the text. Shaded areas are 95% confidence intervals obtained using a wild bootstrap-t procedure with 200 replications, clustered by city, where the null hypothesis is equality of the coefficient to 0. Full estimation results for selected quantiles are on table 6.

I test the plausibility of these estimates using the same checks I made for formal wages in the previous section. The evolution of the density of informal wages, drawn in figure C.7 of the appendix, shows a shift in the distribution after the minimum wage shock and not in other months. For the placebo check, I reestimate the effects in table 6, using “fraction at” as the incidence measure, for 1998q3-1998q4.

Table 6: Effect of minimum wage incidence on informal wage distribution.
 “Fraction at” as incidence measure

	(1)	(2)	(3)	(4)	(5)	(6)
p30	0.0010 (0.0012) [0.677]	0.0010 (0.0012) [0.647]	-0.0001 (0.0009) [0.935]	-0.0002 (0.0009) [0.836]	0.0010 (0.0012) [0.652]	0.0010 (0.0012) [0.632]
p35	0.0007 (0.0008) [0.557]	0.0006 (0.0007) [0.488]	0.0000 (0.0007) [0.985]	0.0000 (0.0007) [0.806]	0.0007 (0.0008) [0.488]	0.0006 (0.0007) [0.468]
p40	0.0015 (0.0007) [0.159]	0.0015 (0.0007) [0.169]	0.0008** (0.0005) [0.020]	0.0007 (0.0005) [0.119]	0.0015 (0.0007) [0.189]	0.0015 (0.0007) [0.159]
p45	0.0018*** (0.0005) [0.000]	0.0017** (0.0005) [0.005]	0.0009* (0.0005) [0.080]	0.0008 (0.0005) [0.174]	0.0018** (0.0005) [0.010]	0.0017** (0.0005) [0.020]
p50	0.0015 (0.0008) [0.179]	0.0014 (0.0008) [0.269]	0.0008 (0.0005) [0.244]	0.0007 (0.0005) [0.249]	0.0015 (0.0008) [0.179]	0.0014 (0.0008) [0.154]
p55	0.0014 (0.0007) [0.149]	0.0012 (0.0007) [0.189]	0.0009 (0.0007) [0.199]	0.0009 (0.0007) [0.259]	0.0014 (0.0007) [0.159]	0.0012 (0.0007) [0.229]
p60	0.0011 (0.0006) [0.209]	0.0010 (0.0006) [0.224]	0.0009 (0.0006) [0.179]	0.0009 (0.0006) [0.199]	0.0011 (0.0006) [0.179]	0.0010 (0.0006) [0.174]
p65	0.0012* (0.0006) [0.065]	0.0011 (0.0006) [0.139]	0.0010 (0.0007) [0.164]	0.0010 (0.0007) [0.184]	0.0012 (0.0006) [0.209]	0.0011 (0.0006) [0.119]
p70	0.0008** (0.0004) [0.045]	0.0007 (0.0004) [0.134]	0.0006 (0.0005) [0.279]	0.0006 (0.0005) [0.254]	0.0008 (0.0004) [0.104]	0.0007 (0.0004) [0.104]
Observations	30835	30835	30835	30835	30835	30835
City FE	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bartik price shocks	Yes		Yes		Yes	
Bartik quantity shocks		Yes		Yes		Yes
City specific trends			Yes	Yes		
City x industry FE					Yes	Yes

Source: Author’s calculations. Each row of the table corresponds to the estimates of unconditional quantile effects for a quantile of the distribution of informal wages. Minimum wage incidence is measured by “fraction at” defined in equation A.1. Columns correspond to specifications on equations 6 - 10 of the text. The sample is described in appendix A.2. Standard errors clustered by city in parentheses. P-values in brackets. P-values are obtained with a wild bootstrap-t procedure with 200 replications, where the null hypothesis is equality of the coefficient to 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

These results are plotted in figure [C.6](#) and shown in table [C.5](#)

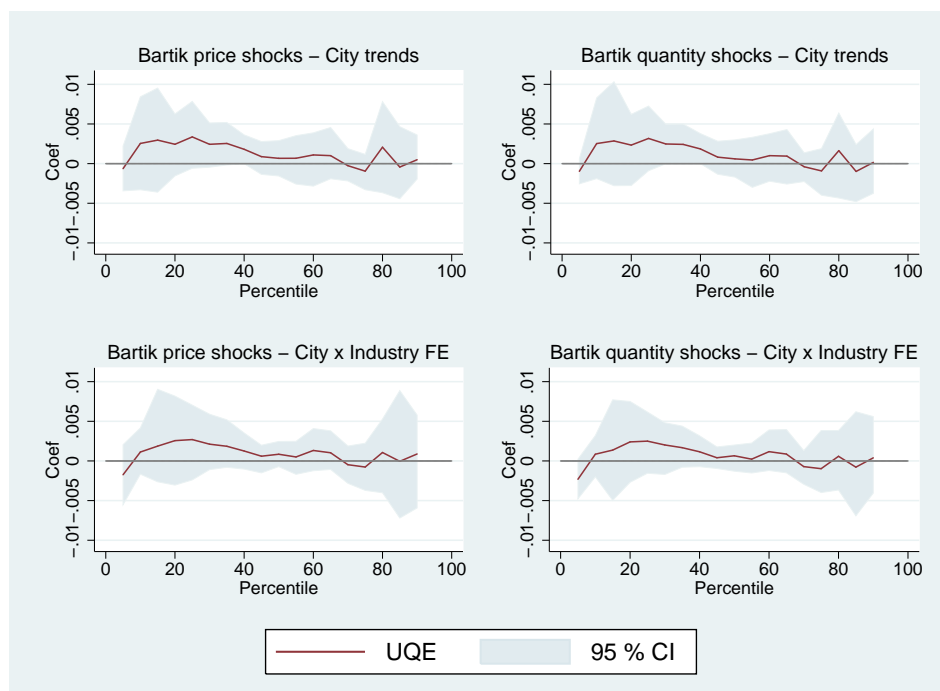
To summarize, I find that higher minimum wage incidence leads to increases in wages in the informal sector around median wages, where the minimum wage binds. These effects are smaller than those for the formal sector, and are less robust across specifications. It is unclear if the effects we observe are due to feedback from the formal into the informal sector or if they are simply due to indexing in the informal sector. I test the feedback hypothesis in the next section.

5.1.3 Effects across markets

One reason why we may observe wage increases in the informal sector in response to the minimum wage shock, in absence of compliance or indexing, is feedback from the formal sector. For example, if workers are dismissed from the formal sector in response to the shock, and are employed in the informal sector paid at their marginal productivity, then we may see increases in informal wages around the minimum wage. One advantage of the incidence measures is that they allow testing of this hypothesis. In figure [7](#), I report estimates of the effect of formal market incidence on the distribution of informal wages. I don't find any significant effects, suggesting that the reaction of informal wages to the minimum wage occurs within the informal market. This test, however, assumes that pass-through occurs within each industry.

An alternative test, using city level incidence in the formal sector as a regressor, is shown in figure [C.8](#) of the appendix. This test also fails to find any impact in the informal sector, suggesting that the role of cross market effects in explaining minimum wage effects in the informal sector is limited.

Figure 7: Effects of formal minimum wage incidence on the distribution of informal wages



Source: ENH, author's calculations. The sample is described in appendix A.2. The red line corresponds to the estimates of unconditional quantile effects for percentiles of the distribution of informal wages. Minimum wage incidence is measured by "fraction affected" in the formal sector defined in equation 8. Upper panels correspond to specifications 6, lower panels to specifications 9 and 10 of the text. Shaded areas are 95% confidence intervals obtained using a wild bootstrap-t procedure with 200 replications, clustered by city, where the null hypothesis is equality of the coefficient to 0.

5.2 Effects on employment

In this section I report estimates of the effect of minimum wage incidence on employment and unemployment for both sectors. I estimate the difference in difference models described in section 3.2 for several measures of employment.

In table 7, I show estimates for formal sector employment. I don't find any significant effects for any of the employment measures, and across any of the specifications. This suggests that the wage increases shown in section 5.1.1 were not accompanied by adjustments on the amount of labor used. While the 1999 crisis increased unemployment at the national level, my results suggest that in the formal sector, industries with larger incidence of the minimum wage did not experience larger unemployment as a response to the minimum wage shock. This is consistent with the recent literature on small unemployment effects of minimum wages (Belman and Wolfson, 2014). My results can only address the short term response to the minimum wage shock, and are silent about long term effects, or effects on employment and unemployment growth.

For the informal sector, I find some evidence of negative employment effects. Table 8 shows these estimates. I find that larger minimum wage incidence is associated with higher industry unemployment and lower industry employment. The results for unemployment are not robust, while the results for employment are robust and stable across specifications. From these estimates, a 10 % higher incidence implies a 1% lower employment share in this city industry block as a response to the minimum wage shock, for an elasticity to incidence of about -0.1. These effects are of a similar magnitude that those found in other studies for developing countries. Using the "fraction at" measure, Lemos (2009) finds elasticities of employment in the Brazilian informal sector following a minimum wage shock, ranging from -0.05 to

Table 7: Effect of minimum wage incidence on employment in the formal sector.

Dep. var. (log)	(1)	(2)	(3)	(4)	(5)	(6)
Industry unemp.	-0.0022 (0.0028) [0.537]	-0.0021 (0.0029) [0.701]	-0.0011 (0.0019) [0.697]	-0.0008 (0.0019) [0.776]	-0.0022 (0.0028) [0.527]	-0.0021 (0.0029) [0.572]
City emp. ind. shr.	-0.0045 (0.0034) [0.269]	-0.0046 (0.0034) [0.343]	-0.0028 (0.0037) [0.458]	-0.0032 (0.0036) [0.343]	-0.0045 (0.0034) [0.428]	-0.0046 (0.0034) [0.299]
Hours worked	0.0055 (0.0082) [0.418]	0.0056 (0.0081) [0.507]	0.0123 (0.0085) [0.239]	0.0125 (0.0080) [0.169]	0.0055 (0.0082) [0.453]	0.0056 (0.0081) [0.423]
City - industry cells	672	672	672	672	672	672
Observations	101656	101656	101656	101656	101656	101656
City FE	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bartik price shocks	Yes		Yes		Yes	
Bartik quantity shocks		Yes		Yes		Yes
City specific trends			Yes	Yes		
City x industry FE					Yes	Yes

Source: Author's calculations. Each row of the table corresponds to the estimates of the coefficient on minimum wage incidence for a different employment variable. Minimum wage incidence is measured by "fraction at" defined in equation A.1. Columns correspond to specifications on equations 6 - 10 of the text. The sample is described in appendix A.2. Standard errors clustered by city in parentheses. P-values in brackets. P-values are obtained with a wild bootstrap-t procedure with 200 replications, where the null hypothesis is equality of the coefficient to 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

0.14, although not significant.

These results suggest that there is some incidence of the minimum wage in the informal sector employment. Together with my results on wages, I argue that this effect is not explained by pass-through from the formal sector. Instead, it could be explained by lower rigidities in the informal sector that make dismissing workers easier. This is consistent with [Mondragón et al. \(2010\)](#), who find that minimum wage increases are associated with transitions from high income to low income within the informal sector.

Table 8: Effect of minimum wage incidence on employment in the informal sector.

Dep. var. (log)	(1)	(2)	(3)	(4)	(5)	(6)
Industry unemp.	0.0024 (0.0016) [0.179]	0.0024 (0.0016) [0.174]	0.0035** (0.0016) [0.010]	0.0037** (0.0016) [0.010]	0.0024 (0.0016) [0.149]	0.0024 (0.0016) [0.184]
City emp. ind. shr.	-0.0098** (0.0035) [0.030]	-0.0099** (0.0035) [0.035]	-0.0059* (0.0031) [0.070]	-0.0064* (0.0032) [0.085]	-0.0098** (0.0035) [0.030]	-0.0099** (0.0035) [0.030]
Hours worked	-0.0043 (0.0135) [0.756]	-0.0037 (0.0130) [0.652]	0.0093 (0.0138) [0.617]	0.0107 (0.0129) [0.438]	-0.0043 (0.0135) [0.766]	-0.0037 (0.0130) [0.791]
City - industry cells	672	672	672	672	672	672
Observations	30835	30835	30835	30835	30835	30835
City FE	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bartik price shocks	Yes		Yes		Yes	
Bartik quantity shocks		Yes		Yes		Yes
City specific trends			Yes	Yes		
City x industry FE					Yes	Yes

Source: Author's calculations. Each row of the table corresponds to the estimates of the coefficient on minimum wage incidence for a different employment variable. Minimum wage incidence is measured by "fraction at" defined in equation A.1. Columns correspond to specifications on equations 6 - 10 of the text. The sample is described in appendix A.2. Standard errors clustered by city in parentheses. P-values in brackets. P-values are obtained with a wild bootstrap-t procedure with 200 replications, where the null hypothesis is equality of the coefficient to 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

6 Concluding remarks

In this paper, I have estimated the effect on a unexpected minimum wage shock on the informal and formal wage distributions in Colombia. By comparing markets with high and low incidence of the minimum wage, I find that wages increase about 4 % and 1.3 % in the informal and formal labor markets at cities with high incidence. I find evidence of negative employment effects in the informal sector, that can not be explained by pass-through from the formal sector.

My results concur with previous literature for developing countries, except with the Colombian literature. The difference in findings is in line with the emerging literature on the compelling research designs in minimum wage research ([Allegretto et al., 2011, 2013](#)). My design exploits cross sectional variation as well as time variation and controls for time varying heterogeneity, which makes my estimates more plausible.

Extrapolating these results to the policy effects of minimum wage changes in Colombia and in developing countries, my results suggest that minimum wages affect the informal sector per se, and not through pass-through, as the competitive model suggests. Future explorations may try to examine the role of other explanations, such as wage indexing, to explain this phenomenon.

References

- ALLEGRETTO, SYLVIA; DUBE, ARINDRAJIT; REICH, MICHAEL and ZIPPERER, BEN (2013). "Credible Research Designs for Minimum Wage Studies". *IZA Discussion Papers 7638*, Institute for the Study of Labor (IZA).
- ALLEGRETTO, SYLVIA A.; DUBE, ARINDRAJIT and REICH, MICHAEL (2011). "Do Mi-

- nimum Wages Really Reduce Teen Employment? Accounting for Heterogeneity and Selectivity in State Panel Data". *Industrial Relations: A Journal of Economy and Society*, **50(2)**, pp. 205–240.
- ARANGO, CARLOS A. and PACHÓN, ANGÉLICA (2007). "The Minimum Wage In Colombia 1984-2001: Favoring The Middle Class With A Bite On The Poor". *Ensayos sobre Política Económica*, **25(55)**, pp. 148–193.
- ARANGO, LUIS EDUARDO; GARCÍA, ANDRÉS FELIPE and POSADA, CARLOS ESTEBAN (2008a). "La metodología de la Encuesta Continua de Hogares y el empalme de las series del mercado laboral urbano de Colombia". *Desarrollo y Sociedad*, **61**, pp. 207–248.
- ARANGO, LUIS EDUARDO; HERRERA, PAULA and POSADA, CARLOS ESTEBAN (2008b). "El salario mínimo: aspectos generales sobre los casos de Colombia y otros países". *Ensayos sobre Política Económica - Banco de la República*.
- ATHEY, SUSAN and IMBENS, GUIDO W. (2006). "Identification and Inference in Non-linear Difference-in-Differences Models". *Econometrica*, **74(2)**, pp. 431–497.
- AUTOR, DAVID H.; KATZ, LAWRENCE F. and KEARNEY, MELISSA S. (2008). "Trends in U.S. Wage Inequality: Revising the Revisionists". *The Review of Economics and Statistics*, **90(2)**, pp. 300–323.
- AUTOR, DAVID H.; MANNING, ALAN and SMITH, CHRISTOPHER L. (2010). "The Contribution of the Minimum Wage to U.S. Wage Inequality over Three Decades: A Reassessment". *Working Paper 16533*, National Bureau of Economic Research.
- AUTOR, DAVID H.; MANNING, ALAN and SMITH, CHRISTOPHER L. (2015). "The Contribution of the Minimum Wage to U.S. Wage Inequality over Three Decades: A Reassessment". *Working Paper 16533*, MIT.

- BARTIK, TIMOTHY J. (1991). *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute for Employment Research.
- BELMAN, DALE and WOLFSON, PAUL J. (2014). *What Does the Minimum Wage Do?* W.E. Upjohn Institute for Employment Research.
- BERTRAND, MARIANNE; DUFLO, ESTHER and MULLAINATHAN, SENDHIL (2004). "How Much Should We Trust Differences-in-Differences Estimates?" *The Quarterly Journal of Economics*, **119(1)**, pp. 249–275.
- BOSCH, MARIANO and MANACORDA, MARCO (2010). "Minimum Wages and Earnings Inequality in Urban Mexico". *American Economic Journal: Applied Economics*, **2(4)**, pp. 128–49.
- CAMERON, A. COLIN; GELBACH, JONAH B. and MILLER, DOUGLAS L. (2008). "Bootstrap-Based Improvements for Inference with Clustered Errors". *The Review of Economics and Statistics*, **90(3)**, pp. 414–427.
- CARD, DAVID (1992). "Using regional variation in wages to measure the effects of the federal minimum wage". *Industrial and Labor Relations Review*, **46(1)**, pp. 22–37.
- CARD, DAVID and DI NARDO, JOHN E. (2002). "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles". *Journal of Labor Economics*, **20(4)**, pp. 733–783.
- CHERNOZHUKOV, VICTOR; FERNÁNDEZ-VAL, IVÁN and MELLY, BLAISE (2013). "Inference on Counterfactual Distributions". *Econometrica*, **81(6)**, pp. 2205–2268.
- DI NARDO, JOHN; FORTIN, NICOLE M. and LEMIEUX, THOMAS (1996). "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach". *Econometrica*, **64(5)**, pp. 1001–44.

- DUBE, ARINDRAJIT; LESTER, T WILLIAM and REICH, MICHAEL (2010). "Minimum wage effects across state borders: Estimates using contiguous counties". *The Review of Economics and Statistics*, **92(4)**, pp. 945–964.
- FIRPO, SERGIO; FORTIN, NICOLE M. and LEMIEUX, THOMAS (2009). "Unconditional Quantile Regressions". *Econometrica*, **77(3)**, pp. 953–973.
- GINDLING, T.H. and TERRELL, KATHERINE (2005). "The effect of minimum wages on actual wages in formal and informal sectors in Costa Rica". *World Development*, **33(11)**, pp. 1905 – 1921.
- GOMEZ-GONZALEZ, JOSE E. and KIEFER, NICHOLAS M. (2006). "Bank Failure: Evidence from the Colombia Financial Crisis". *Working Papers 06-12*, Cornell University, Center for Analytic Economics.
- HARRIS, JOHN R. and TODARO, MICHAEL P. (1970). "Migration, Unemployment and Development: A Two-Sector Analysis". *American Economic Review*, **60**, pp. 126–142.
- KHAMIS, MELANIE (2013). "Does the minimum wage have a higher impact on the informal than on the formal labour market? Evidence from quasi-experiments". *Applied Economics*, **45(4)**, pp. 477–495.
- LEE, DAVID S. (1999). "Wage Inequality in the United States during the 1980s: Rising Dispersion or Falling Minimum Wage?" *The Quarterly Journal of Economics*, **114(3)**, pp. 977–1023.
- LEMONS, SARA (2009). "Minimum wage effects in a developing country". *Labour Economics*, **16(2)**, pp. 224 – 237.

- MALONEY, WILLIAM and MENDEZ, JAIRO (2004). "Measuring the impact of Minimum Wages. Evidence from Latin America". In: *Law and Employment: Lessons from Latin America and The Caribbean*, NBER Chapters, pp. 109–130. National Bureau of Economic Research.
- MATA, JOSÉ and MACHADO, JOSÉ A. F. (2005). "Counterfactual decomposition of changes in wage distributions using quantile regression". *Journal of Applied Econometrics*, **20(4)**, pp. 445–465.
- MEYER, BRUCE D; VISCUSI, W KIP and DURBIN, DAVID L (1995). "Workers' Compensation and Injury Duration: Evidence from a Natural Experiment". *American Economic Review*, **85(3)**, pp. 322–40.
- MONDRAGÓN, CAMILO; PEÑA, XIMENA and WILLS, DANIEL (2010). "Labor Market Rigidities and Informality in Colombia". *Economia*, **11(1)**.
- NEUMARK, DAVID; SCHWEITZER, MARK and WASCHER, WILLIAM (2004). "Minimum Wage Effects throughout the Wage Distribution". *Journal of Human Resources*, **39(2)**.
- NEUMARK, DAVID and WASCHER, WILLIAM L. (2008). *Minimum Wages*. The MIT Press.
- NOTOWIDIGDO, MATTHEW J. (2011). "The Incidence of Local Labor Demand Shocks". *Working Paper 17167*, National Bureau of Economic Research.
- PARRA, CLAUDIA ELENA and SALAZAR, NATALIA (2000). "La crisis financiera y la experiencia internacional". *Boletines de Divulgación Económica 1*, Departamento Nacional de Planeación.

- RUIZ, MAURICIO. (2010). “Costos Laborales, Informalidad y Distribución en Colombia y Chile”. In: *II Congreso de Economía Colombiana - Universidad de los Andes.*, .
- SOLON, GARY; HAIDER, STEVEN J. and WOOLDRIDGE, JEFFREY M. (2015). “What Are We Weighting For?” *Journal of Human Resources*, **50(2)**, pp. 301–316.
- STEWART, MARK B. (2002). “Estimating the Impact of the Minimum Wage Using Geographical Wage Variation”. *Oxford Bulletin of Economics and Statistics*, **64(0)**, pp. 583–605.
- VILLAR, LEONARDO; SALAMANCA, DAVID and MURCIA, ANDRÉS (2005). “Crédito, represión financiera y flujos de capitales en Colombia: 1974-2003”. *Revista Desarrollo y Sociedad*.

Appendices

A Data appendix

This appendix provides details about the data sources, the construction of variables and the sample choices for the empirical analysis in the paper.

A.1 Data sources

The data on wages, demographic and labor market characteristics comes from Colombia’s National Household Survey (ENH) for the years 1996-2001. The ENH was a quarterly rotating cross sectional survey used to calculate labor market indicators at a National and City Level. It is representative for the main metropolitan areas in the country. After 2001, there was a change in the methodology of the survey and it was replaced by the Continuous Household Survey (ECH), with a extended sample

and monthly data collection. As noted by [Arango et al. \(2008a\)](#), the methodological differences between surveys make time comparisons difficult, so I restrict my analysis to ENH data. I only analyse data for the 7 metropolitan areas that are present in all quarters of the survey and that have a large sample size per city per quarter: Barranquilla, Bogotá, Bucaramanga, Cali, Manizales, Medellín and Pasto.

The survey collects labor market information on individuals, including occupation status, salaries and weekly hours of work, along with demographic and labor market characteristics. The survey contains different sections for occupied, unemployed and inactive individuals.

The monthly minimum wage information comes from the Colombian Central Bank⁵. Employees who earn the minimum wage are also entitled to a transportation subsidy, which varies from around 8 to 10 % of the monthly minimum wage. I obtained transportation subsidy information from the Colombian Institute of Tax Law.

To obtain real wages, I use city level consumer price indexes with base year 1998 from the Colombian National Department of Statistics (DANE)⁶. This dataset includes consumer price indices at the city - income group level. I use the city level indices to separate the effects on the real wage distribution that may arise from differential inflation across different income groups.

A.2 Sample selection and classification of workers as formal or informal

For the results on wages, I only consider occupied workers in the private and government sectors, and exclude familiar non remunerated workers, self-employed workers, business owners and workers. I also exclude domestic workers. A large share of

⁵<http://www.banrep.gov.co/es/indice-salarios>

⁶<http://www.dane.gov.co/index.php/indices-de-precios-y-costos/indice-de-precios-al-consumidor-ipc>

these workers earn wages below the minimum wage, but their wages may be nevertheless indexed to it. I consider only workers who report wages for the last month, who are between 12 and 65 years of age, and who work between 30 and 50 hours a week. This is intended to mitigate measurement error in hours, and to ensure that my results are comparable to some degree to [Arango and Pachón \(2007\)](#). Following [Solon et al. \(2015\)](#), all my descriptive statistics use survey weights, but the main results of the paper instead use bootstrapping to account for the heteroskedasticity due to survey design.

Formal workers are defined as workers who are covered by health insurance by their firm, as required by Colombian law. Specifically, in the time period I analyze, the law required the employer to enroll its permanent workers in health insurance, and share its costs with the employee. For transitory workers, a percentage of the worker's salary is intended to be used to pay for health insurance, and the employee has to provide proof of health insurance enrollment to the employer. For the three first quarters of 1996 and the second quarter of 2002, the survey did not ask specifically for health insurance coverage sponsored by the employer, but for general enrollment in health insurance. We use workers who reported to be covered by health insurance for those periods. For the rest of the sample, these variables are highly correlated.

My choice of an informality measure is based on availability and performance. The health measure is available for all but two quarters of the sample, as mentioned above. [Mondragón et al. \(2010\)](#) shows that this measure of informality and alternative measures, such as whether the employer contributes to the employee pension or whether the firm is large, largely concur and exhibit the same dynamics. The firm size definition, as [Mondragón et al. \(2010\)](#) notes, is not related to labor market regulations. The pension based definition is highly correlated with the health based

definition: according to [Mondragón et al. \(2010\)](#), only 1% of workers each year classified as informal under the health based criterion would be labeled formal under the pension criterion. These alternative measures are not available for the entire sample I consider.

I classify formal and informal workers into economic activities using a 1-digit ISIC Rev. 2 classification. Although the survey has information at the 2 digit level, sample sizes within the 2 digit categories are small. From the 9 1-digit categories, I exclude Agriculture, Mining and Utilities due to small sample sizes. Overall these excluded industries comprise no more than 2% of the pooled sample.

For the results on employment, I also use data on unemployed workers and inactive working age individuals. I apply the same industry restrictions for unemployed workers. To classify them into industries, I use the industry of their previous job or the industry in which they have been looking for a job within the last three months.

A.3 Variable construction

My nominal wage variable is the individual's self reported wage. Although most wages are reported at the monthly level, some of them are reported at higher or lower frequencies: for those cases I calculate monthly equivalents. I obtain real wages deflating this variable using city level price indices, and I deflate the minimum wage using the country wide consumer price index. I focus on log real monthly wages throughout all the analysis.

I measure minimum wage incidence using a "fraction affected" measure, described in section 3. Since the survey weights are not intended to make the employee counts representative at the city industry level, I do not use them for the main calculations. For robustness checks, I use two additional measures. The first is a "fraction at" measure, FA_{cjt} defined as

$$FA_{cjt} \equiv \frac{\#(0.9 \times mw_t \leq w_{icjt} \leq 1.1 \times mw_{t+1})}{N_{cjt}} \quad (\text{A.1})$$

This fraction counts the number of people who earn a wage within 10 % of the minimum wage. weakness of this measure, compared to “fraction affected” is that involves a choice of the percent deviation from the minimum wage. Both fraction measures are calculated using real wages. This is in contrast with [Lemos \(2009\)](#), who uses nominal bites. Since the minimum wage shock I consider stems from both an expected increase in the nominal minimum wage as well as a unexpected increase in the real minimum wage, I choose to use a real measure.

The second incidence measure is the minimum to median wage ratio at the city industry level. This variable measures how large is the minimum wage compared to the wages in the market. While easier to interpret, this measure assumes that the minimum wage is more binding in low wage markets. This is not necessary for low wage informal markets where labor regulations may not apply at all.

To account for local labor demand shocks, I use city level Bartik shock variables, which are common in the local labor markets literature ([Bartik, 1991](#); [Notowidigdo, 2011](#)). These are intended to capture local labor demand shocks unrelated to local labor supply. The Bartik price and Bartik quantity shocks are defined as

$$BP_{ct} \equiv \sum_{j=1}^J EmpShare_{cj,t-1} \times (Emp_{-c,j,t} - Emp_{-c,j,t-1}) \quad (\text{A.2})$$

$$BQ_{ct} \equiv \sum_{j=1}^J EmpShare_{cj,t-1} \times (w_{-c,j,t} - w_{-c,j,t-1})$$

where $EmpShare_{cj,t-1}$ is a the preexisting industry share, $Emp_{-c,j,t}$ is the average employment across cities in industry j excluding city c , and $w_{-c,j,t}$ is the average

nominal wage across cities in industry j excluding city c .

B Additional descriptive statistics

Table B.1: Sample percentage by demographic and labor market variables relative to minimum wage

	Relative to Minimum wage							
	Below		At		Above		Total	
	Row %	Cell %	Row %	Cell %	Row %	Cell %	Row %	Cell %
Gender								
Male	23.6	12.4	8.7	4.6	67.7	35.6	100.0	52.6
Female	25.2	11.9	10.0	4.7	64.8	30.7	100.0	47.4
Total	24.4	24.4	9.3	9.3	66.3	66.3	100.0	100.0
Age								
12-17	71.8	1.4	10.0	0.2	18.2	0.4	100.0	2.0
18-25	33.9	8.5	12.0	3.0	54.1	13.5	100.0	24.9
26-50	20.0	13.3	8.5	5.7	71.5	47.6	100.0	66.5
51-65	18.3	1.2	6.9	0.5	74.8	4.9	100.0	6.6
Total	24.4	24.4	9.3	9.3	66.3	66.3	100.0	100.0
Years of schooling								
0-5	43.5	7.1	15.0	2.5	41.5	6.8	100.0	16.4
6-11	29.5	15.5	11.8	6.2	58.7	30.9	100.0	52.7
12-17	5.5	1.6	2.1	0.6	92.4	26.2	100.0	28.3
more than 17	4.7	0.1	1.8	0.0	93.5	2.4	100.0	2.6
Total	24.4	24.4	9.3	9.3	66.3	66.3	100.0	100.0
Sector								
Private	27.3	23.5	10.5	9.0	62.2	53.6	100.0	86.2
Government	5.9	0.8	2.0	0.3	92.1	12.8	100.0	13.8
Total	24.4	24.4	9.3	9.3	66.3	66.3	100.0	100.0
Sample size	34,142		14,940		83,409		132,491	

Source: ENH, author's calculations. Pooled data 1996q2-2001q4. "At minimum wage" includes workers whose real wage is within 3 p.p of the real minimum wage in their city. The sample is described in appendix A.2.

Table B.2: Sample percentage by demographic and labor market variables relative to informality

	Informality					
	Formal		Informal		Total	
	Row %	Cell %	Row %	Cell %	Row %	Cell %
Gender						
Male	74.0	39.0	26.0	13.7	100.0	52.6
Female	82.4	39.0	17.6	8.3	100.0	47.4
Total	78.0	78.0	22.0	22.0	100.0	100.0
Age						
12-17	24.1	0.5	75.9	1.5	100.0	2.0
18-25	70.1	17.4	29.9	7.5	100.0	24.9
26-50	82.3	54.7	17.7	11.8	100.0	66.5
51-65	81.2	5.4	18.8	1.2	100.0	6.6
Total	78.0	78.0	22.0	22.0	100.0	100.0
Years of schooling						
0-5	60.0	9.9	40.0	6.6	100.0	16.4
6-11	75.5	39.8	24.5	12.9	100.0	52.7
12-17	91.8	26.0	8.2	2.3	100.0	28.3
more than 17	91.7	2.4	8.3	0.2	100.0	2.6
Total	78.0	78.0	22.0	22.0	100.0	100.0
Sector						
Private	75.1	64.7	24.9	21.4	100.0	86.2
Government	95.7	13.2	4.3	0.6	100.0	13.8
Total	78.0	78.0	22.0	22.0	100.0	100.0
Sample size	101,656		30,835		132,491	

Source: ENH, author's calculations. Pooled data 1996q2-2001q4. The sample is described in appendix A.2.

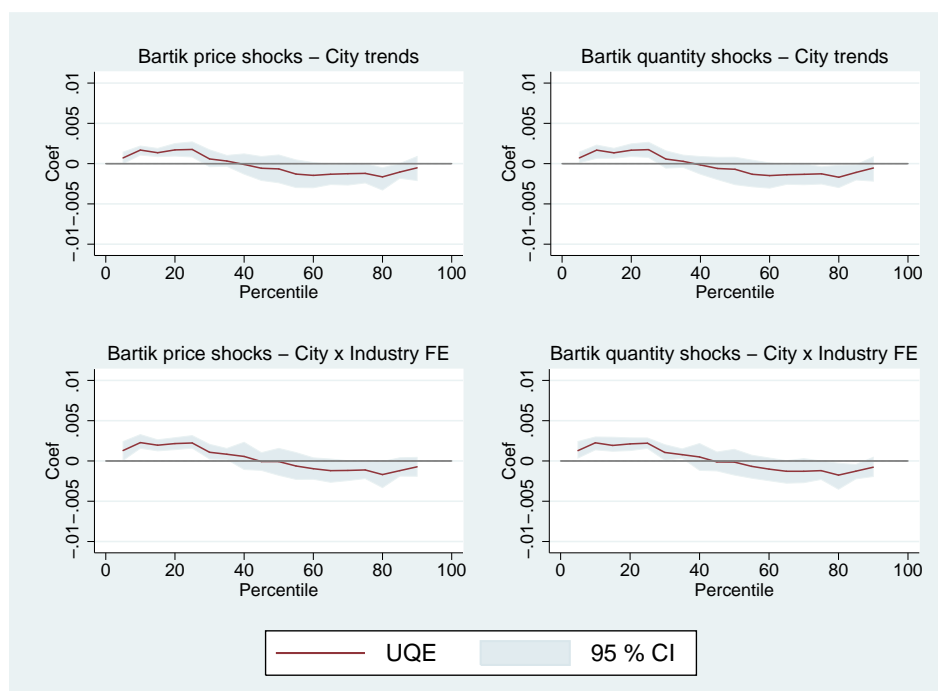
Table B.3: Distribution of minimum wage incidence measured by fraction affected in 1998q4

Formal sector - Industry	City							Total
	<i>Barranquilla</i>	<i>Bogota</i>	<i>Bucaramanga</i>	<i>Cali</i>	<i>Manizales</i>	<i>Medellin</i>	<i>Pasto</i>	
	%	%	%	%	%	%	%	%
Manufacturing	19.9	6.8	28.5	12.8	10.7	18.4	23.3	17.2
Construction	12.5	4.9	24.1	0.0	34.8	18.6	6.7	14.5
Trade, Restaurants, Hotels	16.8	5.2	26.4	12.0	11.8	21.0	15.1	15.5
Transport and Communications	13.4	9.5	17.5	18.8	7.4	8.2	3.2	11.1
Financial services	8.6	5.2	11.5	10.3	14.6	7.6	20.0	11.1
Social and Personal Services	5.5	2.4	9.8	4.5	6.1	6.3	5.3	5.7
Informal sector - Industry								
Manufacturing	15.9	9.1	14.6	19.5	12.1	11.9	11.7	13.5
Construction	15.4	13.2	21.1	10.3	7.4	18.0	8.3	13.4
Trade, Restaurants, Hotels	13.5	10.6	15.3	11.1	9.1	15.8	4.0	11.3
Transport and Communications	9.1	3.6	0.0	11.1	11.8	17.4	0.0	7.6
Financial services	31.2	4.8	22.2	5.6	0.0	0.0	12.5	10.9
Social and Personal Services	12.5	3.6	19.1	8.8	8.9	11.8	12.9	11.1

Source: ENH, author's calculations. Minimum wage incidence is measured by "fraction affected" defined in equation 8. The sample is described in appendix A.2.

C Additional estimation results

Figure C.1: Effects of minimum wage on the distribution of formal wages. “Fraction at” as incidence measure



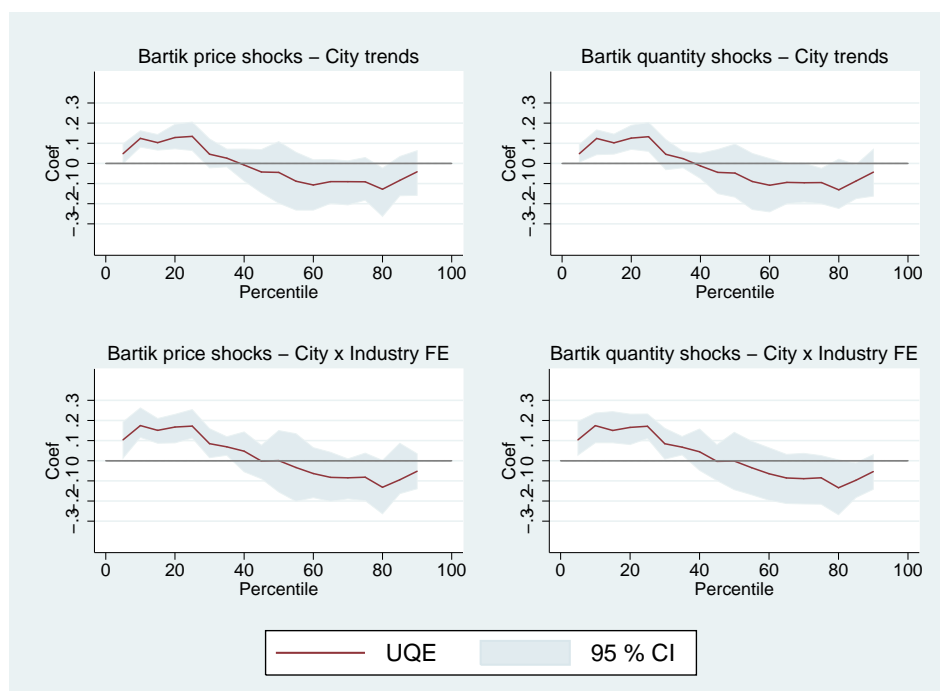
Source: ENH, author’s calculations. The sample is described in appendix A.2. The red line corresponds to the estimates of unconditional quantile effects for percentiles of the distribution of formal wages. Minimum wage incidence is measured by “fraction affected” defined in equation 8. Upper panels correspond to specifications 6, lower panels to specifications 9 and 10 of the text. Shaded areas are 95% confidence intervals obtained using a wild bootstrap-t procedure with 200 replications, clustered by city, where the null hypothesis is equality of the coefficient to 0. Full estimation results for selected quantiles are on table C.1.

Table C.1: Effect of minimum wage incidence on formal wage distribution.
 “Fraction at” as incidence measure

	(1)	(2)	(3)	(4)	(5)	(6)
p5	0.0013** (0.0005) [0.020]	0.0013** (0.0005) [0.020]	0.0007* (0.0003) [0.060]	0.0007* (0.0003) [0.060]	0.0013** (0.0005) [0.005]	0.0013** (0.0005) [0.035]
p10	0.0023** (0.0003) [0.005]	0.0023*** (0.0003) [0.000]	0.0017*** (0.0003) [0.000]	0.0017** (0.0003) [0.010]	0.0023** (0.0003) [0.005]	0.0023** (0.0003) [0.005]
p15	0.0020*** (0.0003) [0.000]	0.0019*** (0.0003) [0.000]	0.0014** (0.0003) [0.020]	0.0013** (0.0003) [0.020]	0.0020*** (0.0003) [0.000]	0.0019*** (0.0003) [0.000]
p20	0.0022** (0.0003) [0.010]	0.0021*** (0.0003) [0.000]	0.0017*** (0.0003) [0.000]	0.0017** (0.0003) [0.010]	0.0022** (0.0003) [0.010]	0.0021** (0.0003) [0.030]
p25	0.0022*** (0.0002) [0.000]	0.0022*** (0.0002) [0.000]	0.0018** (0.0003) [0.020]	0.0017** (0.0003) [0.020]	0.0022*** (0.0002) [0.000]	0.0022*** (0.0002) [0.000]
p30	0.0011** (0.0004) [0.010]	0.0011** (0.0004) [0.010]	0.0006 (0.0004) [0.358]	0.0006 (0.0004) [0.174]	0.0011** (0.0004) [0.005]	0.0011*** (0.0004) [0.000]
p50	-0.0001 (0.0007) [0.886]	-0.0001 (0.0007) [0.846]	-0.0007 (0.0007) [0.468]	-0.0007 (0.0007) [0.498]	-0.0001 (0.0007) [0.935]	-0.0001 (0.0007) [0.776]
p75	-0.0011** (0.0004) [0.050]	-0.0012* (0.0004) [0.070]	-0.0012** (0.0004) [0.030]	-0.0013* (0.0004) [0.060]	-0.0011** (0.0004) [0.040]	-0.0012** (0.0004) [0.050]
p90	-0.0007 (0.0005) [0.189]	-0.0008 (0.0005) [0.139]	-0.0005 (0.0006) [0.483]	-0.0005 (0.0006) [0.458]	-0.0007 (0.0005) [0.284]	-0.0008 (0.0005) [0.239]
Observations	101656	101656	101656	101656	101656	101656
City FE	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bartik price shocks	Yes		Yes		Yes	
Bartik quantity shocks		Yes		Yes		Yes
City specific trends			Yes	Yes		
City x industry FE					Yes	Yes

Source: Author’s calculations. Each row of the table corresponds to the estimates of unconditional quantile effects for a quantile of the distribution of formal wages. Minimum wage incidence is measured by “fraction at” defined in equation A.1. Columns correspond to specifications on equations 6 - 10 of the text. The sample is described in appendix A.2. Standard errors clustered by city in parentheses. P-values in brackets. P-values are obtained with a wild bootstrap-t procedure with 200 replications, where the null hypothesis is equality of the coefficient to 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Figure C.2: Effects of minimum wage on the distribution of formal wages.
 Minimum to median wage ratio as incidence measure



Source: ENH, author’s calculations. The sample is described in appendix A.2. The red line corresponds to the estimates of unconditional quantile effects for percentiles of the distribution of formal wages. Minimum wage incidence is measured by “fraction affected” defined in equation 8. Upper panels correspond to specifications 6, lower panels to specifications 9 and 10 of the text. Shaded areas are 95% confidence intervals obtained using a wild bootstrap-t procedure with 200 replications, clustered by city, where the null hypothesis is equality of the coefficient to 0. Full estimation results for selected quantiles are on table C.2.

Table C.2: Effect of minimum wage incidence on formal wage distribution.
Minimum to median wage ratio as incidence measure

	(1)	(2)	(3)	(4)	(5)	(6)
p5	0.1041** (0.0384) [0.020]	0.1039** (0.0389) [0.010]	0.0486** (0.0175) [0.020]	0.0485** (0.0171) [0.030]	0.1041** (0.0384) [0.005]	0.1039** (0.0389) [0.005]
p10	0.1748** (0.0262) [0.005]	0.1744*** (0.0275) [0.000]	0.1245*** (0.0182) [0.000]	0.1240** (0.0189) [0.010]	0.1748** (0.0262) [0.005]	0.1744** (0.0275) [0.005]
p15	0.1510*** (0.0279) [0.000]	0.1504*** (0.0290) [0.000]	0.1033** (0.0192) [0.020]	0.1022** (0.0193) [0.020]	0.1510*** (0.0279) [0.000]	0.1504*** (0.0290) [0.000]
p20	0.1674** (0.0248) [0.010]	0.1657*** (0.0263) [0.000]	0.1286*** (0.0234) [0.000]	0.1258** (0.0240) [0.010]	0.1674** (0.0248) [0.010]	0.1657** (0.0263) [0.030]
p25	0.1720*** (0.0191) [0.000]	0.1713*** (0.0200) [0.000]	0.1343*** (0.0218) [0.000]	0.1328** (0.0229) [0.020]	0.1720*** (0.0191) [0.000]	0.1713*** (0.0200) [0.000]
p30	0.0848** (0.0284) [0.010]	0.0846** (0.0298) [0.010]	0.0459 (0.0287) [0.358]	0.0453 (0.0292) [0.174]	0.0848** (0.0284) [0.005]	0.0846*** (0.0298) [0.000]
p50	0.0008 (0.0584) [0.955]	-0.0014 (0.0593) [0.915]	-0.0445 (0.0568) [0.537]	-0.0479 (0.0572) [0.557]	0.0008 (0.0584) [0.905]	-0.0014 (0.0593) [0.886]
p75	-0.0815 (0.0375) [0.124]	-0.0845 (0.0395) [0.144]	-0.0912* (0.0325) [0.070]	-0.0950* (0.0308) [0.090]	-0.0815 (0.0375) [0.139]	-0.0845 (0.0395) [0.129]
p90	-0.0522 (0.0416) [0.219]	-0.0538 (0.0433) [0.179]	-0.0416 (0.0501) [0.473]	-0.0432 (0.0500) [0.468]	-0.0522 (0.0416) [0.264]	-0.0538 (0.0433) [0.259]
Observations	101656	101656	101656	101656	101656	101656
City FE	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bartik price shocks	Yes		Yes		Yes	
Bartik quantity shocks		Yes		Yes		Yes
City specific trends			Yes	Yes		
City x industry FE					Yes	Yes

Source: Author's calculations. Each row of the table corresponds to the estimates of unconditional quantile effects for a quantile of the distribution of formal wages. Minimum wage incidence is measured by the minimum to median wage ratio described in section A.3. Columns correspond to specifications on equations 6 - 10 of the text. The sample is described in appendix A.2. Standard errors clustered by city in parentheses. P-values in brackets. P-values are obtained with a wild bootstrap-t procedure with 200 replications, where the null hypothesis is equality of the coefficient to 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Figure C.3: Placebo check: Estimates of the effect of minimum wage incidence on formal wages previous to the minimum wage shock, 1998q3-1998q4



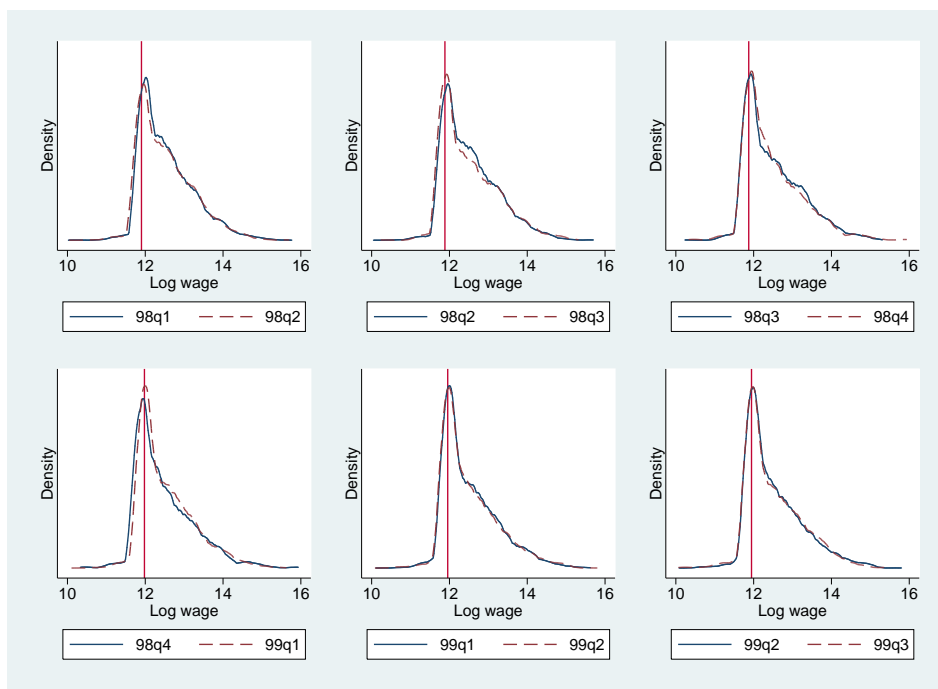
Source: ENH, author’s calculations. The sample is described in appendix A.2. The red line corresponds to the estimates of unconditional quantile effects for percentiles of the distribution of formal wages, for 1998q3-1998q4 when there are not any minimum wage shocks. Minimum wage incidence is measured by “fraction affected” defined in equation 8. Upper panels correspond to specifications 6, lower panels to specifications 9 and 10 of the text. Shaded areas are 95% confidence intervals obtained using a wild bootstrap-t procedure with 200 replications, clustered by city, where the null hypothesis is equality of the coefficient to 0. Full estimation results for selected quantiles are on table C.3.

Table C.3: Placebo check: Estimates of the effect of minimum wage incidence on formal wages previous to the minimum wage shock, 1998q3-1998q4

	(1)	(2)	(3)	(4)	(5)	(6)
p5	0.0016 (0.0008) [0.259]	0.0016 (0.0008) [0.164]	0.0022 (0.0010) [0.413]	0.0021 (0.0010) [0.378]	0.0016 (0.0008) [0.189]	0.0016* (0.0008) [0.090]
p10	0.0014 (0.0009) [0.219]	0.0014 (0.0009) [0.154]	0.0013 (0.0009) [0.552]	0.0014 (0.0009) [0.647]	0.0014 (0.0009) [0.179]	0.0014 (0.0009) [0.139]
p15	0.0021 (0.0009) [0.264]	0.0022 (0.0009) [0.219]	0.0007 (0.0008) [0.647]	0.0008 (0.0009) [0.622]	0.0021 (0.0009) [0.169]	0.0022 (0.0009) [0.189]
p20	0.0024 (0.0010) [0.199]	0.0025 (0.0010) [0.279]	0.0015 (0.0005) [0.527]	0.0015 (0.0006) [0.547]	0.0024 (0.0010) [0.164]	0.0025 (0.0010) [0.289]
p25	0.0034 (0.0011) [0.284]	0.0035 (0.0010) [0.229]	0.0030* (0.0003) [0.100]	0.0030* (0.0003) [0.100]	0.0034 (0.0011) [0.229]	0.0035 (0.0010) [0.279]
p30	0.0034 (0.0009) [0.119]	0.0034 (0.0008) [0.239]	0.0015 (0.0003) [0.318]	0.0016 (0.0004) [0.642]	0.0034 (0.0009) [0.159]	0.0034 (0.0008) [0.179]
p50	0.0055 (0.0013) [0.209]	0.0055 (0.0013) [0.139]	0.0036 (0.0012) [0.209]	0.0039 (0.0011) [0.308]	0.0055 (0.0013) [0.229]	0.0055 (0.0013) [0.159]
p75	0.0025* (0.0007) [0.090]	0.0025 (0.0008) [0.139]	0.0006 (0.0014) [0.886]	0.0010 (0.0011) [0.498]	0.0025 (0.0007) [0.119]	0.0025** (0.0008) [0.050]
p90	0.0020 (0.0007) [0.418]	0.0020 (0.0007) [0.368]	0.0018 (0.0009) [0.398]	0.0020 (0.0008) [0.338]	0.0020 (0.0007) [0.338]	0.0020 (0.0007) [0.378]
Observations	101649	101649	101649	101649	101649	101649
City FE	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bartik price shocks	Yes		Yes		Yes	
Bartik quantity shocks		Yes		Yes		Yes
City specific trends			Yes	Yes		
City x industry FE					Yes	Yes

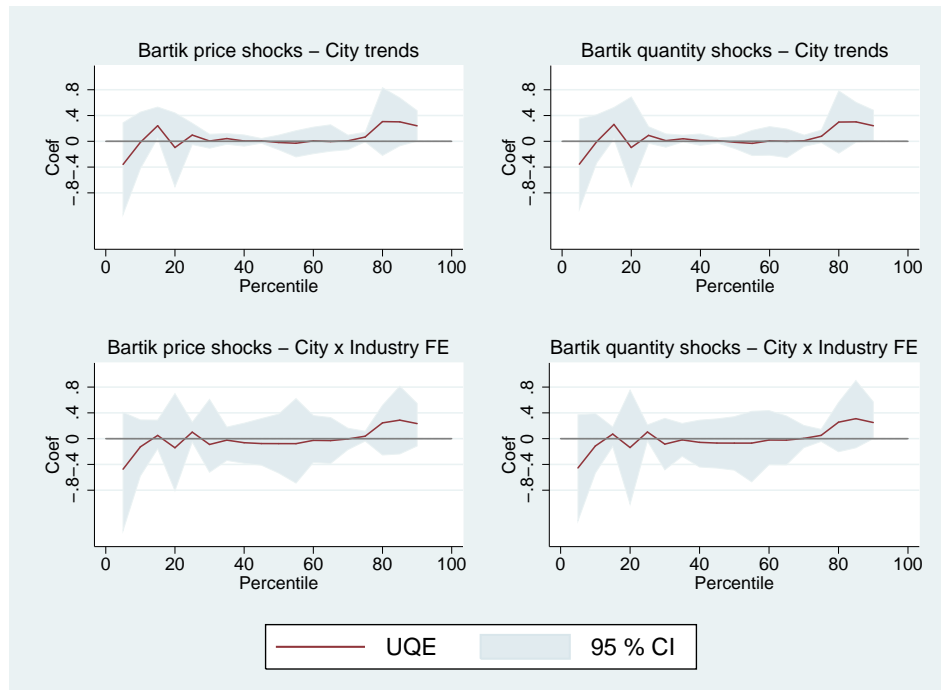
Source: Author's calculations. Each row of the table corresponds to placebo quantile effect estimates of the effect of the minimum wages in absence of minimum wage shocks. Minimum wage incidence is measured by the minimum to median wage ratio described in section A.3. Columns correspond to specifications on equations 6 - 10 of the text. The sample is described in appendix A.2. Standard errors clustered by city in parentheses. P-values in brackets. P-values are obtained with a wild bootstrap-t procedure with 200 replications, where the null hypothesis is equality of the coefficient to 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Figure C.4: Evolution of density of formal wages



Source: ENH, author's calculations. The sample is described in appendix A.2. Vertical line at the level of real minimum wage for the latter quarter.

Figure C.5: Effects of minimum wage on the distribution of informal wages.
 Minimum to median wage ratio as incidence measure



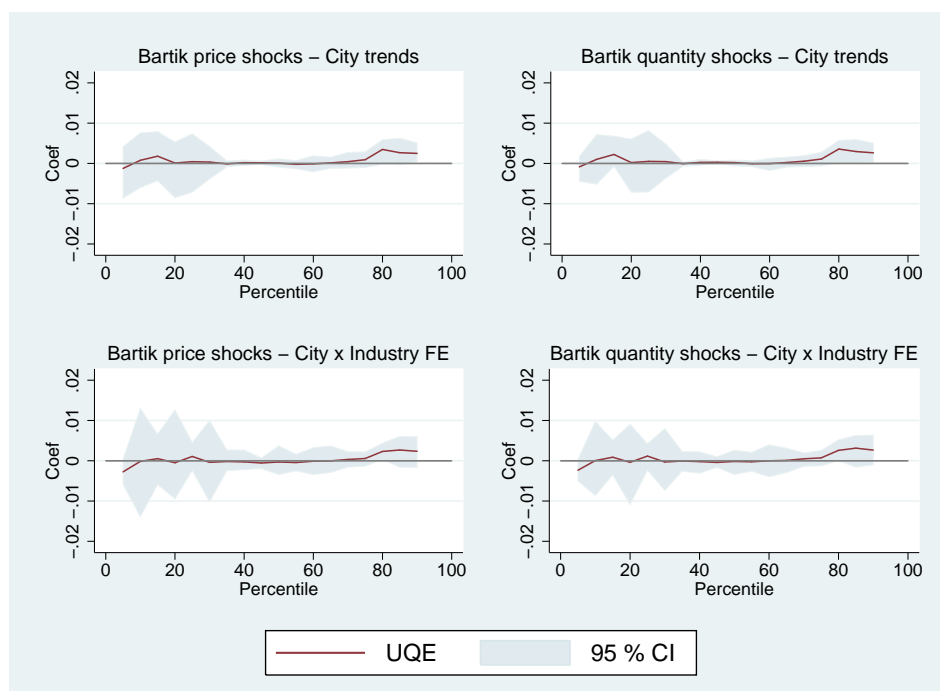
Source: ENH, author’s calculations. The sample is described in appendix A.2. The red line corresponds to the estimates of unconditional quantile effects for percentiles of the distribution of informal wages. Minimum wage incidence is measured by “fraction affected” defined in equation 8. Upper panels correspond to specifications 6, lower panels to specifications 9 and 10 of the text. Shaded areas are 95% confidence intervals obtained using a wild bootstrap-t procedure with 200 replications, clustered by city, where the null hypothesis is equality of the coefficient to 0. Full estimation results for selected quantiles are on table C.4.

Table C.4: Effect of minimum wage incidence on informal wage distribution.
Minimum to median wage ratio as incidence measure

	(1)	(2)	(3)	(4)	(5)	(6)
p30	-0.0903 (0.0708) [0.965]	-0.0846 (0.0726) [0.905]	0.0050 (0.0573) [0.876]	0.0106 (0.0573) [0.896]	-0.0903 (0.0708) [0.846]	-0.0846 (0.0726) [0.836]
p35	-0.0233 (0.0464) [0.935]	-0.0189 (0.0450) [0.995]	0.0428 (0.0274) [0.149]	0.0402 (0.0253) [0.124]	-0.0233 (0.0464) [0.975]	-0.0189 (0.0450) [0.995]
p40	-0.0628 (0.0497) [0.920]	-0.0575 (0.0509) [0.955]	0.0051 (0.0303) [0.866]	0.0100 (0.0327) [0.826]	-0.0628 (0.0497) [0.945]	-0.0575 (0.0509) [0.856]
p45	-0.0760 (0.0385) [0.990]	-0.0682 (0.0381) [0.995]	0.0063 (0.0196) [0.642]	0.0105 (0.0203) [0.562]	-0.0760 (0.0385) [0.970]	-0.0682 (0.0381) [0.945]
p50	-0.0772 (0.0562) [0.965]	-0.0692 (0.0562) [0.995]	-0.0182 (0.0269) [1.000]	-0.0147 (0.0275) [0.801]	-0.0772 (0.0562) [0.985]	-0.0692 (0.0562) [0.965]
p55	-0.0777 (0.0442) [0.851]	-0.0695 (0.0434) [0.935]	-0.0296 (0.0359) [0.896]	-0.0316 (0.0380) [0.871]	-0.0777 (0.0442) [0.861]	-0.0695 (0.0434) [0.975]
p60	-0.0267 (0.0620) [0.886]	-0.0212 (0.0627) [0.831]	0.0070 (0.0468) [0.910]	0.0064 (0.0461) [0.866]	-0.0267 (0.0620) [0.985]	-0.0212 (0.0627) [0.856]
p65	-0.0300 (0.0515) [0.836]	-0.0233 (0.0527) [0.831]	-0.0031 (0.0434) [0.920]	-0.0007 (0.0434) [0.980]	-0.0300 (0.0515) [0.945]	-0.0233 (0.0527) [0.871]
p70	-0.0047 (0.0393) [0.955]	0.0039 (0.0383) [0.781]	0.0072 (0.0338) [0.995]	0.0092 (0.0329) [0.836]	-0.0047 (0.0393) [0.960]	0.0039 (0.0383) [0.930]
Observations	30835	30835	30835	30835	30835	30835
City FE	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bartik price shocks	Yes		Yes		Yes	
Bartik quantity shocks		Yes		Yes		Yes
City specific trends			Yes	Yes		
City x industry FE					Yes	Yes

Source: Author's calculations. Each row of the table corresponds to the estimates of unconditional quantile effects for a quantile of the distribution of informal wages. Minimum wage incidence is measured by the minimum to median wage ratio described in section A.3. Columns correspond to specifications on equations 6 - 10 of the text. The sample is described in appendix A.2. Standard errors clustered by city in parentheses. P-values in brackets. P-values are obtained with a wild bootstrap-t procedure with 200 replications, where the null hypothesis is equality of the coefficient to 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Figure C.6: Placebo check: Estimates of the effect of minimum wage incidence on informal wages previous to the minimum wage shock, 1998q3-1998q4



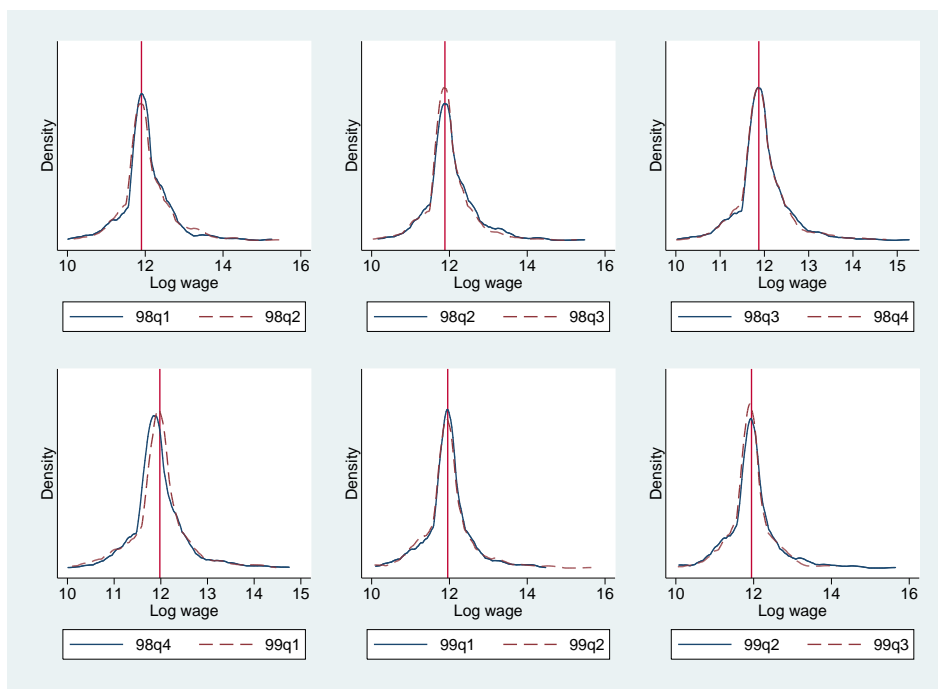
Source: ENH, author’s calculations. The sample is described in appendix A.2. The red line corresponds to the estimates of unconditional quantile effects for percentiles of the distribution of informal wages, for 1998q3-1998q4 when there are not any minimum wage shocks. Minimum wage incidence is measured by “fraction affected” defined in equation 8. Upper panels correspond to specifications 6, lower panels to specifications 9 and 10 of the text. Shaded areas are 95% confidence intervals obtained using a wild bootstrap-t procedure with 200 replications, clustered by city, where the null hypothesis is equality of the coefficient to 0. Full estimation results for selected quantiles are on table C.5.

Table C.5: Placebo check: Estimates of the effect of minimum wage incidence on informal wages previous to the minimum wage shock, 1998q3-1998q4

	(1)	(2)	(3)	(4)	(5)	(6)
p5	-0.0027 (0.0013) [0.219]	-0.0023 (0.0011) [0.219]	-0.0012 (0.0014) [0.512]	-0.0009 (0.0010) [0.408]	-0.0027 (0.0013) [0.269]	-0.0023 (0.0011) [0.279]
p10	-0.0001 (0.0016) [0.965]	0.0000 (0.0015) [0.741]	0.0008 (0.0019) [0.692]	0.0010 (0.0018) [0.562]	-0.0001 (0.0016) [0.975]	0.0000 (0.0015) [0.990]
p15	0.0005 (0.0015) [0.577]	0.0009 (0.0014) [0.498]	0.0018 (0.0018) [0.483]	0.0022 (0.0015) [0.279]	0.0005 (0.0015) [0.716]	0.0009 (0.0014) [0.468]
p20	-0.0005 (0.0015) [0.886]	-0.0004 (0.0015) [0.985]	0.0001 (0.0020) [0.975]	0.0002 (0.0020) [0.836]	-0.0005 (0.0015) [0.900]	-0.0004 (0.0015) [0.975]
p25	0.0011 (0.0011) [0.348]	0.0012 (0.0012) [0.289]	0.0004 (0.0021) [0.816]	0.0005 (0.0020) [0.935]	0.0011 (0.0011) [0.398]	0.0012 (0.0012) [0.264]
p30	-0.0004 (0.0012) [0.995]	-0.0003 (0.0012) [0.841]	0.0003 (0.0013) [0.826]	0.0005 (0.0013) [0.756]	-0.0004 (0.0012) [0.935]	-0.0003 (0.0012) [0.711]
p50	-0.0003 (0.0007) [0.806]	-0.0002 (0.0006) [0.980]	0.0001 (0.0003) [0.811]	0.0002 (0.0003) [0.498]	-0.0003 (0.0007) [0.955]	-0.0002 (0.0006) [0.940]
p75	0.0006 (0.0005) [0.478]	0.0007 (0.0005) [0.338]	0.0009 (0.0007) [0.244]	0.0011 (0.0007) [0.189]	0.0006 (0.0005) [0.433]	0.0007 (0.0005) [0.323]
p90	0.0023 (0.0008) [0.199]	0.0026 (0.0008) [0.154]	0.0025* (0.0009) [0.080]	0.0026** (0.0008) [0.010]	0.0023 (0.0008) [0.204]	0.0026 (0.0008) [0.104]
Observations	30835	30835	30835	30835	30835	30835
City FE	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bartik price shocks	Yes		Yes		Yes	
Bartik quantity shocks		Yes		Yes		Yes
City specific trends			Yes	Yes		
City x industry FE					Yes	Yes

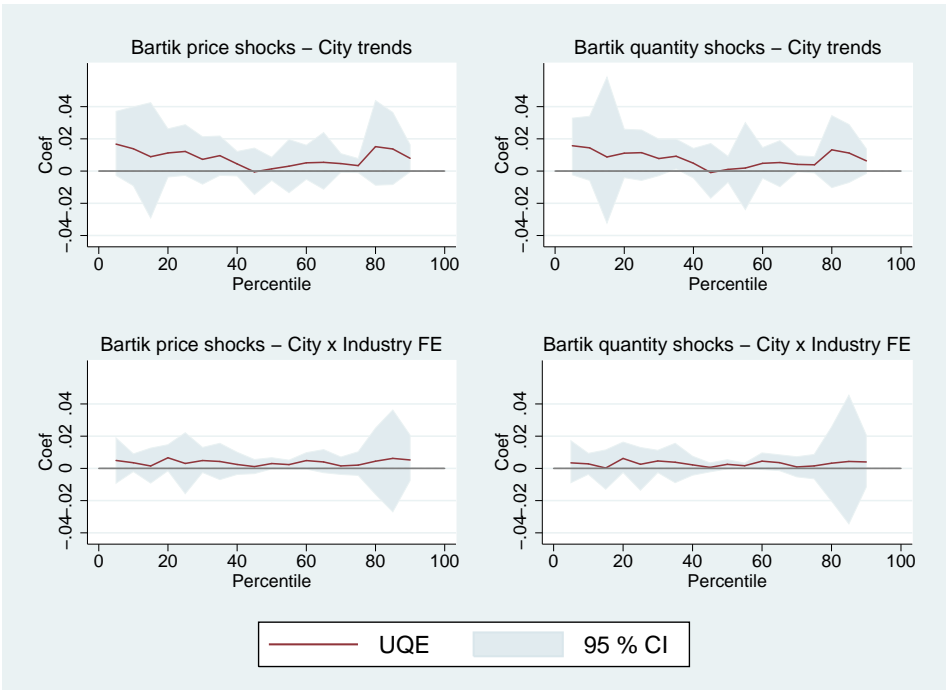
Source: Author's calculations. Each row of the table corresponds to placebo quantile effect estimates of the effect of the minimum wages in absence of minimum wage shocks. Minimum wage incidence is measured by the minimum to median wage ratio described in section A.3. Columns correspond to specifications on equations 6 - 10 of the text. The sample is described in appendix A.2. Standard errors clustered by city in parentheses. P-values in brackets. P-values are obtained with a wild bootstrap-t procedure with 200 replications, where the null hypothesis is equality of the coefficient to 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Figure C.7: Evolution of density of informal wages



Source: ENH, author's calculations. The sample is described in appendix A.2. Vertical line at the level of real minimum wage for the latter quarter.

Figure C.8: Effects of city level minimum wage incidence in the formal sector on the distribution of informal wages



Source: ENH, author’s calculations. The sample is described in appendix A.2. The red line corresponds to the estimates of unconditional quantile effects for percentiles of the distribution of informal wages. Minimum wage incidence is measured by “fraction affected” in the formal sector at the city level, as defined in equation 8. Upper panels correspond to specifications 6, lower panels to specifications 9 and 10 of the text. Shaded areas are 95% confidence intervals obtained using a wild bootstrap-t procedure with 200 replications, clustered by city, where the null hypothesis is equality of the coefficient to 0.