Minimum Wages and Informal Self-Employment: Evidence from Perú

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Abstract

This paper studies the labor market effects and firms' margin of response of a minimum wage increase in a country with large informal self-employment. I show that employment elasticities are negative and larger than recent estimates in the literature; and this is driven by firms facing higher competition with the informal sector. I find that some workers are unequivocally reallocated towards self-employment, which is consistent with a model with worker sorting across formal-informal sector, firms facing imperfect competition, and labor rationing. I also show that medium and large firms were able to pass-through the increased labor cost to consumers through higher prices; and these products were consumed the most by high income individuals and households. Finally, a back-of-the-envelope analysis shows that the minimum wage had muted efficiency gains, as well as negligible redistribution of resources towards lower income households due to the absence of formal workers in their household composition.

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1 Introduction

Economic theory suggests that minimum wage increases can be beneficial through two main channels: the reduction of monopsony power (*efficiency* channel), and shifting resources from business owners to lower-income individuals and households (*redistribution* channel). Many low- and middle-income countries are characterized by frequent transitions between informal self-employment and low-wage work (Donovan et al., 2023), where the former typically exists as a form of subsistence employment for many individuals (Breza et al., 2021). In these economies, we also typically observe competition between the informal and formal sector (Ulyssea, 2018; **?**). If the informal sector competes with formal firms in the labor and product market, then the effects of minimum wage policies, as well as their potential benefits, can be a priori unclear. Whether this feature of developing countries matters to understand the effects of minimum wage policies is, ultimately, an empirical question.

In this paper I provide novel empirical evidence that the large presence of informal self-employment shapes market power and it is thus key to understand why the minimum wage can generate negative employment effects for some workers (Amodio et al., 2023; Felix, 2022). I formalize the key mechanism with a theoretical framework that incorporates both selection into self-employment and involuntary self-employment, as well as oligopsonistic competition among firms (Berger et al., 2022).

I begin by laying out a model where workers choose employment based on a nested discrete choice among wage employment and the firm sector, and then within firms in the firm sector. In addition to this, firms compete in an oligopsonistic style and are able to endogenously choose a cutoff of worker productivity from which they will only hire (Berger, Herkenhoff, and Mongey, 2024; Haanwinckel, 2023). The presence of large informal self-employment changes the structure of both labor and product markets in the following ways. First, low-wage workers have an easily accessible outside option that makes firms post wages closer to a competitive level. Next, due to imperfect competition in the product market between self-employed and firms, the product prices will be pushed closer to competitive levels too. This leads to the prediction that minimum wage increases lead firms exposed to more competition with informal self-employed units to find it harder to adjust wages and prices in response. Therefore, in such cases, one can expect to observe more layoffs, closures and reallocation towards informal self-employment.

To perform the empirical approach in this paper, I exploit a national minimum wage hike in Peru that was enacted in 2016. First, using a firm-level design I find that the minimum wage increase had a negative and sizable employment effect, larger than recent estimates in the context of developed economies (Cengiz et al., 2019, 2022; Harasztosi and Lindner, 2019). In particular, my estimates imply a short-run own-wage elasticity of approximately -0.85 (SE 0.06) one year after the minimum wage increase, and -1.12 (SE 0.08) two years after. By linking occupation-level informality measures constructed from a household survey to a matched employer-employee dataset, I construct firm-level measures of exposure to the informal sector. My estimates show that firms that are highly exposed to informality have muted effects on wages and revenues, and larger employment losses. Next, using a worker-level design I show that not all workers were able to reallocate towards higher quality firms and workers in occupations with more overlap with the informal sector were less likely to remain in the formal sector. I conclude the analysis by combining on the research design developed in Giupponi et al. (2024) with detailed survey data, and show that the size of the formal sector decreased after the minimum wage hike.

The findings in this paper indicate that in labor markets with large informal self-employment, the wage markdowns are smaller due to a more competitive landscape, thus hindering the potential of minimum wages to reduce monopsony power. Additionally, at the expense of some workers reallocating towards the informal sector, the low wage formal workers that remain formally employed after the minimum wage hike tend to receive a wage boost up to the 80th percentile of the earnings distribution[1].

I proceed to study the incidence of the minimum wage on consumers and firms. I find that, among firms that do not close after the minimum wage hike, the burden of the increased labor costs lies almost completely on the consumers. Furthermore, I find that rich households are the ones that consume a higher share of goods produced using minimum wage workers [2]. By combining these results with detailed consumption information in the ENAHO dataset, I compute the expected price and expense increase in an individual- and household-level analysis.

Next, by using the reduced form estimates from the worker-level approach, I find that the increase in expected income - that is, accounting for the fact that workers could exit formal employment after a minimum wage hike and receive income from this outside option - is positive for low-wage workers. In addition, workers in the informal

[1]This is consistent with recent evidence of the distributional gains of the minimum wage in Brasil (Engbom and Moser, 2022).

[2]This is a qualitatively different result to what you find in developed countries. See, e.g., Harasztosi and Lindner (2019) for the case of Hungary.

sector do not seem to perceive any income increases due to this policy.

Among formal workers below the 80th percentile of the wage distribution, the positive income effect dominates the increase in expected expenses from the price pass-through of the minimum wage. Workers beyond this percentile perceive no boost in earnings and, additionally, bear the burden of paying for most of the pass-through to prices. Finally, I show that lower income households do not perceive any income increases due to their employment composition. These households are mostly composed by informal workers and thus there is no redistribution from rich to poor households. This highlights that the presence of the informal sector poses difficulties of minimum wages to generate redistribution.

Related Literature This paper contributes to several strands of the literature. First, I contribute to the empirical literature that examines the effect of the minimum wage on labor market outcomes (Card and Krueger, 1994; Dube et al., 2016; Cengiz et al., 2019). In particular, the context studied in this paper corresponds to a country where the bite of the minimum wage is large and thus may yield qualitatively different responses than smaller minimum wage hikes. The empirical approach in this paper relies on a comprehensive analysis of the impacts of the minimum wage based on firm-level exposure (Harasztosi and Lindner, 2019) complemented with a worker-level research design as in Dustmann et al. (2022).

Next, this paper contributes to the literature on market power and how they operate in developing countries. Evidence in the U.S. shows that employers exert market power (Berger et al., 2022; Azar et al., 2022). Translating the micro-foundations towards developing countries requires incorporating how the informal sector interacts with respect to workers and firms. Most notably, Amodio, Medina, and Morlacco (2023) propose a framework where sorting between wage work and self-employment is based on Roy's (1951) selection model. A limitation of this framework in the context of minimum wages is that it does not incorporate involuntary reallocation towards the outside option sector (that is, the existence of excess supply when the minimum wage is large enough). Therefore, in this paper I adapt the theoretical foundation in Haanwinckel (2023) that describes how firms can endogenously choose a cutoff of worker productivity from which they do not want to hire from, and captures the same idea as rationing labor (Berger et al., 2022). I incorporate oligopsonistic competition that will generate a gradient of market power and the presence of the informal sector.

In addition, this paper relates to a vast literature related to informality and labor markets (Meghir et al., 2019; Jales, 2019; Ulyssea, 2018, 2020). In particular, this paper sheds light on which theories of informality (e.g., Haanwinckel, 2021) can be ruled out based on quasi-experimental evidence in low- and middle-income countries that are similar to the Peruvian context.

Finally, this paper also relates in general to the literature on distributional effects of minimum wages (Autor et al., 2024; Giupponi et al., 2024; Engbom and Moser, 2022). A comprehensive view requires to estimate the consequences on consumption (Macurdy, 20115; Aaronson et al., 2012). An important qualitative contribution of this paper is to show that inflation inequality across different groups of individuals is important to understand the overall consequences of minimum wages (Jaravel, 2021; Autor et al., 2024).

Overview The remainder of this paper is organized as follows. Section 2 provides a layout of the conceptual framework. Section 3 explains the institutional context in Peru. Section 4 describes the data sources used for the empirical analysis. Section 5 presents the main empirical results on the labor market. Section 6 presents the analysis on other firms' margins of adjustment and Section 7 studies the incidence of the minimum wage in Peru. Next, Section 9 performs a cost-benefit analysis based on the empirical evidence presented. Finally, Section 10 concludes the paper.

2 Conceptual Framework

In this section, I outline a partial equilibrium model of oligopsonistic competition for labor that incorporates transitions from wage employment and self-employment that can be involuntary due to the existence of the minimum wage. The purpose of this model is to illustrate the key role of the informal sector and how it shapes market power, which will then help interpret the empirical results of this paper. In particular, I show that the labor supply elasticity depends on the employment concentration of the informal sector, and thus affect the wage markdowns and employment choices of formal firms.

On the labor supply side, workers maximize indirect utility and sort based on a nested discrete choice. These workers first decide between between self-employment and wage employment, and then among firms within the wage sector. In the labor demand side there is a minimum wage and firms can choose which workers to hire from based on their productivity[3]. I use this to rationalize the existence of both voluntary

[3]This concept is similar to what Berger et al. (2022) refer to as *rationing*. It captures the idea that firms can endogenously choose to "close its doors" to some workers and thus generate excess supply when there is a high minimum wage.

and involuntary transitions towards self-employment. I then incorporate imperfect competition in the product market, in which the mechanism is qualitatively similar to the one in the labor market.

I use this model to interpret my empirical analysis as suggesting that, when there is a high degree of competition between firms and the informal sector for labor and product, a minimum wage hike is more likely to induce involuntary transitions towards self-employment. This is due to firms paying wages closer to competitive level and to a reduced capability to pass-through labor cost to price increases.

2.1 Setup

Labor markets are built upon the model of monopsonistic competition among firms described in Haanwinckel (2023). As in Card et al. (2018), the model in Haanwinckel (2023) assumes that firms do not interact strategically. I will relax this assumption to allow for oligopsonistic competition. In such environment, the size - in terms of employment - of the self-employment sector will be relevant to determine the labor supply elasticity to the firm.

Workers are ex-ante heterogeneous in their efficiency units $\varepsilon \sim G(\cdot)$, that is supported over the real line. This means that there will be a distinction between quantity of workers n, and quantities of labor ℓ. I also denote worker earnings as y and the price for labor w.

As in Haanwinckel (2023), firms have to pay at least a total compensation of $\underline{y}$, which I will refer to as the minimum wage[4]. Because some workers with low ε can have a marginal product of labor smaller than $\underline{y}$, firms $j \in \{1, \dots, J\}$ are allowed to reject workers with efficiency units smaller than an endogenously choice $\underline{\varepsilon}_j$. Therefore, this cutoff which will also depend on their productivity $z_j \sim F(\cdot)$, so that higher productivity firms can afford hiring workers with smaller efficiency units.

Formally, the household preferences are given by

$$U(c, j) = c \cdot \left[\exp(\eta_{i,j})\right]^{\frac{1}{\lambda}},$$

where c is a final good composed of firm-produced goods and the good produced by the self-employment sector. In particular, I assume these are combined using a CES

[4] In this model, there is no variation in hours worked.

aggregator

$$q_F = \left[\sum_{j=1}^{J} \gamma_j q_j^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \quad , \quad c = \left[\alpha_F q_F^{\frac{\rho}{\rho-1}} + \alpha_S q_S^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho}{\rho-1}} ,$$

where q_F denotes firm production and q_S denotes production at the informal sector. For the time being, product markets will be assumed to be competitive.

Furthermore, aggregate prices are given by

$$p_F = \left[\sum_{j=1}^{J} \gamma^{\sigma} p_j^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \quad , \quad P = \left[\alpha_F^{\rho} p_F^{1-\rho} + \alpha_S^{\rho} p_S^{1-\rho}\right]^{\frac{1}{1-\rho}}$$

2.1.1 Firm-level labor supply

The timing of the labor market is as follows. Firms post rejection cutoffs $\underline{\varepsilon}_j$ and wages w_j. The self-employment sector operates as one large firm that post a wage w_S. Second, workers observe firm choices in the wage sector $(\underline{\varepsilon}_j, w_j)$, as well as w_S. Based on these, they choose employment option that maximizes indirect utility. Third, firms observe ε of workers who applied and hire those with $\varepsilon > \underline{\varepsilon}_j$. Finally, production occurs and workers are paid. Rejected workers become unemployed and earn zero income.

The choices in the second step will be based on a nested discrete choice. In particular, let $j = 0$ denote self-employment option and $j = 1, \ldots, J$ denote an employment option at one of the firms. Workers draw a vector of idiosyncratic taste shifters $\{\eta_{i,j}\}_{j=0}^{J}$. These preference shocks have a cumulative distribution function given by

$$\text{CDF}\left(\{\eta_{i,j}\}_{j=0}^{J}\right) = \exp\left\{-\exp(\eta_{i,0}) - \left[\sum_{j=1}^{J} \exp\left(-\eta_{i,j} \cdot \frac{\beta}{\lambda}\right)\right]^{\frac{\beta}{\lambda}}\right\},$$

where the parameter β governs the correlation of taste shocks within the firm sector, and the parameter λ governs the correlation across self-employment and the firm sector. I will assume that $\beta \geq \lambda$.

The indirect utility at different employment options are given by

$$V_i(\varepsilon, j) = \exp\left(\lambda \log(\varepsilon w_S) + \eta_{i,S}\right)^{\frac{1}{\lambda}} \qquad \text{if } j = 0,$$

$$V_i(\varepsilon, j) = \mathbf{1}\{\varepsilon \geq \underline{\varepsilon}_j\} \exp\left(\lambda \log\left(\max\{\varepsilon w_j, \underline{y}\}\right) + \eta_{i,j}\right)^{\frac{1}{\lambda}} \qquad \text{if } j \geq 1.$$

In addition, the probabilities are given by

$$\mathbf{Pr}_{\text{informal}}(\varepsilon, \mathbf{w}) = \frac{(\varepsilon w_S)^\lambda}{(\varepsilon w_S)^\lambda + \Omega_\varepsilon^\lambda},$$
$$\mathbf{Pr}_{\text{formal, j}}(\varepsilon, \mathbf{w}) = \frac{\Omega_\varepsilon^\lambda}{(\varepsilon w_S)^\lambda + \Omega_\varepsilon^\lambda} \frac{\mathbf{1}\{\varepsilon \geq \underline{\varepsilon}_j\} \max\{\underline{y}, \varepsilon w_j\}^\beta}{\Omega_\varepsilon^\beta},$$

where $\Omega_\varepsilon = \left(\sum_{k=1}^J \mathbf{1}\{\varepsilon \geq \underline{\varepsilon}_k\} \max\{\underline{y}, \varepsilon w_k\}^\beta\right)^{1/\beta}$ is a measure for demand of skills among firms. High values of Ω_ε mean that many firms are posting high wages and willing to hire workers with ε efficiency units, despite the minimum wage. Importantly, I will allow firms to internalize that their choice of wages and cutoffs affects poaching from other employment options.

The number of workers choosing firm j and the resulting supply of labor in efficiency units are given by

$$n(w_j, \underline{\varepsilon}_j, w_{-j}) = N \int_{\underline{\varepsilon}_j}^\infty \frac{\Omega_\varepsilon^\lambda}{(\varepsilon w_S)^\lambda + \Omega_\varepsilon^\lambda} \frac{\max\{\underline{y}, \varepsilon w_j\}^\beta}{\Omega_\varepsilon^\beta} dG(\varepsilon),$$
$$\ell(w_j, \underline{\varepsilon}_j, w_{-j}) = N \int_{\underline{\varepsilon}_j}^\infty \frac{\Omega_\varepsilon^\lambda}{(\varepsilon w_S)^\lambda + \Omega_\varepsilon^\lambda} \frac{\max\{\underline{y}, \varepsilon w_j\}^\beta}{\Omega_\varepsilon^\beta} \varepsilon dG(\varepsilon).$$

Next, labor costs are given by

$$C(w_j, \underline{\varepsilon}_j, w_{-j}) = N \int_{\underline{\varepsilon}_j}^\infty \frac{\Omega_\varepsilon^\lambda}{(\varepsilon w_S)^\lambda + \Omega_\varepsilon^\lambda} \frac{\max\{\underline{y}, \varepsilon w_j\}^{\beta+1}}{\Omega_\varepsilon^\beta} dG(\varepsilon)$$

The elasticity of labor supply, denoted as e_j^S, is given by

$$e_j^S = \beta$$
$$\underbrace{- (\beta - \lambda) \int_{\underline{\varepsilon}_j}^\infty \frac{\Omega_\varepsilon^\lambda}{(\varepsilon w_S)^\lambda + \Omega_\varepsilon^\lambda} \frac{(\varepsilon w_j)^{2\beta}}{\Omega_\varepsilon^{2\beta}} \varepsilon \, dG(\varepsilon) \left[\int_{\underline{\varepsilon}_j}^\infty \frac{\Omega_\varepsilon^\lambda}{(\varepsilon w_S)^\lambda + \Omega_\varepsilon^\lambda} \frac{(\varepsilon w_j)^\beta}{\Omega_\varepsilon^\beta} \varepsilon \, dG(\varepsilon)\right]^{-1}}_{\text{Concentration within firm sector}}$$

$$
\underbrace{-\lambda \int_{\underline{\varepsilon}_j}^{\infty} \frac{\Omega_{\varepsilon}^{2\lambda}}{[(\varepsilon w_S)^{\lambda} + \Omega_{\varepsilon}^{\lambda}]^2} \frac{(\varepsilon w_j)^{2\beta}}{\Omega_{\varepsilon}^{2\beta}} \varepsilon \, dG(\varepsilon) \left[\int_{\underline{\varepsilon}_j}^{\infty} \frac{\Omega_{\varepsilon}^{\lambda}}{(\varepsilon w_S)^{\lambda} + \Omega_{\varepsilon}^{\lambda}} \frac{(\varepsilon w_j)^{\beta}}{\Omega_{\varepsilon}^{\beta}} \varepsilon \, dG(\varepsilon) \right]^{-1}}_{\text{Concentration overall}}
$$

This differs the standard monopsony model with discrete choice (Card et al., 2018), in which firms ignore their contribution to Ω_ε due to being small relative to the size of the labor market. In that model, the elasticity of labor supply will be given by β. On the other hand, we will obtain such result in my proposed model only if the firm is very small relative to the labor market. Furthermore, as firms become more concentrated the labor supply elasticity tends to zero.

2.1.2 Firm's problem

Firms choose the posted wages per efficiency unit and the productivity cutoff that maximizes profits

$$
\max_{w_j, \underline{\varepsilon}_j} \quad p_j z_j f\left(\ell(w_j, \underline{\varepsilon}_j, w_{-j})\right) - C(w_j, \underline{\varepsilon}_j, w_{-j}),
$$

and the first order conditions yield

$$
p_j z_j f'(\ell) = \left(1 + \frac{1}{e_j^S}\right) w_j \tag{1}
$$

$$
p_j z_j f'(\ell) \underline{\varepsilon}_j = \underline{y} \tag{2}
$$

The first condition states that wages are set as a markdown of the marginal revenue product of labor, and this markdown depends on the firms' employment concentration. The second condition states that the threshold is selected optimally such that the lowest productivity worker is compensated for their labor with the minimum wage.

This result implies that firms that are more concentrated will be able to markdown wages more so than firms with less concentration. The less productive firms will have a low marginal revenue product and will be small relative to the market, thus will be more likely to reduce employment as a response to the minimum wage increase.

2.1.3 Informal Sector

Production at the informal sector is linear en efficiency units of labor:

$$q_S = \ell_S \quad , \quad \ell_S = N \int_{\underline{\varepsilon}_j}^{\infty} \frac{(\varepsilon w_S)^\lambda}{(\varepsilon w_S)^\lambda + \Omega_\varepsilon^\lambda} \varepsilon dG(\varepsilon).$$

That is, we can think of this sector as a very large firm that sells a product at marginal cost $p_S = W_S$.

2.2 Minimum Wage

In this section I will explain how minimum wages operate in this framework. In this model where firm concentration matters, each firm internalizes that increasing their posted wage w_j will attract workers who are supplying labor to other firms, or choosing to be self-employed. Thus low-productivity firms will be much less concentrated than high-productivity firms. Furthermore, high-productivity firms are able to afford hiring workers with lower ε than the other type of firms.

An increase in the minimum wage increase the hiring thresholds of all firms $\underline{\varepsilon}_j$, as can be seen from Equation (2). Furthermore, as stated in Equation (1) firms with low z_j will post lower wages due to a lower marginal revenue product. In other words, low-quality firms will pay wages closer to competitive levels, will be more atomistic, and will face a larger bite with respect to the minimum wage. Under the assumption of a concave production function $f(\cdot)$, this implies that the firms with lowest productivity in the market will have to set larger hiring thresholds compared to a monopsonistic competition scenario.

This mechanism is consistent with the theoretical model proposed in Berger et al. (2022), in which oligopsonistic competition reduces the potential efficiency gains from the minimum wage. In Berger et al. (2022) a minimum wage increase labor market power of surviving firms due to reallocation. In this model, however, labor market power can be reduced when labor is reallocated out of the formal sector and into self-employment.

2.3 Incorporating imperfect competition in product market

The discussion so far shows that when the size of the informal sector is large, de-facto labor market power is reduced due to smaller employment concentration of firms. This implies that it will be harder for some firms to adjust wages when there is an increase in the minimum wage. In addition to this mechanism, another response from firms is to pass-through the increased labor costs to prices (Harasztosi and Lindner, 2019).

The mechanism in this case will be similar to the case of the labor market: oligopolistic competition and concentration restricts firms to adjust prices in response to a minimum wage hike. In particular, by allowing formal firms to internalize that their pricing decision affects aggregate prices p_F, we obtain the modified first order conditions:

$$p_j \left(1 - \frac{1}{e_j^Q}\right) z_j f'(\ell) = \left(1 + \frac{1}{e_j^S}\right) w_j \tag{3}$$

$$p_j \left(1 - \frac{1}{e_j^Q}\right) z_j f'(\ell) \underline{\varepsilon}_j = \underline{y}, \tag{4}$$

where $e_j^Q \equiv \frac{\partial \log q_j}{\partial \log p_j}$ denotes the product demand elasticity. Equations (3) and (4) show that under imperfect competition in the product market, firms have more freedom to adjust in response to a minimum wage increase. For example, a firm that has a large degree of concentration in the product market can increase the output price without having to layoff any worker.

3 Institutional Background

In Peru, most workers are informal and self-employed. Informal firms are defined as those firms that are not registered under tax authorities. In addition, a worker is classified as having informal labor if she reports (i) not having health insurance, or (ii) is self-employed, is classified as working for an informal firm, and has five or fewer employees. Figure A.4 shows that the set of informal firms, henceforth referred as informal sector, in much larger in terms of employment relative to the set of formal firms. Furthermore, more than half of the individuals in the informal sector can be classified as informal self-employed in my data. This can be contrasted with a very small unemployment rate that sits around 3%. Due to the large prominence of self-employment within the informal sector, I will use the terms *informal sector* and *informal self-employment* interchangeably throughout the rest of this dissertation [5].

[5] Additionally, close to 90% of self-employed individuals in my data are classified as informal. Therefore, whenever I mention self-employment I will implicitly refer to informal self-employment.

The minimum wage is set in terms of monthly earnings of its national currency, *soles* (henceforth referred as *PEN*), and these are set at a national level only[6]. Typically, there is loose enforcement of some labor contract conditions such as the number of hours worked. Therefore, I will use the terms wages and earnings interchangeably throughout the rest of this dissertation. As opposed to other countries in the region (e.g., Ecuador, Colombia, Chile), the minimum wage increases have no particular periodicity, and often depend on the political interest of the president at that particular period.

On March, 2016, the president announced that the national minimum wage would increase from 750 *PEN* to 850 *PEN*, which corresponds to an approximately 13 percent increase in nominal terms, and 15 percent in real terms. This change came into force on May 1st, 2016. Figure 1 shows that the ratio of the minimum wage with respect to the median earnings (among formally employed workers) in Peru sits around 0.6. Therefore, the bite of the minimum wage in Peru was particularly large around the time of the policy, and had the potential to destroy a significant number of jobs.

The Peruvian economy was characterized by robust economic growth in the years surrounding the implementation of the minimum wage policy. Over the period of 2011 to 2017, nominal GDP grew by 44% (see Panel (a) of Figure A.1). At the same time, unemployment was stable around 3.2% throughout the 2011-2016 period (see Panel (b)). The 2014-2016 period was characterized by some slight increase in inflation (Panel (c)), which later reverted back towards values within 1% and 3%. These time series show that the Peruvian economy was stable throughout these years, which will pose an important feature for part of the empirical strategy in this paper.

4 Data

This section describes the data used for the empirical analysis. Section 4.1 describes the administrative records that represent my primary data source. Section 4.2 outlines the firm-level financial dataset that complements the firm-level analysis. Section 4.3 describes the household survey used to obtain measures of informality status among workers. Summary statistics are presented in Section 4.4. Appendix B provides further details about these data sources.

[6]In Peru it is called *Remuneración Minima Vital* (RMV). This quantity correspond to full-time employment of 8 hours per day, or, equivalently, 48 hours per week. Workers in the mining industry have a 25% larger RMV.

4.1 Social Security Data

My main data source comes from social security records collected monthly by the Peruvian National Superintendency of Customs and Tax Administration (*Superintendencia Nacional de Aduanas y de Administración Tributaria*, SUNAT), and stored by the Peruvian Ministry of Labor (*Ministerio de Trabajo y Promoción de Empleo*, MTPE). This dataset provides information, between January-2015 and December-2019, on the universe of formal employees working at firms that are registered under SUNAT (i.e., formal firms). I use the information recorded as of February in each year to perform the empirical analysis.

This administrative data - henceforth labelled as PLAME - is a matched employer-employee dataset that contains information on approximately 3 million workers and their current jobs. For each worker-job combination occurred in a given year, I have information on earnings, six-digit occupation codes, industry, labor contract information, as well as detailed demographic information on the employee. [7] Individuals who participate in the informal sector are not observed in this dataset, which means that we cannot distinguish unemployment, non-participation in the labor force, and participation in the informal sector from these records.

A feature of this dataset that is instrumental for my purposes is that it provides detailed information about each workers' occupation. In my analysis I leverage measures of informality at the occupation level that I can merge to the occupation codes in this dataset. Furthermore, there is rich information on the type of contract, which allows me to observe whether a worker is hired under a temporary vs permanent contract.

My analysis involves two main empirical approaches. The first empirical approach is at the firm level and compares the trajectories of firms who were highly exposed to the minimum wage versus firms who were not exposed to the policy. To implement this approach, I collapse the information at the firm-year level and exclude some sectors. I omit the finance sector, communitary services, household domestic services, non-governmental, and firms with missing industry information. I focus on firms that existed between 2015 and 2016[8], and I drop firms with no wage cost information in either of those years. I also drop firms with top 1 percent and bottom 1 percent employment growth rate between pre-policy years, as well as firms where the average wage per

[7] Earnings do not include overtime payment or bonuses. Earnings are top-coded at the 95th percentile of each year (around 7,500 *PEN* in terms of monthly earnings).

[8] Since I use the records as of February in each year, these two years correspond to the pre-policy periods.

worker was less than 90 percent of the minimum wage in any year between 2015 and 2016. In addition, I omit firms with less than 5 employees on average between 2015 and 2016 from my analysis.[9] The final dataset includes 23,477 firms that represent around 1.3 million workers (or close to a third of the total formal employment in Peru).

The second empirical approach compares job trajectories of workers who earned less or close to the minimum wage prior to its increase with the job trajectories of workers who earned a substantially higher wage, in the same spirit as Dustmann et al. (2022). To do so, I keep the highest paying job for every worker-year combination and those who earned a monthly earning between 550 and 2250 *PEN* - as of February 29th - in 2016. I follow these individuals from 2015 to 2017. I focus on workers who were between 18 and 60 years old throughout the period of analysis and omit workers who were hired under part-time contracts.[10]

4.2 Annual Economic Survey

I complement the matched employer-employee data with a firm-level cross-sectional dataset. This dataset is effectively a census for medium and large firms —based on their annual net revenues— and provides survey-quality information for smaller firms that is representative at a regional and industry level. This dataset - henceforth referred to as EEA - include information at the annual level on employment counts across different categories (e.g., across gender, managerial status, permanent versus temporary contracts), geographical location, balance sheet information, and it also records product-level information such as quantities and prices for a subset of firms.

Unfortunately, both PLAME and this dataset are de-identified and thus their firm identifiers cannot be matched across datasets. To circumvent this problem, I follow an approach described in Harasztosi and Lindner (2019), Appendix A5. In particular, I use a battery of observable characteristics at the firm level such as employment counts and average wage cost per worker across different occupational categories and gender status to predict the fraction affected at the firms in the EEA data using machine learning methods. The preferred model corresponds to a random (regression) forest. The model performs well in terms of out-of-sample prediction: the slope of the regression between actual and predicted fraction affected is 0.98, which is very close to

[9]The reason for this is that the firm-level financial information mostly covers medium-to-large firms. By imposing this restriction, it is easier to compare and reconcile the analysis across different data sources.

[10]I do not observe hours in my main data source. This restriction helps me focus on workers who are more likely working full-time.

one. Further discussion of this procedure can be found in Appendix B. As a result, I am able to apply the same firm-level empirical strategy on outcomes found either in PLAME or EEA, and can provide a comprehensive analysis on the firms' margins of response to the minimum wage increase.

This dataset records information as of the end of December in each year. Therefore, for the empirical analysis I restrict to firms that existed between 2014 and 2015 and had at least 1 employee in those years. I exclude firms that registered employment or wage cost equal to zero in either 2014 and 2015. Additionally, I drop firms with top 1 percent and bottom 1 percent employment and revenue growth rate between pre-policy years, as well as firms where the average wage per worker was less than 90 percent of the minimum wage in any year between 2014 and 2015. Finally, I omit firms with less than 5 employees on average between 2014 and 2015 from my analysis. The final dataset contains 4,343 firms observed in 2014 and 2015.

4.3 National Household Survey

Finally, my third data source is the Peruvian National Household Survey (ENAHO), collected by the Peruvian National Institute of Statistics and Information (*Instituto Nacional de Estadísticas e Informática*, INEI). This dataset is cross-sectional but also follows some households over time as a rotating panel. Among many other characteristics of the household members, this dataset gathers information on wages, employment characteristics and household expenses. Starting from 2014, INEI also computes a set of variables that measure the informality status of workers and their firms [11]

I use the occupation codes in this dataset to collapse informality measures at this level and match with the employer-employee data. For individual-level analysis using this dataset, I restrict the sample to workers who work between 35 and 72 hours per week and who were between 18 and 60 years old within the period of analysis.[12] One problem with the information on hours in this data is that some individuals report actual versus contractual hours. This sample restriction attempts to mitigate this problem by assuming that workers who report to work more than 35 hours are full-time workers.

[11] These measures are inferred from key questions in the survey, and consistent with informality definitions used by the International Labour Organization (ILO).

[12] The exception to this rule are workers who reported to have worked a smaller number of hours due to illness or vacations and receive a monthly salary.

4.4 Summary Statistics

In this section I provide some summary statistics from the main datasets used in the empirical results. First, I provide some information about the workers and firms' characteristics in the PLAME dataset. And next, I summarize some firm characteristics in the EEA dataset.

Table 1 provides a description of the characteristics of workers that earned below the new minimum wage (850 *PEN*) in early 2016 (whom I'll refer as minimum wage workers), workers who earned slightly above the new minimum wage, and then workers who are higher up in the earnings distribution. Minimum wage workers are, compared to workers who earn more than 1250 *PEN* per month, more likely to be residing outside of Lima, female, low-skilled, and younger than 24 years old; they are also more likely to hold a permanent contract. Furthermore, minimum wage workers are more likely to be working in small firms and in the non-tradable sector.

Next, Table 2 reports some characteristics at the firm-level in 2016, aggregating all sectors and then for the three main sectors in terms of employment size: manufacture, commerce, and services. The average firm in my sample employs 115 workers, has 13 years of existence, and a female share of approximately 33% of its workforce. The median fraction of workers affected by the minimum wage hike for the average firm is 17 percent. As expected, firms in the services sector employ less workers on average, and are also more exposed to the minimum wage than those in tradable sectors.

Table 3 shows the characteristics of firms in the EEA dataset, which contains financial information. I compute statistics the year prior to the minimum wage hike up to the year after the increase. Firms in this sample are, by construction, slightly older and with more employees than my PLAME estimation sample. In particular, in this dataset the average firm age in 2016 is 17.69, whereas it is 13.22 in the matched employer-employee dataset. Furthermore, in Table 4 I also provide some statistics by different quartiles of exposure to the minimum wage, measured by the fraction of workers below the new minimum wage. This Table shows that the firms who would've had to adjust their wages more - in compliance with the policy increase - were less likely to be located in Lima, payed lower wages on average, and were smaller and younger. It also shows that highly exposed firms are more likely to be in the manufacture and services sector.

Lastly, Figure A.4 shows the composition of the labor force in Peru in the years around my analysis. It shows that (i) unemployment was very small and roughly constant over that time frame; (ii) informal contracts within formal firms is not that common in this context; and (iii) the informal sector is very large relative to the formal sector. Additionally, more than half of the orange area in this graph corresponds to informal self-employment.

5 Labor Market Effects of the Minimum Wage

The current section presents the main results using different research designs: a firm level approach, and a worker level approach. Section 5.1 describes the firm-level approach and Section 5.2 shows that the minimum wage increase did have disemployment effects while increasing the average wage at the firm among firms that didn't close. Next, Section 5.3 describes the worker-level approach and Section 5.4 then shows that the mechanisms in play are not consistent with large reallocation effects towards higher paying firms. In addition, I show that the effects found in this section seem to be driven by the presence of the informal sector, which is consistent with the proposed conceptual framework.

5.1 Firm Research Design

I estimate the employment effects of the minimum wage by comparing the evolution of key outcome variables at firms with many workers affected by the minimum wage increase to those firms with few affected workers. I follow Harasztosi and Lindner (2019) estimate regression models of the following form:

$$\frac{y_{jt} - y_{j2016}}{y_{j2016}} = \alpha_t + \beta_t \mathrm{FA}_j + \gamma_t X_{jt} + \varepsilon_{jt}, \tag{5}$$

where the left hand side is the percentage change in outcome y relative to May 2016, the final pre-policy year, and year t. This specification allows time effects and the impact of firm characteristics, γ_t, to vary flexibly over time.

I winsorize the percentage changes, $\frac{y_{jt}-y_{j2016}}{y_{j2016}}$, to take values between the 1st and 99th percentile in each year. I run the later analysis including versus excluding firms that shut down in the analysis period, where they experience a 100 percent decline in their outomes. I measure exposure to the minimum wage, FA_j by calculating the fraction of workers for whom the minimum wage increase binds. I predict FA_j from the average wage cost and employment counts (observed in PLAME data) to be able to run the analysis using the firm-level financial data. I invite interested readers to go to

Appendix B for further details of the procedure. This specification above assumes that the dependent variable is linear in terms of the exposure measure. In Figure A.6 and Figure A.7 I show that the binscatter between such outcomes and the exposure measure are consistent with a linear relationship.

I restrict my sample to firms that existed in 2015 and 2016. I estimate robust standard errors using the logarithm of total employment in 2016 as weights in the regression.[13] In my benchmark regression I control for the following variables and their squares: fraction of censored earnings between 2015 and 2016; fraction of female workers between 2015 and 2016; and the fraction of university degree holders between 2015 and 2016. In addition, I control for fixed effects for firm age, province, and 1-digit industry.

Identification Assumption. The regression specification described above relies on the assumption that firms with fewer minimum wage workers are a valid estimate of the counterfactual for firms with many affected workers, so that these firms would follow a parallel trends in the absence of the minimum wage increase. The existence of differential trends before the minimum wage hikes would threaten the credibility of this assumption. Reassuringly, I reject the presence of differential trends in the results that will be shown next.

5.2 Labor Market Effects: Firm Approach

Employment Effects. Panel A of Table 5 shows the regression results from Equation (5). Columns 1 to 4 show the effects of the minimum wage in the two following years after the minimum wage increase. The point estimate in column 1 indicates that a year after the minimum wage hike employment declines by 9.9 percent (SE 0.7 percent) more at firms where 100 percent of the workforce is directly affected by the minimum wage relative to firms with no exposure. This results include both the extensive margin (firm closure) and intensive margin (layoffs). Column 2 then shows the point estimates after we control for the set of covariates described in Section **??**. The point estimate then drops to 7.6 percent (SE 0.8).

Columns 3 and 4 repeat the same exercise for the effects two years after the minimum wage hike. In particular, Column 4 shows that employment is reduced by approximately

[13] For the EEA data I can also use the logarithm of total revenues in 2015 as weights, and the results remain similar. The reason for using logarithms is that the distribution of employment size and revenues is highly skewed. This can obscure the interpretation of my results given that the central limit theorem might not hold in the firm-level weighted regressions.

9.5 percent (SE 1.0 percent) lower at firms with 100 percent exposure relative to firms with no exposure.

Panel (a) of Figure 2 shows that there is no evidence of any differential trends prior to the minimum wage hike between exposed and non-exposed firms. In Panel (b) of Figure 2 I exclude the extensive margin responses. The disemployment effects are just slightly smaller (5.1 percent decrease, SE 0.8 percent) and, again, there is no sign of differential trends among treated and untreated firms.

Wage Effects.I now compute the average wage at the firm as the wage cost divided by a statistic of full-time employment at the firm, and use it to construct the dependent variable in Equation (5). Therefore, these regressions unavoidably exclude those firms that closed after the minimum wage increase.

Columns 1 and 2 in panel B of Table 5 show that the average wage at the firm increased significantly in the two following years after a minimum wage hike. In particular, column 2 in panel B of Table 5 indicates that the average wage increases by 11.4 percent (SE 0.4 percent) at firms with 100 percent exposure to the minimum wage increase relative to firms with no affected workers.

Columns 3 and 4 in panel B of Table 5 compute the point estimates two years after the minimum wage hike. These columns show that the average wage are 11.2 percent (SE 0.4 percent) higher at exposed firms compared to non-exposed firms. Furthermore, Figure 2B shows that there is no indication that exposed firms were trending any differently than non-exposed firms prior to the minimum wage increase.

In Figure A.8 I compute the implied own-wage elasticity, which is the ratio of the employment effects and wage effects, and compare it to recent estimates of this elasticity parameter. To construct standard errors I jointly estimate both effects and perform a test on the non-linear combination. The short-run elasticity is around -0.85 (SE 0.06) one year after the minimum wage increase, and -1.12 (SE 0.08) two years after. The confidence intervals of these two estimates can reject most of the recent estimates of the own-wage elasticity, which are statistically closer to zero.

Heterogeneity and the Informal Sector.I then explore heterogeneous effects across industries, and whether the informal sector has any salience in explaining this heterogeneity. Figure A.3 plots the point estimates across different industries one year after the minimum wage increase. The employment effects are - as expected - more pronounced in the manufacture, commerce , and services sectors. Furthermore, within the construction sector I find employment effects that are statistically indistinguishable from zero across all years. I also find that largest negative employment effects in the medium term (3 years after the increase) is in the commerce sector.

To address whether the presence of the informal sector plays a role in explaining these differences, I compute a firm-specific measure of exposure to the informal sector. More precisely, I observe 3-digit occupations in the ENAHO dataset, and I compute the share of workers in these occupations that work in the informal sector. I classify an occupation as informal if they belong to the highest quartile of this share [14]. Next, I compute the fraction of workers at the firm that belong to an informal occupation, and estimate a modified version of Equation (5):

$$\frac{y_{jt} - y_{j2016}}{y_{j2016}} = \alpha_t^0 + \alpha_t^1 \text{FA}_j + \beta_t^0 \text{FA}_j + \beta_t^1 \text{FI}_j + \beta_t \text{FA}_j \text{FI}_j + \gamma_t X_{jt} + \epsilon_{jt} \tag{6}$$

Figure 3 plots the employment and wage estimates among firms that were highly exposed to the informal sector and those who were not. In particular, we can observe that firms that have to compete less for their labor can increase their wages without having to layoff many workers compared to firm who have 100 percent of their workforce in those occupations classified as informal. In particular, the employment effects are statistically different between firms with high exposure and no exposure to the informal sector (p-value=0.03), whereas the wage effects are not statistically different in the year after the minimum wage increase (p-value=0.19).

5.3 Worker Research Design

The effects at the firm-level may not provide a comprehensive analysis of this policy if workers are able to reallocate across different firms (Dustmann et al., 2022), so that workers can be better off at the expense of the closure unproductive firms. In this sense, minimum wage increases can generate more firm-to-firm transitions in the economy and help workers climb-up the ladder, thus creating wage spillover effects above the minimum wage (Engbom and Moser, 2022; Berger et al., 2024).

In this approach I leverage the fact that I can follow workers over time and closely follow the empirical strategy described in (Dustmann et al., 2022). The idea is to compare outcome changes between two pre-policy periods ($t-2$ and $t-1$) to outcome changes between the year prior to the minimum wage hike and the year after the increase ($t-1$ and t) along the distribution of earnings in the baseline period (t–2 and t–1, respectively).

[14] For example, some highly informal occupations are weavers, knitters, and street vendors. On the other hand, occupations such as lawyers and doctors are classified as not informal.

In the benchmark specification, I assign workers to 15 small (100 soles) earnings bins b (where the first bin $b = 1$ refers to monthly earnings between 650 and 750 soles, ..., and the 15th bin to monthly earnings between 2,250 and 3,500 soles) based on their monthly earnings in $(t-1)$.[15] I then regress individual outcome changes for both pre-treatment period $t = 2016$ and post-treatment $t = 2017$ using the following specification:

$$y_{i,t} - y_{i,t-1} = \sum_{b=1}^{15} \gamma_{t,b} \mathbf{1}\{earnings_{i,t-1} \in bin_b\} + \beta X_{i,t-1} + \epsilon_{i,t}, \tag{7}$$

where the parameters $\gamma_{t,b}$ measure the outcome change between $t-1$ and t of workers in bin wage b conditional on a vector of individual baseline characteristics $X_{i,t-1}$. For the post-policy period (2016 vs 2017), the coefficients $\gamma_{t,b}$ capture the effect of the minimum wage across different wage bins b, subject to mean reversion and macroeconomic time effects as potential confounders. To eliminate these confounding effects, I substract the $\gamma_{t,b}$ corresponding of the pre-policy period (2015 vs 2016). This can be performed by running the following re-parametrized regression:

$$\begin{aligned} y_{i,t} - y_{i,t-1} = &\sum_{b=1}^{15} \gamma_{2016,b} \mathbf{1}\{earnings_{i,t-1} \in bin_b\} \quad + \\ &\sum_{b=1}^{15} \delta_b \mathbf{1}\{earnings_{i,t-1} \in bin_b\} \times POST_t + \beta X_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{8}$$

where $\delta_b := \gamma_{2017,b} - \gamma_{2016,b}$ and $POST_t$ indicates the post-treatment year $t = 2017$. In other words, the coefficients δ_b trace out the outcome change in the post-policy years relative to the outcome change in the pre-policy years.

Identifying Assumption.the parameters δ_b will capture the causal effect of the minimum wage increase under the assumption that mean reversion and macroeconomic time effects are stable over time (i.e. $\gamma_{2016,b} = \gamma_{2017,b} \quad , b \in \{1, \ldots, 15\}$ in the absence of MW hike). Given that the upper tail shouldn't be affected by this policy, I can test whether there were any macroeconomic time effects in the earnings distribution by investigating whether $\gamma_{2016,15} = \gamma_{2017,15}$ are close to zero or not. Reassuringly, this is the case for most of my specifications. However, if it was the case that macroeconomic time effects in the post-policy period is different from the pre-policy period, I can con-

[15] I pool individuals at the upper tail up to 3,500 PEN to increase precision of my estimates in the control group.

struct generalized difference-in-differences estimates by substracting $\gamma_{2017,b=15}$ from any other bin effect $\gamma_{2017,b}$, $b \neq 15$. The assumption behind this approach is that the changes in macroeconomic time effects are constant across all earnings bins.

5.4 Labor Market Effects: Worker Approach

Wage Effects. Panel A of Figure 4 provides evidence that the minimum wage increased earnings of low-wage workers. In particular, this panel plots one-year earnings growth separately for the years 2015 vs 2016 to 2016 vs 2017, as obtained from regressing Equation 7 in these two separate samples. We can observe that low-wage workers typically experience higher wage growth relative to those at the highest part of the earnings distribution. To address the fact that the wage growth at the bottom of the distribution is partly due to macroeconomic time effects and mean reversion, we substract both curves. This is systematically performed by regressing equation (8).

In panel B of Figure 4 I plot the point estimates of the difference between both curves of panel A. These results show that log earnings increased by 0.075 (SE 0.004) for those who earned between 750 and 850 prior to the minimum wage increase. Consistent with the identification strategy, we also observe that the earnings increase at the very top of the distribution is small (-0.01 , SE 0.003). This suggests that macroeconomic conditions were sufficiently stable during the period 2015-2017. We also observe that the minimum wage increase had substantial spillover effects for workers who earned above the new minimum wage.

The estimates are summarized on Panel A of Table 6. In particular, Columns 5 and 6 of Table 6 compute the difference between the coefficient at different bins and the control group (the highest bin). Reassuringly, the difference-in-differences estimates remain statistically significant and closer to the baseline results shown in the Figure 4.

Employment Effects. Next, I investigate whether the minimum wage increase forced workers out of formal employment. To do so, I use the probability of remaining formally employed as the dependent variable in Equation (8). Panel A of Figure 5 shows that low-wage workers are much more likely to exit formal employment compared to those who are higher in the earnings distribution. Furthermore, the difference between these probabilities between 2015 vs 2016 and 2016 vs 2017 is significantly smaller at the top of the earnings distribution. This suggests that, as we would expect, workers at the top of the earnings distribution have no change in their employment prospects after the minimum wage hike.

Panel B of Figure 5 computes the probability of being employed in t relative to the 2015 vs 2016 period, obtained from Equation (8). This figure shows that workers who earned close to the minimum wage experienced a negative impact on their employment prospects. For example, workers who earned between 750 and 850 were 0.011 pp. (SE 0.005) less likely to be formally employed after the minimum wage increase. Reassuringly, I cannot reject any effect at the top of the earnings distribution, which confirms that macroeconomic conditions were stable in this study period.

Moreover, Panel B of Table 6 show the estimates across different bins. The last three columns compute difference-in-differences estimates by substracting the main effects at different bins to the effect in the control group

Reallocation Effects. To address whether part of the wage increases can come from workers climbing up the ladder, I estimate the AKM firm fixed effects using the time periods prior to the minimum wage increase, and then I compute a change in quality as $q^{k=t-1}_{j(i,t),i} - q^{k=t-1}_{j(i,t-1),i}$, where $q^{k=t-1}_{j(i,t),i}$ is the time k firm fixed effect of firm j at which worker i is employed in period t. The advantage of this measure is that it captures compositional changes rather than mechanical increases in the firm effects due to the minimum wage increase. This measure is by construction zero among workers who remain at their firm between $t-1$ and t, and can only be defined among firms that existed in both time periods.

Panel A and B of Figure 6 show that workers who earned slightly above the minimum wage were more likely to transition to higher paying firms and would partly explain the presence of spillovers in the wage effects. Additionally, there is no evidence of worker reallocation at the top of the minimum wage, which reaffirms the assumption of stable macroeconomic effects. On Table 7, I show the main effects for the bins around the old and new minimum wage. Panel A shows the baseline earnings effects and Panel B shows the coefficients using the change in AKM firm effects, measured prior to the minimum wage hike. In the last two rows of Table 7 I compute the percent of the earnings effect due to reallocation. The results suggest that the reallocation channel was very small in general, which means that most of the earnings gains come mainly from compliance to the new legislation.

Heterogeneity and the Informal Sector. Figure 7 shows the relationship between the wage and employment effects and how informal the workers' occupation is. To determine whether an occupation is highly exposed to informality I compute - using the ENAHO dataset - the share of individuals classified as informal at each occupation, and then select the highest quartile of this measure. Panel A of Figure 7 shows that workers at occupations that are more common to observe in the informal sector face the largest disemployment effects, whereas the rest of workers have employment effects statistically indistinguishable from zero. On the other hand, Panel B of Figure 7 shows that, conditional on remaining employed, workers tend to receive a wage boost regardless of whether their occupation was classified as exposed to informality or not.

5.5 Do workers exit the formal sector?

The evidence gathered up to this point suggests that workers exit formal employment after a minimum wage increase, especially at occupations commonly observed in the informal sector. A possible explanation of these results could be that firms switch workers under a formal contract to being hired informally (i.e. informal employment within the formal sector). In this sub-section I show evidence that the size of the formal sector is indeed smaller after the minimum wage increase, suggesting that workers are reallocating towards the informal sector.

First, in Figure 8 I check using employment counts whether the number of workers with a formal contract decreases among individuals who earned close to the new minimum wage. Panel A of Figure 8 shows the employment counts two years after the minimum wage hike (2018) and the baseline year (2016). Next, Panel B of Figure 8 computes the difference in each bin, as well as the cumulative difference. This Figure shows that there is a missing mass of workers below the new minimum wage that is not compensated by the new mass above the minimum wage. This would indicate that workers are exiting formal employment.

I then turn to the ENAHO dataset, where I can observe formality status among different workers, to evaluate whether employment in the formal sector decreases. To do so, I follow the approach described in Giupponi et al. (2024) that combines regional variation with a frequency distribution approach. The idea is to select high-wage provinces and use them as a control group and then compare workers with the same skill level - defined as wages net of time and place effects - across high- and low-wage provinces. In other words, workers with the same skill would've earned the same had they lived in the same location. The details of the empirical implementation of this methodology is carefully explained in Section III.B in Giupponi et al. (2024).

Figure 12 shows the results of this methodology on the entire formal sector. In particular, Panel A shows the distribution of province fixed effects that comes from a

Mincer-style regression of wages against individual characteristics, and fixed effects of location and year. The individual characteristics include a quadratic polynomial of age, a female indicator, educational level, industry sector, and occupation. Panel B of Figure 12 shows the employment percent changes at 100 PEN bins relative to the new minimum wage. The change in employment below the new minimum wage (Δb) is equal to -3.10% (SE=0.53%), and the cumulative employment percentage change up to 11 bins relative to the new minimum wage is also negative and larger. This indicates that there was a statistically significant employment decrease in the formal sector among low-wage workers.

6 Firms' Margins of Adjustment to the Minimum Wage

In this section, I focus my attention to other firm outcomes that can be relevant for a comprehensive understanding of the effects of minimum wage policies on firms.

Using the EEA dataset, I leverage the same firm-level approach described above. In particular, I estimate Equation (5) using the cost of labor, total revenues, profits, and material expenses as dependent variables in the analysis. For the manufacturing sector, I have information at the product level that allows me to compute a price index to use as a dependent variable in these regressions.

Effects on Cost of Labor. Panel A of Table 8 and Table 9 show the main effects on total labor costs. In particular, the Column 1 and Column 2 in Table 9 indicate that surviving firms faced a 12.3% and 21.9% increase in total labor costs during the two years following the minimum wage increase. The last column computes the placebo effect in the year prior to the increase, which is statistically insignificant. The coefficients along with 95% confidence intervals are also shown in Figure 9, Panel (a).

Effects on Revenue. Panel B of Table 9 show the coefficients on total revenues. Column 1 and Column 2 in Table 9 show that firms that didn't close after a minimum wage increase had larger revenues in the year after policy enactment (7.4% increase, SE=3.6%). The results of Column 3 show that there is no differential pre-trends between high- and low-exposed firms.

Effects on Material Expenses. Panel C of Table 8 and Table 9 show that there is no statistically significant evidence that there was a change in material expenses among firms.

Effects on Capital. Panel D of these tables show some mild evidence that there could have been some substitution between labor and capital. However, given the statistically significant effects on revenue, wages and employment, this channel is likely not key to the rest of my analysis.

Effects on Profits.I find that profits do not change on average during the period of analysis, in response to the minimum wage hike. These results potentially mean that firms are not bearing the burden of the increased labor costs, but instead passing through the burden onto consumers. This will be further explored in the next section of this paper.

Effects on Price. Figure 10 plots the coefficients of Equation (5) using changes of the Laspeyres index as dependent variable. While it seems to be underpowered, it does suggest that prices increase as a response to the minimum wage hike. A limitation of this index is that it can only be computed among products that existed before and after the policy change.

Heterogeneity and the Informal Sector. Figure 11 shows the effects on labor costs and revenue separately for provinces where informality is common and provinces where it is not. Panel (a) of Figure 11 shows that labor costs are statistically closer to zero among firms in highly informal locations. Furthermore, firms in highly informal locations were also less likely to increase total revenues. This suggests that the price pass-through is muted in such cases, consistent with the conceptual framework described in Section 2.

7 The Incidence of the Minimum Wage in Peru

In this section I first explore which households are the ones that consume more of the goods produced by minimum wage workers. These results set the stage to then decompose the incidence of the minimum wage on consumers and firm owners to estimate how much expenses change across different workers and households after the minimum wage hike.

I begin by laying out two additional research designs that are used to compute (i) the gains from the minimum wage on incumbent informal workers, and (ii) the consumption responses to the minimum wage at the household level.

7.1 Research Design: Informal Workers

I follow a similar strategy than the one described in Section 5.3. In particular, using the subset of informal workers, I assign each individual to eight income bins b based on their monthly income in $(t-1)$. The bins have twice the width as in Section 5.3, and are given by $[450, 650)$, $[650, 850)$, $[850, 1050)$, $\cdots$, $[1650, 1850)$, and beyond 1850 *PEN*. I assign wider bins relative to Section 5.3 due to a small size of observations within some bins in the ENAHO dataset when using smaller bins. While the results are qualitatively the same, the coefficients are much noisier.

Next, I estimate the following regression:

$$\begin{aligned} y_{i,t} - y_{i,t-1} = & \sum_{b=1}^{8} \gamma_{2016,b} \mathbf{1}\{income_{i,t-1} \in bin_b\} \quad + \\ & \sum_{b=1}^{8} \theta_b \mathbf{1}\{income_{i,t-1} \in bin_b\} \times POST_t + \beta X_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{9}$$

where $\theta_b := \gamma_{2017,b} - \gamma_{2016,b}$ and $POST_t$ indicates the post-treatment year $t = 2017$. In other words, the coefficients θ_b trace out the outcome change in the post-policy years relative to the outcome change in the pre-policy years.

Identifying Assumption.the parameters θ_b will capture the causal effect of the minimum wage increase under the assumption that mean reversion and macroeconomic time effects are stable over time (i.e. $\gamma_{2016,b} = \gamma_{2017,b} \quad , b \in \{1, \ldots, 8\}$ in the absence of MW hike). Given that informal workers at the upper tail shouldn't be affected by this policy, I can test whether there were any macroeconomic time effects in the earnings distribution by investigating whether $\gamma_{2016,8} = \gamma_{2017,8}$ are close to zero or not.

7.2 Research Design: Households

I compute the fraction of workers below the new minimum wage in PLAME at the regional level (more precisely, at the *departamento* geographical level)[16]. I then estimate regressions of the form:

$$\frac{y_{ht} - y_{j2015}}{y_{j2015}} = \alpha_t + \beta_t \mathrm{FA}_{\mathrm{Department}(h)} + \gamma_t X_{ht} + \varepsilon_{ht}, \tag{10}$$

[16] These delimitations are effectively state-level. Peru has 25 of these geographical units.

where the left hand side is the percentage change in outcome y relative to year 2015, the final pre-policy year, and year t. This specification allows time effects and the impact of household characteristics, γ_t, to vary flexibly over time.

I winsorize the percentage changes, $\frac{y_{ht}-y_{h2015}}{y_{h2015}}$, to take values between the 1st and 99th percentile in each year. I restrict my sample to households followed from 2014 to 2016. I estimate robust standard errors using the logarithm of total number of household members in 2015 as weights in the regression. In my benchmark regression I control for the following variables and their squares: fraction of female household members between 2014 and 2015, fraction of university degree holders between 2014 and 2015. In addition, I control for fixed effects for macro-region (northern coast, central coast, southern coast, northern highlands, central highlands, southern highlands, rainforest area, and metropolitan Lima).

Identification Assumption. The regression specification described above relies on the assumption that households in regions with low exposure to the minimum wage are a valid counterfactual for households in highly exposed regions, so that these households would follow a parallel trends in the absence of the minimum wage increase. The existence of differential trends before the minimum wage hikes would threaten the credibility of this assumption. Reassuringly, I reject the presence of differential trends in the upcoming results.

7.3 Who pays for the minimum wage?

I follow Macurdy (20115) and Harasztosi and Lindner (2019) and compute how much each industry s is exposed to the MW. By using input-output tables for Peru, where $B(i,j)$ denote share of commodity j produced by industry s, and $U(i,j)$ denote share of commodity j used by industry s, I compute

$$e_s = (\mathbf{I} - \mathbf{BU})^{-1}\mathbf{B}\frac{\text{wagebill}_s^{MW}}{\text{wagebill}_s} \times \frac{2}{3}, \tag{11}$$

where the term 2/3 corresponds to the participation of labor in production.

Next, using consumption information in the ENAHO dataset, I match every product to a particular industry that produces it [17]. I then compute the following measure:

$$\text{Sh. cons produced by MW workers} = \sum_{s} \text{share of expenses in s} \times e_s$$

Figure 13 shows a binscatter between this measure and household income distribution. A somewhat unexpected result is that richer households tend to have a higher share of consumption produced by minimum wage workers compared to poor households. This result implies that if consumers bear the burden of the increases in labor costs, it will most likely rest on the shoulders of richer individuals.

7.4 Decomposing the change in labor cost

The results in this section are built on the following identity:

$$Profit \equiv Revenue - Material - LaborCost - Depr - MiscItems,$$

where *Depr* represents depreciation costs, and *MiscItems* represents other miscellaneous expenses. The identity implies the following expression:

$$\frac{\Delta LaborCost}{Revenue2016} = \underbrace{\frac{\Delta Revenue}{Revenue2016} - \frac{\Delta Material}{Revenue2016} - \frac{\Delta MiscItems}{Revenue2016}}_{\text{Consumers Pay}} \tag{12}$$
$$- \underbrace{\frac{\Delta Depr}{Revenue2016} - \frac{\Delta Profit}{Revenue2016}}_{\text{Firm Owners Pay}}.$$

I estimate Equation (5) on each term of the previous expression to decompose the incidence of the minimum wage. Table 11 shows the estimates of this approach. Column 2 of this Table shows that, one year post policy, the burden lies almost entirely on consumers (98.35% of labor costs are financed by consumers). Two years after the minimum wage hike this percentage falls to 61%, approximately.

[17] For example, if a household reports to have bought a TV, I assign that expense to manufacturing sector.

7.5 Estimating the Change in Expenses

The approach I will follow to estimate how much expenses change for a given individual or household (ΔE) is to compute the following product

$$\begin{aligned}\Delta E = &\textit{Pass-through of Labor Cost onto Price}\\ &\times \textit{Change in Labor Cost}\\ &\times \textit{Total Expense in MW-produced Goods}.\end{aligned}$$

The product of the first two terms in right hand side of the previous expression represent the change in prices due to the minimum wage. My benchmark estimate of the *Pass-through of Labor Cost onto Price* is 0.98, as it was obtained in the previous subsection. Furthermore, the results in Section 6 provide an estimate of the *Change in Labor Cost* given by 0.123. These imply a baseline estimate of the price effect of $0.98 \times 0.123 = 0.12$.

In addition, I use the effects on the Laspeyres price index for the manufacturing sector computed in Section 6 as an alternative measure of the price effect. This measure is rather noisy, and will use it as a referential upper bound. Lastly, I construct a food price Laspeyres index using consumption information in the panel version of ENAHO from 2014 to 2016. I use this index as a dependent variable in Equation (10). The results are shown in Figure A.13. This graph indicates that one year after the minimum wage was raised, food consumption prices rose by roughly 6.5%. This increase is larger than the annual inflation of that year of roughly 3.3%.

8 The Gains of the Minimum Wage in Peru

To estimate the expected change in income (ΔI) for different individuals and households I need to account for the employment effects that, as discussed in Section 5.5, reallocate workers towards the informal sector.

My benchmark approach is to analyze these changes within the different bins defined in Section 5.3. In particular, for a formal worker at bin b and earning w_b on average, I compute:

$$\frac{\Delta I_b}{w_b} := \underbrace{\frac{\Delta w_b}{w_b}}_{\text{Gain from MW if stay}} + \underbrace{\frac{(w_b^{\text{inf}} - w_b)}{w_b} \Delta \mathbf{P}_b(\text{leave})}_{\text{Earn at informal sector if leave}}, \tag{13}$$

where $\frac{\Delta w_b}{w_b}$ and $\Delta P_b(\text{leave})$ are proxied by the estimates obtained in Figures 4 and 5, respectively. Furthermore, w_b^{inf} is a measure of how much a particular worker would earn if they transition from the formal to the informal sector. In the panel version of ENAHO, I can compute on average how much a worker at a particular bin b loses if they transition towards the informal sector.

I jointly estimate the elements of Equation (13) and bootstrap standard errors. The resulting expected gains at each bin are shown in Figure 14. In particular, I find that low-wage formal employees have gains well beyond the old and new minimum wage despite having a greater risk of being displaced out of the formal sector. Part of the reason for this result is that these type of workers tend to earn similar amounts (despite being slightly smaller) to what they previously earned in the formal sector.

An alternative approach to compute the expected gains is described in Appendix F, although the results are qualitatively similar.

9 A cost-benefit analysis

My estimates provide sufficient information to perform a cost-benefit analysis of the minimum wage under the following assumptions:

(a) No substitution away from goods produced by minimum wage workers as a response to the minimum wage hike.

(b) There is no income effect in the informal sector.

Reassuringly, Figure 15 shows the estimates from Equation (10) on different consumption categories. The dependent variables in these regressions are the changes in total household income and consumption categories relative to the total household income in 2015. These results suggest no substitution across consumption categories as a response to the minimum wage increase.

Additionally, Figure 17 shows the estimates from the design described in 7.1. I show that there is no evidence that the income of incumbent informal workers increased after the minimum wage hike. These previous results further support the approach following next.

9.1 Cost-benefit: Individual Analysis

Using the ENAHO, I obtained at the household level the share of consumption in goods produced by minimum wage workers. Next, I compute the average per-capita expenses, and the average share of consumption in goods produced by minimum wage workers at each wage bin b.

Table 12 shows the implied changes in income and expenses for workers at different earnings bins. I find that low-wage workers are better off after the minimum wage increase. The opposite is true for high-wage individuals, as they bear the burden of the increased labor costs of firms and they don't perceive any spillover gain in terms of income. For example, workers who earned between the old and new minimum wage were expected to gain 65 *PEN* on average, and increase their expenses by 11.8 *PEN*. Everything considered, these results suggest that low-wage formal workers are the clear winners from this policy change.

9.2 Cost-benefit: Household Analysis

To perform a similar exercise on households, I compute the average gain of minimum wage workers as the average gain in the first 5 earnings bins estimated in Figure 14:

$$\frac{\Delta I_{MW}}{I_{MW}} \equiv \frac{1}{5}\sum_{b=1}^{5} \Delta I_b / w_b.$$

Next, I multiply the gain defined above by the average household income at decile d, denoted as $I^l_{MW,d}$, to obtain the expected income change. The expected changes in expenses are computed in a similar fashion to the previous section, where I now compute the average share of consumption of goods produced by minimum wage workers at each household decile. I then multiply that number by the household-level total expenditures to obtain the (average) total expenditures in production by minimum wage workers.

Table 13 shows that poor households have very few members engaged in formal employment and are thus not perceiving income gains. In particular, households at the first two deciles in the household income distribution have less than 3% of their workers under formal employment. As a matter of fact, minimum wage workers are more common from the 50th percentile onwards. This shows that there is a lack of redistributive gains from the minimum wage. While rich individuals finance the minimum wage raises on low wage formal workers, these mechanisms are operating within the richer household deciles.

10 Conclusions

Minimum wages, while being a commonly used tool, remain a controversial policy. The results of this paper suggests that the presence of informal self-employment mutes the two main channels from which minimum wages can benefit: *efficiency* and *redistribution*. In terms of the former channel, I find that, consistent with the theoretical model of discrete choice involving formal versus informal sector choice and oligopsonistic firm competition, the presence of informal self-employment can shape the effects of the minimum wage. After the minimum wage increase, I find that (i) firms who were more exposed to presence of the informal sector - either in terms of occupational composition or geographic location - exhibit larger disemployment effects, and (ii) workers were more likely to exit formal employment altogether. My findings also indicate that - on average - surviving firms didn't experience profit losses, as their revenues increased along with total labor costs. Furthermore, despite the fact that mainly rich consumers enjoy the goods and services produced and provided by minimum wage workers, the overwhelming presence of informal workers in low-income households makes it hard for any sort of income redistribution towards them to exist.

This paper has focused on a cost-benefit analysis from a pecuniary perspective. While these results point out that low-income individuals and households are certainly not harmed by the minimum wage increase, it could be that some workers are negatively impacted through other non-monetary outcomes. In Appendix C I show, for instance, that minimum wage increases could perpetuate a cycle of being trapped in temporary jobs, but a more comprehensive analysis of these type of outcomes fall beyond the scope of this dissertation.

One avenue of future research in this direction is to use the results of this paper along with a theoretical model to optimally design minimum wage policies that are not set uniformly (i.e., at a national level), taking into account the heterogeneous exposure to the informal sector across different industries or cities.

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TABLE 1. Who are the minimum wage workers?

	Earnings bin in 2016 (PEN)		
	[650, 850]	(850, 1250]	(1250, 3250]
Lima	0.14	0.18	0.18
Female	0.42	0.38	0.27
By education			
Share low skilled	0.05	0.05	0.03
Share medium skilled	0.48	0.50	0.44
Share high skilled	0.47	0.45	0.53
By age			
Share less than 24	0.09	0.08	0.02
Share 24-44	0.63	0.72	0.76
Share 45-65	0.27	0.19	0.22
By contract			
Part-time (PT)	0.02	0.01	0.01
Permanent (P-FT)	0.36	0.22	0.30
Temporary (T-FT)	0.62	0.77	0.69
By firm size			
1-4 employees	0.06	0.03	0.03
5-19 employees	0.11	0.09	0.09
20-49 employees	0.06	0.06	0.06
50+ employees	0.77	0.82	0.82
By industry structure			
Agriculture; mining	0.09	0.06	0.06
Manufacturing; electricity; waste management	0.11	0.13	0.14
Construction; wholesale and retail	0.16	0.15	0.17
Transportation; accommodation; food services	0.09	0.09	0.09
Information; finance; real estate	0.04	0.11	0.11
Professional, administrative, support services	0.12	0.10	0.10
Public administration; education; human health	0.03	0.04	0.05
Arts, entertainment; other services	0.36	0.31	0.28
Number of observations	324,134	488,347	834,485

Note: This table shows the characteristics of individuals who were below the new minimum wage in 2016 (i.e. minimum wage workers), and workers higher up in the earnings distribution. Source: PLAME.

TABLE 2. Firm characteristics in PLAME dataset

		All	Manufacturing	Commerce	Services
		(1)	(2)	(3)	(4)
Avg Wage (PEN)	Mean	1,632.22	1,540.34	1,726.81	1,155.93
Number of Workers	Mean	115.29	135.10	89.81	59.98
Firm Age	Mean	13.22	15.91	12.44	10.15
Female Share	Mean	0.33	0.29	0.36	0.39
Avg Age (Workers)	Mean	39.59	39.62	38.80	37.28
Fraction Affected	Mean	0.32	0.34	0.31	0.49
	p5	0	0	0	0
	p25	0.04	0.05	0.02	0.04
	p50	0.17	0.19	0.16	0.5
	p75	0.60	0.67	0.6	0.8
	p95	1	1	1	1
Observations		23,477	4,520	8,007	2,260

Note: This table shows some characteristics across different firms in the PLAME dataset. The first row compares the average wage at the firm, which is defined as the wage bill divided by employment (FTE). The second row computes the number of workers at the firm. The third and fourth row compare the firm age (in years) and the share of female employment at the firm, respectively. The fifth row compares the average age of the firm workers. Finally, the sixth row and onwards compute the fraction affected, defined as the share of employment who earned below the new minimum wage of 850 *PEN*. Source: PLAME.

Table 3. Firm characteristics in EEA dataset

Firm Characteristics	2015		2016		2017	
	Mean	St.d.	Mean	St.d.	Mean	St.d.
Firm Age	18.79	14.61	17.69	14.72	19.00	14.84
Number of Establishments	5.06	19.93	4.44	13.00	4.96	15.56
Number of Executives	4.53	16.99	4.17	10.17	4.68	11.41
Number of Perm Employees	93.75	424.22	97.48	386.31	121.19	534.00
Number of Non-Rem Emp	1.25	8.82	1.32	9.61	1.84	20.79
Number of Third-Party Emp	4.06	42.38	4.43	73.19	2.94	32.91
Wage Bill (10^6 PEN)	10.10	20.81	9.53	20.43	10.90	20.82
Value Added (10^6 PEN)	22.80	86.70	22.00	83.20	24.00	102.20
Net Revenue (10^6 PEN)	5.06	19.93	4.44	13.00	4.96	15.56
Number of Observations	4,901		5,319		4,781	

Note: This table shows the mean and standard deviation of some firm characteristics in the EEA dataset from year 2015 to 2017. Source: EEA.

TABLE 4. Who are the exposed firms?

	Quartiles of FA_j in 2016			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Lima	0.47	0.41	0.38	0.39
Avg Wage (PEN)	2480.81	1693.09	1170.64	888.55
Number of Workers	129.60	157.78	127.36	16.20
Firm Age	16.03	14.44	11.53	9.39
Manufacture	0.18	0.21	0.19	0.22
Commerce	0.35	0.31	0.30	0.31
Services	0.04	0.06	0.12	0.15
Observations	5,875	5,908	5,849	5,845

Note: This table shows some firm characteristics in the EEA dataset across diferent quartiles of the fraction affected variable in 2016. The second column shows the average characteristics of firms who were less exposed to a minimum wage increased, and the last column shows the characteristics of firms who were the most exposed. Source: EEA.

TABLE 5. Employment and Wage Effects

	Main changes between 2016 and 2017		Main changes between 2016 and 2018		Placebo changes between 2016 and 2015	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Change in firm-level employment (including closures)						
Fraction affected	-0.099	-0.076	-0.138	-0.095	0.002	0.013
	(0.007)	(0.008)	(0.007)	(0.010)	(0.005)	(0.006)
Constant	-0.030		-0.045		0.002	
	(0.003)		(0.005)		(0.002)	
Observations	23,488	21,088	23,488	21,088	23,477	21,081
Employment elasticity with	-0.75	-0.58	-1.06	-0.73		
respect to MW (directly affected)	(0.05)	(0.06)	(0.07)	(0.08)		
Panel B. Change in firm-level employment (excluding closures)						
Fraction affected	-0.057	-0.051	-0.088	-0.072	0.002	0.013
	(0.006)	(0.008)	(0.008)	(0.009)	(0.005)	(0.006)
Constant	0.008		0.024		0.002	
	(0.006)		(0.004)		(0.002)	
Observations	22,073	19,902	21,208	19,173	23,477	21,081
Employment elasticity with	-0.44	-0.39	-0.68	-0.55		
respect to MW (directly affected)	(0.04)	(0.05)	(0.06)	(0.07)		
Panel C. Change in firm-level average wage						
Fraction affected	0.116	0.114	0.113	0.112	0.031	0.031
	(0.003)	(0.004)	(0.003)	(0.004)	(0.001)	(0.001)
Constant	0.041		0.075		-0.024	
	(0.001)		(0.002)		(0.001)	
Observations	22,073	19,902	21,208	19,173	23,477	21,081
Employment elasticity with	-0.85	-0.59	-1.22	-0.74		
respect to wage	(0.06)	(0.08)	(0.09)	(0.11)		
Controls	No	Yes	No	Yes	No	Yes

Note: This table shows the main effects on wages and employment at the firm-level. Panel A and B compute the employment effect including and excluding the extensive margin, respectively. Panel C computes the effect on the firm-level average wage, defined as the wage bill divided by FTE employment. The own-wage employment elasticity is then computed by dividing the results from Panel A and panel C. The set of controls include some characteristics measures in 2016: the fraction of censored workers' earnings, the fraction of females, fraction of college graduates, and fixed effects of firm age, province, and industry sector. Regressions are weighted by the logarithm of employment in 2016. Source: PLAME.

TABLE 6. Effects of the Minimum Wage on Wages and Employment: Individual Approach

	Changes relative to 2015 versus 2016				Difference-in-differences		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bin at $t-1$	[650, 750)	[750, 850)	[850, 950)	[2250, 3500]	(1) - (4)	(2) - (4)	(3) - (4)
Panel A. Earnings							
2016 versus 2017	0.0955	0.0751	0.0441	-0.0104	0.1060	0.0855	0.0546
	(0.0050)	(0.0042)	(0.0038)	(0.0029)	(0.0038)	(0.0040)	(0.0042)
Baseline change (2015 versus 2016)	0.0383	0.0410	0.0383	-0.1253			
	(0.0212)	(0.0224)	(0.0232)	(0.0252)			
Panel B. Employment (1 if remain employed)							
2016 versus 2017	-0.0127	-0.0115	-0.0131	-0.0000	-0.1268	-0.0114	-0.0131
	(0.0023)	(0.0049)	(0.0071)	(0.0054)	(0.0050)	(0.0040)	(0.0055)
Baseline change (2015 versus 2016)	0.4196	0.4318	0.4378	0.5374			
	(0.0150)	(0.0145)	(0.01523)	(0.01638)			

Note: This table shows robustness checks. The dependent variable in Panel A is an indicator of whether the head of household's spouse is working (employee or self-employed); in Panel B is an indicator of whether the head of household's spouse is working (employee only); Panel C is an indicator of whether head of household's spouse is an unpaid family worker; Panel D is an indicator of whether all teens living in the household go to school; and Panel E uses an indicator of whether all teens go to school while they don't work at all. All regression controls for age, education, gender, and district fixed effects in the baseline period $t-1$. Robust standard errors are reported in parentheses. Source: PLAME.

Table 7. Reallocation Effects of the Minimum Wage: Individual Approach

	Main effects (2016 vs 2017)		
Earnings Bin at $t-1$	[650, 750)	[750, 850)	[850, 950)
	(1)	(2)	(3)
Panel A. Earnings			
Estimated effect	0.1060	0.0855	0.0546
	(0.0038)	(0.0040)	(0.0042)
Panel B. Firm's AKM effects			
Estimated effect	-0.0037	-0.0008	0.00167
	(0.0011)	(0.0019)	(0.0017)
Earnings growth due to reallocation (% of total effect)			
Calculated using all switchers	0.00	0.00	3.05
Calculated using upward switchers	2.15	4.70	5.21

Note: This table shows the reallocation effects of the minimum wage using the individual-level design. Panel A computes the main treatment effects on earnings. Panel B compute the effect on firm premia, measured by the AKM firm fixed effects. By dividing the effect on firm premia with respect to the effect on earnings I can compute the earnings growth due to reallocation. Source: PLAME.

Table 8. Firms' Margins of Adjustment (incl. closures)

	Main changes between 2015 and 2016	Main changes between 2015 and 2017	Placebo changes between 2015 and 2014
	(1)	(2)	(3)
Panel A. Change in total labor cost			
Fraction affected	-0.495	0.185	0.031
	(0.069)	(0.075)	(0.022)
Panel B. Change in revenue			
Fraction affected	-0.504	0.055	0.011
	(0.064)	(0.066)	(0.027)
Panel C. Change in materials			
Fraction affected	-0.446	-0.152	-0.147
	(0.140)	(0.152)	(0.151)
Panel D. Change in capital			
Fraction affected	0.135	0.165	0.006
	(0.068)	(0.087)	(0.055)
Panel E. Change in profits (relative to revenue in 2015)			
Fraction affected	-0.043	-0.008	-0.008
	(0.003)	(0.010)	(0.008)
Observations	4,343	4,343	4,343
Controls	Yes	Yes	Yes

Note: This table shows the effects on labor costs, revenue, materials, capital and profits. This table restricts the sample to exclude firms that closed after the minimum wage increase. The first two columns outline the effects one and two years after the policy, respectively. In Column 3 I compute a placebo effect between 2015 and 2014. The set of controls include quadratic polynomials of the following variables: average profitability between 2014 and 2015, average wage between 2014 and 2015, average depreciation rate between 2014 and 2015, and average labor share of income. It also includes fixed effects of sector, region, firm age, and type of firm. Regressions are weighted by the logarithm of employment in 2015. Source: EEA.

TABLE 9. Firms' Margins of Adjustment (excl. closures)

	Main changes between 2015 and 2016	Main changes between 2015 and 2017	Placebo changes between 2015 and 2014
	(1)	(2)	(3)
Panel A. Change in total labor cost			
Fraction affected	0.123	0.219	0.031
	(0.039)	(0.051)	(0.022)
Observations	3,440	3,185	4,343
Panel B. Change in revenue			
Fraction affected	0.074	0.051	0.011
	(0.036)	(0.046)	(0.027)
Observations	3,440	3,185	4,343
Panel C. Change in materials			
Fraction affected	0.079	-0.140	-0.147
	(0.152)	(0.176)	(0.151)
Observations	1,995	1,796	2,428
Panel D. Change in capital			
Fraction affected	0.135	0.165	0.006
	(0.068)	(0.087)	(0.055)
Observations	3,440	3,185	4,343
Panel E. Change in profits (relative to revenue in 2015)			
Fraction affected	-0.002	-0.006	-0.008
	(0.010)	(0.012)	(0.008)
Observations	3,440	3,185	4,343
Controls	Yes	Yes	Yes

Note: This table shows the effects on labor costs, revenue, materials, capital and profits. This table restricts the sample to exclude firms that closed after the minimum wage increase. The first two columns outline the effects one and two years after the policy, respectively. In Column 3 I compute a placebo effect between 2015 and 2014. The set of controls include quadratic polynomials of the following variables: average profitability between 2014 and 2015, average wage between 2014 and 2015, average depreciation rate between 2014 and 2015, and average labor share of income. It also includes fixed effects of sector, region, firm age, and type of firm. Regressions are weighted by the logarithm of employment in 2015. Source: EEA.

TABLE 10. Effect on Firm-Level Price Index in the Manufacturing Sector

	All firms		Exists between 2015 and 2018	
	(1)	(2)	(3)	(4)
Panel A. Change between 2015 and 2016 (short-term)				
Fraction affected	-0.006	0.086	0.040	0.038
	(0.133)	(0.204)	(0.091)	(0.174)
Constant	1.108	0.796	1.088	1.153
Observations	531	530	368	368
Panel B. Change between 2015 and 2017 (medium-term)				
Fraction affected	0.010	0.155	0.057	0.384
	(0.114)	(0.175)	(0.134)	(0.192)
Constant	2.089	2.322	2.082	2.515
Observations	325	325	275	275
Controls	No	Yes	No	Yes

Note: This table shows the price effect in the manufacturing sector. The first two rows compute the estimates using all firms and the last two rows restrict the analysis to firms that existed throughout 2015 to 2018. The set of controls include quadratic polynomials of the following variables: average profitability between 2014 and 2015, average wage between 2014 and 2015, average depreciation rate between 2014 and 2015, and average labor share of income. It also includes fixed effects of sector, region, firm age, and type of firm. Regressions are weighted by the logarithm of employment in 2015. Source: EEA.

TABLE 11. Incidence of the Minimum Wage

	Changes between 2015 and 2016 (1)	Changes between 2015 and 2017 (2)
Change in total labor cost relative to revenue in 2015	0.0243	0.0327
Change in revenue relative to revenue in 2015 ($\Delta Revenue$)	0.0757	0.0614
Change in materials relative to revenue in 2015 ($\Delta Material$)	0.0065	-0.0028
Change in miscitems relative to revenue in 2015 ($\Delta MiscItems$)	0.0453	0.0442
Incidence on consumers ($\Delta Revenue$ - $\Delta Material$ - $\Delta MiscItems$)	0.239	0.02
Change in profits relative to revenue in 2015 ($\Delta Profit$)	-0.0007	-0.0095
Change in depreciation relative to revenue in 2015 ($\Delta Depr$)	0.0004	-0.0032
Incidence on firm owners (- $\Delta Profit$ - $\Delta Depr$)	0.004	0.0127
Fraction paid by consumers (percent)	98.35	61.12
Fraction paid by firm owners (percent)	1.65	38.88

Note: This table shows an accounting exercise to decompose the sources of changes in labor costs relative to revenue in 2015 (the year prior to the minimum wage hike). The first five rows compute the incidence on consumers and the next three rows compute the incidence on firm owners. Finally, the last two rows divide the incidence with respect to the change in labor costs to compute the fraction paid by consumers and firm owners, respectively.

TABLE 12. Do workers benefit from MW increase?

Baseline bin $t-1$	[650, 750)	[750, 850)	[950, 1050)	[1050, 1150)	[1150, 2050)	[2050, max)
Panel A. Income Change						
Mean MW formal wage ($\bar{w}_b$)	746	818	903	1,001	1,479	2,630
Effect exp. income ($\Delta I_b/w_b$)	0.11	0.08	0.05	0.04	0.02	0.00
$\Delta\ I_b/w_b \times \bar{w}_b$	82.06	65.44	45.15	40.04	29.58	0.00
Panel B. Expenses Change						
Share cons by MW workers (s^e_{MW})	0.23	0.23	0.24	0.24	0.24	0.26
Mean per cap. expenses (E_b)	590	643	700	613	792	1379
$\Delta\ E_b$ (labor cost): $0.98 \times 0.123 \times s^e_{MW} E_b$	16.35	17.82	20.25	17.73	22.91	43.22
$\Delta\ E_b$ (manuf. price): $0.40 \times s^e_{MW} E_b$	54.28	59.15	67.20	58.85	76.03	143.42
$\Delta\ E_b$ (food price): $0.08 \times s^e_{MW} E_b$	10.85	11.83	13.44	11.77	15.21	28.68

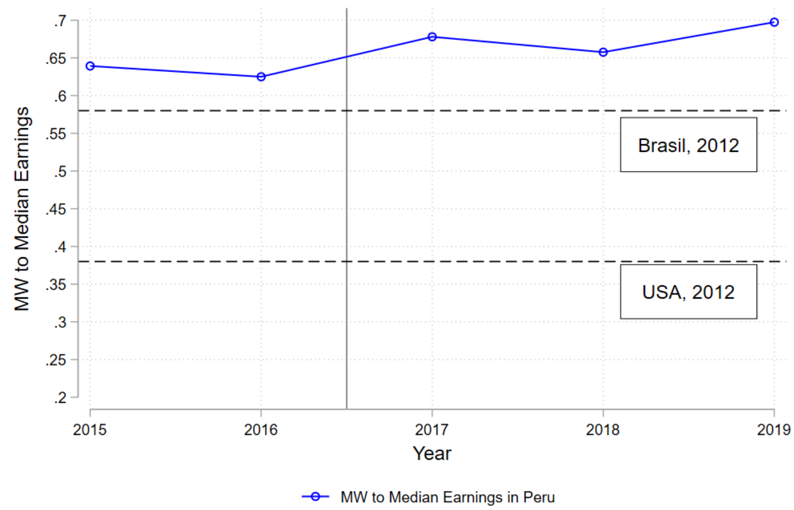
Note: This table shows a cost-benefit analysis of the minimum wage at a worker-level. Columns indicate different earnings bins of formal workers, and minimum wage workers are those who earned below 850 PEN. Panel A computes the expected income gains - in levels - of formal workers based on the reduced form estimates. Next, Panel B uses different approaches to estimate the expected change in expenses based on the reduced form estimates. I can thus compare, for each bin, changes in income versus changes in expenses.

TABLE 13. Do households benefit from MW increase?

HH income decile	1	2	3	4	5	6	7	8	9	10
Panel A. Income Change										
Share formal emp	0.01	0.03	0.11	0.19	0.26	0.34	0.46	0.60	0.72	0.82
Share MW formal emp (s^l_{MW})	0.00	0.02	0.05	0.1	0.13	0.15	0.19	0.21	0.22	0.15
Mean MW formal income (I^l_{MW})	1	7	40	128	242	316	462	570	705	586
$\frac{\Delta I_{MW}}{I_{MW}} \times I^l_{MW}$	0.00	0.42	2.40	7.68	14.52	18.96	27.72	34.20	42.30	35.16
Panel B. Expenses Change										
Share cons by MW workers (s^e_{MW})	0.16	0.19	0.2	0.21	0.22	0.22	0.23	0.23	0.24	0.27
Mean expenses (E)	639	732	991	1,206	1,485	1,786	2,069	2,466	2,964	4,801
Δ E (labor cost): $0.98 \times 0.123 \times s^e_{MW}E$	12.32	16.76	23.89	30.52	39.38	47.36	57.36	68.36	85.74	156.25
Δ E (manuf. price): $0.40 \times s^e_{MW}E$	40.90	55.63	79.28	101.3	130.7	157.2	190.3	226.8	284.5	518.5
Δ E (food price): $0.08 \times s^e_{MW}E$	8.18	11.13	15.85	20.26	26.14	31.43	38.07	45.37	56.91	103.7

Note: This table shows the expected income changes versus expenses changes at the household level. It is divided by household income deciles across columns. The first two rows in Panel A show the share of workers under formal employment and then restricting only to those who earn below 850 *PEN* (i.e. minimum wage workers), respectively.

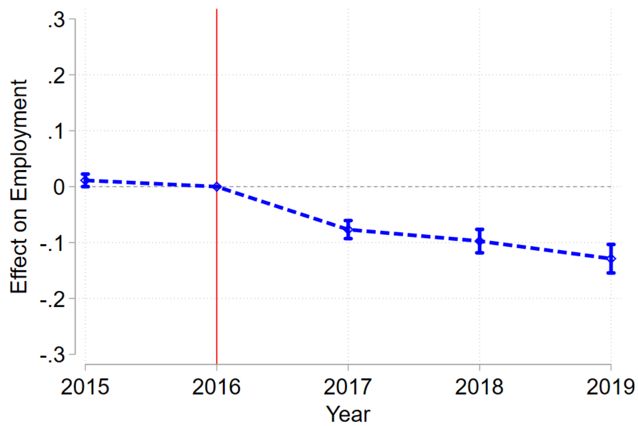
FIGURE 1. Minimum Wage to Median Earnings



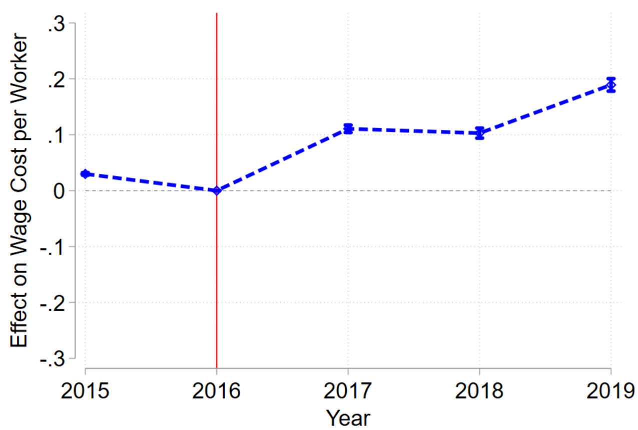
Note: The blue line shows the evolution of the ratio of the minimum wage to median earnings from 2015 to 2019. The dashed lines show, as a reference, the ratio of minimum wage to median earnings in Brasil and the US in 2012. Source: PLAME.

FIGURE 2. Employment and Wage Effects: Firm Approach

A. Employment Effects



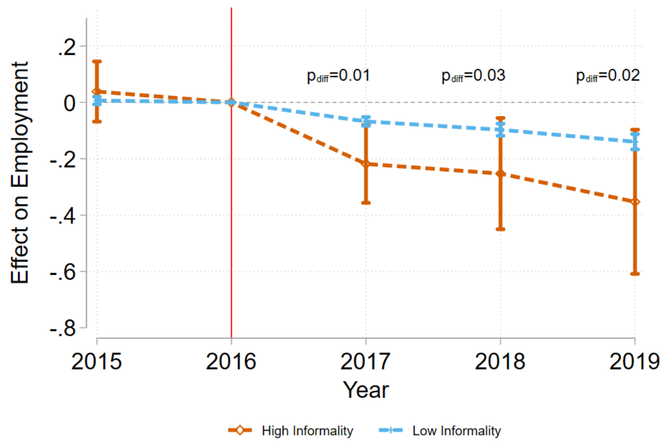
B. Wage Effects



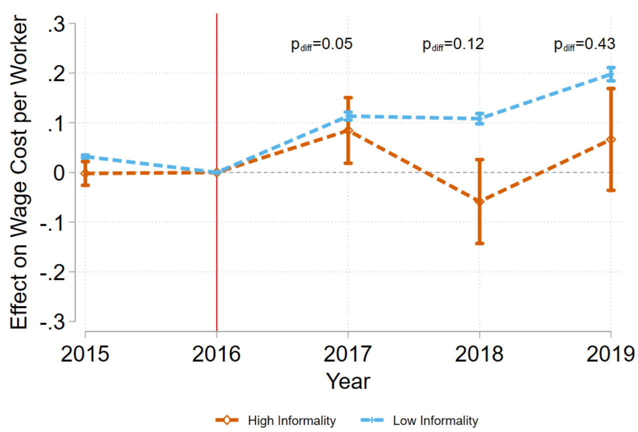
Note: This figure shows the estimates from Equation (5) using firm employment and average wage as the outcome variables, respectively. Panel (a) plots the estimates on total employment, and Panel (b) plots the estimates on the average wage at the firm, defined as the total wage cost divided by the FTE statistic. Regressions are weighted by the logarithm of total employment in 2016, and robust standard errors are computed. Point estimates and their 95% confidence intervals are shown in this figure. The vertical red line corresponds to the baseline year, prior to the minimum wage hike. Source: PLAME.

FIGURE 3. Employment and Wage Effects, by Informality

A. Employment Effects

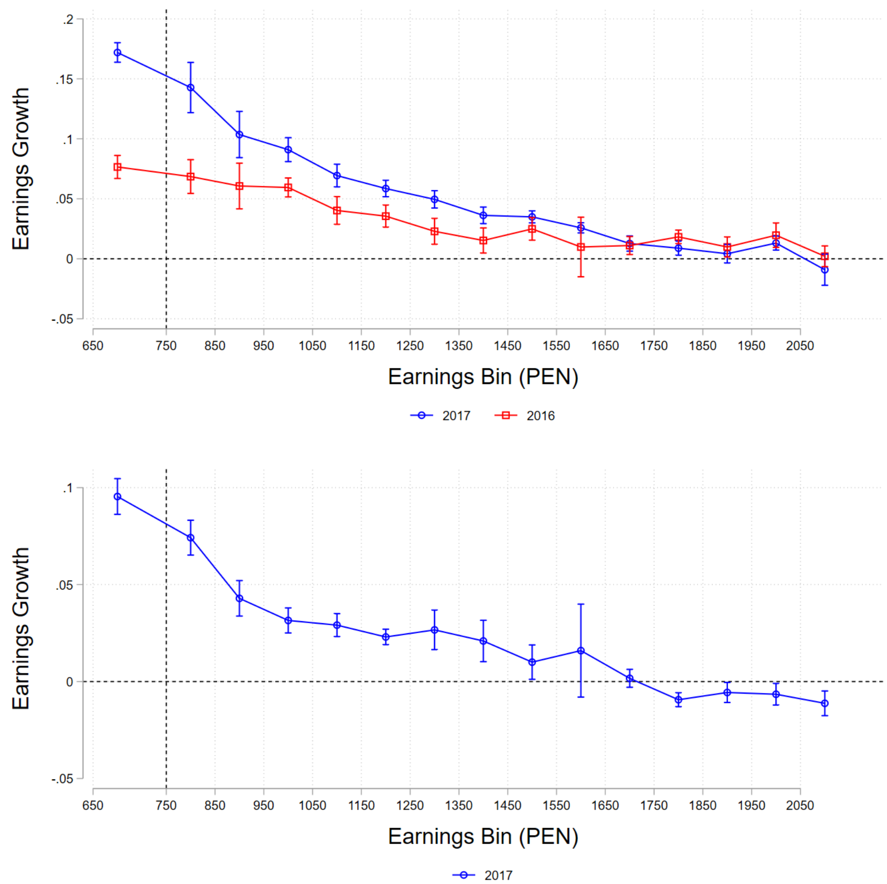


B. Wage Effects



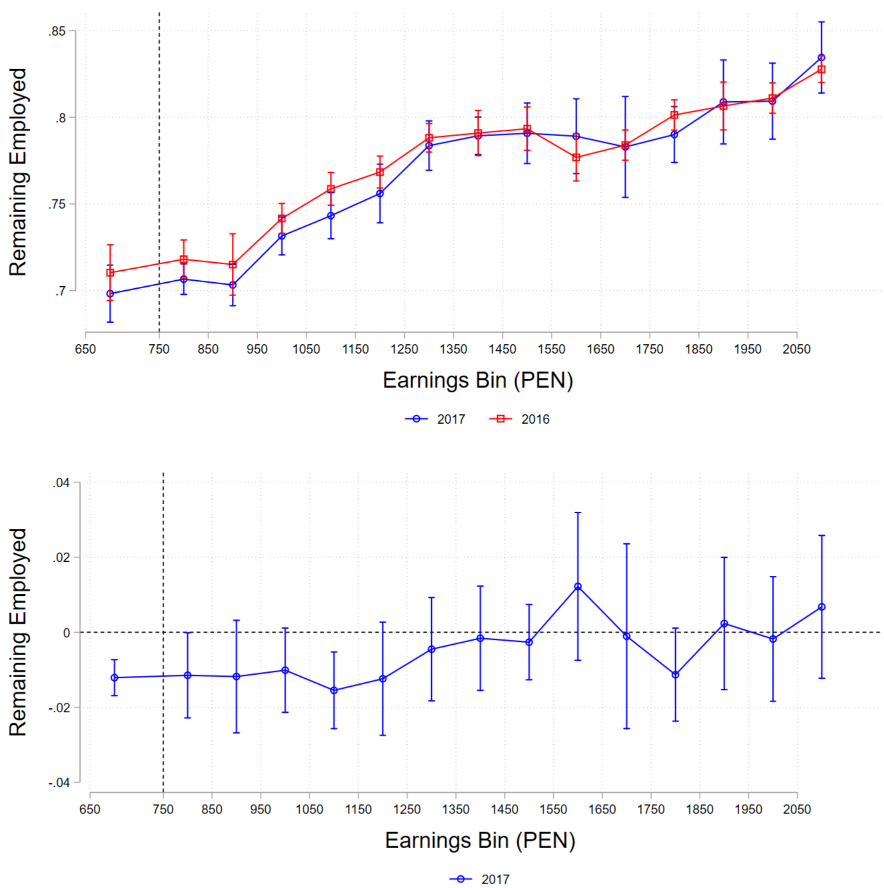
Note: This figure shows the estimates from Equation (6) using firm employment and average wage as the outcome variables, respectively. The darker line represents the estimates among firms who were highly exposed (in terms of occupational composition) to the informal sector, whereas the lighter line represents the effect among firms with low exposure. Regressions are weighted by the logarithm of total employment in 2016, and robust standard errors are computed. Point estimates and their 95% confidence intervals are shown in this figure. The vertical red line corresponds to the baseline year, prior to the minimum wage hike. Furthermore, the p-value of the difference between the dark and light lines are shown. Source: PLAME.

FIGURE 4. Earnings Effects: Worker Approach



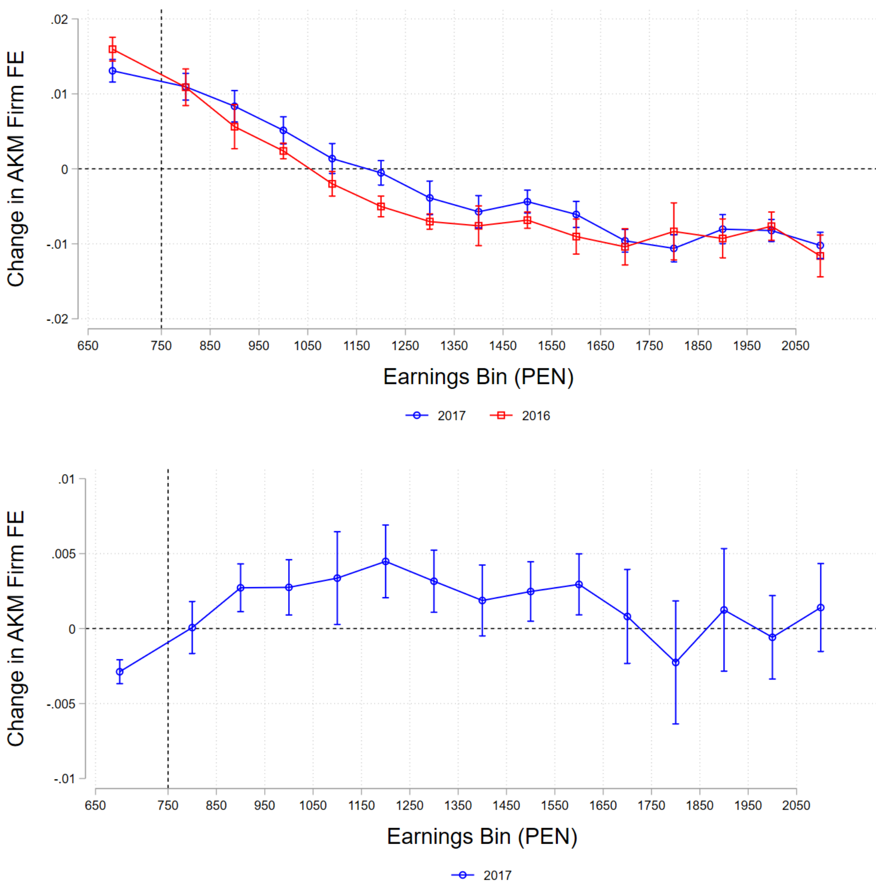
Note: This figure plots the wage effects under the worker approach described in Section **??**. The dependent variable is the logarithm of monthly earnings. The upper panel plots the coefficients from Equation (7) as of February 2016 (pre-policy period) and February 2017 (post-policy period). The lower panel shows the difference between the blue and red line in the upper panel, which correspond to the coefficients of Equation (8). Point estimates and their 95% confidence intervals are shown in this figure. Standard errors are clustered at the province level. Source: PLAME.

FIGURE 5. Employment Effects: Worker Approach



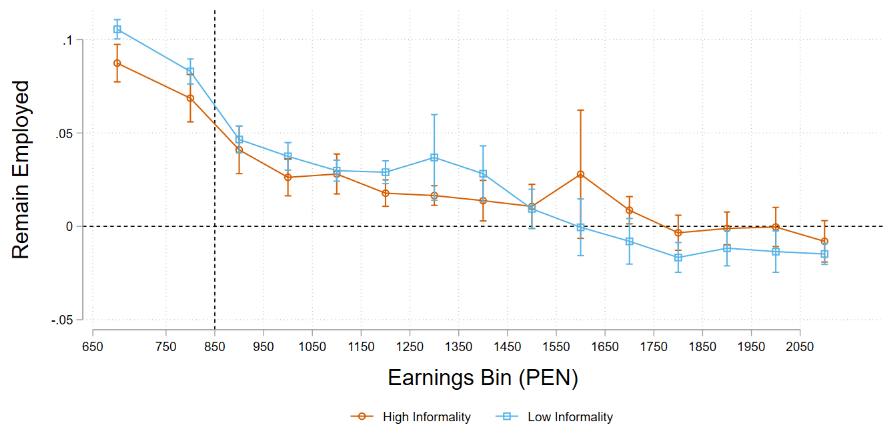
Note: This figure plots the employment effects under the worker approach described in Section **??**. The dependent variable is an indicator equal to 1 if the worker remains employed. The upper panel plots the coefficients from Equation (7) as of February 2016 (pre-policy period) and February 2017 (post-policy period). The lower panel shows the difference between the blue and red line in the upper panel, which correspond to the coefficients of Equation (8). Point estimates and their 95% confidence intervals are shown in this figure. Standard errors are clustered at the province level. Source: PLAME.

FIGURE 6. Reallocation Effects: Worker Approach

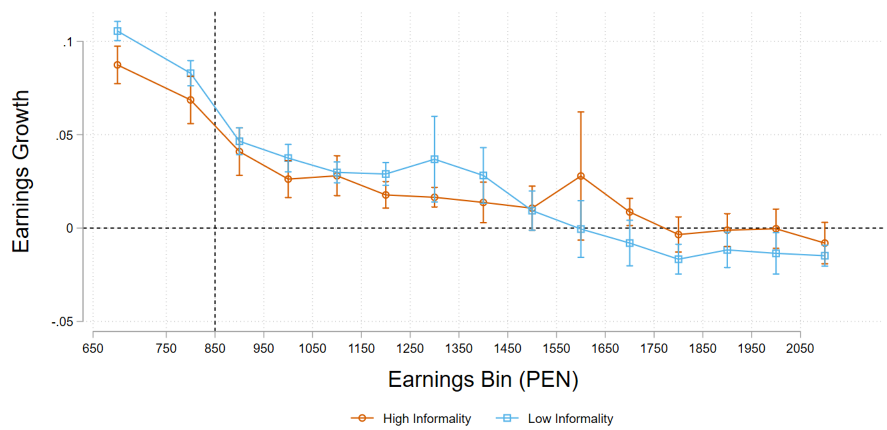


Note: This figure plots the reallocation effects using the worker approach described in Section **??**. The dependent variable is the change in firm AKM fixed effects, which is measured prior to the minimum wage increase. The upper panel plots the coefficients from Equation (7) as of February 2016 (pre-policy period) and February 2017 (post-policy period). The lower panel shows the difference between the blue and red line in the upper panel, which correspond to the coefficients of Equation (8). Point estimates and their 95% confidence intervals are shown in this figure. Standard errors are clustered at the province level. Source: PLAME.

FIGURE 7. Employment and Wage Effects, by Informality



A. Employment

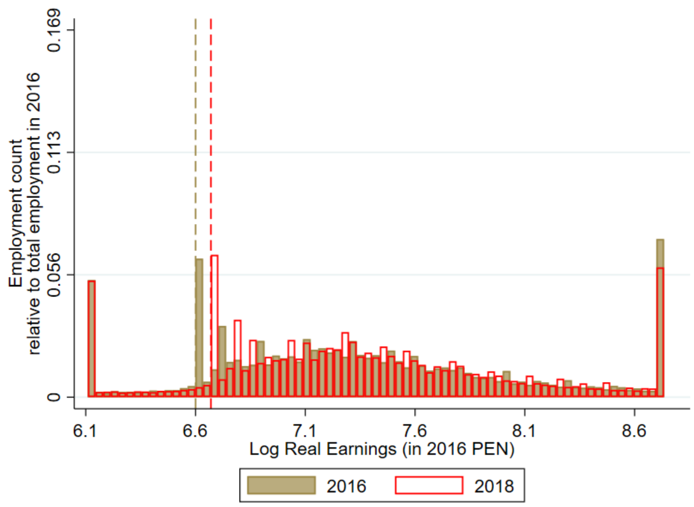


B. Earnings

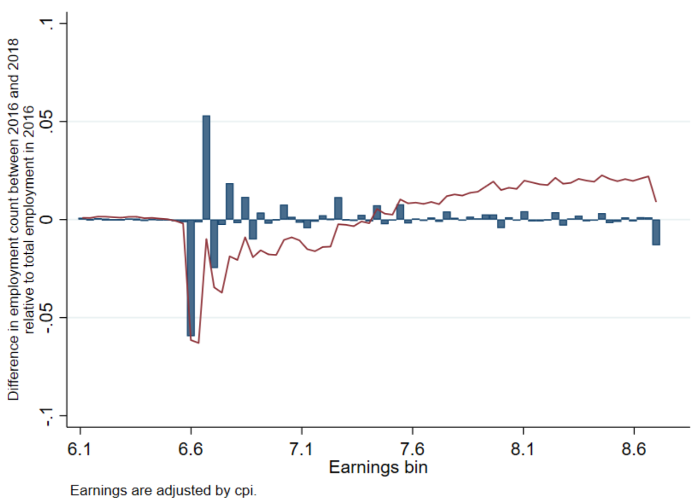
Note: This figure plots the employment and wage effects using the worker approach described in Section **??**, respectively. The upper panel plots the coefficients from Equation (8) for workers in occupations that are highly versus lowly exposed to informality separately. The dependent variable used is an indicator that equals 1 when the worker remains employed. The lower panel does the same exercise with the logarithm of earnings as the dependent variable. An occupation is defined as highly exposed to informality if it belongs to the top quartile of share of informal employment for that occupation (3-digits). Point estimates and their 95% confidence intervals are shown in this figure. Standard errors are clustered at the province level. Source: PLAME.

FIGURE 8. Frequency of earnings distribution in 2016 and 2018

A. Employment counts



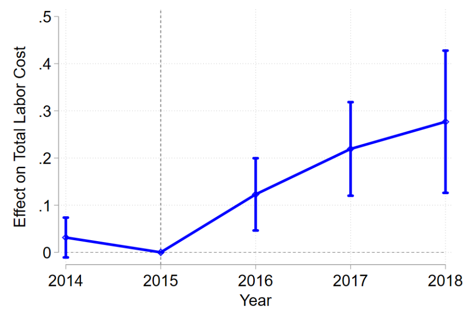
B. Cumulative difference



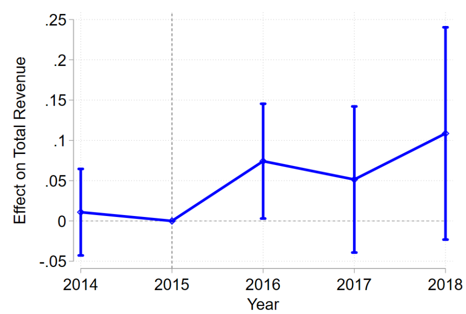
Note: This figure shows the employment counts along the distribution of log real earnings (adjusted by cpi) in the upper panel. The lower panel then shows the difference between the counts in 2016 and 2018 . Negative values on the blue bars indicate that there is a missing mass of workers at those bins. The red line in the lower panel indicates the cumulative difference. Source: PLAME.

FIGURE 9. Firms' Margins of Adjustment

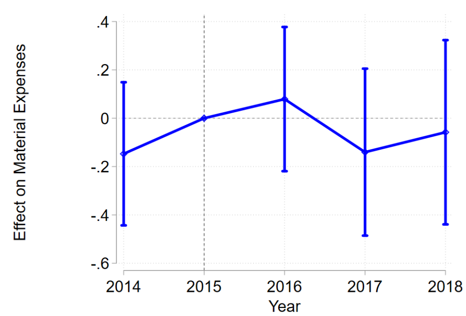
A. Labor Costs



B. Total Revenue

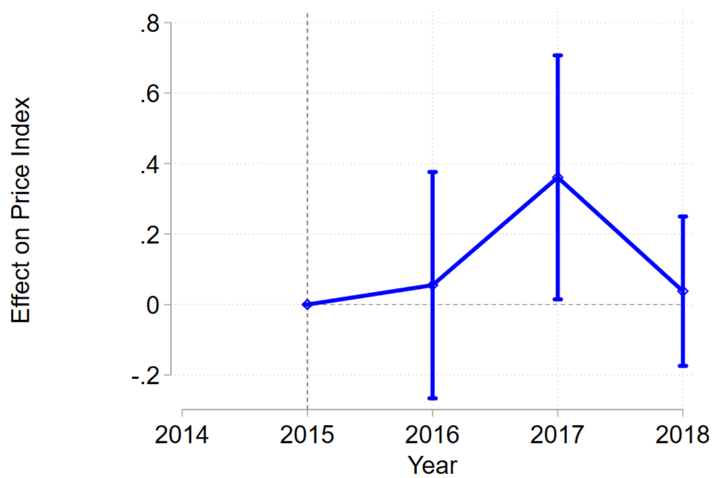


C. Material Expenses



Note: This figure plots the effects of the minimum wage on some firm-level measures based on Equation (5). These regressions are run on the set of firms that existed throughout the entire period of analysis (i.e., it excludes closures). Panel (a) shows the effects on total labor costs; Panel (b) shows the effects on total revenue; and Panel (c) shows its effects on material expenses. Regressions are weighted by the logarithm of total employment in 2016, and robust standard errors are computed. Point estimates and their 95% confidence intervals are shown. Source: EEA.

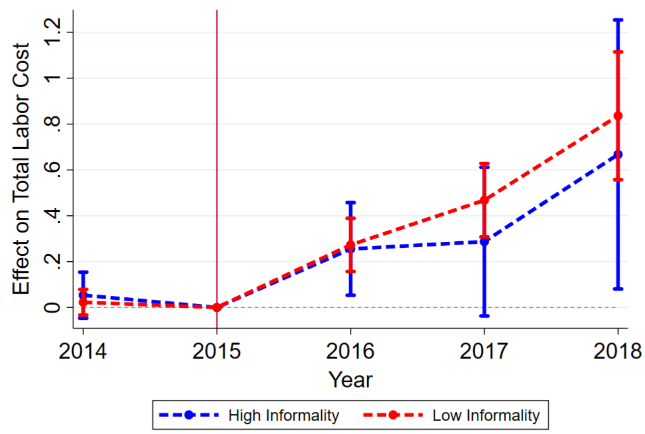
FIGURE 10. Effect on Laspeyres Price Index in Manufacture



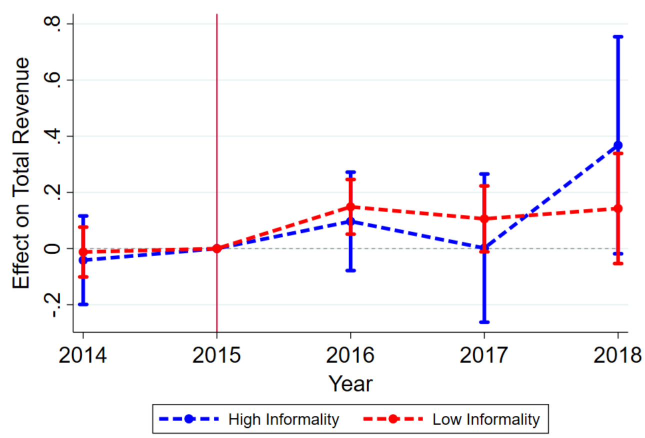
Note: This figure shows the coefficients of Equation (5) where the dependent variable is a Laspeyres price index constructed for the manufacture sector. These regressions, by construction, can only be computed on the set of products that exist within any two consecutive years. Regressions are restricted to firms that existed throughout the entire period of analysis, weighted by the logarithm of total employment in 2016, and robust standard errors are computed. Point estimates and 95% confidence intervals are shown. Source: EEA.

FIGURE 11. Effects on Labor Cost and Revenue, by Informality

A. Labor Cost



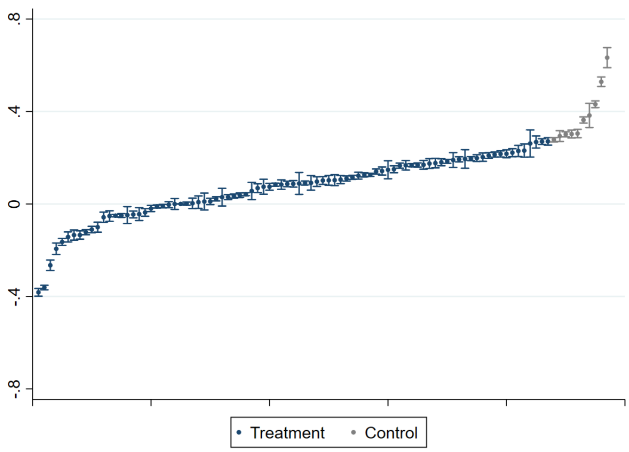
B. Total Revenue



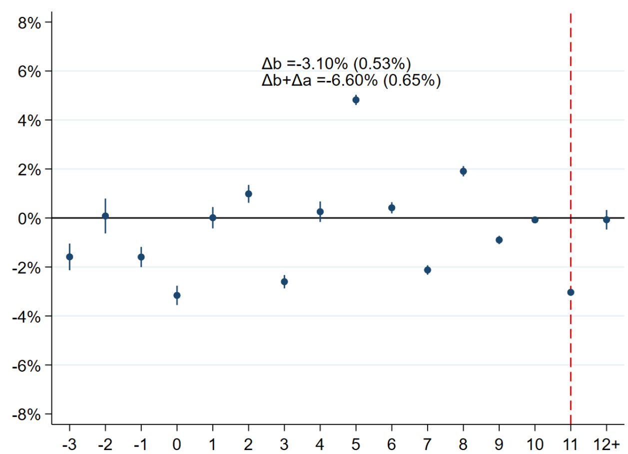
Note: This figure plots the effects of the minimum wage on total labor costs and total revenue, separately for firms located in provinces with high exposure to informality versus provinces with low exposure. A highly exposed province is defined as a province in the highest quartile of the share of informal employment across provinces. Regressions are weighted by the logarithm of total employment in 2016, and robust standard errors are computed. Point estimates and their 95% confidence intervals are shown. Source: EEA.

FIGURE 12. Aggregate Employment Change in the Formal Sector

A. Distribution of province-level premia

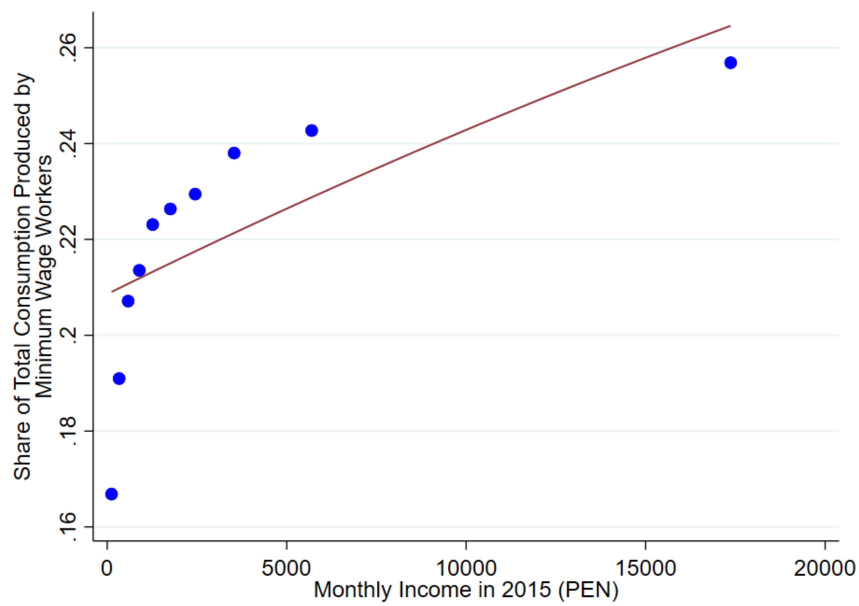


B. Employment changes in the formal sector



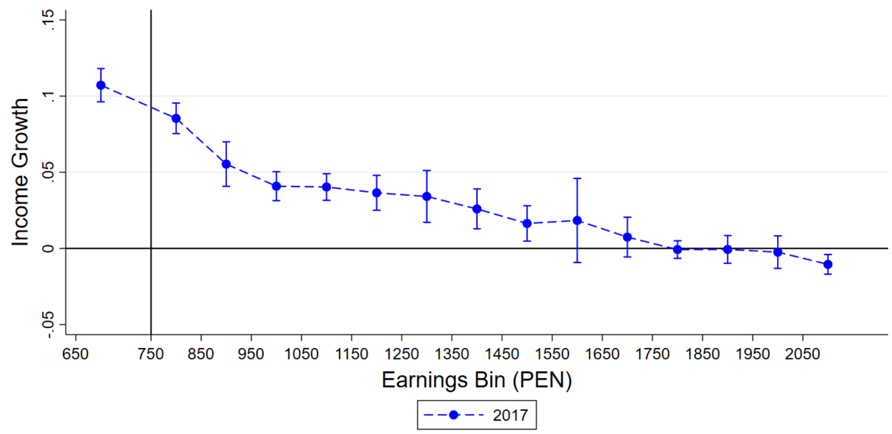
Note: This figure shows the approach described in Giupponi et al. (2024) to estimate employment changes along the wage distribution. The upper panel shows the distribution of province-level premia, measured by province fixed effects. High paying provinces are thus selected as a control group. The lower panel shows the employment changes in the earnings bins relative to the minimum wage. The 0 in the X-axis indicate the earnings bin corresponding to those earning the old minimum wage. Source: ENAHO.

FIGURE 13. Consumption of goods produced using MW workers



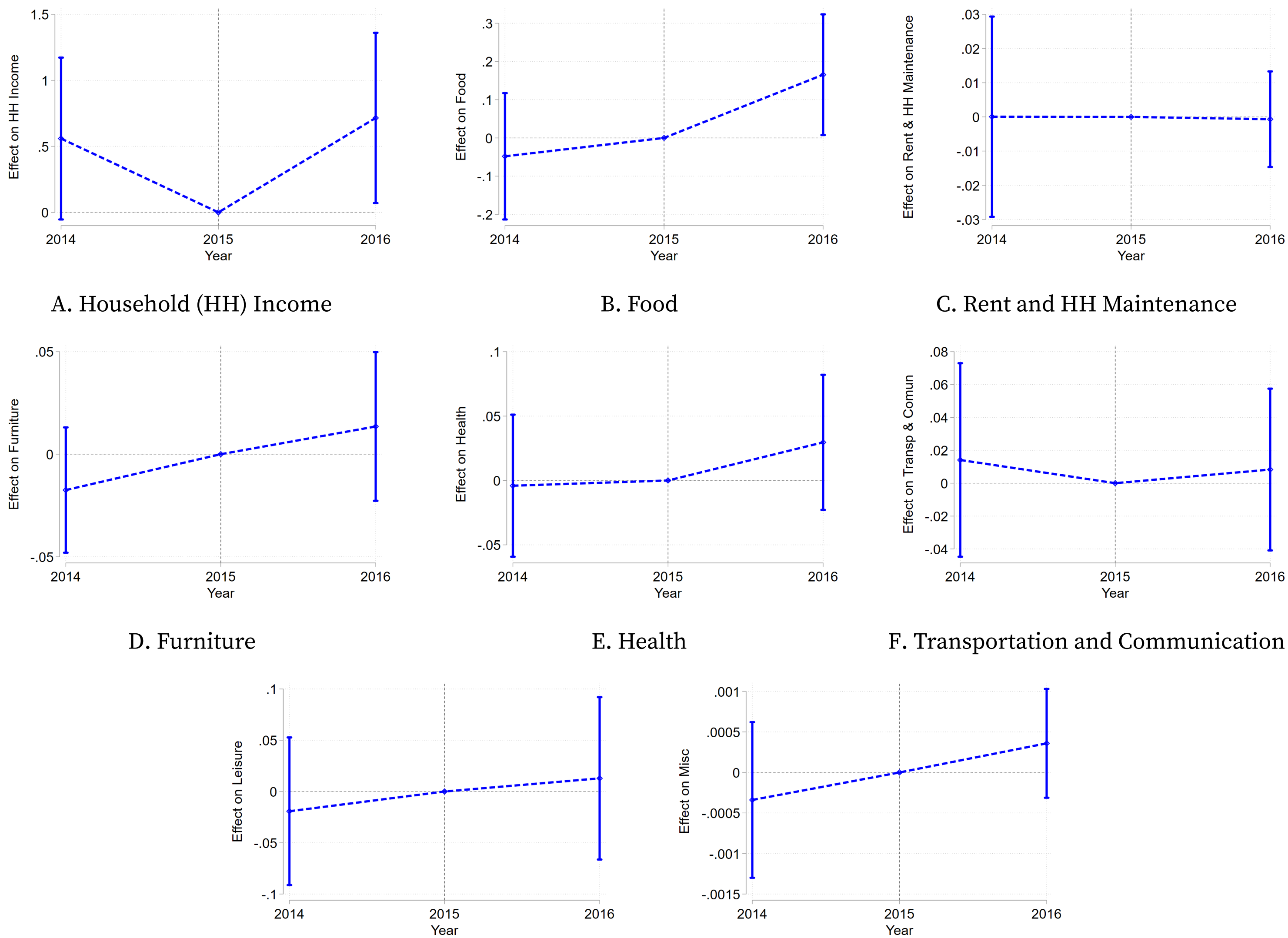
Note: This figure plots a binscatter of the share of total consumption produced by minimum wage workers - as described in Equation (11) - against the household monthly income in 2015. The red line corresponds to the best linear fit of that relationship. Source: ENAHO.

FIGURE 14. Expected gains from MW



Note: This figure plots the expected gains from the minimum wage as described in Equation (13). The elements of this Equation are jointly estimated and standard errors are bootstrapped. Source: PLAME and ENAHO.

FIGURE 15. Effects on Household Income and Consumption



A. Household (HH) Income

B. Food

C. Rent and HH Maintenance

D. Furniture

E. Health

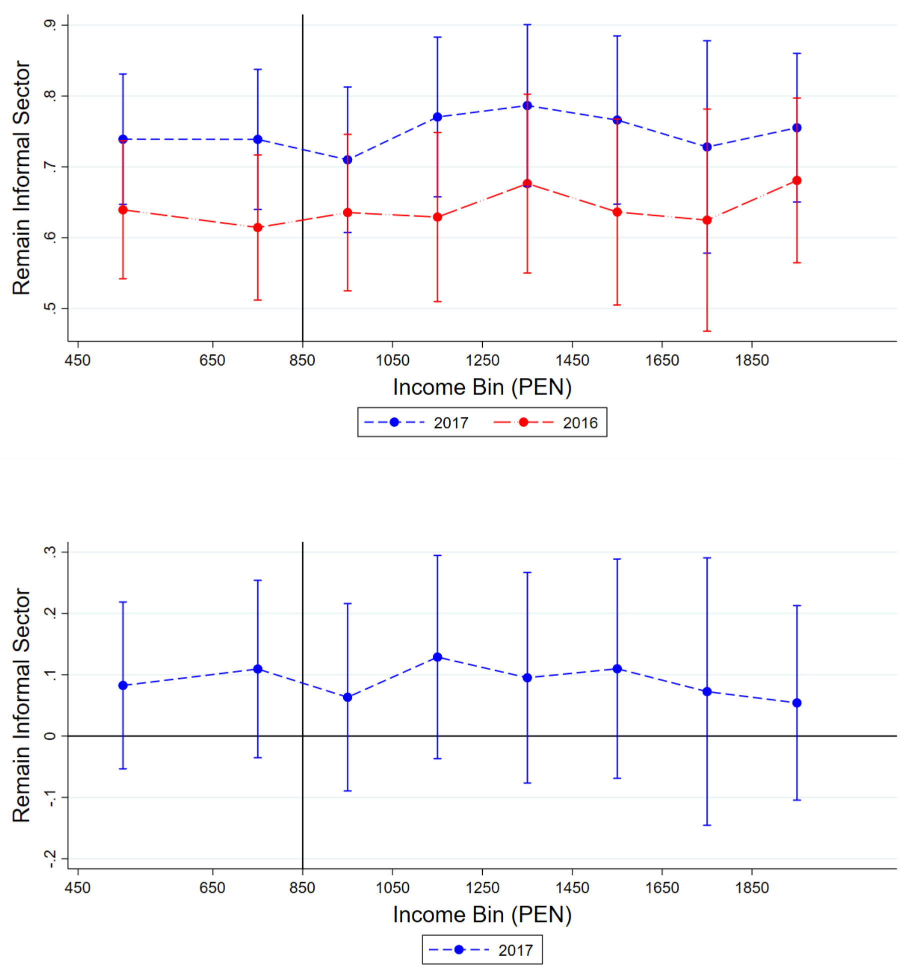
F. Transportation and Communication

G. Leisure

H. Miscellaneous

Note: This figure shows the effects of the minimum wage on changes in household income and consumption categories relative to household consumption in 2015. These estimates are computed based on Equation (10). Regressions are weighted by the logarithm of number of household members in 2015, and robust standard errors are computed. Point estimates and 95% confidence intervals are shown. Source: ENAHO.

FIGURE 16. Remaining in Informal Sector



Note: This figure plots the minimum wage effects on remaining in the informal sector for workers who were in that sector at baseline. The dependent variable is an indicator equal to 1 if the worker remains informal. The upper panel plots the coefficients from Equation (7) as of February 2015 (pre) and February 2016 (post). The lower panel shows the difference between the blue and red line in the upper panel, which correspond to the coefficients of Equation (8). This regression is run using the panel sample in the ENAHO dataset, which contains incumbent informal workers. Source: ENAHO.

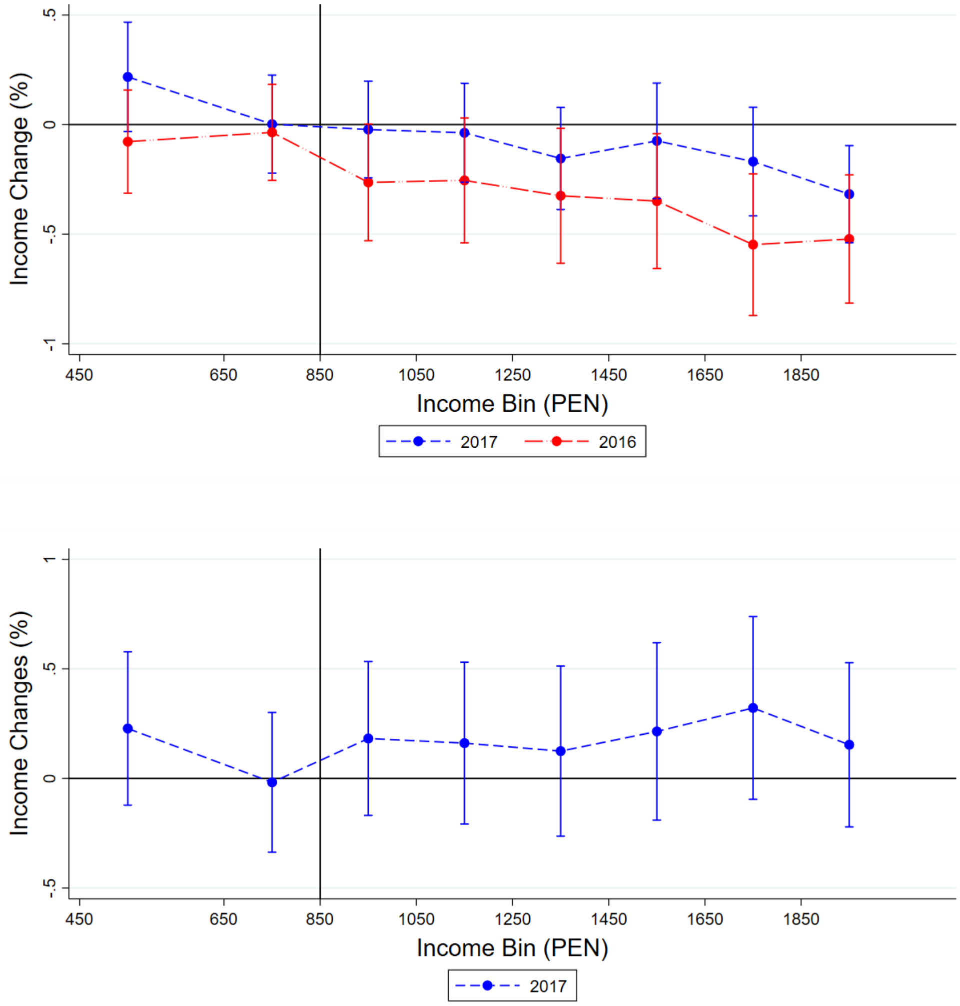
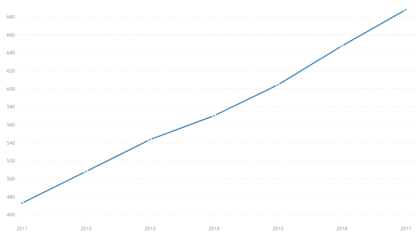


FIGURE 17. Effects on Income for Informal Incumbents

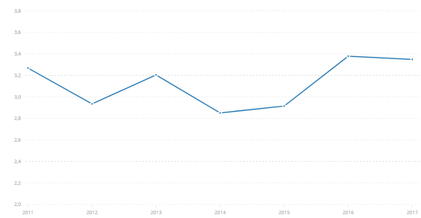
Note: This figure plots the minimum wage effects on remaining in the informal sector for workers who were in that sector at baseline. The dependent variable is the change in income for workers who were informal at baseline. The upper panel plots the coefficients from Equation (7) as of February 2015 (pre) and February 2016 (post). The lower panel shows the difference between the blue and red line in the upper panel, which correspond to the coefficients of Equation (8). This regression is run using the panel sample in the ENAHO dataset, which contains incumbent informal workers. Source: ENAHO.

A Additional Figures

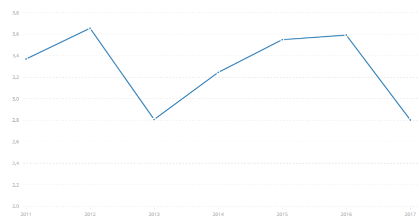
FIGURE A.1. Macroeconomic Variables between 2011 and 2017



A. Gross Domestic Product



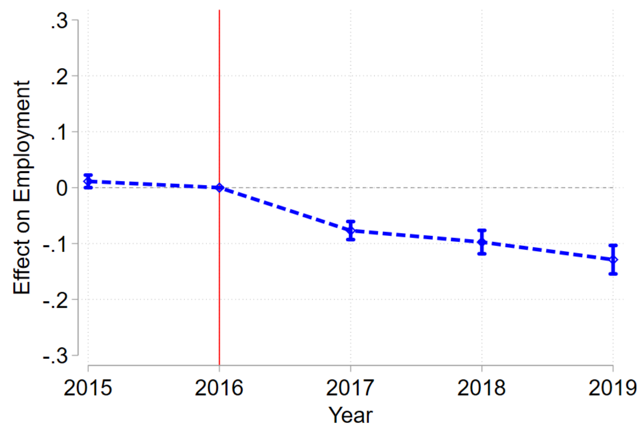
B. Unemployment



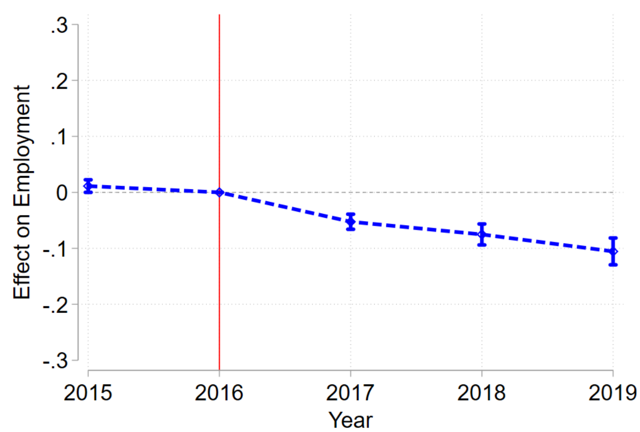
C. Inflation

Note: This figure shows some macroeconomic indicators around the time period of analysis. Panel (a) shows the nominal GDP, Panel (b) the unemployment rate, and Panel (c) shows the inflation rate. Source: World Bank.

FIGURE A.2. Employment Effects, Extensive and Intensive Margins



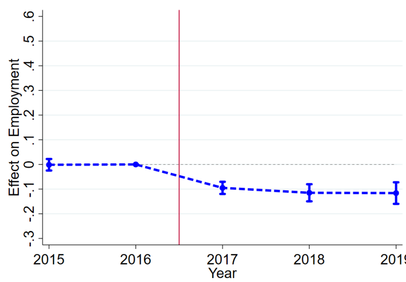
A. Intensive and Extensive Margin



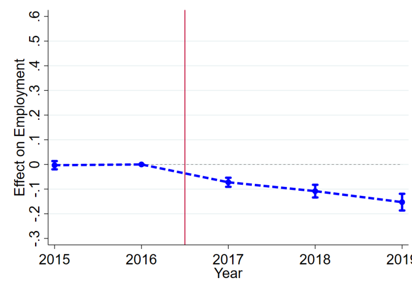
B. Excluding Extensive Margin

Note: This figure shows the estimates from Equation (5) using firm employment as the outcome variable. Panel (a) includes firms that closed after the minimum wage increase and thus record zero employment, and Panel (b) excludes these firms. Regressions are weighted by the logarithm of total employment in 2016, and robust standard errors are computed. Point estimates and their 95% confidence intervals are shown in this figure. The vertical red line corresponds to the baseline year, prior to the minimum wage hike. Source: PLAME.

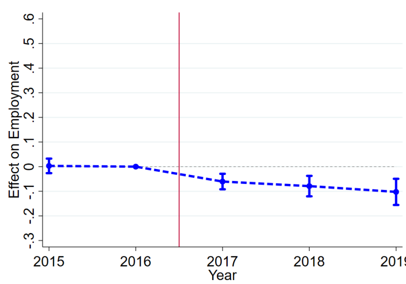
FIGURE A.3. Employment Effects, by Sector: Firm Approach



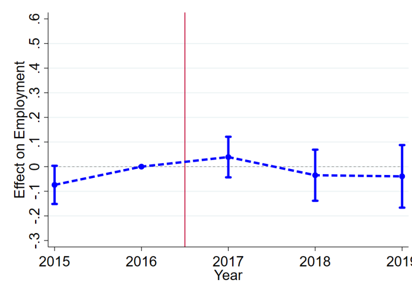
A. Manufacture



B. Commerce



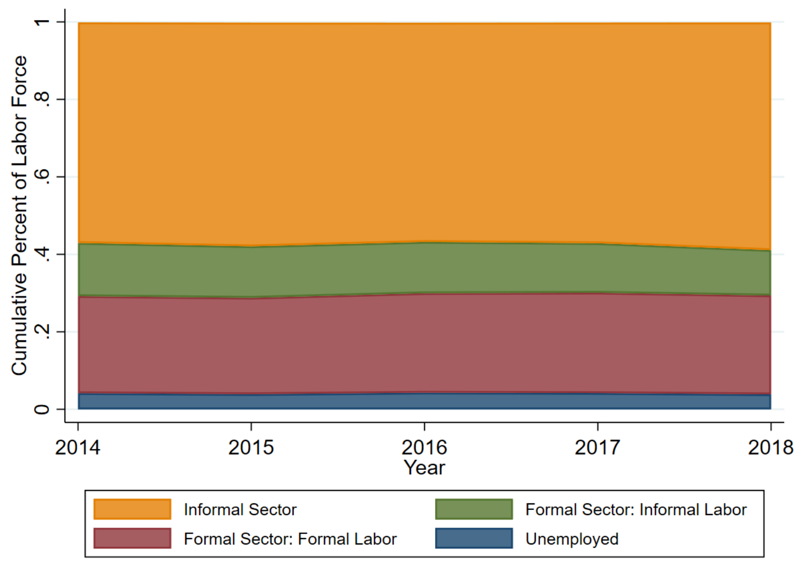
C. Restaurants



D. Construction

Note: This figure shows the estimates from Equation (5) using firm employment as the outcome variable. The different panels compute the estimates within the subset of firms in a particular industry. Regressions are weighted by the logarithm of total employment in 2016, and robust standard errors are computed. Point estimates and their 95% confidence intervals are shown in this figure. The vertical red line corresponds to the baseline year, prior to the minimum wage hike. Source: PLAME.

FIGURE A.4. Composition of Labor Force in Peru



Note: This figure shows the employment status composition of the labor force in Peru around the years of analysis. The orange area corresponds to workers in the informal sector, more than 80% of that area corresponds to self-employment. Source: ENAHO.

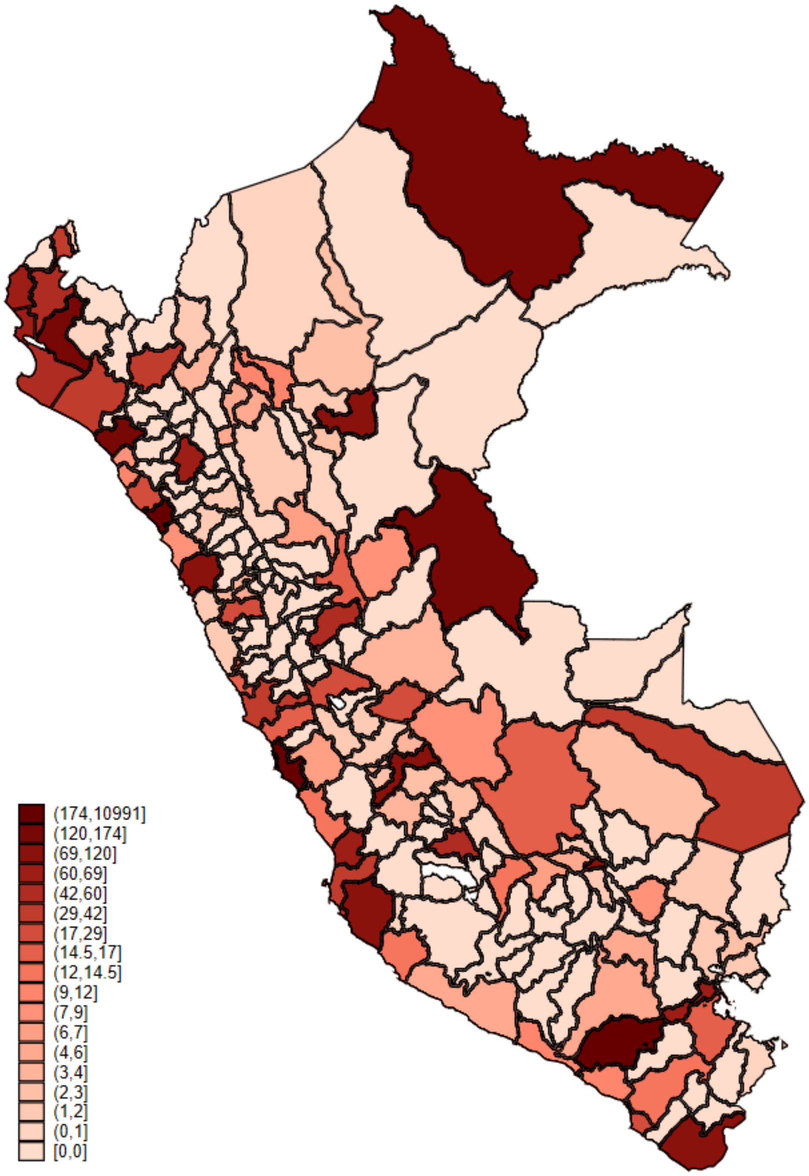


FIGURE A.5. Number of Firms in EEA across provinces

Note: This figure shows the geographical (province-level) distribution of firms in the EEA dataset. Darker colours indicate larger number of firms in that province. Source: EEA.

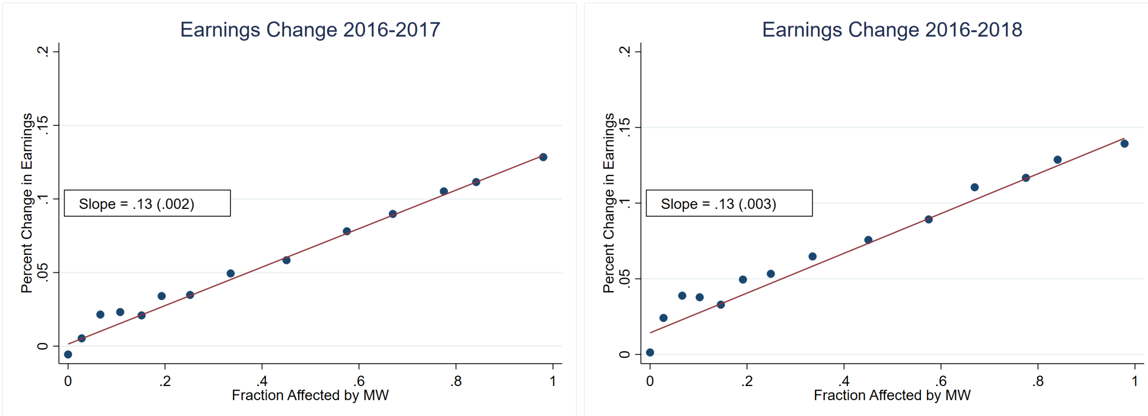


FIGURE A.6. Linearity between Exposure and Wage Growth

Note: This figure shows the slope between the exposure variable in Equation (5) and changes in average wages (dependent variable). A non-linear relationship would threat the identification strategy of this approach.

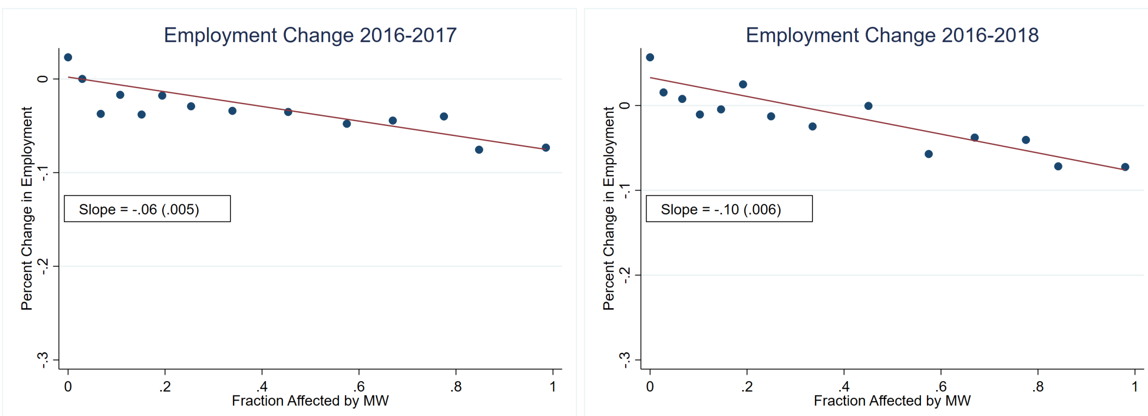


FIGURE A.7. Linearity between Exposure and Employment Growth

Note: This figure shows the slope between the exposure variable in Equation (5) and employment changes (dependent variable). A non-linear relationship would threat the identification strategy of this approach. Source: PLAME.

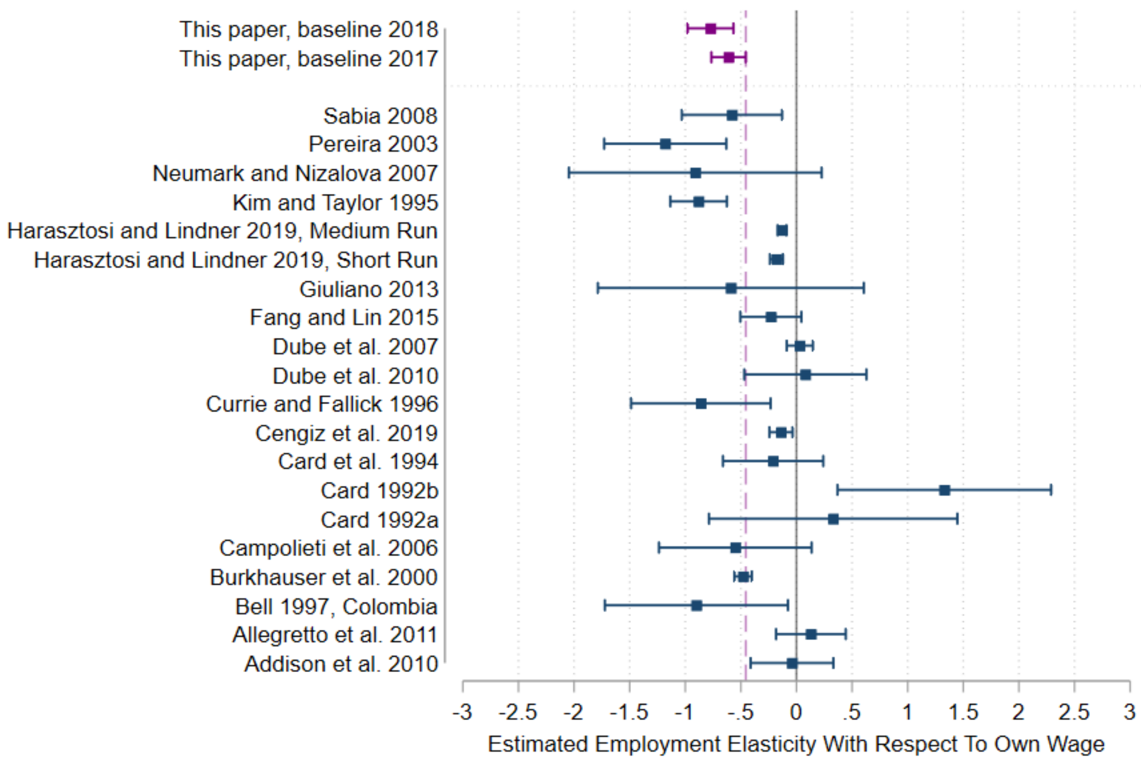


FIGURE A.8. Own-Wage Elasticity in the Literature

Note: This figure shows the implied own-wage elasticities of my reduced form estimates based on Equation (5). To construct confidence intervals I jointly estimate the regression using both outcomes (i.e. stacking influence functions). The graph compares these elasticities to the list of papers shown in Harasztosi and Lindner (2019). Source: PLAME.

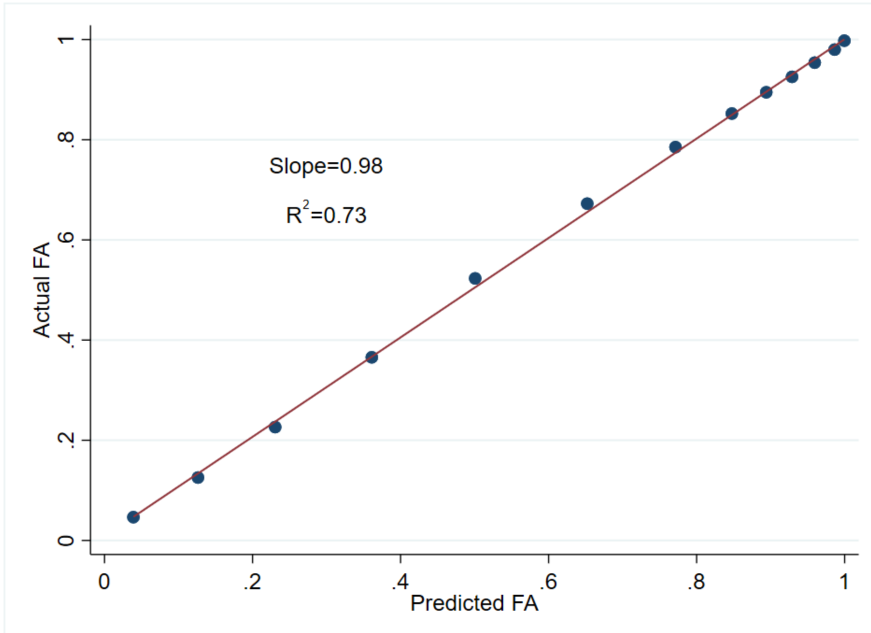


FIGURE A.9. Out-of-sample prediction of Fraction Affected (FA)

Note: This figure shows the slope of the regression between the actual fraction affected and the predicted one, based on a regression forest model used on a training sample. This plot is constructed using a sample not used for training the regression model. Source: PLAME.

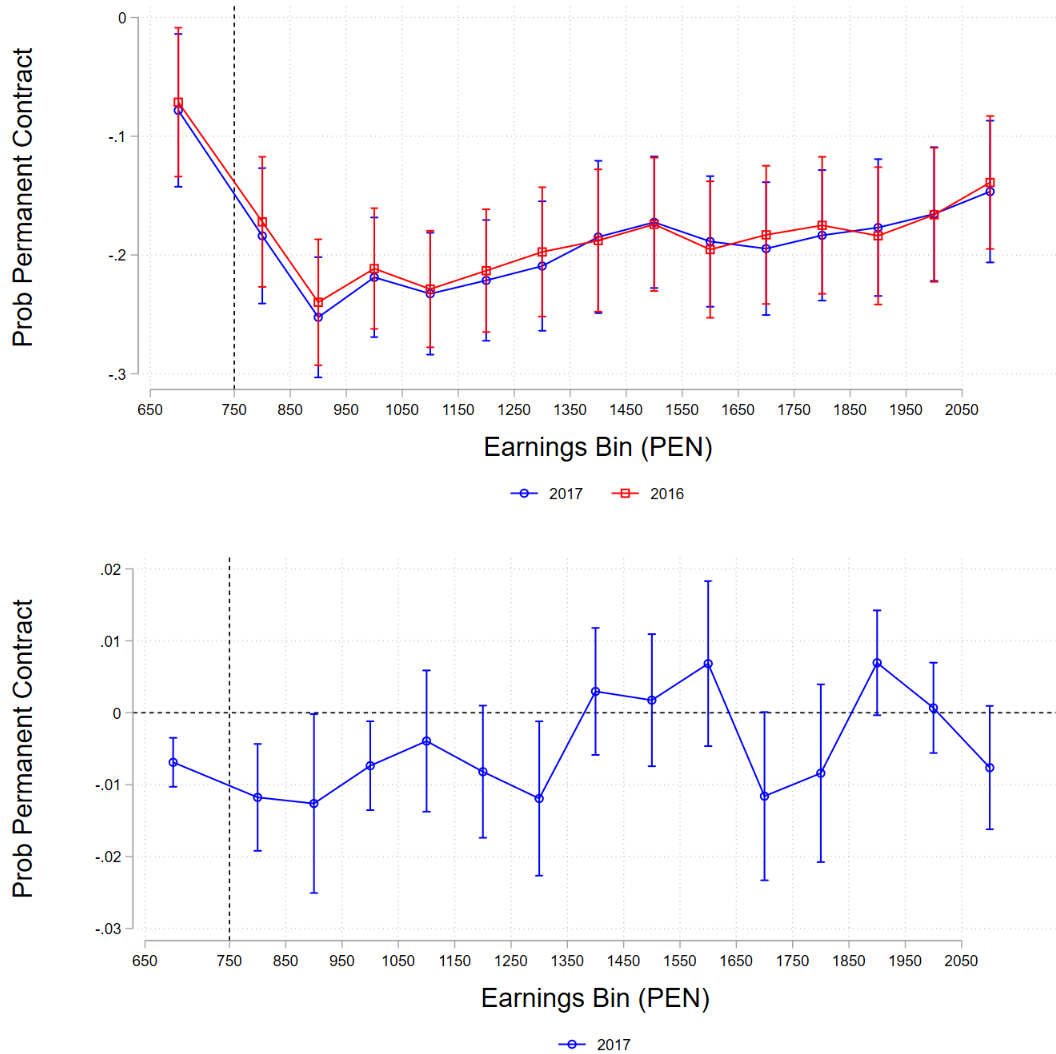


FIGURE A.10. Effects on Type of Contract: Worker Approach

Note: This figure plots the effects on job stability using the worker approach described in Section ??. The dependent variable is an indicator equal to 1 if the worker has a permanent contract. The upper panel plots the coefficients from Equation (7) as of February 2016 (pre-policy period) and February 2017 (post-policy period). The lower panel shows the difference between the blue and red line in the upper panel, which correspond to the coefficients of Equation (8). Source: PLAME.

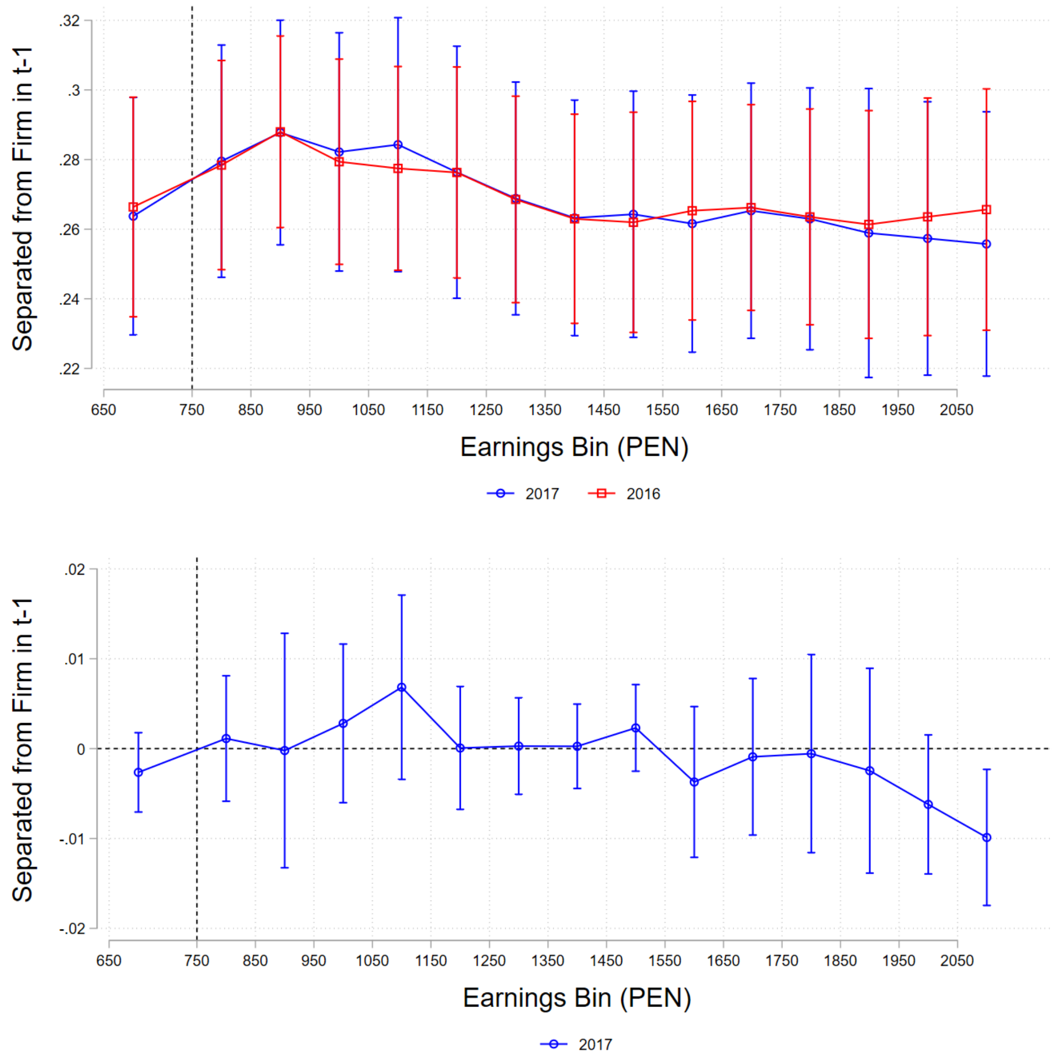


FIGURE A.11. Effects on $J \rightarrow J$ Transition: Worker Approach

Note: This figure plots the effects on job-to-job transitions using the worker approach described in Section **??**. The dependent variable is an indicator equal to 1 if the worker separated from his old firm and remained formally employed. The upper panel plots the coefficients from Equation (7) as of February 2016 (pre-policy period) and February 2017 (post-policy period). The lower panel shows the difference between the blue and red line in the upper panel, which correspond to the coefficients of Equation (8). Source: PLAME.

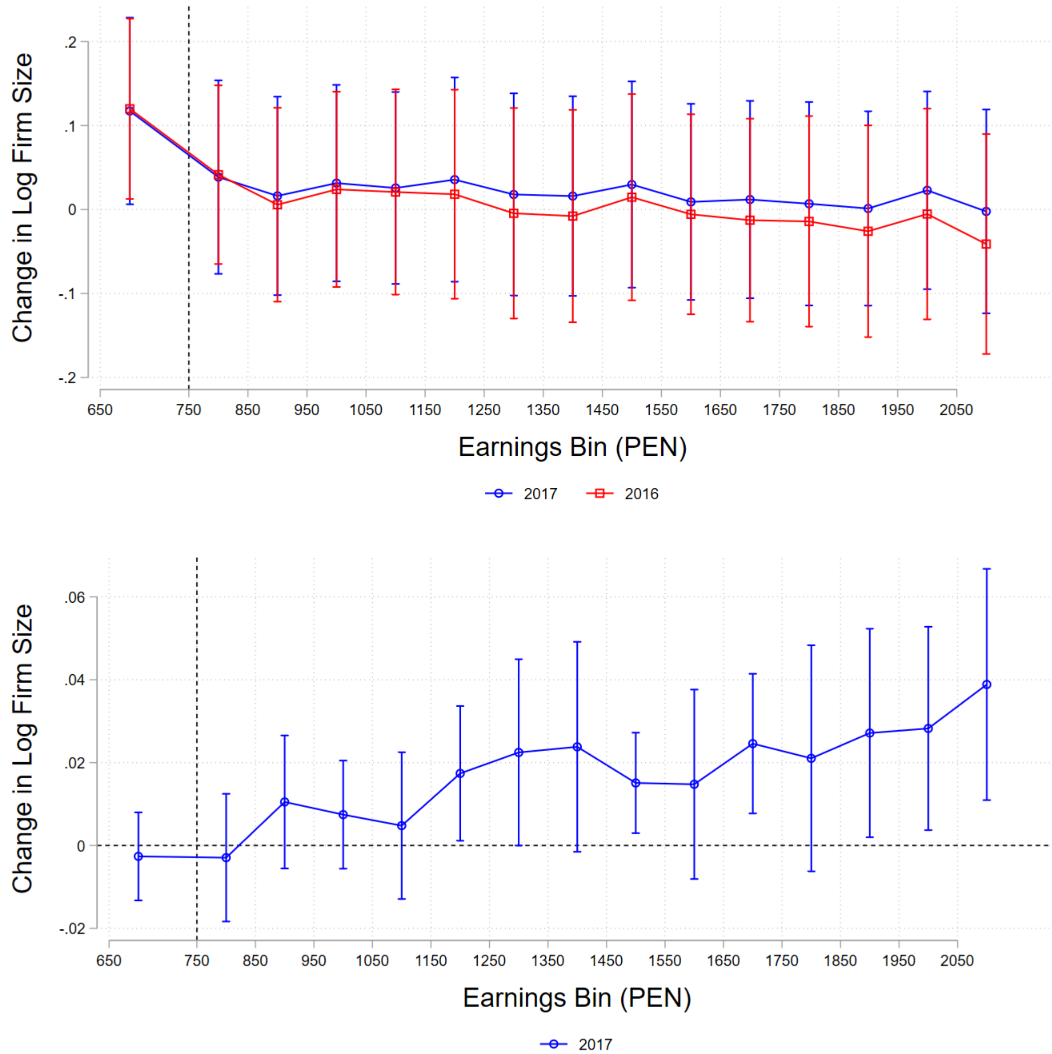
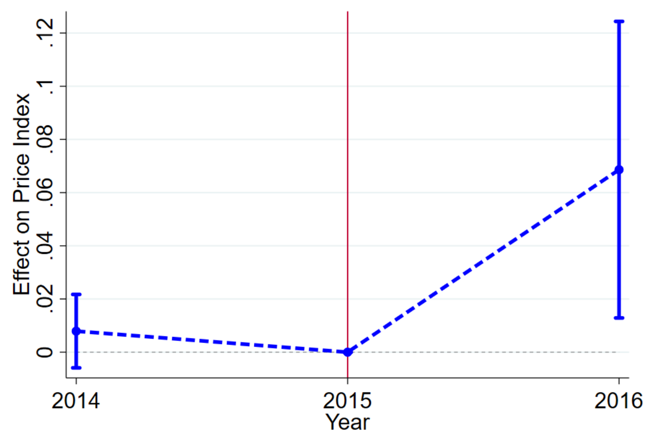


FIGURE A.12. Effects on Firm Size: Worker Approach

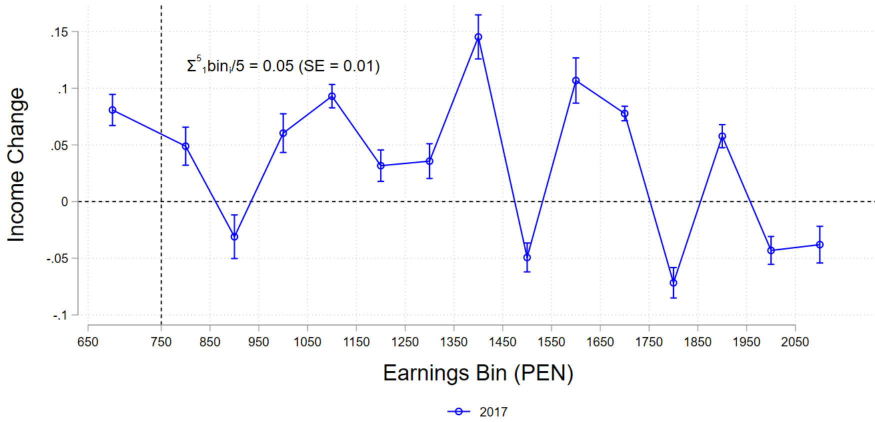
Note: This figure plots the effects on firm quality using the worker approach described in Section **??**. The dependent variable is the change in firms' size. The upper panel plots the coefficients from Equation (7) as of February 2016 (pre-policy period) and February 2017 (post-policy period). The lower panel shows the difference between the blue and red line in the upper panel, which correspond to the coefficients of Equation (8). Source: PLAME.

FIGURE A.13. Effect on Household's Consumption Price Index



Note: This figure plots the effect of the minimum wage on a Laspeyres price index of food consumption at the household level. These regressions are run on a household-level panel from the ENAHO dataset. Point estimates and their 95% confidence intervals are shown. Source: ENAHO.

FIGURE A.14. Expected gains from MW



Note: This figure plots the expected gains from the minimum wage as described in Section F Point estimates and their 95% confidence intervals are shown. Source: PLAME and ENAHO.

B Data Appendix

In this appendix I discuss some details that were left out in the main discussion of the paper.

B.1 Linking PLAME and EEA

As mentioned in the main text, there is no way to link both datasets based on the firm identifier. Instead, I opt to train a predictive model in the PLAME dataset to predict out-of-sample the fraction affected in the EEA dataset.

Both datasets share a set of observables for each year throughout 2015 to 2018:

- Total employment among males and females in each of these categories: managers, permanent employees, temporary employees, permanent laborers (*obreros*), and temporary laborers.
- Total wage cost among permanent and temporary workers
- Industry group
- Date of firm creation

The goal is to fit a prediction model, using these variables, in the PLAME dataset and then make an out-of-sample prediction on the EEA dataset. A similar exercise is performed in Harasztosi and Lindner (2019), where they show that a quadratic polynomial in average wage cost per worker is highly predictive of the fraction affected variable.

In this paper, I choose to leverage existing machine learning methods to perform this step. First, I draw a random 75% sample of the PLAME dataset to be used as training data to predict FA_j on the firm-level census. The results of the prediction model are shown in Figure A.9. In particular, it plots a linear fit between the actual FA of the remaining 25% PLAME sample, and the predicted estimates. The slope between both is very close to one, which suggests that the prediction model has performed sufficiently well for my purposes.

B.2 Firm concentration observed in EEA

Figure A.5 shows the firm counts for each province of the EEA dataset. As can be observed in the map, there is a high degree of concentration in many locations, mainly outside of the coastal (left) area. If we excluded the presence of the informal sector in the analysis we would - perhaps incorrectly - assume that these firms exert a lot of market power. However, if these firms are competing with the informal sector, it could be the case that the de-facto market power is smaller than expected.

C Additional Empirical Evidence

In this section I show additional empirical evidence not discussed in the main text.

Job Stability. In Figure A.10 I show the results of running the worker-approach on a dependent variable equal to 1 if the worker holds a permanent contract. The results show that, conditional on remaining formally employed, workers were less likely to hold a permanent contract after the minimum wage increase. This suggests that this policy can perpetuate a cycle of being trapped within jobs with no stability.

Combining these results with the previous evidence in the main text, it would suggest that some workers separate from their firms and land in similar-quality firms but on a temporary contract instead. Temporary contracts are a common feature in the context of Peru since a reform enacted in 2002, and this might be a potentially important non-pecuniary channel that can negatively impact welfare.

Reallocation . In Figure A.11 I provide additional evidence that the reallocation channel (Dustmann et al., 2022) is muted in my context. This figure plots the estimated coefficients on the probability of transitioning from job to job within formal employment. In particular, by comparing with the employment effects in Figure 5, it suggests that workers are exiting formal employment rather than reallocating across firms. Additionally, Figure A.12 plots the effects on firm size (conditional on formal employment), and shows that low-wage workers are not switching to larger firms.

D Upper Tail Imputation

The results are robust to imputing the upper tail of the earnings distribution. To address censoring at the 95th percentile of each year, I can impute upper tail earnings following Card et al. (2013).

In particular, I create 10-year age cells (20 to 29, 30 to 39, $\ldots$, 50 to 59), and 6 education cells (missing, no qualifications, secondary, some post sec, univ graduate, post graduate). I then construct the mean log-earnings of individual i in all other periods, and for all their coworkers. For singleton workers or singleton firms I use the sample mean of gender $g(i)$. Finally, I fit a series of Tobit models separately by year, gender, education level, and age range cells that include the following variables: age, mean log earnings, in other years, fraction of censored earnings in other years, number of full-time employees of gender g and its square, dummy for 11 or more employees, fraction of univ graduates at the firm, mean log wage co-workers and fraction of coworkers with censored earnings, dummy for singleton individuals, and a dummy for employees of 1-worker firms.

If $y \sim N(X'\beta, \sigma)$ and censoring is such that $y \geq c$ is censored. Let $k = \Phi\left[(c - X'\beta)/\sigma)\right]$, where $\Phi(\cdot)$ is the standard normal CDF. Let $u \sim U[0, 1]$, then

$$y^u = X'\beta + \sigma\Phi^{-1}\left[k + u(1 - k)\right].$$

With the estimates $\hat{\beta}$ and $\hat{\sigma}$ from the Tobit models along with random draws from the uniform distribution supported on the unit interval, I can then impute $\hat{y}^u$ on the censored observations in my dataset.

E AKM Effects

In this section I provide additional details to the construction of the AKM effects used in Table 7 to characterize the impacts of the minimum wage on reallocation. Using the PLAME data for the years 2015 and 2016 (prior to the minimum wage increase), I estimate a model of log earnings against a cubic polynomial in age and firm fixed effects and then residualize the outcome.

Then, I estimate an AKM model of the form:

$$y_{it} = \alpha_i + \Psi_{J(i,t)} + \lambda_t + u_{it}, \tag{1}$$

where y_{it} are log-earnings; α_i represent a time-invariant ability component of workers; $J(i, t)$ is a function that returns the firm of worker i at time t, so that $\Psi_{J(i,t)}$ represent firm-specific premia; λ_t are time fixed effects.

Identification in the AKM model relies on the existence of worker transitions across firms, and requires these movements to be uncorrelated with time-varying residual components of earnings (conditional on worker and firm fixed effects).

The estimated firm fixed effects are labelled AKM effects and measure an employer-specific pay premium shared across all workers at that firm.

That estimates of the firm and worker effects are identified within a connected set of firms that are linked through by workers' moves. The initial sample has $5,515,960$ worker-year observations and the largest connected set restricts the sample to $4,429,096$ observations.

F Alternative Computation of the Gains of the Minimum Wage

In this section I explore an alternative approach to compute the gains of the minimum wage shown in Figure 14 of the main text.

First, using the ENAHO dataset, I estimate the relationship with formal earnings at baseline and the logarithm of income in the informal sector in the next year. I use the subset of individuals who transition from formal employment to informal self-employment and estimate the following model:

$$\log(\textit{informal income}_{i,t}) = \sum_{b=1}^{8} \gamma_{2016,b} \mathbf{1}\{\textit{formal earnings}_{i,t-1} \in \textit{bin}_b\} \quad + \\ + \lambda_{\textit{sector(i,t-1)}} + \epsilon_{i,t}, \tag{2}$$

where $\lambda_{\textit{sector(i,t-1)}}$ are industry group fixed effects at baseline year $t-1$.

I then use the estimated coefficients to predict, in the PLAME dataset, the counterfactual income in the informal sector among those who were characterized by transitioning from employment to non-employment in this dataset.

Finally, I estimate the income effects by running Equation (8) on the imputed logarithm of income produced in the previous step. Figure A.14 plots the estimates across different wage bins. While the coefficient in the [850, 950) bin is small and negative, these results do not qualitatively change the main results.