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Wage Reforms and Equality Gains: Evidence from Greece

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Contents

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ABSTRACT

This paper examines whether minimum wage reforms affect income inequality among low-wage workers. We construct a novel "within-occupation" measure of wage dispersion, using a Greek dataset between 2010 and 2020. Using modern difference-in-differences analysis for causal inference, our findings show non-symmetrical effects on wage dispersion when a minimum wage reform is imposed. In particular, the minimum wage cut of 2012 did not alter the wage dispersion of low-wage workers, while the minimum wage increase of 2019 led to a decrease in wage inequality at the bottom segment of the labor market. Our paper equips policymakers with a solid understanding of the effects of minimum wage reforms on wage inequality and highlights the important role of wage rigidities in shaping these effects.

JEL classification: C31, J08, J31

Keywords: *income inequality, wage inequality, minimum wage reform; modern difference-in-difference analysis; quantile regression*

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Introduction

Over the past decade, the rising income inequality across countries has caused concerns of economic stagnation and social exclusion (Fredriksen, 2012). This is particularly true for the case of European Union (EU) member-countries, where the growth in household incomes and economic convergence until 2008 has been followed by years of crisis and stagnation, leading to concerns over issues of economic integration and fairness in the EU.[5] Although the impact of recession has been visible in communities, the hardship has not fallen equally on all economic players, as Milanovic (2016) argues in his book, especially in the developed world. In this context, it is no surprise that the recent literature, among them Piketty (2003) and Piketty and Saez (2003), has stimulated a fierce debate on inequality among academics and policy makers.

Wage inequality is one of the main drivers of income inequality within countries, which is gradually increasing as low-income people fall behind, while capital income and wealth are increasingly more concentrated at the top of the distribution. To address the rise of wage inequality, countries introduced several labor market interventions. Such reforms attracted the interest of a handful of recent studies that focus on the role of policy intervention in shaping wage inequality. Most notably, Autor et al. (2016) examine the effect of the minimum wage on the US wage inequality, Caliendo et al. (2019) focus on Germany and discuss the short-run effects of a statutory hourly minimum wage on the wage inequality in Germany, and Redmond et al. (2021) study the impact of a rise in the Irish minimum wage on the distribution of hourly wages. Nevertheless, there was no unanimous conclusion as to the effect of labor policy interventions on wage inequality. In particular, the study of Caliendo et al. (2019) reports small negative employment effects following an increase in minimum wage, while there is no reduction of poverty and inequality. Evidence, however, from Irish (Redmond et al., 2021) and US labor markets (Autor et al., 2016) support an inequality reduction between high and low earners and an inequality reduction in the lower tail of the wage distribution, respectively.

This paper studies the impact of wage reforms on wage inequality. Particularly, we focus on interventions on the institutionally defined minimum wage (the state can have a direct and instant impact on it) and how such interventions shape a country's wage distribution. A still unsettled major issue in the labor economics literature (Cámara et al., 2024; Filauro et al., 2025; Lombardo et al., 2024) is the efficiency of labor market reforms and their implications on the most vulnerable group of workers, which are part of the lowest segment of wage distribution. We, therefore, first examine whether wage inequality in the lower tail of the wage distribution is shaped differently when a minimum wage change takes place in the labor market. Labor market outcomes can be substantially different depending on whether the responsiveness of wages to the economic environment is either flexible or rigid (Goette et al., 2007). An interesting question in this respect is whether opposing minimum wage reforms have (non-)symmetric effects on wage inequality, which is the second task of this paper.

The main contribution of this paper is the introduction of a novel measure of wage dispersion. By building on a theoretical basis using the Mincer (1958) equation, we propose a new measure of wage dispersion defined as the difference between the nominal and the occupation-mean wage, which is

[5] The 2007 global financial crisis stopped the process of convergence across countries, while within-country inequality for several countries, especially for those in the industrialized world, has increased (Nolan and Valenzuela, 2019).

the mean wage for each employee per economic occupation for each year. The introduction of this new measure has at least two important benefits. First, it controls for market segmentation as it accounts for the involvement of employees in different occupations alleviating potential heterogeneity bias. Second, it allows for potentially different impacts of business cycles on different economic occupations. As not all economic activities are shaped in the same manner during the ups and downs of the economy, so does the wage performance of those occupations; therefore, by allowing for heterogeneous responses, through our new measure, we obtain more insights into the labor market dynamics.

Once our measure is constructed, we proceed as follows: we study the effect of minimum wage reforms on the wage distribution and perform comparative analysis on the efficiency of two reverse minimum wage reforms on the labor market's wage inequality. A particular challenge in any empirical work is the issue of identification. To draw causal inference, we apply modern difference-in-differences estimation techniques (inter alia Sant'Anna and Zhao, 2020). Among low-wage workers (i.e., workers paid below occupation-mean wage), we define as a treatment group the minimum wage workers and as a control group the rest of low-wage workers who are paid a wage determined (not institutionally but) by labor market outcomes. We compare workers who share similar characteristics between those two groups, while the only difference is that the treatment group gets a reform on its institutional (minimum) wage. In this way, we alleviate the causality issue and establish the direction of the impact.[6] As a result, any change in wage distribution and consequently of a country's income distribution at the lower tail, is because of this policy reform and not of any other potential effects.

We apply our methodology using Greece as a case study, a country that was severely hit in magnitude and duration by both the financial crisis of 2007 and the subsequent debt crisis of 2010. Greece lost almost one-fourth of its GDP over a period of eight years (European Commission, 2019) and, at the same time, the inequality varied a lot.[7] To support its economy, the Greek government implemented, in accordance with the European Commission (on behalf of the Eurogroup, the European Central Bank and the International Monetary Fund), a series of two memorandum agreements in 2010 and 2012 that among other economic adjustments, targeted at the liberalization of labor markets. More specifically, in the second memorandum of understanding, a large minimum wage cut of around 22% was imposed in 2012. The minimum wage was later increased in 2019, making Greece an even more peculiar case to study the effects of minimum wage reforms on wage inequality.

Using survey data from the Greek labor market over the 2010-2013 and the 2017-2020 periods, when a minimum wage cut and increase were respectively introduced in the labor market, our findings show that the minimum wage increase of 2019 (a 12% average minimum wage increase) is strongly associated with a similar decrease (in absolute terms) in the dispersion of minimum wage from the occupation-mean wage compared to the dispersion of other low wages from the occupation-mean wage; instead, the minimum wage cut of 2012 did not lead to a significantly different effect between

[6] Following Roth et al. (2023), we relax the parallel trends assumption in the "canonical" difference-in-differences model. Thus, we put emphasis on conditional parallel trends incorporated by applying the Neyman's nonparametric model by using the regression adjustment or by using the inverse probability weighting proposed by Abadie (2005) or the doubly robust estimators proposed by Sant'Anna & Zhao (2020).

[7] Evidence from our data, shows that the ratio of minimum wage to median wage (a typical measure of wage dispersion known as Kaitz index) varies substantially and drops by 12 percentage points after 2012 (from 66% to 54%), with a drop representing a higher wage dispersion.

the dispersion of wages of the treatment and control groups. We then take our analysis a step further by applying a quantile regression for the 2019 reform[8] and find that this relative wage dispersion tends to decrease more when the lower quantile is considered. We further provide a great number of robustness checks, including those workers whose job status has changed over the sample period or part-time workers, as well as by excluding potential outliers or low-involved activities of the dependent variable; our results do not change significantly compared to those of the baseline.

Importantly, our findings unveil the non-symmetric effects of two reverse minimum wage reforms. In the post-2011 period, Greece shows a low and decreasing value of adjusted collective bargaining coverage rate[9] (this value declines from 51.5% in 2012 to 14.2% in 2018); over this period, most European Union countries, among them Austria, Belgium, Italy, France, Netherlands, Portugal and Spain show values higher than 80%. According to Babecký et al. (2010), low values of collective bargaining coverage rate are strongly associated with either upward wage rigidity or absence of downward wage rigidity. Based on the literature, labor market flexibility or rigidity may determine the effectiveness of policy reforms on wage inequality, especially on the lower tail of the wage distribution. Low wages, which typically correspond to youth and unskilled workers, a group usually characterized by low or no labor mobility, are sticky upwards but not downwards (see e.g., Chen, 2018). Hence, the presence of upward wage rigidity in the Greek labor market explains the negative impact of the 2019 reform on wage dispersion, while the absence of downward wage rigidity leads to an insignificant impact of the 2012 minimum wage cut on wage dispersion in the lower tail of the wage distribution.

Our paper relates to a voluminous body of literature that examines wage inequality (Autor et al., 2016; Fortin and Lemieux, 1997) and its potential drivers including the role of institutional changes, the unionization rate, the economic deregulation in wage inequality, labor quality changes, and inter-industry characteristics (see e.g., Krueger and Summers, 1988; Gibbons and Katz, 1992; Fortin and Lemieux, 1997; Autor et al., 2016; Nolan and Valenzuela, 2019). Our paper particularly adds to a major long-standing debate in the labor economics literature on the effect of the minimum wage on wage inequality (Gibbons and Katz, 1992; Cámara et al., 2024; Filauro et al., 2025; Lombardo et al., 2024; Sotomayor, 2021). Our paper contributes to this debate and to a recently emerged literature focusing on policy reforms (Caliendo et al., 2019; Redmond et al., 2021; Sotomayor, 2021) by proposing a novel measure of wage dispersion that provides more insights. To our knowledge, this is the first time in the literature such a new "within-occupation" measure of wage dispersion for low-wage workers is introduced. Additionally, the application of up-to-date methodologies that ease causal concerns allow us to draw robust conclusions useful to academics and policymakers.

The remainder of the paper is structured as follows. Section 2 presents the theoretical considerations, the empirical setup and the econometric framework. Data are analysed in Section 3. Section 4 discusses the empirical findings. Section 5 offers robustness to our results. Section 6 summarizes and concludes.

[8] In both groups, the distribution of wage dispersion is chi-squared. If we consider the change of wage dispersion from pre-intervention to post-intervention periods, we observe between 11% (for the 10th percentile of wage dispersion) and 19% (for the 90th percentile of wage dispersion) change in the treatment group. As for the control group, there is no substantial percentage change among the different percentiles of the wage dispersion, which all remain around 4%.

[9] The OECD defines the adjusted collective bargaining coverage rate as the number of employees covered by a collective agreement in force as a proportion of the number of eligible employees equipped (i.e., the total number of employees minus the number of employees legally excluded from the right to bargain).

Analytical Framework

Theoretical Considerations

Our paper relates to and builds on several important contributions in the wage inequality literature. Firstly, it lies in the broader literature discussing developments in wage inequality. Our theoretical framework (presented in the following section) starts by focusing on the wage determinants as first introduced in Mincer's (1958) seminal paper. This paper changed the emphasis from age to labor market experience and participation in training programs (see also an extensive discussion by Rosen, 1992). Further, inter alia Krueger and Summers (1988) and Gibbons and Katz (1992) extend this work by focusing on the role of industry affiliation in better explaining the wage differentials for equally skilled workers. Based on cross-sectional data on individuals older than 16 years old from the Census Bureau for three different years (1974, 1978 and 1984) and controlling human capital and demographics, the authors estimate cross-section wage equations, and find that a worker's industry exerts a substantial impact on his wage. Our paper is motivated by this strand of research and additionally provides new evidence about the development of wage dispersion in low-wage employment when minimum wage reforms are established in the labor market.

Secondly, our paper relates to a large body of empirical literature which studies the potential drivers of wage inequality. A stream of the relevant research focuses on the inter-industry wage determinants of the wage dispersion that unveil unobserved characteristics which alleviate the estimation results from potential bias (see e.g., Krueger and Summers, 1988; Gibbons and Katz, 1992). In similar lines, an extensive discussion regarding the inter-industry wage differentials is provided by Thaler (1989), which highlights that large firms usually pay more than small firms, even when all labor quality measures are held constant. Further, Autor et al. (2016) study the effect of minimum wages on U.S. earnings inequality over the period between 1979-2012 and find that the minimum wage reduces inequality in the lower tail of the wage distribution. Sotomayor (2021) examines the impact of minimum wage reforms in Brazil, finding that annual increases in the minimum wage contributed to reductions in both poverty and inequality. Similarly, Lombardo et al. (2024) analyze six Latin American countries and identify varied effects of minimum wage policies, depending on the stage of the business cycle and the position of workers within the wage distribution. Filauro et al. (2025) explore whether minimum wage policies in EU countries help reduce income inequality. Their findings suggest that setting a hypothetical minimum wage at 60% of the median wage could lower income disparities both within and between EU member states. Finally, Fortin and Lemieux (1997) emphasize the role of institutional changes, including the value of minimum wage, the unionization rate and the economic deregulation in wage inequality. Along the same vein, Nolan and Valenzuela (2019), analyzing the forces driving the rising inequality in rich countries in recent decades, conclude that policy matters. Our paper builds on these insights and additionally introduces a novel disaggregated measure of wage inequality defined as the difference between the nominal wage and the occupation-mean wage per year. The proposed measure allows one to unveil the differences in wage dispersion within labor market occupations when official interventions are used in this market.

Thirdly, our paper also relates to a stream of research that has applied non-parametric techniques, namely quantile regression analysis to study inequality in the labor economics literature (Chamberlain, 1994; Buchinsky, 1994). Such techniques allow one to study relationships between variables outside of the mean of the data -i.e., the assumption that variables operate the same at the upper tails of the distribution as at the mean is relaxed- making it useful in understanding outcomes that are non-normally distributed and that have nonlinear relationships with predictor variables. Potentially different estimation values at different quantiles may be interpreted as differences in the dependent variable's responses (see an extensive discussion in Buchinsky, 1998). Our paper adds to this literature by carefully addressing, first, the issue of endogeneity by applying up-to-date appropriate estimators (such as difference-in-differences) and then, for robustness purposes, proceeds with the application of non-parametric analysis.

The section that follows presents the empirical model under estimation and how it unfolds, building on the important aforementioned contributions.

The Empirical Setup

The seminal work of Mincer (1958) describes a fundamental relationship between education and work experience with earnings. In its simplest form, the Mincerian equation is a semi-log form that displays how the worker's annual earnings can be explained from changes in the educational level, the work experience and a square term of work experience that captures the falling returns to on-the-job investments during one's working life (Rosen, 1992).[10]

Although the Mincerian equation has proven effective in cross-country analyses of earnings (see Rosen, 1992), it does not account for industry (occupation) effects and therefore cannot capture wage variation across industries (occupations) (Krueger and Summers, 1988).[11] Moreover, it assumes that the (unmeasured) productive ability[12] is time-invariant and equally rewarded within each industry (occupation) (Gibbons and Katz, 1992). To facilitate an occupation-based analysis[13] and mitigate omitted-variable bias[14], we employ the following extended specification:

$$logW_{ijt} = logW_0 + b_1 Educ_{ijt} + b_2 Exp_{ijt} + b_3 Exp_{ijt}^2 + a_j + u_{ijt} \quad (1)$$

where the dependent variable ($logW_{ijt}$) is the worker's annual earnings (gross wage in log), the constant term ($logW_0$) represents the gross wage of workers with no education background or job

[10] For detailed presentation of the Mincer equation, consult Rosen (1992).
[11] Krueger and Summers (1988) also assume that industry wage structure stays rather constant over time.
[12] The observable dimensions of human capital that are usually associated with higher wages are education and job experience. However, there are other factors, possibly explained by industry differences, that cannot be measured and affect both the productive ability and the wages.
[13] Since industry affiliation data is unavailable, we rely on occupation data, which is broader in scope, as a given occupation can span across multiple industries. Thus, the assumptions previously discussed are not violated.
[14] We assume that job-specific skills, either technical skills, known as hard skills, or soft skills that include interpersonal and communication skills, which enable workers to be successful at job, are attained either by attending training programs or through acquiring new knowledge on the job.

experience that does not vary over time[15], $Educ_{ijt}$ is the number of years of education with b_1 being the marginal rate of return on education, Exp_{ijt} refers to the number of working years to proxy work experience, the subscripts i, j, t denote individual, activity and year, respectively; α_j is a fixed effect for the activity affiliation and u_{ijt} refers to the remainder disturbance.

We build on the Mincerian relationship as shown in the previous equation and following insights offered by the studies of Krueger and Summers (1988) and Autor et al. (2016), we propose a demeaned version expressed below:

$$logW_{ijt} - \overline{logW_{jt}} = b_1\left(Educ_{ijt} - \overline{Educ_{jt}}\right) + b_2\left(Exp_{ijt} - \overline{Exp_{jt}}\right) + b_3\left(Exp_{ijt}^2 - \overline{Exp_{jt}^2}\right) + \left(u_{ijt} - \overline{u_{jt}}\right) \quad (2)$$

where the dependent variable is the difference between the nominal and occupation-mean wage, for those workers who are not paid the minimum wage, for occupation j and year t.

One advantage of the "within-occupation" wage dispersion measure is that it has time and occupation dimension and accounts for wage differentials among workers in the same occupation over the years. This allows one to also control for business cycles effects. The "within-occupation" wage dispersion could be in absolute terms either positive (nominal wage higher than occupation-mean wage; so-called high-waged workers) or negative (nominal wage lower than occupation-mean wage; so-called low-waged workers). Our analysis focuses on the negative values of our constructed measure, i.e., on the low-waged workers and how policy reforms affect the wage distribution withing this group.

To control for individual characteristics, we follow Krueger and Summers (1988), Gibbons and Katz (1992) and Buchinsky (1998), and assume that the difference between the disturbance term (u_{ijt}) and its mean value per activity and year $\left(\overline{u_{jt}}\right)$ can be substituted by a vector X of dummies capturing demographics (gender, marital status, age group) and other employment characteristics (sector, professional status) to control for potential omitted variable bias and a white noise v_{ijt}, and therefore equation (2) becomes:

$$logW_{ijt} - \overline{logW_{jt}} = b_1'\left(Educ_{ijt} - \overline{Educ_{jt}}\right) + b_2'\left(Exp_{ijt} - \overline{Exp_{jt}}\right) + b_3'\left(Exp_{ijt}^2 - \overline{Exp_{jt}^2}\right) + b_4'X_{ijt} + v_{ijt} \quad (3)$$

Equation (3) serves as the base model to proceed to the main research question of our paper, which is the impact of the minimum wage reforms on our new measure, the log dispersion of minimum wage from the occupation-mean wage per year - the dependent variable of equation (3). The section that follows unfolds a suitable estimation methodology appropriate for event studies such as policy reforms.

[15] Rosen (1992) argues that the constant term represents the equivalent annuitized income of initial human capital value. Without any loss of generality, this term could also be the official minimum wage, if any official changes in the minimum wage are infrequent.

2.3. Estimating the Effects of Minimum Wage Reforms

We apply a difference-in-differences estimation technique, which allows one to isolate the effect of a policy reform concerning the minimum wage. The basic idea of difference-in-differences (henceforth, DD) is a quasi-experimental design that makes use of panel data from treatment and control groups to obtain an appropriate counterfactual to estimate a causal effect. DD is typically used to estimate the effect of a specific treatment (policy reforms about minimum wage, in our case) by comparing the changes in outcomes (wage dispersion) over time between a population that is enrolled in a policy reform (the treatment group) and a population that is not (the control group).

Recent literature has addressed some new aspects of DD analyses by emphasizing on different key assumptions relaxed in the "canonical" DD model. As previously discussed, the traditional DD model puts emphasis on the average treatment effect on the treated group (the group exposed to the treatment) under the parallel-trends[16] and the no-anticipation[17] assumptions. However, we will not always be sure for the validity of the parallel-trends assumption for many reasons, among them concerns about time-varying confounding factors and potential sensitivity of the parallel trends to the outcome's functional form (Roth et al, 2023; Roth and Sant'Anna, 2023). In the current paper, we consider potential violations of parallel trends, assume conditional parallel trends[18] and strong overlapping condition[19], and use new estimators valid under these assumptions (regression adjustment, inverse probability weighting and doubly-robust estimators).

In our case, the treatment and control groups are the minimum wage workers and the rest of low wage workers paid the market wage, respectively. A challenge in our analysis is to determine the former group, which represents workers with institutional (minimum) wage. In Greece, the minimum wage is determined by the official minimum wage of a given year, as well as the age[20], the job experience and the marital status of the worker[21]. Hence, based on the individual characteristics of a specific respondent, we can compute the potential wage of a minimum wage worker with these characteristics. For instance, in 2013, a 30-year-old worker, married, with 5 years of work experience receiving an annual gross wage of 9,850€ as well as a 20-year-old worker, single, with less than 3 years of work experience receiving 7,150€ are both included in the minimum wage group.

To operationalize the effects of the reform(s), equation (3) is extended to include two-way fixed effects, i.e., individual fixed effects (a_i) and time fixed effects (φ_t), under parallel trends assumption

[16] This assumption states that the average outcome for both the treated and untreated groups would have evolved similarly, if the treatment effect had not occurred (Roth et al., 2023).
[17] To identify the causal effect of the treatment, we assume that the latter has no causal effect on the outcome before implementing it.
[18] The treatment is randomly assigned conditional on a set of covariates (Roth et al., 2023).
[19] This assumption says that the conditional probability to be in the treatment group (given observed control variables/characteristics) is lower than one and the proportion of treated units is above zero.
[20] The age factor helps us to divide the sub-minimum wage paid to very young workers (17-24) from the minimum wage paid to the rest of minimum-wage workers; this dividing is introduced in 2012 and is repealed in 2019 in Greece.
[21] Based on the National General Collective Agreement, all allowances in Greece are calculated by reference to the official minimum wage. All married workers receive 10% marriage allowance. Regarding the working experience allowance, for 0-3, 3-6, 6-9 and above 9 years of employment experience, workers do not receive any allowance, receive 10%, 20% and 30%, respectively.

and no anticipatory effects, to obtain consistent estimates of the policy intervention on wage dispersion. The following equation refers to the 2012 policy intervention:

$$WageDisp_{it} = a_i + \varphi_t + a_1' \mathbb{1}_{[t>2012]_t} * \mathbb{1}_{[treatment]_{it}} + c_1' Z_{it} * \mathbb{1}_{[treatment]_{it}} + v_{it} \tag{4}$$

where $WageDisp_{it}$ is the log dispersion of nominal wage from the occupation-mean wage per year, $\mathbb{1}_{[t>2012]_t}$ is an indicator taking the value 1 if the year is 2013 and 0 if the year is 2010 or 2011, $\mathbb{1}_{[treatment]_{it}}$ is an indicator that takes the value 1 when an individual is included in the treatment group (minimum wage workers) and 0 when an individual is included in the control group (low-wage worker who does not receive the minimum wage) and Z_{it} includes all covariates involved in eq. (3) that should be multiplied with the time indicator to augment the specification of the canonical DD with controls for time-by-covariate interaction for estimation under conditional parallel trends. Consequently, the coefficient a_1' captures the impact of the reform on the log wage dispersion from the occupation-mean wage per year of the treatment group.

In similar fashion, for the 2019 policy intervention, we estimate:

$$WageDisp_{it} = a_i + \varphi_t + a_1'' \mathbb{1}_{[t>2019]_t} * \mathbb{1}_{[treatment]_{it}} + c_1'' Z_{it} * \mathbb{1}_{[treatment]_{it}} + v_{it} \tag{5}$$

where $\mathbb{1}_{[t>2019]_t}$ is an indicator taking the value 1 if the year is 2020 and 0 if the year is 2017 or 2018.

In both specifications, we exclude the year of the reform implementation to account for potential non-anticipatory effects, as workers might self-select into the labor market or specific occupations in response to expected minimum wage changes. Additionally, we omit 2021 due to significant labor market disruptions, following the COVID-19 pandemic. To ensure consistency between the two reform cases (2012 and 2019), we retain only one year of post-reform data in each specification.

Following the relevant literature, we also apply quantile regression (QR) estimates, first introduced by Koenker and Bassett (1978), and established by Chamberlain (1994) and the influential work of Buchinsky (1994) in labor economics, to search for different impact of reforms in different quantiles of the wage dispersion distribution.

The Estimation technique

Under the basic assumptions of conditional parallel trends, no anticipation effects and strong overlapping conditions, the augmented specification (equations 4, 5) does not yield consistent estimates without adding homogeneity assumptions (Roth et al., 2023). Thus, we apply several semi-/non-parametric methods that give us consistent estimates of the average treatment effects on the treated group under weaker homogeneity assumptions. More specifically, we apply the following estimators: (1) regression adjustment (RA) proposed by Heckman et al. (1997) to remove interference, (2) inverse probability weighting (IPW) as shown by Abadie (2005), who use weights to equally distribute confounders across treated and untreated groups, and (3) augmented inverse probability weighting (AIPW) proposed by Sant'Anna & Zhao (2020) to increase efficiency, since IPW estimator is sensitive to propensity model misspecification for small estimated propensities (Kang and Schafer, 2007).

Data

In this section, we present the data analysis over the period 2010-2020 in the Greek labor market. We initially use survey (cross-sectional) data from the "Statistics on Income and Living Conditions" (SILC) to construct the dependent variable, i.e., the wage dispersion from the occupation-mean per year. To estimate equations (4) and (5), we aim at finding respondents who participate in the survey in the pre- and post-reform periods so as to produce a panel dataset appropriate for our analysis. Below, we offer an analytical discussion of both the cross-section and panel datasets.

A rich cross-section dataset

Our survey data are drawn from the SILC of the Hellenic Statistical Authority database. The survey is mostly conducted between May and September of each year, inter alia covers the income distribution and living conditions, and corresponds to 10,000-20,000 respondents per year. The empirical analysis is performed over the period between 2010 and 2013, a period around the year of the minimum wage cut, and over the period between 2017 and 2020, a period around the year of the minimum wage increase. The survey collects data on a wide range of labor characteristics, including employment, wage, professional status, activity and working experience, as well as education attendance and demographics such as the respondent's age and gender.

Following the standard OECD definition of the working age population, we drop from our dataset all individuals aged 65+ years old.[22] Thus, the final cross-section sample includes the working age population between 17 and 64 years old in the Greek labor market. Further, our focus is limited to full-time jobs for low-wage workers, ensuring comparability of annual wages. Table 1 below provides important information regarding the log annual wage dispersion of low-wage workers from the occupation-mean wage.

[Insert Table 1]

The whole cross-section sample of full-time low-wage workers includes 7,402 and 22,443 observations for the 2010-2013 and 2017-2020 periods, respectively. For the 2010-2013 (2017-2020) period, the log

[22] In our dataset, the employment rate of this group is less than 3%, including mainly pensioners.

wage dispersion ranges between -4.25 (-4.27) and -2.0*10-4 (-8.8*10-6) and its mean value is -0.48 (0.46). Table 1 also sheds some light on both demographical and employment level characteristics. As for the first group, it seems that females, on average, show a slightly higher mean value of wage dispersion, in absolute terms, in relation to males (-0.50 vs -0.46 for 2010-2013 and -0.49 vs -0.44 for 2017-2020). Married workers tend to have lower wage dispersion, in absolute terms, compared to single ones (-0.43 vs -0.59 for 2010-2013 and -0.40 vs -0.58 for 2017-2020); the 10% marriage allowance may partially explain part of this gap. Further, independently of time period, the wage dispersion, among different age groups, is quite higher, in absolute terms, for younger workers; this might be due to the 10% work experience allowance for every 3 years of the first 9 years in the job market. Regarding the educational attainment, it seems that higher level of education is equal to lower wage dispersion from the occupation-mean wage for both time periods.

We proceed to employment level characteristics of low-wage workers. Professional status is divided into employees and self-employees, with more than 97% for both periods considered being employees. Further, as for the job experience groups, i.e., entry (0-5 years), intermediate (6-15 years) and senior level (15+ years), we observe an inverse order of wage dispersion for both time periods of interest. Based on the International Standard Classification of Occupations (ISCO-08) with one digit, we end up in our database with 10 different occupations in which workers are involved. While the majority of the occupations report very similar wage dispersion, managers, primary sector workers and army forces, show extremely different values. The later three occupations represent less than 5% of the total number of sample workers.[23] Finally, the secondary and tertiary sector include more than 97% of the total number of observations in both periods showing a mean value of wage dispersion close to that of the whole sample.

We now look at the wage dispersion from the occupation-mean wage of minimum wage workers - the treatment group of the empirical analysis. Table 2 below replicates all subcategories of descriptive statistics of Table 1 and, in brief, shows that the mean values of the wage dispersion from the occupation-mean wage for minimum wage workers is almost double, in absolute terms, compared to the respective values of Table 1. Again, this holds for both the 2010-2013 and the 2017-2020 periods.

[Insert Table 2]

A longitudinal (panel) dataset

As discussed in the previous section, to obtain consistent estimates of the impact of minimum wage reforms on the wage dispersion, we need to use a panel dataset. To benefit from a rich cross-section dataset, presented in the previous sub-section, we constructed the outcome variable - in our case the wage dispersion from the occupation-mean wage per year - so as to be a good proxy of the population wage dispersion. Further, we keep those individuals who respond before (1 or 2 years) and after (1 year) the reform implementation.[24] Thus, we manually construct a balanced panel dataset including

[23] For robustness, we exclude all three low-involved occupations, and our empirical results remain quantitatively unchanged.
[24] We limit the analysis to a maximum of two years before and two years after the minimum wage reforms in 2012 and 2019, respectively, as each respondent is observed for no more than six semesters. As previously discussed, we omit 2021 due to significant labor market disruptions, following the COVID-19 pandemic. Retaining only one year of post-reform data in each specification also ensures analytical consistency between the two reforms.

the same individuals pre- and post-reform for each one of the two reforms. In Table 3 below, we display statistics for the wage dispersion between the two groups and the two sub-periods.

[Insert Table 3]

The newly constructed dataset includes 276 individuals over the period that the 2012 reform is imposed and 1,401 individuals over the period that the 2019 reform is applied. As Part A and Part B of Table 3 report, both minimum wage workers and the rest of low-wage workers do not show significant different average wage dispersion values (that of the former group lies between -0.81 and -0.84 and that of the latter group lies between -0.26 and -0.23). However, this table does not provide information as to whether the wage dispersion pre- and post- reforms changes for both groups. Thus, we display Figures 1 and 2 below, showing the wage dispersion pre- and post-2012 and 2019 reforms for both groups, respectively.

[Insert Figures 1,2]

Some initial findings from Figure 1 are that, for both groups, the median value (the horizontal line in the box) of wage dispersion does not change when the 2012 reform is implemented, and similarly the distributions of wage dispersion pre- and post-reform for both groups do not change significantly. Further, Figure 2 shows that following the 2019 reform, both the median value and the distribution of wage dispersion of the control group (the rest of low-wage workers) remain unaltered pre- and post-reform. However, the treatment group shows significant changes both in the median value and the distribution of wage dispersion.

In the following section, we examine the extent to which the wage dispersion of minimum wage workers changes in relation to the dispersion of the rest of low-wage workers when two opposing wage reforms take place in Greece.

Empirical results

This section examines the effects of two opposite wage reforms: (1) the minimum wage cut reform for the 2010-2013 period, and (2) the minimum wage increase reform for the 2017-2020 period.

A minimum wage cut reform: 2010-2013 period

Table 4 below reports estimates of equation (4) of the effect of minimum wage cut on the wage dispersion when the 2012 reform was implemented. Column (1) displays TWFE-OLS estimates under the basic assumptions of conditional parallel trends, no anticipation effects and strong overlapping conditions. In columns (2) to (4), we relax the homogeneity assumption and thus, present the regression adjustment (RA) proposed by Heckman et al. (1997), the inverse probability weighting (IPW) as shown by Abadie (2005) and the augmented inverse probability weighting (AIPW) proposed by Sant'Anna & Zhao (2020) estimators, respectively. In all specifications, the dependent variable is the absolute value of wage dispersion from the occupation-mean wage per year in logs, i.e., the difference between the log wage and its yearly log occupation-mean value. Further, in all cases, the average treatment effect on the treated group is estimated, individual- and time-fixed effects are considered and the time-by-covariate interaction under conditional parallel trends is included; covariates are dummies of gender, marital status, age group, sector and education, experience and experience square as deviation from the occupation-mean per year. For brevity reasons, the coefficients of covariates (c_1') are not directly reported in Table 4 but are presented in the Appendix (Table A1).[25]

[Insert Table 4]

As presented in Figure 1, the median value of the wage dispersion of both the treatment and the control groups does not change significantly when the minimum wage reform is implemented in 2012. Based on the empirical findings of Table 4, it is obvious that the average treatment effect from the policy intervention on the treated group (minimum wage workers) is not significant. In other words, the 2012 reform does not differently impact the wage dispersion from the yearly occupation-mean in the treated group compared to the control group, which remains unaffected by the intervention.

In the Eurozone, nominal hourly wages remained unaltered in the post-financial crisis period (Schmitt-Grohe and Uribe, 2013). The presence of a fixed-exchange rate and a downward nominal wage rigidity prevent labor market clearing and increase involuntary unemployment. Greece, however, did not follow this pattern. The decreasing value of both the nominal hourly wage in the post-2010 period[26] and the collective bargaining coverage rate,[27] that is positively related to a downward wage rigidity as discussed in Babecký et al. (2010), shape a framework without downward nominal wage rigidity. Therefore, it is straightforward that the minimum wage cut in 2012 triggered a similar cut in wages of

[25] For robustness and consistency, we repeat our analysis using two years following the reform imposition, that is we include the year 2014; our empirical results remain unaltered.
[26] From 2010 to 2012, the nominal hourly wages drop by more than 10%. See the Figure 1 in Schmitt-Grohe and Uribe (2013).
[27] From 2010 to 2012, it drops from 100% to almost 50%.

the rest of low-wage workers, leaving unchanged the wage inequality in the lower tail of the wage distribution in the Greek labor market. As for the estimated coefficients c_1' from eq. (4), they are reported in column 1 of Table A1 in the Appendix showing an insignificant impact on the wage dispersion.

A minimum wage increase reform: 2017-2020 period

In similar fashion as in Table 4, Table 5 below presents estimates of equation (5) of the effect of minimum wage increase on the wage dispersion from the occupation-mean per year, when the 2019 reform was implemented in the Greek labor market. All assumptions and specifications are identically equal to those in Table 5.

[Insert Table 5]

As presented in Figure 2, both the median value and the distribution of wage dispersion of the treatment group show an apparent change when the 2019 reform was implemented; on the contrary, there is no change in those of the control group. Empirical results clearly show that the effect of the minimum wage reform on the log dispersion of the minimum wage from the occupation-mean wage per year is significant at 1% in all specifications (the coefficient of our interest is c_1'').[28] An average minimum wage increase of 12% in 2019 leads to an equal decrease in wage dispersion of the treated group.

To understand this significant outcome, we should place this policy intervention effect within the national legislative and policy framework of the Greek labor market over the period 2017-2020. Labor market rigidities may shape the effectiveness of policy interventions on wage inequality, especially on the lower segment of the wage distribution. Low wage workers are characterized by low or even no labor mobility and their wages are sticky upwards but not downwards (see e.g., Chen, 2018). Hence, given that (i) the collective bargaining coverage rate in Greece in 2018 is less than 20%, (ii) minimum wages can shape aggregate wage dynamics (see e.g., Gautier et al., 2023), and (iii) our group of interest shows sticky upward wages (see e.g., Chen, 2018), we observe a clear effect of the minimum wage reform on the wage dispersion of the treatment group. In other words, the market does not follow the increase in minimum wages and keeps unaltered low wages, leading to an evident wage inequality decrease in the lower segment of the wage distribution.

In line with Fortin and Lemieux (1997), a minimum wage change may have employment implications. Thus, to control for such potential employment effects, we exclude from our sample all those workers who change their employment status and thus keep only those workers who continue to work. Perhaps, a part of the initial effect presented in Table 5 may be explained by an employment effect, which in many cases is rather elusive (see e.g., Manning, 2021). These results are presented in Table 6 below.

[28] Table 5 shows that there are not significant changes in all specifications. This finding may arise from the fact that there are no heterogeneous treatment effects depending on covariates; as a result, the average treatment effect on the treated group is not biased in linear case (see e.g., Roth et al., 2023).

[Insert Table 6]

Table 6 suggests that for all specifications, results are similar to those presented in Table 5; on average, we find that the average treatment effect on the treated group is 0.02 lower than that displayed in Table 5, which shows that the potential employment effects on wage dispersion must be 0.02.

Robustness analysis

To cement our results, we perform a number of robustness checks. Firstly, we investigate the differential changes of the minimum wage increase at distinct points of the log wage dispersion distribution.

[Insert Table 7]

The distribution of wage dispersion is chi-squared. Following the influential works of Chamberlain (1994) and Buchinsky (1994), we use quantile regression (QR) estimates to explore the varying impact of the 2019 reform across different quantiles in the wage dispersion distribution. The empirical findings clearly show that the effect of the reform implementation at the lower tail of the wage dispersion distribution of the treatment group is rather small or even insignificant; however, when we focus on the higher quantiles (75th or 90th) this effect is getting much higher. This finding is rather associated with the fact that at the higher level of wage dispersion distribution the allowances are also high and therefore the inequality between minimum wage workers and the rest of the low wage workers is further reduced.

Secondly, in Table 8 we replicate all empirical results of Table 6 by using, for the sake of simplicity, only the AIPW estimator (column 4), while performing a number of robustness checks. In particular, (i) we perform the analysis, following Autor et al. (2016), by using median values instead of mean values to construct an occupation-median wage value; (ii) we use the mean value of annual wages per occupation including minimum wage workers; (iii) we exclude from the analysis the three occupations with extremely low representation (i.e., managers, primary sector workers and army forces); (iv) we exclude extreme values from our dataset, that is all wages of more than 100,000€; and finally, (v) we replicate the analysis following the OECD definition of low-wage workers, which are those workers who receive less than two-thirds of the national median wage.

[Insert Table 8]

As Table 8 shows results remain nearly unaltered.

Finally, following the discussion of Roth et al. (2023) and Ryan (2018), we test our model in pre-treatment period. Specifically, we use low-wage workers, including minimum wage workers, using 2017 as a pre-treatment year and 2018 as a post-treatment year. Applying the doubly-robust estimator, we obtain an insignificant result which reduces potential bias from unobserved confounders (see e.g., Ryan, 2018).[29]

Conclusion

The last decades have witnessed increased income inequality in almost all developed economies. This paper focuses on wage dispersion among workers, which is a contributor to income inequality. More specifically, the paper poses a question of great policy relevance: have wage reforms been effective in achieving desirable equality gains, particularly among the most vulnerable ones, which are at the lowest wage ladder - an unaddressed topic in the labor economics literature. The paper aims to equip policymakers with a solid understanding of the effects of minimum wage reforms on the wage inequality at the bottom segment of the labor market.

To unfold important insights, we propose a new "within-occupation" measure of wage dispersion from the occupation-mean wage by considering both the wage differentials across occupations and potential changes over the years. To properly discuss identification and alleviate causality issues, we apply modern difference-in-differences methodology, controlling meanwhile for other potential drivers of wage inequality namely technological change, globalization among others using a set of appropriate fixed effects.

Greece has been an interesting case study, as the country has been severely hit by both the 2007 global financial crisis and the Greek debt crisis, in early 2010, forcing the country to undergo a series of bailouts and a number of severe austerity measures and reforms imposed by the Troika. Among them, we focus our attention on two labor market reforms: the 2012 minimum wage reduction and the 2019 minimum wage increase. These two reverse events offer an excellent testable ground of our methodology.

Based on a rich dataset from the Greek labor market over the periods 2010-2013 and 2017-2020, we find two key results: first, under the absence of downward wage rigidity in 2012, the minimum wage cut had no impact on wage inequality; and, second, with the existence of upward wage rigidity in 2019, the minimum wage increase led to wage equality gains.

Overall, despite the painful austerity measures, the record-high unemployment levels and the unprecedented drop in Greek GDP growth, our results document an overall equality gain as the implementation of minimum wage reforms have been overall beneficial in reducing inequality amongst Greece's low wage workers.

An important question for future research arises: do different levels of wage rigidity among sectors/activities/occupations create differential effects of labor market policy interventions on wage inequality.

[29] For brevity reasons, results are not displayed and are available upon request.

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Table 1: Descriptive statistics of the log wage dispersion (all groups of low-wage workers)

Variables	Obs.		Mean		Std. Dev.		Min		Max	
	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020
Whole sample	7,402	22,443	-0.48	-0.46	0.46	0.45	-4.25	-4.27	$-2*10^{-4}$	$-88*10^{-7}$
Gender										
Male	3,984	11,847	-0.46	-0.44	0.47	0.44	-4.01	-4.27	$-2*10^{-4}$	$-88*10^{-7}$
Female	3,418	10,596	-0.50	-0.49	0.45	0.46	-4.25	-4.13	$-3*10^{-4}$	$-21*10^{-5}$
Marital status										
Single	2,491	7,383	-0.59	-0.58	0.51	0.51	-4.25	-4.27	$-9*10^{-4}$	$-11*10^{-4}$
Married	4,433	13,352	-0.43	-0.40	0.42	0.41	-3.67	-4.13	$-2*10^{-4}$	$-88*10^{-7}$
Other	478	1,708	-0.44	-0.43	0.44	0.43	-3.99	-3.99	$-3*10^{-4}$	$-88*10^{-5}$
Age groups										
17-24	306	864	-0.86	-0.89	0.58	0.69	-3.49	-4.27	-0.05	$-33*10^{-4}$
25-29	1,017	2,219	-0.64	-0.67	0.54	0.49	-4.25	-3.81	$-41*10^{-4}$	$-11*10^{-4}$
30-44	3,715	9,930	-0.47	-0.45	0.43	0.41	-3.66	-4.13	$-2*10^{-4}$	$-21*10^{-5}$
45-64	2,364	9,430	-0.40	-0.40	0.43	0.43	-3.99	-4.12	$-3*10^{-4}$	$-88*10^{-7}$
Educational level										
No school	24	82	-0.63	-0.65	0.41	0.55	-1.85	-2.60	$-15*10^{-4}$	-0.05
Primary	775	1,848	-0.54	-0.59	0.49	0.51	-3.66	-3.60	$-7*10^{-4}$	$-88*10^{-7}$
Secondary	4,241	12,771	-0.49	-0.48	0.45	0.46	-3.52	-4.26	$-3*10^{-4}$	$-21*10^{-5}$
Tertiary	2,362	7,742	-0.45	-0.40	0.46	0.41	-4.25	-4.13	$-2*10^{-4}$	$-21*10^{-5}$
Professional status										
Employees	7,203	22,202	-0.46	-0.46	0.43	0.44	-4.25	-4.27	$-2*10^{-4}$	$-88*10^{-7}$
Self-employees	199	241	-1.12	-1.07	0.82	0.73	-3.47	-3.61	$-54*10^{-4}$	-0.01
Job experience (years)										
Entry level (0-5)	1,267	3,628	-0.71	-0.74	0.57	0.57	-4.25	-4.27	$-41*10^{-4}$	$-33*10^{-4}$
Intermediate level (6-15)	2,809	6,985	-0.48	-0.46	0.42	0.41	-3.30	-4.13	$-4*10^{-4}$	$-88*10^{-5}$
Senior level (15+)	3,326	11,830	-0.39	-0.38	0.40	0.40	-3.99	-4.12	$-2*10^{-4}$	$-88*10^{-7}$

Activity										
Managers	148	530	-0.74	-0.44	0.62	0.44	-3.47	-3.54	$-61*10^{-4}$	$-69*10^{-4}$
Professionals	1,091	3,855	-0.44	-0.36	0.45	0.36	-4.25	-3.51	$-9*10^{-4}$	$-21*10^{-5}$
Technicians	811	2,000	-0.46	-0.43	0.45	0.42	-4.16	-3.81	$-4*10^{-4}$	$-41*10^{-5}$
Clerical support workers	1,314	3,683	-0.43	-0.45	0.42	0.46	-3.14	-4.02	$-3*10^{-4}$	$-10*10^{-4}$
Service and sales workers	1,456	5,671	-0.50	-0.54	0.44	0.47	-4.01	-3.99	$-2*10^{-4}$	$-13*10^{-4}$
Primary sector workers	112	280	-1.06	-0.83	0.80	0.59	-3.34	-2.86	-0.02	$-11*10^{-4}$
Craft workers	919	1,907	-0.49	-0.45	0.42	0.45	-3.03	-4.12	$-19*10^{-4}$	$-65*10^{-5}$
Plant and machine operators	622	1,779	-0.42	-0.42	0.39	0.44	-3.22	-4.27	$-12*10^{-4}$	$-88*10^{-7}$
Elementary occupations	790	2,381	-0.54	-0.56	0.49	0.50	-3.99	-3.54	$-4*10^{-4}$	$-45*10^{-5}$
Army forces	139	357	-0.24	-0.18	0.20	0.14	-1.55	-1.57	$-10*10^{-4}$	$-36*10^{-4}$
Sector										
Primary	184	593	-0.92	-0.70	0.76	0.54	-3.66	-2.86	$-63*10^{-4}$	$-89*10^{-5}$
Secondary	1,519	3,352	-0.48	-0.42	0.43	0.42	-4.16	-4.12	$-9*10^{-4}$	$-21*10^{-5}$
Tertiary	5,69	18,498	-0.47	-0.46	0.45	0.45	-4.25	-4.27	$-2*10^{-4}$	$-88*10^{-7}$

Notes: The variable of interest is the dependent variable of eqs. (4)-(5), i.e., the log wage dispersion. The data reported in this table refer to full-time low-wage workers, i.e., those with a negative log wage dispersion.

Table 2: Descriptive statistics of the log wage dispersion (minimum wage workers)

Variables	Obs.		Mean		Std. Dev.		Min		Max	
	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020
Whole sample	2,209	7,340	-0.92	-0.91	0.57	0.52	-4.25	-4.27	-0.20	-0.21
Gender										
Male	1,104	3,559	-0.95	-0.91	0.60	0.52	-4.01	-4.27	-0.20	-0.21
Female	1,105	3,781	-0.89	-0.91	0.55	0.51	-4.25	-4.13	-0.22	-0.21
Marital status										
Single	711	2,481	-1.10	-1.07	0.64	0.57	-4.25	-4.27	-0.30	-0.28
Married	1,343	4,310	-0.83	-0.81	0.51	0.46	-3.66	-4.13	-0.20	-0.21
Other	155	549	-0.87	-0.88	0.54	0.48	-3.99	-3.99	-0.33	-0.29
Age groups										
17-24	133	379	-1.27	-1.45	0.60	0.68	-3.49	-4.27	-0.55	-0.44
25-29	331	848	-1.10	-1.10	0.68	0.51	-4.25	-3.81	-0.33	-0.34
30-44	1,069	3,155	-0.88	-0.85	0.53	0.46	-3.66	-4.13	-0.20	-0.21
45-64	676	2,958	-0.83	-0.85	0.53	0.49	-3.99	-4.12	-0.22	-0.21
Educational level										
No school	18	54	-0.75	-0.85	0.40	0.59	-1.85	-2.60	-0.23	-0.29
Primary	398	1,101	-0.83	-0.86	0.52	0.49	-3.66	-3.61	-0.22	-0.23
Secondary	1,447	4,779	-0.88	-0.89	0.53	0.51	-3.52	-4.27	-0.20	-0.21
Tertiary	346	1,406	-1.18	-1.03	0.73	0.56	-4.25	-4.13	-0.30	-0.22
Professional status										
Employees	2,075	7,165	-0.88	-0.90	0.54	0.51	-4.25	-4.27	-0.20	-0.21
Self-employees	134	175	-1.49	-1.33	0.75	0.67	-3.47	-3.61	-0.35	-0.29
Job experience (years)										
Entry level (0-5)	417	1,354	-1.26	-1.27	0.68	0.60	-4.25	-4.27	-0.42	-0.41
Intermediate level (6-15)	892	2,416	-0.85	-0.85	0.51	0.46	-3.30	-4.13	-0.22	-0.21
Senior level (15+)	900	3,570	-0.83	-0.81	0.52	0.46	-3.99	-4.12	-0.20	-0.21

Activity										
Managers	18	46	-2.06	-1.54	0.68	0.60	-3.47	-3.54	-1.27	-0.89
Professionals	95	386	-1.49	-1.15	0.74	0.56	-4.25	-3.50	-0.65	-0.54
Technicians	97	299	-1.31	-1.17	0.72	0.58	-4.16	-3.81	-0.57	-0.53
Clerical support workers	286	1,026	-0.99	-1.00	0.54	0.51	-3.14	-4.02	-0.43	-0.41
Service and sales workers	622	2,781	-0.82	-0.86	0.50	0.47	-4.01	-3.99	-0.29	-0.26
Primary sector workers	90	217	-1.27	-1.02	0.76	0.54	-3.34	-2.86	-0.20	-0.27
Craft workers	393	626	-0.81	-0.88	0.45	0.54	-3.03	-4.12	-0.33	-0.34
Plant and machine operators	133	514	-0.95	-0.89	0.50	0.53	-3.02	-4.27	-0.47	-0.35
Elementary occupations	473	1,445	-0.79	-0.81	0.50	0.49	-3.99	-3.54	-0.22	-0.21
Army forces	2	-	-1.45	-	0.13	-	-1.55	-	-1.36	-
Sector										
Primary	137	415	-1.15	-0.91	0.74	0.51	-3.66	-2.86	-0.20	-0.24
Secondary	523	998	-0.85	-0.85	0.48	0.53	-4.16	-4.13	-0.25	-0.21
Tertiary	1,549	5,927	-0.93	-0.92	0.58	0.52	-4.25	-4.27	-0.22	-0.21

Notes: The variable of interest is the dependent variable of eqs. (4)-(5), i.e., the log wage dispersion of full-time minimum wage workers.

Table 3: Descriptive statistics of the panel dataset

Part A – Minimum wage workers

Variables	Obs.		Mean		Std. Dev.		Min		Max	
	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020
Whole sample	116	754	-0.81	-0.84	0.54	0.40	-4.25	-3.10	-0.29	-0.25

Part B – Low-wage workers (not institutionally paid)

Variables	Obs.		Mean		Std. Dev.		Min		Max	
	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020	2010-2013	2017-2020
Whole sample	436	2,048	-0.26	-0.23	0.17	0.6	-0.80	-0.98	-0.00	-0.00

Figures

Figure 1: The change in wage dispersion within groups (reform 2012)

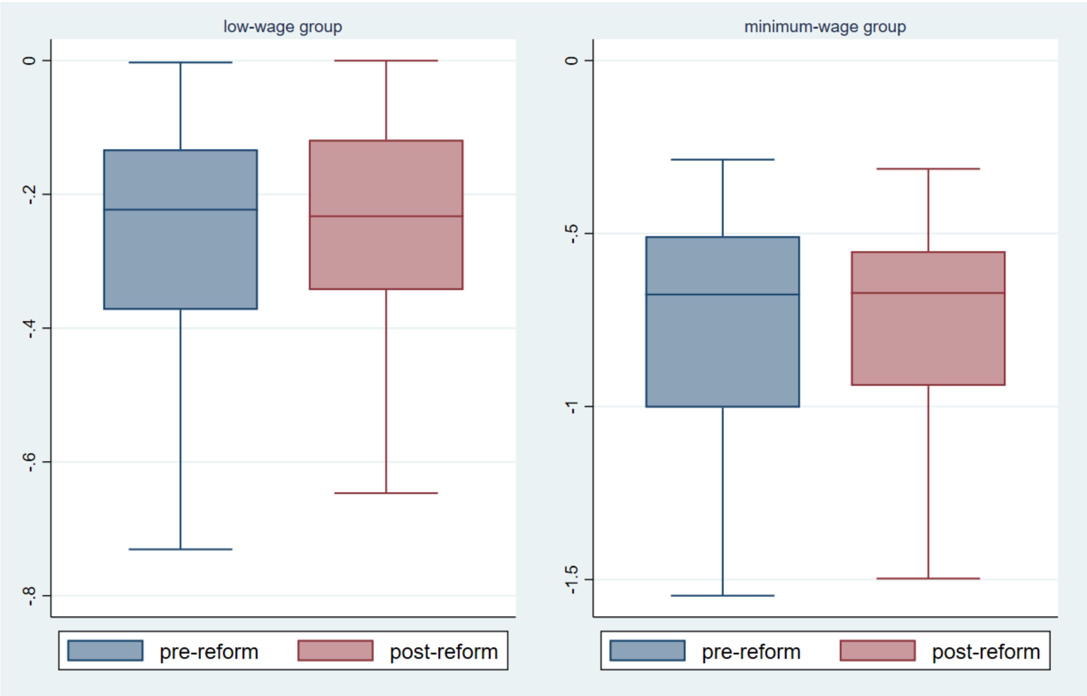

Figure 2: The change in wage dispersion within groups (reform 2019)

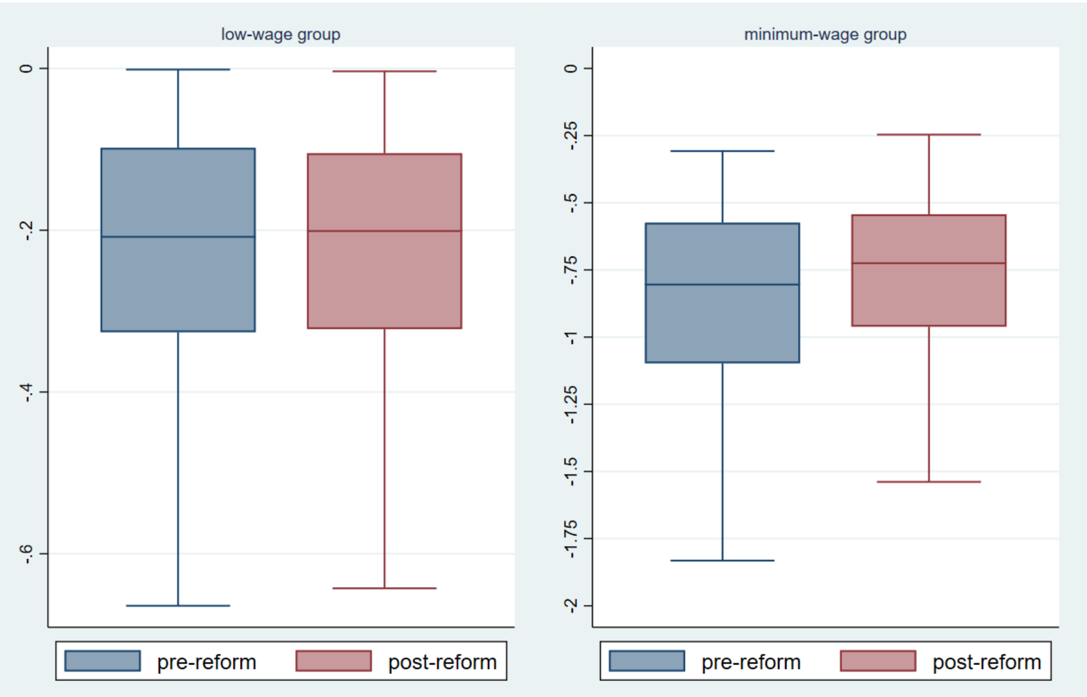

Table 4: The average treatment effect on the treated group (reform 2012)

	OLS	RA	IRW	AIPW
	(1)	(2)	(3)	(4)
Treatment effect (a_1')	-0.05 (0.08)	-0.03 (0.07)	-0.03 (0.07)	-0.03 (0.07)
Observations	552	276	276	552
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Individual	Individual	Individual	Individual
Time effects	Year	Year	Year	Year
Within R-sq	0.04	-	-	-

Notes: The dependent variable is the absolute value of the wage dispersion from the occupation-mean wage in logs. The treatment group refers to minimum wage workers, while the control group includes the rest of low-wage workers. Column (1) presents the Two-Way-Fixed-Effects (TWFE) OLS estimates under the basic assumptions of conditional parallel trends, no anticipation effects and strong overlapping conditions. Column (2) to (4) further assume weaker homogeneity assumption and present regression adjustment (RA) proposed by Heckman et al. (1997), inverse probability weighting (IPW) as shown by Abadie (2005) and the augmented inverse probability weighting (AIPW) proposed by Sant'Anna & Zhao (2020) estimators, respectively. In all cases, the average treatment effect on the treated group is estimated by applying individual- and time-fixed effects, and by using time-by-covariate interaction under conditional parallel trends; several covariates are included in the model among them dummies of gender, marital status, age group, sector and education, experience and experience square as deviation from the occupation-mean per year. (*), (**), (***) are significance levels at 10%, 5% and 1%, respectively and standard errors are reported in parenthesis.

Table 5: The average treatment effect on the treated group (reform 2019)

	OLS	RA	IRW	AIPW
	(1)	(2)	(3)	(4)
Treatment effect (a_1'')	-0.12*** (0.02)	-0.12*** (0.02)	-0.12*** (0.02)	-0.11*** (0.02)
Observations	2,802	1,401	1,401	2,802
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Individual	Individual	Individual	Individual
Time effects	Year	Year	Year	Year
Within R-sq	0.08	-	-	-

Notes: The dependent variable is the absolute value of the wage dispersion from the occupation-mean wage in logs. The treatment group refers to minimum wage workers, while the control group includes the rest of low-wage workers. Column (1) presents the Two-Way-Fixed-Effects (TWFE) OLS estimates under the basic assumptions of conditional parallel trends, no anticipation effects and strong overlapping conditions. Column (2) to (4) further assume weaker homogeneity assumption and present regression adjustment (RA) proposed by Heckman et al. (1997), inverse probability weighting (IPW) as shown by Abadie (2005) and the augmented inverse probability weighting (AIPW) proposed by Sant'Anna & Zhao (2020) estimators, respectively. In all cases, the average treatment effect on the treated group is estimated by applying individual- and time-fixed effects, and by using time-by-covariate interaction under conditional parallel trends; several covariates are included in the model among them dummies of gender, marital status, age group, sector and education, experience and experience square as deviation from the occupation-mean per year. (*), (**), (***) are significance levels at 10%, 5% and 1%, respectively and standard errors are reported in parenthesis.

Table 6: The average treatment effect on the treated group – unchanged job status (reform 2019)

	OLS	RA	IRW	AIPW
	(1)	(2)	(3)	(4)
Treatment effect (a_1'')	-0.09*** (0.02)	-0.10*** (0.02)	-0.10*** (0.02)	-0.09*** (0.02)
Observations	2,598	1,299	1,299	2,598
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Individual	Individual	Individual	Individual
Time effects	Year	Year	Year	Year
Within R-sq	0.11	-	-	-

Notes: The dependent variable is the absolute value of the wage dispersion from the occupation-mean wage in logs. The empirical results include only those respondents who do not change his/her job status pre- and post-reform. The treatment group refers to minimum wage workers, while the control group includes the rest of low-wage workers. Column (1) presents the Two-Way-Fixed-Effects (TWFE) OLS estimates under the basic assumptions of conditional parallel trends, no anticipation effects and strong overlapping conditions. Column (2) to (4) further assume weaker homogeneity assumption and present regression adjustment (RA) proposed by Heckman et al. (1997), inverse probability weighting (IPW) as shown by Abadie (2005) and the augmented inverse probability weighting (AIPW) proposed by Sant'Anna & Zhao (2020) estimators, respectively. In all cases, the average treatment effect on the treated group is estimated by applying individual- and time-fixed effects, and by using time-by-covariate interaction under conditional parallel trends; several covariates are included in the model among them dummies of gender, marital status, age group, sector and education, experience and experience square as deviation from the occupation-mean per year. (*), (**), (***) are significance levels at 10%, 5% and 1%, respectively and standard errors are reported in parenthesis.

Table 7: The average treatment effect on the treated group – unchanged job status (reform 2019)

	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
	(1)	(2)	(3)	(4)	(5)
Treatment effect	-0.02* (0.01)	0.00 (0.01)	0.03** (0.01)	-0.09* (0.04)	-0.23* (0.14)
Observations	2,598	2,598	2,598	2,598	2,598
Control variables	Yes	Yes	Yes	Yes	Yes
Fixed effects	Individual	Individual	Individual	Individual	Individual
Time effects	Year	Year	Year	Year	Year
Within R-sq	0.02	0.04	0.05	0.05	0.06
Adjusted R-sq	0.67	0.53	0.67	0.74	0.61

Notes: The dependent variable is the absolute value of the wage dispersion from the occupation-mean wage in logs. The empirical results include only those respondents who do not change his/her job status pre- and post-reform. The treatment group refers to minimum wage workers, while the control group includes the rest of low-wage workers. In all cases, the estimation of eq. (5), at different points of the log wage dispersion distribution, is conducted by using TWFE-OLS estimates under the basic assumptions of conditional parallel trends, no anticipation effects and strong overlapping conditions. The average treatment effect on the treated group is estimated by applying individual- and time-fixed effects, and by using time-by-covariate interaction under conditional parallel trends; several covariates are included in the model among them dummies of gender, marital status, age group, sector and education, experience and experience square as deviation from the occupation-mean per year. (*), (**), (***) are significance levels at 10%, 5% and 1%, respectively and standard errors are reported in parenthesis.

Table 8: The average treatment effect on the treated group – unchanged job status (reform 2019)

	Median	Minimum wage	excluding low-involved	excluding extreme values	OECD
	(1)	(2)	(3)	(4)	(5)
Treatment effect (a_1'')	-0.08*** (0.02)	-0.08*** (0.02)	-0.09*** (0.02)	-0.09*** (0.02)	-0.19*** (0.01)
Observations	2,032	1,880	2,422	2,562	518
Control variables	Yes	Yes	Yes	Yes	Yes
Fixed effects	Individual	Individual	Individual	Individual	Individual
Time effects	Year	Year	Year	Year	Year

Notes: In each column, the dependent variable is defined differently. In column (1), the wage dispersion from the occupation-median wage in logs is considered. In column (2), minimum wage is included in the calculation of the occupation-mean per year. Column (3) excludes low-involved occupations from the dataset, while column (4) excludes extreme values (nominal wages higher than 100,000). In column (5), OECD definition for low-wages is taken into account (nominal wages lower than two-thirds of the national median wage). The empirical results include only those respondents who do not change his/her job status pre- and post-reform. The treatment group refers to minimum wage workers, while the control group includes the rest of low-wage workers. In all cases, we apply the augmented inverse probability weighting (AIPW) proposed by Sant'Anna & Zhao (2020) estimator. The average treatment effect on the treated group is estimated by applying individual- and time-fixed effects, and by using time-by-covariate interaction under conditional parallel trends; several covariates are included in the model among them dummies of gender, marital status, age group, sector and education, experience and experience square as deviation from the occupation-mean per year. (*), (**), (***) are significance levels at 10%, 5% and 1%, respectively and standard errors are reported in parenthesis.

Appendix

Table A1: The average treatment effect on the treated group (all covariates)

	2012	2019
	(1)	(2)
Treatment effect (a_1')	-0.05	-0.11***
Post*Experience dispersion	0.19	0.09
Post*Experience dispersion (squared)	-0.03	-0.02
Post*Education dispersion	-0.02	-0.01
Post*Gender	0.01	0.02
Post*Age group	-0.01	0.04***
Post*Marital status	0.04	-0.01
Post*Sector	-0.01	0.01
Observations	552	2,802
Control variables	Yes	Yes
Fixed effects	Individual	Individual
Time effects	Year	Year
Within R-sq	0.04	0.08

Notes: The dependent variable is the absolute value of the wage dispersion from the occupation-mean wage in logs. The treatment group refers to minimum wage workers, while the control group includes the rest of low-wage workers. In both columns Two-Way-Fixed-Effects (TWFE) OLS estimates under the basic assumptions of conditional parallel trends, no anticipation effects and strong overlapping conditions are presented. In all cases, the average treatment effect on the treated group is estimated by applying individual- and time-fixed effects, and by using time-by-covariate interaction (*Post*) under conditional parallel trends; several covariates are included in the model among them dummies of gender, marital status, age group, sector and education, experience and experience square as deviation from the occupation-mean per year. Column (1) refers to the 2012 period and column (2) displays the estimation results of 2019 reform. (*), (**), (***) are significance levels at 10%, 5% and 1%, respectively and standard errors are reported in parenthesis.