PRE The Philippine Review of Economics
Vol. LI No. 2, December 2014 pp. 97-120

The effects of a minimum wage on employment outcomes: an application of regression discontinuity design

Kristine Laura S. Canales

In this paper, I ask whether a minimum wage increase results in adverse employment outcomes in terms of work hours and the probability of gaining or retaining employment. Regression discontinuity design (RDD) is employed on a household-level panel survey dataset, using the minimum wage as the forcing variable that determines whether a sample is assigned to either the treatment group (minimum wage worker) or the control group (above minimum wage worker). The RDD graphs and the regressions seem to point to a negative effect of a higher minimum wage on work hours, not only for workers earning the minimum wage but also for workers earning 50 percent more than the minimum wage. The probability of gaining/retaining employment is lower for minimum wage workers and for workers earning 50 percent above the minimum wage.

JEL Classification: J31
Keywords: minimum wage, regression discontinuity design, employment

1. Introduction

The debate over the possible adverse employment effects of a higher minimum wage has simmered for several decades now. More recently since the Great Recession, the debate has gained new traction in U.S., where "The New Minimum Wage Research" (see, e.g., the surveys by Neumark and Wascher [2007] and Schmitt [2013]) has fed into the larger issue of growing inequality and of whether a higher minimum wage might hasten the recovery by stimulating consumer demand. In the Philippines, meanwhile, it has been a long-standing and influential opinion that the country's minimum wage laws have been a barrier to higher industrial employment (see, e.g., Sicat [2010] and Nye [2011]).

Different models and various statistical/econometric techniques have been employed to answer the question. Some studies point to net gains in employment

(Card [1992a, 1992b]; Katz and Krueger [1992]; Card and Krueger [1994]; Fiscal Policy Institute [2004]), while most studies point to net losses following legislated increases in the wage floor (Gilroy and Kohen [1982]; Neumark and Wascher [1992, 1994, 1996a, 1996b]; Sabia [2006]; Bazen and Le Gallo [2006]; Zavodny [2000]; Couch and Wittenburg [2001]). Other studies also point to increased earnings after an increase in the minimum wage (Freeman [1996]; Bazen and Martin [1991]). Recent studies in developing countries find mostly net losses in employment. Sugiyarto and Endriga [2008] study the effect of minimum wages on labor market outcomes in neighboring Indonesia. The authors use unique firm-level data to study how minimum wages affect skilled and unskilled workers at different types of firms. However, they use average wages as proxy for minimum wages, their assumption being that the minimum wage is binding and that variation in minimum wages strongly drives the variation in average wages. They conclude that minimum wages adversely affect hiring. In particular, a doubling of the minimum wage reduces employment of unskilled workers by two percent.

This paper studies the labor market in the Philippine. A recent study by Lanzona [2014] also found evidence that minimum wages decrease the probability of employment of workers with relatively low levels of education. Lanzona employed a fixed effects approach using panel data on firms and workers extracted from Annual Survey of Philippine Business and Industry and Labor Force Survey. With this dataset, Lanzona is able to conclude that labor-intensive firms are the ones hardest hit by the minimum wage. This finding suggests that relatively more skilled workers who earn more than the minimum wage can also be adversely affected because minimum wage increases make labor costs higher in general. This conjecture is also investigated in this paper.

A possible limitation of previous approaches is that a typical regression of employment outcomes on wage variables can produce inconsistent estimates when the source of the variation in wages is not known, especially when there are insufficient controls for observable or unobservable characteristics. The wage that an individual receives is related to his characteristics, and the prevailing wage can affect the decision of whether or not to work and how much to work. Even the use of fixed effects on panel data might not solve the problem, since there may be time-varying factors that affect labor market outcomes. To avoid confounding the effect of minimum wage increases with the effect of other factors, this paper focuses on examining how an increase in the legislated minimum wage affects labor market outcomes of workers with identical characteristics. A finding of negative effects serves to reinforce the findings of recent studies on developing countries.

This study is a contribution to the larger literature mentioned above. Specifically, however, it utilizes the relatively novel procedure of regression discontinuity design (RDD) to answer the following questions: (a) After a minimum wage increase, is there a significant difference in the hours of work between those earning the minimum wage (the treatment group) and those earning above the minimum wage (the control group)? (b) Is there a change in the probability of gaining/retaining employment for the treatment group compared with the control group?

In the process, the usefulness of the RDD approach—applied to these issues for the first time in the Philippines—is illustrated and assessed.

2. The quasi-experimental framework

2.1. The rationale for quasi-experimental techniques

The welfare effects of a minimum wage increase would be best analysed if one could track workers from a point in time sufficiently before the increase to another point sufficiently after. Ideally, a panel dataset might be prepared that randomized the assignment of samples to either a control group (say, those earning above the minimum wage) or a treatment group (say, those earning the minimum wage). This would be done before the experiment itself, and before evaluation, so that the sample is equally likely as the rest of the population to be assigned to one or the other group.

With observation data such as that available from official statistical agencies, however, a random assignment of samples is not possible, since the information will have been collected without regard for the objectives of the experiment. To use observation data and treat it as if it had the characteristics of experimental data, quasi-experimental evaluation techniques may be employed. Since there can be no random assignment in using quasi-experimental techniques, bias due to selection is possible. The best that can be claimed is that a sample in the control group has similar, or almost similar, observed characteristics as another sample in the treatment group. How randomness in the assignment of samples may be introduced into the analysis depends on both the nature of the inquiry and the structure of the data.

In some cases, a random variable may be found that either assigns enrolment to the treatment or assigns promotion (if the former is not available). A comparison of outcomes in the two groups would give the estimated effect of the treatment.

In other cases, however, there is no way to assign either enrolment or promotion to the treatment. Such is the case in this study. The target sample of this study is wage and salary workers and assignment to control or treatment groups depends on whether a worker is earning the minimum wage or not. Earning a minimum wage cannot be assigned to a worker by enrolment or promotion, but the minimum wage itself introduces randomness by assigning samples into either the control or the treatment group by being an eligibility criterion into the treatment. This use of a cutoff value/score is the main feature of regression discontinuity design. Given the framework of the RDD approach, its internal validity is comparable to the ideal setting where the dataset used is the result of a randomized experiment. This is afforded by the randomization due to the use of the minimum wage as an eligibility criterion. Unlike an instrumental variables approach, RDD does not require the minimum wage to be highly correlated with the outcome variable (i.e., hours of work or probability of gaining/retaining employment). Unlike fixed effects models, RDD also does not require unmeasured individual characteristics that were assumed fixed to not change over time.

2.2. The regression discontinuity design

RDD is one of several quasi-experimental approaches that have been used to evaluate the impact of various programs.[1] Introduced in 1960 by Thistlewaite and Campbell, it was originally used to study the impact of students' receiving a National Merit Award on their success in obtaining additional college scholarships, where receipt of the award is conditioned on obtaining a minimum score on a scholarship examination. Since then the method has been widely applied in the social sciences. The defining feature of RDD is its use of an eligibility criterion (the cutoff value or score) to introduce randomness to observation data and treat it to some extent as if it had come from a purely randomized experiment. The cutoff value assigns each observation unit to whether or not it has received treatment from the intervention or program.

Since the assignment criterion is known, the reason for the systematic differences in the outcome between the control group and the treatment group is also known. These systematic differences may be due to certain factors or characteristics of persons that enable them to meet the cutoff value. However, observation units immediately around the cutoff value are likely to have the same characteristics in the limit (or to have been affected by the same factors). The identifying assumption is that expected outcomes would have been smooth through the cutoff in the absence of treatment. Measuring the difference in outcomes between these two groups of almost identical units, therefore, will give the local average treatment effect of the intervention or program.

In this paper, the local average treatment effect being measured is that of a minimum wage increase between two periods. The basic RDD is a two-group pretest-posttest model of the following form:

$$y_i = \beta_0 + \beta_1 \tilde{X}_i + \beta_2 T_i + \beta_{3.} \tilde{X}_i T_i + e_i$$

where

y_i the posttest or outcome value/score for the *i*th unit

$\tilde{X}_i$ the transformed pretest value, such that $\tilde{X}_i = X_i - X_c$, where is the cutoff value

[1] Besides RDD, other quasi-experimental techniques that have recently been applied include randomized promotion, propensity score matching, difference-in-difference, and instrumental variables.

T_i	the dummy variable for the treatment which is equal to 1 for the treatment group and 0 for the control group
$\beta_0, \beta_1, \beta_2, \beta_3$	the parameters (to be estimated)
e_i	the error term

Imbens and Wooldridge [2009] and Imbens and Lemieux [2008] frame RDD in the context of causal effects and treatment effects using the Rubin Causal Model set up with potential outcomes. In its basic setting, the primary interest lies in the causal effect of a binary intervention or treatment. The effect of the treatment is potentially heterogeneous across the units that are divided into two groups that were either exposed or not exposed to the treatment. The objective is to compare the potential outcomes for a unit denoted as *i*. Let $Y_i(0)$ denote the outcome without exposure to the treatment, and $Y_i(1)$ be the outcome with exposure to the treatment. Hence, a comparison of the outcomes for unit is equivalent to the difference $Y_i(1) - Y_i(0)$.

The fundamental problem of causal inference is that one never observes the pair and together (Holland [1986]). Therefore the typical focus is on average effects of the treatment, that is, averages of $Y_i(1) - Y_i(0)$ over (sub)populations, rather than on unit-level effects. Let $T_i \in \{0, 1\}$ denote the treatment received, with $T_i = 0$ if unit was not exposed to the treatment, and $T_i = 1$ otherwise. The outcome observed can then be written as

$$Y_i = (1 - T_i) \cdot Y_i(0) + T_i \cdot Y_i(1) = \begin{cases} Y_i(0) \text{ if } T_i = 0, \\ Y_i(1) \text{ if } T_i = 1. \end{cases}$$

In addition to the assignment T_i and the outcome Y_i, we may observe a vector of covariates or pretreatment variables denoted by (X_i, Z_i), where X_i is a scalar and Z_i is an M-vector.

The basic idea behind RDD is that assignment to the treatment is determined, either completely or partly, by the value of a predictor (the covariate X_i) being on either side of a fixed threshold. This predictor may itself be associated with the potential outcomes, but this association is assumed to be smooth, and so any discontinuity of the conditional distribution of the outcome as a function of this covariate at the cutoff value is interpreted as evidence of a causal effect of the treatment. (Imbens and Lemieux [2008;616]).

RDD has two general settings: the sharp and the fuzzy regression discontinuity designs. In the sharp regression discontinuity design, the assignment T_i is a deterministic function of X_i such that

$$T_i = 1 \{X_i \geq c\}$$

where c is the cutoff value/fixed threshold.

In the sharp regression discontinuity design we look at the discontinuity in the conditional expectation of the outcome given the covariate to uncover an average causal effect of the treatment:

$$\lim_{a\downarrow c} \mathrm{E}[Y_i \mid X_i = a] - \lim_{a\uparrow c} \mathrm{E}[Y_i \mid X_i = a],$$

which is interpreted as the average causal effect of the treatment at the discontinuity point

$$\tau_{SRD} = \mathrm{E}[Y_i(1) - Y_i(0) \mid X_i = c]$$

which can also be expressed as

$$\tau_{SRD} = \lim_{a\downarrow c} \mathrm{E}[Y_i \mid X_i = a] - \lim_{a\uparrow c} \mathrm{E}[Y_i \mid X_i = a].$$

In the fuzzy regression discontinuity design, the probability of receiving the treatment does not have to change abruptly from 0 to 1. It allows for smaller jumps in the probability of assignment to the treatment at the threshold such that

$$\lim_{a\downarrow c} \Pr(T_i = 1 \mid X_i = a) \neq \lim_{a\uparrow c} \Pr(T_i = 1 \mid X_i = a).$$

In this design, the ratio of the jump in the regression of the outcome on the covariate to the jump in the regression of the treatment indicator on the covariate is interpreted as an average causal effect of the treatment.

$$\tau_{SRD} = (\lim_{a\downarrow c} \mathrm{E}[Y \mid X = a] - \lim_{a\uparrow c} \mathrm{E}[Y \mid X = a]) \,/\, (\lim_{a\downarrow c} \mathrm{E}[T \mid X = a] - \lim_{a\uparrow c} \mathrm{E}[T \mid X = a])$$

3. Methodology used

In evaluating the impact of an increase in the minimum wage on a worker's ability to gain/retain employment and hours of work, we focus only on wage-and-salary workers in their primary occupation. Basic daily pay will be used as the covariate X_i, while the minimum wage in the pre-intervention period will serve as the cutoff value also called the treatment-forcing variable [Imbens and Lemieux 2008]. This introduces randomness to the observation data, enabling the researcher to use the dataset as if it were a result of a purely randomized experiment.

In most regions in the Philippines, the recorded basic minimum wage is not a point estimate but an interval. In regions where it is stated as an interval, the higher value is taken as the cutoff, c. As used here, the basic minimum wage does not include allowances (e.g., cost of living allowances).

The assignment T_i is equal to one if the worker is within the interval of basic minimum wage coverage. It is equal to zero if the worker earns above the cutoff, c.

$$T_i = \begin{cases} 1 \text{ if } X_i \leq c, \\ 0 \text{ if } X_i > c. \end{cases}$$

This study will first look at the effect of a minimum wage increase on hours of work using sharp regression discontinuity design. The local average treatment effect is the difference in expected hours of work between minimum wage workers and above minimum wage workers, conditional on wage being equal to the cutoff c,

$$\tau_{ours} = \mathrm{E}[Y_i(1) - Y_i(0) \mid X_i = c]$$

where c is the high estimate of the basic minimum wage in a region.

In RDD graphs, the values of the covariate on the horizontal axis are called "bins". However, the bins require the covariate to be centered on the regional minimum wage. Running the regression on the centered covariate ensures that the coefficient on the treatment dummy is the treatment effect [Barry 2011]. This entails taking the difference between the basic pay per day and the regional minimum wage for each worker. This results in having a transformed covariate, $\tilde{X}_i$. Since minimum wages differ among regions, the cutoff varies among regions as well. For graphing purposes, the share of $\tilde{X}_i$ to the highest estimate of the regional minimum wage is computed. This is the bin used to define the covariate on the horizontal axis of the graph. Defining the bin in this way ensures uniformity of the cutoff across regions.

The outcome, y_i, of the workers in both treatment and control groups is graphed around the cutoff. Visual inspection of the graph enables the researcher to see if there is a discontinuity in the outcomes between the treatment group and the control group.

Regressions are run to test for the significance of the discontinuity, using two methods: ordinary least squares with polynomials and local linear regression. In ordinary least squares with polynomials, the treatment assignment of the worker is tested along with the polynomial transform of the transformed covariate and its interaction with the treatment assignment. This allows for checking whether there are nonlinearities present in the data. On the other hand, local linear regression is run by performing ordinary least squares (i.e., without the polynomial transforms) restricted on a specified bin interval. In both methods, the discontinuity is significant if the treatment assignment is significant.

Estimation of the probability of gaining/retaining employment after an increase is also of interest. With respect to a minimum wage increase, wage-salary workers are classified into four types: (a) employed before, employed after;

(b) unemployed before, employed after; (c) employed before, unemployed after; and finally (4) unemployed before, unemployed after. For the purposes of this paper, type 4 is the least interesting.

Using RDD with binary outcomes, the effect of a minimum wage increase on the probability of employment will then be explored using fuzzy regression discontinuity design. The local average treatment effect here is the difference in probabilities of employment weighted by the differences in the probabilities of treatment between the treatment and control groups.

$$\tau_{emp} = (\lim_{a \downarrow c} \mathrm{E}[Y \mid X = a] - \lim_{a \uparrow c} \mathrm{E}[Y \mid X = a]) \,/\, (\lim_{a \downarrow c} \mathrm{E}[T \mid X = a] - \lim_{a \uparrow c} \mathrm{E}[T \mid X = a])$$

Fuzzy regression discontinuity design involves instrumental variables estimation. The treatment assignment is instrumented by the worker's years of education and age, which approximate years of work experience. Similar to the estimation for change in hours worked, the polynomial transform of the transformed covariate and its interaction with the treatment assignment are tested for significance along with the treatment assignment of the worker. In addition, local linear regression is also performed.

3.1. Empirical models of the study

The first model to estimate is of the form:

$$y_i = \alpha + \tau T_i + \sum_{j=1}^{4} \beta_j \tilde{X}_i^j + \sum_{k=1}^{4} \beta_k \tilde{X}_i^k \cdot T_i + e_i$$

where

y_i	change in hours of work from pre-increase to post-increase period of worker *i* (that is, $y_i = hours_{i,2008} - hours_{i,2007}$)
T_i	assignment of worker (i.e., exposure to treatment or no exposure);
$\tilde{X}_i^j$	transformed pretest value (basic pay per day - cutoff value) for the ith worker on the *j*th polynomial order, $j = 1,...,4$
$\tilde{X}_i^k \cdot T_i$	interaction term between the transformed basic pay per day and assignment of worker *i* on the kth polynomial order, $k = 1,...,4$
e_i	error term
$\alpha, \tau, \beta_j, \beta_k$	the parameters

For the probability of gaining/retaining employment, the estimation proceeds in two stages since treatment assignment is instrumented. The second model to estimate is of the form:

$$Emp_i = \alpha + \tau T_i + \sum_{j=1}^{4} \beta_j \tilde{X}_i^j + \sum_{k=1}^{4} \beta_k \tilde{X}_i^k \cdot T_i + \mu_i$$

where

$$T_i = \delta + \theta_1 educ_i + \theta_2 age_i + \varepsilon_i$$

Emp_i	Employment status of worker *i*; equal to 1 if worker gains/retains employment after the minimum wage increase and 0 if the worker loses employment after the increase
T_i	assignment of worker (i.e., exposure to treatment or no exposure);
$\tilde{X}_i^j$	transformed pretest value (basic pay per day - cutoff value) for the ith worker on the *j*th polynomial order, $j = 1,...,4$
$\tilde{X}_i^k \cdot T_i$	interaction term between the transformed basic pay per day and assignment of worker *i* on the kth polynomial order, k = 1,...,4
$educ_i$	years of education of worker *i*
age_i	age of worker *i* (to approximate years of work experience)
μ_i, ε_i	error terms
$\delta, \tau, \beta_j, \beta_k, \theta_1, \theta_2$	the parameters

3.2. Empirical procedure in estimation

Observations on the employment outcomes of interest are graphed on either side of the cutoff value to see whether there is discontinuity between the treatment group and the control group. The graphs show whether the discontinuity is significant at the 1 percent level of significance. To check further and to estimate the effect of the treatment, regressions are executed.

The first model requires running ordinary least squares with polynomials. Different polynomial functions are fitted on both sides of the cutoff value including interactions between the treatment dummy and the transformed regressor, $\tilde{X}$. Common practice points to the use of the fourth order polynomial, which may be due to the quartic function being the highest order of polynomial that can be solved by radicals. Through inclusion of the polynomial transform, unknown nonlinearities in the function may be detected in the regression result.

The results of ordinary least squares (OLS) regression with polynomials are supplemented with local linear regression. Local linear regression fits a linear regression line through the observations in a specific neighborhood of the dataset. The estimator from local linear regression is free of bias if the true model were linear. Relative to a kernel estimator, this estimator performs better at the boundaries and has smaller mean squared error at all data points. In this method, a linear regression is performed within some bandwidth of the cutoff. Bands of 20 percent-30 percent before and after the cutoff are tested. Optimal bandwidth selection is an open question [Berry 2011].

The second model entails an estimation of a fuzzy regression discontinuity, which is implemented through instrumental variables estimation. Since both the employment dummy and the treatment dummy are binary variables, calculation requires running a probit model with endogenous binary regressor. In Stata, this is the *treatreg* command. Local linear regression is also performed in *treatreg*. Finally, specificity of the *treatreg* equations tested is assessed through the expectation-prediction classification table.

3.3. The data

A panel dataset is utilized by merging two years, 2007 and 2008, of the July run of the Philippine Labor Force Survey through the respondent line number, which enables aligning characteristics of an individual in the two time periods considered. The choice of using these editions of the Labor Force Survey is primarily due to their availability and the seemingly optimal timing in the implementation of the minimum wage increase, which occurred roughly halfway between July 2007 and 2008.

Data on the level of regional minimum wages came from National Wages and Productivity Commission. Table 1 presents the minimum wage rates for every region in the pre- and post-increase periods.

The control group is defined as workers earning *more than 100 percent* of the highest estimate of the regional minimum wage rate. The treatment group is defined as workers earning *less than or equal to 100 percent* of the highest regional minimum wage rate.

TABLE 1. Regional minimum wage rates (basic pay) in the pre- and post-increase periods

Region	Minimum wage rate (basic pay per day)			
	Pre-increase minimum wage rates		Post-increase minimum wage rates	
	Low	High	Low	High
NCR	288	300	325	362
CAR	219	225	229	235
I	205	225	210	230
II	187	195	192	200
III	197	243.5	227	278
IV-A	218	287	224	300
IV-B	209	230	225	237
V	189	220	183	226
VI	199	222	215	235
VII	200	241	205	250
VIII	220	220	220	220
IX	215	215	215	215
X	203	218	203	218
XI	222	224	222	224
XII	213.5	213.5	213.5	213.5
ARMM	190	190	200	200
XIII	202	202	202	202

Source: National Wages and Productivity Commission

4. Empirical results

4.1. Descriptive analysis

The analysis uses only consistently matched workers aged 15 years and above. The share of employed persons in the working-age population grew from 60.51 percent in 2007 to 61.46 percent in 2008. In 2007, unemployed persons were 4.11 percent of the working-age population while 35.38 percent were not in the labor force. For 2008, the corresponding figures were 3.73 percent unemployed and 34.81 percent not in the labor force.

Of the employed in 2007, 5,317 were wage and salary workers, which include those in private establishments and government/government corporation. This number increased to 5,751 in 2008. As a share to total employed persons, wage-salary workers comprise 42.19 percent in 2007 and 43.10 percent in 2008, respectively.

Wage and salary workers in non-agricultural businesses made up 76.0 percent of the total in both years. Minimum wage workers comprised roughly 8 percent of all wage and salary workers and roughly 10-11 percent of non-agriculture wage and salary workers. Mean basic pay per minimum wage class is given in Table 2. Non-agriculture wage and salary workers, on average, earn higher than the broader class of wage and salary workers.

A tabulation of the workers by employment status in the two periods considered is provided in Table 3. Approximately 70-72 percent of wage and salary workers have retained employment after the minimum wage increase in 2007. Around 17-18 percent gained employment after the increase while 12 percent lost employment. Further data on the unemployed is not included in the regular Philippine Labor Force Survey.

TABLE 2. Mean basic pay per day, by minimum wage class (in Pesos)

	All wage and salary workers Minimum wage class		Non-agriculture wage and salary workers	
	2007	2008	2007	2008
Below minimum wage	124.33	142.44	138.13	157.72
Within minimum wage	237.42	267.83	238.83	269.63
Above minimum wage	462.70	471.07	465.07	477.32
Overall mean	275.82	282.80	323.69	330.94
Median	200.00	220.00	250.00	265.00

TABLE 3. Employment status before and after the minimum wage increase

	All	Non-agriculture
Employed before, employed after	3,888 (70.54%)	3,020 (71.61%)
Unemployed before, employed after	984 (17.85%)	702 (16.65%)
Employed before, unemployed after	640 (11.61%)	495 (11.74%)
Unemployed before, unemployed after	0	0
Total	5,512	4,217

4.2. RDD results

The range of basic pay per day of workers covered by the Labor Force Survey is quite large. For the purposes of this study, the control group includes workers earning at most twice the regional minimum wage.

4.2.1. Effects on hours of work

To see the difference in hours worked during the past week between the pre-increase period and the post-increase period, change in hours of work is explored. A graph is supplied to see whether the treatment (minimum wage) has a significant impact on the hours worked of the employees.

The bins are defined as the percentage share of the basic pay per day on the highest estimate of the regional minimum wage. Hence, the highest estimate of the regional minimum wage is set at 100 percent. The ceiling for the basic pay per day of the control group, which is twice the highest estimate of the minimum wage, is set at 200 percent. The variable on the vertical axis is the change in hours of work between the pre-increase and the post-increase periods.

In the RDD graphs that follow, the local averages per bin of the change in weekly hours worked are presented for the minimum wage workers (blue dots) and for the above minimum wage workers (red dots). Figure 1 below shows the change in hours worked. Panel A presents the RDD graph for all wage-salary workers while panel B for non-agricultural wage-salary workers only. It can be seen that although there is a discontinuity at the cutoff point, at 100 percent, the 99 percent confidence intervals of the treatment group and control group can be observed to be overlapping. Hence, there seems to be no significant difference in the hours worked between the two groups after the minimum wage increase in the year 2007.

An examination of Figure 1, however, reveals that there might be a possibility of a more defined discontinuity at bin 150 percent. At this point, workers earn 50 percent higher than the highest paid minimum wage worker in the region. In Figure 2, the possibility of a discontinuity at bin 150 percent is entertained.

It can be observed from Figure 2 that the discontinuity at bin 150 percent is indeed significant with 99 percent confidence. The narrower 99 percent confidence interval before the discontinuity suggests smaller variance among observations. Those earning 50 percent higher than the cutoff point appear to have experienced the minimum wage workers' change in hours worked after the minimum wage increase. In essence, these workers share a more similar pattern in hours worked with the treatment group than with the control group. One may point to the distribution of the observations as the reason for why these workers appear to be more similar to the treatment group.

To test the significance of the discontinuity and to estimate the effect of the treatment, two methods are performed: ordinary least squares (OLS) with polynomials and local linear regression. Table 4 presents the results of the OLS with polynomials. Since there is hardly any difference in the outcomes of non-agricultural wage-salary workers from all wage-salary workers, regressions will be performed on the latter only. The basic OLS results are included for comparison.

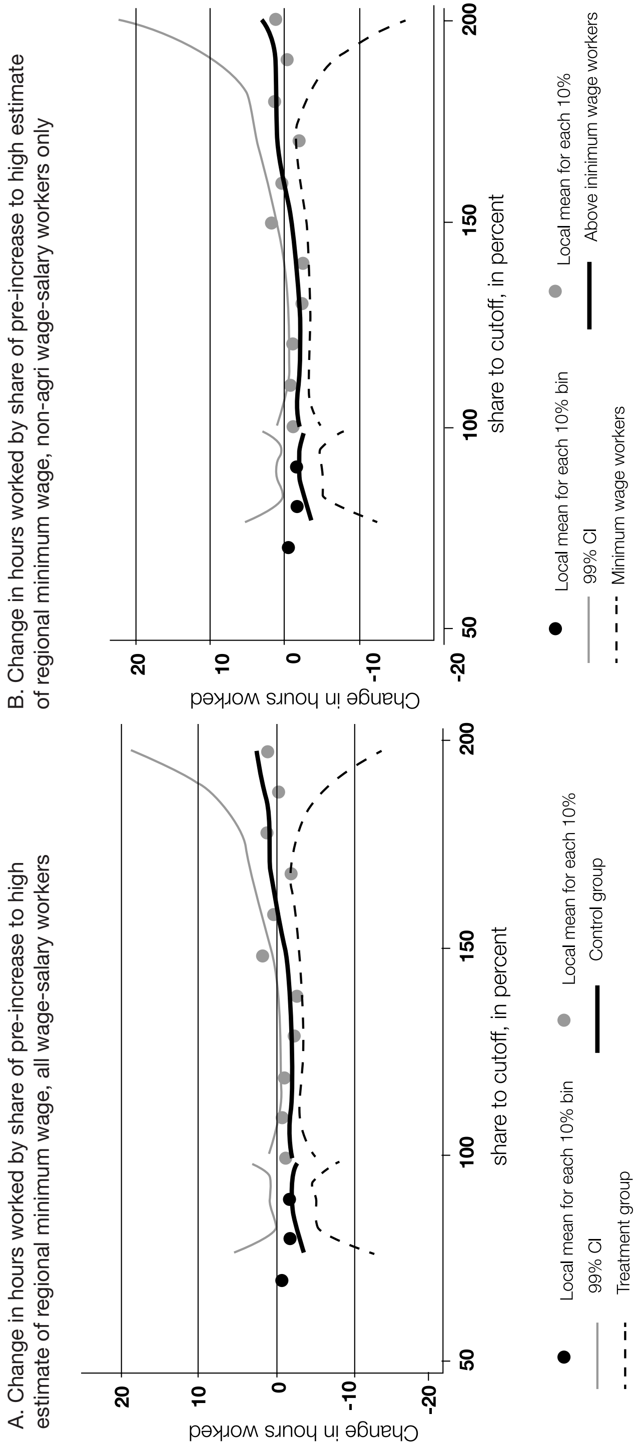

FIGURE 1. RDD graph of change in hours worked by pre-increase basic pay

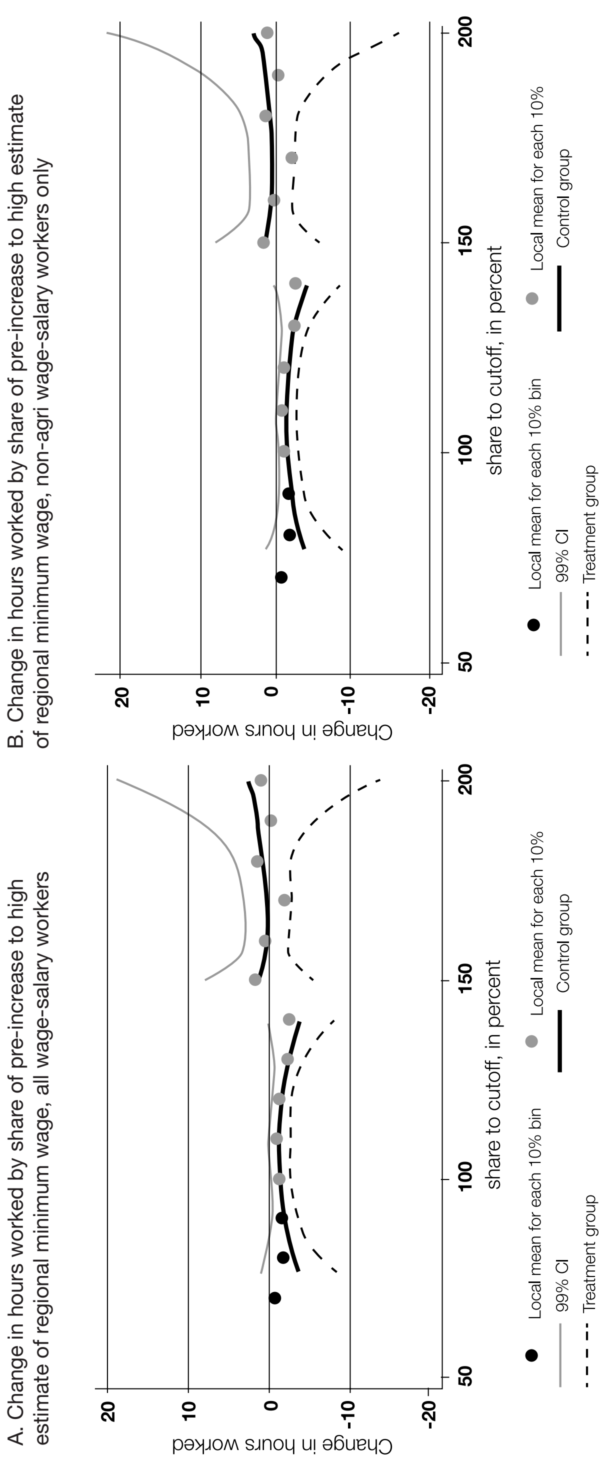

FIGURE 2. RDD graph of change in hours worked by pre-increase basic pay, discontinuity at bin=150%

TABLE 4. Ordinary least squares results

Dependent variable: Change in hours worked

	Cutoff at bin 100%		Cutoff at bin 150%	
Variable	OLS	OLS with polynomials	OLS	OLS with polynomials
Treatment	0.25632156	0.90718651	-2.6054741***	2.1715973
Basic pay per day - Cutoff (Centered basic pay)	.00437022*	-0.02625291	-0.00537223	-0.00382059
Treatment x Centered basic pay	-0.00372362	0.34865186	0.00207457	.27393081**
Centered basic pay^2		.0003902*		0.00006379
Centered basic pay^3		-1.388e-06*		-3.94E-07
Centered basic pay^4		1.434e-09*		6.07E-10
Treatment x Centered basic pay^2		0.02171303		.00460937*
Treatment x Centered basic pay^3		0.00054879		0.0000305
Treatment x Centered basic pay^4		4.53E-06		6.52E-08
Constant	-1.3700002***	-1.0818643	0.79079371	0.31585668
Adjusted R-squared	0.0003	0.0002	0.005	0.0057
F-stat	1.19	1.04	4.2	2.22
Prob>F	0.3106	0.4022	0.0057	0.0182
Root MSE	11.485	11.486	11.462	11.458
Observations	1914	1914	1914	1914

Legend: * p < .1; ** p < .05; *** p < .01

At bin 100 percent, there appears to be no treatment effect. Nonlinearity seems to be plausible for Figure 1 considering the result of the OLS with polynomials. Meanwhile, the OLS results for the cutoff at bin 150 percent supports the discontinuity shown in Figure 2. The OLS result points to a highly significant negative effect of the treatment on the hours of work of the treatment group, defined here as minimum wage workers and workers earning 50 percent more than the highest regional minimum wage. On average, the treatment group appears to have decreased their weekly hours of work by 2.6 hours. The result of OLS with polynomials suggests nonlinearity in the effects of the treatment.

Local linear regression is estimated within a selected bandwidth in both sides of the cutoff. In Table 5, regressions are run for bins 80 percent-120 percent where the cutoff is 100 percent and bins 120-180 percent for cutoff at bin 150 percent.

The results shown in Table 5 support the results of the OLS with polynomials. There seems to be no treatment effect at cutoff bin 100 percent. On the other hand, the effect of the treatment at cutoff bin 150 percent is a reduction of 2.76 hours in a week. The result is significant at a 5 percent level of significance.

TABLE 5. Local linear regression results

Dependent variable: Change in hours worked

	Cutoff at bin 100%	Cutoff at bin 150%
Treatment	0.11101289	-2.757342**
Basic pay per day - Cutoff (Centered basic pay)	-0.00393083	-0.00771012
Constant	-1.3134293*	0.45035315
R-squared	0.0002	0.0073
F-stat	0.13	3.29
Prob>F	0.8801	0.0376
Root MSE	12.584	12.079
Observations	1173	900

Legend: * p < .1; ** p < .05; *** p < .01

4.2.2. Effects on the probability of gaining/retaining employment

We classify workers into two types: (1) those employed after the increase; and (2) those unemployed after the increase. In the RDD graphs that follow, the local averages per bin of the probability of type 1 are presented for minimum wage workers (bins to the left of and including "share to cutoff"=100) and for above minimum wage workers (bins to the right of "share to cutoff"=100).

Reverting to the classification provided in Table 3, Type 1 comprises the following classes; (a) employed before, employed after; and (b) unemployed before, employed after. In Table 3, Type 2 is defined as workers in class (c) employed before, unemployed after.

Figure 3 shows the RDD graphs for (A) all wage-salary workers and (B) for non-agriculture wage-salary workers only. The outcome with respect to the discontinuity at bin 100 percent appears to be similar to the case of change in weekly hours worked. There seems to be no significant difference between minimum wage workers and above minimum wage workers.

Figure 4 shows the RDD graph where the cutoff is at bin 150 percent. The discontinuity that can be observed is significant considering the 99 percent confidence interval of the two groups considered.

The average treatment effect is estimated using a probit model with a dichotomous endogenous regressor. Table 6 presents the results of *treatreg* and *treatreg* with polynomials for two cutoff points, bin 100 percent and 150 percent. In both cutoff points, the treatment seems to have a negative treatment effect. Being a minimum wage worker decreases the probability of being employed by roughly 22 percent after the minimum wage increase. If workers earning at most 50 percent higher than the minimum wage are included in the treatment group, the disemployment effect of the increase is lower at 8-13 percent.

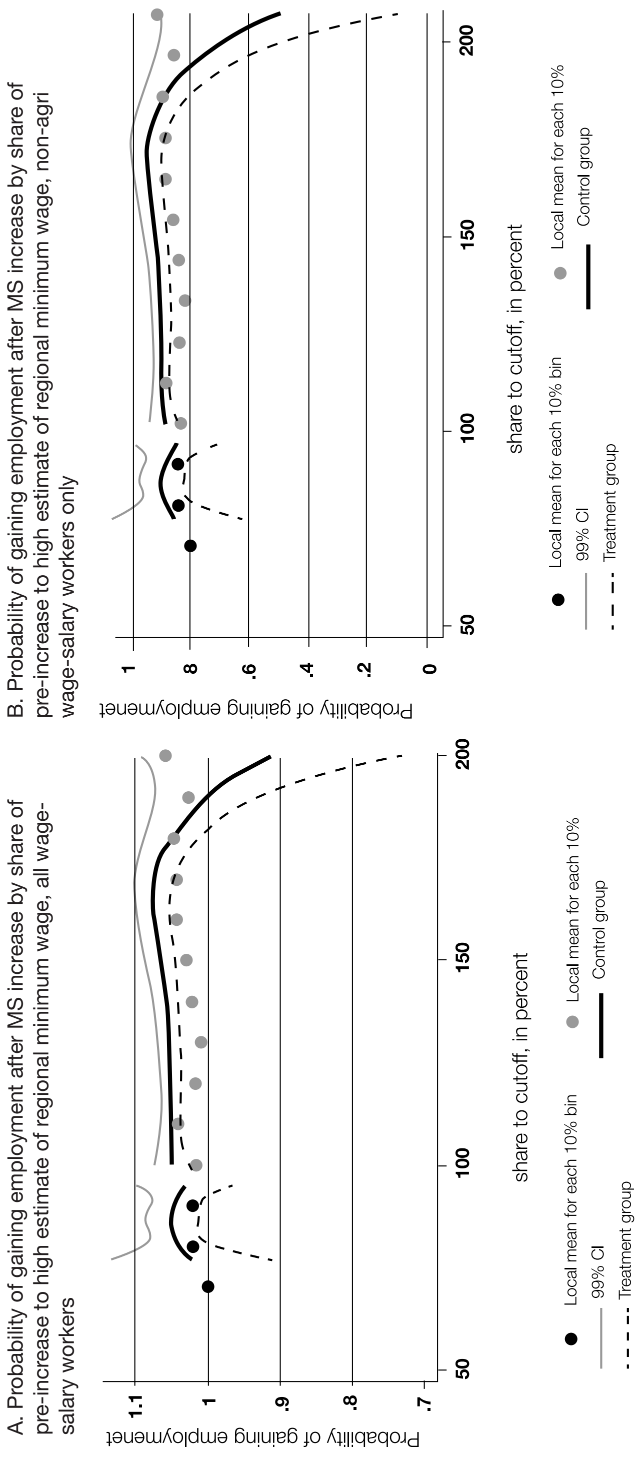

FIGURE 3. RDD graph of probability of gaining/retaining employment after the minimum wage increase

A. Probability of gaining employment after MS increase by share of pre-increase to high estimate of regional minimum wage, all wage-salary workers

B. Probability of gaining employment after MS increase by share of pre-increase to high estimate of regional minimum wage, non-agri wage-salary workers only

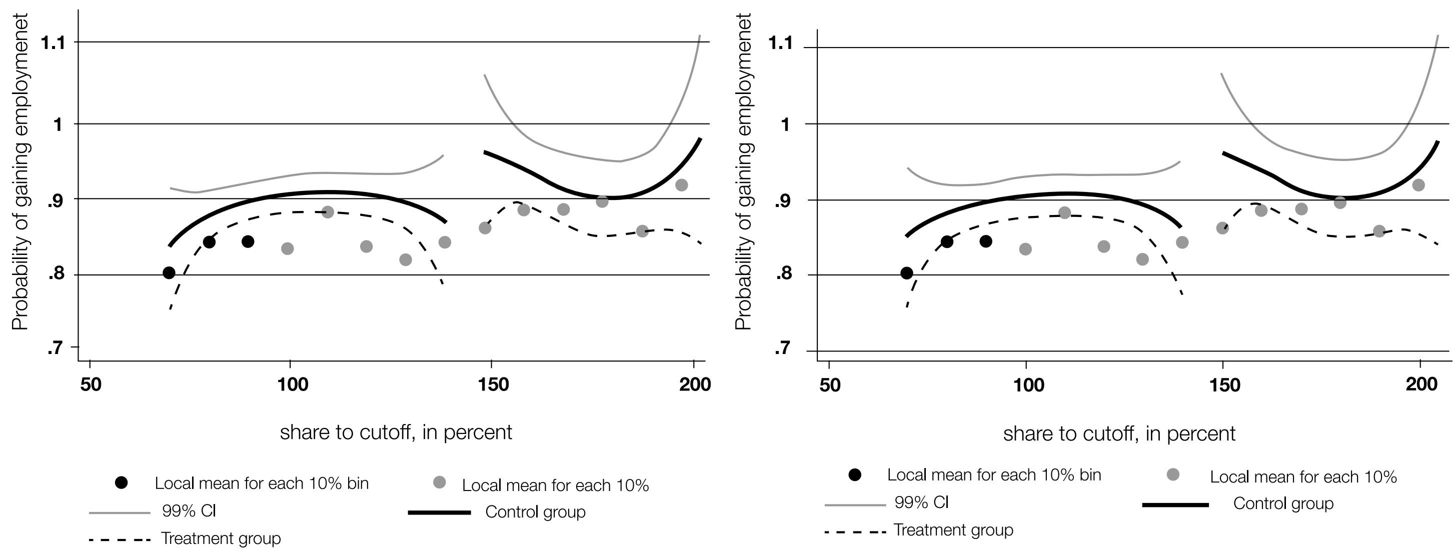

FIGURE 4. RDD graph of probability of gaining/retaining employment after the minimum wage increase, discontinuity at bin 150%

TABLE 6. Results of instrumental variables regression (*treatreg*)

Dependent variable: P(Employed) after minimum wage increase

Variable	Cutoff at bin 100%		Cutoff at bin 150%	
	Treatreg	Treatreg with poly	Treatreg	Treatreg with poly
Treatment	-.22564681***	-.22162158**	-.08309906**	-.13357334**
Basic pay per day - Cutoff (Centered basic pay)	0.0000647	-0.00044551	0.00004018	-.00331341**
Treatment x Centered basic pay	0.00078644	.02680083*	0.00007578	.00661714**
Centered basic pay^2		3.57E-06		.00003524**
Centered basic pay^3		-8.96E-09		-1.318e-07*
Centered basic pay^4		7.57E-12		1.613e-10*
Treatment x Centered basic pay^2		.00272388**		0.00004028
Treatment x Centered basic pay^3		.00008929**		7.36E-07
Treatment x Centered basic pay^4		8.767e-07**		1.36E-09
Constant	.94128357***	.95877322***	.97756109***	1.0540809***
Instrumented variable: Treatment				
Years of education	-.08314639***	-.08314639***	-.2096095***	-.2096095***
Age	-.03221802***	-.03221802***	-.03213607***	-.03213607***
Constant	.89396079***	.89396079***	4.0463695***	4.0463695***
hazard (Inverse Mills ratio)	.12881713***	.13577028***	.0492689**	.04979209***
1st stage pseudo R-squared	0.076	0.076	0.1669	0.1669
2nd stage Wald chi2	14.78	21.51	13.19	16.2
Prob > chi2	0.002	0.0059	0.003	0.0233
Observations	1964	1964	1964	1964

Legend: * p < .1; ** p < .05; *** p < .01

Table 7 presents the results of *treatreg* limiting the coverage to a bandwidth before and after the cutoff. Regressions were run for bins 80 percent-120 percent where the cutoff is 100 percent and bins 120 percent-180 percent for cutoff at bin 150 percent. Being a minimum wage worker decreases the probability of gaining/retaining employment by 28.8 percent after a minimum wage increase. Adjusting the cutoff to bin 150 percent, workers in the treatment group are 19.4 percent less likely than workers in the control group to have employment after the minimum wage increase.

TABLE 7. Results of local linear regression: Instrumental variables regression (*treatreg*)

Dependent variable: P(Employed) after minimum wage increase

Variable	Cutoff at bin 100%	Cutoff at bin 150%
Treatment	-.28841789**	-.19387267**
Basic pay per day - Cutoff (Centered basic pay)	-0.00026136	-.00121116*
Treatment x Centered basic pay	0.00117123	.00161187**
_cons	.97613506***	1.0784009***
Instrumented variable: Treatment		
Years of education	-.03357318**	-.11770991***
Age	-.02547034***	-.01642182***
Constant	0.3763139	2.5142089***
hazard (Inverse Mills ratio)	.16583381**	.08788585*
1st stage pseudo R-squared	0.034	0.0497
2nd stage Wald chi2	7.34	8.09
Prob > chi2	0.0618	0.0441
Observations	1220	931

Legend: * p < .1; ** p < .05; *** p < .01

The results suggest adverse employment outcomes after the minimum wage increase not only for minimum wage workers but also for those earning 50 percent above the minimum wage. Hours of work have declined and probabilities of gaining/retaining employment are lower for workers covered by the treatment.

To assess the ability of the models for inference, the share of correctly specified observations is computed. The probability of the presence of the treatment is first calculated [Pr(treat = 1)] for every observation. Second, the expected value of the dependent variable conditional on the presence of the treatment, $E(y \mid \text{treatment} = 1)$, is computed. Third, the expected value of the dependent variable conditional on the absence of the treatment, $E(y \mid \text{treatment} = 0)$, is computed. Then, observations are classified according to whether the predicted value of the response variable is approximately equal to its actual value.

For the first-stage probit regression, an observation is considered "correctly specified" as belonging to the treatment group if $\Pr(\text{treat} = 1) \geq 0.50$. For the second-stage regression, an observation is correctly specified to being employed if $E(y \mid \text{treatment} = 1) > E(y \mid \text{treatment} = 0)$. The expectation-prediction classification table is provided as Table 8.

TABLE 8. Expectation-prediction classification table for treatreg

	Cutoff at bin 150%		
Response variable	Treatreg	Treatreg with poly	Local linear regression
Pr(treat=1)			
0	45.197	45.197	10.468
1	87.063	87.063	98.254
E(Employed| treat=1)			
0	67.803	99.621	99.621
1	38.606	1.162	0.498

The results suggest that the number of years of education and age predict fairly well whether a worker belongs to the treatment group (workers earning within the minimum wage or earning 50 percent higher than the minimum wage). Furthermore, the model for gaining/retaining employment seems better able at predicting the effect of the treatment to loss of employment than for gaining/retaining employment.

5. Conclusion

The RDS graphs and the regressions performed do suggest adverse employment outcomes after the minimum wage increase. This is true not only for minimum wage workers but even for those earning at most 50 percent more than the minimum wage. The OLS results point to a reduction of hours of work at around 2.7 hours per week following the minimum wage increase in 2007. Moreover, it seems to reduce the probability of gaining/retaining employment by 8 percent-22 percent.

At a fundamental level, the question of the minimum wage's adverse employment effect turns on whether the specific labor-market under study is better described as being competitive or tending towards a monopsony (on the part of employers). In principle, higher minimum wages would not lead to negative employment effects under a monopsony. The adverse effects on labor market outcomes observed here suggest that the Philippine labor market is better described as closer to being competitive. On the institutional aspect of minimum wages and their role within industrial relations, the decline in the hours of work and probability of gaining or keeping employment is suggestive of the weakness of collective bargaining agreements in the country.

Finally, the pronounced discontinuity of employment outcomes at wages that are 50 percent above the minimum wage may be a result of firms' response to the minimum wage increase. Firms are possibly adjusting by increasing hours of work of either or both the minimum wage workers and the highly skilled workers to compensate for the need to reduce the employment of workers earning 50 percent above the minimum wage.

Department of Economics, Texas A&M University

References

Bazen, S. and J. Martin [1991] "The impact of the minimum wage on earnings and employment in France", *OECD Economic Studies* **16** (Spring): 199-220.

Bazen, S. and J. Le Gallo [2006] "The differential impact of federal and state minimum wages on teenage employment", unpublished paper, University of Savoie.

Berry, Chris [2011] "Regression Discontinuity Designs", EITM Summer Institute Lecture, The University of Chicago - The Harris School. Available at: http://harris.uchicago.edu/Blogs/EITM/wp-content/uploads/2011/06/RD-Lecture.pdf

Card, D. [1992a] "Using regional variation in wages to measure the effects of the federal minimum wage", *Industrial and Labor Relations Review* **46**(1): 22-37.

Card, D. [1992b] "Do minimum wages reduce employment? A case study of California, 1987-1989", *Industrial and Labor Relations Review* **46**(1): 38-54.

Card, D. and A. Krueger [1994] "Minimum wages and employment: a case study of the fast-food industry in New Jersey and Pennsylvania", *American Economic Review* **84**(5): 772-793.

Fiscal Policy Institute (FPI) [2004] *State minimum wages and employment in small businesses*. New York.

Freeman, R. [1996] "*The minimum wage as a redistributive tool",* The Economic Journal **106**: 639-649.

Imbens, G. W. and T. Lemieux [2007] "Regression discontinuity designs: A guide to practice", *Journal of Econometrics*.

Imbens, G. and J. Wooldridge [2009] "Recent developments in the econometrics of program evaluation", *Journal of Economic Literature* **47**(1): 5-86.

Katz, L. F. and A. Krueger [1992] "The effect of the minimum wage on the fast food industry", *Industrial and Labor Relations Review* **46**(1): 6-21.

Lanzona, L. [2014] "Effects of Minimum Wage on the Philippine Economy", PIDS Discussion Paper No. 2014-21. Quazon City: Philippine Institute for Development Studies.

Neumark, D. and W. Wascher [1992] "Employment effects of minimum and subminimum wages: panel data on state minimum wage laws", *Industrial and Labor Relations Review* **46**(1): 55-81.

Neumark, D. and W. Wascher [1994] "Employment effects of minimum and subminimum wages: reply to Card, Katz, and Krueger", *Industrial and Labor Relations Review* **47**(3): 497-512.

Neumark, D. and W. Wascher [1996a] "Minimum wage effects on employment and school enrollment: reply to Evans and Turner", FEDS Working Paper 1996-28. Board of Governors of the Federal Reserve System.

Neumark, D. and W. Wascher [1996b] "The effects of minimum wages on teenage employment and enrollment: evidence from matched CPS surveys", in S. Polachek, ed., *Research in Labor Economics.* Vol. 15. Greenwich, Conn.: JAI Press.

Neumark, D. and W. Wascher [2007] "Minimum wages and employment", IZA DP No. 2570. Institute for the Study of Labor.

Nye, J. V. C. [2011] "Taking institutions seriously: rethinking the political economy of development in the Philippines", *Asian Development Review* **28**: 1-21.

Sabia, J. J. [2006] "The effect of minimum wage increases on teenage, retail, and small business employment", unpublished paper, University of Georgia.

Schmitt, J. [2013] "Why does the minimum wage have no discernible impact on employment?" Washington, D.C.: Center for Economic Policy and Research.

Sicat, G. [2010] "Spotlighting on high economic growth, employment of the poor, and poverty reduction: a three-pronged strategy", UPSE Discussion Paper No. 2010-07. Quezon City: University of the Philippines School of Economics.

Sugiyarto, G. and B. Endriga [2008] "Do minimum wages reduce employment and training?", ERD Working Paper No. 113. Asian Development Bank. Manila.