“From Many to One: Minimum Wage Effects in Thailand”

Dilaka Lathapipat
World Bank

Cecilia Poggi
University of Sussex

July 9, 2016

Introduction

This study evaluates the effect of the Minimum Wage Policy on labor market outcomes and wage distribution in a middle income country context

Focus on the recent Thai Minimum Wage Policy change from provincial-level to statutory minimum wage

- Employment: Employment/Population

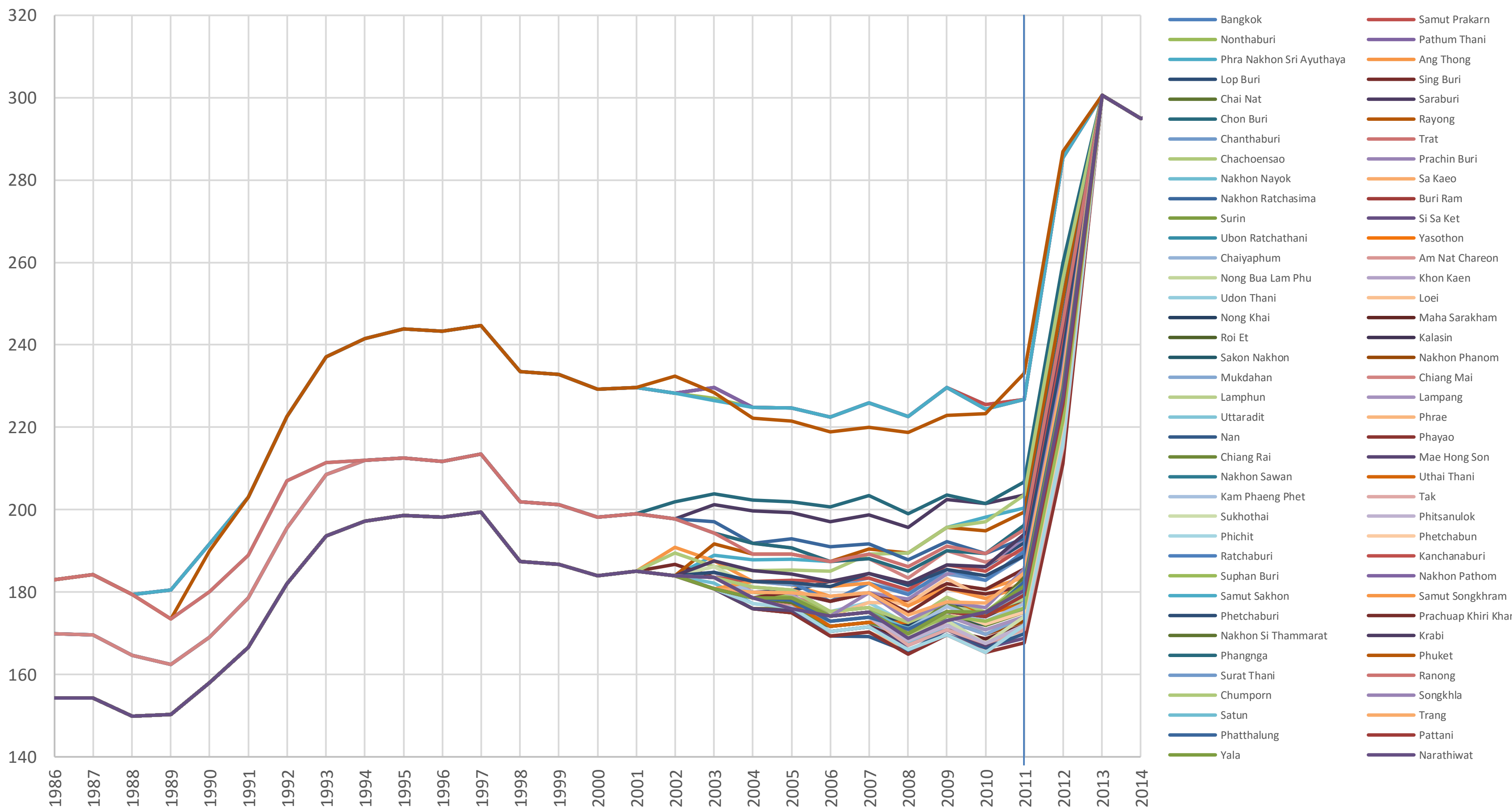
- Wage redistribution: Application of the Unconditional Quantile Regression (Firpo et al., 2009) to a panel of provincial wage distributions (Lathapipat, 2016)

Minimum wage in Thailand

"The payment sufficient for a "skill-needed worker" to make a living in the current social and economic condition and to have a living standard that is appropriate with the capability of businesses in that locality" (Labor Protection Act 2008)

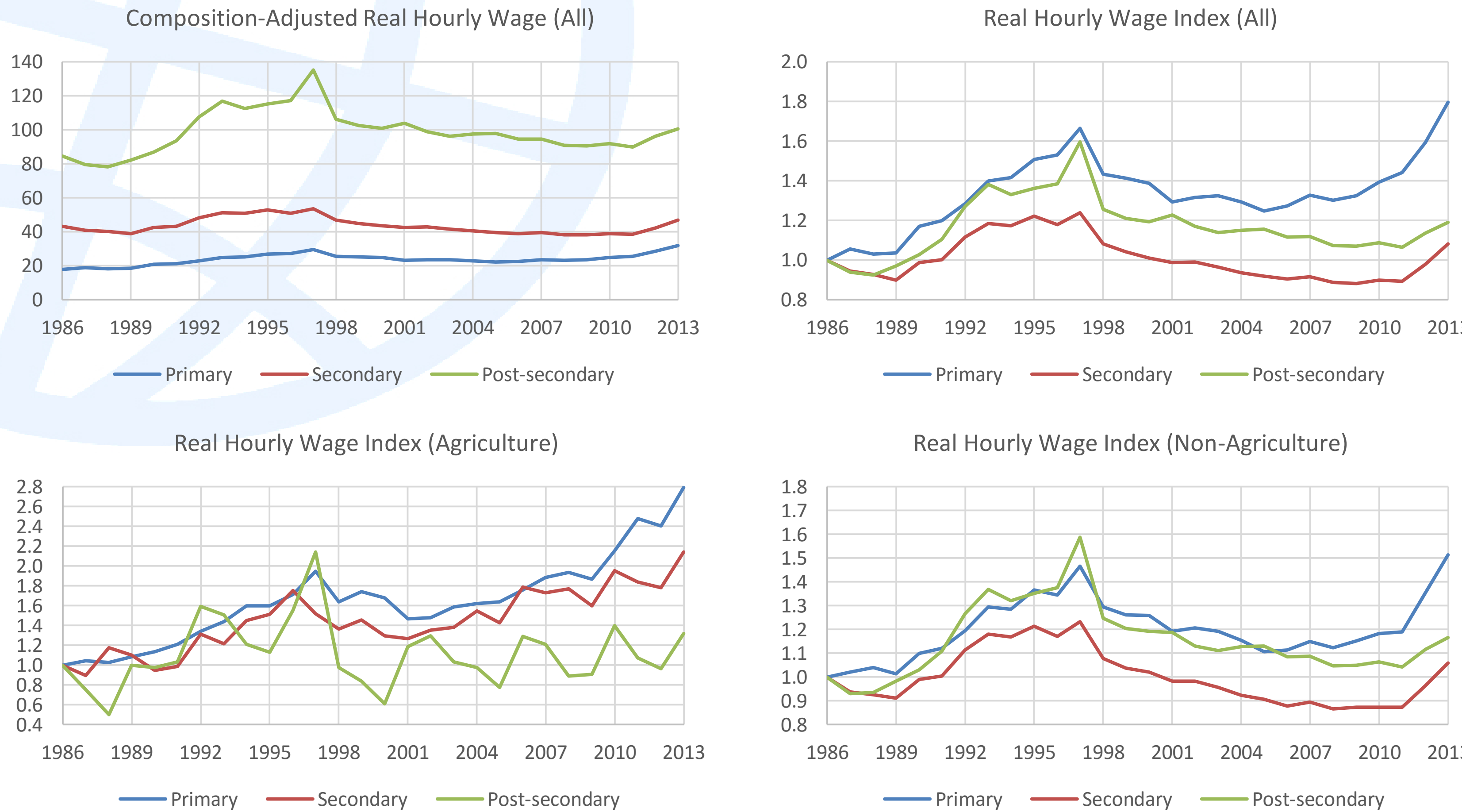
- Daily minimum wage (working day of eight hours)
- Coverage: all industries except for
  - Agricultural work, fishery, any government administration or state-owned enterprises, homeworkers and domestic workers
  - No restriction on age, gender or nationality
- Setting: collective bargaining in a tripartite committee (government, employer, and employee representatives)
- Time: (1973) regional bands (1998) provincial (2011) NMW

Evolution of the real minimum wage by province

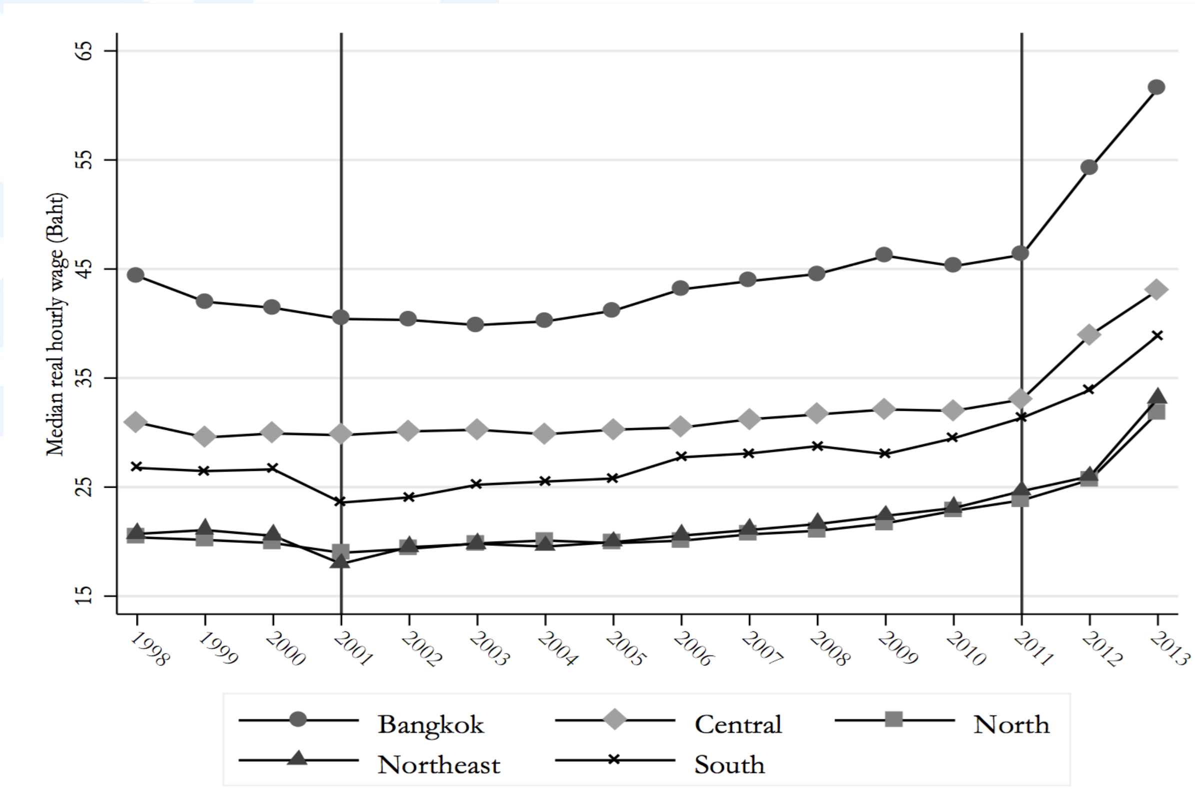


Note: Authors' own calculations using daily minimum wage data 1986-2014 (annual average) from the Ministry of Labor. Mean provincial daily wages (represented by the solid lines) are expressed in constant 2013 Thai Baht.

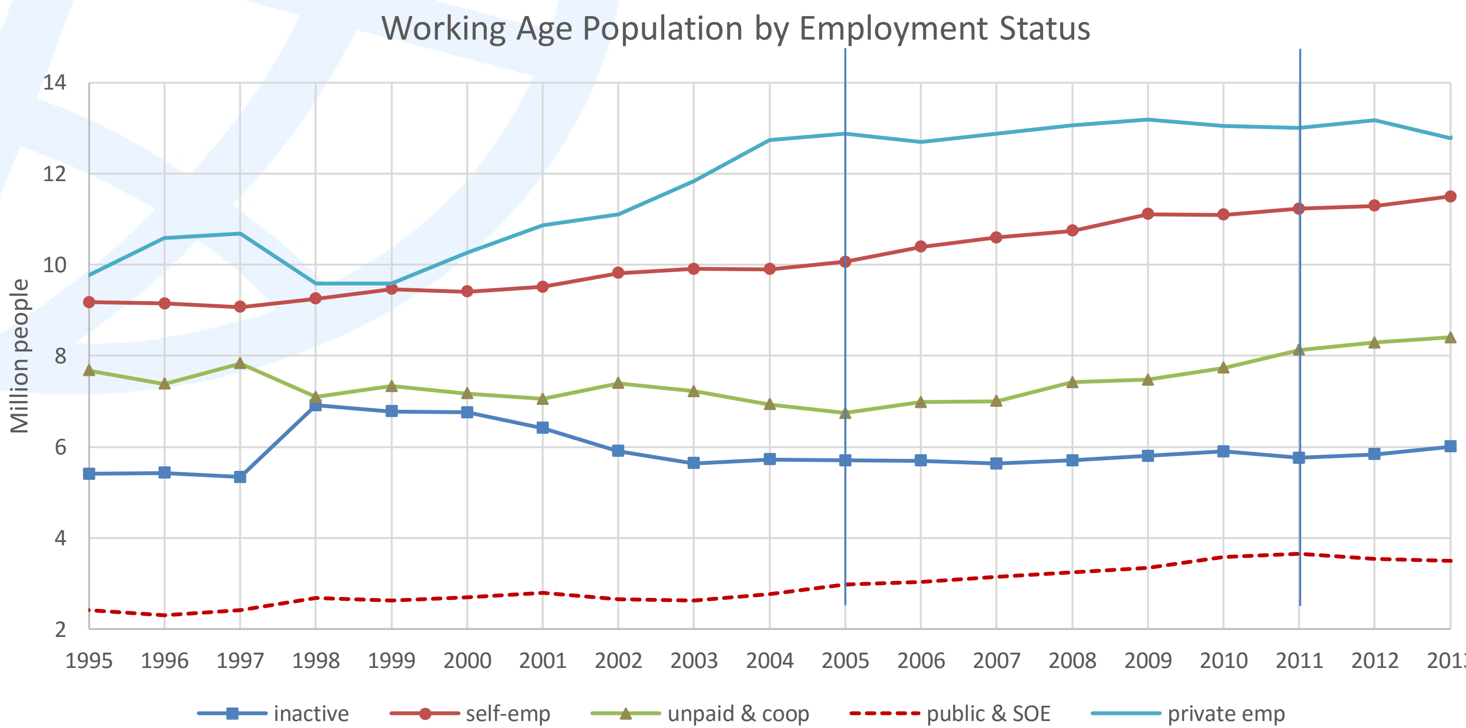
Since 2005, the tightening labor market for low-skilled workers (due largely to the commodity boom and decline in primary labor) has put upward pressure on their hourly wages despite stagnant or falling provincial minimum wages

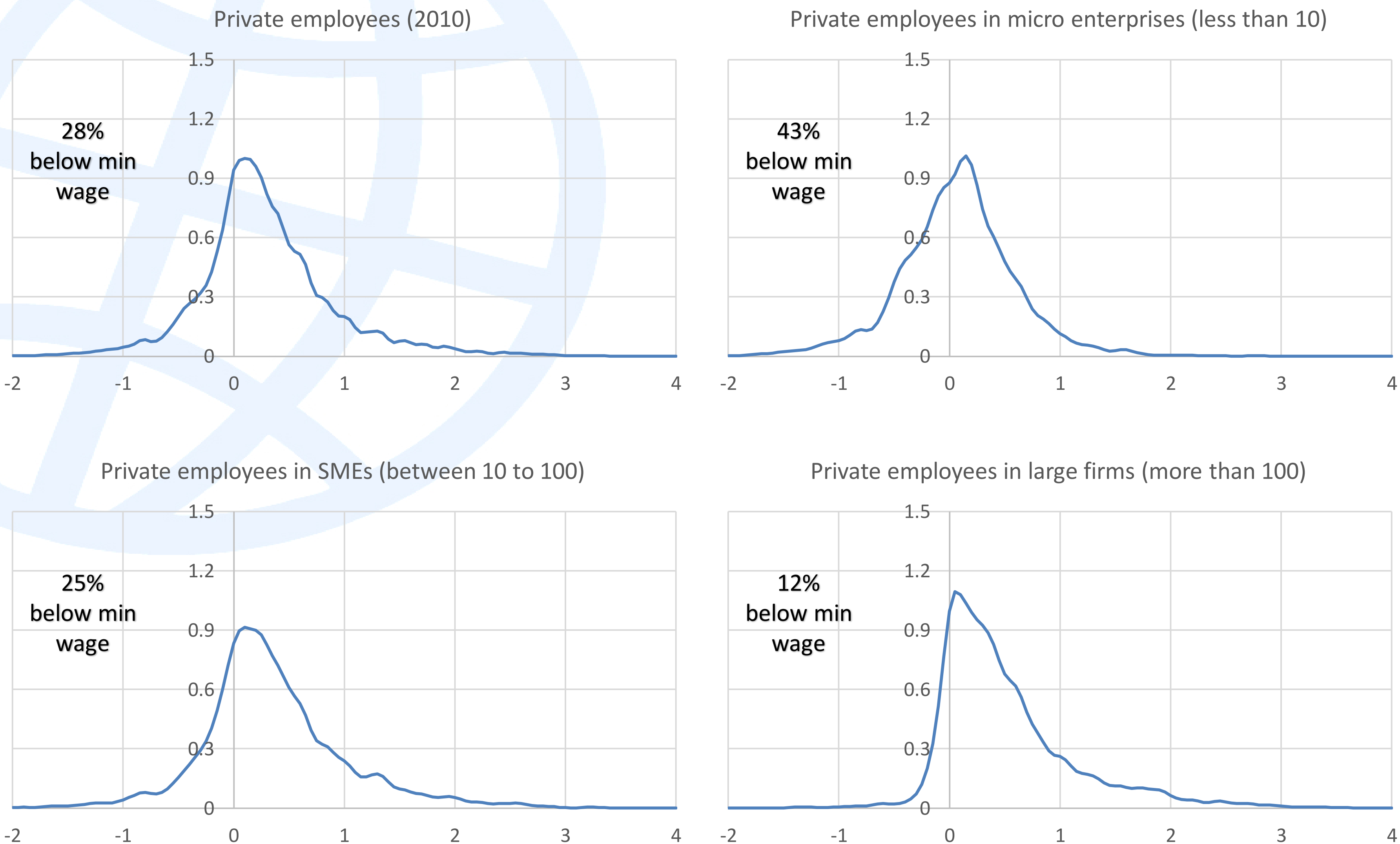


Evolution of the real median wage by geographical region



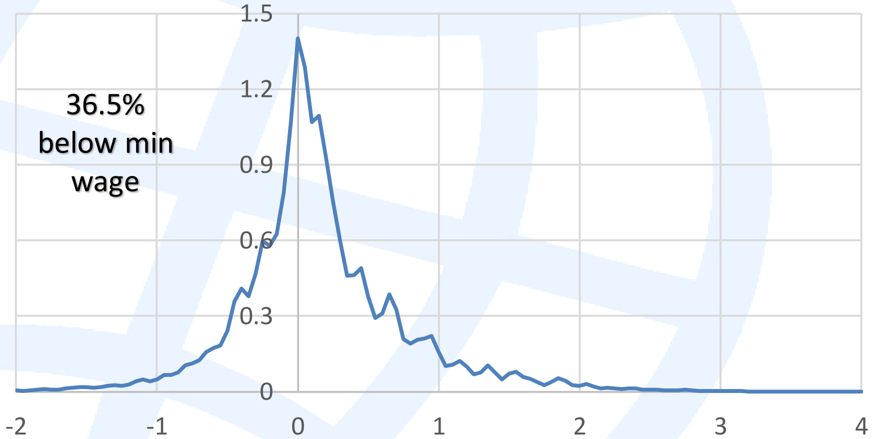
The change in the employment composition of 15 to 65 year-olds suggests that many private firms had been struggling with the rising low-skilled wages



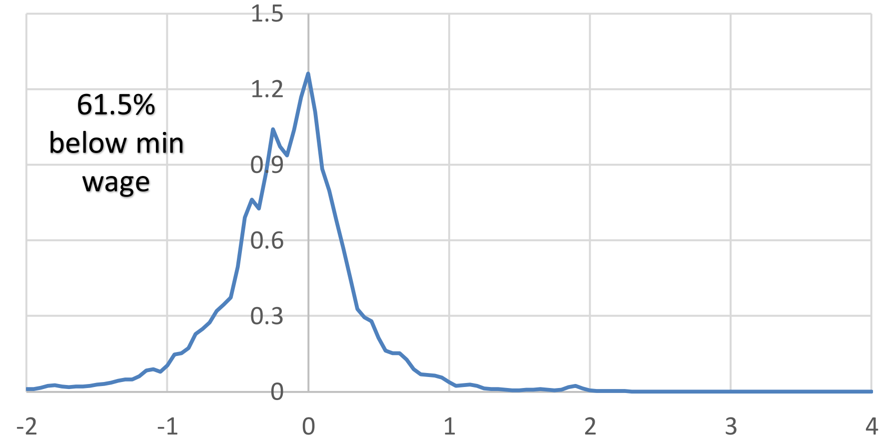


Private employees (2010)
28% below min wage
Private employees in micro enterprises (less than 10)
43% below min wage
Private employees in SMEs (between 10 to 100)
25% below min wage
Private employees in large firms (more than 100)
12% below min wage
1.5
1.2
0.9
0.6
0.3
0
-2
-1
0
1
2
3
4

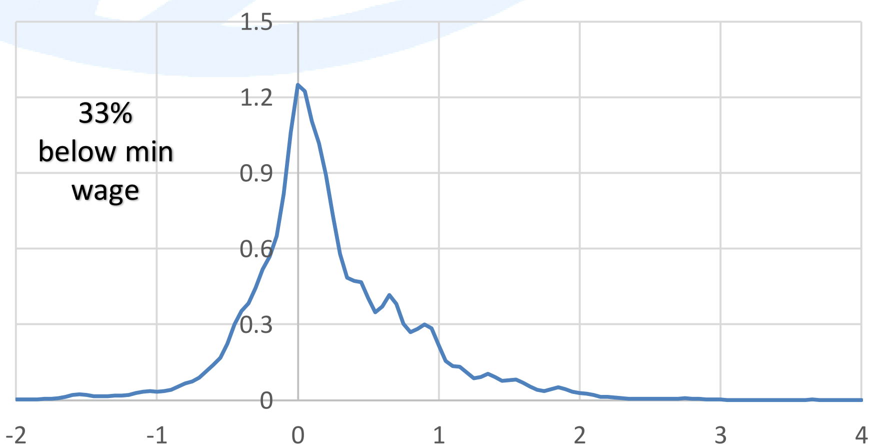
Private employees (2013)



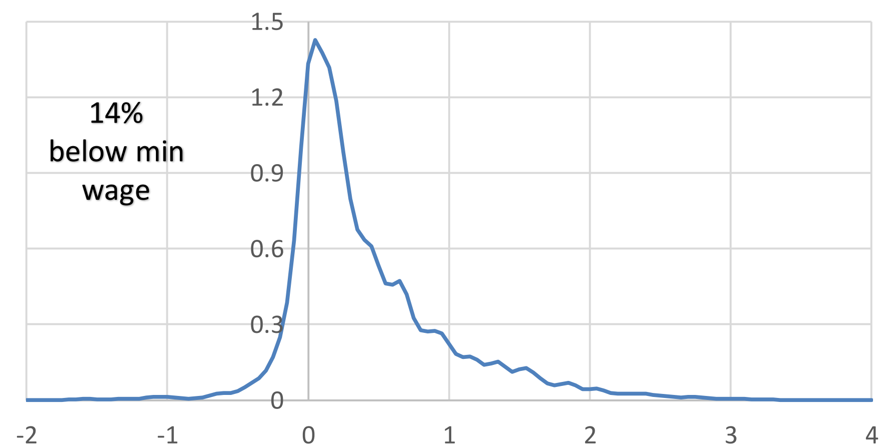
Private employees in micro enterprises (less than 10)



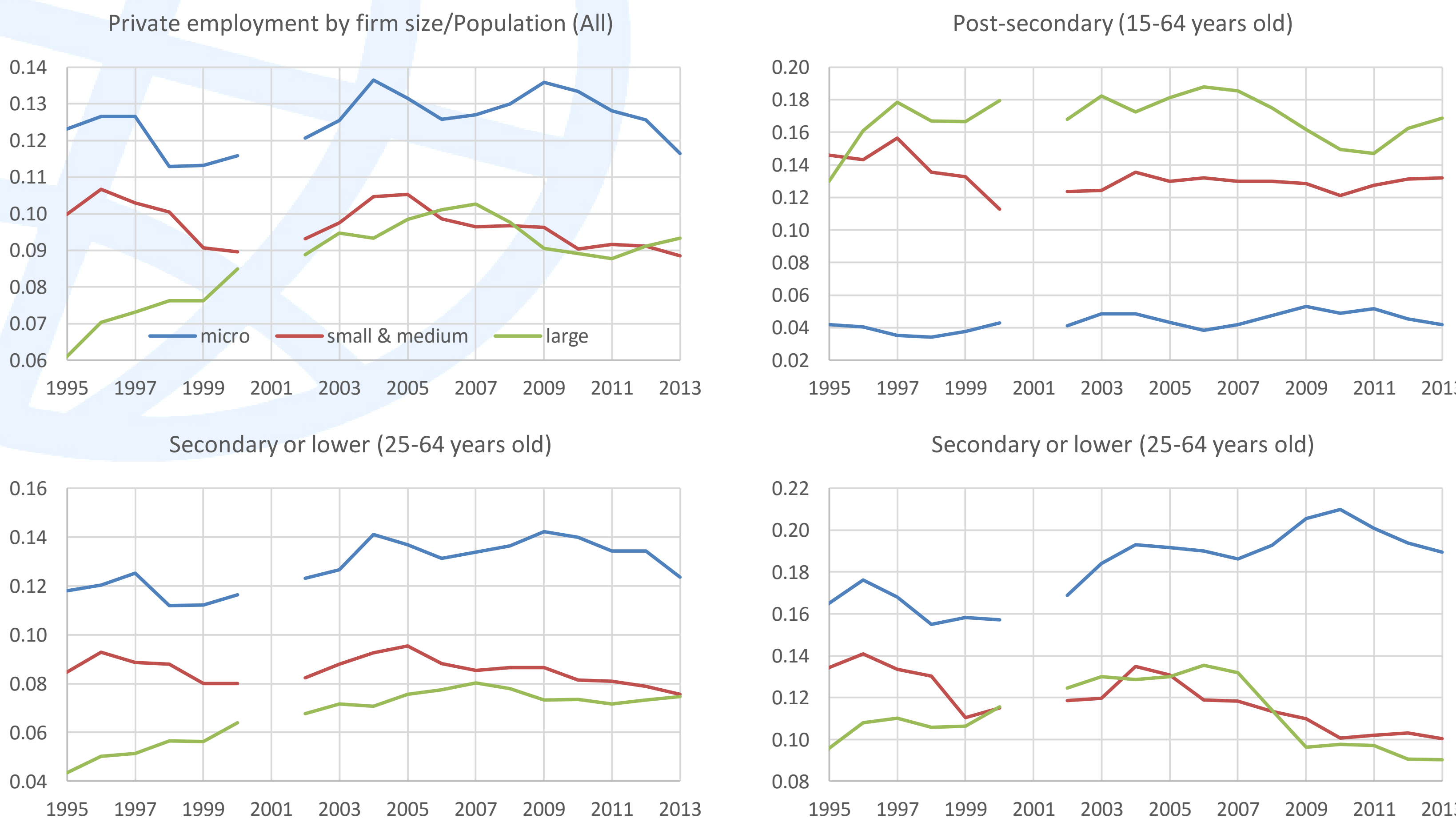
Private employees in SMEs (between 10 to 100)



Private employees in large firms (more than 100)



Evidences indicate that private micro enterprises (with less than 10 workers) were most-affected by the sharp and rapid increase in the minimum wage



Formal framework for estimating the effects of the minimum wage on employment, labor mobility between sectors, and weekly hours worked

In particular, we study the effects on Employment/population ratio:

- Overall and by employment status (self employment, and unpaid family workers, public, and private sector)
- Across major industries
- By firm size category (micro enterprises/SMEs/large private sector firms)

The analysis will shed light on the patterns of labor mobility between sectors, and movement into and out of employment

- We are interested in the effects on the overall population (or workers) between 15-65 years of age, as well as on the sub-populations of youth (15-24 years old) and adults (25-65 years old) with secondary education or less, and those with higher than secondary education (15-65 years old)

Modeling framework

The basic fixed effects model specification is follows (quarterly data 2001-2013) :

$$y_{pt} = \beta MW_{pt} + X_{pt}\gamma + \phi_p + \tau_t + \varepsilon_{pt}$$

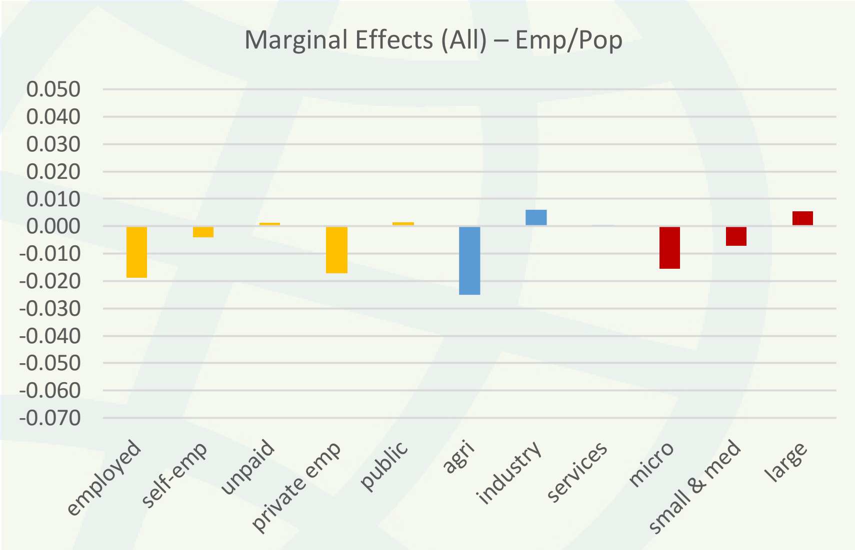
- MW_{pt} is the log of real minimum wage for province p at time t
- X_{pt} includes population group controls: for average years of schooling, female share, average years of potential work experience, share rural; and provincial controls: youth population share (15-24 years of age), senior (more than 55 years of age), and high skilled labor force share (completed post-secondary education), log real provincial product per capita, quarter and year dummies, and provincial fixed effects.

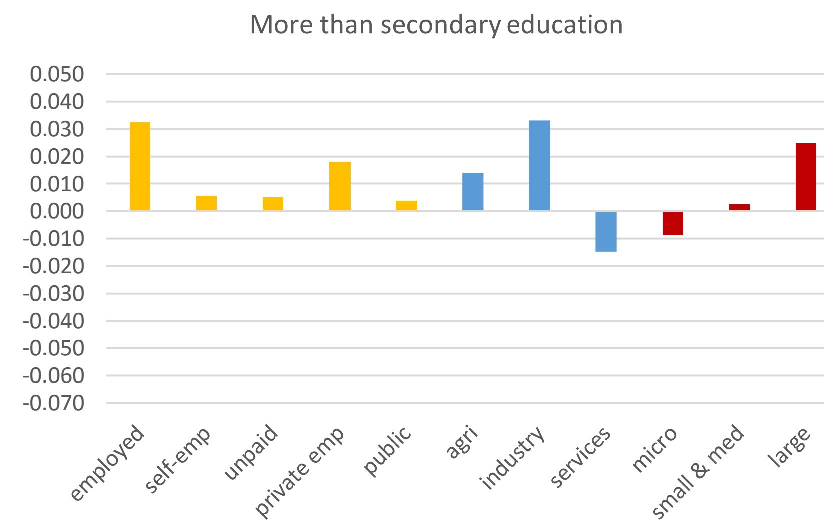
Another specification uses a dynamic model which employs distributed leads and lags over a 10-quarter window to capture anticipation and long-run effects:

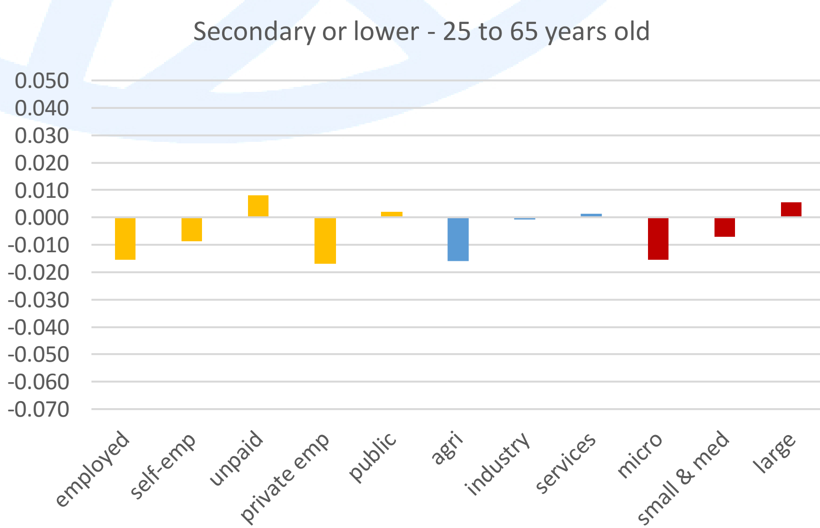
$$y_{pt} = \sum_{k=-4}^{6} \beta MW_{pt+k} + X_{pt}\gamma + \phi_p + \tau_t + \varepsilon_{pt}$$

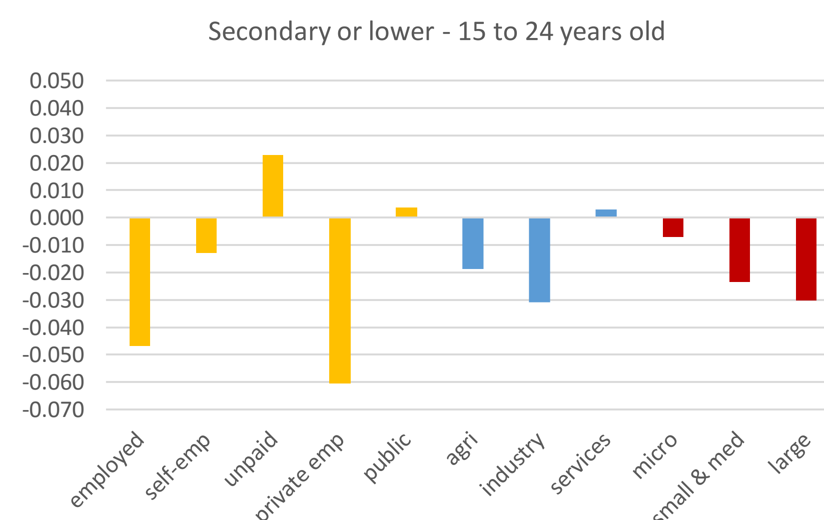
Estimation Results

Basic fixed effects panel data model


Marginal Effects (All) – Emp/Pop
0.050
0.040
0.030
0.020
0.010
0.000
-0.010
-0.020
-0.030
-0.040
-0.050
-0.060
-0.070
employed
self-emp
unpaid
private emp
public
agri
industry
services
micro
small & med
large


More than secondary education
0.050
0.040
0.030
0.020
0.010
0.000
-0.010
-0.020
-0.030
-0.040
-0.050
-0.060
-0.070
employed
self-emp
unpaid
private emp
public
agri
industry
services
micro
small & med
large


Secondary or lower - 25 to 65 years old
0.050
0.040
0.030
0.020
0.010
0.000
-0.010
-0.020
-0.030
-0.040
-0.050
-0.060
-0.070
employed
self-emp
unpaid
private emp
public
agri
industry
services
micro
small & med
large


Secondary or lower - 15 to 24 years old
0.050
0.040
0.030
0.020
0.010
0.000
-0.010
-0.020
-0.030
-0.040
-0.050
-0.060
-0.070
employed
self-emp
unpaid
private emp
public
agri
industry
services
micro
small & med
large

Fixed effects regression of employment-to-population in high vs. low minimum wage regime provinces, 2002-13 (marginal effects shown) show greater disemployment effects in low MW regime provinces

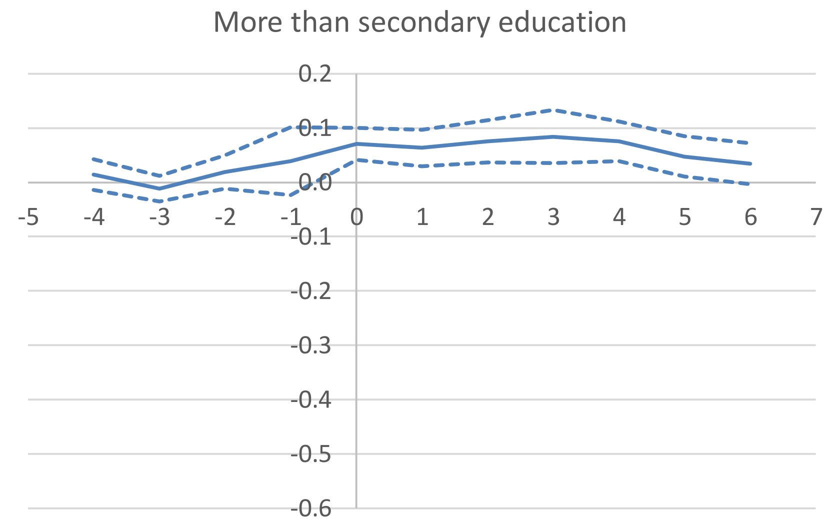
	Low Minimum wage provinces								
	Any	Non wage	Private	Agri.	Indus.	Service	Micro	SM	Large
Working age	-0.022***	-0.010	-0.011	-0.020*	-0.001	-0.000	-0.017	0.002	0.004
	(0.008)	(0.018)	(0.018)	(0.012)	(0.008)	(0.007)	(0.012)	(0.009)	(0.005)
Low skilled	-0.025***	-0.015	-0.015	-0.027**	-0.007	0.008	-0.017	0.002	0.001
	(0.009)	(0.019)	(0.018)	(0.013)	(0.009)	(0.008)	(0.013)	(0.010)	(0.005)
Low skilled (15-24)	-0.007	0.018	-0.036	-0.008	-0.023	0.023	-0.021	-0.013	-0.001
	(0.022)	(0.035)	(0.034)	(0.029)	(0.021)	(0.024)	(0.025)	(0.021)	(0.013)
Low skilled (25-65)	-0.027***	-0.019	-0.011	-0.027**	-0.004	0.005	-0.016	0.004	0.002
	(0.008)	(0.019)	(0.017)	(0.013)	(0.008)	(0.007)	(0.013)	(0.009)	(0.004)
	High Minimum wage provinces								
	Any	Non wage	Private	Agri.	Indus.	Service	Micro	SM	Large
Working age	0.006	0.024	-0.025	0.005	0.012	-0.011	-0.005	-0.024	0.003
	(0.009)	(0.030)	(0.031)	(0.028)	(0.016)	(0.022)	(0.013)	(0.018)	(0.019)
Low skilled	0.003	0.025	-0.035	0.011	-0.000	-0.007	-0.002	-0.030	-0.005
	(0.011)	(0.033)	(0.033)	(0.032)	(0.017)	(0.024)	(0.016)	(0.020)	(0.019)
Low skilled (15-24)	-0.066*	0.001	-0.080	-0.004	-0.025	-0.037	0.029	-0.043	-0.066
	(0.032)	(0.050)	(0.070)	(0.047)	(0.058)	(0.040)	(0.031)	(0.037)	(0.055)
Low skilled (25-65)	0.012	0.028	-0.028	0.011	0.006	-0.005	-0.005	-0.032	0.008
	(0.013)	(0.032)	(0.032)	(0.033)	(0.015)	(0.024)	(0.016)	(0.021)	(0.018)

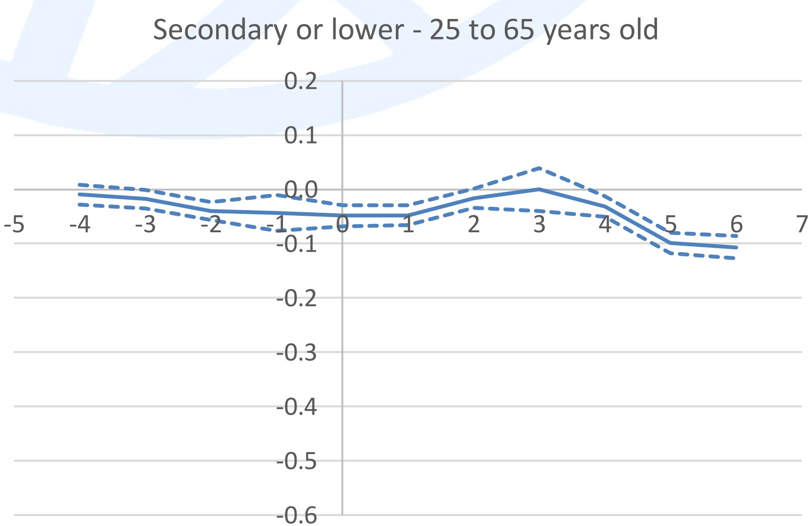
Note: LFS 2002-13. High (Low) minimum wage provinces are defined as those provinces with a real mean minimum wage higher (lower) than the national average over the period. High regime provinces are 20: Bangkok, 13 from the Centre, 1 from the North, 1 from Northeast, and 4 from the South (low regime are the remaining 56 provinces). Controls as main specification (significance: * p<.10, ** p<.05, *** p<.01).

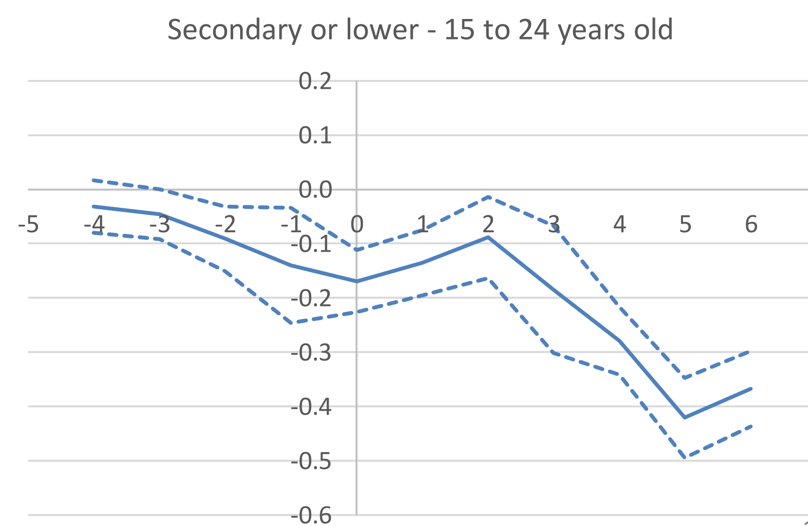
Cumulative response to changes in the minimum wage of employment and log weekly hours elasticities

Note: The figures in the following slides show the time paths of minimum wage elasticities of selected outcomes. For employment, the elasticities are computed by dividing the estimated regression coefficients by the relevant employment-to-population ratio


Employment/population - All
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7


More than secondary education
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

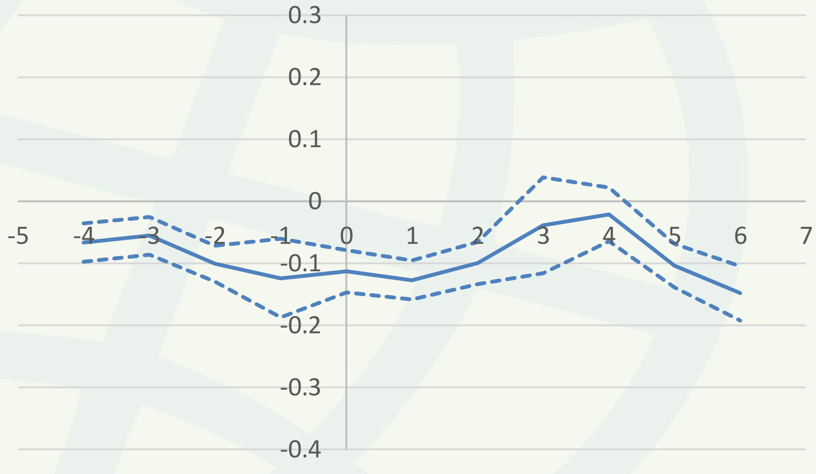

Secondary or lower - 25 to 65 years old
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7


Secondary or lower - 15 to 24 years old
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

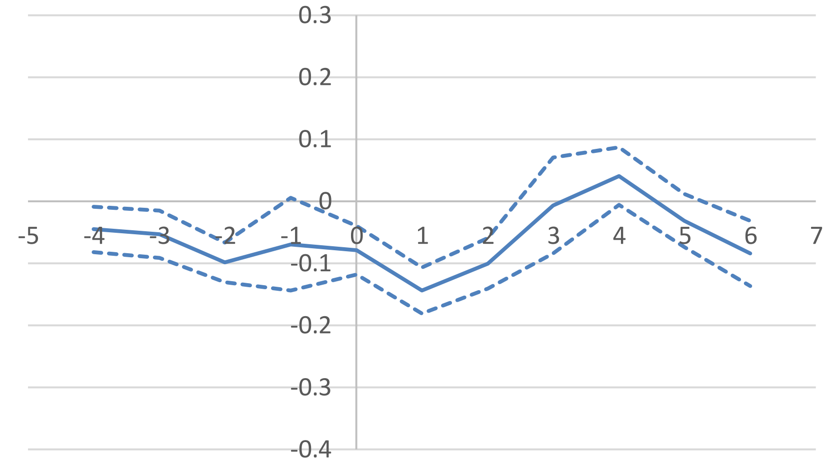

Wage employment/population - All
More than secondary education
Secondary or lower - 25 to 65 years old
Secondary or lower - 15 to 24 years old
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7


Private employee/population - All
More than secondary education
Secondary or lower - 25 to 65 years old
Secondary or lower - 15 to 24 years old
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
-1.0000
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7

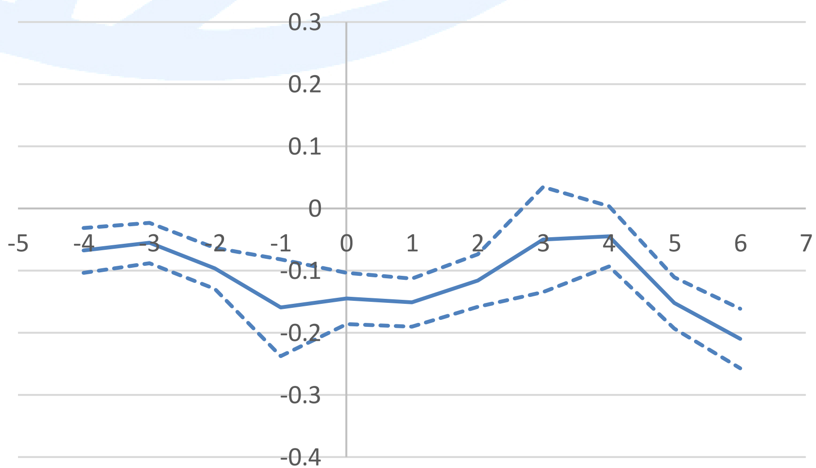
(Log) Weekly hours (Wage employment) - All



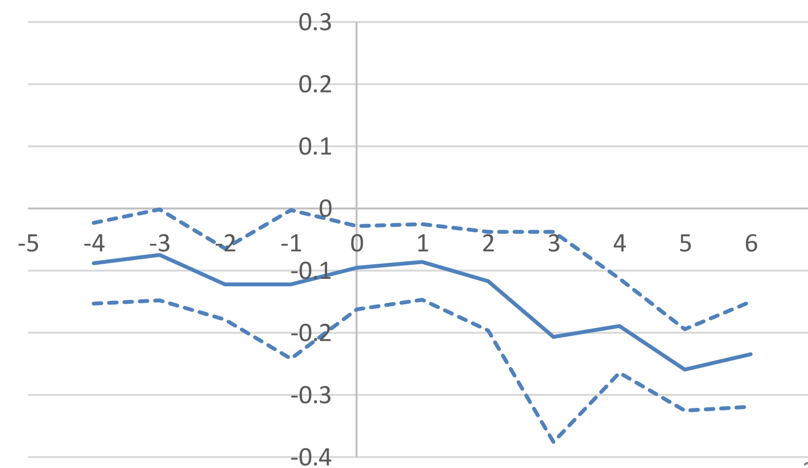
More than secondary education

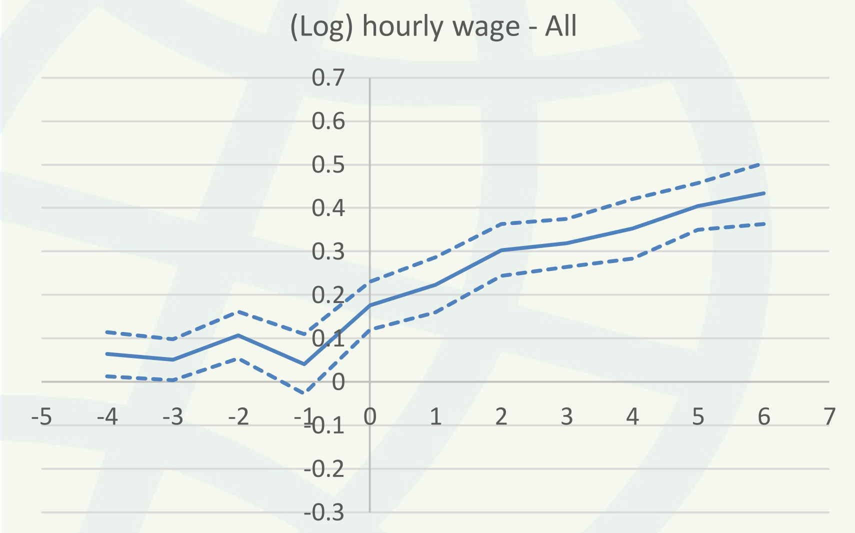


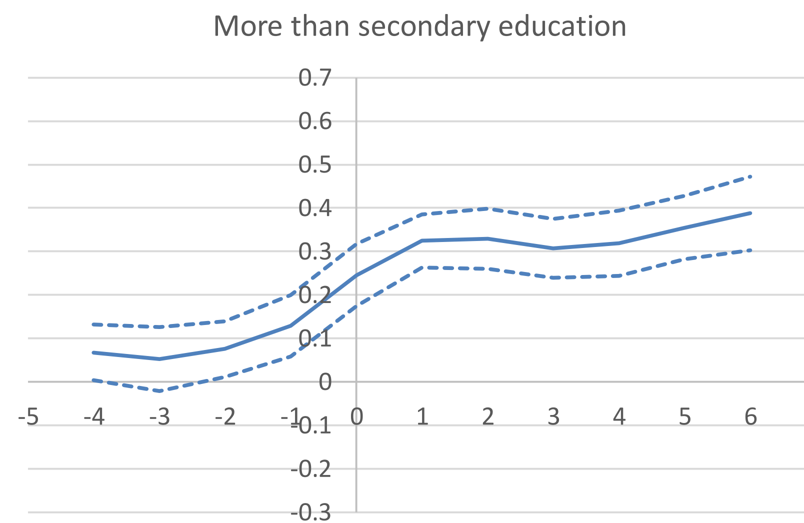
Secondary or lower - 25 to 65 years old

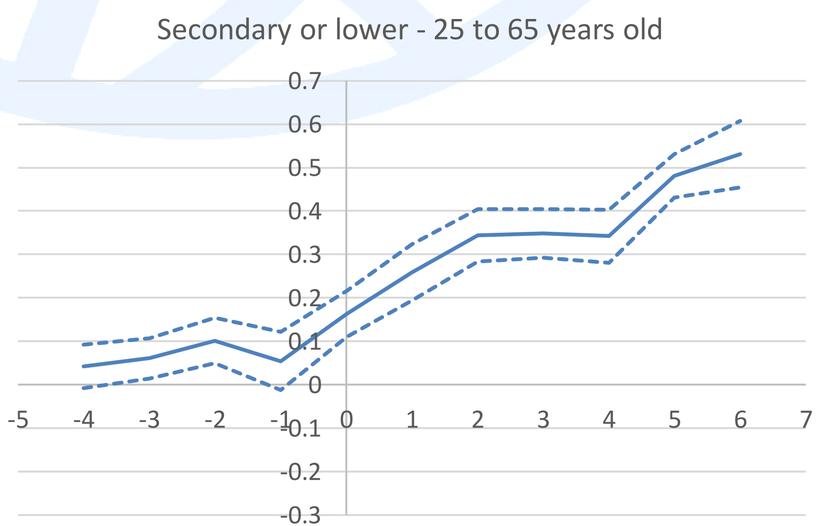


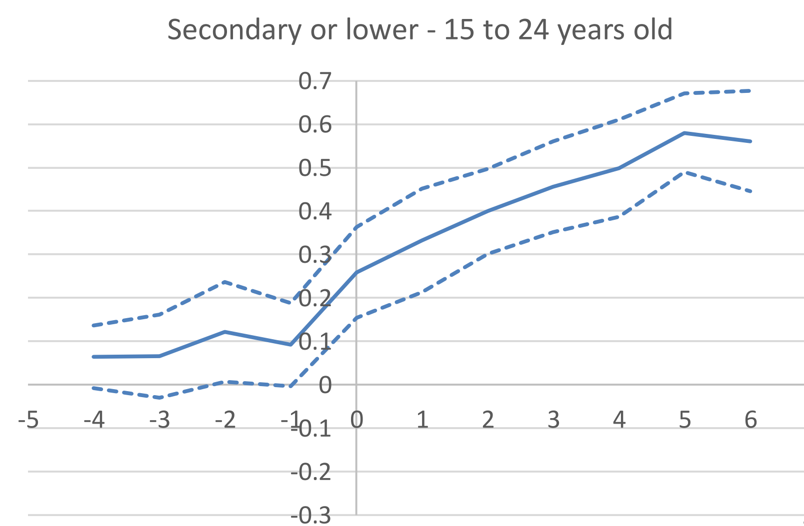
Secondary or lower - 15 to 24 years old

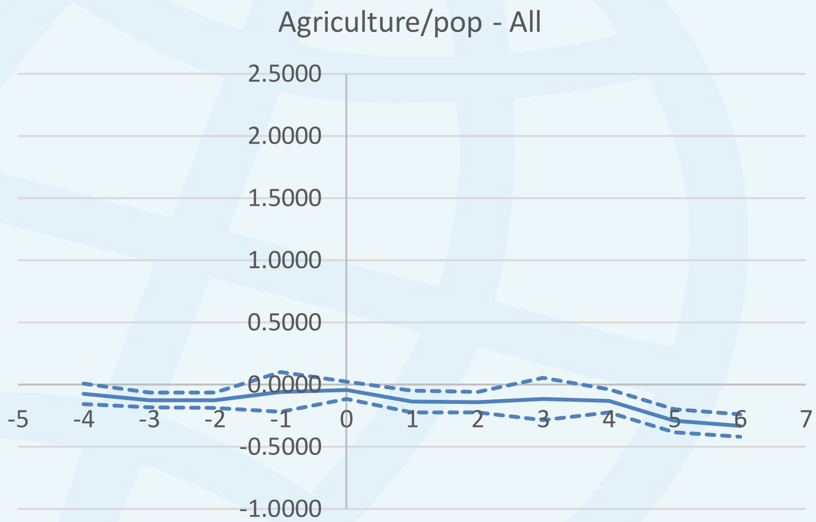


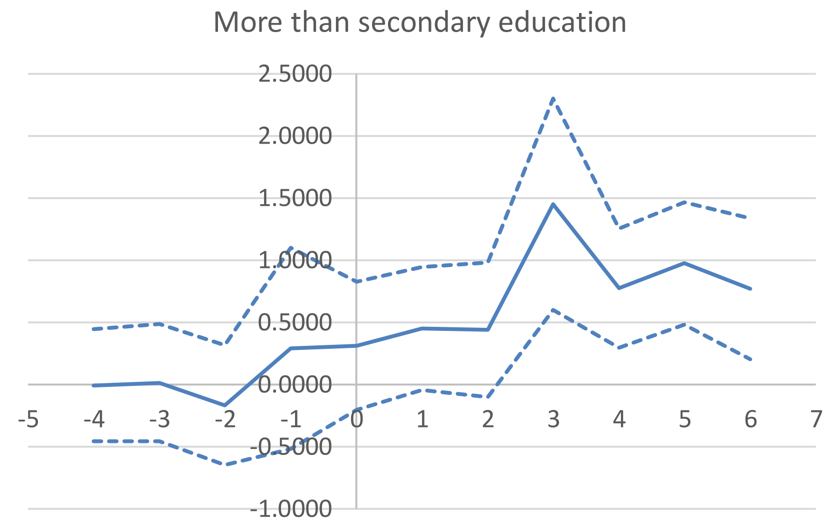

(Log) hourly wage - All
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

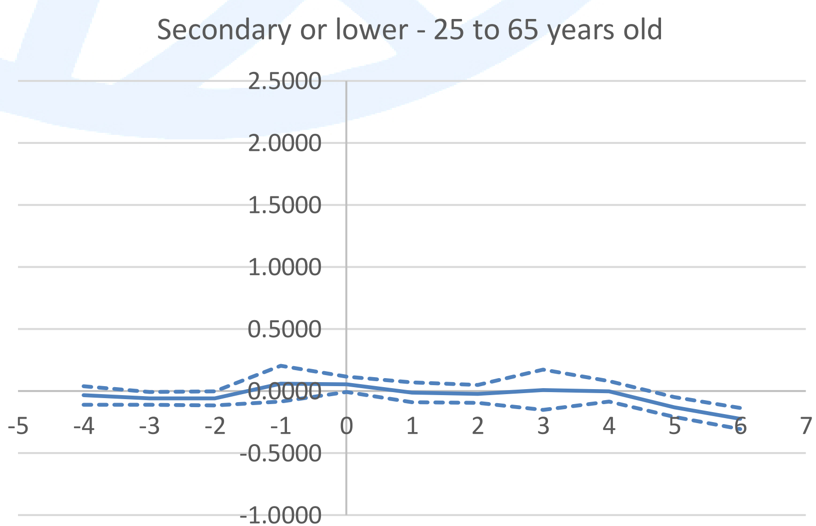

More than secondary education
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

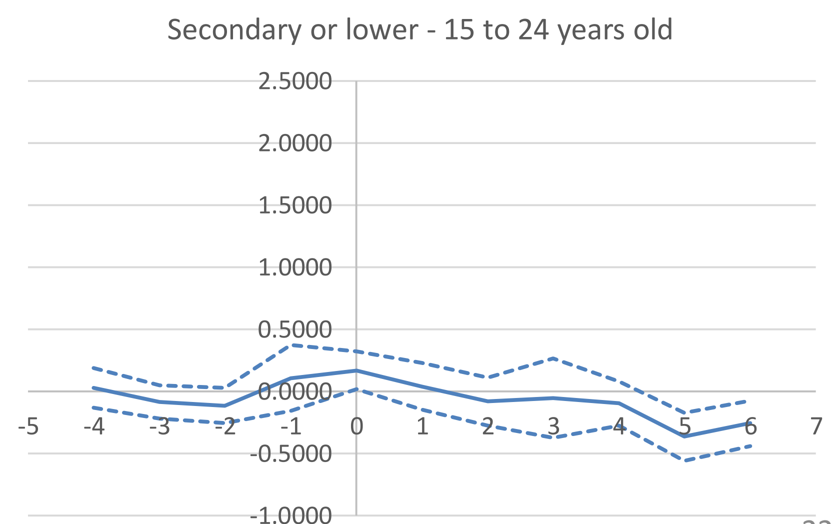

Secondary or lower - 25 to 65 years old
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7


Secondary or lower - 15 to 24 years old
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

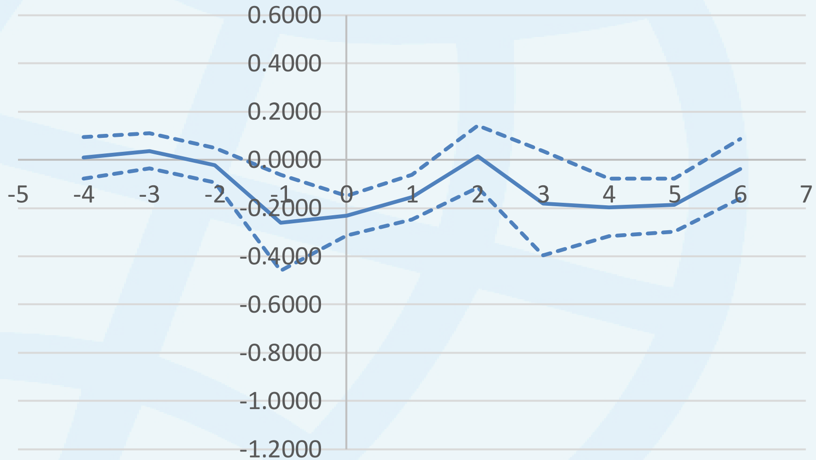

Agriculture/pop - All
2.5000
2.0000
1.5000
1.0000
0.5000
0.0000
-0.5000
-1.0000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7


More than secondary education
2.5000
2.0000
1.5000
1.0000
0.5000
0.0000
-0.5000
-1.0000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

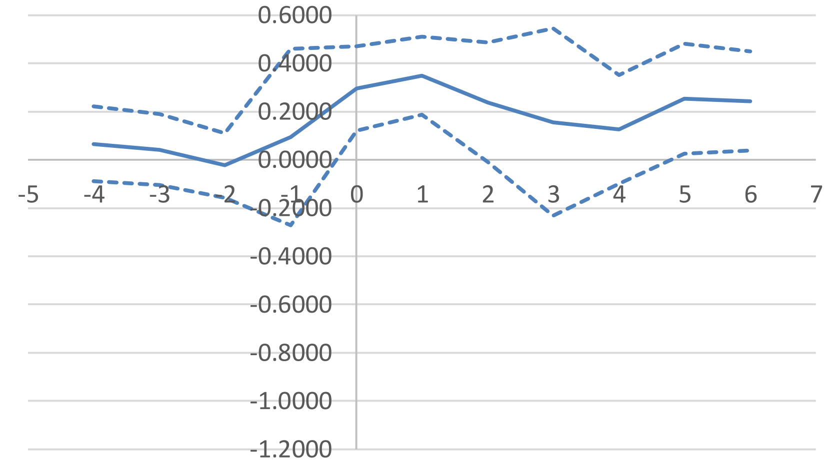

Secondary or lower - 25 to 65 years old
2.5000
2.0000
1.5000
1.0000
0.5000
0.0000
-0.5000
-1.0000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7


Secondary or lower - 15 to 24 years old
2.5000
2.0000
1.5000
1.0000
0.5000
0.0000
-0.5000
-1.0000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

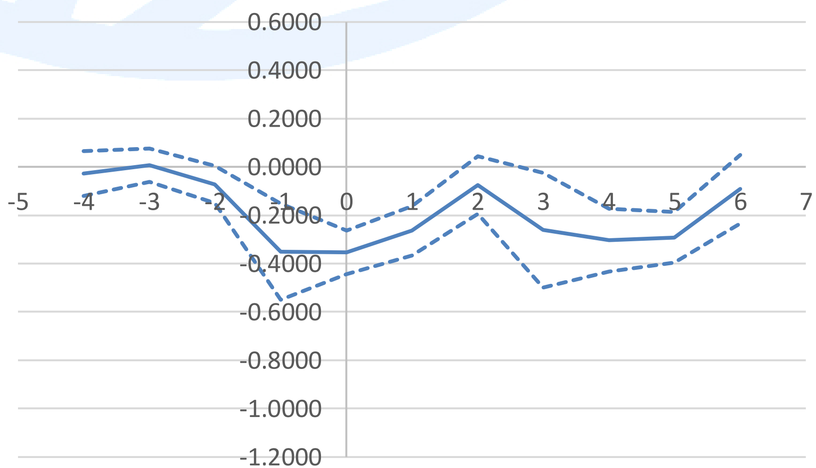
Industry/pop - All



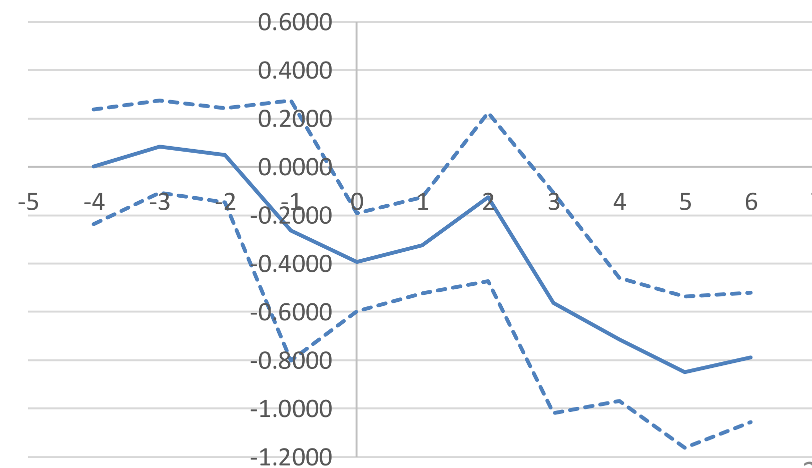
More than secondary education

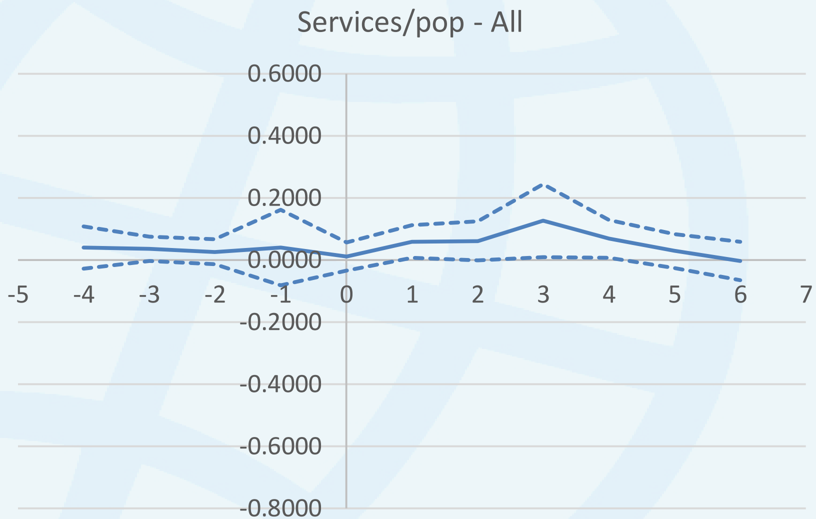


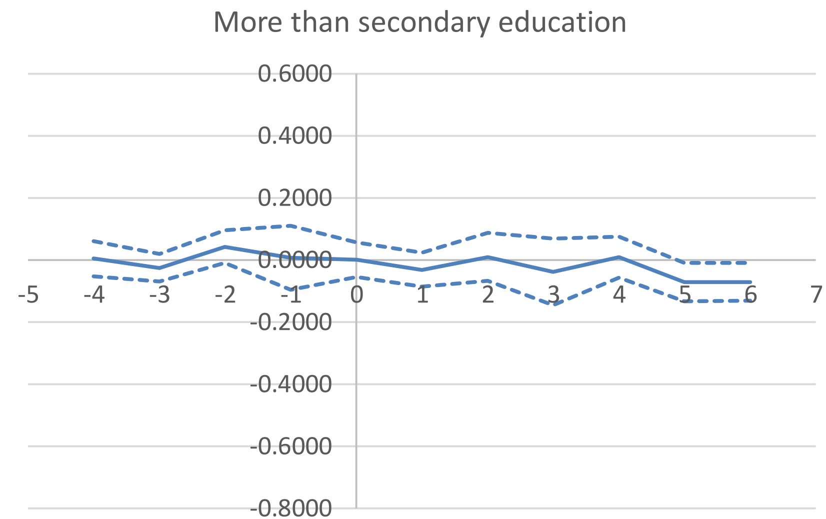
Secondary or lower - 25 to 65 years old

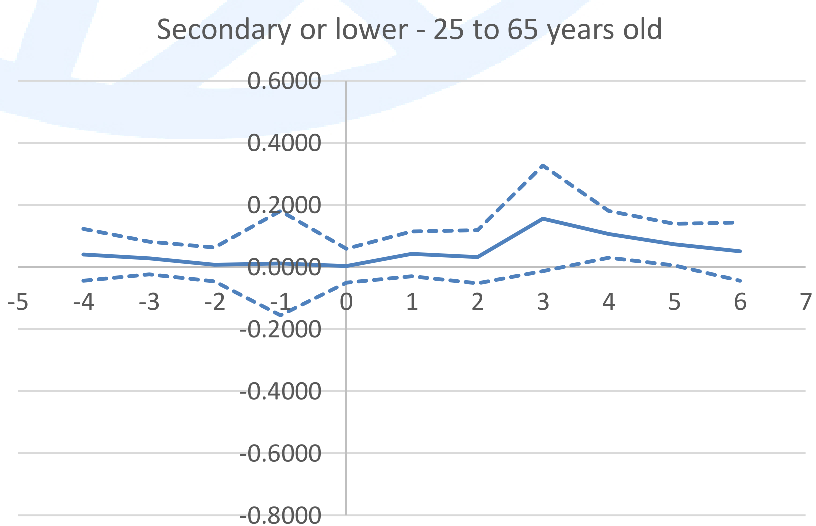


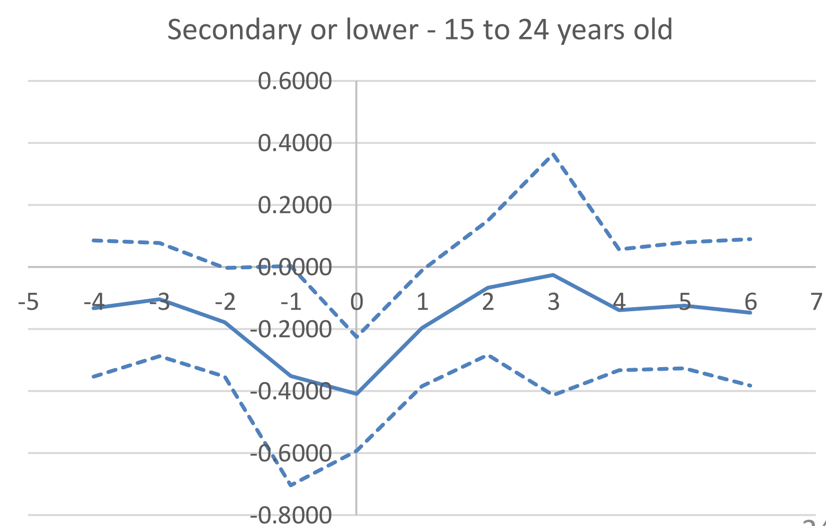
Secondary or lower - 15 to 24 years old

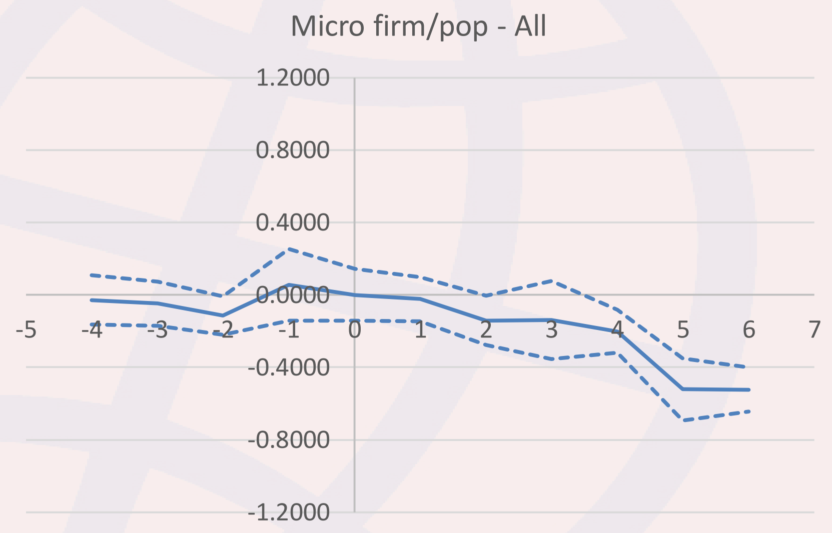


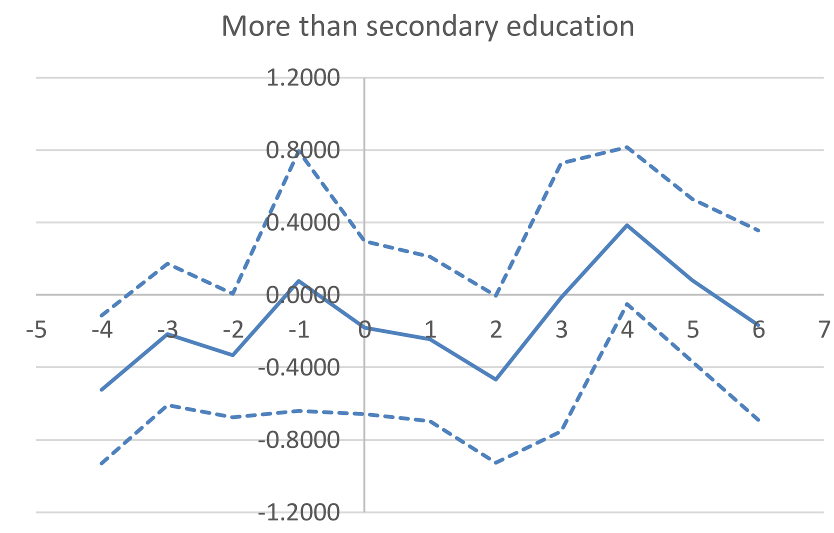

Services/pop - All
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

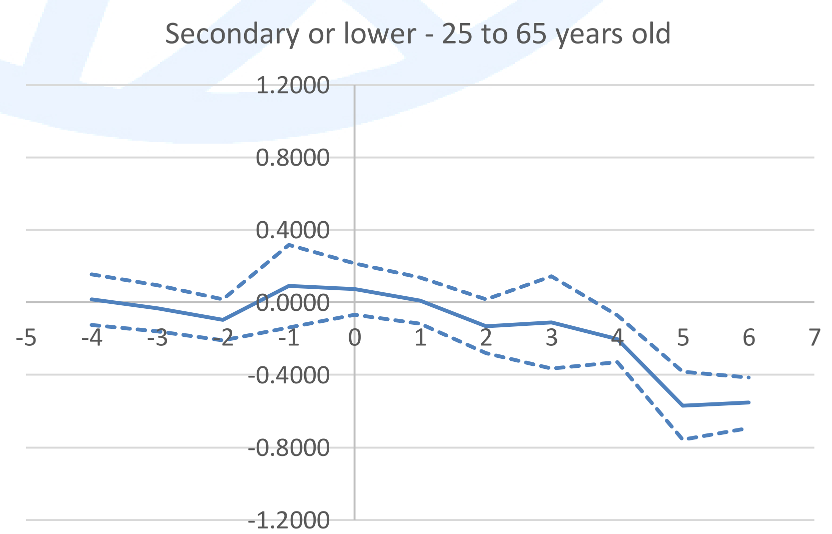

More than secondary education
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

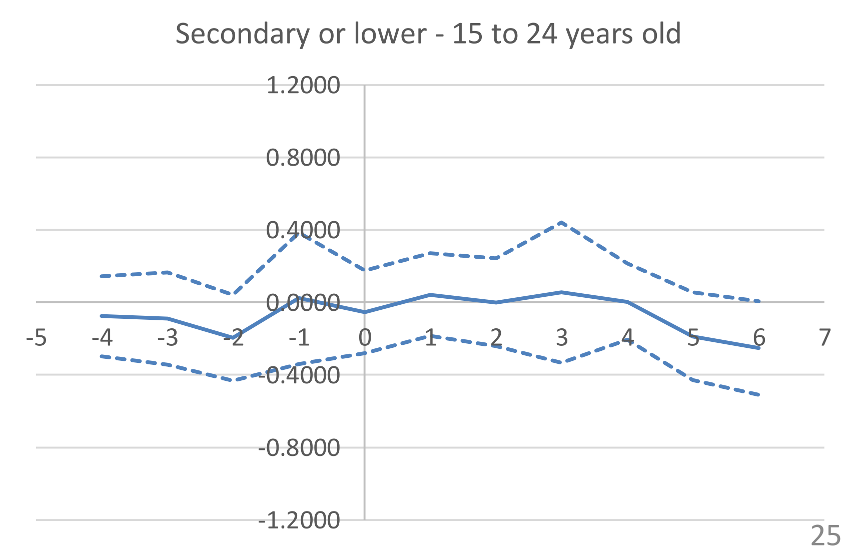

Secondary or lower - 25 to 65 years old
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7


Secondary or lower - 15 to 24 years old
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

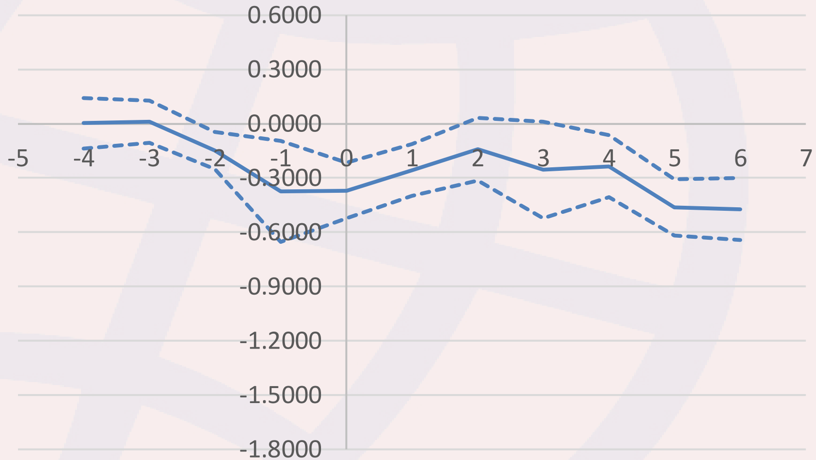

Micro firm/pop - All
1.2000
0.8000
0.4000
0.0000
-0.4000
-0.8000
-1.2000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7


More than secondary education
1.2000
0.8000
0.4000
0.0000
-0.4000
-0.8000
-1.2000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

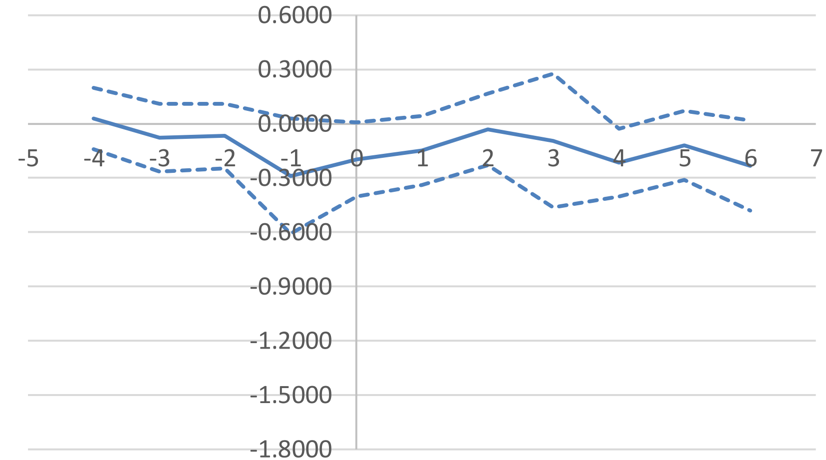

Secondary or lower - 25 to 65 years old
1.2000
0.8000
0.4000
0.0000
-0.4000
-0.8000
-1.2000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7


Secondary or lower - 15 to 24 years old
1.2000
0.8000
0.4000
0.0000
-0.4000
-0.8000
-1.2000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

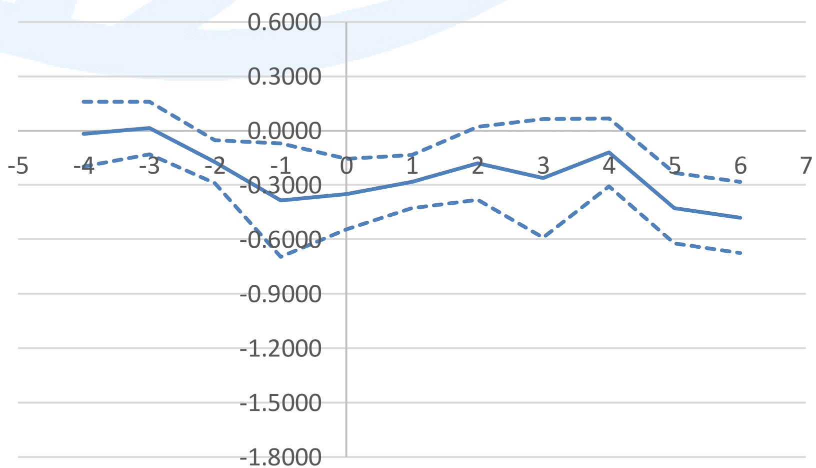
Small & medium firm/pop - All



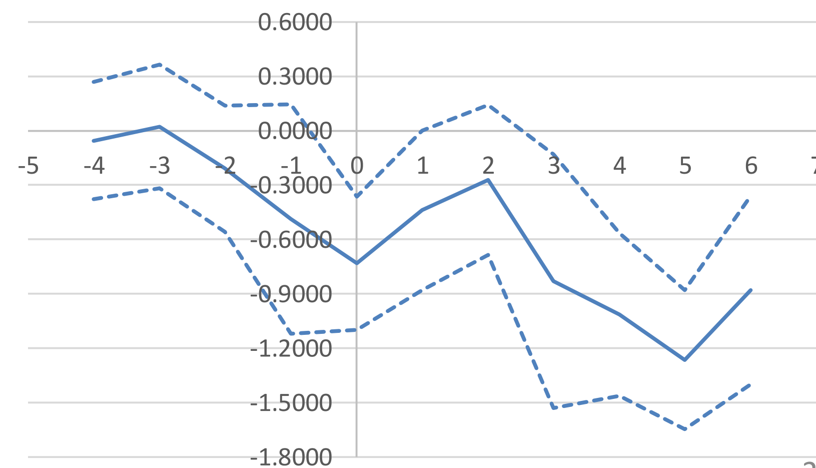
More than secondary education

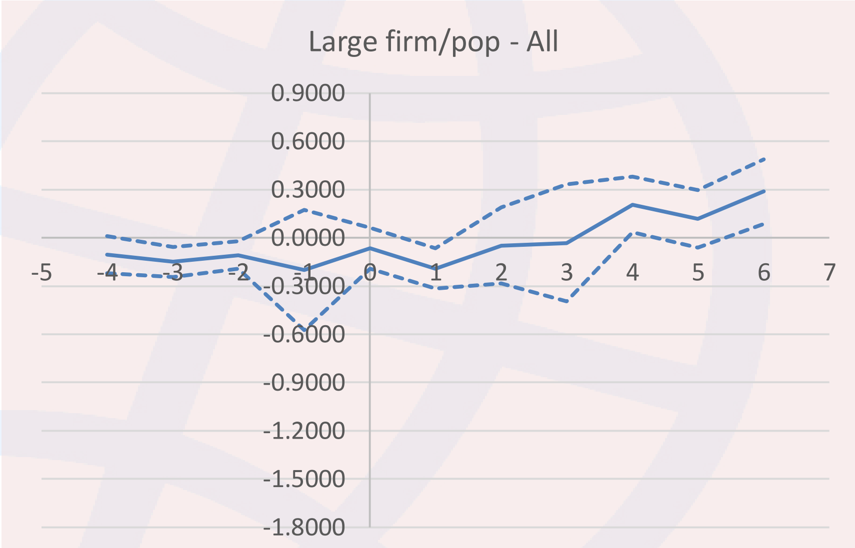


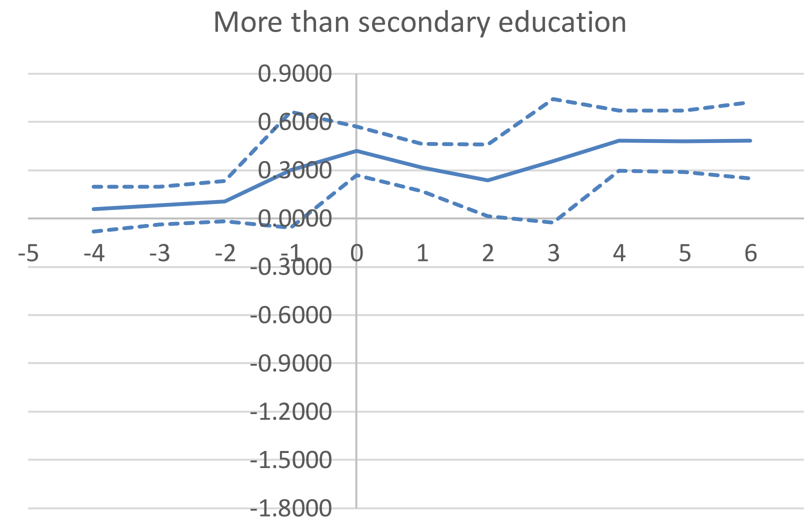
Secondary or lower - 25 to 65 years old

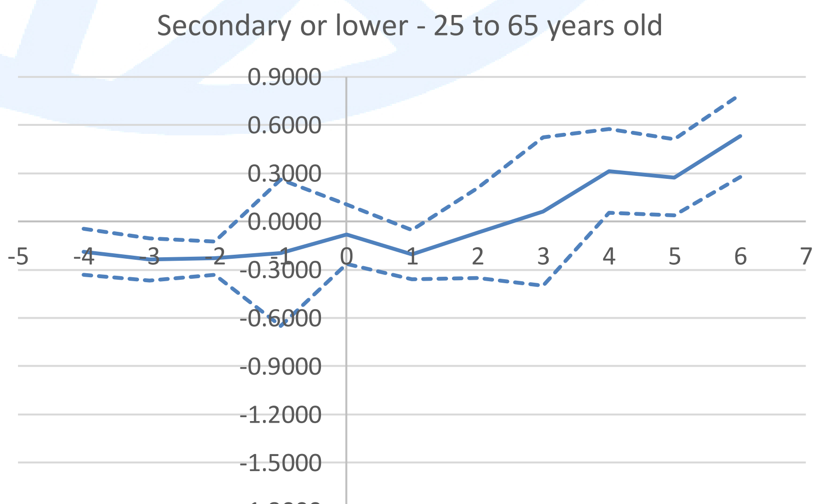


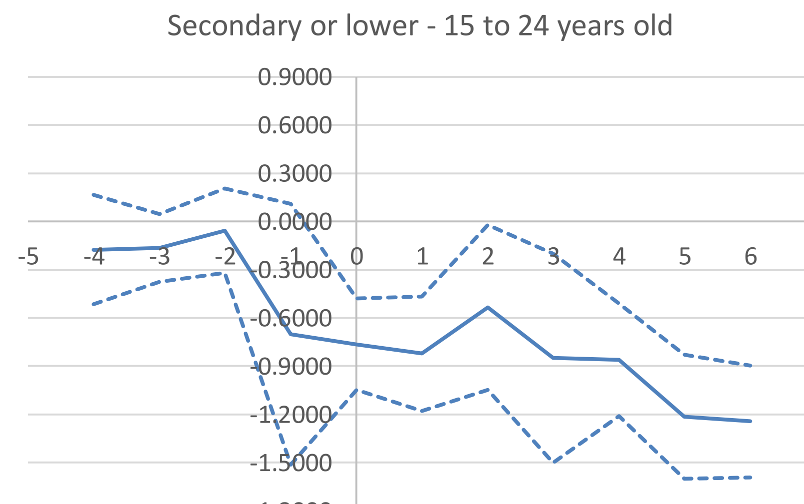
Secondary or lower - 15 to 24 years old




Large firm/pop - All
0.9000
0.6000
0.3000
0.0000
-0.3000
-0.6000
-0.9000
-1.2000
-1.5000
-1.8000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7


More than secondary education
0.9000
0.6000
0.3000
0.0000
-0.3000
-0.6000
-0.9000
-1.2000
-1.5000
-1.8000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7


Secondary or lower - 25 to 65 years old
0.9000
0.6000
0.3000
0.0000
-0.3000
-0.6000
-0.9000
-1.2000
-1.5000
-1.8000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7


Secondary or lower - 15 to 24 years old
0.9000
0.6000
0.3000
0.0000
-0.3000
-0.6000
-0.9000
-1.2000
-1.5000
-1.8000
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7

Wage distribution analysis

- Based on the Unconditional Quantile Regression model (a special case of the Recentered Influence Function Regression) by Firpo, Fortin, and Lemieux, 2009
- The RIF for the τ^{th} quantile, q_τ, is given by (see Annex 1):

$$RIF(Y; q_\tau, F_Y) = q_\tau(F_Y) + IF\left(y; q_\tau, F_Y\right)$$

$$= q_\tau + \frac{\tau}{f_Y(q_\tau)} - \frac{1(Y \leq q_\tau)}{f_Y(q_\tau)}$$

where $F_Y(y)$ is the marginal (or unconditional) distribution function of outcome variable Y, and $f_Y(q_\tau)$ is its density evaluated at q_τ

- FFL (2009) shows that the RIF integrates up to the quantile q_τ of interest

$$\int_{\mathbb{R}} RIF(y; q_\tau, F_Y) dF_Y(y) = q_\tau$$

Wage distribution analysis

- Applying the Law of Iterated Expectation to the previous expression yields

$$E_{\mathbb{X}}\big[E[RIF(y; q_\tau, F_Y)|X)]\big] = E_{\mathbb{X}}[m^{q_\tau}(X)] = q_\tau$$

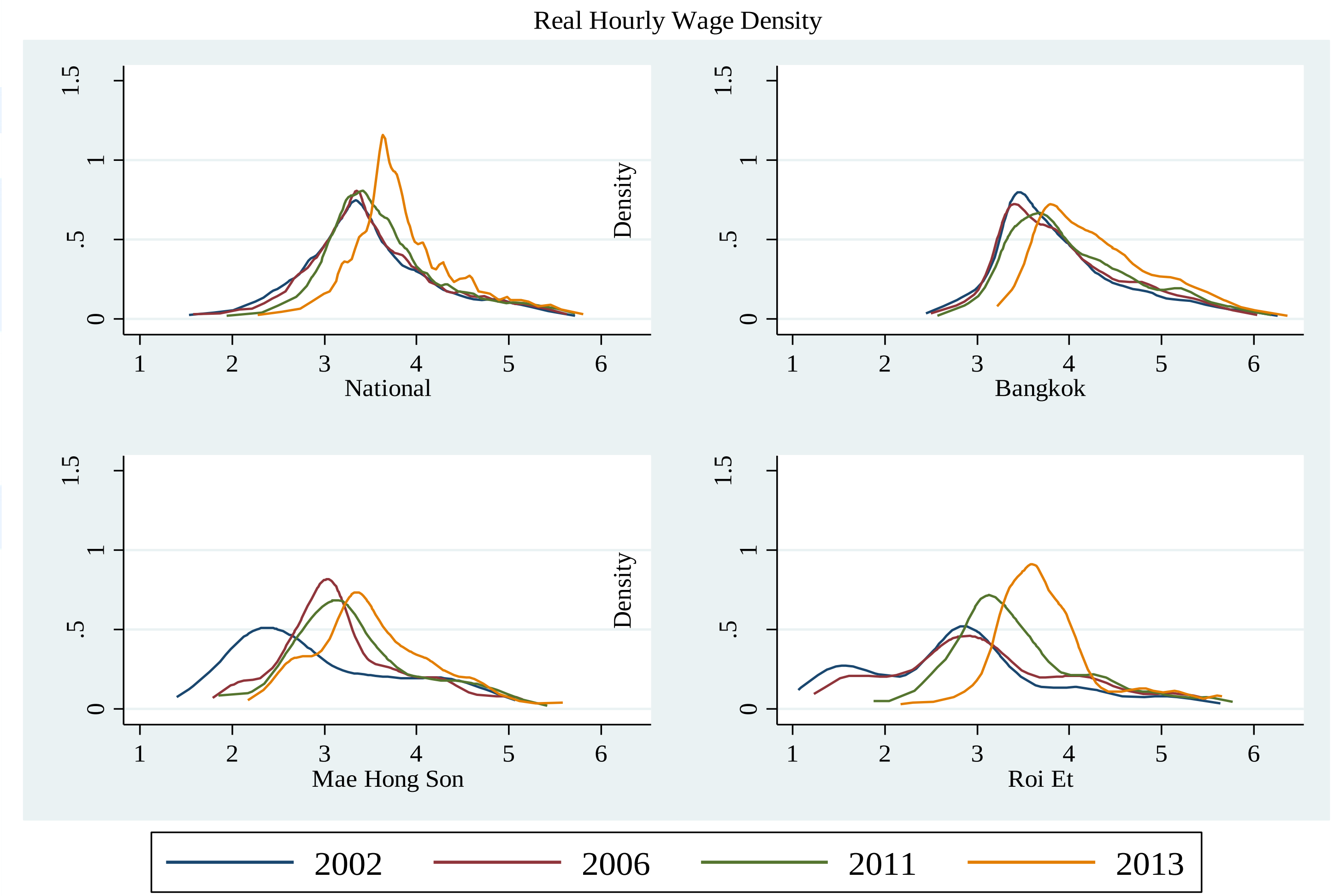
where $E_{\mathbb{X}}[\cdot]$ denotes that the expectation is taken over the covariate space of X and $m^{q_\tau}(X)$ is the RIF regression model

- The model is easily estimated using conventional regression methods on a transformed dependent variable

The Dube (2013) Approach (see Annex 2):

- Dube (2013) employs the traditional RIF technique to estimate the unconditional quantile partial effects (UQPR) of changes in the minimum wage on the distribution of equivalized family income in the US
- However, as noted by Dube (2013) himself the approach could be problematic if the treated and the control units had very dissimilar distributions for the outcome variable (see Annex 2 for details)

Identification Strategy – Example of wage density distributions



Exploiting the heterogeneous response of provincial distributions

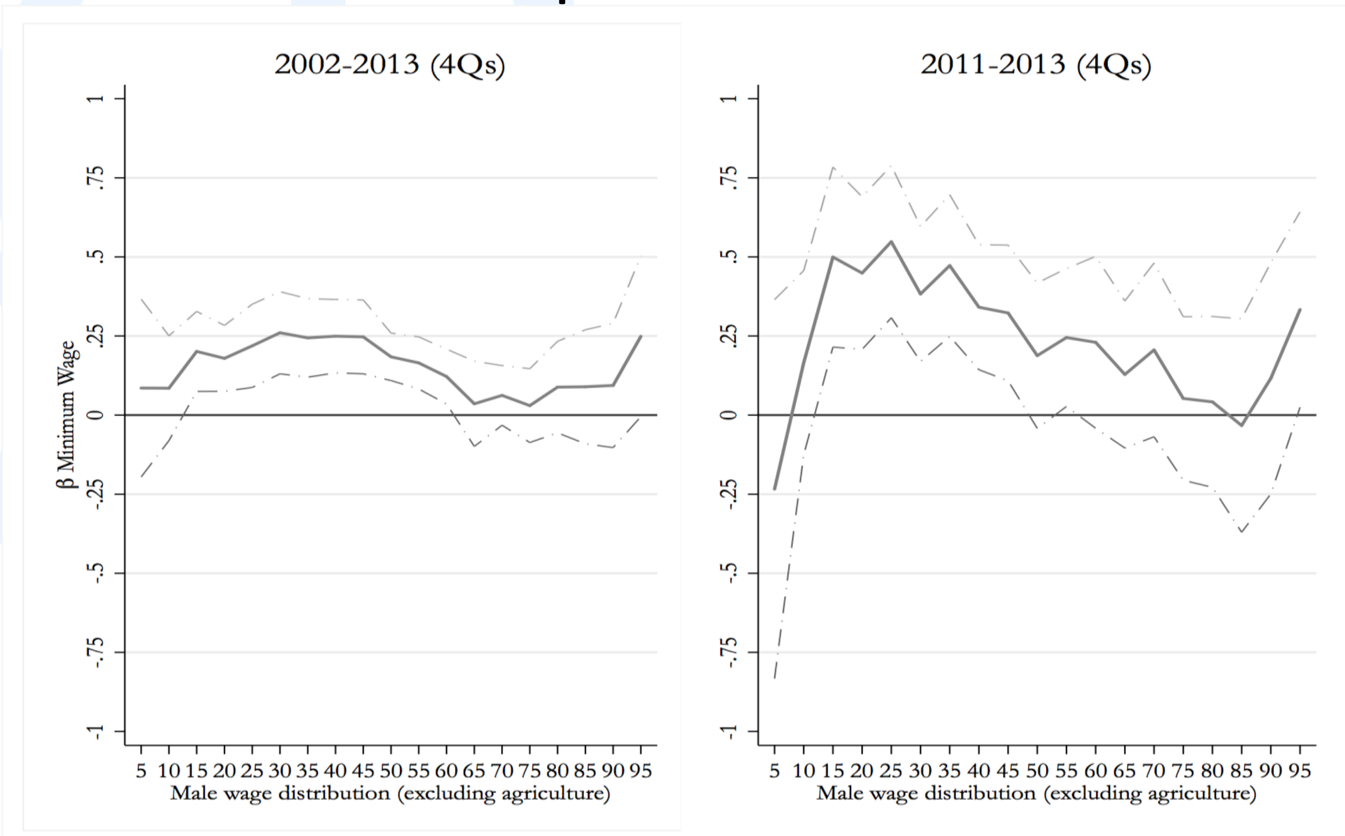
- To make the approach applicable more generally, we apply the RIF transformation to a panel of provincial wage distributions
- For each province p and time t the approach specifies the following RIF transformation to individual wage i (Lathapipat, 2016) :

$$RIF\left(Y_{i,p,t}; q_{\tau,p,t}, F_{Y,p,t}\right) = q_{\tau,p,t} + \frac{\tau}{f_{Y,p,t}\left(q_{\tau,p,t}\right)} - \frac{\boldsymbol{I}\left(Y_i \leq q_{\tau,p,t}\right)}{f_{Y,p,t}\left(q_{\tau,p,t}\right)}$$

- In contrast to the traditional RIF, the transformation is performed locally
- Since $q_{\tau,p,t}$, $f_{Y,p,t}(q_{\tau,p,t})$, and $\boldsymbol{I}(Y_i \leq q_{\tau,p,t})$ vary across province and time, we include in our RIF-OLS regressors province and time fixed effects, together with individual and provincial time-varying covariates

$$RIF_{w_{i\,p\,t}, q_{\tau pt}} = \beta_0 + \beta_1 \, ln\left(MW_{p\,t}\right) + \beta_2 \, X_{i\,p\,t} + \psi_p + \psi_t + \phi_{p*t} + \mu_{i\,p\,t}$$

Estimated minimum wage elasticities across the wage percentile



Note: Provincial RIF regressions of hourly wage for male private sector workers (excluding agricultural workers, pooled quarterly LFS 2002-2013). The left figure displays coefficient and confidence intervals for log real hourly minimum wage for the period 2002-2013, and the right figure for the period 2011-2013.

Summary of key findings

Weak localized disemployment effects of the minimum wage

- Young low-skilled workers are much more affected
- Micro enterprises and SMEs

Evidence of monopsony power among large private sector firms

Evidence of non-compliance

- Mainly among micro enterprises and SMEs

Positive MW spillovers (up to 60th percentile) with no effect on the lowest percentiles

Annex 1

Recentered Influence Function

- The influence function $IF(y; \nu, F_Y)$ introduced by Hampel (1968, 1974) is a widely used tool in studies on local robustness properties of functionals, and is defined as:

$$IF(y; \nu, F_Y) = \left.\frac{\partial \nu\left(F_{Y,\epsilon.\delta_y}\right)}{\partial \epsilon}\right|_{\epsilon=0} = \lim_{\epsilon \downarrow 0} \frac{\nu\left(F_Y + \epsilon\left(\delta_y - F_Y\right)\right) - \nu(F_Y)}{\epsilon}, \qquad 0 < \epsilon < 1$$

  if this limit is defined for every point $y \in \mathbb{R}$, and δ_y denotes the probability measure that puts the mass 1 at the value y

- If a statistical functional (von Mises (1947) functional) is Gâteaux differentiable at F_Y, Firpo, Fortin, and Lemieux (2009) show that the following approximation holds for some distribution function G_Y close to F_Y:

$$\nu(G_Y) = \nu(F_Y) + \int_{\mathbb{R}} IF(y; \nu, F_Y) d(G_Y - F_Y)(y) + r$$

  where r is a remainder term

Recentered Influence Function

- Noting that $\int_{\mathbb{R}} IF(y; \nu, F_Y) dF_Y(y) = 0$ by definition, we have:

$$\nu(G_Y) = \nu(F_Y) + \int_{\mathbb{R}} IF(y; \nu, F_Y) dG_Y(y) + r$$

- For a particular case that G_Y=δ_y, FFL call this first order approximation term the “Recentered Influence Function” (RIF):

$$RIF(y; \nu, F_Y) = \nu(F_Y) + \int_{\mathbb{R}} IF(s; \nu, F_Y) d\delta_y(s)$$
$$= \nu(F_Y) + IF(y; \nu, F_Y)$$

- For any quantile $\tau \in (0,1)$, denote by $q_\tau(F_Y)$ the τ^{th} quantile of the dependent variable Y. It can be shown that the influence function for the quantile can be written as:

$$IF(y; q_\tau, F_Y) = \frac{\tau - 1(Y \leq q_\tau)}{f_Y(q_\tau)}$$

Annex 2

The Dube (2013) approach

- Key intuition underlying the FFL (2009) approach (Dube, 2013): the method can be used to invert the impact of a policy on the proportion of individuals under an income cutoff to arrive at the effect of the policy on an income quantile q_τ of the outcome variable
- For simplicity, let the policy variable be a binary variable denoted by $T = 0,1$ and the outcome variable by $Y \sim F_Y$
- Under the assumptions of conditional independence (i) $Y_i \perp T_i | X_i = x$ and overlapping support (ii) $0 < Pr(T = 1 | X = x) < 1$ for all $x \in \mathbb{X}$, the counterfactual distributions under treatment $(T = 1)$ and control $(T = 0)$ are identified and the impact of the policy on the τ^{th} quantile (or UQPE) of the outcome variable can be estimated:

$$UQPE \approx E_{\mathbb{X}}\big[E[RIF(y; q_\tau, F_Y) | X, T = 1)]\big] - E_{\mathbb{X}}\big[E[RIF(y; q_\tau, F_Y) | X, T = 0)]\big]$$

$$= q_{T=1,\tau} - q_{T=0,\tau}$$

The Dube (2013) approach

- For the τ^{th} quantile of the outcome variable (q_τ), Dube (2013) uses the following RIF transformation

$$RIF(Y; q_{A,\tau}, F_{A,Y}) = q_{A,\tau} + \frac{\tau}{f_{A,Y}(q_{A,\tau})} - \frac{1(Y \leq q_{A,\tau})}{f_{A,Y}(q_{A,\tau})}$$

  where the subscript A denotes the actual full-sample distribution

- This simplifies matters considerably as the regression estimate for the UQPE becomes a rescaled effect of the impact on the proportion under the cutoff $q_{A,\tau}$, where the scaling factor is $-1/(f_{A,Y}(q_{A,\tau}))$
- However, as is acknowledged in Dube (2013), the use of the full sample distribution to estimate the cutoff $q_{A,\tau}$ and the density function $f_{A,Y}(q_{A,\tau})$ could be problematic if the treated and the control units had very dissimilar distributions for the outcome variable
- This makes the approach very restrictive and cannot be applied in more general settings

For more information about the study:

- Please contact Dilaka Lathapipat dlathapipat@worldbank.org