The London School of Economics and Political Science

Essays on Labour Economics

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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Abstract

Empirical studies in labour economics often suffer from endogeneity problems. Employing exogenous variations in policies and natural shock, this thesis investigates three topics. The first two topics concern labour market phenomena in Thailand, whereas the third provides a case study of labour demand adjustment after an international supply chain shock.

Chapter 2 assesses the impact of minimum wage policy on wage inequality in Thailand. The result is rather mixed. Although the minimum wage effectively reduces wage inequality among workers in formal sectors, it does not affect the wage distribution in the informal sector at all. The evidence suggests that such a result is mainly driven by weak law enforcement.

Meanwhile, using changes in compulsory schooling law, chapter 3 provides consistent estimates of the rates of return to education in Thailand. Based on the IV method, only female employees experience a positive and significant return to (upper primary) education. Interestingly, the size and direction of bias of the estimator, especially for male sub-sample, are not consistent with the conventional result. The possible reasons underlying these findings are elaborated.

Chapter 4 relies on a different type of shock. The Great Tohoku Earthquake and Tsunami 2011 is treated as an external shock to the international supply chain of Auto industry. Then I estimate the impact of the supply chain disruption on labour inputs adjustment in the US auto industry. Despite the break down in supply chain of motor vehicle parts and accessories among Japanese auto companies, these firms do not seem to reduce their labour inputs (used as a proxy for changes in production) significantly except for a small drop in average monthly earnings of workers in Japanese assembly plants.

Also, their competitors make only slight adjustment to capitalize on the Japanese loss. Regarding other margins of adjustment, there is no evidence in support of the adjustment through import or price. Yet inventories and sales incentive appear to be major tools employed to mitigate either positive demand or negative supply shocks on both groups of companies.

To my parents and my late grandparents

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1 Introduction

Endogeneity is one of the major statistical concerns in empirical economic research attempting to uncover causal relationships. There are two main frameworks used in econometrics to estimate "causal effects", namely the potential-outcome framework and the structural equation model (Pearl, 2009). Following identification strategies proposed in the recent treatment effect literature (such as Angrist, 2004; Imbens, 2004), this thesis exploits external variations in labour law (chapter two), education policy (chapter three), and natural disaster (chapter four) to evaluate effects of such intervention, estimate causal parameters consistently, and explore adjustments in labour market through firms' and households' decision.

The second chapter concerns one of the most popular labour market intervention policies, the minimum wage, and its impacts on wage inequality in Thailand. Most minimum wage literature in developing countries provide supporting evidence on its effectiveness in reducing wage inequality (e.g. Maloney et al., 2001; Neumark and Wascher, 2008). Using the Thai Labor Force Survey (LFS) from 1985 to 2010, I find rather mixed outcomes. The minimum wage seems to help compress the lower part of wage distribution for employees in large businesses. Yet the effect does not extend to either the whole labour market or small firms in sectors obliged to pay the minimum wage. These results are not sensitive to changes in identification strategies and are not influenced by periods of incremental increases in nominal minimum wages after the 1997 Asian financial crisis.

In contrast with its role as a benchmark for wage adjustment in Latin America (Maloney and Mendez, 2003), the minimum wage in Thailand does not reduce overall wage inequality owing to high non-compliance rate and weak law enforcement, particularly in the informal sector. However, such conclusion agrees with the segmented labour market (or Welch-Gramlich-Mincer) model (Lewis, 1954; Harris and Todaro, 1970; Gramlich, 1976; Mincer, 1974a; Welch, 1974) and other studies in Indonesia (e.g. Suryahadi et al., 2001; Alatas and Cameron, 2003). Hence, more research is needed to identify reasons behind differential effects across developing countries (especially those in Latin America and Asia-Pacific regions).

The third chapter investigates the effect of human capital accumulation on earnings and health outcomes in Thailand. In order to circumvent the endogeneity problems, changes in compulsory school law during 1960s and 1970s are used as an instrumental variable for observed year of schooling from Thai LFS. Firstly, the paper confirms that changes in compulsory schooling laws have positive and significant effect on educational level of affected cohorts, especially for the female. Then I present the estimated rates of return to education based on the IV method. The differential effect between genders is still observed.

Particularly, only female sub-sample yields a positive and robustly significant rate of return to schooling regardless of model specifications. Although the previous study in Thailand using pseudo-panel approach confirms higher rate of return to women's education (Warunsiri and McNown, 2010), their estimates for both genders are larger and significantly different from zero. Therefore, this chapter extensively discusses two findings, which are the direction of bias in OLS regression and the zero return to men's compulsory education, and tries to reconcile with existing literature (such as Card, 2001; Duflo, 2001; Pischke and von Wachter, 2008). In addition, I employ the Health and Welfare Survey (HWS) to assess the relationship between education and health outcomes. All estimates from IV method are neither significant nor strongly identified owing to a much smaller sample size.

The last chapter attempts to empirically assess the impacts of international supply chain disruptions on labour demand and other margins of adjustment. Using, as a natural experiment, the sharp drop in Japanese exports of motor vehicles and parts to the USA after the Great Tohoku Earthquake and Tsunami 2011, the impacts of the supply chain disruption on labour inputs adjustment in the US auto industry are estimated. Exploiting state-level variation in numbers of direct employment by Japanese auto makers and location of auto manufacturing factories, this paper identifies the adjustment among Japanese companies, their suppliers as well as their competitors based on the Current Population Survey (CPS) and the Quarterly Workforce Indicators (QWI) data.

Notwithstanding significant losses of the Japanese firms' market share, I find that the disaster negatively affects only average monthly earnings of workers in Japanese assembly plants whereas their competitors, specifically the American and German manufacturers, do not seem to significantly increase any labour inputs in their US assembly plants. Moreover, other than a slight change in inventory and sales incentive, there is no evidence of any adjustments on other margins of factors such as import substitution, or spikes in prices. These results suggest that the overall impact of this disaster on the US economy through the auto industry is rather small. Nevertheless, the role of incentive and inventory management as potential mechanisms to stabilize the shock deserve a thorough assessment in future research.

In sum, this thesis generates several new insights through the use of different types of natural experiments. Those new insights involve how labour market in developing countries operates and reacts to government intervention, how high and heterogeneous the rates of return to human capital accumulation are, as well as how labour demand adjusts after a disaster shock on international supply chain.

2 Minimum Wage and Wage Inequality in Thailand

2.1 Introduction

The effects of minimum wages on various groups of workers have been a popular subject of vigorous debate in the long history of economic literature, as reviewed by Card and Krueger (1995), Machin and Manning (1997), Brown (1999), and Neumark and Wascher (2008). A few of the supporting reasons for the minimum wage policy are its potential to reduce wage inequality, especially among the low paid workers, and its potential to lift these workers and their families out of poverty (Saget, 2001). Therefore, it is crucial to verify any effects the minimum wages have on wage distributions. Researches from the US, UK and Canada in the 90s (Card and Krueger, 1994; DiNardo et al., 1996; Lee, 1999; Machin and Manning, 1994; Fortin and Lemieux, 2000) found that minimum wages significantly reduce wage dispersion. Recent studies in these countries find smaller direct and spillover effects of the minimum wage on the overall wage distribution because minimum wages were set at the level where only a small fraction of workers were directly affected (Dickens and Manning, 2004; Autor et al., 2010). Hence, it is interesting to investigate the impacts of such policy in the context of developing countries where minimum wages affect larger fraction of workers.

However, the compliance with the minimum wage law in developing countries is far from perfect and a significant proportion of their workers is in the informal sector. So, the expected result is rather ambiguous (Although the law enforcement and compliance are not the main concern in developed countries, Ashenfelter and Smith (1979) proved that non-compliance with the minimum wage law is reasonable for profit maximizing firms and recommended that compliance issue should be taken into account in future research on the minimum wage). Moreover, comparisons across studies in developing countries are more complicated due to differences in minimum wage levels, enforcement and labour market institutions (Lemos, 2009). Though these studies mostly agree on the positive wage compression effect of the minimum wages in the formal sector, the results in the informal sector are rather mixed (see Maloney and Mendez, 2003; Neumark and Wascher, 2008, for some literature survey).

In spite of expected ineffectiveness of the minimum wage on informal workers, most literature in Latin America and the Caribbean report positive wage compression effects of the minimum wage in both sectors (with few exceptions such as Honduras in Gindling and Terrell, 2009). For example, Freeman and Freeman (1992) observe spikes around the minimum wage in overall Puerto Rican earning distribution whereas Gindling and Terrell (2005) detect higher wages after increases in minimum wages in

Costa Rica not only for large urban enterprises (formal sector) but also small urban and all rural enterprises (informal sector). Other than the classification of wage employees into formal and informal sectors, Lemos (2009) finds that the minimum wage in Brazil compresses the wage distribution of low-educated workers and self-employed workers as well. As one of the most thorough analyses of the minimum wage policy in the Latin America, Maloney et al. (2001) use Kernel-density plots and find that minimum wages could influence the distribution of wages in both the formal and the informal sectors of eight Latin American countries. Surprisingly, their results indicate stronger distortion around the minimum of the informal wage distribution than the formal in Brazil, Mexico, Argentina and Uruguay.

In case of Mexico where real minimum wages deteriorated in the 80s and 90s, early literatures find mixed results on minimum wage and employment (Bell (1997) detects no employment effect in Mexican manufacturing sector but Feliciano (1998) finds disemployment effects of the minimum wage on female workers in all industries). However, based on modification of Lee (1999) model, Bosch and Manacorda (2010) conclude that the deterioration of the real minimum wages contributes to the rise in wage inequality. While minimum wages compress the bottom part of Mexico's wage distribution, the effects in the informal sector are more pronounced (up to the eight decile of the informal wage distribution). They also observe a positive correlation between minimum wages and inequality of sub-minimum wage workers and stronger spillover effects in the informal sector.

There are several reasons why the minimum wage can affect the informal wage distribution. First, the minimum wage could induce the relocation of capital from formal sector to the labour intensive informal sector leading to higher informal sector wages (Harrison and Leamer, 1997). Though the minimum wage might simply indicate the wage level in high inflation countries, Maloney and Mendez (2003) argue that such a reason does not apply to Brazil, Columbia, and Mexico where inflation rates were moderate during the sample period. They propose that the minimum wage could act as a benchmark for "fair" remuneration (the so-called 'lighthouse effect'). Moreover, Khamis (2013) provides evidence from Argentina that employers might comply with the minimum wage law but not other benefit entitlements such as social security contribution (which is widely used to classify workers into formal or informal sectors). In addition, Boeri et al. (2010) use the matching model to show that if the introduction of the minimum wages changes skill composition between formal and informal sectors, such sorting of workers by skill could result in higher average skills of workers in the informal sector, thus, higher average wages.

Outside Latin America and the Caribbean, studies on the effects of minimum wages on wage inequality in other developing countries are less common (for a review of evidence from developing countries in other regions, see Saget, 2001). In particular, there is a paucity of evidence for minimum wage effects on the wage distribution in Southeast Asian economies. Despite rising or persistent wage and income inequality in East and Southeast Asian economies, existing literature focus on economic liberation or Foreign Direct Investment (FDI) as the underlying factors of such trends (Jomo, 2006; Te Velde and Morrissey, 2004). The only exception is Indonesia where researchers find conflicting results.

Rama (2001) and Suryahadi et al. (2001) show that the minimum wage hikes have a positive impact on average wages of all workers and all segments of workforce but mostly insignificant except for the sub-sample of blue-collar workers. On the contrary, using the simulation framework, Bird and Manning (2008) report negative effects on wages in the informal sector. In terms of the impact on employment, Suryahadi et al. (2001) and Alatas and Cameron (2003) report differential effects varied by firm size. While small domestic firms experience employment losses, large firms (both domestic and foreign) are not negatively affected or even experience rises in employment. Yet Bird and Manning (2008) suggest increases in informal employment.

With respect to wage inequality in Thailand, similar to the Anglo-Saxon economies, Lathapipat (2009) finds evidence for wage polarisation in Thailand during the late 1980s to early 2000s (table 4.1 in Lathapipat 2008 and figure 5 in Lathapipat 2009). Particularly, wage inequality at the top had risen whereas wage gaps between the median and the first decile were narrowed down. He proposes that the rise of the bottom part of the wage distribution could result from an internal migration of labourers from hidden unemployment in rural area to the modern sector in urban area. Yet it is interesting to investigate if other factors such as labour market institution contribute to such a trend. Hence, the objective of this paper is to assess the role of the minimum wage policy in narrowing the wage gap of low paid workers in Thailand. Additionally, it contributes to the small literature on the differential effects of minimum wages on the formal and informal wage inequality in Southeast Asia.

This paper uses the Thai Labor Force Survey (LFS) in the first and third quarter (dry and rainy season) from 1985 to 2010. Due to high and fluctuating non-compliance rates throughout the period of study, the Dinardo, Fortin and Lemieux decomposition methodology is not applied in this paper. Instead, I exploit variation in the 'effective minimum', which is defined as the difference between the statutory minimum wage and median wage in each province (Lee, 1999), to identify impacts of minimum wage on different percentiles of wage in that province. Moreover, to acknowledge criticisms on Lee's econometric specification, the methodology proposed in Autor, Manning, and Smith (2010) is applied.

The results show no discernible wage compression effect on the overall labour market and in sectors obligated to pay the minimum wage (the so-called 'covered sectors'). In other words, the minimum wage does not result in significant wage compression for either all employees or workers in covered sector. However, the evidence suggests that the minimum wage significantly compresses the wage distribution of workers in large establishments in covered sectors. Nevertheless, such policy might be driven by periods of incremental rises in statutory minimum wage after the 1997 Asian financial crisis. Therefore, I use the methodology based on "Fraction of Affected Workers" by Card and Krueger (1995) to assess the effect of minimum wage on wage distribution of periods with significant hikes. Still, the distinctive outcomes among sub-groups of workers are affirmed.

Further, the data from Department of Labour Protection on labour inspection show rather weak law enforcement. This statistic is in line with the ineffectiveness of minimum wage policy observed. Thus, the result of this paper highlights the role of a difference in the compliance rate between formal and informal sectors on effectiveness of minimum wage policy provided that firm size can be used to classify workers into either formal or informal sector. Although such finding is in contrast to most literature from Latin America, where minimum wages effectively influence both formal and informal wage distribution, it is in line with diverse employment effects across sectors observed in Indonesia.

The paper is structured as follows. Section 2.2 describes the data and descriptive statistics of minimum wage and hourly wage in Thailand. Section 2.3 outlines the methodologies while Section 2.4 briefly discusses the main results. Section 2.5 presents some robustness check and Section 2.6 discusses the results with respect to law enforcement and economics theories.

2.2 Data and descriptive analysis

2.2.1 Minimum wage in Thailand

The minimum wage was first introduced for private employees outside the agricultural sector in Bangkok and adjacent cities in April 1973. Later in October 1974, its coverage was expanded to the whole country. The statutory minimum wages have been set differently across zones as wage in baht per day which, in general, is defined as 8 hours of work.[1] As for part-time workers, they are also entitled to receive hourly minimum wage which is equal to the daily minimum wage divided by 8 hours.

At first, the minimum wage setting process was centralized and categorized into 3 zones by geographic region. From October 1981, the legislation stated that minimum wage setting took factors of each region such as inflation, living standard, competitive-

[1] There is an exception for some hazardous jobs as defined by Ministry of Labour (such as jobs related to work under water, inside tunnel, hazardous chemicals or radioactive materials). Employees in these jobs are not allowed to work more than 7 hours per one regular working day. Yet this paper disregards such an exception and transforms minimum wage per day into hourly by dividing statutory minimum wage per day by 8.

ness, economic and labour market condition into consideration. However, the number of minimum wage zones was stable around 3-4 zones during 1981-2001. After the enactment of the Labour Protection Act 1998, the minimum wage setting was decentralized from the national tripartite committee (comprised of representatives from employers, employees and government) to regional tripartite sub-committee in each province or sub-region. Then number of minimum wage bands started to increase dramatically from 8 zones in 2002 to 28 zones in 2010.

Yet differences between these zones are small and move along with their counterparts in the same zone before 2001. In addition, figure 2.1 shows an upward trend from late 80s until it reached its peak slightly before the Asian economic crisis. Then it dropped sharply and has not attained such level even in 2011.

2.2.2 Wages

I employ the Labor Force Survey (LFS) conducted by the National Statistics Office of Thailand (NSO). NSO adopts a stratified two-stage sampling of the whole country (blocks or villages and private households) for these surveys. From 1984 to 1997 the surveys were conducted three rounds in each year; the first round enumeration is held in February coinciding with the non-agricultural season, the second round is normally held in May when new labor force from graduated students just finish their study and the third round is conducted in August, during the agricultural season. From 1998, the fourth round of the survey has been conducted in November (NSO, 2003). Then since 2001 the surveys have been conducted monthly with three months combined for each round of survey.

LFS provides data on individual characteristics for every member of the household including work status, occupation, industry and hours worked for all employed persons. Also, for all workers, the LFS records information on wage / salary, overtime payments, bonuses and some other fringe benefits in the first and third round, yet after 1999 this wage data is also available for the second and fourth round. In order to ensure comparability across years, only the first and third round (dry and rainy season) of the LFS from 1985 to 2010[2] are utilized. Typically, sample sizes of each surveys is large and represents regional level. Only after February 1994, NSO expanded the sample size to assure statistical representation at provincial level (NESDB and NSO, 2004)[3]. Hence, due to small sample size in these early surveys (especially for wage earners), this study will provide a robustness check where provinces or rounds with too small observations are dropped.

In this paper, the sample covers all wage earners in private, public and state en-

[2] With an exception of three rounds which are 1986 1^{st}, 1990 1^{st}, and 2010 3^{rd}

[3] Sample size of employees for the whole country in the third round is ranging from 13,313 (out of total 78,214) in 1985 to 37,828 (177,821) in 1994 and 53,342 (219,538) in 2007.

Figure 2.1: *Real Minimum wage by provinces (Baht per day in 2007) 1981-2011*

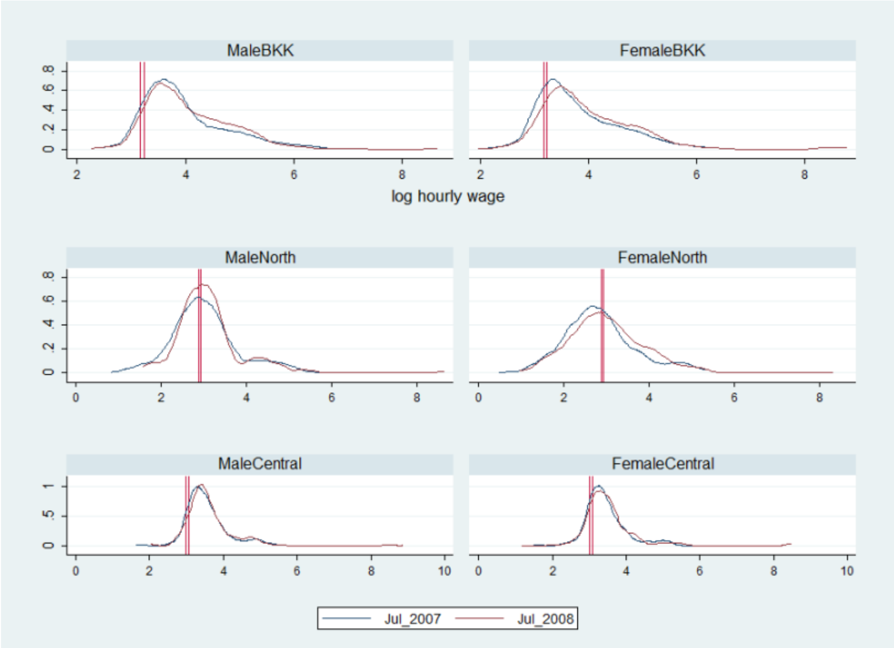

Figure 2.2: *Kernel Density of Log hourly wage (weighted) for all workers July 2007 VS 2008 in selected provinces*
1) BKK stands for Bangkok.
2) North includes 2 provinces in the north of Thailand which are among the lowest pay scale of minimum wage.
3) Central comprises of 2 provinces in the central with many industrial estates.

terprises who report their wages and number of hours worked in the preceding week of the survey. As the minimum wage law in Thailand primarily determines the basic wage for regular working hours, the wage variable used is hourly wages excluding other compensation such as bonus, over time, clothes or any benefits.[4]

According to the kernel density of log hourly wage in figure 2.2 where two vertical lines refer to minimum wage in each zone during July 2007 and 2008 respectively, male workers seem to earn slightly higher than their female counterpart in all zones as expected. Yet the surprising feature is that there is no distinct spike around the minimum wage in any zones. In Bangkok and the central region, peaks of female wage distribution are only slightly higher than the statutory minimum, on the contrary about half of female workers in the north receive basic hourly wage that is higher than the minimum wage in their provinces. This result indicates a possibility of a severe non-compliance problem in many provinces, especially in low minimum wage zones.

[4]Hourly wage is calculated from dividing basic wage by total hours worked for principle occupation. In several cases, this total hours worked contains hours of over time work. In order to obtain total regular hours worked corresponding to basic wage, I employ over time payment adjusted by 1.5 (because employers are required to pay over time at least 50% higher than hourly wage during regular hours). However, this procedure might overestimated the number of regular hours worked but it should provide a lower bound of observed hourly wage.

Table 2.1: Summary statistics for bindingness of provincial minimum wages

	All			Female			Male		
Year(Q3)	Max. pctile	Min. pctile	Median pctile	Max. pctile	Min. pctile	Median pctile	Max. pctile	Min. pctile	Median pctile
1989	85.1	15.5	48.5	95.1	27.4	61.4	80.6	5.0	39.8
1994	72.2	14.2	48.9	85.1	17.6	61.0	62.4	11.2	43.1
1999	62.4	7.5	35.4	75.5	9.6	42.1	59.3	5.8	30.5
2004	65.2	10.8	40.9	74.8	12.4	44.5	62.3	9.4	37.1
2009	51.4	9.5	29.9	62.1	8.4	34.8	53.2	7.6	26.2

The definition for Max. pctile, Min. pctile and Median pctile are as follows: All percentiles (pctile) display in this table are a proportion of workers who received basic wage less than their provincial minimum wage. For Max. pctile, it is such percentile in a province with the highest level of non-compliance to the law in each year. Meanwhile, Min. pctile is a percentile in a province with the highest compliance to the law whereas Median pctile is the percentile in a province with non-compliance rates at the middle of all provinces in that year.

In the subsequent table, I provide examples of variation in bindingness percentile[5] of the minimum wage across provinces over the sample periods.

Although table 2.1 does not show a clear upward trend in compliance with minimum wage law[6], binding percentile in Max, Median and Min. provinces decrease slightly over the sample period. Still, non-compliance rates are higher than 30 % for half of the country even in 2009. Consequently, the wage compression effect from minimum wage law might be partially effective. I will then employ various strategies to investigate this hypothesis in the following sections.

2.3 Methodology

This paper follows the strategy used in Lee (1999) to exploit inter-province variation in the gap between the provincial median wage and its minimum wage (i.e. effective minimum) to estimate the effect of changes in minimum wage on wage inequality in Thailand. However, in the case of Thailand, one of the key identifying assumptions -that the provincial latent wage inequality is uncorrelated with the median- is likely to be violated. Therefore, to address omitted variables resulting from this correlation, I adopt a technique employed by Autor, Manning, and Smith (2010). Provincial fixed effect and provincial trends are included as a control for shocks to the wage distribution that are correlated with changes in minimum wages. The main OLS specification is:

$$w_{nt}^P - w_{nt}^M = d_{tP} + d_{nP} + d_{nP} \times T + \beta_1^P (MW_{nt} - w_{nt}^M) + \beta_2^P (MW_{nt} - w_{nt}^M)^2 + \epsilon_{nt}^P \quad (2.3.1)$$

where w_{nt}^P is the P^{th} percentile of the observed log wage (per hour), w_{nt}^M is the Median (in this paper I used the 6th decile) of the observed log wage; d_{tP} is year dummy, d_{nP} is provincial dummy, T is time trend; MW_{nt} is the statutory minimum wage and ϵ_{nt}^P

[5]That is a fraction of employees in each province who receive wages less than legislative minimum wage

[6]There is no pattern for this fluctuation either despite including all years in the sample.

is an error term in province n at time t for P^{th} percentile. Also, all regressions are weighted by multiplication of sampling weight and number of total hours worked.

Moreover, to tackle with Division bias[7], I follow a 2SLS strategy as in Card, Katz, and Krueger (1993) and Autor, Manning, and Smith (2010) by instrumenting the effective minimum with statutory minimum wage in each province and year. This instrument should be correlated to provincial effective minimum but uncorrelated to any measurement errors in the sampling median. Thus, it relies on a key assumption that legislated changes in minimum wage are not correlated with changes in latent province wage inequality conditional on year and province dummies and provincial trends. Therefore, the second stage is the same to equation 2.3.1 while the first stage for the effective minimum is specified as:

$$(MW_{nt} - w^M_{nt}) \;=\; d_{tP} + d_{nP} + d_{nP} \times T + \delta^P MW_{nt} + \nu^P_{nt} \tag{2.3.2}$$

Likewise, an instrument for the square of the effective minimum is computed from a square of predicted value from regression 2.3.2. Yet this instrument might suffer from limited variation because there were few minimum wage zones before 2002. As a robustness check, I adopt a reduced form approach by Autor, Manning, and Smith (2010) and use predicted instead of observed provincial median wage in equation 2.3.1. The predicted median can be estimated as follow:

$$w^M_{nt} \;=\; d_t + d_n + d_n \times T + u_{nt} \tag{2.3.3}$$

which specifies provincial median wage, $\widehat{w^M_{nt}}$,as a function of year dummies, province dummies and provincial trends. Then define the reduced form effective minimum $\widetilde{mw}_{nt}$ as $(MW_{nt} - \widehat{w^M_{nt}})$. Equation 2.3.1 can be rewritten as:

$$w^P_{nt} - w^P_{nt-1} \;=\; d_{tP} + d_{nP} + d_{nP} \times T + \tilde{\beta}^P_1 \widetilde{mw}_{nt} + \tilde{\beta}^P_2 \widetilde{mw}^2_{nt} + \tilde{\epsilon}^P_{nt} \tag{2.3.4}$$

Further, the other identification strategy proposed in the literature called "fraction affected" (Card and Krueger, 1995) is adopted so as to circumvent potential weak instruments problem as well as a decline of real minimum wage. The primary OLS model is specified as:

$$w^P_{nt} - w^P_{nt-1} \;=\; c^P + \theta^P (FA_{nt}) + \eta^P_{nt} \tag{2.3.5}$$

where $w^P_{nt} - w^P_{nt-1}$ is change in log hourly wage at P^{th} percentile from year t-1 to t in province n, FA_{nt} is fraction affected in province n year t defined as the fraction

[7]This bias results from a spurious correlation between the variables (Borjas, 1980). In this case, median of the observed log wage (potentially measured with errors) is used on both sides of the regression equation.

of workers in year t-1 who earn wages between the old and new minimum wage i.e. between year t-1 and t, c^P is a constant and η^P_{nt} is an error term[8]. Nevertheless, this technique relies on an assumption that workers directly affected by the increase in minimum wage are those receiving wages either exactly at the former minimum wage or between the former and new minimum wage. Therefore, provinces with a higher fraction affected should show a larger effect on lower part of wage distribution. I will present results from selected years with substantial increase in statutory minimum wages which in turn leads to potentially more variation in fraction affected.

2.4 Results

To investigate the effect of minimum wages on wage inequality in developing countries, compliance rate is one of the major concerns. Although employers in formal sectors are expected to comply with the minimum wage law, the LFS does not provide any information on the social security contribution of each worker which is widely used as an indication of being a formal worker in the literature. To identify the degree of the non-compliance problem, I employ descriptive statistics of the data from various groups of workers as shown in Appendix 2.A table 2.11 - 2.14.

The results demonstrated in this section are classified into three groups of sample according to coverage of the law and level of compliance rate, namely (1) all employees in the sample regardless of their age or industry, (2) male employees in private firms outside the agricultural sector and finally (3) male employees in large private firms. These three classifications will help to analyse the effectiveness of minimum wage policy on wage inequality in different section of Thai labour market.

The empirical strategy employed in the first set of results is derived from models 2.3.1 and 2.3.4. Regression results for all workers are presented in table 2.2. The OLS regressions of all workers both with and without provincial trends have positive and significant coefficients in all percentiles. These results coincide with the criticism about division bias highlighted in Autor, Manning, and Smith (2010)[9]. The next two columns show the results after using the legislative minimum wage in each province as an instrument for the effective minimum. These marginal effects have positive and significant coefficients in some percentiles of the 2SLS regressions without provincial trends (model (1)). However, results from 2SLS regressions including provincial trend are not significantly different from zero in any percentiles. Lastly, the regressions based on predicted median as in equation 2.3.4 does confirm a pattern of results observed from the 2SLS[10]. In particular, the minimum wage does not have any significant effects

[8] In order to control for different labour market condition across provinces, regressions which include average provincial wages in year t-1 as a control are presented alongside.

[9] The results from OLS regressions of other two sub-samples also suffer from this division bias problem. So, those results will be omitted from the following sub-samples.

[10] Weak instruments is one of the concerns for Two Stages Least Squared. The last row of table 2.2

Table 2.2: The effect of minimum wage on log wage gap of selected percentiles, log(p^{th}) - log(p60), All workers from 1985 Q1 to 2010 Q1

Percentile	OLS		2SLS		Predicted Median		
	(1)	(2)	(1)	(2)	(1)	(2)	(3)
5	0.72***	0.585***	3.973***	-0.815	1.256***	-1.041	-2.648**
	(0.082)	(0.042)	(1.003)	(0.622)	(0.401)	(0.669)	(1.259)
10	0.654***	0.578***	2.669***	-0.308	0.956***	-0.395	-2.314*
	(0.059)	(0.035)	(0.67)	(0.404)	(0.255)	(0.483)	(1.268)
20	0.537***	0.55***	0.622***	-0.304	0.462***	-0.389	-2.067***
	(0.031)	(0.031)	(0.214)	(0.387)	(0.08)	(0.442)	(0.753)
25	0.489***	0.524***	0.154	-0.093	0.334***	-0.119	-2.004***
	(0.029)	(0.026)	(0.235)	(0.322)	(0.084)	(0.404)	(0.561)
30	0.433***	0.481***	-0.128	-0.031	0.225***	-0.04	-1.061**
	(0.03)	(0.025)	(0.224)	(0.257)	(0.082)	(0.333)	(0.416)
40	0.319***	0.367***	-0.252	0.093	0.118*	0.119	-0.818*
	(0.027)	(0.022)	(0.157)	(0.153)	(0.068)	(0.217)	(0.436)
75	0.008	-0.015	0.502**	-0.08	0.113	-0.102	1.784***
	(0.034)	(0.028)	(0.207)	(0.198)	(0.078)	(0.264)	(0.447)
90	0.293***	0.254***	0.915**	0.152	0.471***	0.191	2.15***
	(0.058)	(0.046)	(0.407)	(0.36)	(0.171)	(0.488)	(0.662)
95	0.525***	0.495***	0.4	0.128	0.657***	0.162	1.671**
	(0.05)	(0.041)	(0.443)	(0.382)	(0.164)	(0.518)	(0.837)
F-test (weak IV)			30.923	17.996			
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial trend	No	Yes	No	Yes	No	Yes	No

Note: These coefficients are marginal effect calculated from linear and square terms of the effective minimum. Standard errors are clustered at provincial level and displayed in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively. Model (1) controls for time and province fixed effect while model (2) also controls for provincial trend. Model (3) is the First-Differenced of equation 2.3.4.

Table 2.3: The effect of minimum wage on log wage gap of selected percentiles, log(p^{th}) - log(p60), Sub-sample Male Private Employees outside Agricultural sector from 1985 Q1 to 2010 Q1 different age groups

Percentile	Adult workers				Young workers			
	2SLS		Predicted Median		2SLS		Predicted Median	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
5	5.122	-0.912	-0.118	-1.178*	1.41**	-1.204*	0.731***	-1.661**
	(3.556)	(0.608)	(0.198)	(0.647)	(0.601)	(0.628)	(0.264)	(0.828)
10	0.787	-0.79	-0.055	-1.02**	1.011***	-0.696	0.433**	-0.965
	(1.234)	(0.507)	(0.141)	(0.493)	(0.361)	(0.477)	(0.186)	(0.655)
20	-0.655	-0.293	0.071	-0.376	0.108	-0.348	0.219*	-0.487
	(0.852)	(0.301)	(0.089)	(0.34)	(0.235)	(0.401)	(0.13)	(0.534)
25	-0.902	-0.227	0.066	-0.291	-0.005	-0.325	0.172	-0.456
	(0.893)	(0.264)	(0.091)	(0.308)	(0.217)	(0.318)	(0.118)	(0.41)
30	-1.454	-0.209	0.092	-0.269	-0.035	-0.197	0.203**	-0.276
	(1.227)	(0.269)	(0.094)	(0.322)	(0.195)	(0.267)	(0.092)	(0.356)
40	-1.111	-0.058	0.111	-0.073	-0.245*	-0.041	0.144**	-0.05
	(0.96)	(0.211)	(0.068)	(0.27)	(0.146)	(0.191)	(0.067)	(0.267)
75	1.944	-0.331**	-0.086	-0.425*	-0.094	-0.334*	-0.012	-0.467*
	(1.521)	(0.149)	(0.094)	(0.256)	(0.102)	(0.191)	(0.066)	(0.25)
90	4.99	-0.411	-0.196	-0.533	0.063	-0.673	0.144	-0.95
	(3.832)	(0.361)	(0.243)	(0.51)	(0.234)	(0.475)	(0.14)	(0.64)
95	4.918	-0.733	-0.173	-0.942*	0.238	-1.173*	0.268	-1.606**
	(3.743)	(0.456)	(0.306)	(0.566)	(0.332)	(0.68)	(0.221)	(0.795)
F-test (weak IV)	2.565	18.458			21.023	9.807		
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial trend	No	Yes	No	Yes	No	Yes	No	Yes

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively.

on wage inequality of all workers after taking provincial trends into account[11].

Table 2.3 presents the regression results from the sub-sample of male private employees outside the agricultural sector for two different age groups. According to the legislation, the minimum wage applies for all workers, both part-time and full-time, in private companies outside the agricultural sector. However, the reason for choosing only the male instead of both genders is due to higher prevalence of non-compliance among female labours. So, the results from this male sub-sample should provide an upper bound of the effect of minimum wage policy on this group. Considering the adult workers, 2SLS regressions do not show significant results in any percentiles. The only exception is percentile 75^{th} in the model with provincial trends where minimum wage seems to compress workers' wage in this percentile towards the median. However, results from models using predicted median show similar patterns of significance with

presents the Kleibergen-Paap rk Wald F-statistic for weak identification test of each column first stage regression. The F-statistic has the same value for every percentile because the same endogenous regressors and the same instrumental variables are employed in all of them. These F-statistics are significantly larger than the Stock-Yogo weak ID test critical value at 10% (Stock and Yogo, 2005). Similar results are also observed in the sub-sample male private employees outside agriculture. Hence, weak instrument is not a major concern for the results in table 2.2 and 2.3

[11] As for the first-differenced specification, although it is more efficient than the fixed effect when standard errors are random walk (Wooldridge, 2002), pattern of significance for these results is the same as the predicted median without provincial trends but in reverse sign.

Table 2.4: The effect of minimum wage on log wage gap of selected percentiles, log(p^{th}) - log(p60), Sub-sample Private Employees age 25-54 in large firms (more than 100 workers) outside Agricultural sector by Gender from 1987 Q3 to 2010 Q1

	All workers				Only Male workers			
Percentile	2SLS		Predicted Median		2SLS		Predicted Median	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
5	-0.378	0.729*	0.083	1.337	0.551	0.519*	0.33	1.354
	(1.013)	(0.375)	(0.262)	(0.839)	(0.694)	(0.28)	(0.215)	(0.833)
10	-1.25	0.499*	0.239	0.927	0.174	0.543**	0.281	1.418**
	(1.603)	(0.283)	(0.212)	(0.676)	(0.652)	(0.22)	(0.196)	(0.603)
20	-0.688	0.63**	0.404***	1.165**	0.443	0.352**	0.23	0.92*
	(1.073)	(0.247)	(0.113)	(0.59)	(0.462)	(0.149)	(0.167)	(0.513)
25	-0.478	0.649***	0.374***	1.192**	0.516	0.415***	0.282**	1.084**
	(0.913)	(0.209)	(0.094)	(0.508)	(0.377)	(0.129)	(0.118)	(0.462)
30	-0.305	0.63***	0.363***	1.158***	0.489	0.412***	0.274***	1.074**
	(0.719)	(0.192)	(0.083)	(0.403)	(0.312)	(0.124)	(0.09)	(0.432)
40	0.214	0.478***	0.238***	0.879***	0.468	0.433***	0.157**	1.128***
	(0.354)	(0.166)	(0.058)	(0.314)	(0.333)	(0.096)	(0.07)	(0.28)
75	0.096	-0.373	-0.037	-0.671*	0.474	0.218	0.014	0.571
	(0.353)	(0.242)	(0.071)	(0.374)	(0.394)	(0.171)	(0.068)	(0.436)
90	0.695	-0.037	0.296**	-0.059	0.042	0.098	0.121	0.258
	(0.877)	(0.382)	(0.146)	(0.714)	(0.528)	(0.3)	(0.155)	(0.816)
95	-0.205	0.465	0.405**	0.842	-1.004	-0.032	0.194	-0.088
	(0.909)	(0.519)	(0.174)	(1.01)	(0.952)	(0.562)	(0.196)	(1.535)
F-test (weak IV)	2.408	8.942			3.494	10.884		
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial trend	No	Yes	No	Yes	No	Yes	No	Yes

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively. This sample does not include both quarters of 2001 due to a change in definition of a variable "firm size" in that year.

two additional negative coefficients at the bottom[12]. It can be interpreted that the minimum wage might result in widening the wage gap between the median worker and the low wage workers in this sub-sample, though the result is not very robust.

Moreover, other than positive and significant results among the bottom two percentiles in those models without provincial trends, the effects of minimum wage on youth workers (age 16-24) after allowing for different provincial trends are similar to the ones for adults. From this finding, it can be inferred that minimum wage policy could contribute to the widening wage gap for the male low paid workers in private companies outside the agricultural sector.

Lastly, we consider the sub-sample of adult workers in large private firms (with more than 100 workers) outside the agricultural sector. As shown in table 2.12, the median province in this group has the lowest percentage of sub-minimum workers among all three classifications. Table 2.4 illustrates that, after controlling for provincial trends, the minimum wage policy narrows wage gap between percentile 25^{th} - 40^{th} and

[12] Although the wage compression at the top of wage distribution is still pronounced for percentile 75^{th} and also 95^{th}, these results are significant only at 10% level.

the median (percentile 60^{th}) regardless of gender[13] or model specifications (2SLS[14] or predicted median). Moreover, the coefficients from regression with provincial trends comply with the models underlying assumption that minimum wage should not affect the upper side of wage distribution.

In sum, minimum wage policy seems to have different effects on wage inequality depending on segments of the labour market. Only low paid workers in large private firms (which can be considered as the formal segment of labour market) benefit from such wage compression effect. However, workers in the lowest wage percentile (5^{th} - 10^{th}) in this sub-group still do not benefit from the policy. Thus, non-compliance seems to be one of the important factors contributing to the failure to reduce wage inequality in both formal and informal sectors through minimum wage policy.

Yet erosion of real minimum wage for a decade after the Asian financial crisis in 1997 could be another factor causing such a widened wage gap. In order to assess the important of this concern, the empirical strategy using fraction of workers affected by minimum wage (Card and Krueger, 1995) is adopted with the LFS data for the third quarter of 1994/95 and 1996/97. The reasons why I choose these periods is because they are the last two periods of sizable increase in minimum wage before the Asian financial crisis (around 8.6 - 9.8% rise for every province in July 1995 and 8.2 - 8.7% in October 1996 relative to July 1994 and 1996 respectively). Further, descriptive statistics in table 2.15 and 2.16 show that the characteristics of every sub-group of workers[15] in 1994 such as gender, age, average years of education and firm size are quite similar to those in 1996.

Table 2.5 and 2.6 classify workers into three sub-groups as discussed earlier[16]. According to the results, only the minimum wage rise in October 1996 has a positive and significant effect (at 5% level) on wage in subsequent year of the 30^{th} percentile for the sub-sample private employees outside the agricultural sector regardless of firm size. This result is still robust after controlling for the average provincial wage in 1996. Conversely, the rise of minimum wage in July 1995 results in negative and significant effects on change in wage of the 25^{th} and 30^{th} percentile of sub-sample male private employees and large firm employees respectively[17]. Nevertheless, these results are not

[13] At 5% significant level, the wage compression effect also extends to the 10^{th} percentile of male only and 20^{th} percentile of both genders. This result implies that female workers in large firms who are normally received lower wage than male also benefit from the policy.

[14] The Kleibergen-Paap rk Wald F-statistic for first stage regression of 2SLS without provincial trend is very low. So, the null hypothesis of Weak identification cannot be rejected even at the maximal IV size of 25% significant level. Still, the model with provincial trend does have a significantly high F-statistic

[15] which are sub-minimum wage workers, directly affected workers and other workers with higher wage

[16] To get comparable results between these sub-groups, I employ only 32 provinces with sizable data during these periods

[17] In addition, there is a robust negative and significant result (at 5% level) for the 75^{th} percentile of sub-sample male private employees. It implies that the change in wage from 1994 to 1995 for this

Table 2.5: The effect of minimum wage (measured by fraction of affected workers) on changes in log wage of different sub-sample from 3^{rd} quarter 1994 to 1995

Percentile	All workers (1)	All workers (2)	Male Private employees (1)	Male Private employees (2)	Large Firms employees (1)	Large Firms employees (2)
5	-0.375	-0.389	0.880	-0.711	-0.320	-0.692
	(0.644)	(0.514)	(1.076)	(0.664)	(0.456)	(0.486)
10	0.111	0.102	-0.00874	-0.499	0.295	-0.434
	(0.463)	(0.371)	(0.399)	(0.318)	(0.465)	(0.413)
20	-0.386	-0.394	-0.0143	-0.524	0.609	-0.178
	(0.357)	(0.301)	(0.468)	(0.390)	(0.419)	(0.344)
25	-0.409	-0.416*	-0.192	-0.544**	0.791**	-0.0609
	(0.274)	(0.219)	(0.243)	(0.258)	(0.386)	(0.240)
30	-0.378	-0.389	0.109	-0.259	0.457	-0.312**
	(0.417)	(0.276)	(0.287)	(0.224)	(0.296)	(0.145)
40	-0.217	-0.228	0.0411	-0.335	0.442	-0.207
	(0.389)	(0.258)	(0.304)	(0.265)	(0.372)	(0.188)
50	0.187	0.174	0.607	0.0254	0.232	-0.203
	(0.366)	(0.233)	(0.409)	(0.211)	(0.258)	(0.186)
75	0.0638	0.0580	-0.413**	-0.530***	0.121	-0.394
	(0.529)	(0.549)	(0.184)	(0.180)	(0.369)	(0.323)
90	0.438	0.433	0.724	0.109	0.258	-0.462
	(0.704)	(0.729)	(0.496)	(0.472)	(0.381)	(0.392)
95	-0.0351	-0.0402	-0.268	-0.831	0.575	-0.105
	(0.512)	(0.532)	(0.822)	(0.882)	(0.573)	(0.628)
Average wage	No	Yes	No	Yes	No	Yes

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively.

Table 2.6: The effect of minimum wage (measured by fraction of affected workers) on changes in log wage of different sub-sample from 3^{rd} quarter 1996 to 1997

Percentile	All workers (1)	All workers (2)	Male Private employees (1)	Male Private employees (2)	Large Firms employees (1)	Large Firms employees (2)
5	-0.833**	-0.829**	-0.790	-1.120*	-0.575	-0.267
	(0.307)	(0.308)	(0.477)	(0.636)	(0.578)	(0.603)
10	-0.732**	-0.754**	0.0343	-0.170	-0.914*	-0.763
	(0.304)	(0.324)	(0.240)	(0.309)	(0.493)	(0.548)
20	-0.163	-0.151	0.856**	0.749*	0.289	0.247
	(0.341)	(0.322)	(0.324)	(0.376)	(0.189)	(0.214)
25	-0.0793	-0.0671	0.621**	0.455	0.231	0.342
	(0.372)	(0.354)	(0.270)	(0.272)	(0.209)	(0.206)
30	-0.274	-0.280	0.610***	0.489**	0.395**	0.591***
	(0.297)	(0.305)	(0.205)	(0.200)	(0.170)	(0.172)
40	-0.384	-0.386	-0.637	-0.235	0.0170	0.440*
	(0.266)	(0.279)	(0.705)	(0.459)	(0.290)	(0.240)
50	-0.413	-0.484	-0.820	-0.515	-0.399	0.0953
	(0.395)	(0.374)	(0.599)	(0.449)	(0.457)	(0.364)
75	-0.274	-0.435	-1.314	-0.891	-0.445	-0.451
	(0.515)	(0.497)	(0.966)	(0.630)	(0.384)	(0.448)
90	-0.490	-0.642	-2.154	-1.733	-0.597	-0.959
	(0.893)	(0.865)	(1.476)	(1.023)	(0.468)	(0.583)
95	-1.340	-1.432	-3.977*	-3.577*	-0.853	-1.307
	(0.882)	(0.861)	(2.220)	(1.783)	(1.080)	(1.099)
Average wage	No	Yes	No	Yes	No	Yes

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively.

significant in the regressions without average provincial wage as a control variable.

Although these tables portray conflicting results, timing of the increase in minimum wage could be an explanation for this discrepancy. In particular, the minimum wage hike in July 1^{st}, 1995 is right at the beginning of the third quarter in 1995, whereas the rise in October 1^{st}, 1996 is nine months before the third quarter of 1997. So, it seems that the wage compression effect of the minimum wage depends on not only the market segmentation but also a time lag for 'law-abiding' employers to change their wage accordingly. However, the result from 1996/97 supports the claim that only the workers around the second and third decile (in private firms outside the agricultural sector) receive higher wage rises relative to their median counterparts.

After considering results from both methods, it can be concluded that the minimum wage does have a very limited effect on wage inequality. Only employees in large private companies outside agriculture benefit from the reduction in wage gap. Yet within such sub-group, workers with the lowest wage per hour still do not gain from the minimum wage law. Moreover, the series of incremental increases in minimum wages, especially after the Asian financial crisis, do not seem to be an important factor underlying such results. Thus, effectiveness of law enforcement is the most plausible explanation for these results. Some descriptive statistics concerning labour law compliance and models for segmented labour market will be addressed in the discussion.

2.5 Robustness checks

One of the major concerns of using LFS data to analyse the wage inequality at the provincial level is the sample size for wage earners in each province. Moreover, the classification of samples into smaller sub-groups threatens the validity of observed percentiles of wages due to the smaller sample available for percentile calculation. To address this concern, I restrict the sample of provinces to those 32 (out of 76) which consistently have more than 10 respondents in any quarters of the three categories. With the same number of province-quarters in all sub-groups, models 2.3.1 and 2.3.4 are re-estimated.

Regressions based on this restricted sample provide supporting evidence for the results in previous section with a distinct pattern of significance. According to table 2.7 and 2.8, with or without controlling for provincial trends, changes in minimum wage do not have any significant effects (at 5% level) on wage distribution of all wage earners or adult male private employees outside agriculture[18]. Therefore, the ineffectiveness

specific percentile is smaller in the province with higher fraction of workers affected by minimum wage. Unless there exist significant spillover effect or measurement errors in wage per hour (Autor, Manning, and Smith, 2010), this interpretation is at odds with the fact that the binding of minimum wage in any provinces does not exceed 65^{th} percentile for this sub-sample in those periods. Hence, I decide not to interpret these counter-intuitive sign of coefficients in this paper.

[18]The only exception comes form a Predicted Median model without provincial trends for adult

Table 2.7: The effect of minimum wage on log wage gap of selected percentiles, log(p^{th}) - log(p60), All workers in 32 provinces with sizable sample from 1994 Q1 to 2010 Q1

Percentile	OLS		2SLS		Predicted Median	
	(1)	(2)	(1)	(2)	(1)	(2)
5	0.69***	0.685***	5.056*	-5.267	0.604	-1.811
	(0.102)	(0.088)	(2.887)	(10.348)	(0.598)	(1.256)
10	0.647***	0.653***	2.853*	-4.099	0.537	-1.411
	(0.073)	(0.06)	(1.496)	(8.248)	(0.419)	(1.024)
20	0.53***	0.587***	0.258	-3.004	0.252*	-1.036*
	(0.039)	(0.033)	(0.388)	(5.692)	(0.138)	(0.626)
25	0.494***	0.573***	-0.321	-1.855	0.152	-0.644
	(0.048)	(0.03)	(0.567)	(3.958)	(0.123)	(0.553)
30	0.425***	0.519***	-0.399	-1.645	0.039	-0.569
	(0.049)	(0.032)	(0.523)	(3.374)	(0.111)	(0.445)
40	0.282***	0.365***	-0.281	-0.569	-0.042	-0.2
	(0.028)	(0.02)	(0.339)	(1.629)	(0.086)	(0.355)
75	-0.054*	-0.073**	-0.181	0.032	0.019	0.006
	(0.032)	(0.036)	(0.25)	(0.786)	(0.072)	(0.282)
90	0.013	-0.062	-0.281	0.331	0.298	0.119
	(0.057)	(0.095)	(0.623)	(1.748)	(0.22)	(0.664)
95	0.142**	0.09	-0.394	0.998	0.34*	0.339
	(0.057)	(0.074)	(0.71)	(2.223)	(0.189)	(0.762)
F-test (weak IV)			1.515	0.217		
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
Provincial trend	No	Yes	No	Yes	No	Yes

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively.

Table 2.8: The effect of minimum wage on log wage gap of selected percentiles, log(p^{th}) - log(p60), Sub-sample Male Private Employees age 25-54 outside Agricultural sector in 32 provinces with sizable sample from 1994 Q1 to 2010 Q1

Percentile	OLS		2SLS		Predicted Median	
	(1)	(2)	(1)	(2)	(1)	(2)
5	0.601***	0.645***	2.443*	-0.127	0.308	-0.123
	(0.087)	(0.108)	(1.284)	(0.931)	(0.34)	(0.978)
10	0.642***	0.717***	0.321	-0.464	0.161	-0.463
	(0.057)	(0.06)	(0.655)	(0.731)	(0.17)	(0.683)
20	0.581***	0.635***	0.139	-0.137	0.233*	-0.141
	(0.031)	(0.036)	(0.444)	(0.538)	(0.122)	(0.546)
25	0.518***	0.57***	0.219	-0.175	0.183*	-0.175
	(0.026)	(0.026)	(0.303)	(0.481)	(0.108)	(0.481)
30	0.51***	0.568***	0.227	0.025	0.156*	0.024
	(0.028)	(0.025)	(0.244)	(0.439)	(0.094)	(0.472)
40	0.399***	0.436***	0.372*	-0.43	0.147**	-0.431
	(0.025)	(0.025)	(0.214)	(0.442)	(0.068)	(0.34)
75	0.034	0.035	-0.024	0.03	0.026	0.02
	(0.043)	(0.05)	(0.311)	(0.341)	(0.079)	(0.353)
90	0.02	0.001	0.875	0.355	0.148	0.35
	(0.067)	(0.08)	(0.792)	(0.651)	(0.168)	(0.689)
95	-0.001	-0.062	0.747	1.277	0.408*	1.251
	(0.116)	(0.124)	(0.905)	(1.008)	(0.232)	(1.133)
F-test (weak IV)			1.507	3.015		
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
Provincial trend	No	Yes	No	Yes	No	Yes

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively.

Table 2.9: The effect of minimum wage on log wage gap of selected percentiles, log(p^{th}) - log(p60), Sub-sample Private Employees age 25-54 in large firms (more than 100 workers) outside Agricultural sector in 32 provinces with sizable sample from 1994 Q1 to 2010 Q1

Percentile	OLS		2SLS		Predicted Median	
	(1)	(2)	(1)	(2)	(1)	(2)
5	0.728***	0.776***	-0.23	1.603***	0.458**	1.881*
	(0.063)	(0.059)	(0.672)	(0.609)	(0.222)	(0.98)
10	0.718***	0.745***	-0.482	1.084***	0.558***	1.268**
	(0.04)	(0.041)	(0.826)	(0.266)	(0.127)	(0.569)
20	0.653***	0.673***	0.339	0.919***	0.532***	1.072**
	(0.031)	(0.037)	(0.339)	(0.316)	(0.077)	(0.475)
25	0.592***	0.613***	0.459	1.072***	0.48***	1.257***
	(0.032)	(0.035)	(0.285)	(0.337)	(0.08)	(0.438)
30	0.531***	0.551***	0.51**	1.076***	0.425***	1.261***
	(0.034)	(0.037)	(0.221)	(0.395)	(0.067)	(0.36)
40	0.413***	0.432***	0.553**	0.915**	0.308***	1.072***
	(0.026)	(0.029)	(0.225)	(0.358)	(0.056)	(0.325)
75	0.03	0.043*	-0.145	-0.594	-0.073	-0.705
	(0.019)	(0.024)	(0.209)	(0.48)	(0.103)	(0.5)
90	0.241***	0.237***	0.852	0.291	0.263	0.336
	(0.055)	(0.054)	(0.731)	(0.649)	(0.227)	(0.868)
95	0.288***	0.292***	0.429	1.422	0.307	1.675
	(0.072)	(0.067)	(0.727)	(1.33)	(0.308)	(1.594)
F-test (weak IV)			1.749	2.535		
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
Provincial trend	No	Yes	No	Yes	No	Yes

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively. This sample does not include both quarters of 2001 due to a change in definition of a variable "firm size" in that year.

of minimum wage policy in reducing wage inequality for the whole labour market, or even among eligible workers, is robustly pronounced. Hence, an exclusion of outlier provinces with too small sample in some periods does not seem to alter the main conclusion of this paper.

Furthermore, table 2.9 illustrates even clearer effects of minimum wage on narrowing wage gaps among workers in the 'formal' segment of the labour market. After controlling for provincial trends, all percentiles in the lower part of the wage distribution (5^{th} - 40^{th}) experience positive and significant wage compression pressures towards the median irrespective of model specification. This result leads to a slightly different conclusion that, instead of just the 20^{th} - 40^{th} percentile, the whole lower part of the wage distribution is moved closer to the median wage due to minimum wage policy. This minor discrepancy could result from the inclusion of data calculated from provinces with too few respondents in some survey rounds. Hence, some outliers might influence those insignificant results among the low paid workers in previous session while they

male private employees outside agriculture which shows a positive and significant coefficient in 40^{th} percentile. Nevertheless, this result is similar to the one based on full sample for young male private employees outside agriculture.

Table 2.10: The effect of minimum wage on log wage gap of selected percentiles, log(pth) - log(p60), Sub-sample Private Employees age 25-54 in small and medium firms (fewer than 100 workers) outside Agricultural sector in 32 provinces with sizable sample from 1994 Q1 to 2010 Q1

Percentile	OLS		2SLS		Predicted Median	
	(1)	(2)	(1)	(2)	(1)	(2)
5	0.364***	0.426***	8.731	-0.073	-0.163	-0.056
	(0.108)	(0.118)	(7.926)	(1.707)	(0.5)	(1.332)
10	0.432***	0.496***	5.429	-0.956	-0.182	-0.702
	(0.102)	(0.101)	(5.202)	(1.576)	(0.339)	(1.067)
20	0.449***	0.5***	0.835	-0.045	0	-0.025
	(0.064)	(0.062)	(1.657)	(0.738)	(0.201)	(0.573)
25	0.468***	0.523***	-0.117	-0.438	-0.049	-0.315
	(0.054)	(0.054)	(1.251)	(0.798)	(0.182)	(0.531)
30	0.406***	0.454***	-0.625	-0.221	-0.031	-0.167
	(0.044)	(0.044)	(1.008)	(0.542)	(0.151)	(0.384)
40	0.298***	0.328***	-0.555	-0.124	0.028	-0.088
	(0.035)	(0.038)	(0.667)	(0.428)	(0.105)	(0.323)
75	0.116***	0.115**	0.058	0.848	0.171**	0.627**
	(0.04)	(0.046)	(0.402)	(0.585)	(0.071)	(0.308)
90	0.176**	0.172*	1.086	0.672	0.243	0.478
	(0.089)	(0.09)	(1.412)	(0.819)	(0.221)	(0.516)
95	0.128	0.097	2.782	1.015	0.441	0.742
	(0.108)	(0.104)	(2.716)	(1.117)	(0.298)	(0.68)
F-test (weak IV)			0.828	2.362		
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
Provincial trend	No	Yes	No	Yes	No	Yes

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively. This sample does not include both quarters of 2001 due to a change in definition of a variable ”firm size” in that year.

could not induce the results with more robust data from these 32 provinces[19]. Thus, wage compression effects of the minimum wage law among these large firms could be stronger than what table 2.4 suggests.

2.6 Discussion

The evidence for the impacts of minimum wages on wage inequality in Thailand suggests that wage compression effect is confined to only low paid workers in the formal sector of the labour market (as classified by firm size). Although increases in the minimum wage did not fully compensate for the rise in inflation after the Asian financial crisis, it is shown that this is unlikely to be the major force behind the result. Specifically, even in the years with significant increase in real minimum wage, the impact of minimum wage is still determined by market segmentation. Therefore, imperfect compliance with minimum wage law (not the non-coverage[20]), especially in the informal sector, is the most plausible factor driving this pattern.

One explanation of the high non-compliance rates could be the relatively low expected loss from such illicit act. In terms of penalty, according to Labour Protection Act 1998[21], any employers paying wages lower than the legislative minimum are liable for a fine not exceeding 100,000 baht or up to 6-month imprisonment or both. Based on minimum wages in 2001, the upper limit of this fine is worth more than 600 worker-days for every province, which is a high penalty for employers in smaller firms.

However, the probability of being caught and severely punished is another factor forming employers' expectation of the cost of non-compliance. To assess the effectiveness of minimum wage law enforcement, I explore the data on labour inspection conducted by Department of Labour Protection and Welfare from 2006 to 2010 as shown in table 2.17. Although the inspection rate is 12-13 % of all establishments each year, more than 94% of firms violating any labour law receive only a warning. Less than 0.3% of all wrong-doing establishments are fined or prosecuted. Such a small probability of being severely penalized should lower the employers' expected loss from paying sub-minimum wage. Thus, this weak law enforcement is in line with the ineffective minimum wage policy observed[22].

[19] However, insignificant Kleibergen-Paap rk Wald F-statistic for all 2SLS in table 2.7 - 2.9 does raise a concern on weak identification of instrumental variables. This might be a result of restricting the sample to just 32 out of 76 provinces. All in all, the weak identification problem does not invalidate the whole results because models based on predicted median still consistently provide supporting evidence for the same conclusion.

[20] Unlike developed countries where non-coverage can be one of the major concerns, developing countries seems to suffer more from non-compliance even in the covered sector (Strobl and Walsh, 2003)

[21] Such law dates back to the period before the first minimum wage law. However, this one is still enforced up to present

[22] Considering a model with imperfect competition, imperfect enforcement and imperfect commitment, Basu, Chau, and Kanbur (2007) show that a weak enforcement of minimum wage policy can be

Another explanation for higher compliance among larger firms is the efficiency wage theory. Rebitzer and Taylor (1995) set up a simple efficiency wage model where employers use dismissal as a disciplinary device to prevent shirking. Further, they assume that the supervisory resources of firms are fixed and the firms capacity to closely supervise is decreasing with number of employees[23]. So, an increase in minimum wages raises the cost of dismissal and induces workers in large firms to assert higher effort. Using the survey data from the UK residential care homes industry after the introduction of National Minimum Wage in 1999, Georgiadis (2013) finds the evidence that supports this efficiency wage hypothesis.

Interestingly, table 2.17 shows that the non-compliance rate had been decreasing from 4.7% in 2006 (2,100 out of 44,658 establishments) to 1.26% in 2010 (625 out of 49,463 establishments). This improvement in compliance can be depicted from the data through Kernel density and Cumulative distribution plots of log hourly wage in figure 2.3 - 2.6. The comparison between wage distribution in 1994/95 and 2007/08 shows a strong surge in compliance rates of both the formal and informal sectors. While the peak of wage distribution in the formal sector is around the highest provincial minimum wage in 1995 and 2008, the peak does not prevail among informal workers until recently.

It is worth noting that our discussion on compliance problem and ineffectiveness of minimum wage policy is consistent with the segmented labour market (or two-sector) models such as Lewis (1954), Harris and Todaro (1970), Gramlich (1976), Mincer (1974a) and Welch (1974). Although the Lewis model, which comprises of backward agricultural sector in rural area and modern urban (manufacturing and service) sector, seems to be plausible framework for a country with large agricultural sector, the effects of minimum wage do not differ pointedly between urban and rural nor the covered industrial and uncovered agricultural sector. It is divided by formal (compliance) sector and informal (non-compliance) sector. Hence, if the formal sector is treated as covered sector, the Welch-Gramlich-Mincer two-sector model can be adopted to analyse the results.

Firstly, wage compression effects happen only in the formal sector with a single peak of wage distribution around the legislative minimum wage. Second, those informal workers in covered sector do not appear to experience any wage compression effects. Moreover, the legislative minimum wage does not generate any spikes in informal wage distribution except for periods of expansion in compliance. These observations are in

an equilibrium phenomenon for a government with a credibility problem.

[23] Acknowledging skepticism of monitoring difficulties as an explanation for employer size wage premia, Rebitzer and Taylor (1995) refer to both theoretical and empirical studies which suggest that the monitoring and incentive problem still persist in incentive schemes with minimal monitoring difficulties such as the piece rate.

accordance with the prediction of the Welch-Gramlich-Mincer model[24]. However, this conclusion is opposed to many literature in Latin America (such as Maloney, 1998; Pratap and Quintin, 2006; Lemos, 2009) which conclude that the two-sector model does not seem to correctly predict the wage and employment effect of minimum wage in spite of a sizable informal sector. Specifically, these papers find significant wage compression effect in both formal and informal sectors. Yet there is no adverse effect on employment.

Nevertheless, since the employment effect of minimum wage law is beyond the scope of this paper, it is not clear whether a significant fall in total employment as predicted by Welch-Gramlich-Mincer model will be found in Thai data. In order to explore such topic, a more concrete definition of formal workers, which does not depend on being employed, has to be adopted. In particular, without good employment history or panel data, it is difficult or impossible to assign any unemployed workers to either large or small firm. Otherwise, other proxies for formal sector such as social security entitlement must to be used. However, the main challenge, as mentioned earlier, is that the LFS data during these entire periods do not contain such information.

2.7 Conclusion

This paper examines the impact of minimum wage policy on wage inequality in Thailand using Labor Force Survey in the first and third quarter from 1985 to 2010. The evidence suggests that the minimum wage does not significantly affect overall wage distribution after allowing for provincial trends. Despite restricting sample to covered sectors, the minimum wage does not help to compress the lower part of wage distribution towards the median. Conversely, it might widen wage gaps between the lowest decile and the median, though such a result is not robust. The wage compression effect is detected only after confining the sample to formal workers (classified by firm size) in the covered sectors. These findings are robust to different empirical strategies and are not driven by small sample sizes in any provinces or periods. Hence, the difference in compliance rate between formal and informal sector (not between covered and uncovered sector) seem to be the prominent factor behind the fragmented effects of minimum wage policy on wage inequality.

As for policy implication, weak law enforcement seems to partly sustain subminimum pay among small firms in covered sectors. Without tackling the non-compliance issue, minimum wages will not be effective in creating a wage floor for low paid workers in small firms (or the informal sector) but it might serve as another form of collective wage setting between formal workers and their employers through regional tripartite

[24]Though median wages of informal sector in the data are lower than their formal counterpart, Gramlich-Mincer version of the model does not unambiguously predict the direction of wage in uncovered (or informal) sector after minimum wage is imposed (Brown, 1999).

sub-committees. Yet better enforcement and higher compliance could potentially (but not always) lead to higher unemployment among low paid workers.

In terms of coherence between empirical findings and theoretical model, significant wage compression effect only in formal sector coincides with standard two-sector model's prediction. However, to draw any conclusion, sectoral employment effects need to be verified. Again this is beyond the scope of this paper and requires additional information to properly distinguish formal workers from their informal counterparts. In addition, one possible extension of the models is to incorporate the self-employed into the analysis. Although the self-employed are not covered by minimum wage, comparing self-employed to uncovered workers as well as non-compliance covered workers could provide interesting results.

Lastly, it is worth noting that at the time of writing this paper, the Thai government have just implemented the largest two-step minimum wage hike in 2012 and 2013 which led to a single national minimum wage at 300 baht per day[25]. This movement corresponds to a two-step reduction in corporate income tax from 30% to 23% and from 23% to 20% on January, 1^{st} 2012 and 2013 respectively[26]. While the government claims that the main objective of corporate tax reduction is to increase businesses' competitiveness in preparation for the opening of the ASEAN Economic Community (AEC) in 2015 (Alexander et al., 2013), it is arguable that tax reduction not only offers businesses (particularly in the formal sector) some compensation for the wage hike but also weaken any resistance of employers in the national tripartite committee (Parker, 2013). Depending on data availability, such a parallel move should provide an opportunity to assess the impacts of minimum wage on employment and wage distribution among different segments of Thai labour market, particularly, any disparities between large and small firms in the covered sectors.

[25] On April, 1^{st} 2012, in order to push minimum wage in provinces with the highest band to 300 baht per day, minimum wage in every province were raised by approximately 40%. Then on January, 1^{st} 2013, minimum wage in the rest of the country are lifted up to 300 baht per day. This results in almost doubling minimum wage among provinces in the lowest band.

[26] With exception of some Small Enterprises subjecting to lower tax rate and foreign businesses under the Board of Investment scheme

2.A Bindingness of Provincial Minimum Wages (other sub-samples)

These following tables show some descriptive statistics of percentage of employees across provinces who receive wages less than statutory minimum wage over the sample periods.

Table 2.11: Summary statistics for bindingness of provincial minimum wages
Sub-sample Private Employees age 25-54 outside Agricultural sector

	All			Female			Male		
Year(Q3)	Max. pctile	Min. pctile	Median pctile	Max. pctile	Min. pctile	Median pctile	Max. pctile	Min. pctile	Median pctile
1989	91.8	11.9	41.7	100.0	0.0	70.1	90.2	0.0	26.7
1994	79.2	15.8	47.6	100.0	24.7	67.6	75.2	8.0	38.6
1999	62.7	4.7	35.4	88.3	6.9	51.6	57.7	2.9	25.0
2004	73.5	12.2	40.5	89.5	13.5	50.0	70.4	6.7	32.1
2009	57.9	9.1	30.8	77.4	12.9	37.7	62.8	5.4	23.7

All numbers are proportion of workers who received basic wage less than their provincial minimum wage. Max. pctile comes from a province with the highest non-compliance to the law in each year while Min. pctile and Median pctile are provinces with the lowest and middle non-compliance to the law in that year respectively.

Table 2.12: Summary statistics for bindingness of provincial minimum wages
Sub-sample Private Employees age 25-54 in large firms (more than 100 workers) outside Agricultural sector

	All			Female			Male		
Year(Q3)	Max. pctile	Min. pctile	Median pctile	Max. pctile	Min. pctile	Median pctile	Max. pctile	Min. pctile	Median pctile
1989	78.3	0.0	18.6	100.0	0.0	20.0	100.0	0.0	0.0
1994	100.0	0.0	20.2	100.0	0.0	29.2	100.0	0.0	8.8
1999	100.0	0.0	12.3	92.7	0.0	14.4	100.0	0.0	2.2
2004	96.1	0.0	21.8	100.0	0.0	27.3	100.0	0.0	13.7
2009	75.6	0.0	13.9	100.0	0.0	16.2	90.1	0.0	9.8

All numbers are proportion of workers who received basic wage less than their provincial minimum wage. Max. pctile comes from a province with the highest non-compliance to the law in each year while Min. pctile and Median pctile are provinces with the lowest and middle non-compliance to the law in that year respectively.

Table 2.13: Summary statistics for bindingness of provincial minimum wages (only 32 provinces with sizable sample)
Sub-sample Private Employees age 25-54 outside Agricultural sector

	All			Female			Male		
Year(Q3)	Max. pctile	Min. pctile	Median pctile	Max. pctile	Min. pctile	Median pctile	Max. pctile	Min. pctile	Median pctile
1994	60.7	15.8	43.2	89.0	24.7	56.9	52.8	8.0	32.0
1999	51.7	4.7	25.5	75.2	6.9	34.9	39.9	2.9	17.9
2004	47.3	12.2	27.7	63.2	13.5	34.4	39.9	6.7	24.3
2009	50.5	9.1	23.8	62.9	12.9	29.0	43.3	6.8	17.5

All numbers are proportion of workers who received basic wage less than their provincial minimum wage. Max. pctile comes from a province with the highest non-compliance to the law in each year while Min. pctile and Median pctile are provinces with the lowest and middle non-compliance to the law in that year respectively.

Table 2.14: Summary statistics for bindingness of provincial minimum wages (only 32 provinces with sizable sample)
Sub-sample Private Employees age 25-54 in large firms (more than 100 workers) outside Agricultural sector

	All			Female			Male		
Year(Q3)	Max. pctile	Min. pctile	Median pctile	Max. pctile	Min. pctile	Median pctile	Max. pctile	Min. pctile	Median pctile
1994	66.9	1.0	20.9	74.3	1.6	29.1	59.1	0.0	11.7
1999	71.6	0.1	6.1	62.0	0.0	12.4	79.1	0.0	4.1
2004	66.0	5.8	19.2	80.1	6.0	24.2	43.5	2.2	13.7
2009	46.5	4.6	17.0	54.7	6.9	19.1	39.2	2.7	11.5

All numbers are proportion of workers who received basic wage less than their provincial minimum wage. Max. pctile comes from a province with the highest non-compliance to the law in each year while Min. pctile and Median pctile are provinces with the lowest and middle non-compliance to the law in that year respectively.

2.B Descriptive statistics

Table 2.15: Descriptive statistics of all employees in the LFS 1994 sample

LFS 1994	Below Min Wage 93	Between Min Wage 94/93	Between Min Wage 95/94	Above Min Wage 95
Female	0.516	0.356	0.462	0.338
	(0.4998)	(0.479)	(0.4987)	(0.4732)
Age	30.443	29.370	27.755	34.102
	(12.0203)	(10.1998)	(8.8799)	(9.9641)
Urban	0.322	0.384	0.440	0.592
	(0.4673)	(0.4867)	(0.4965)	(0.4915)
Year of Education	5.205	6.237	6.783	10.091
	(2.4708)	(2.8967)	(2.9868)	(4.821)
Log hourly Wage	2.172	2.668	2.765	3.512
	(0.4041)	(0.128)	(0.139)	(0.6039)
Working hours per week	54.635	52.447	49.799	44.288
	(12.4123)	(10.8359)	(7.907)	(9.6329)
Firm size fewer than 10 ppl	0.577	0.388	0.186	0.192
	(0.494)	(0.4875)	(0.3893)	(0.3939)
Firm size more than 100 ppl	0.086	0.194	0.428	0.182
	(0.2806)	(0.3959)	(0.4949)	(0.3862)
Obs (weighted)	4,401,933	307,065	792,427	5,426,519

Table 2.16: Descriptive statistics of all employees in the LFS 1996 sample

LFS 1996	Below Min Wage 94	Between Min Wage 96/94	Between Min Wage 97/96	Above Min Wage 97
Female	0.520	0.468	0.477	0.331
	(0.4996)	(0.4991)	(0.4995)	(0.4707)
Age	31.889	30.720	29.148	34.020
	(12.9363)	(10.8289)	(10.2624)	(10.2763)
Urban	0.313	0.379	0.418	0.546
	(0.4638)	(0.4852)	(0.4933)	(0.4979)
Year of Education	5.080	5.817	6.081	9.454
	(2.5717)	(2.7148)	(2.6229)	(4.7432)
Log hourly Wage	2.327	2.720	2.828	3.559
	(0.3617)	(0.1107)	(0.1359)	(0.6093)
Working hours per week	55.846	53.451	50.351	45.785
	(12.8271)	(12.0062)	(8.0229)	(9.7505)
Firm size less than 10 ppl	0.596	0.385	0.251	0.223
	(0.4908)	(0.4868)	(0.4335)	(0.4164)
Firm size more than 100 ppl	0.098	0.159	0.422	0.208
	(0.2976)	(0.3662)	(0.494)	(0.4059)
Obs (weighted)	3,465,337	498,048	1,172,664	6,646,047

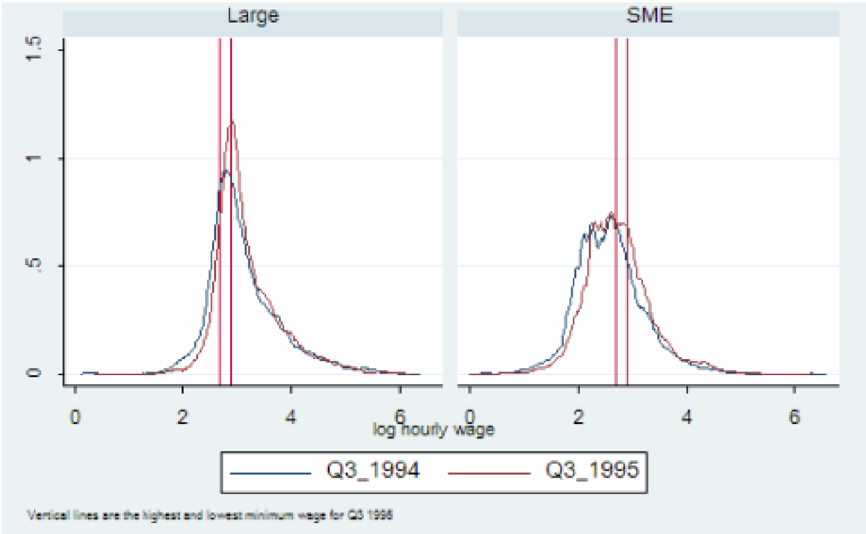

Figure 2.3: *Kernel Density of Log hourly wage (weighted) in Thailand for formal and informal workers 3^{rd} quarter 1994 VS 1995*

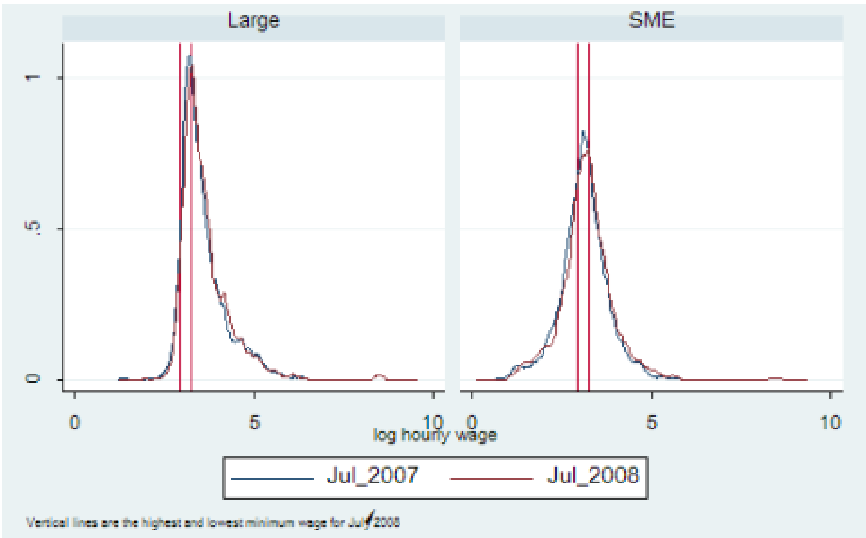

Figure 2.4: *Kernel Density of Log hourly wage (weighted) in Thailand for formal and informal workers July 2007 VS 2008*

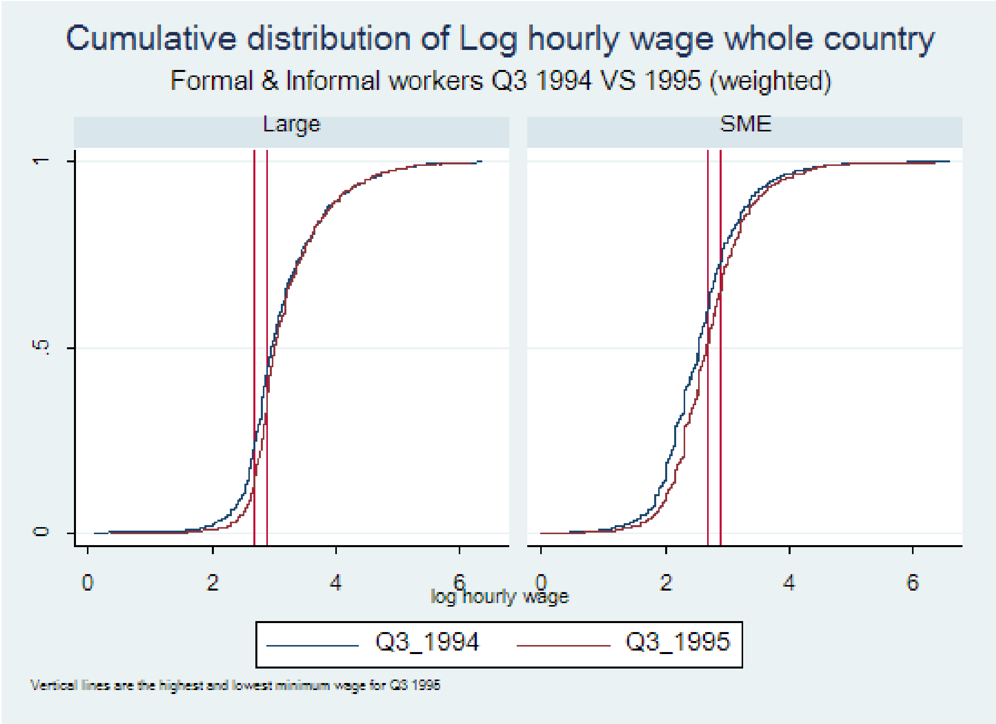

Figure 2.5: *Cumulative Distribution of Log hourly wage (weighted) in Thailand for formal and informal workers 3rd quarter 1994 VS 1995*

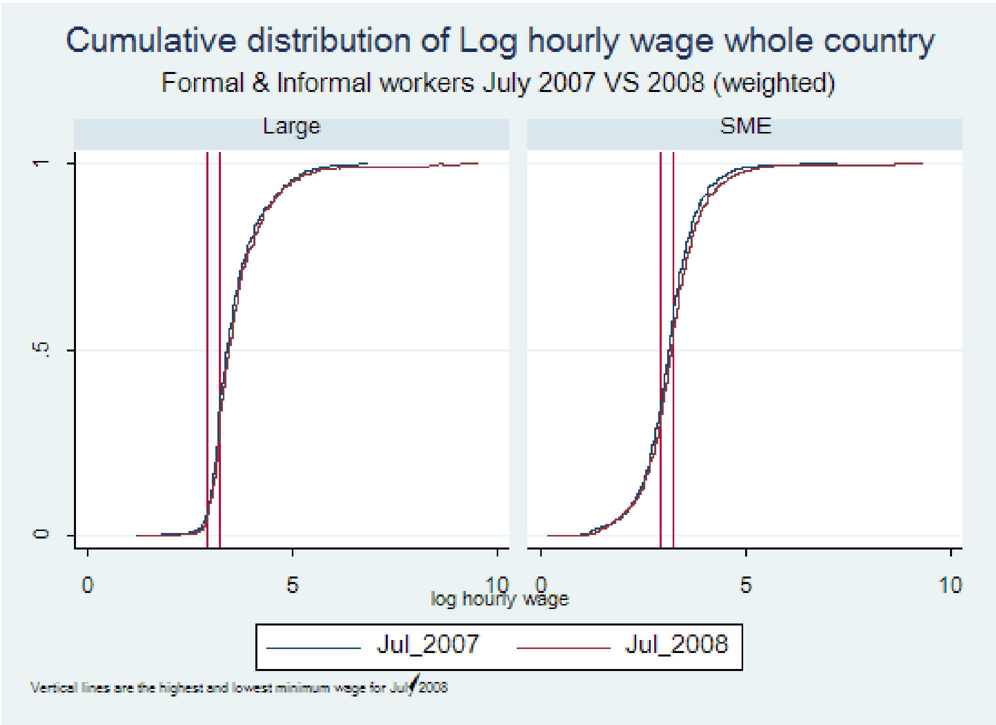

Figure 2.6: *Cumulative Distribution of Log hourly wage (weighted) in Thailand for formal and informal workers July 2007 VS 2008*

Table 2.17: Labour inspection in the whole country 2006 - 2010 (number of establishments)

Year	Establishments Inspected		Non-compliance with labour law			Conduction of Labour Inspector				
	Number	Percentage	All types of Illegal Conduct	Minimum Wage Est.	Minimum Wage Persons	Warning issued	Summon	Order of Compliance	Fine	Criminal Action Submission
2006	44,658	11.89	7,982	2,100	7,730	7,570	251	145	6	10
2007	50,993	13.37	7,725	2,005	6,752	7,300	329	76	11	9
2008	47,940	12.54	5,667	1,287	4,018	5,509	118	38	2	-
2009	50,669	12.99	5,150	880	4,137	4,946	119	76	2	7
2010	49,463	12.49	2,447	625	4,033	2,366	50	26	1	4

Source : Labour Standard Development Bureau, Department of Labour Protection and Welfare

3 Compulsory Schooling, Earnings and Health in Thailand

3.1 Introduction

The Mincer (or Mincer-Becker-Chiswick) earnings equation (Mincer, 1974b; Becker, 1962; Chiswick, 1969) has been a major workhorse employed by economists to estimate the rate of return to education (for the compilation of the return to education across countries and periods of time, see Psacharopoulos, 1985, 1994; Psacharopoulos and Patrinos, 2002). Yet due to endogeneity problems, there are doubts about the validity of the estimate of the returns to education in the standard Mincer equation. Plenty of studies propose techniques to consistently estimate this coefficient. For example, Griliches and Mason (1972), Griliches (1977), and Blackburn and Neumark (1995) include a proxy for ability in the Mincer equation. Other studies cope with the unobserved ability by focusing on twins or sibling (Ashenfelter and Krueger, 1994; Ashenfelter and Zimmerman, 1997) or using panel data to exclude unobserved individual fixed effect (Angrist and Newey, 1991). Moreover, instrumental variables such as compulsory schooling and college proximity are applied to circumvent the endogeneity problem (for instance Angrist and Krueger, 1991; Harmon and Walker, 1995; Card, 1993; Butcher and Case, 1994). Card (2001) provides an extensive review for this IV method.

Although several papers in Southeast Asia provide estimates of the rate of return to education based on the IV methods (e.g. Duflo, 2001, 2004; Maluccio, 1998), there is a little research applying such techniques in the case of Thailand. One of a few exceptions is Warunsiri and McNown (2010) which employ pseudo panel technique on the repeated cross section Labor Force Survey of workers born during 1946 - 1967. They report the overall rate of return between 14% and 16% which indicates a downward bias of the standard Mincer regression (Their ordinary least square result is around 10% - 11% which is similar to earlier studies such as Hawley (2004)). Interestingly, they find higher return to education for female workers than the male counterparts. Further, they provide a robustness check using availability of universities or teacher training colleges in each province as an IV and the estimate support the pseudo panel result.

The main objective of this paper is to provide another consistent estimate of the rate of return to education in Thailand. Using changes in compulsory schooling laws as an instrumental variable, I employ the Thai Labor Force Survey (LFS) from 1994 to 2009 to estimate the return to investment in schooling for wage-earners who were born slightly before and after the nationwide change in the law in 1978 (which implicitly raised compulsory schooling from four to six years of education). First, I provide evidence demonstrating the effect of compulsory schooling on the highest level of education completed. The result confirms that the law successfully raised the educational level of children in these cohorts to at least upper primary education. In other words, it contributed to an increase in at least two years of education from lower to upper primary education. Interestingly, the effect seems to be more profound among the women in the labour force.

Then I compare the estimators of the rate of return to education calculated from the IV method with Ordinary Least Square (OLS) regression. I find that the OLS yields an upward biased estimator for the rates of return to education. While the estimated return to schooling based on the IV method for female workers is moderately lower than the one from OLS, the male's estimate is not significantly different from zero at all. One of the concerns for the IV method is the weak identification problem. Even though the F-statistic for the first stage regressions in this study are not as high as those studies using changes in compulsory schooling such as Harmon and Walker (1995), it is high enough to reject the null hypothesis of weak identification at reasonable significance level.

The challenge is how to interpret such findings and reconcile with the literature on the opposite direction of bias (for an extensive review on the downward bias of OLS found by studies based on fixed effect and IV methods, see Card, 1993, 2001) and the observed zero return to education among the male employees. As for the direction of bias in Thai studies, Warunsiri and McNown (2010) employ very different instruments from compulsory schooling laws. Although the authors do not report educational levels where their IV based on availability of universities directly affect, their instruments should capture differences in higher levels of education than upper primary school. Moreover, almost all the cohorts used in their study were born before the nation wide change in compulsory schooling laws.

In terms of zero return to compulsory schooling for the male employees, Pischke and von Wachter (2008) provide evidence why such result is plausible in case of Germany. Particularly, they argue that German students are better prepared in basic skills relevant to the labour market before they reach the grade affected by changes in compulsory schooling laws. Thus, this paper has tried its best to explain these findings follow the logic of Card (2001) and Pischke and von Wachter (2008). However, further research is needed to understand these exceptional results.

Lastly, to assess the relationship between education and health outcomes, I use the same IV technique with the Heath and Welfare Survey (HWS) 2006. According to Grossman's demand for health capital (Grossman, 1972, 2004), more schooling leads to better health because human capital, as measured by schooling, increases efficiency in production of good health. But in his early work in Grossman 1973, the limited data do not allow him to draw any causal conclusion. Hence, several literatures employ the IV method to estimate the effect of education on health outcomes such as mortality rate in the US (Lleras-Muney, 2001), self-assessed health status (Oreopoulos, 2007), and risk of hypertension in the UK (Powdthavee, 2010). In this study, I try to assess the causal effect of an increase in years of schooling on self-assessed health status of Thai people. The relatively small sample size seems to be the major factor behind an insignificant and weakly identified result. Other surveys or different definition of health outcomes might help future research to shed some light on this issue in Thailand.

The plan of this paper is as follows. Section 3.2 describes the education system and compulsory schooling law in Thailand. Section 3.3 outlines the data and descriptive statistics while Section 3.4 briefly discusses the methodology. Section 3.5 presents the results with some robustness checks as well as discussion on possible reasons underlying these findings.

3.2 Education system and compulsory schooling law in Thailand

The compulsory schooling law in Thailand was first enacted in 1921. It required that every child age 8-15 must attend school unless they had completed their lower primary education (four years of full time study)[27]. In 1960, the 1^{st} National Education Plan aimed to increase the compulsory level of education to upper primary education in several areas of the country subject to local capabilities. Starting from academic year 1963 to 1977[28], the ministry of education announced decrees to extend compulsory schooling of children in specific area to upper primary education. Although such a requirement was enforced in hundreds of lower districts (Tumbons)[29] each year, it affected less than 47% of the total number of lower districts in 1977[30].

A nationwide increase in compulsory schooling from 4 years to 6 years of education was implemented implicitly by a major change of education system following the 3^{rd} National Education Plan in academic year 1978. While the 4:3:3:2 system (4 years of lower primary, 3 years of upper primary, 3 years of lower secondary and 2 years upper secondaryeducation) were employed during the 1^{st} and 2^{nd} National Education Plan (1960 - 1976), the 3^{rd} National Education Plan (1977 - 1982) classified basic education into three levels (6:3:3) which are 6 years of primary school, 3 years of lower secondary

[27] There are exemptions to some children because of reasons such as disabilities or remoteness. Moreover, due to limited availability of schools and ineffectiveness of law enforcement, a few children in those early cohorts, especially in the rural area, had not completed or never attended primary education.

[28] Academic year in Thailand starts from May to March of the following year.

[29] There were around 7,400 lower districts in 1993. Normally, each Tumbon consists of 4 - 10 villages with average population around 7,800 persons.

[30] Moreover, from academic year 1971 to 1976, the changes were implemented in specific schools of each lower district rather than the whole district. See table 3.6 for number of Tumbons affected in each year.

and 3 years of upper secondary school. Hence, despite no explicit change in the law itself, every child in half of the country's lower districts had to complete 6 years of schooling instead of just 4 years in order to fulfill a requirement of primary education by the compulsory schooling law.

According to statistical reports from the ministry of education, though the change in 1977 did not achieve full compliance, it successfully increased the number of students studying beyond grade 4. In particular, students dropping out after grade 4 was reduced from 35.49% in academic year 1976/77 to 12% in 1977/78 and just 7% in 1978/79. Yet the number of drop-outs between grade 5 and 6 remained relatively high around 11-17% from 1976 to 1981 and started to drop to 7% in the academic year 1983/84.

In terms of changes in supply of education, the number of schools did not increase dramatically. For example, from 1979 to 1980, there were 1.77% more schools in the Central region whereas the north experienced only 0.15% increase in that period. Conversely, the number of classrooms and teachers rose markedly in the same period. The rise in number of classrooms ranged from 1.78% in Bangkok to 6.39% in the northeast. As for the number of teachers, it rose 6.46% in Bangkok while the northeast had the highest rise at 10.1%. Hence, it seems that the change in compulsory schooling law rather than other supply side factors (such as more teachers or classrooms) accounted for a significant increase in year of education after 1977.

The latest changes in education law were implemented by the National Education Act 1999.Maintaining the 6:3:3 system, the act assured that every student either in public or private school were entitled to the same level of government's support for free 12-year basic education. In terms of compulsory schooling, the act declared an increase in compulsory schooling from primary to lower secondary education, in other words from 6 to 9 years of schooling. Further, Thai legislators enacted the Compulsory Education Act, which provides a detailed procedure of enforcement and penalty for violation, later in 2002[31]. Yet this change is beyond the scope of this paper because the cohorts affected by the law in 2002 are not old enough to provide any meaningful analysis on the return to education in Thailand.

3.3 Data and descriptive analysis

To estimate the return to education, I employ the Thai Labor Force Survey (LFS) conducted by National Statistic Office (NSO) from 1994 to 2009. Although the NSO has done this survey quarterly since 1998, this paper focuses on the survey during the agricultural (rainy) season in the third quarter of each year because it coincides with

[31] These laws require "all children at the age of 7 to enroll in basic education institutions until the age of 16 except for those who have already completed lower secondary education or grade 9" (Office of the Education Council, 2004).

the peak time in labour demand, especially in the agricultural sector. The number of respondents randomly selected into the LFS in each round is large ranging from 177,821 persons in 1994 to 220,704 persons in 2009.

Then I compute log hourly wage and compensation (including bonus, overtime, and other fringe benefits) for all employees in both public and private sectors from 1994 to 2009. The number of employees in the sample is around 64,000 and 86,000 persons in 1994 and 2009 respectively[32]. Moreover, I restrict the sample of this study to cohorts born from 1961 to 1970 which would reach grade 4 slightly before and after the nationwide change in compulsory schooling law. Further, these restrictions ensure that all cohorts in the sample are at least 24 years old or older. Therefore, most people in this sample should have finished their higher education and already participate in the labour market. Thus, selectivity bias from the choice between higher education and labour force participation should not be a major concern.

Regarding the compulsory schooling variable, a proxy variable is constructed to capture a relative effect of changes in compulsory schooling at Tumbon level for each cohort in any provinces. This variable is calculated from a proportion of population in that province which is affected by increases in compulsory schooling at Tumbon or national level. In particular, I match the name of Tumbon from the ministry of education's decrees during 1963 to 1977 with the number of population in each Tumbon from household registration record in 1993[33]. I then compute a ratio of population in those affected Tumbons to total population of that province in 1993 for each cohort-province. Only cohorts born after 1967 experience an increase in years of compulsory schooling nationwide. Hence, a compulsory schooling variable is equal to 1 for cohort 1967 onwards while the older cohorts in this sample has a value between 0 and 1.

Tables 3.7 - 3.9 show descriptive statistics of the sample by gender before and after the 1967 cohort. Due to the range of age in this sample, it is not surprising that we see a slightly higher log hourly real wage of the elder cohorts. Nevertheless, mean and standard deviation of the compulsory schooling variable are almost the same across these sub-groups. And it seems to coincide with a sharp drop in fraction of workers completing only 4 years of education or less. In terms of gender differences, it is worth noting that female workers' average years of education are slightly higher than those of men in all sub-samples[34]. Moreover, the fraction of workers who do not continue

[32]However, due to the NSO's attempt to create short waves of panel data during 2002 - 2006, the households which appears in more than one rounds of the LFS are filtered out. And I uniquely select only their last entry into this sample. As a result, the sample size for workers in LFS 2002 and 2004 are much smaller (only 8,610 and 25,156 persons respectively).

[33]However, due to limited information on number of schools in each Tumbon in those periods, the changes implemented at the school level from 1971 to 1976 are not included to the calculation of this compulsory schooling variable.

[34]This finding is in contrast to the trend in overall population. The main reason is the potential selection bias arising from the decision of female to become wage-earners. See figure 3.2 - 3.4 for such trends.

their study after lower primary school is reduced more among the female. All other variables seem to be quite similar among both genders.

Furthermore, another survey by the NSO called Health and Welfare Survey (HWS) is employed to assess a relationship between education and health outcome in Thailand. HWS was first conducted annually from 1974 to 1978. Then it was reduced to once in every five years from 1981 to 2001. Since HWS is one of a very few surveys records statistics such as number of illness, access to health facilities and type of health insurance, after the implementation of universal health coverage scheme in October 2001, the Ministry of Public Health requested the NSO to conduct HWS annually from 2003 to 2007 (National Statistical Office, 2008). Although the NSO has conducted this survey for many years, the questionnaire, especially for proxies of health outcome, changes from one survey to another. Therefore, this preliminary study decide to concentrate on a self-assessed health status by each respondent. Unfortunately, only HWS 2006 contains such a question. Specifically, it asks every respondent of 15 years of age or older what do they think of their health status by rating from 1 (very bad) to 5 (very good). There are 74,057 persons in the survey but the number of people in these cohorts (cohort 1961 - 1970) who respond to the self-assessed health status question are just around 10%. The descriptive statistics of the sample (by gender) are presented in tables 3.10 - 3.12.

3.4 Methodology

The main objective of this paper is to consistently estimate the rate of return to education in Thailand. Exploiting the changes in compulsory schooling law in the 1970s, I follow the conventional approach of using the Two Stages Least Square (2SLS) estimation. The model specification of the second stage is the standard Mincer equation (Mincer, 1974b) with some additional control variables as shown in equation 3.4.1.

$$\begin{aligned}\ln w_{ijt} = {} & \beta_0 + \beta_1 yearedu_{ijt} + \beta_2 age_{ijt} + \beta_3 age^2_{ijt} + \beta_4 female_{ijt} + \beta_5 urban_{ijt} \\ & + \beta_{6j} region_j + \beta_{7t} year_t + \epsilon_{ijt}\end{aligned} \tag{3.4.1}$$

where lnw_{ijt} is the natural log of real wage per hour (baht in 2002)[35] of individual i in region j in year t, $yearedu$ is the years of schooling derived from the highest educational level observed in LFS. As for control variables, $female$ is a dummy variable for female workers; $urban$ is a dummy variable which is equal to one if the respondent lives in urban area whereas $region_j$ and $year_t$ are regional and year (of the survey) dummies respectively. More importantly, I have decided to use age and age^2 in place of the

[35] It is computed from a ratio of wages (including bonus and overtime) to hours of work reported by each respondent.

conventional potential work experience[36] owing to the potential error in the experience variable induced by mis-measurement in schooling (Harmon and Walker, 1995). Finally, all regressions (pooled-sample, male and female employees) are weighted by the LFS's sampling weight.

$$\begin{aligned} yearedu_{ijt} = \delta_0 + \delta_1 CompTB_{ikl} + \delta_2 age_{ijt} + \delta_3 age_{ijt}^2 + \delta_4 female_{ijt} \\ + \delta_5 urban_{ijt} + \delta_{6j} region_j + \delta_{7t} year_t + \nu_{ijt} \end{aligned} \tag{3.4.2}$$

The identification strategy of the 2SLS for the return to education is achieved by the inclusion of a compulsory schooling variable ($CompTB_{ikl}$; Compulsory schooling Tumbon of individual i in province l born in cohort k) in the first stage in equation 3.4.2. Specifically, the changes in compulsory schooling law should be highly correlated to years of schooling but exogenous to unobserved ability or mis-measurement in schooling confounded in the error component of equation 3.4.1. The second part on exogenous assumption is needed in order to consistently estimate the rate of return to education while the first part of this statement can be verified. In addition to the first stage of the main regressions presented in table 3.15, I provide the Kleibergen-Paap rk Wald F-statistic of each 2SLS regression and test the hypothesis of weak identification based on the critical value from Stock and Yogo (2005). Then I analyse the impact of the reform on schooling using OLS and Linear Probability Model (LPM) in equation 3.4.3 as follows:

$$\begin{aligned} S_{ijt} = \theta_0 + \theta_1 CompTB_{ikl} + \theta_2 cohort60_{ik} + \theta_3 cohort60sq_{ik} + \theta_4 female_{ijt} \\ + \theta_5 urban_{ijt} + \theta_{6j} region_j + \theta_{7t} year_t + \vartheta_{ijt} \end{aligned} \tag{3.4.3}$$

where S_ijt represents different schooling variables of individual i in region j at time t. This variable is the years of schooling (*yearedu*) for the OLS while the dependent variables for LPM are each year of education dummy variables as well as other dummies indicating if the person has 4 years of education or less (G4 or lower), at least 6 years of education or more (G6 and higher), at least 9 years of education or more (G9 and higher), or has at least 7 but not more than 9 years of education (G7 - G9). Furthermore, I used the cohort variable in place of age. Cohort60 is set to be zero for the cohort born in 1960 (i.e. its value is from 1 to 10 for cohorts of interest) whereas cohort60sq represents the squared of such a cohort variable. All other variables are as defined earlier. These OLS and LPM regressions should provide evidence on the effectiveness of the compulsory schooling law in raising educational level of these cohorts. Especially, the LPM with dummies for different levels of education could indicate whether the law effectively drive targeted population to complete higher stages of education credential or not.

[36]In some models, age-cube is included so as to check for robustness of the model.

Regarding the preliminary study of the relationship between schooling and health, I follow Adams (2002) in the US and Oreopoulos (2007) in the UK to estimate the effect of schooling on self-assessed health status. I employ the model with similar settings to the 2SLS for the return to education. The only two differences in the second stage as shown in equation 3.4.4 are the dependent variable which is the self-assessed health ranking (*health*) from 1 (very bad) to 5 (very good), and exclusion of the year dummies[37].

$$\begin{aligned} health_{ij} = \gamma_0 + \gamma_1 yearedu_{ij} + \gamma_2 age_{ij} + \gamma_3 age_{ij}^2 + \gamma_4 female_{ij} + \gamma_5 urban_{ij} \\ + \gamma_{6j} region_j + \eta_{ij} \end{aligned} \tag{3.4.4}$$

3.5 Results

This section is organized into three sub-sections. In the first, I show the effect of changes in compulsory schooling law (at Tumbon level and nationwide) on educational level of employees in the sample. I then exploit such changes to estimate the return to education for the cohorts slightly before and after the nationwide change in 1977. In the third sub-section, the effect of education on health outcomes is assessed through the similar model as the previous sub-section.

3.5.1 Effect on schooling

Figure 3.1 demonstrates coefficients of a compulsory schooling variable in equation 3.4.3 which varies by year of education on the horizontal axis. The workers[38] in cohort-area affected by the law have significantly lower probability of leaving schools after four years of education. On the other hand, these affected workers have 24% more chance to complete six years of education. However, the law does not have positive and significant effect at 5% level for any level of education beyond primary school (Grade 6). This pattern is also confirmed by the results from linear probability model (LPM) in table 3.1. In particular, the compulsory schooling law contributes to a 11% increase in probability of completing at least 6 years of education whereas it reduces a chance of children leaving school before reaching upper primary education by 10.8%. In terms of control variables, the person who lives in urban area are more likely to complete at least 6 years of education. As for gender, being female in these cohorts has negative and significant effect on the probability to graduate from upper primary education[39].

[37] The reason is straightforward because only HWS in year 2006 is used.

[38] The sample considered in this part includes all workers in the labour force rather than just the wage earners as in the latter analysis.

[39] However, educational level of female in the labour force started to overtake the male's from the cohort 1971 onwards whereas this trend is observed in general population after cohort 1973 (see figure 3.2 and 3.3).

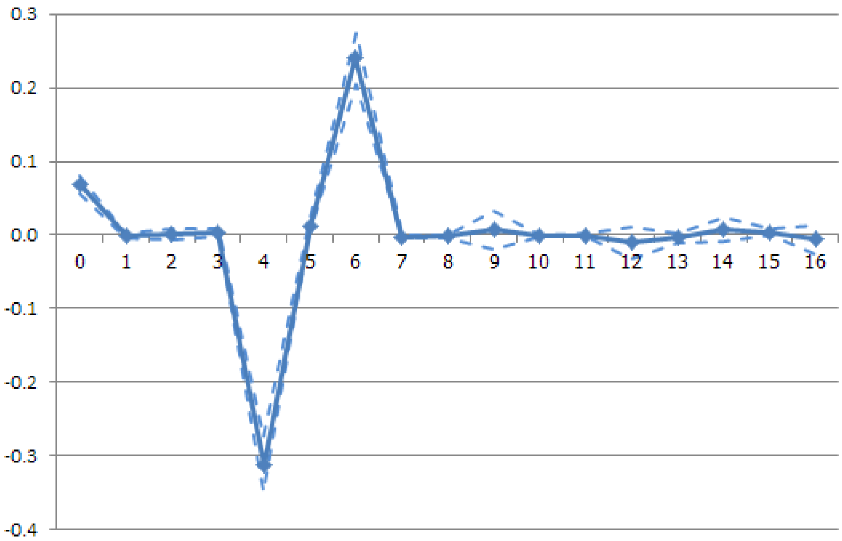

Figure 3.1: *Effect of Compulsory Schooling on Years of Education (estimated from Linear Probability Model) with 95% confident interval*

Table 3.1: The impact of the changes in compulsory schooling law on level of education

	OLS	LPM			
	Year Edu	G4 or lower	G6 and higher	G9 and higher	G7 - G9
CompTB	0.321***	-0.108***	0.110***	0.0080	-0.0277***
	(0.0483)	(0.0057)	(0.0057)	(0.0057)	(0.0038)
female	-0.382***	0.0870***	-0.0861***	-0.0626***	-0.0468***
	(0.0192)	(0.0023)	(0.0023)	(0.0022)	(0.0015)
urban	2.499***	-0.173***	0.177***	0.273***	0.0409***
	(0.0175)	(0.0019)	(0.0019)	(0.0020)	(0.0015)
coht60	0.0649***	-0.0341***	0.0350***	0.0043**	0.0034***
	(0.0152)	(0.0018)	(0.0018)	(0.0017)	(0.0012)
coht60sq	0.0046***	-0.0008***	0.0008***	0.0004**	0.0005***
	(0.0015)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Year dummy	Yes	Yes	Yes	Yes	Yes
Region dummy	Yes	Yes	Yes	Yes	Yes
Observations	406,158	406,158	406,158	406,158	406,158
R^2	0.149	0.181	0.184	0.132	0.019

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively.

Nevertheless, the puzzling part is a negative and significant result for the LPM of grade 7 - 9. This counter-intuitive finding could be driven by the change in the education system from 4:3:3:2 to 6:3:3 itself. The compulsory school variable might not only capture the effect of an increase in compulsory schooling from 4 to 6 years but also the extension in compulsory schooling to 7 years (previous upper primary school) in several areas before the implementation of the new education system (with 6 years of primary education) nationwide. Thus, the latter effect which implicitly reduces years of education in some areas from 7 to 6 could be one of the reasons for such negative and significant of the compulsory schooling variable observed in table 3.1. In sum, the changes in compulsory schooling law do help to significantly increase years of education of these cohorts from 4 to 6 or 7 years. Yet the effect does not extend to any level of education after primary school.

3.5.2 Return to Education

The second part concerns the estimation of return to education. Using the series of changes in compulsory schooling law as an instrument for year of education, table 3.2 shows theresults for both OLS and 2SLS regression from equation 3.4.1. The return to education estimated by OLS (the coefficient of a variable yearedu) is 11.3% and is robust to an inclusion of the term age-cube. Although the results from 2SLS vary slightly between the model with and without age cube, the estimates are quite robust and significant at 5% level of significance too. However, after including age-cube, the term age-squared and age-cube are not significant at 5% level. Therefore I decide to use the model base on age and age-squared only. Interestingly, the 2SLS estimation for return to education is only 5.6% which is substantially lower than the estimate from OLS.

Regarding the differential effect between genders, the regression for the male sub-sample shows lower rates of return to education in both OLS and 2SLS. Surprisingly, the 2SLS estimation using changes in compulsory schooling as an instrumental does not give any significant rate of return of education at all. Conversely, the rates of return to education for female estimated by OLS and 2SLS are higher than those from the pooled sample. The OLS regression produces a rate of return at 11.8% which is significantly different from zero at 1% significant level. Meanwhile, the rate of return to education from 2SLS displays a positive and significant result at 8.73% which is much higher than those of the male and the pooled sample.

One major concern of the IV method is a weak instrument problem. I provide the Kleibergen-Paap rk Wald F-statistic for first stage regressions of all 2SLS regressions in table 3.2. According to Stock and Yogo (2005), the F-statistic for first stage regressions of the pooled sample is large enough to reject the null hypothesis of weak identification

Table 3.2: Return to Education for cohorts born in 1961 to 1970 by gender

	All				Male		Female	
	OLS (1)	OLS (2)	2SLS (1)	2SLS (2)	OLS (1)	2SLS (1)	OLS (1)	2SLS (1)
yearedu	0.113***	0.113***	0.0577**	0.0560**	0.109***	0.0279	0.118***	0.0873***
	(0.0005)	(0.0005)	(0.0277)	(0.028)	(0.0007)	(0.0492)	(0.0006)	(0.0297)
female	-0.169***	-0.169***	-0.161***	-0.160***				
	(0.0042)	(0.0042)	(0.0059)	(0.0059)				
urban	0.102***	0.102***	0.240***	0.244***	0.107***	0.293***	0.0951***	0.179**
	(0.0039)	(0.0039)	(0.0689)	(0.0698)	(0.0053)	(0.113)	(0.0056)	(0.0812)
age	0.0154***	0.0854**	0.0126**	0.0946**	0.0114	0.013	0.0194**	0.0149
	(0.0054)	(0.0428)	(0.0059)	(0.0472)	(0.0074)	(0.0088)	(0.0078)	(0.0091)
agesq	0.000185**	-0.00181	0.000166**	-0.00217	0.000279***	0.000197	0.0000851	0.000102
	(0.0001)	(0.0012)	(0.0001)	(0.0013)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
agecb		1.85e-05*		2.16e-05*				
		(0.00001)		(0.00001)				
constant	1.783***	0.983**	2.377***	1.456***	1.835***	2.562***	1.576***	1.976***
	(0.097)	(0.497)	(0.305)	(0.557)	(0.132)	(0.45)	(0.141)	(0.41)
F-test			22.533	22.324		10.315		12.613
Year D	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. D	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	180,728	180,728	180,728	180,728	95,515	95,515	85,213	85,213
R^2	0.563	0.563	0.468	0.462	0.520	0.327	0.606	0.576

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively. Model (1) includes only age and age squared as control variables while model (2) also includes age cube as an extra control variable.

at 10% maximal IV size. Although the F-statistic for first stage regressions of both male and female sub-samples are smaller than the pooled one, both of them are larger than the critical value of the Stock-Yogo weak identification test at 15% maximal IV size. Thus, weak identification does not seem to be a critical issue for the use of IV method in table 3.2.

Further, I try to check for robustness of these results on two aspects. First, the LFS does not provide any information on region or province where the respondent was born or lived during her childhood but rather the area in which she currently lives. Therefore, the underlying assumption of compulsory schooling variable could be jeopardized as a result of large internal migration during the 80s and 90s. Thus, I follow Duflo (2001) (which excludes Jakarta from her study in Indonesia) and re-run all the regressions without any respondents currently living in Bangkok[40]. Table 3.3 illustrates similar results for both OLS and 2SLS in all sub-samples. The only difference is that the 2SLS for male workers gives a positive and significant estimate for the rate of return to education at 20 % level. Moreover, the Kleibergen-Paap rk Wald F-statistic for first stage regressions in this case are slightly higher than those from the regression including Bangkok.

In addition, since the choice of cohorts employed in table 3.2 is arbitrary, I re-estimate all regressions using the cohorts from 1958 to 1975 (nine cohorts before and eight cohorts after the nationwide change in compulsory schooling law). These results

[40]This exclusion should reduce the mismatch between the current province in which the respondent lives and the province where she attended the primary school.

Table 3.3: Return to Education for cohorts born in 1961 to 1970 by gender (Excluding Bangkok)

	All				Male		Female	
	OLS (1)	OLS (2)	2SLS (1)	2SLS (2)	OLS (1)	2SLS (1)	OLS (1)	2SLS (1)
yearedu	0.113***	0.113***	0.0596***	0.0587***	0.108***	0.0415	0.117***	0.0862***
	(0.0005)	(0.0005)	(0.0222)	(0.0222)	(0.0007)	(0.0314)	(0.0007)	(0.0306)
female	-0.163***	-0.163***	-0.159***	-0.159***				
	(0.0043)	(0.0043)	(0.0049)	(0.0049)				
urban	0.103***	0.103***	0.235***	0.237***	0.109***	0.262***	0.0967***	0.181**
	(0.0039)	(0.0039)	(0.0553)	(0.0552)	(0.0054)	(0.072)	(0.0056)	(0.0837)
age	0.0131**	0.0663	0.0110*	0.0572	0.0133*	0.0135	0.0115	0.00854
	(0.0056)	(0.0435)	(0.0061)	(0.0465)	(0.0076)	(0.0083)	(0.0083)	(0.0091)
agesq	0.000222***	-0.00129	0.000192**	-0.00112	0.000252**	0.000186	0.000199*	0.000199*
	(0.0001)	(0.0012)	(0.0001)	(0.0013)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
agecb		0.000014		0.0000122				
		(0.00001)		(0.00001)				
constant	1.534***	0.925*	2.056***	1.537***	1.517***	2.062***	1.463***	1.842***
	(0.101)	(0.503)	(0.243)	(0.595)	(0.135)	(0.314)	(0.148)	(0.376)
F-test			34.920	35.155		21.892		13.478
Year D	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. D	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	166,475	166,475	166,475	166,475	88,292	88,292	78,183	78,183
R^2	0.525	0.525	0.436	0.433	0.477	0.341	0.572	0.540

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively. Model (1) includes only age and age squared as control variables while model (2) also includes age cube as an extra control variable.

are presented in table 3.4. The rates of return to education estimated by OLS are almost the same as the results in table 3.2. However, the estimates from 2SLS are quite different. Unlike the sample of cohorts 1961-1970, neither the male nor the pooled sample shows any significant rates of return to education. Only the female sub-sample is robust to the change in cohorts of study. The estimated rate of return to education is 10.2% (slightly less than the OLS estimate) and significant at 1% level. In contrast to table 3.2 and 3.3, the Kleibergen-Paap rk Wald F-statistic is sensitive to a change in model specification (with or without age-cube). Furthermore, while we can still reject the null hypothesis of weak identification for female sub-sample at 15% maximal IV size, the male counterpart has a weaker first stage regression which can only reject such a hypothesis at 20% maximal IV size[41].

Every 2SLS result suggests an upward bias in the OLS due to endogeneity problems such as omitted ability in the OLS regression. Yet this upward bias found is not consistent with several studies using IV methods and the previous study in Thailand (Warunsiri and McNown, 2010). For example, Card (1993), Butcher and Case (1994), and Harmon and Walker (1995) find that the returns to education using IV methods are almost or more than double the OLS estimates[42]. Other than measurement error in

[41] Nevertheless, the Kleibergen-Paap rk Wald F-statistic of the female workers is not robust to an inclusion of age-cube either. In particular, the F-statistic is 5.19% which is not significant even at 25% level.

[42] Using twins and sibling data respectively, Ashenfelter and Krueger (1994) and Ashenfelter and Zimmerman (1997) also report larger rates of return to education than the OLS estimates.

Table 3.4: Return to Education for cohorts born in 1958 to 1975 by gender

	All				Male		Female	
	OLS (1)	OLS (2)	2SLS (1)	2SLS (2)	OLS (1)	2SLS (1)	OLS (1)	2SLS (1)
yearedu	0.113***	0.113***	0.0432	-0.0315	0.108***	-0.0247	0.117***	0.102***
	(0.0004)	(0.0004)	(0.0304)	(0.0703)	(0.0006)	(0.0677)	(0.0005)	(0.0277)
female	-0.159***	-0.159***	-0.141***	-0.122***				
	(0.0032)	(0.0032)	(0.0082)	(0.0184)				
urban	0.0913***	0.0913***	0.254***	0.429***	0.0966***	0.383***	0.0853***	0.126*
	(0.0029)	(0.0029)	(0.0713)	(0.164)	(0.004)	(0.146)	(0.0041)	(0.0716)
age	0.0240***	0.0730***	0.0307***	0.297***	0.0276***	0.0399***	0.0191***	0.0207***
	(0.0022)	(0.0137)	(0.004)	(0.112)	(0.003)	(0.008)	(0.0032)	(0.0044)
agesq	4.71e-05	-0.00140***	-0.000116	-0.00797**	1.99e-05	-0.000246	8.99e-05*	4.53e-05
	(0.00003)	(0.0004)	(0.0001)	(0.0033)	(0.00004)	(0.0002)	(0.00005)	(0.0001)
agecb		1.39e-05***		7.35e-05**				
		(0.000004)		(0.00003)				
constant	1.681***	2.255***	1.149***	0.0513	1.632***	2.679***	1.598***	1.740***
	(0.0386)	(0.251)	(0.152)	(0.593)	(0.0529)	(0.532)	(0.0556)	(0.25)
F-test			20.958	7.187		7.837		14.735
Year D	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. D	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	318,608	318,608	318,608	318,608	166,544	166,544	152,064	152,064
R^2	0.558	0.410	0.558	-0.075	0.522	0.005	0.595	0.587

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively. Model (1) includes only age and age squared as control variables while model (2) also includes age cube as an extra control variable.

schooling (Griliches, 1977), Card (1993, 2001) provide a theoretical model explaining why the IV methods can produce much larger estimates than the standard OLS ones. In his model, the interplay between heterogeneity in the returns to education and the IV based on supply-side innovation, affecting sub-groups in the sample unevenly, could be one of the explanations. Particularly, when the individuals with low schooling have higher-than-average costs of schooling (higher discount rate) rather than lower-than-average returns to schooling (lower ability), the IV estimators -based on compulsory schooling or school proximity- could yield an estimated “local average treatment effect”[43] above the average marginal return to schooling in the population. Thus, it is possible that both the OLS and IV methods do not consistently estimate the average marginal return to education and are likely to be biased upward (Card, 2001).

Nevertheless, observing the IV estimators below those from OLS is not totally at odds with data from developing economies. For example, Duflo (2001, 2004) shows that the IV estimates based on a school building programme in Indonesia in the 1970s are slightly smaller than the OLS estimates[44]. Interestingly, only 2SLS estimations of the female employees are significantly different from zero and robust to changes in

[43]This term refers to “the average treatment effect among those who alter their status because they react to the (dichotomous) instrument.” (Imbens and Angrist, 1994 cited in (Powdthavee, 2010, p. 6))

[44]Although I could argue that this study is comparable to Duflo (2001) in many aspects such as the period of intervention and the level of education concerned (both studies focus on the increase in primary education during the 70s, there are several papers conclude that the OLS estimates are downward-biased. See Maluccio (1998) which employs distance to the nearest high school in the rural Philippines and Warunsiri and McNown (2010) who use a pseudo-panel approach with Thai LFS for cohorts 1946-1967, for instance

sample coverage. Such a finding suggests that despite the effectiveness of the compulsory schooling law in raising educational level for both genders, only marginal female workers who were forced to stay in schools after lower primary education benefit a positive and significant rate of return to education[45].

In case of the male workers, the zero return to education seems to be even more counterintuitive. However, Pischke and von Wachter (2008) found zero returns to compulsory schooling for secondary schools (grade 9) in West Germany during 1948-1970 as well. They conjectured that "the basic skills most relevant for the labor market are learned earlier in Germany than in other countries". Following their argument, it might be possible that Thai labour market for the low-educated did not value extra 2-3 years of upper primary education. Yet the fact that I find positive and significant rate of return for female questions the credibility of this argument[46]. Unless the underlying differences between male and female employees are uncovered, it is hard to push forward any plausible reasons for the zero returns to education in Thailand.

Following the model in Card (2001), the upward bias (in the OLS) found among female sub-sample can be rationalized if the changes in compulsory schooling law in Thailand do not primarily reduce the cost of schooling or induce someone with a high discount rate (high dis-utility from education) to continue their study but rather force individuals to stay further in schools regardless of their ability. Under this scenario, the 2SLS regressions should yield the estimated return to education of the marginal individual who complies to the compulsory schooling law. Owing to the slightly lower average years of education of female workers during 1960s, if the distribution for ability by gender are the same, it is more likely that the marginal female worker forced to acquire more education is more able than the male counterpart[47]. Hence, the positive and significant rate of return to education among female workers might result from the different position of marginal female individuals on the ability distribution comparing it with that of the male. All in all the concerns on size and direction of bias as well as relatively low F-statistic urge us to interpret these results with extreme caution.

3.5.3 Education and Self-Assessed Health Status

Finally, I present the estimates of equation 3.4.4 in table 3.5. Since the dependent variable is a self-assessed health status from HWS ranging from 1 (very bad) to 5 (very

[45] Figure 3.3 and 3.4 shows accelerated rise in average year of schooling of female in the labour force and female workers after changes in compulsory schooling affecting cohort 1965 and 1967.

[46] Another potential explanation is the selection of female into wage employees but it is beyond the scope of this paper.

[47] Or the effect of compulsory schooling on women's education is more profound than the men's. As shown in table 3.13 and 3.14, the compulsory schooling variable significantly increases a probability of completing at least lower secondary education of female pupils but does not have any effect on the male pupils. Furthermore, the selection into wage-earners of female is another concerns that could lead to such results.

Table 3.5: The effect of schooling on self-assessed health status cohorts born in 1961 to 1970 by gender (HWS 2006)

	All				Male		Female	
	OLS (1)	OLS (2)	2SLS (1)	2SLS (2)	OLS (1)	2SLS (1)	OLS (1)	2SLS (1)
yearedu	0.0191***	0.0190***	0.244	0.172	0.0188***	0.140	0.0192***	0.416
	(0.0029)	(0.0029)	(0.187)	(0.196)	(0.0045)	(0.153)	(0.0038)	(0.547)
female	-0.0571**	-0.0576**	0.0634	0.0242				
	(0.0249)	(0.0249)	(0.104)	(0.107)				
urban	0.0302	0.0299	-0.512	-0.337	-0.0405	-0.362	0.0717***	-0.818
	(0.0221)	(0.0221)	(0.453)	(0.471)	(0.0373)	(0.408)	(0.0275)	(1.229)
age	-0.180	5.484	0.359	3.663	-0.0677	0.280	-0.260	0.574
	(0.138)	(3.388)	(0.487)	(4.914)	(0.222)	(0.517)	(0.177)	(1.18)
agesq	0.00209	-0.138*	-0.00406	-0.0881	0.000813	-0.00325	0.00302	-0.00631
	(0.0017)	(0.0838)	(0.0056)	(0.125)	(0.0027)	(0.0061)	(0.0022)	(0.0133)
agecb		0.00115*		0.000708				
		(0.00069)		(0.00105)				
constant	7.263***	-68.77	-6.009	-48.42	4.923	-3.289	8.878**	-12.19
	(2.793)	(45.54)	(11.67)	(63.35)	(4.486)	(11.75)	(3.58)	(29.43)
F-test			2.67	2.217		2.609		0.659
Reg. D	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7,615	7,615	7,615	7,615	2,882	2,882	4,733	4,733
R^2	0.033	-1.316	0.033	-0.585	0.029	-0.367	0.036	-4.086

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively. Model (1) includes only age and age squared as control variables while model (2) also includes age cube as an extra control variable.

good), coefficients for year of schooling are expected to be positive and significant. In other words, higher level of education should lead to better health status after controlling for other covariates. Such a positive relationship is significantly confirmed through the OLS regression in all sub-samples. However, all 2SLS estimates are not significantly different from zero. Low values of Kleibergen-Paap rk Wald F-statistic in every regression suggests that the compulsory schooling variable employed might suffer from weak instrument problem. As the specification of the first stage is the same as those used to estimate the return to education, small sample size is very likely to be the reason behind such a weak identification. Other definitions of health outcomes are needed for a further investigation in this topic.

3.6 Conclusion

This paper tries to use several changes in compulsory schooling law during the 1960s and 1970s as an instrumental variable to consistently estimate the rates of return to education in Thailand. It suggests that, despite the significant effect of the compulsory schooling law on the completion rate of upper primary education in both genders, only female employees has positive and significant estimate for the rates of return to education. Such a result for women seems to be robust to slight alteration in the regions and cohorts under consideration. However, zero returns to education among male workers is also robust to changes in model specification as well. This finding highlights the importance of further research on factors underlying the differences between male and female in the low skills labour market. Otherwise, this conflicting result could cast doubt on the validity of the IV method based on changes in compulsory schooling as a whole.

Further, although an upward bias in OLS regression is found by some studies in developing countries, similar IV methods used in many studies (such as Indonesia, and the Philippines) provide supporting evidence for a downward bias. Thus, the size and direction of bias implied by this paper encourages us to search for more evidence in developing countries, such as the role of labour market institutions or schooling systems, to foster further discussion.

Finally, the paper attempts to draw the linkage between education and health outcome in Thailand. All 2SLS estimates do not show any significant relationship mainly due to weakly identified first stage regressions. To get more precise estimates, a larger sample size is needed. One possible solution is to try various definitions for health outcomes in order that other years of Health and Welfare Survey can be utilized.

3.A Changes in Compulsory Schooling Law

In order to identify the changes in compulsory schooling laws at Tumbon level, I research various decrees of the Ministry of Education and Royal Thai Government Gazette documents. However, I benefit greatly from a compilation of all these documents and online discussion by Mr. Kanin Udomkuamsuk, a senior educational administrative officer in Phitsanulok province[48]. The number of Tumbons needed to raise compulsory schooling level to upper primary education in each academic year are presented in the following table:

Table 3.6: The number of Tumbons affected by the changes in compulsory schooling law 1963-1977

Academic Year	Number of Tumbons affected	Level of Coverage
1963	394	All children in the area
1964	96	All children in the area
1965	4	All children in the area
1966	5	All children in the area
1967	5	All children in the area
1968	21	Only in specific schools
1969	109	All children in the area
1971	192	Only in specific schools
1972	304	Only in specific schools
1973	373	Only in specific schools
1974	338	Only in specific schools
1975	305	Only in specific schools
1976	590	Only in specific schools
1977	729	All children in the area
Total	3,465	Less than 47% of all Tumbons in the coountry

Source: Author's calculation based on Ministry of Education and Royal Thai Government Gazette (various years)

Note: Since 1978, the compulsory schooling law required every children in the country (roughly cohorts born after 1967 onwards) to complete at least six years of primary education.

[48]As a side note, Mr. Udomkuamsuk started to write about the compulsory schooling law in those periods because he was involved in a legal challenge regarding village head election in his district. One of the qualifications required by the Department of Provincial Administration for candidates of the village head election is to complete compulsory education. Hence, he decided to investigate into changes in compulsory schooling laws and made such information available online at http://www.gotoknow.org/posts/329844 .

3.B Descriptive statistics

Table 3.7: Labor Force Survey 1994 - 2009 (workers both genders cohorts 1961 - 1970)

	All cohorts		Cohort 1961 - 1966		Cohort 1967 - 1970	
Variable	Mean	SD	Mean	SD	Mean	SD
ln(RealWage)	3.386	0.820	3.421	0.858	3.343	0.767
Year of Education	8.641	4.753	8.418	4.977	8.919	4.441
Grade 4 or less	0.281	0.449	0.380	0.485	0.157	0.364
Grade 6 or more	0.710	0.454	0.609	0.488	0.835	0.371
Female	0.441	0.497	0.441	0.496	0.441	0.497
Urban area	0.465	0.499	0.461	0.498	0.469	0.499
Age	35.483	5.649	37.650	5.180	32.779	5.007
Compulsory school	0.504	0.448	0.107	0.078	1.000	0.000
Central	0.175	0.380	0.169	0.375	0.182	0.386
East	0.079	0.270	0.076	0.266	0.083	0.276
West	0.060	0.237	0.061	0.239	0.059	0.236
Upper North	0.097	0.296	0.101	0.302	0.092	0.289
Lower North	0.070	0.256	0.075	0.264	0.064	0.245
Upper Northeast	0.077	0.266	0.078	0.268	0.075	0.264
Lower Northeast	0.117	0.321	0.117	0.322	0.116	0.320
Upper South	0.086	0.280	0.087	0.281	0.085	0.278
Lower South	0.028	0.164	0.027	0.162	0.028	0.166
Bangkok Metropolis	0.212	0.408	0.208	0.406	0.216	0.411
Year = 1994	0.075	0.264	0.077	0.267	0.072	0.259
Year = 1995	0.073	0.259	0.071	0.256	0.075	0.263
Year = 1996	0.071	0.256	0.073	0.261	0.068	0.251
Year = 1997	0.073	0.261	0.072	0.259	0.074	0.263
Year = 1998	0.067	0.251	0.067	0.250	0.068	0.251
Year = 1999	0.068	0.252	0.068	0.252	0.069	0.253
Year = 2000	0.071	0.256	0.069	0.254	0.072	0.258
Year = 2001	0.071	0.257	0.072	0.259	0.070	0.254
Year = 2002	0.009	0.094	0.008	0.091	0.010	0.098
Year = 2003	0.053	0.225	0.054	0.227	0.052	0.222
Year = 2004	0.022	0.148	0.023	0.149	0.022	0.148
Year = 2005	0.060	0.238	0.059	0.235	0.062	0.240
Year = 2006	0.072	0.259	0.074	0.262	0.070	0.256
Year = 2007	0.071	0.256	0.070	0.256	0.071	0.257
Year = 2008	0.073	0.260	0.072	0.258	0.074	0.262
Year = 2009	0.071	0.256	0.070	0.255	0.072	0.258
Obs.	180,728		104,827		75,901	

Table 3.8: Labor Force Survey 1994 - 2009 (male workers cohorts 1961 - 1970)

	All cohorts		Cohort 1961 - 1966		Cohort 1967 - 1970	
Variable	Mean	SD	Mean	SD	Mean	SD
ln(RealWage)	3.441	0.787	3.491	0.828	3.380	0.728
Year of Education	8.539	4.478	8.377	4.710	8.742	4.162
Grade 4 or less	0.256	0.437	0.349	0.477	0.141	0.348
Grade 6 or more	0.733	0.442	0.639	0.480	0.851	0.356
Urban area	0.452	0.498	0.450	0.498	0.455	0.498
Age	35.356	5.657	37.532	5.198	32.638	4.993
Compulsory school	0.504	0.448	0.107	0.079	1.000	0.000
Central	0.168	0.374	0.165	0.371	0.173	0.378
East	0.081	0.273	0.078	0.269	0.085	0.279
West	0.060	0.237	0.060	0.237	0.059	0.236
Upper North	0.096	0.294	0.099	0.299	0.091	0.288
Lower North	0.071	0.256	0.074	0.263	0.066	0.248
Upper Northeast	0.082	0.274	0.083	0.276	0.081	0.273
Lower Northeast	0.123	0.329	0.125	0.331	0.121	0.326
Upper South	0.090	0.287	0.089	0.285	0.092	0.289
Lower South	0.030	0.171	0.029	0.169	0.031	0.175
Bangkok Metropolis	0.198	0.399	0.197	0.398	0.200	0.400
Year = 1994	0.078	0.268	0.083	0.275	0.072	0.259
Year = 1995	0.076	0.264	0.073	0.260	0.079	0.269
Year = 1996	0.075	0.264	0.078	0.268	0.072	0.258
Year = 1997	0.074	0.262	0.072	0.258	0.077	0.267
Year = 1998	0.067	0.250	0.066	0.248	0.068	0.251
Year = 1999	0.069	0.253	0.067	0.250	0.071	0.256
Year = 2000	0.070	0.255	0.070	0.255	0.070	0.256
Year = 2001	0.072	0.258	0.072	0.258	0.072	0.258
Year = 2002	0.009	0.095	0.008	0.091	0.010	0.100
Year = 2003	0.054	0.226	0.055	0.228	0.053	0.223
Year = 2004	0.022	0.148	0.022	0.147	0.023	0.149
Year = 2005	0.058	0.233	0.057	0.232	0.058	0.235
Year = 2006	0.069	0.254	0.071	0.256	0.068	0.251
Year = 2007	0.068	0.252	0.068	0.252	0.068	0.251
Year = 2008	0.070	0.256	0.071	0.256	0.070	0.255
Year = 2009	0.069	0.254	0.068	0.252	0.070	0.255
Obs.	95,515		55,432		40,083	

Table 3.9: Labor Force Survey 1994 - 2009 (female workers cohorts 1961 - 1970)

	All cohorts		Cohort 1961 - 1966		Cohort 1967 - 1970	
Variable	Mean	SD	Mean	SD	Mean	SD
ln(RealWage)	3.316	0.854	3.333	0.887	3.296	0.810
Year of Education	8.769	5.077	8.469	5.297	9.143	4.761
Grade 4 or less	0.312	0.463	0.419	0.493	0.178	0.383
Grade 6 or more	0.680	0.467	0.571	0.495	0.815	0.388
Urban area	0.480	0.500	0.475	0.499	0.487	0.500
Age	35.644	5.633	37.799	5.152	32.958	5.020
Compulsory school	0.504	0.448	0.107	0.078	1.000	0.000
Central	0.184	0.387	0.175	0.380	0.194	0.395
East	0.077	0.266	0.074	0.262	0.080	0.271
West	0.060	0.238	0.062	0.241	0.059	0.235
Upper North	0.099	0.299	0.104	0.306	0.093	0.290
Lower North	0.070	0.255	0.077	0.266	0.062	0.241
Upper Northeast	0.070	0.255	0.071	0.257	0.068	0.252
Lower Northeast	0.108	0.311	0.108	0.310	0.109	0.311
Upper South	0.080	0.271	0.083	0.276	0.076	0.264
Lower South	0.024	0.154	0.024	0.154	0.024	0.154
Bangkok Metropolis	0.228	0.420	0.222	0.416	0.236	0.425
Year = 1994	0.072	0.258	0.071	0.257	0.072	0.259
Year = 1995	0.069	0.253	0.068	0.251	0.070	0.255
Year = 1996	0.065	0.246	0.067	0.250	0.062	0.242
Year = 1997	0.072	0.259	0.073	0.260	0.071	0.257
Year = 1998	0.068	0.252	0.068	0.252	0.068	0.251
Year = 1999	0.068	0.251	0.069	0.254	0.066	0.248
Year = 2000	0.071	0.257	0.069	0.254	0.074	0.262
Year = 2001	0.070	0.255	0.073	0.259	0.067	0.250
Year = 2002	0.009	0.092	0.008	0.090	0.009	0.094
Year = 2003	0.053	0.223	0.054	0.225	0.052	0.221
Year = 2004	0.023	0.149	0.023	0.151	0.022	0.146
Year = 2005	0.063	0.243	0.061	0.239	0.065	0.247
Year = 2006	0.076	0.265	0.078	0.269	0.074	0.261
Year = 2007	0.074	0.262	0.073	0.261	0.076	0.264
Year = 2008	0.076	0.264	0.073	0.260	0.079	0.270
Year = 2009	0.073	0.260	0.071	0.258	0.074	0.262
Obs.	85,213		49,395		35,818	

Table 3.10: Health and Welfare Survey 2006 (All respondents cohorts 1961 - 1970)

	All cohorts		Cohort 1961 - 1966		Cohort 1967 - 1970	
Variable	Mean	SD	Mean	SD	Mean	SD
Year of Education	7.119	3.976	6.687	4.036	7.836	3.767
Grade 4 or less	0.406	0.491	0.536	0.499	0.191	0.393
Grade 6 or more	0.584	0.493	0.456	0.498	0.796	0.403
Female	0.628	0.483	0.635	0.481	0.616	0.486
Urban area	0.290	0.454	0.283	0.451	0.301	0.459
Age	40.620	2.874	42.499	1.762	37.510	1.130
Compulsory school	0.445	0.436	0.109	0.076	1.000	0.000
Health status						
Very bad	0.009	0.095	0.010	0.100	0.008	0.087
Bad	0.082	0.275	0.092	0.289	0.065	0.247
Moderate	0.000	0.000	0.474	0.499	0.432	0.496
Good	0.458	0.498	0.395	0.489	0.459	0.498
Very good	0.419	0.493	0.029	0.168	0.036	0.185
Central	0.122	0.327	0.119	0.324	0.126	0.332
East	0.064	0.245	0.065	0.246	0.063	0.242
West	0.056	0.231	0.054	0.226	0.061	0.238
Upper North	0.091	0.288	0.098	0.297	0.080	0.271
Lower North	0.110	0.312	0.110	0.313	0.109	0.311
Upper Northeast	0.134	0.340	0.133	0.340	0.134	0.341
Lower Northeast	0.205	0.404	0.212	0.409	0.194	0.395
Upper South	0.103	0.303	0.097	0.296	0.112	0.315
Lower South	0.028	0.165	0.030	0.171	0.024	0.153
Bangkok Metropolis	0.088	0.284	0.082	0.274	0.099	0.298
Obs.	7,615		4,759		2,856	

Table 3.11: Health and Welfare Survey 2006 (Male respondents cohorts 1961 - 1970)

	All cohorts		Cohort 1961 - 1966		Cohort 1967 - 1970	
Variable	Mean	SD	Mean	SD	Mean	SD
Year of Education	7.495	4.053	7.098	4.122	8.118	3.861
Grade 4 or less	0.353	0.478	0.458	0.498	0.189	0.391
Grade 6 or more	0.639	0.480	0.537	0.499	0.800	0.401
Urban area	0.295	0.456	0.299	0.458	0.289	0.454
Age	40.546	2.842	42.457	1.728	37.542	1.146
Compulsory school	0.456	0.438	0.110	0.081	1.000	0.000
Health status						
Very bad	0.011	0.106	0.011	0.103	0.012	0.111
Bad	0.068	0.252	0.073	0.260	0.061	0.239
Moderate	0.443	0.497	0.453	0.498	0.427	0.495
Good	0.440	0.496	0.428	0.495	0.458	0.498
Very good	0.037	0.190	0.034	0.183	0.042	0.201
Central	0.132	0.339	0.130	0.336	0.136	0.343
East	0.067	0.251	0.070	0.256	0.063	0.243
West	0.062	0.241	0.059	0.235	0.068	0.251
Upper North	0.097	0.295	0.109	0.312	0.077	0.266
Lower North	0.116	0.320	0.115	0.319	0.118	0.323
Upper Northeast	0.124	0.330	0.130	0.336	0.115	0.319
Lower Northeast	0.182	0.386	0.181	0.385	0.184	0.387
Upper South	0.108	0.311	0.095	0.293	0.129	0.336
Lower South	0.027	0.161	0.028	0.164	0.025	0.158
Bangkok Metropolis	0.085	0.278	0.085	0.278	0.084	0.278
Obs.	2,882		1,811		1,071	

Table 3.12: Health and Welfare Survey 2006 (Female respondents cohorts 1961 - 1970)

	All cohorts		Cohort 1961 - 1966		Cohort 1967 - 1970	
Variable	Mean	SD	Mean	SD	Mean	SD
Year of Education	6.897	3.913	6.450	3.967	7.659	3.698
Grade 4 or less	0.437	0.496	0.581	0.493	0.192	0.394
Grade 6 or more	0.552	0.497	0.410	0.492	0.793	0.405
Urban area	0.287	0.452	0.274	0.446	0.308	0.462
Age	40.664	2.892	42.523	1.781	37.490	1.119
Compulsory school	0.438	0.434	0.109	0.073	1.000	0.000
Health status						
Very bad	0.008	0.088	0.010	0.098	0.005	0.068
Bad	0.090	0.287	0.103	0.304	0.068	0.252
Moderate	0.467	0.499	0.486	0.500	0.436	0.496
Good	0.407	0.491	0.375	0.484	0.460	0.499
Very good	0.028	0.165	0.026	0.159	0.031	0.174
Central	0.115	0.319	0.113	0.317	0.119	0.324
East	0.062	0.241	0.061	0.240	0.062	0.242
West	0.053	0.224	0.051	0.220	0.056	0.230
Upper North	0.088	0.283	0.091	0.288	0.082	0.274
Lower North	0.106	0.307	0.107	0.310	0.103	0.304
Upper Northeast	0.140	0.347	0.135	0.342	0.146	0.354
Lower Northeast	0.219	0.414	0.230	0.421	0.200	0.400
Upper South	0.099	0.299	0.098	0.297	0.101	0.302
Lower South	0.028	0.166	0.032	0.175	0.023	0.150
Bangkok Metropolis	0.091	0.287	0.080	0.272	0.108	0.310
Obs.	4,733		2,948		1,785	

3.C Compulsory Schooling Law & Years of Education by Gender

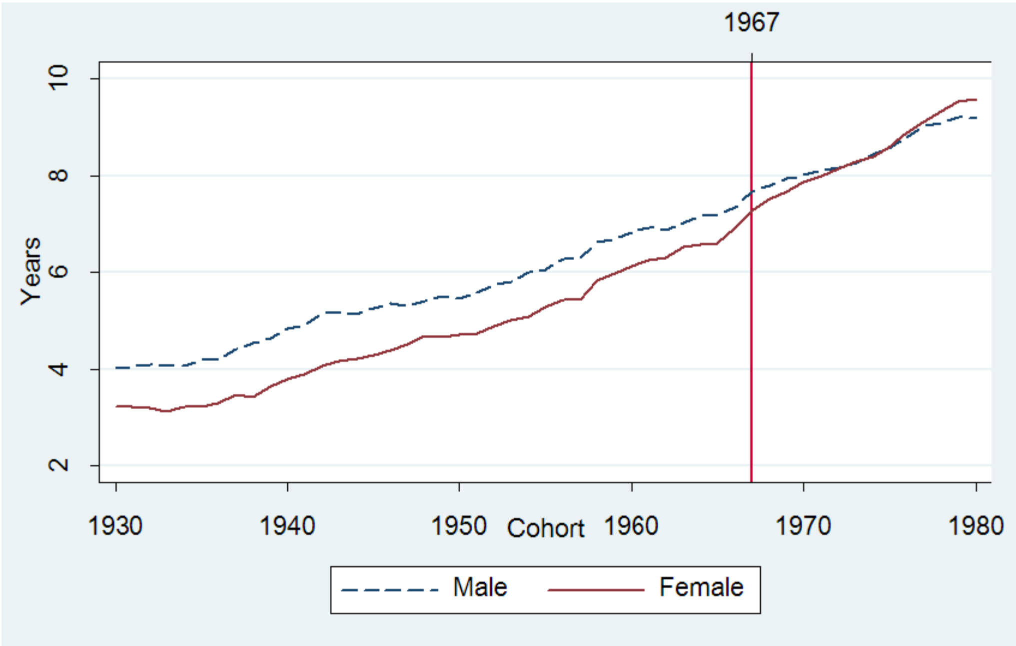

Figure 3.2: *Average Years of Education of the Population by cohort and gender, LFS 1994-2009*

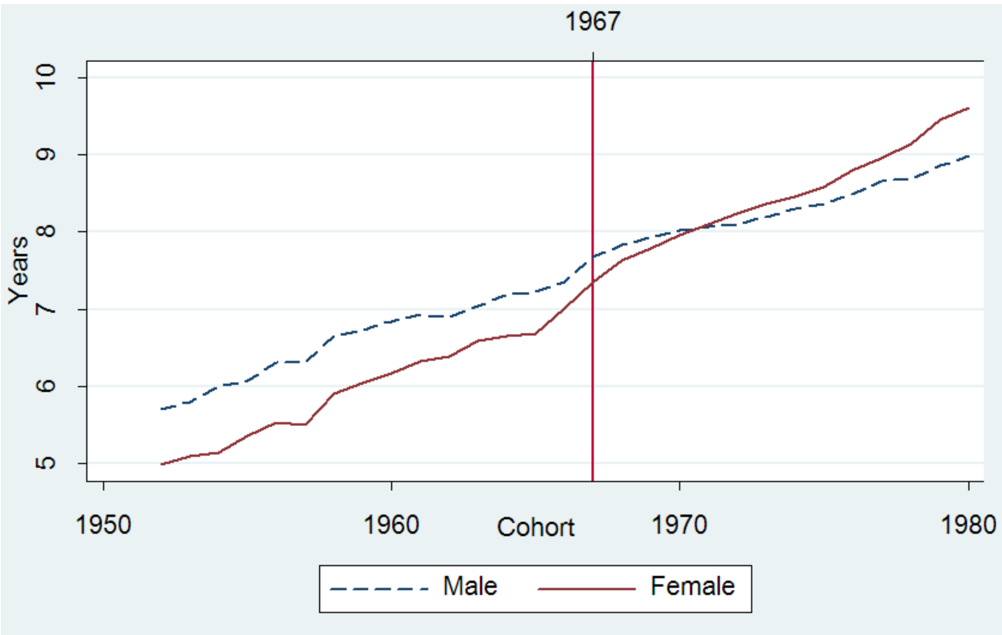

Figure 3.3: *Average Years of Education of All in the Labour Force by cohort and gender, LFS 1994-2009*

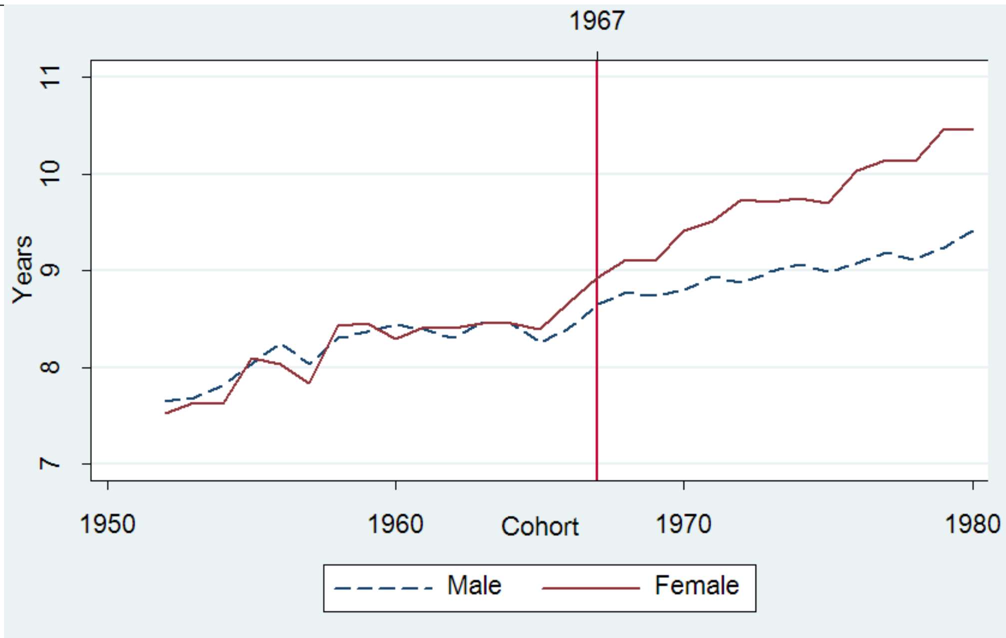

Figure 3.4: *Average Years of Education of All Employees by cohort and gender, LFS 1994-2009*

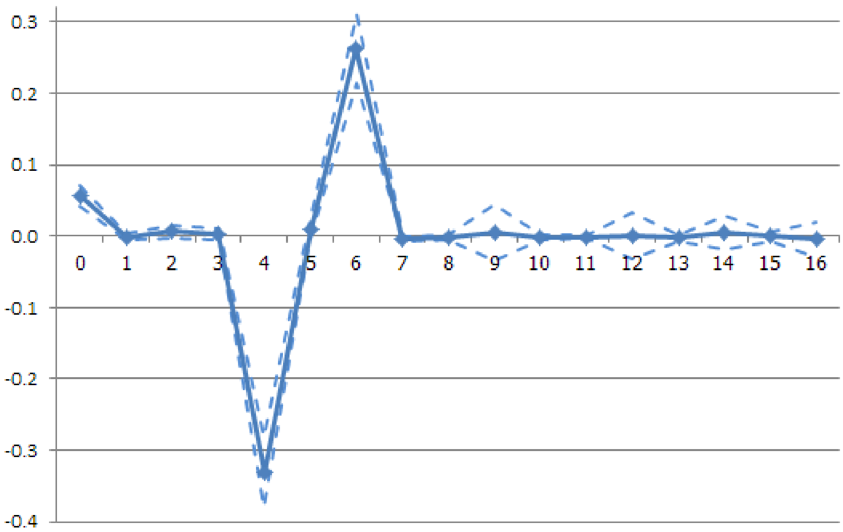

Figure 3.5: *Effect of Compulsory Schooling on Years of Education of Male in Labour force (estimated from Linear Probability Model) with 95% confident interval*

Table 3.13: The impact of the changes in compulsory schooling law on level of education (Male)

	OLS	LPM			
	Year Edu	G4 or lower	G6 and higher	G9 and higher	G7 - G9
urban	2.375***	-0.159***	0.162***	0.270***	0.0414***
	(0.0240)	(0.0026)	(0.0026)	(0.0029)	(0.0022)
CompTB	0.269***	-0.0934***	0.0950***	-0.0013	-0.0392***
	(0.0666)	(0.0081)	(0.0081)	(0.0083)	(0.0058)
coht60	0.0637***	-0.0382***	0.0394***	0.0050**	0.0036**
	(0.0211)	(0.0025)	(0.0025)	(0.0025)	(0.0018)
coht60sq	0.0032	-0.0003	0.00026	0.00027	0.00049***
	(0.0020)	(0.0002)	(0.0002)	(0.00026)	(0.00018)
Year dummy	Yes	Yes	Yes	Yes	Yes
Region dummy	Yes	Yes	Yes	Yes	Yes
Observations	201,747	201,747	201,747	201,747	201,747
R^2	0.137	0.159	0.162	0.115	0.012

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively.

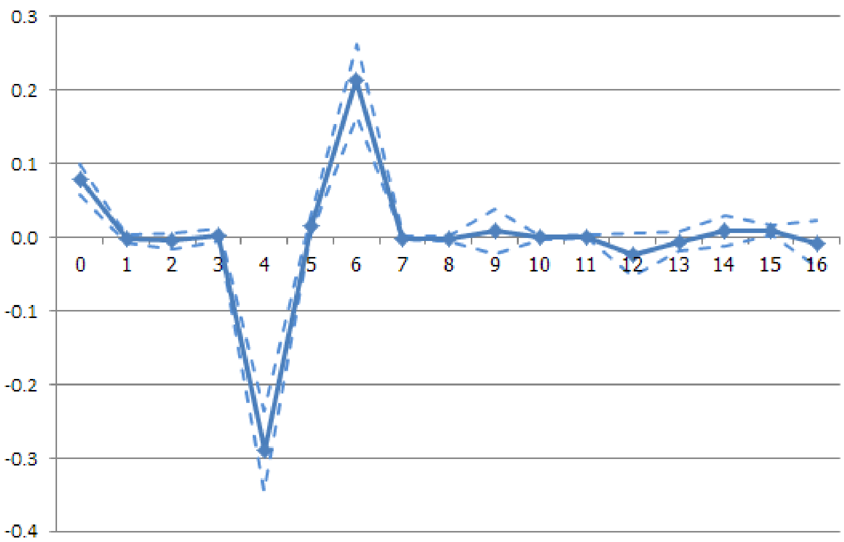

Figure 3.6: *Effect of Compulsory Schooling on Years of Education of Female in Labour force (estimated from Linear Probability Model) with 95% confident interval*

Table 3.14: The impact of the changes in compulsory schooling law on level of education (Female)

	OLS	LPM			
	Year Edu	G4 or lower	G6 and higher	G9 and higher	G7 - G9
urban	2.642***	-0.189***	0.194***	0.277***	0.0402***
	(0.0256)	(0.0027)	(0.0027)	(0.0028)	(0.0019)
CompTB	0.385***	-0.126***	0.127***	0.0186**	-0.0146***
	(0.0690)	(0.0079)	(0.0079)	(0.0075)	(0.0048)
coht60	0.0668***	-0.0295***	0.0301***	0.0035	0.0032**
	(0.0217)	(0.0025)	(0.0025)	(0.0023)	(0.0014)
coht60sq	0.0062***	-0.0014***	0.00135***	0.0006***	0.00048***
	(0.0021)	(0.00023)	(0.00023)	(0.00023)	(0.00015)
Year dummy	Yes	Yes	Yes	Yes	Yes
Region dummy	Yes	Yes	Yes	Yes	Yes
Observations	204,411	204,411	204,411	204,411	204,411
R^2	0.161	0.192	0.195	0.147	0.018

Note: Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively.

Table 3.15: First stage regressions for Return to Education (cohorts born in 1961 to 1970 by gender)

	All (1)	All (2)	Male (1)	Female (1)
CompTB	0.395***	0.394***	0.349***	0.452***
	(0.0832)	(0.0833)	(0.109)	(0.127)
age	0.0226	0.174	0.0849	-0.0621
	(0.0482)	(0.355)	(0.0627)	(0.0742)
agesq	-0.000630	-0.00493	-0.00126	0.000238
	(0.000624)	(0.00998)	(0.000812)	(0.000961)
agecb		3.98e-05		
		(9.19e-05)		
female	0.151***	0.151***		
	(0.0361)	(0.0361)		
urban	2.487***	2.487***	2.296***	2.728***
	(0.0311)	(0.0311)	(0.0403)	(0.0487)
Constant	7.831***	6.112	6.485***	9.786***
	(1.030)	(4.144)	(1.339)	(1.584)
Year D	Yes	Yes	Yes	Yes
Reg. D	Yes	Yes	Yes	Yes
Observations	180,728	180,728	95,515	85,213
R^2	0.093	0.093	0.090	0.099

Note: These are the first stage regressions of Two-Stage Least Square in table 3.2. Standard errors are in parentheses while ***, ** and * indicate significant at 1% , 5% and 10% level respectively.
Model (1) includes only age and age squared as control variables while model (2) also includes age cube as an extra control variable.

4 The Impact of Supply Chain Disruptions: Evidence from the Japanese Tsunami

4.1 Introduction

International supply chain has enhanced its role in the manufacturing sector during the last two decades. Advancement in Information and Communication Technology (ICT) as well as trade and investment liberalization both reduces costs of coordination in production process and makes geographical separation of manufacturing stages driven by scale economies and comparative advantage become more viable (Humphrey, 2003; Baldwin, 2011). This growing interdependence of the supply chain could, however, make output and price more vulnerable. Either demand or supply shock in one country could potentially jeopardize other countries manufacturing industries along its global production chain. For example in 2011, the media expressed their concerns about supply chain disruption of electrical components and motor vehicles after the destruction of Japan′s Great Tohoku Earthquake and Tsunami in March (Lohr, 2011) and hard disk drives shortage made a headline during Thai floods around the last quarter of the year (BBC, 2011; Arthur, 2011). Yet there is little evidence of the impacts of such disruptions on production or other possible adjustments among producers and suppliers in countries on the downstream. While the expected negative outcomes on severely affected firms are obvious, the reaction of competitors and domestic suppliers are ambiguous, especially, when the shock is abrupt and massive but potentially involves uncertainty on the exact time of recovery.

There are several challenges to empirical research on the impacts of shock on the international supply chain. First, the literature on economic impacts of natural or man-made disasters tends to overlook the role of trade and the global value chain as a channel for shock transmission across countries. They mostly emphasize, for instance, estimation techniques for national or regional economies (e.g. Cochrane, 2004; Hallegatte, 2008), volume of trade (Gassebner et al., 2010), local labour markets (Belasen and Polachek, 2009; Lopamudra, 2007) or local business survival (such as after the 2004 Tsunami in Sri Lanka by Dickson and Kangaraarachchi, 2006). In addition, major supply shocks to one group of companies but not their counterpart in the same industry are rare events. Moreover, there is a paucity of economic papers discussing impact on producers as well as dealers and their adjustment to demand shock(s) in an oligopoly market like the auto industry (Copeland et al., 2005; Albuquerque and Bronnenberg, 2012) but none on a supply shock.

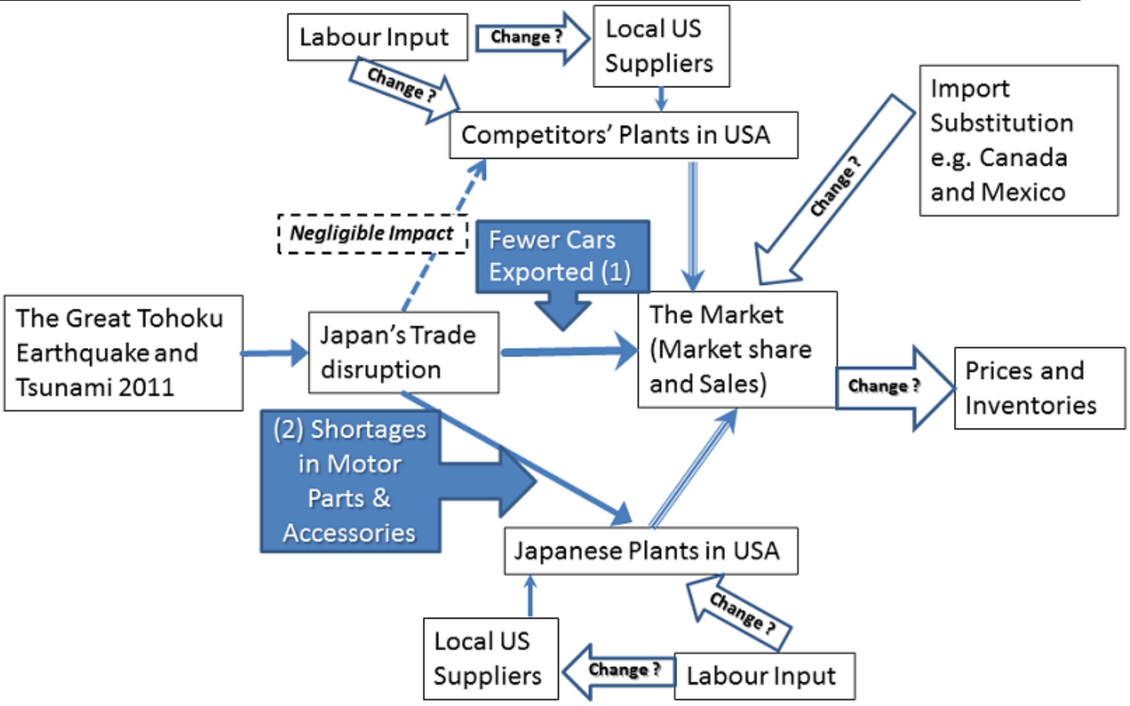

Figure 4.1: *Transmission Mechanism of the Shock and Potential Channels of Adjustment*

Hanlon (2013) is one of the very few papers exploiting similar exogenous shock along the international supply chain to study effects on industries in another country. He uses a sharp drop in raw cotton supplies to Britain during the US Civil War as an exogenous shock to the British textile industry. His results indicate that the shock caused reduction in employment and employment growth in industries related to cotton textile and in towns specializing in cotton textile production relative to the less specialized ones. Such impacts had continued for over two decades after the end of the US Civil War. He concludes that a large, exogenous and temporary shock can change the long-term distribution of industrial activity across locations through inter-industry connections.

The objective of this paper is, however, to investigate the effects of a more salient shock to the international supply chain of a group of firms on the adjustment of all firms within that industry. Particularly, this paper simultaneously estimates impacts of international supply shock on auto companies through alteration in labour inputs, price and other margins using the Great Tohoku Earthquake and Tsunami 2011 as a natural experiment. According to Figure 4.1, the Great Tohoku Earthquake and Tsunami has potential to cause disruption on infrastructure and production capacity of Japan. This shock reflects through an abrupt drop in Japanese exports to the USA. More specifically to the auto industry, there are two channels of supply shock on Japanese auto companies in the US market. First, fewer cars can be imported from Japan. This shortfall offers other manufacturers an opportunity to grasp the Japanese market share through adjustment in production and inventory. The second mechanism is shortages in various motor vehicles parts and accessories which hampers production in plants inside the USA. The immediate direct effect of this mechanism reduces production among Japanese auto makers while the secondary effect amplifies the shortfall in finished cars available in the US market[49]. Furthermore, Figure 4.1 suggests potential channels of adjustment, that is, a reduction in labour inputs[50] of Japanese auto makers and their suppliers, a possible increase in labour inputs among Japanese competitors and their suppliers, and other margins of adjustment such as spikes in price and import substitution.

I employ monthly Current Population Survey (CPS) data from January 2005 to April 2012 and Quarterly Workforce Indicators (QWI) from 1^{st} quarter of 2001 to 3^{rd} quarter of 2011 to estimate changes in labour inputs between Japanese auto makers and their counterparts. Since there is no information on nationality of firms in the CPS or QWI, the state-level variation in numbers of direct employment by Japanese auto companies is exploited to estimate the relationship between a share of Japanese employment and labour inputs alteration in those states. Only a small negative effect of the Japanese's employment share on average monthly earnings of workers in motor vehicles manufacturing (chassis and assembly plants) is observed. Yet this negative effect is not sustained under a broader classification of auto industry which includes not only motor vehicles manufacturing but also bodies, parts and engines manufacturing. Hence, the effect of intermediate inputs shortage on Japanese production in the US seems to be small and contained in just one sub-industry of auto manufacturing.

In spite of a modest adjustment in Japanese production in the US, a sharp drop in imported cars still gave other companies an opportunity to gain market share and capitalize on the Japanese loss. I therefore employ various techniques to model trend and seasonality in the data for each groups of auto makers and I then identify the impacts of this shock as any significant deviation from underlying trend and seasonal effects during the second and third quarters of 2011. The findings based on CPS data suggest that auto companies and suppliers in the US production bases, that is, the states of Michigan and Illinois increase their hours of overtime per week, with significance level at 20%, while none of other auto groups shows any movement. However, the results based on QWI data depict different patterns of the adjustment. None of the counties that are the location of the US auto or parts manufacturing has any significant results,

[49] Although it is plausible to assume that Japanese competitors do inevitably rely on some auto parts from Japan, most competitors such as GM and Hyundai claim that they can manage to get through the aftermath relatively unscratched.

[50] Since auto industry has enough spare capacity after the financial crisis, it is suffice to use an adjustment in labour inputs as a proxy for change in production

except for one outlier county in Indiana[51]. Meanwhile, the only significant change at 5% level comes from a rise in average monthly earnings of those counties with German owned parts and engines plants. Although this could be a sign of adjustment corresponding to a gain in market share from the Japanese, it must be interpreted with caution because there is no change detected among the German assembly plants.

In addition, this paper tests for any linkages between auto makers' assembly plants and suppliers for parts and engines around their locality during this shock. The results do not indicate any labour inputs adjustment in the counties where parts and engines plants are located alongside assembly plants. The exception is in two counties where both assembly and parts plants belong to the same auto companies. In sum, the overall labour inputs adjustments among Japanese firms and their competitors are modest.

Due to the difficulty of obtaining the data, some descriptive statistics are used to verify adjustment in other margins. As for import substitution, value of imports from Canada and Mexico does not illustrate any change due to the shock. Moreover, there is no evidence of any spikes in prices based on the CPI data. Yet other indices depict a slight change in inventory management and sales incentive which could be important mechanisms used by auto companies to implicitly adjust their price and manage their output flow. Nevertheless, all available results suggest that the overall impact of this disaster on the US economy through the auto industry is surprisingly small.

The paper is structured as follows. Section 4.2 outlines the shock and US Auto industry. Section 4.3 describes the data while Section 4.4 briefly discusses the theoretical background and empirical strategies. Section 4.5 presents the results and Section 4.6 examines other margins of adjustment.

4.2 The shock and US Auto industry

4.2.1 The disaster and Japanese exports

The scale of destruction caused by the Great Tohoku Earthquake and Tsunami 2011 is immense. It claimed 15,870 lives and 2,814 people missing across Japan. The economic damage is estimated to be 210 billion USD, the highest among all natural and unnatural disasters in decades (CRED, 2011). Yet it is not straightforward how impacts of this disaster ranging from loss of human lives and demolition of physical capital to energy crisis involving a number of nuclear accidents can be identified. This paper primarily identifies a shock from Great Tohoku Earthquake and Tsunami 2011 as losses of production capacities in three prefectures, namely, Iwate, Miyagi and Fukushima, which are the most severely affected areas classified by number of casualties, missing persons and buildings damaged (National Police Agency of Japan, 2012).

[51] This result contrasts to the one from CPS. Yet it can coincide because a small adjustment in overtime might not lead to a significant change in average monthly earnings, the only proxy for average hours of worked available in the QWI.

According to the Japan Census of Manufactures 2009, the three prefectures are not highly industrialized. The total value of manufactured goods shipments from these prefectures accounts for only 3.6% of the whole country. However, there are some intermediate goods which are intensively produced in these prefectures; for example, 40.9% of country-wide production of metal / combined with non-metal packing and gaskets, 32.5% of parts, attachments and accessories of cameras and motion picture equipment, 22.66% of digital camera module and 33.6% of car heaters. Specifically, for auto companies like Toyota, their motor plants in these prefectures were closed for around a month and operated under restricted capacity during the second quarter of 2011[52].

This disruption in the supply chain and damage to the transportation system lead to a drastic drop in Japanese exports in manufacturing goods to USA and the world. Among these products, export value of motor vehicles (with the first two digits Harmonised System (HS) code 87) to USA was reduced the most comparing to its predicted trend. Within this category, export of motor cars and vehicles for transporting persons (HS 8703) dropped more than half, while a decrease in parts and accessories for motor vehicles (HS 8708) was less severe. Yet investigating into sub-categories depicted sharp shortfalls in some auto parts and accessories such as safety seat belts, brakes, radiators and clutches as shown in Figure 4.14[53].

Further, as for the relative importance of Japanese exports to USA in both cars and vehicles for transporting persons and parts and accessories, they constitute 28% and 17% of the total value of US imports in 2010 respectively. Therefore, an impact to the auto industry in US could be significant since they cannot easily offset any shortage in Japanese motor vehicles and parts by other trade partners.

I identify a supply shock on Japanese car makers in the US as either (1) a shortage of finished cars imported from Japan or (2) a production disruption in their US plants due to parts shortage (They are (1) and (2) in Figure 4.1). The main result on labour inputs for Japanese companies focuses on the second type of shock, whereas the first effect indirectly affects labour inputs of Japanese competitors if they increase their production in response to the shortage. Moreover, other margins of adjustment due to this supply shock are discussed in Section 4.6.

[52]Although the number of casualties are much smaller in nearby prefectures such as Aomori, Ibaraki and Chiba, high levels of destruction in these prefectures lead to several immediate disruptions in the auto industry especially in March and April. For example, thousands of Nissan cars about o be exported to USA were wiped out in the port of Hitachi, Ibaraki (Greimel, 2011).

[53]There are examples of disruptions on Media. For instance, according to a Toyota News Release (Toyota Motor Corporation, 2011b), there are approximately 150 parts affecting new-vehicle production, mainly electronic, rubber and paint-related. However, replacement parts for sales service and repair are available.

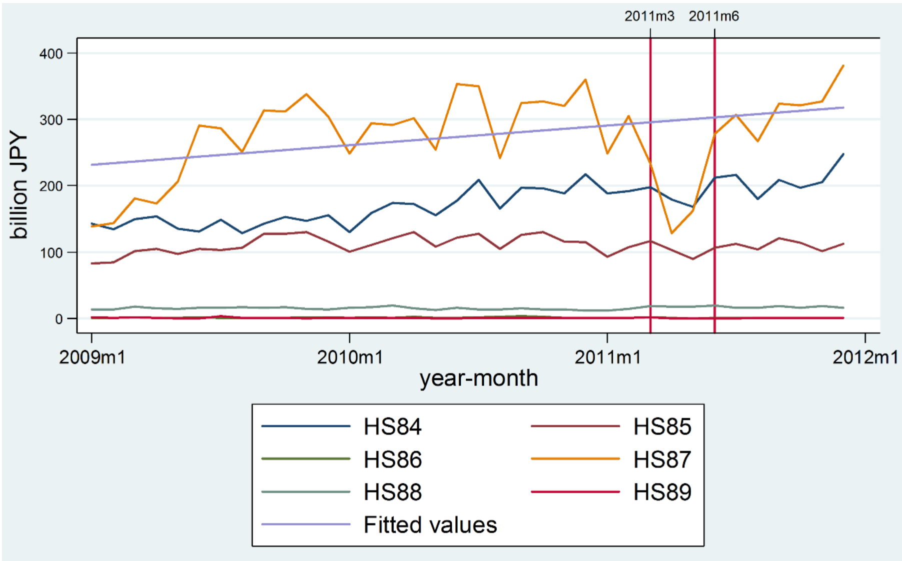

Figure 4.2: *Japan's Export Value to USA 2009-2011 by HS code industry 84-89*

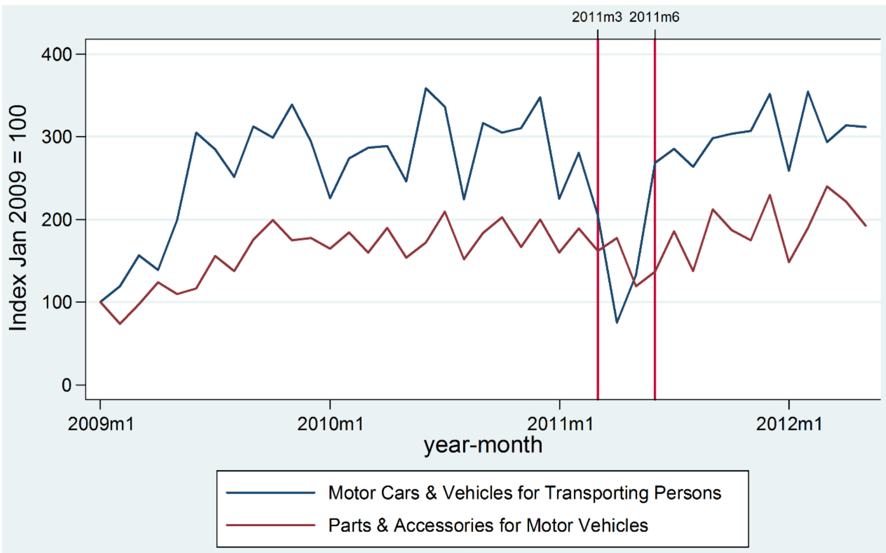

Figure 4.3: *Japan's Export Value to USA (Monthly Indices)*

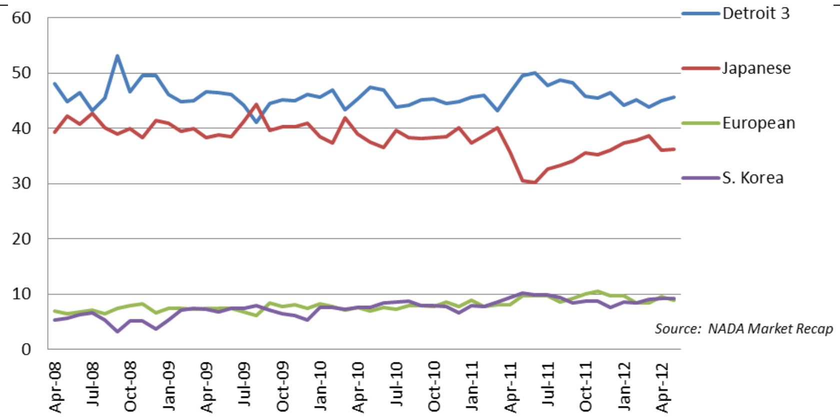

Figure 4.4: *Market Share of Auto Industry by firms' nationality*

4.2.2 US Auto industry and the market aftermath

Motor vehicle manufacturing industry is one of the biggest employers in USA. Apart from the Detroit 3 (GM, Ford, and Chrysler LLC), foreign auto-makers have been investing in several assembly plants such as German and Japanese from the 80s and South Korean since 2005. These foreign-owned Original Equipment Manufacturers (OEMs) recently become important employers for manufacturing workers in states like Alabama, Georgia, Kentucky, Mississippi, and South Carolina.

Although the industry has experienced a series of declines in employment since 2000, in 2008, it still employed approximately 6.6% of the U.S. manufacturing work-force (Platzer and Harrison, 2009). During and after the financial crisis, the auto industry suffered a sharp drop in demand forcing auto makers to cut their capacity utilization from 73.7% in 2007 to a trough of 44.8% in the recession-led 2009. Then the utilization gradually rebounded to 65.1% and 70.7% in 2010 and 2011 respectively (Stoddard, 2012).

In terms of market share, the Detroit 3 domestic share decreased from 64.5% in 2001 to 47.5% in 2008. After the restructuring and bankruptcy of Chrysler and General Motors in 2009 until early 2011, the US auto makers retained the share of around 45% while the Japanese sales accounted for 35-40%. Yet the disaster caused a major setback for Japanese firms. According to Figure 4.4, their market share dropped sharply from 40% in March to just over 30% in July before they regained their position in early 2012 (see Figure 4.15 for the detailed movement in sales among major auto companies). The magnitude and length of loss in market share by Japanese companies illustrates the severe but transitory effects of this shock on these firms' supply chain and performance. This is, however, consistent with a reduction in Japan's export in Figure 4.2. In the following section, labour market data is used to shed some light on a reaction to a temporary supply shock by Japanese producers and their competitors.

4.3 Data

Two sets of data are employed to estimate impacts of the shock on labour inputs adjustment in the auto industry. They are the Current Population Survey (CPS) conducted by the Bureau of Census for the Bureau of Labor Statistics (BLS) and the Quarterly Workforce Indicators (QWI) published by the Longitudinal Employer-Household Dynamics (LEHD) Program at the U.S. Census Bureau[54]. First, I analyse monthly data of the CPS from January 2005 to April 2012. The starting point of this data is chosen to achieve a balanced representation between pre and post financial crisis. Moreover, it might be misleading to include CPS data during the 90s or early 2000s because the auto industry had experienced different trends and turning points due to shocks and changes, for instance, oil price hikes or a dot-com bubble burst.

The sample consists of individuals aged sixteen and over who had their primary jobs in selected industries during the CPS survey week and for whom data are available for weekly hours of work and overtime. Then I aggregate the data to state-level for total employment, average hours of work and overtime per week in motor vehicles and motor vehicle equipment manufacturing and other related industries[55].

Further, analyses in this paper rely on an external shock on Japanese auto makers but there is no information concerning nationality of employers in CPS. I therefore exploit state-level variation in employment among groups of motor vehicles manufacturers. Specifically, the number of direct employment by Auto companies in each state is used to compute the share of Japanese firms' direct employment in those states (See section 4.C.1 for the detailed calculation of this variable). Moreover, to compare the impacts between Japanese auto makers and their competitors, I use these numbers to classify such states according to employment share by firms' nationality. Consequently, five groups of states are categorized, that is, US intensive states (Illinois and Michigan), Japan (California and Mississippi), Germany (North Carolina and South Carolina), Mixed states (Indiana, Kentucky, Ohio, Tennessee, Alabama, and Texas) and the rest (share of Japanese employment in each of these states which have more than 400 direct employees is presented in Table 4.9).

Table 4.1 shows descriptive statistics for employment, weekly hours of work and overtime as well as sample sizes of the first three categories in each group-month. The CPS sampling weights are used in the aggregation process but all of the statistical calculations reported here are unweighted estimates among sampling periods. In general, Japanese intensive states seem to have lower average hours of work and overtime than their US and German counterparts. A main concern is the relatively low number of

[54] The data I used are compiled from public-use data files by the Cornell Virtual RDC version R2012Q3.

[55] I ignore hourly earnings data because only one-fourth of CPS samples answer questions on earning. Thus, sample sizes of any specific groups in each month are small and unrepresentative.

Table 4.1: Descriptive Statistics of the CPS Sample

Variable	JP	USA	DE	Mix	Rest
Weekly hours	40.98	42.51	42.38	42.28	41.66
	(2.23)	(1.03)	(2.55)	(1.39)	(1.15)
Overtime	0.88	1.17	1.15	1.58	1.27
	(0.74)	(0.41)	(1.01)	(0.55)	(0.42)
Employment	66,019.8	360,012.3	55,307.1	384,780.4	261,167.9
	(19,782.7)	(71,621.31)	(17,559.4)	(60,537)	(60,859)
Average sample size	21.25	115.51	19.51	131.67	136.81

All numbers are mean of variables in each group-month while standard errors are in parentheses.

respondents used to compute aggregate level data for Japanese and German intensive states. Thus, the QWI data is also employed for crosschecking the estimation.

The QWI offers some advantages over the CPS. Firstly, the QWI is estimated from administrative data[56], so it does not severely suffer from a small sample bias, as in CPS. Moreover, QWI provides detailed estimates of employment and earnings data at county level by detail industry (4-digit North American Industry Classification System; NAICS), gender and age groups of workers. Nevertheless, owing to disclosure-proofing methods used to protect the confidentiality of individuals and businesses that contribute to the underlying data, employment and earnings for specific industries in most counties are either suppressed or distorted[57].

I use both state and county level QWI data for all workers in auto manufacturing or related industries from 2001Q1 to 2011Q3. The choice of starting and ending point is mainly restricted by data availability. Unlike the CPS, 2005 is not chosen as a starting point because longer series are needed for properly modelling trend and seasonality of the data. In terms of identification strategy, other than applying the share of Japanese direct employment with state level data, I use the location of each manufacturer's plants to classify counties into three groups. There are 25 counties categorized as Japanese, 36 as the US and 12 as German[58]. Three variables are employed from the QWI as indicators for adjustment in labour inputs, that is, number of employment on the last day of the quarter (EmpEnd), average monthly earnings of employees who worked on the last day of the reference quarter (EarnEnd) and total quarterly payroll (Payroll)[59]. Table 4.2 presents descriptive statistics of natural logarithm of these variables by group of firms' nationality.

[56]such as wage records from state unemployment insurance (UI) system and Quarterly Census of Employment and Wages (QCEW) reported to the BLS.

[57]These disclosure-proofing methods are noise infusion into micro data, weighting procedure and suppression of data based on fewer than three persons or establishments when the combination of noise infusion and weighting may not distort the publication data with a high enough probability to meet the criteria. See Abowd et al. (2005) for further discussion.

[58]I acquire these location from the Auto Alliance's data. Only counties with manufacturing plant(s) from the same group are included. This results in an exclusion of 2 counties in Michigan.

[59]As a result of disclosure-proofing methods, EmpEnd for many counties are suppressed while most of EarnEnd for specific industry at county level are distorted.

Table 4.2: Descriptive Statistics of the QWI Sample

Variable	JP	USA	DE
LogEmpEnd	8.485	8.668	8.250
	(2.775)	(2.836)	(2.297)
	[1,767]	[3,810]	[505]
LogEarnEnd	8.084	8.207	7.882
	(0.403)	(0.411)	(0.474)
	[2,321]	[4,832]	[869]
LogPayroll	16.648	16.891	15.428
	(3.256)	(3.596)	(3.235)
	[2,369]	[4,967]	[898]

All numbers are mean of variables in each group-month.
Standard errors are in parentheses while number of observations are in square blankets.

4.4 Methodology

Considering the number of auto manufacturers and makes (models) sold in USA, the auto market can be viewed as an oligopoly with heterogeneous products. In this type of market, companies can choose to compete in either quantity (Cournot competition) or price (Bertrand competition). Singh and Vives (1984) show that if the goods are substitutes, larger profits can be obtained by deploying output over price competition. In particular, each car manufacturer can set sales target for its own dealers. Then dealers will set monthly inventories and adjust prices to clear the market according to the sales goal (Tremblay et al., 2010)[60]. Hence, this paper analyses effects of the shock in the auto industry through the framework of Cournot competition under an assumption that motor vehicles from different firms have certain degrees of substitution between each other.

Because of slackness in capital utilization during the recession, as well as a temporary nature of this shock[61], output adjustment through capital investment could be negligible. Thus, it is reasonable to assume that adjustment in level of outputs could be done by changes in labour and intermediate inputs. Therefore, production function for auto makers proposed by Copeland and Hall (2011) has been combined with perfect complementarity in materials. I specify production function for each manufacturing plant as follows:

$$q_t = Min(\frac{m_1}{a_1}, ..., \frac{m_i}{a_i}, ..., \frac{m_n}{a_n}, D_t \times S_t \times h_t \times LS) \tag{4.4.1}$$

[60]However, according to (Tremblay et al., 2010), it is optimal for firms to compete in price over output or a mix of both strategies provided that there are sufficient demand, cost, or strategic asymmetry between firms. They argue that in the small car market, Honda and Subaru use output strategy while Saturn and Scion (a nameplate of Toyota) first set prices and then fill consumers' demand at those prices.

[61]Although there was uncertainty in the first month after the disaster concerning energy shortage and whether the damage of Fukushima Daiichi Nuclear Plant could be contained, analysts in auto industry and stock market (such as Trefis Team, 2011) expected sales of Japanese auto makers to have recovered by the end of 2011.

where m_i is a quantity of material type i (i = 1,...,n) which requires a_i units to produce one unit of q_t. Meanwhile, each plant can operate in period t for D days with S shifts (either 1 or 2) per day and h hours per shift. Moreover, Copeland and Hall (2011) assume that number of employees per shift n and line speed LS are fixed. So, the production function is linear in hours[62] provided that there is no constraint on any materials m_i. Finally, total output of each firm at time t, Q_t, is a summation of output from all of its domestic plants (in the US) and its import (from Japan, Canada, Mexico, Germany, etc.).

However, the disaster could temporarily constrain levels of production through availability of intermediate inputs, m_i. With downward sloping best-response function (strategic substitutes) in the Cournot model for two sellers (Shy, 1995; Pepall et al., 2011), this constraint would force firm $1'$s (suppose that it is a groups of Japanese companies) to produce less than the original equilibrium, that is, the former best-response function with a vertical kink at the constrained level of output[63]. Depending on the slope of their best-response function, firm 2 (Japanese competitors) might not increase their output enough to fulfill all supply shortage. Thus, the shock could lead to a lower equilibrium output but higher equilibrium price.

Due to limited data availability, the focus is mainly on adjustment in labour inputs. Nevertheless, I will present some descriptive statistics to infer any adjustment through import substitution, hikes in prices, and inventory management in Section 4.6.

To identify the effect of this shock on demand for labour in auto industry, it is not obvious what the best strategy is. Since the main objective is to measure labour inputs adjustment due to the disaster among Japanese auto makers and their competitors, the first stage is to assess the direct effect of motor vehicles parts and accessories shortage on the choices of labour inputs among Japanese firms. I compute share of Japanese OEMs direct employment in every state as presented in Table 4.9 and use it as a proxy for exposure of the shock in each state. Then the CPS and QWI data are estimated with the following specifications:

$$y_{it} = \beta_0 + \beta_{1i} State_i + \beta_{2t} YM_t + \beta_3 Dis_t + \beta_4 ShareJP_i * Dis_t + e_{it} \tag{4.4.2}$$

$$y_{it} = \beta_0 + \delta_{1i} State_i + \delta_{2c} Trend_t^c + \delta_{3s} Season_t^s + \delta_4 Dis_t + \delta_5 ShareJP_i * Dis_t + u_{it} \tag{4.4.3}$$

$$\begin{aligned} y_{it} = \theta_0 + \theta_{1i} State_i + \theta_{2ic} State_i * Trend_t^c + \theta_{3is} State_i * Season_t^s \\ + \theta_4 Dis_t + \theta_5 ShareJP_i * Dis_t + v_{it} \end{aligned} \tag{4.4.4}$$

where y_{it} are dependent variables of state i at time t. For CPS, they are average

[62] In their paper, Copeland and Hall (2011) also introduce several non-convexities in production costs through labour contract but it is beyond the scope of this paper.

[63] To be precise, this production constraint is resulted from shortages in both intermediate goods needed for production in USA and final products, that is, imported cars from Japan.

hours of work per week (HR), average overtime per week (OT) and natural logarithm of employment in the industry (LogEmp) (all are aggregated to state level using the CPS weight) whereas the dependent variables for QWI are natural logarithm of employment (LogEmpEnd), average monthly earnings (LogEarnEnd) and total quarterly payroll (LogPayroll). $State_i$ is a vector of dummy variables taking value 1 for state i and 0 for all other states. $ShareJP_i$ is a share of Japanese OEMs' direct employment (with value 0 - 1) computed from Auto Alliance's data[64] and Dis_t is a disaster dummy which is equal to 1 if t are April - July 2011 for CPS data and 2011 quarter 2 and 3 for the QWI[65].

The main difference between these specifications is how to model trend and seasonality. In equation 4.4.2, time dummies are used for each month-year, YM_t, in CPS (or quarter-year for QWI) while time trend and seasonal dummies are used in equation 4.4.3 where $Trend_t^c$ represents linear, quadratic as well as cubic time trend for period t[66] and $Season_t^s$ are monthly or quarterly dummies for season s in the CPS or QWI respectively. On the contrary, equation 4.4.4 explicitly models trend and seasonality for each state using $State_i * Trend_t^c$ and $State_i * Season_t^s$. In addition, I decide to allow for differences in states' fixed effect by using state dummies rather than relying on $ShareJP$ to pick up variations among states. Lastly, standard errors in all regressions are clustered at state level.

Nevertheless, the share of Japanese employment does not provide any information on adjustment by the competitors. With the CPS data, trend and seasonality of these series (HR, OT and LogEmp) are modeled separately for each group of states according to the firms' nationality categorized earlier. Allowing for stochastic rather than deterministic trend and seasonality, I employ Augmented Dickey Fuller test (Said and Dickey, 1984) and HEGY test for monthly series (Hylleberg et al., 1990; Franses, 1990; Beaulieu and Miron, 1993) to determine whether each series has unit root or seasonal unit root respectively. Then the multiplicative seasonal ARIMA model; $SARIMA(p,d,q)(P,D,Q)_S$ (Box, Jenkins, and Reinsel, 1994) for each series is specified as follows:

$$\phi_p(B)\Phi_P(B^S)\Delta^d\Delta_S^D Y_t = \alpha + \theta_q(B)\Theta_Q(B^S)\epsilon_t \tag{4.4.5}$$

where Y_t is a series of dependent variable. B, B^S are backward shift operators for non-seasonal and seasonal component. d, p, and q (D, P, and Q) are number of differences required for (seasonal) stationarity, order of (seasonal) autoregressive and

[64] This number reflects the share of Japanese employment around the end of 2010 to early 2011 when it is compiled by Auto Alliance (2011). Hence, it is a constant for any state i.

[65] The timing of this dummy is arbitrary but it corresponds to a sharp drop in Japanese's motor vehicles and parts export. The results are robust to a slight change in periods of the shock e.g. from Apr-Jul 2011 to Mar-Aug 2011.

[66] At the starting point of each data, t is set to be 1.

moving average component respectively. Δ^d, Δ_S^D are differences of order d and D. $\phi_p(B), \theta_q(B)[\Phi_P(B^S), \Theta_Q(B^S)]$ are polynomial of [seasonal] autoregressive and moving average component respectively. α is a constant and ϵ_t are white noise errors.

Moreover, SARIMA with intervention model (Box and Tiao, 1975) is employed to assess any adjustment owing to the shock. It can be specified as

$$Y_t = \zeta_t + N_t \tag{4.4.6}$$

where N_t is the Noise series from $SARIMA(p,d,q)(P,D,Q)_S$ and ζ_t is the intervention which is a function of a dummy Dis_t.

To find the optimal order of (seasonal or non-seasonal) Autoregressive (AR) and Moving Average (MA) component, I follow the Box Jenkins Methodology. Potential orders of p, q, P, and Q are identified by observing the sample autocorrelation and partial autocorrelation plot. I run several variations of SARIMA and choose the model with the lowest value of estimated Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Lastly, the Ljung−Box Q test (Ljung and Box, 1978) is applied to the residuals of the fitted model to check whether the model still suffers from autocorrelation. Only the models which the Q test cannot reject the null hypothesis of no autocorrelation are presented in the following section.

On the other hand, slightly different trend and seasonality modelling techniques are used with the QWI data. Since the QWI is estimated from the administrative records, I can employ county-level data without being concerned about a small sample bias[67]. First, the Box-Jenkins Methodology is applied to some series of county-level data to find optimal orders of AR and MA[68]. I then pool counties in each group of nationality together[69] and estimate unbalanced panel regression with autoregressive components (Baltagi and Wu, 1999) as follows:

$$y_{it} = \gamma_0 + \gamma_{1s} Season_t^s + \gamma_2 Dis_t + u_{it} \tag{4.4.7}$$

where y_{it} are dependent variables of county i at time t. $Season_t^s$ are quarterly dummies for quarter s (using 1^{st} quarter as a reference) and Dis_t is a disaster dummy which is equal to 1 if t are 2^{nd} and 3^{rd} quarter of 2011. I follow Baltagi and Wu (1999) and assume that the disturbances follow a one-way error component model i.e. $u_{it} = \mu_i + \eta_{it}$ with county effects $\mu_i \sim IID(0, \sigma_\mu^2)$ while the remainder disturbances η_{it} follows a

[67] This contrasts to the CPS which aggregated data are used to increase the sample size in each group.

[68] I try to compare the ARMA model with other techniques, for example, deterministic trend with quarterly dummies (as in equation 4.4.3), or smoothing methods such as Holt-Winters exponential smoothing with both multiplicative and additive seasonal model. I found that the predicted series are not much different and ARMA model with seasonality seems to perform better in ex-post forecasting.

[69] Only counties which have at least 16 data points (4 years) are included.

stationary AR(1) process, i.e. $\eta_{it} = \rho\eta_{i,t-1} + \epsilon_{it}$ with $|\rho| < 1$ and ϵ_{it} is $IID(0, \sigma_\epsilon^2)$. Further, the $\mu_i's$ are independent of the $\eta_{it}'s$, and $\eta_{i0} \sim (0, \sigma_\epsilon^2/(1-\rho^2))$.

Using this specification with fixed effect, it is implicitly assumed that all counties in the same group share the same seasonal dummies and the coefficient of autoregressive component (ρ). If this method is approximately correct in modelling the underlying trend and seasonality, the coefficient of interest, γ_2, would illustrate the average adjustment effect of the shock on each dependent variable between the second and third quarter of 2011.

4.5 Results

This section illustrates the impact of Great Tohoku Earthquake and Tsunami 2011 on the labour market in the US auto industry through various empirical specifications discussed earlier. First, I verify the trivial impacts of the shock on labour inputs among Japanese auto makers[70] using $ShareJP$ in each state. Only 27 states with more than 400 direct employees are included in the sample. Table 4.3 presents estimates of changes in average weekly hours, overtime and employment from the CPS data. None of the regressions yields significant coefficients for share of Japanese employment. The relative intensity of Japanese auto makers in each state does not significantly affect any labour inputs in the motor vehicles manufacturing industry.

However, there are two concerns regarding this conclusion. First, owing to a small sample size in the CPS, these models involve an inclusion of more than 10 states with a very small sample size of auto workers in each month, that is, average sample sizes are fewer than five persons. This leads to an imprecise estimation of labour inputs at state level. Importantly, the CPS cannot be used to categorize workers into more detailed industries than a broad definition of auto mobile manufacturing (NAICS 3361-3363). Hence, these insignificant estimates might result from a cancellation of effects between sub-industries. For instance, a reduction in hours of work by OEM's assembly plants could be offset by a rise in working hours of local parts suppliers. Conversely, since the QWI provides 4-digit NAICS data, I can classify auto mobile manufacturing into three sub-industries[71], and identify any differential effects within the auto industry.

According to Table 4.4 and 4.5, none of the coefficients is significant at the 5% level. However, allowing for a significance level of 10%, the negative impacts of the shock, through relative employment of Japanese auto companies in each state, can be verified in two sub-industries. In auto assembling, workers in the states where all OEMs'

[70] Companies such as Toyota and Honda operated at adjusted levels of production or suspended their production on certain dates during April to July in their US plants due to parts and materials shortage (Toyota Motor Corporation, 2011a; Honda, 2011).

[71] These sub-industries are motor vehicle manufacturing, that is, chassis and assembly plants (NAICS 3361), motor vehicle body and trailer manufacturing (NAICS 3362) and motor vehicle engines and parts manufacturing (NAICS 3363).

Table 4.3: Share of direct employment by Japanese auto makers and impacts on labour inputs (CPS data)

Dep. variables	(1)	(2)	(3)
HR_{it}[1]	-1.169	-1.243	-0.756
	(2.131)	(2.109)	(2.322)
OT_{it}	-1.301	-1.307	-1.221
	(1.029)	(1.020)	(1.190)
$LogEmp_{it}$	0.115	0.113	-0.0725
	(0.361)	(0.354)	(0.386)

Note: Standard errors are in parentheses. All results are coefficients of $Dis_t * ShareJP_i$ from equation 4.4.2 - 4.4.4 corresponding to model $(1) - (3)$ respectively.

direct employment are belonged to Japanese firms experience a 0.237% reduction in average monthly earnings during 2011Q2 - Q3[72]. In other words, a worker in a state with $ShareJP = 1$ whose earnings is at the mean of Japanese counties receives \$7.68 less than his/her counterpart in a state with $ShareJP = 0$ per month. Also, a small negative employment effect can be observed in body and trailer manufacturing. In this sub-industry, employment in the states with $ShareJP = 1$ is reduced by 0.307% comparing to those states with $ShareJP = 0$[73].

Nevertheless, these negative impacts are not robust enough to withstand a variation in modelling of trend and seasonality. If the model which allows for different trend and seasonal effects among states (model (3)) is the correct one, only the trivial negative effect on Japanese assembly plants is supported by the data. Moreover, the coefficients of $ShareJP$ in Table 4.5 using all sub-industries confirm no significant effect on any labour inputs similar to those using the CPS data[74].

It seems that production adjustment of Japanese auto makers as a result of intermediate inputs shortage has small and negligible effects on labour inputs in the US auto industry. However, a constraint on the US operation among Japanese firms and a sharp drop in number of imported vehicles from Japan could benefit their competitors[75]. Using time series technique to model trend and seasonality, I estimate the adjustment in labour inputs (and implicitly production) by each group of OEMs and their local suppliers. Table 4.6 illustrates the impacts of the disaster shock on different

[72]Since average earnings of workers in manufacturing sector depend on hourly wage and total number of hours worked, This surprisingly small effect could result from an adjustment in hours of work in the first few months after the shock.

[73]Because payroll is a multiplication of employment and average earnings, the similar size of negative and significant effect on payroll indicates that reduction in employment is a primary driving force of a change in payroll.

[74]The aggregation of these sub-industries is straightforward for numbers of employment and payroll. However, due to missing values in employment data, weighted average earnings data are computed by using a ratio of payroll to average earning per month as a proxy for employment.

[75]33% of Japanese auto makers' sales in the US are imported from outside North America with variations among companies, for instance, 28% for Toyota, 21% for Honda and 35% for Nissan (Visnic, 2011).

Table 4.4: Share of direct employment by Japanese auto makers and impacts on labour inputs based on QWI data

	Motor Vehicle Manufacturing[1]			Motor Vehicle Parts Manuf.[2]		
Dep. variables	(1)	(2)	(3)	(1)	(2)	(3)
LogEmpEnd	-0.032	-0.026	-0.344	0.165	0.166	0.212
	(0.302)	(0.300)	(0.485)	(0.133)	(0.131)	(0.292)
LogEarnEnd	-0.049	-0.049	-0.237*	-0.029	-0.028	0.012
	(0.074)	(0.073)	(0.131)	(0.050)	(0.049)	(0.063)
LogPayroll	-0.017	-0.015	0.002	0.140	0.140	0.108
	(0.457)	(0.449)	(0.288)	(0.123)	(0.121)	(0.183)

Note: Standard errors (clustered by states) are in parentheses while * indicate significant at 10% level.
All results are coefficients of $Dis_t * ShareJP_i$ from equation 4.4.2 - 4.4.4 corresponding to model $(1) - (3)$ respectively.
[1] Numbers of observations are ranging from 918 to 999 state-quarter for LogEmpEnd and LogPayroll respectively.
[2] Numbers of observations are ranging from 1,003 to 1,027 state-quarter.

Table 4.5: Share of direct employment by Japanese auto makers and impacts on labour inputs based on QWI data (cont.)

	Body and Trailer Manufacturing[1]			Motor Vehicle, Body and Parts Manuf.[2]		
Dep. variables	(1)	(2)	(3)	(1)	(2)	(3)
LogEmpEnd	-0.307*	-0.306*	0.496	0.085	0.086	0.238
	(0.165)	(0.161)	(0.345)	(0.147)	(0.145)	(0.298)
LogEarnEnd	-0.0333	-0.0323	0.00914	-0.046	-0.045	-0.018
	(0.0677)	(0.0666)	(0.156)	(0.0499)	(0.0493)	(0.0587)
LogPayroll	-0.309*	-0.310*	0.262	0.049	0.052	0.241
	(0.165)	(0.161)	(0.292)	(0.145)	(0.144)	(0.333)

Note: Standard errors (clustered by states) are in parentheses while * indicate significant at 10% level.
All results are coefficients of $Dis_t * ShareJP_i$ from equation 4.4.2 - 4.4.4 corresponding to model (1) $-$ (3) respectively.
[1] Numbers of observations are ranging from 1,003 to 1,027 state-quarter for LogEmpEnd and LogPayroll respectively.
[2] Numbers of observations are 1,003 state-quarter.

Table 4.6: Optimal specification for each SARIMA(p,d,q)(P,D,Q)$_{12}$ with impacts of the shock intervention

	JP	US	DE
Series for HR			
$SARIMA$	$(2,1,0)(0,1,1)_{12}$	$(1,0,1)(1,1,0)_{12}$	$(1,0,0)(0,0,0)_{12}$
$\widehat{Dis}_t$[1]	0.262	0.311	-0.353
	(1.370)	(0.814)	(2.752)
Series for OT			
$SARIMA$	$(3,1,0)(0,0,0)_{12}$	$([2,3],0,[2,3])(0,0,0)_{12}$[2]	$(0,0,1)(1,0,0)_{12}$
$\widehat{Dis}_t$	-0.227	0.548†	0.451
	(1.301)	(0.396)	(0.457)
Series for LogEmp			
$SARIMA$	$(4,1,1)(1,0,0)_{12}$	$([1,4,5],1,0)(1,0,1)_{12}$	$(4,1,[3,4])(1,0,0)_{12}$
$\widehat{Dis}_t$	-0.185	0.010	0.009
	(0.248)	(0.077)	(0.294)
Obs.	88	88	88

Standard errors in parentheses; † denote significance at 20% level
[1] The exact specification of shock dummies is varied with the model
[2] This ([2,3],0,[2,3]) notation stands for the ARMA(3,3) model excluding the first order term for both AR and MA

groups of auto companies as categorized earlier. None of the results is statistically different from zero at 10% significance level. With a significance level of 20%, overtime of workers in US intensive states is significantly increased by 0.55 hours per week on average during April to July 2011.

It is worth noting that all nine series have totally different optimal SARIMA specification. This striving for an optimal model in each series could cause common factors affecting any groups of auto companies equally (such as overall demand for motor vehicles or supply of labour in auto industry) to be overlooked. Yet owing to aggregation process needed for mitigating a small sample bias in the CPS data, applying same specification to just three groups for each dependent variables in CPS data might not be appropriate. Therefore, I estimate unbalanced panel regression with autoregressive components of order one employing the county level QWI data as presented in Table 4.7.

On the one hand, Table 4.7 shows that there is no significant adjustment in labour inputs in the counties with the OEMs' assembly plants. On the other hand, workers employed in parts and engines manufacturing experience some adjustments. In the counties with German parts and engines plants, there are positive changes in all dimensions. Workers in this groups receive 0.182% higher average monthly earnings during the shock period. Meanwhile, rises in employment and payroll of these counties are only significant at the 20% significance level. Nonetheless, these results for German counties should be inferred with caution because they are based on just three counties. Further, after removing one outlier county in Indiana, all negative and significant effects among counties with the US parts and engines factories are deleted.

Moreover, the indirect effect of the OEMs' assembly plants on local parts and

Table 4.7: Impacts on labour inputs by groups based on QWI data

	Assembly plants/data[1]			Parts & Engines plants/data[2]		
Dep. variables	JP	US	DE	JP	US	DE
LogEmpEnd	-0.083	0.053	NA	0.020	-0.238**[3]	0.136†
	(0.215)	(0.158)		(0.034)	(0.100)	(0.082)
	[33]	[335]	[21]	[318]	[1,032]	[42]
LogEarnEnd	0.028	0.064	0.105	0.079	0.008	0.182***
	(0.056)	(0.047)	(0.110)	(0.082)	(0.033)	(0.067)
	[362]	[584]	[259]	[407]	[1,050]	[126]
LogPayroll	0.011	-0.100	0.021	0.002	-0.186*[3]	0.134†
	(0.152)	(0.080)	(0.156)	(0.094)	(0.098)	(0.089)
	[374]	[600]	[269]	[418]	[1,075]	[129]

Note: All results are coefficients of Dis_t from Fixed Effect regression with AR(1) disturbances, that is, equation 4.4.7.
[1] These results estimate motor vehicles manufacturing data from counties with assembly plants.
[2] These results estimate motor vehicles parts and engines manufacturing data from counties with OEMs' parts and engines plants.
[3] After removing one outlier county, these negative and significant results disappear.
Standard errors are in parentheses while number of observations are in square blankets.
***, **, * and † indicate significant at 1% , 5% , 10% and 20% level respectively.

engines plants in the same county are estimated. Table 4.8 presents these results. Consistently, there is no significant change among the US counties. However, if allowing for a 20% significance level, there is a positive employment effect on parts and engines factories in the counties with Japanese assembly plants[76]. Also, in German counties, average monthly earnings of workers in parts and engines manufacturing is increased by 0.062%. Yet interpretation of these indirect effects relies on the assumption that OEMs' assembly plants are the major purchasers of suppliers in their locality. This assumption might first sound at odds in a paper emphasizing a role of an international supply chain. But, many car producers such as Toyota do encourage suppliers to consider locating themselves near their assembly plants. Finally, according to the right column in Table 4.8, there is no significant effect in any groups after restricting the sample to counties with OEMs' assembly plants but not OEMs' parts and engines factories. It seems that the significant results on the left of Table 4.8 are driven by these excluded counties where assembly and parts plants owned by the same firm are located. Hence, the production interlink between assembly and parts plants in the same locality appears to be strong only if they are under the same auto company.

4.6 Other margins of adjustment

In this section, the focus is on other channels of adjustment briefly introduced earlier, namely substitution through import, hikes in price and changes in inventory. The analyses rely on descriptive trends and statistics rather any rigorous causal interferences. Regarding trade, Canada and Mexico are the major trade partners in motor

[76]This could be a signal of substitution of intermediate inputs from Japan for local products.

Table 4.8: Indirect Impacts on labour inputs by groups based on QWI data

	Assembly plants/Parts data[1]			Assembly w/o Parts plants/Parts data[2]		
Dep. variables	JP	US	DE	JP	US	DE
LogEmpEnd	0.065†	0.009	0.078	0.072	0.005	0.071
	(0.0469)	(0.046)	(0.087)	(0.056)	(0.056)	(0.099)
	[411]	[597]	[342]	[345]	[387]	[300]
LogEarnEnd	-0.041	0.029	0.062†	-0.018	0.037	0.047
	(0.060)	(0.037)	(0.041)	(0.064)	(0.049)	(0.045)
	[592]	[672]	[378]	[508]	[462]	[336]
LogPayroll	-0.044	-0.064	0.029	-0.026	-0.021	0.016
	(0.072)	(0.042)	(0.072)	(0.081)	(0.053)	(0.081)
	[609]	[688]	[387]	[523]	[473]	[344]

Note: All results are coefficients of Dis_t from Fixed Effect regression with AR(1) disturbances, that is, equation 4.4.7.
[1] These results estimate motor vehicles parts and engines manufacturing data from counties with assembly plants.
[2] These results estimate motor vehicles parts and engines manufacturing data from counties with assembly plants but none OEMs' parts and engines plants.
Standard errors are in parentheses while number of observations are in square blankets.
***, **, * and † indicate significant at 1% , 5% , 10% and 20% level respectively.

vehicles and parts who gain reasonable trade surpluses from USA. In 2010, imports from Canada and Mexico accounted for 23% and 25.6% of total import value of US motor vehicles and parts respectively[77].

Figure 4.5 and 4.6 display the import value of automobiles and parts. They move along normal trends and seasonality without any significant jumps during the shock (the shaded area). However, considering numbers of Detroit 3 and the Japan big 3 (Toyota, Honda and Nissan) assembly and parts manufacturing plants located along the US border, it is plausible not to detect any increases in the US import because the Japanese plants in Canada and Mexico could experience the same production set back as those in USA. Unless detailed data are available, the role of import substitution is inconclusive[78].

As for price, I explore a publicly available Consumer Price Index (CPI) from Bureau of Labor Statistics (BLS) to find any hikes in price as predicted by a simple Cournot competition model. Figure 4.7 and 4.8 show CPI for new and used vehicles respectively. Although CPI for used cars and trucks had a steeper rise in price during the shock period, both CPIs did not illustrate any noticeable hikes rather than upwards trend and seasonal effect due to higher demand for motor vehicles as a whole in 2011. Thus, any effects of the shock on overall prices were too small to be distinguishable.

However, in Figure 4.9, another measure computed by Edmunds.com called True Cost of Incentives^{SM} (TCI)[79] provides supporting evidence for a spike in price. In May

[77] Passenger cars imported from Canada makes up almost a third of US import while trucks as well as engines and parts from Mexico constitutes of more than 84% and 31% respectively.

[78] The US Bureau of census has data on import for each product by trade partner and state. With geographical variation, it could shed some light on substitution of motor vehicle parts. However, these data are not free for public-use.

[79] According to Edmunds.com, this measure is average incentive cost per retail vehicle sold in the

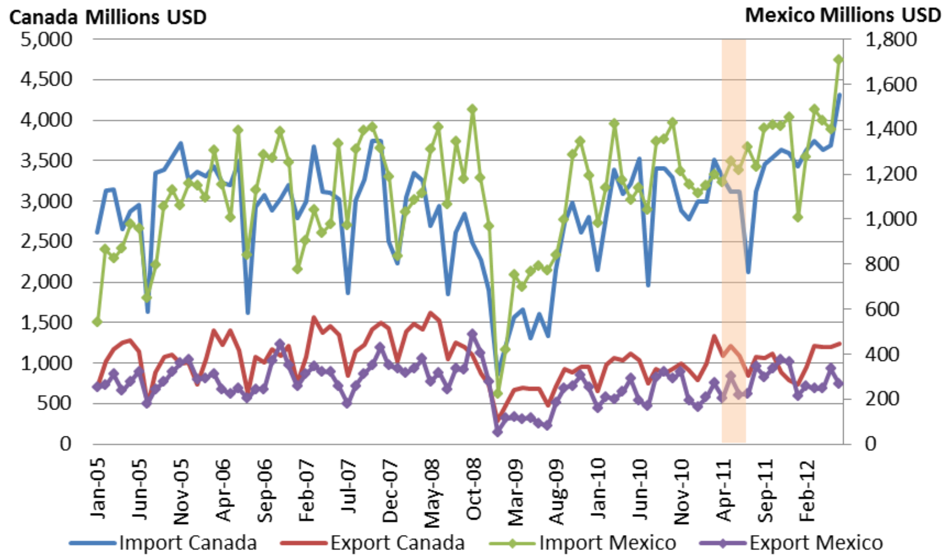

Figure 4.5: *US monthly trade in Automobiles and Light Duty Motor Vehicles, Including Chassis*

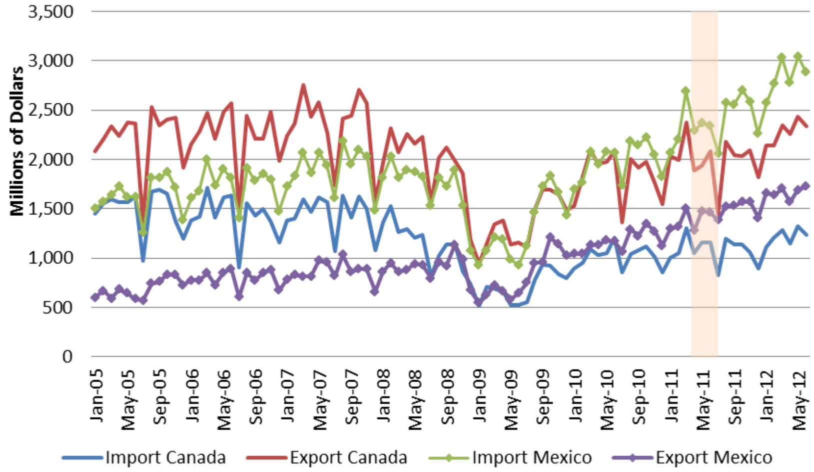

Figure 4.6: *US monthly trade in Motor Vehicle Engines and Parts*

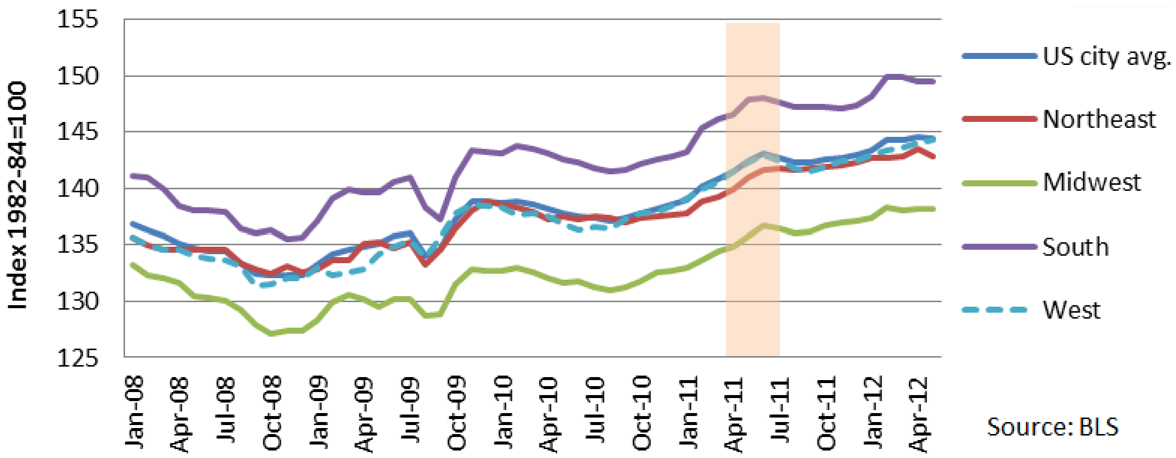

Figure 4.7: *CPI urban area for New Vehicles by region*

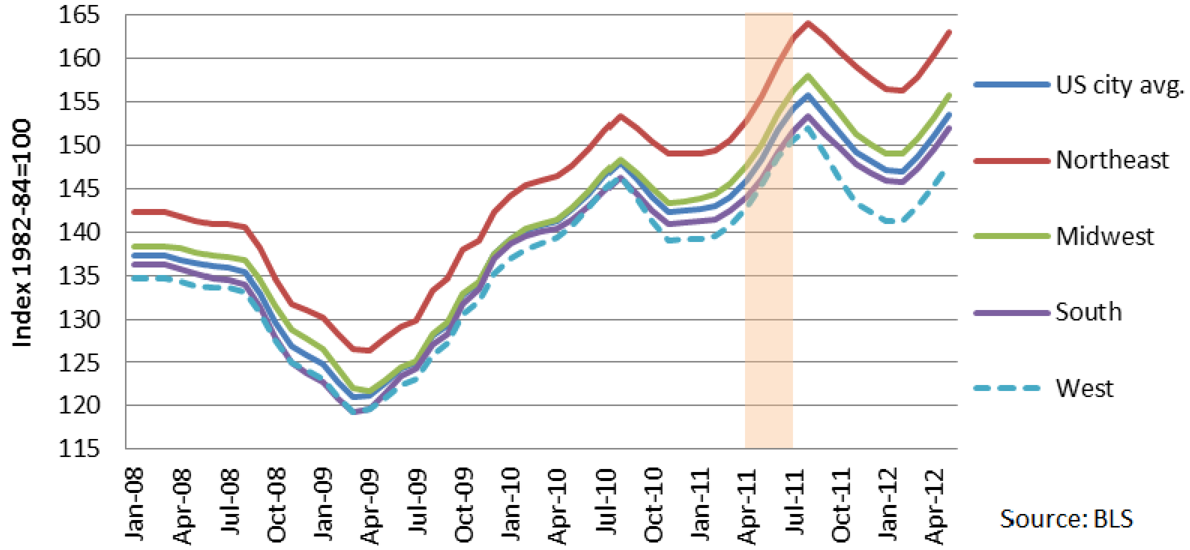

Figure 4.8: *CPI urban area for Used Cars and Trucks by region*

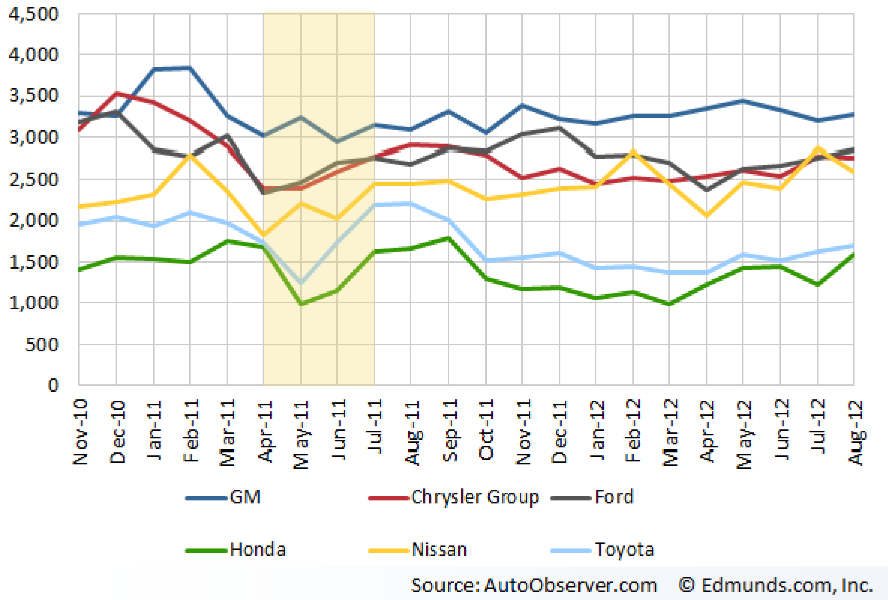

Figure 4.9: *Manufacturer True Cost of Incentives (USD) Detroit 3 and Japan big 3*

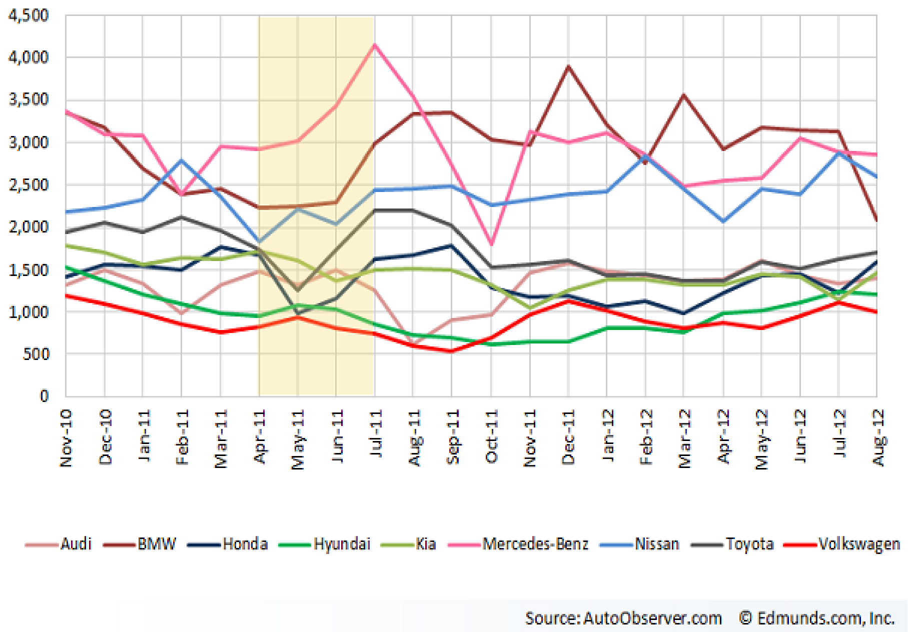

Figure 4.10: *Manufacturer True Cost of Incentives (USD) Germany, South Korea and Japan*

2011, consumers (dealers) of those worst hit Japanese companies like Toyota and Honda did pay higher prices (receive less profit) implicitly by receiving less incentive from these companies while there was no significant reduction in TCI of other competitors. This contrasts to October 2011 when TCI dropped industry-wide because of an abrupt jump in demand for the newer model year '2012' vehicles[80] (Edmunds.com, 2011).

The final margin of adjustment is inventory. A measure called Day-To-Turn (DTT) from Edmunds.com is employed as a proxy for the level of each manufacturer's inventory. Days to Turn is the average number of days vehicles were in dealer inventory before being sold during the months indicated. The lower number of days the manufacturers get, the fewer inventories their dealers have on hand. Figure 4.12 displays significant drops in DTT for Hyundai, Kia and Volkswagen during the shock periods and thereafter which are corresponding to their gain in market share. Nevertheless, the South Korean auto makers could not fully benefit from the shock since they were constrained by their production capacity in US even before the disaster (Buss, 2011). Meanwhile, the DTT of the US and Japanese Big 3 did not change much apart from a decrease between March and April 2011. US auto makers seemed to accumulate more inventory after the event, yet as discussed earlier, it did not translate into a significant increase in labour inputs.

As for the Japanese firms, their DTT decreased markedly after the shock periods coinciding with a start to gain back their market share. It can be inferred that dealers of Japanese cars used their inventory as well as postpone transactions in order to cope with supply shortage. Soon after the shock had subsided, they completed any delayed deals before starting to gradually rebuild their inventory. This observation confirms the role of inventory on mitigating any adverse effects of supply shortage.

However, this temporary supply shock which caused a demand surge among Japanese's competitors does not seem to generate the 'Bullwhip' effect[81] as expected by some studies (Sucky, 2008). Partly, it could result from the temporary nature of the shock. Hence, competitors and their dealers would expect only a transitory rise in demand. Any reaction might be constrained by nature of car production which requires advanced planning such as intermediate inputs management and capacity enhancement. Yet some companies who gained from the Japanese market share like Chrysler and Kia did accumulate their inventory markedly after the shock. Then they seemed to reach their new stable DTT after Oct 2011.

U.S. for the months indicated. It takes into account subvented interest rates and lease programs, as well as cash rebates to consumers and dealers based on sales volume, including the mix of vehicle makes and models for each month, as well as on the proportion of vehicles for which each type of incentive was used.

[80]Normally, the newer models are barely discounted compared to the older, 2011, models.

[81]It is an effect of wrong expectation on demand variation which leads to excessive hoarding of inventory among downstream supplier. Then this accumulated effect forces manufacturer to produce too many goods with all its available capacity.

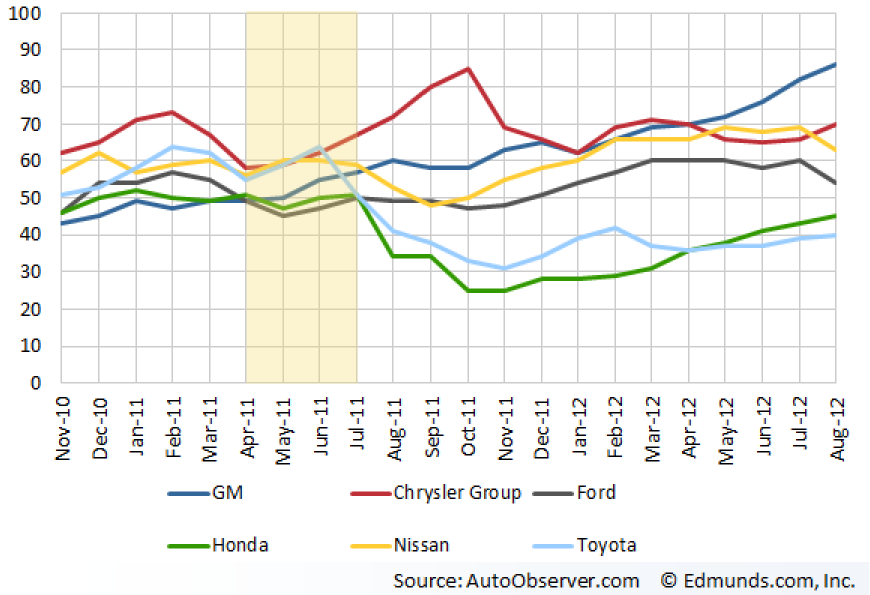

Figure 4.11: *Manufacturer Days To Turn (days) Detroit 3 and Japan big 3*

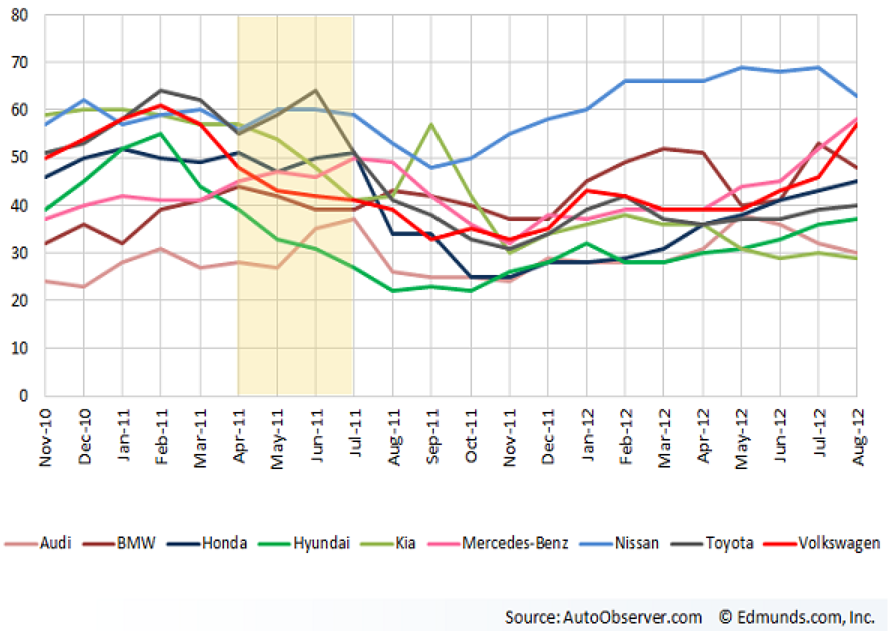

Figure 4.12: *Manufacturer Days To Turn (days) Germany, South Korea and Japan*

4.7 Conclusion

In examining the Great Tohoku Earthquake and Tsunami as an external shock to Japanese auto makers in the US, this paper has found relatively small changes in response to such an abrupt yet transitory international supply shock. Although the disaster caused a major disruption on Japanese motor vehicles and motor parts export and lead to a significant drop of Japanese auto makers market share in the US, Japanese companies regained their position less than a year after the event. The level of labour inputs (used as a proxy for changes in production) was not significantly reduced among Japanese companies and their local suppliers, whereas their competitors (particularly, plants in the US intensive states and German parts and engines plants) seemed to adjust their labour inputs slightly to capitalize on Japanese losses.

In terms of other margins of adjustment, inventories and sales incentive appear to be major tools employed to mitigate either positive demand or negative supply shocks on both groups of companies. Meanwhile, there is no clear evidence in support of import substitution or spikes in price. Yet movement in production and sales incentive are consistent with a prediction from a simple Cournot model. That is an overall price should rise as a result of a supply shock on one producer because it is not optimal for its competitors to increase their output enough to fully offset the shortfall.

However, a major challenge in any extension on this topic is data availability. With more data, several potential research questions can be answered using this disaster and the auto industry as a case study. For example, detailed import data by state and product could shed some light on the role of import substitutability in the event of a shock along the global production chain. Regarding supply shock and oligopoly market, better data on production and price by manufacturer and model would enable empirical testing of the prediction of the theory on movement of output and price after a temporary supply shock. Finally, detailed inventory data could illustrate a role for inventory management as a buffer to the supply shock in contrast to the so-called Bullwhip effect, where poor inventory management amplifies adverse effects of demand variability.

4.A Japanese Export in Motor vehicle and Motor parts & accessories

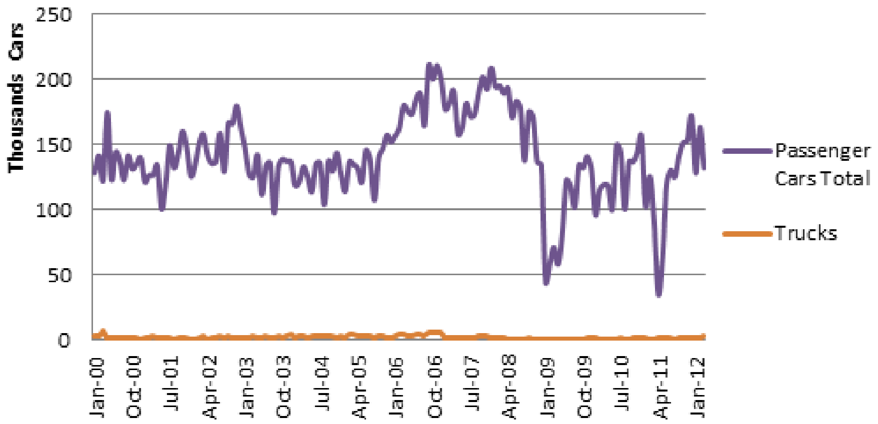

Figure 4.13: *Japan's Export in Motor Vehicles (units) to USA Jan 2000 - Mar 2012*

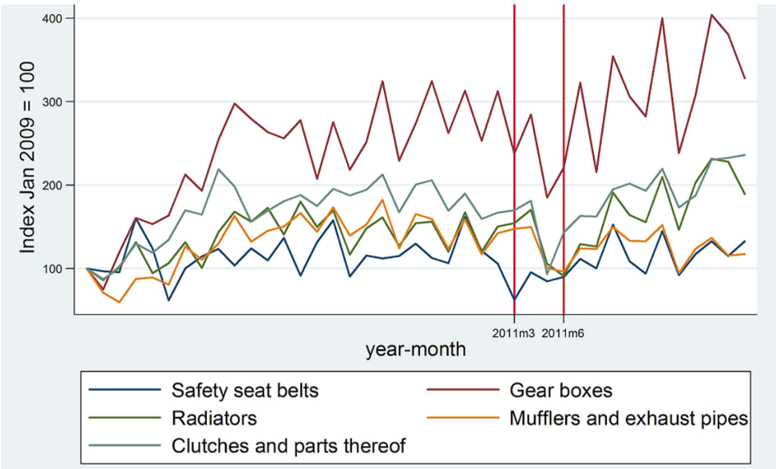

Figure 4.14: *Japan's Export Value to USA (Monthly indices) for Selected Motor Vehicles Parts & Accessories*

4.B Car sales in the US market by manufacturers (units)

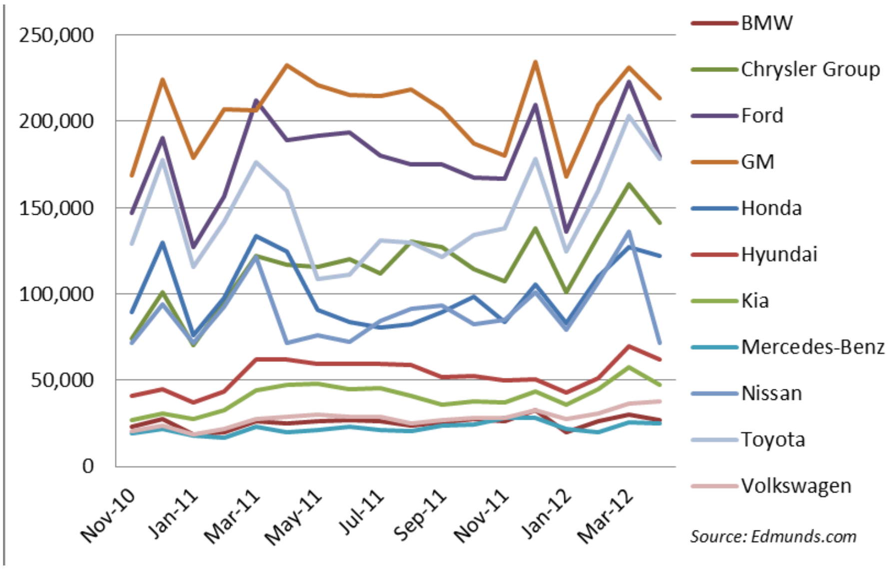

Figure 4.15: *Car sales in the US market by manufacturers (units) Nov 2010 - Apr 2012*

4.C Data Appendix

4.C.1 Japanese auto makers direct employment

The data on number of direct employment of each manufacturer comes from various sources (i.e. Center for Automotive Research, National Automobile Dealers Association, Ward's Auto and Automotive Who's Who) compiled by the Alliance of Automobile Manufacturers (Auto Alliance) which is an association of 12 new vehicle manufacturers in the US. The main objective of the Auto Alliance is to illustrate the importance of auto industry on the US economy through statistics such as number of direct and indirect employment and tax contribution from the industry.

At the time I retrieved the data on direct employment, Auto Alliance provides numbers of employment by each auto companies in each state around the end of 2010 and early 2011 with details on types of the plants (e.g. assembly, parts, R & D, etc.) and cities where they are located. Using Auto Alliance's data, I calculate share of direct employment by Japanese auto makers in each state. The following table includes states with more than 400 direct employees of any auto companies.

Table 4.9: Share of Japanese auto makers direct employment in each state

State	Share	State	Share
Alabama	48.96%	Michigan	1.33%
Arizona	49.37%	Mississippi	97.68%
Arkansas	100%	Missouri	11.34%
California	80.91%	New Jersey	12.78%
Colorado	8.64%	New York	1.08%
Florida	1.76%	North Carolina	0.58%
Georgia	45.07%	Ohio	35.26%
Illinois	16.54%	Oregon	9.41%
Indiana	41.32%	South Carolina	0%
Iowa	100%	Tennessee	56.04%
Kansas	0%	Texas	26.96%
Kentucky	57.96%	Virginia	9.29%
Maryland	62.00%	West Virginia	90.42%
Massachusetts	64.96%		

Moreover, I match the location of each plant with the county-level data from QWI. Therefore, I can identify each county by the firm's nationality and the type of such plants i.e. assembly plants or parts and engines plant. Since almost all the counties have only plants from the same nationality, the data can be classified into groups of nationalities with different types and used to estimate results in table 4.7 - 4.8.

Table 4.10: Data Sources

Data	Source	Table/Figure/Section
Trade		
Japan's export value to USA (various products)	Trade Statistics of Japan, Ministry of Finance	Figure 4.2, 4.3, and 4.14
Japan's export in motor vehicles (units) to USA	Japan Automobile Manufacturers Association, INC.	Figure 4.13
US Auto Industry		
Market share by firms' nationality	National Automobile Dealers Association (NADA) monthly Industry Sales Recap	Figure 4.4
Car sales (units) by manufacturer	Autoobserver.com and Edmunds.com	Figure 4.15
Labour Inputs in Auto industries		
Hours of worked, Overtime, and Employment (State level)	Monthly Current Population Survey (CPS) by Bureau of Labor Statistics (BLS)	Table 4.1 and Section 4.3
Employment, Earning, and Payroll (State and County level)	Quarterly Workforce Indicators (QWI) by LEHD Program at the US Bureau of Census	Table 4.2 and Section 4.3
Share of direct employment by Japanese auto makers (State level)	Author's own calculation based on Auto Alliance data	Table 4.9 and Section 4.3
Other Margins		
Import and Export value of automobiles and parts	US Bureau of Census	Figure 4.5, and 4.6
Consumer Price Index	Bureau of Labor Statistics (BLS)	Figure 4.7, and 4.8
Average incentive per retail vehicle sold	True Cost of Incentives (TCI) by Edmunds.com	Figure 4.9, and 4.10
Inventory by manufacturer	Day-To-Turn (DTT) by Edmunds.com	Figure 4.11, and 4.12

5 Conclusion and Future Research

Using external variations in labour market law, education policy, and natural disaster as instruments, this thesis studies their impacts on the labour market as well as the whole economy and estimates consistent economic parameters of interest. One lesson I learned from these studies is that deeper investigation into statistically insignificant results could produce some thought-provoking insights. For example, in this thesis, non-significance results among the whole sample highlight the usefulness of categorizing the sample into sub-groups and re-estimating each group separately. Particularly, the second chapter uses firm size to classify wage-earners into formal and informal workers and shows that the minimum wage policy in Thailand reduces wage inequality among employees in the formal sector but not in the informal one. Meanwhile, the third chapter finds a positive rate of return to compulsory schooling only for female workers whereas the male workers do not seem to benefit from additional years of compulsory education. Lastly, despite an abrupt shock on Japanese automobile manufacturers in the US, the negative impact on labour inputs is found in only one sub-sector of this industry. Moreover, using various data sources and performing robustness checks against different model specifications could verify the validity of these null results. In the fourth chapter, different data sets are deployed so as to confirm the rather small effects found.

Regarding extensions to this thesis, each chapter addresses several possibilities for future research. First, the differential effects of the minimum wage policy on formal and informal wage distribution among developing countries, especially between Latin America and Asia-Pacific, emphasize the needs for further study to clarify underlying reasons of this discrepancy. According to the literature (previously discussed in section 2.1), there are differences between these two regions which potentially cause such divergence. For instance, studies in Asia usually use firm size to distinguish between different sectors while social security contribution is a main classification criterion for those researches from Latin America. Moreover, labour market institution in Latin America seems to influence different compliance patterns across various labour regulations. Specifically, compliance with one labour law i.e. the minimum wage does not imply compliance with others such as social security contribution (Khamis, 2013). Yet there is no thorough research testing such hypothesis against data from Asian economies.

As for the chapter on compulsory schooling, even though the estimated rates of return to education in this thesis are much lower than previous studies in Thailand (e.g. Warunsiri and McNown, 2010), the results substantiate the claim of higher return to education for female employees. In addition, zero-return to schooling found among male workers spawns even more puzzling. One possible explanation is that the market might not value extra two to three years of education among the low-educated workers. But why do we observe positive rates of return for female workers? Does education affect the selection process of workers into employment in different sectors? Recommended extension is to verify whether more years of education (particularly among female) induce people to work in wage employment rather than non-wage employment or not. Finally, different data sets are needed to identify any impacts of education on health outcomes in Thailand since such causal researches are still scarce in developing countries.

The final chapter explores the interconnection between labour market and international supply chain from a new perspective. Using the Japanese Tsunami in 2011 as an external shock to the supply chain of Japanese auto companies in the US, this chapter assesses the impacts and adjustments among Japanese firms and their competitors through labour market data. Notwithstanding significant drops in market share of Japanese cars, any adjustments in labour inputs observed are rather small. However, descriptive statistics of other margins of adjustment such as sales incentive and inventory show some notable responses. Thus, further investigation using details production, price and inventory data should be able to shed light on the firms' reaction in oligopoly market as well as the role of incentive and inventory management after a huge shock along the supply chain. Hopefully, this chapter would help to inspire more economic researches on the importance of the international supply chain as transmission and propagation mechanisms of shocks across countries during the time that huge natural or man-made disasters are not rare events anymore.

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