The Effect of the Minimum Wage on the Employment Rate in Canada, 1979 – 2016

by Eliana Shumakova

(8494088)

Major Paper presented to the

Department of Economics of the University of Ottawa

in partial fulfillment of the requirements of the M.A. Degree

Supervisor: Professor Pierre Brochu

ECO 6999

Ottawa, Ontario

December 2017

Abstract

The main focus of this paper is to evaluate the impact of the minimum wage on the teenage employment rate using Canadian Labour Force Survey data (1979 – 2016). The impact is both economically and statistically significant. In particular, my findings suggest that a 10% increase in the minimum wage decreases the teenage employment rate by approximately 1.4 percentage points. There appears to be some lag effect of the minimum wage (up to 12 months). Finally, the results remain similar when broken down by gender, although slightly larger effects are found for males.

1. Introduction

The judicious design of labour market policies, such as the minimum wage, is of particular importance given current economic conditions. The decision whether to increase the minimum wage, and if so by how much, should therefore rest on a full understanding of the consequences of such a policy. There are two reasons why the impact of the minimum wage on Canadian employment rate needs to be further analyzed. First, there is no clear evidence in the literature on whether the minimum wage causes the employment rate to fall (Williams, 1993; and Dube, Lester, and Reich, 2010), or to rise (Card, and Krueger, 1994). Even in the case where dis-employment effects are found, there is some evidence that suggest that they may be economically insignificant (Wellington, 1989). Second, most studies which assess the effects of minimum wage are done using U.S. data. However, Canadian data provide a richer source of variation in minimum wages than is typically found in U.S. data. For these reasons, this paper investigates the effect of minimum wage changes on the Canadian employment.

This paper expands upon the existing literature in at least three ways. First, the analysis is conducted over a long time frame (1979 to 2016), one that covers multiple business cycles. Second, the paper tackles both the problems of endogeneity and serial correlation.[1] For instance, minimum wage usually increases in periods of expansions which, in turn, raises the possibility of endogeneity. The problem of serial correlation is often occurs when one uses panel data in regression analysis which leads to the problem at the inference stage, i.e. an over-rejection of the null hypothesis. Finally, it explores different weighting approaches. Although it is natural, and

[1] Few studies address the potential endogeneity of the minimum wage (e.g., Sen, Rybczynski and Van De Waal, 2011). In addition, I am aware of only one paper, in addition to mine, that addresses the problems of serial correlation using Feasible Generalized Least Squares (FGLS) (Brochu and Green, 2013).

common, to account for the relative size of provinces, how to account for the time series component of the data is less obvious.

The panel data used to estimate the impact of the minimum wage on the employment rate is collected from different sources, such as the Canadian Labour Force Survey (LFS), Services Canada and CANSIM. The analysis involves various specifications that include instantaneous and lagged minimum wage terms. The main focus of the paper is teenagers; however, the analysis is also conducted for young adults. Finally, the paper also explores gender differences in the impact of minimum wage policies.

Overall, the results suggest that teenagers are negatively affected by minimum wage changes. Young adults are also affected, but to a lesser extent. A 10% increase in the real minimum wage diminishes the employment rate by approximately 1.4 percentage points for teenagers and by approximately 0.7 percentage points for young adults. The results of the specifications with lagged minimum wage terms suggest that the adjustment can take up to 12 months, and this holds true for both age categories. Interestingly, once the lagged real minimum wage terms are added to the regression, the effect for young adults becomes stronger and closer to the teenage effect. The results broken down by gender are similar, but are slightly larger for males than for females, and this holds true for both age categories.

A number of robustness checks address such issues related to the use of alternative measures of the minimum wage, endogeneity, weights and serial correlation. The use of an alternative measure of minimum wage (the ratio of the nominal minimum wage to the average manufacturing wage) does not materially affect my findings. The results from using an IV approach, with right- and left-wing binary variables as instruments, are in line with the main findings. Different weighting approaches generate very similar results, as long as more populated provinces count for more in the analysis. Finally, using Feasible Generalized Least Squares (FGLS) as a substitute method for dealing with serial correlation provides more muted coefficient estimates than OLS.

The rest of the paper is divided as follows. The next section provides a review of the literature. Section 3 describes the data, while the econometric model and main results are presented in section 4 and 5, respectively. Section 6 discusses the result of the robustness checks. Section 7 summarizes the main points of the paper.

2. Literature Review

In this section, I present a review of the existing minimum wage literature. I start by presenting the Canadian evidence. Then, I move on to the U.S. literature, and finally conclude by discussing some of the international findings.

2.1 Canada

Schaafsma and Walsh (1983) examine the impact of minimum wages on employment, labour supply and unemployment in Canada. Their Statistics Canada data are for the years 1975 through 1979. One interesting feature of the study is that it focuses on multiple age groups (teenagers, young adults and prime age workers), and the analysis is further broken down by gender. The study provides evidence of a significant negative effect of the minimum wage on employment and labour force participation for all age and gender categories. However, the effect lessens with age. Kan and Sharir (1996) carry out a similar study, but extend the data through 1991, and they find similar results.

Similarly, Baker, Benjamin and Stanger (1999) investigate the impact of minimum wages on Canadian employment rates over the 1975 – 1993 period. Their data is obtained from special tabulations performed by Statistics Canada, and through CANSIM. Contrary to the previous studies, their group of interest is more narrowly defined. They only focus on teenagers i.e. 15 – 19 year old, who are employed full-time. They also find dis-employment effects. The results of their preferred specification show that a 10% increase in minimum wage causes the teenage employment rate to fall by 2.5%. Finally, they find that their results are somewhat sensitive to the estimation approach (i.e. demeaning versus using first differences).[2]

Yuen (2003) uses panel data from the Labour Market Activity Survey (LMAS) over the 1988 – 1990 period. The paper estimates the effect of 19 minimum wage increases on employment for two age categories: for teenagers (i.e. 16 – 19 year olds) and young adults (i.e. 20 – 24 year olds). His main findings indicate that young workers with more than 9 months of low-wage employment are more affected by the minimum wage changes than those with job tenure of 9 months and less. In contrast to the previous studies, the dis-employment effect is more severe for young adults than for teenagers. More precisely, an 8.4 % increase in the minimum wage decreases the probability of being employed next year by 7 % for teenagers and by 10 % for young adults.

Similar to Yuen (2003), Campolieti, Fang, and Gunderson (2005) evaluate the effects of the minimum wage on employment transitions. The study focuses on individuals who are 16 to

[2] In contrast, Goldberg and Green, 1999, found that the effect of the minimum wage on employment is very small for different age and gender groups except for male young adults. They conduct similar analysis using data on four Canadian provinces (i.e. British Columbia, Alberta, Ontario and Quebec) during 1976 to 1997. The data is obtained from the Survey of Labour and Income Dynamics (SLID).

24 years old who were employed over the 1993 to 1999 period. The data for this analysis is obtained from the Master Files of the Survey Labour and Income Dynamics. The paper relies on three identification strategies - at-risk, gap, and gap variant methods. While at-risk and gap methodologies are commonly used in the minimum wage literature (Currie and Fallick, 1996; and Yuen, 2003), the gap variant method is new to this study. This methodology accounts for unobserved differences between the treatment and control groups, which are hard to measure but might affect employment for the youth. The results show that increasing the minimum wage by 1% leads to an approximately 1% to 2% increase in the transition from employment to non-employment.

Sen, Rybczynski and Van De Waal (2011) estimate the effect of minimum wage changes on teenage employment as well as on poverty. The provincial poverty levels are determined by the Low Income Cut Offs (LICOs). Two methods of estimation are used in this paper: OLS with clustering at the provincial level, and IV. For the IV approach their instruments include political binary variables (which represent the provincial political parties in power), the regional average minimum wage, the unionization rate and the proportion of working individuals in the trade and retail sectors. The OLS results are very similar to the IV results. Overall, the findings imply that a 10 % increase in the minimum wage leads to a 3% - 5% decline in teenage employment while it increases the percentage of people who are living in poverty by 4% - 6%.

Brochu and Green (2013) investigate the effect of minimum wage changes on labour market transition rates, in particular, the separation and hiring rates. They take advantage of panel features of the LFS – that households are interviewed over six consecutive months. The analysis focuses on individuals with high school degrees or less (i.e. low-skill workers). It is known that OLS in the presence of serial correlation will generate incorrect standard errors. As such all regressions are estimated using Feasible Generalized Least Squares (FGLS). The main results of this paper suggest that an increase in minimum wage has a negative impact on separation and hiring rates. For instance, a 10% increase in the minimum wage decreases the separation rate by 5% for workers with less than a one-year of job tenure. This result is mainly caused by a drop in layoffs rather than in quits. In addition, the results suggest that prime age workers have the most significant decline in the hiring rate compared to other age group categories. Using different measures of the minimum wage, instrumenting for it, or restricting the time period of the analysis (i.e. excluding recessionary years) does not affect the main findings.

2.2 The U.S.

Using the National Longitudinal Survey of Youth (NLSY),[3] Currie and Fallick (1996) focus on two increases in the federal minimum wage in the US: from $2.90 to $3.10 in 1980, and from $3.10 to $3.35 one year later. In contrast to the two previous studies, Currie and Fallick (1996) provide two alternative approaches to measuring the gap between the old and new minimum wage. The first measure is defined as the difference between the minimum wage in the current year and the worker's wage in the previous period. The second measure is a binary variable which equals 1 if the individual's wage was equal to or not more than 51 cents above the old minimum wage. They used three comparison groups for these measures of the minimum wage: individuals whose wage was below the old minimum wage, individuals whose wage was above the old minimum wage and individuals working in sectors mostly uncovered by the federal minimum wage law (i.e. state or local government). The results imply that the probability

[3] The NLSY provides annual data on 14-21 year old individuals.

of being employed next year decreases by 3% for young individuals who are most likely to be affected by the new minimum wage.

Card and Krueger (1994) estimate the short run impacts of the minimum wage on the employment rate in the restaurant industry. They take advantage of a 80 cent increase (i.e. $4.25 to $5.05) in the minimum wage that was introduced by the state of New Jersey on April 1, 1992. 450 fast-food restaurants were interviewed through a survey that was carried out 1 to 2 months before the minimum wage increase and a second time 7 to 8 months after. They estimate the impact of the minimum wage by conducting a natural experiment where New Jersey is the treatment group, and Pennsylvania the control group. The study finds a positive effect on the employment rate, which contradicts the predictions of a standard neoclassical model.

Singell and Terborg (2007) evaluate the impact of a minimum wage increase on employment for low-wage workers in different industries in Oregon and Washington. The minimum wage increased by approximately 37% in Oregon from 1997 – 1998 and in Washington from 2000 – 2001, while the minimum wage did not change in both states from 1994 – 1996 and increased in both states during 1999. Similar to Card and Krueger (1994), they used bordering states for which there were no minimum wage changes as control groups. The data is obtained from the Occupational and Employment Statistics Survey. The results indicate that the minimum wage increases have a significant negative effect on employment growth for drinking and eating industries, while there is no impact for hotel and lodging workers.[4]

Wellington (1989) estimates the impact of the minimum wage on the employment rate of young workers. The study uses monthly data from the Current Population Survey (CPS) over the 1954 to 1986 period. They do not find any significant impact of the minimum wage on the

[4] Although Card and Krueger (1994) and Singell and Terborg (2007) do not explicitly focus on teenager or young adult, the low-wage workers in the fast food industry in the Card and Krueger case (or in other restaurant industries in the Singell and Terborg case) are mainly young people.

employment rate, either for teenagers or for young adults. A 10% increase in the minimum wage reduces teenage employment by approximately 0.6%, and employment of young adults by approximately 0.02%. Even when the age groups are broken down by gender and race, the effect of the minimum wage remains economically small.

In contrast, Williams (1993) finds a significant dis-employment effect for teenagers in some U.S. regions. He estimates the regional impact of minimum wage increases on teenage employment rates over the 1977 – 1989 period. The paper uses panel data drawn from different sources, such as the Department of Labor, the Bureau of Labor Statistics, the Geographic Profile of Employment and Unemployment, and the U.S. Census Bureau. The results imply that the effect of the minimum wage is more severe in some regions than others. In the most affected regions (e.g. the Pacific region) a 10% increase in the minimum wage causes the teenage employment rate to fall by approximately 7%.[5] The results are robust to the choice of specification or alternative measures of minimum wage.

Burkhauser, Couch and Wittenburg (2000) evaluate the effect of minimum wage increases on teenage employment. The data is obtained from the Current Population Survey (1979 – 1997). The purpose of this paper is to explore why Card and Krueger, 1995, find an insignificant effect of minimum wage changes on teenage employment. To do so, they use specifications of the model where macroeconomic controls are added to the regression analysis sequentially, and they rely on both annual and monthly data. Once year dummies are added to the regression, the effect of the minimum wage becomes statistically and economically insignificant. More precisely, the elasticity of teenage employment varies from -0.2 to -0.6 for all specifications, except the specification with year fixed effects. The authors argue that including year dummies in the regression eliminates 93% of variation in the minimum wage. This happens

[4] In West South Central region the effect was only 0.3%.

because the federal minimum wage usually increases once per year. They propose alternative approaches to control for macroeconomics effects which do not affect the results, such as the inclusion of recessionary dummies or having a one year lagged real minimum wage term in the regression.

Dube, Lester and Reich (2010) examine the effect of the minimum wage changes on the employment rate and earnings focusing on low-wage industries (e.g. restaurants). The data is primary collected from the Quarterly Census of Employment and Wages. One of the unique characteristics of this paper is that it addresses two crucial concerns, serial correlation and endogeneity. To deal with the endogeneity problem, the authors rely on contiguous border county-pair. The paper addresses the problem of the serial correlation by clustering at the county and state levels. The paper also uses traditional method such as a panel approach with time and state fixed effects. The earnings estimates are very similar for both approaches. The results imply that a 10% increase in the minimum wage leads to a 1.49% to 2.32% increase in earnings. However, the effect on employment is slightly larger when using the traditional approach as opposed to the contiguous county-pair approach, (-0.149 compared to -0.137). The results also suggest a labour demand elasticity of -0.787 and -0.482 for the traditional and county-border methods, respectively.

Dube, Lester and Reich (2016) estimate the effect of minimum wage changes on employment flows and stocks. The paper focuses on the two most affected groups - teenagers and restaurant workers. The paper evaluates the minimum wage effects using data from the U.S. Quarterly Workforce Indicators for the period 2000 – 2011. A border discontinuity design is used as the main identification strategy. The results are similar to those found in Brochu and Green (2013). More precisely, increases in the minimum wage do not affect employment stocks significantly while employment flows decline. The results are robust to the inclusion of additional controls such as county-specific trends, private sector-level outcome and lagged and leading minimum wage variables.

2.3 International Evidence

Bell (1997) estimates the effect of a minimum wage increase on wages and employment rate for skilled and unskilled workers in developing countries i.e. Mexico and Columbia. Although this paper does not focus on teenagers, the unskilled workers in these countries are mainly young people. Bell (1997) relies on several datasets for her analysis such as Mexico's and Columbia's Annual Industrial Surveys. The main method of estimation used is OLS with fixed effects for industry, city, region and year. She finds that minimum wage changes have a significant negative impact on workers in Columbia, while no minimum wage effect is found in Mexico.

Similarly, Neumark and Wascher (2004) evaluate the effect of minimum wage changes on youth employment using data on 17 OECD countries over the 1975 – 2000 period. The data is mostly drawn from published OECD sources, such as Labour Force Statistics and the annual Employment Outlook reports. Their analysis focuses on teenagers and young adults. The results from the fixed effects model imply that young adults are less affected by minimum wage changes than teenagers. In particular, the elasticity of employment equals -0.15 for young adults while it is -0.18 for teenagers. After accounting for other labour market policies, the results imply that the negative effect of minimum wages on youth employment is most significant in countries where labour markets are least regulated including countries such as the United States, Canada, and the United Kingdom.

Most papers that find a significant negative effect of the minimum wage on employment, only find it for teenagers. However, some papers provide evidence that other age groups (especially young adults) are also at-risk (Schaafsma and Walsh, 1983; Wellington, 1989; Goldberg and Green, 1999; Neumark and Wascher, 2004). The few papers that separate the analysis by gender find very little difference between men and women (Schaafsma and Walsh, 1983). Methodologically, different identification strategies have been used to estimate the effect of the minimum wages on employment: difference-in-differences (Card and Krueger, 1994; Singell and Terborg, 2007), instrumental variables (Brochu and Green, 2013; Sen, Rybczynski and Van de Waal, 2011) and fixed effect models (which is commonly used).

This paper expands upon the existing literature along a few dimensions. First, I update the Canadian evidence to include post financial recession period (i.e. up to 2016). This paper also addresses the problem of endogeneity (using political instruments), which is rarely done in the literature. I also explore different ways for dealing with serial correlation, such as using FGLS, which is also used by Brochu and Green (2013). Finally, I explore different approaches for the weighting of the Canadian provinces included in the analysis.

3. Data and Summary Statistics

This section contains the description of the datasets used in this study and provides summary statistics of the main variables and figures showing the rich variation in the provincial real minimum wage over time.

This paper uses panel data, where a unit of observation is a province at a particular time. The biannual data (i.e. March and September) covers the 1979 – 2016 period.[6] The variables in the panel data are gathered from different sources, such as the (public-use) Canadian Labour Force Survey (LFS), CANSIM, and Canadian administrative data.

The LFS dataset is a monthly survey which gathers labour market information on households living in Canada. The number of individual observations in each monthly LFS varies from 94,041 to 124,789 over the 1979 – 2016 period. The LFS includes, among others, information on labour status, education, gender, wages, and age. These information are used to calculate the employment rates by age group and by gender.[7] Although the main focus is on teenagers, I will also look at young adults (20 – 24 year olds), and each gender separately. The information on industries and wages in the LFS are used to compute the alternative measure of the minimum wage (i.e. the ratio of the minimum wage to the mean manufacturing wage) which is used later in the robustness check section (i.e. section 7).

The adult provincial nominal minimum wages dating back to 1979 are obtained from the Services Canada website.[8] The provincial Consumer Price Index (CPI), which is used to deflate

---

[6] The LFS follows the same individuals for six months. Using data six month apart ensures there are no repeated individuals in the sample.

[7] The employment rates for each age and gender category are weighted using the person weights available in the LFS. The teenage employment rate obtained from the LFS is the same as the employment rate reported in CANSIM. This is not surprising, since the employment rate in CANSIM is computed using the LFS. However, CANSIM does not provide data on the provincial employment rate for other age and gender categories.

[8] http://srv116.services.gc.ca/dimt-wid/sm-mw/rpt2.aspx?GoCTemplateCulture=en-CA

the minimum wage, is obtained through CANSIM.[9]

While some of the papers such as Baker, Benjamin, and Stanger (1999) focus on teenage employment rates, others such as Campolieti, Fang, and Gunderson (2005) claim that young adults might be also affected by minimum wage changes. Figure 1 shows the percentage of at-risk individuals for three age groups over the 1997 – 2016 period.[10] The three age categories are the following: 15 – 19 year old (teenagers), 20 – 24 year old (young adults) and 25 – 54 year old (prime age) individuals. At-risk is defined as individuals who earn no more than 10% of the current provincial minimum wage.[11] Figure 1 suggests that teenagers are more likely to be affected by minimum wage changes. Approximately 65% of teenagers are at or below the minimum wage, with a low of 54% in 2009 and a high of 75% in 2016. Only 20% of the young adults earn around the minimum wage, while for the prime age group it is even smaller, at 5%.

Brochu and Green (2013) evaluate the effect of the minimum wage on the employment rate looking at low-skill workers (i.e. workers with some post-secondary education or less). Figure 2 shows the proportion of at-risk workers by age group, but focuses on the low-skilled. The figure shows that 71% of low-skilled teenagers are at-risk. The number is similar to that found in Figure 1. This is not surprising because most of them are in high-school due to their age. However, the numbers are also similar for other age groups. Only 25% of the low-skilled young adults are at-risk, while it is 10% for the prime age low-skilled workers.

Very few prime age workers (whether they be low-skill or not) are at-risk; for this reason the focus of this paper is on younger workers, more precisely teenagers. I do not impose any skill

[9] The provincial CPI is March of 2002 price-based.
[10] Figures 1 and 2 start from 1997 because there is no data on the wages in the LFS before 1997.
[11] Currie, and Fallick (1996) and Yuen (2003) used the low bounds of 1 and 2 dollars, respectively, in their papers when they defined the individuals at-risk. My sample is not restricted by the low bound because there are no individuals whose wage is 1 or 2 dollars. 10% is used due to the fact that it is the average percentage amount minimum wage increased from 1979 to 2016.

restriction because of the similarity of numbers across all skill and low skill workers for those young age groups. However, given that some researchers such as Schaafsma and Walsh (1983), have looked at how the effect of the minimum wage varies by gender, the analysis will be carried out for males and females separately as well.

I provide below a brief overview of labour market outcomes for teenagers. Between 1979 and 2016, the teenage employment rate varied from 12.7 to 58.6 percent across Canada. On average, the employment rate was approximately 40 percent for teenagers while it was around 65 percent for young adults.

Figures 3 through 5 demonstrate the variation in the real minimum wage for each province from 1979 to 2016.[12] The real minimum wage varies significantly overtime for all provinces. However, one can notice similar real minimum wage patterns over this period of time. The real minimum wage tended to decline from 1979 up until the early 90's, only to rise from 2000 and onwards. Having said that, there are clear regional differences, and within each region there is substantial variation across province and time. Central provinces, such as Ontario and Quebec, consistently have higher real minimum wage than provinces in other regions. For example, the average real minimum wage in Ontario is 17% higher than the average real minimum wage in Newfoundland and Labrador. However, Newfoundland had the most rapid rise in the real minimum wage from 2005 to 2010. On the other hand, Quebec had the most severe drop of the real minimum wage. In particular, it decreased by approximately 30% from 1979 to 1986. British Columbia experienced different patterns of the real minimum wage compared to other Western provinces. Indeed, from early 90's until early 2000's all Western provinces experienced a decline in the real minimum wage while the real minimum wage in

[12] For ease of presentation, Figures 3 – 5 are constructed using annual data as of March of each year.

British Columbia was rapidly increasing. This behavior of the real minimum wage is very similar to that of the Central provinces.

4. Econometric Model

The econometric model takes the following form:

$$ER_{p,t} = \alpha + \sum_{k=0}^{K} \beta_k \ln(RMW)_{p,t-k} + \lambda_p + \delta_t + \varepsilon_{p,t} \quad (1)$$

where $ER_{p,t}$ represents the teenage employment rate in province p and at time t.[13] $\ln(RMW)_{p,t}$ is the natural log of the real provincial minimum wage. The real minimum wage is calculated as follows:

$$RMW_{p,t} = \frac{NMW_{p,t}}{CPI_{p,t}} \times 100 \quad (2)$$

where $NMW_{p,t}$ is the nominal minimum wage in province p at time t. $CPI_{p,t}$ represents the provincial Consumer Price Index. K ranges from 0 to 4, depending on the specification. As such, the most parsimonious specification (i.e. when K=0) will have the logged real minimum wage without lags, and the fullest specification (i.e. when K=4) will include the logged minimum wage at time t, and lagged terms for every six month up to two years.[14] The lagged real minimum wage

[13] I rely on March and September data covering a 38 year period. As such, there are 76 time periods in my sample.
[14] Recall that a time period reflects a six month time interval. If period t, for example, represents March 2015, then period $t+1$ is September 2015.

variables allow one to evaluate the long term impact of minimum wage changes on the teens' employment.

λ_p and δ_t are province and year fixed effects, respectively. The province fixed effects take into account time-invariant differences across provinces that could result in an endogeneity problem if unaccounted for. For example, some well-preforming economies, like Alberta, have tended to have relevantly low minimum wages. Similarly, the time fixed effects capture Canada-wide shocks that may be correlated with the minimum wage, such as the tendency of the minimum wage rising in periods of expansion.

5. Results

5.1 Teenagers

As discussed in section 3, teenagers are the ones most affected by minimum wage changes, and as such are the main focus of this analysis. Table 1 shows the OLS regression results of equation (1) for teenagers where there are no lagged minimum wage terms and where time and province control are added sequentially. I weight the observations by the relative size of the target population of each province, but where the years count equally. [15] With panel data usually comes the problem of serial correlation. The Ordinary Least Squares (OLS) estimator will be consistent and unbiased, but the standard errors will be incorrect because of serial correlation. Since the OLS standard errors tend to be too small in such a case, they usually lead to an over-rejection of the null hypothesis. The standard approach is to cluster the standard errors, an approach I follow in my main analysis. More precisely, I cluster the standard errors at

[15] See equation (A3) of Appendix A. In the robustness check section, I verify the sensitivity of the results to alternative weighting approaches.

the provincial level. However, the small number of clusters, i.e. 10 clusters, can be a concern. As part of my robustness check, I address the problem of serial correlation using an alternative approach, the FGLS estimator.

Column (1) of Table 1 shows the regression results without any controls, i.e. the teenage employment rate is regressed on the real minimum wage only. The results imply that an increase in the real minimum wage negatively affects the employment rate for 15 – 19 year old Canadians. More precisely, a 10% increase in the real minimum wage would lead to a 1.3 percentage point decrease in the teenage employment rate. Given that the teenage employment rate is, on average, 40% over my sample period, this represents an elasticity of demand of approximately -0.33. Adding time fixed effects in the regression, which captures Canada-wide shocks, reduces the negative effect of the real minimum wage (and it remains statistically insignificant). Once province controls are further added to the regression, the coefficient estimate of the real minimum wage term becomes larger, going back to levels found in column (1), and most importantly becomes statistically significant at the 5% level. The preferred specification of this analysis is the specification with time and province fixed effects. The minimum wage tends to go up in period of expansions, as do the employment rates. As such, it is important to account for business cycle variations through the use of time dummies. Similarly, it is important to have province fixed effects because provinces for which the employment rate is lower tend to have higher minimum wages historically.

Table 2 presents the regression results of equation (1) with the addition of real minimum wage lags. Column (1) is the preferred specification of Table 1 (i.e. it reports the same results as column (3) in Table 1) which includes time and province controls and no lags. In columns (2) through (5), 6-month lagged real minimum wage terms are added to the regression sequentially.

The full specification, i.e. column (5), will include 6-month, 12-month, 18-month and 24-month lagged real minimum wage terms.

The results of Table 2 suggest that there are some lagged effects of the real minimum wage. Specifically, the effect of minimum wage changes on the teenage employment rate might take from 6 to 18 months to appear. The estimates from column (2), for example, show that a minimum wage increase will affect the teenage employment rate only 6 month later, i.e. there is no instantaneous effect on the employment rate. More precisely, increasing the real minimum wage by 10% will diminish the teenage employment rate by 1.4 percentage points 6 months later, a finding which is statistically significant at the 10% level. Adding the 12-month lagged real minimum wage term (i.e. column (3)) does not change the magnitude of the effect of the real minimum wage on the teenage employment rate, but now it takes one year for the effect to appear. Also, the coefficient estimates become more statistically significant, as the estimates are statistically significant at the 1% level as compared to the 10% level in column (2). The results in column (4) suggest that the effect of real minimum wage changes can even appear 18 month later. A 10% increase in the minimum wage will decrease the teenage employment rate by 0.3 percentage points 12 months later, and by even a larger number, i.e. 1.3 percentage points, 18 months later. Again there is no instantaneous effect. These longer lagged terms are both statistically significant. In the last columns of Table 1, the results imply that the effects of real minimum wage changes occur only after 18 months, but they are lower compared to the previous specification. In more detail, an increase in the real minimum wage by 10%, is associated with a 0.9 percentage point drop in the teenage employment rate 18 months later.

Table 3 reports the effect of the real minimum wage broken down by gender. In particular, the dependent variable for columns (1), (3) and (5) is the male teenage employment rate, whereas in columns (2), (4) and (6), it is the female one. In addition, since the results in Table 2 suggest that the long term effect of the real minimum wage on the teenage employment rate is more likely to occur 6 months or 12 months later, the real minimum wage lagged by 6 and 12 months are sequentially added in the regression.

The results in columns (1) and (2) imply that the analysis by gender has little impact on the overall findings, but the instantaneous effect of the real minimum wage changes is slightly larger for males than for females. A 10% increase in the real minimum wage decreases the male teenage employment rate by 1.4 percentage points, while the female teenage employment rate where declines by 1.3 percentage points (the coefficient is statistically significant at the 5% level for both genders). Columns (3) through (6) show similar patterns of the lagged real minimum wage for males and females to those found for the full sample. The 6-month lagged effect remains larger for males than for females. A 10% increase in the real minimum wage will result in a 1.6 percentage point drop in the male teenage employment rate and 1.2 percentage point drop in the female rate 6 months later. The effect is statistically significant at the 1% level for males, but insignificant for females. In contrast, the effect for females is larger than for males in the specification with 6-month and 12-month lagged real minimum wage terms. Increasing the minimum wage by 10% decreases the female teenage employment rate by 1.5 percentage points and the male teenage employment rate by 1.3 percentage points 12 months later. The effects for both genders are statistical significance at the 1% level.

To conclude, the results imply that the teenage employment rate is negatively affected by the minimum wage changes during the period 1979 – 2016. A 10% increase in the real minimum wage diminishes the teenage employment rate by approximately 1.4 percentage points. This results imply an elasticity of demand of approximately -0.33 which is similar to the results found by Brown, Gilroy and Kohen (1982). The results of the specifications with lags show that a similar effect will appear 6 and 12 months later. Finally, the results suggest that the effect of the minimum wage increase is slightly larger for males than for females.

5.2 Young Adults

As discussed in section 3, young adults (i.e. 20 – 24 year olds) might also be affected by minimum wage changes. Table 4 reports the regression results of equation (1) in which the dependent variable is the employment rate for young adults. Column (1) shows the results of the specification with time and province controls, but no lagged minimum wage terms. Since the regression results for teenagers show that there is a possibility of some lagged effect of the real minimum wage changes, in columns (2) and (3) the real minimum wage lagged by 6 and 12 months are added to the regression sequentially.[16]

The results in column (1) suggest that young adults are less affected by the minimum wage changes than teenagers. A 10% increase in the minimum wage leads to a 0.6 percentage point drop in the employment rate for young adults compared to a 1.3 percentage point drop in the teenage employment rate. However, the coefficient estimate for young adults is not statistically significant, while it is at the 5% level for teenagers. Column (2) reveals that the 6-month lagged effect of the minimum wage for young adults becomes similar to the effect found for teenagers. A 10% increase in the real minimum wage decreases the employment rate by 1.2 percentage points for young adults and by 1.4 percentage points for teenagers, with an effect that

[16] Also, I added even more lags in the regression sequentially up to 2 years. The coefficient estimates are very similar to those presented in columns (2) and (3) of Table 4. The effect of the minimum wage changes appears only 6 months later. Since the results show that adding more lags to the regression does not change the effect, the results with more lags are not reported.

occurs only 6 months later. The estimates of the coefficient on the 6-month lagged real minimum wage term are statistically significant for both age categories. The results in column (3) show that the effect of the real minimum wage for young adults still occurs 6 months later, while in the same specification it occurs 12 months later for teenagers. Increasing the real minimum wage by 10% causes the employment rate for young adults to fall by 0.9 percentage points 6 months later and by 1.4 percentage points for teenagers 12 months later. The effects are statistically significant at the 5% level and at the 1% level, respectively.

Table 5 shows the results of analysis for young adults by gender. The structure of Table 5 is exactly the same as the structure of Table 3, but for a different age category i.e. young adults. Similar to the results found for teenagers, male young adults are more affected by the changes in the minimum wage than females, but the effect is still larger for teenagers than for young adults. Columns (1) and (2) reveal that a 10% increase in the real minimum wage leads to a 0.8 percentage point decline in the employment rate for male young adults compared to a 0.5 percentage point decrease for females. Columns (3) and (4) show that adding lags of the real minimum wage the effect becomes stronger for both genders. In fact, in this case the effect for young adults becomes almost the same as for teenagers. If the minimum wage increases by 10% the young adult employment rate will decline by 1.6 percentage points for males and by 0.8 percentage points for females 6 months later compared to 1.6 and 1.2 percentage points for male and female teenagers respectively. Columns (5) and (6) show that adding one more lagged real minimum wage to the regression slightly diminishes the effect on young adults of both genders. According to this specification, increasing the real minimum wage by 10% decreases the young adult employment rate by 1.4 percentage points for males and by 0.6 percentage points for females 6 months later.

To sum up, young adults are less affected by the changes in the minimum wage compared to teenagers. The effect of minimum wage policies is half as much for young adults as for teenagers. However, once the lagged real minimum wage terms are added to the regression the effect for young adults becomes stronger and almost identical to the effect for teenagers. Also, males tend to be slightly more affected by minimum wage changes than females for both age categories. Nevertheless, the effect of the real minimum wage is statistically insignificant for female young adult for all specifications.

6. Robustness Check

6.1 Alternative Minimum Wage Measure

Although it is common in the minimum wage literature to use the real minimum wage as the key explanatory variable (as is done in this paper), some researchers have instead relied on a relative measure - the ratio of the minimum wage to the average manufacturing wage.[17] Column (2) of Table 6 reports the results of the analysis preformed using the log of this relative minimum wage as dependent variable instead of the real minimum wage. Because LFS wage data is only available from 1997 onwards, this specification only covers the 1997 – 2016 period. For comparison sake, I present in column (1) the results for my preferred specification (where I use the real minimum wage), but for the same restricted time period. One observes a dis-employment effect in both cases, although the effect is slightly larger when using the relative minimum wage measure. Having said this, neither effect is statistically significant. However, it should be noted

[17] See for instance, Walsh (1983) and Williams (1993). Some, such as Brochu and Green (2013), chose to use the ratio of the minimum wage to the median wage.

that the point estimates of the coefficient are very similar to the ones found for my preferred specification (using the full sample).

6.2 Endogeneity

The minimum wage is not created in a vacuum. One typically observes, for example, minimum wage increases in periods of expansions. Although the inclusion of province and time fixed effects has the purpose to deal with such issues, the possibility of endogeneity still remains. This subsection looks more into this issue. It is commonly believed that left-leaning governing parties, like the New Democratic Party, are more willing to increase minimum wages than right-wing ones. This suggests potential instruments for the minimum wage. Following Brochu and Green (2013), I compute binary variables that account for whether the provincial government is left- or right-leaning with central being the base group.[18] The results of applying an instrumental variable approach using these two political instruments are shown in column (4) of Table 6. The effect of the real minimum wage on teenage employment is still negative, but it doubles in magnitude; a 10% increase in the minimum wage causes the teen employment rate to fall by 3.5 percentage points, as compared to drop of 1.3 percentage points when using OLS (see column (3)). The standard errors, however, become much larger, and as such, the findings are statistically insignificant.

Another way to deal with the potential endogeneity of the minimum wage is to eliminate some cyclical variation. Following Brochu and Green (2013), I exclude recessionary years from the sample. The recessionary years are defined as years in which the economy was not strong,

[18] See Brochu and Green (2013) for more detail on the construction of these variables.

i.e. when the overall unemployment rate was 8% and over.[19] The results of this specification are reported in column (5). These results imply that excluding the years with a high unemployment rate does not significantly affect the real minimum wage estimates, despite an increase in the size of the standard errors, which makes these estimates only significant at the 10% level. The results would seem to imply that there is not a strong correlation between the minimum wage changes and economic conditions (once the common time trend has been removed).

6.3 Weights

My preferred approach is to weight the observations by the relative size of the target population (of each province), but with the years counting equally. There are, however, other possible approaches that can be used. The results of using different weight measures, which I discuss below, are presented in columns (1) through (4) of Table 7.[20]

The preferred approach of weighting provinces is presented in Column (1).[21] Column (2) reports the regression results using weights that account for the size of the target population of each province at each point in time. In column (3), the weights still account for the relative size of provinces, but the years are weighted according to the sample size of each year. Finally, the un-weighted regression results are presented in column (4). This last approach implies that each province in each year count equally in the regression analysis.

---

[19] Based on the information found in CANSIM, the unemployment rate was over 8% several times during 1979 – 2016. In column (5), the following recessionary time period are dropped from the sample: March of 1979, September of 1981 – September of 1987, September of 1990 – September of 1997 and March of 2009 – September of 2010. Hence, 33 time period are excluded from the sample.

[20] See Appendix A for a detailed discussion of how the various weights are constructed.

[21] For ease of presentation, column (1) of Table 7 is exactly the same as column (3) of Table 1.

The results imply that the choice of how to weight has little impact on the results. In fact, the coefficient estimates in columns (2) and (3) are very similar to the preferred weighting approach, and still significant at the 5% level. The fact that the results are different when not using weights is not a concern as this is not commonly used approach in the literature. It was only presented for sake of completeness.

6.4 Serial Correlation

In the case where clustering is less appropriate, i.e. when there are too few clusters,[22] the Feasible Generalized Least Squares (FGLS) approach is a suitable alternative, as it generates appropriate standard errors, while still providing a consistent and unbiased estimator for the parameter of interest.[23] Columns (5) and (6) of Table 7 report the FGLS results for autoregressive models of order 1 and 2, respectively.

The results show that using an alternative estimator generates different coefficient estimate of the real minimum wage effect. Column (5) reveals that using an AR(1) FGLS approach provides much smaller coefficient estimates of the real minimum wage as compared to those estimated by OLS with clustering (i.e. column (1)). More precisely, if one increases the real minimum wage by 10%, the teenage employment rate will fall by 0.2 percentage points, while the OLS estimate suggests a 1.3 percentage point decline in the teenage employment rate. While the effect of the real minimum wage changes remains negative using an AR(1), the effect becomes slightly positive when using an AR(2) model. Having said that, the impact is very small, i.e. essentially zero. In particular, increasing real minimum wage by 10% increases the

[22] There are 10 provinces hence 10 clusters, but according to Angrist and Pischke (2008), the appropriate number of clusters should at least equal 42.
[23] See Appendix B for more details of how the FGLS results are estimated.

teenage employment rate by 0.037 percentage points. In fact, testing to identify the order of error process suggests that the error terms follow an autoregressive process of order two. The fact that FGLS generates different estimates than OLS is to be expected as it is a different estimator. Having said this, the economic importance of the minimum wage effect is sensitive to the estimation chosen.[24]

7. Conclusion

This paper investigates the effect of the minimum wage on the employment rate for young workers in Canada. The analysis is conducted for two age categories (teenagers and young adults) for both genders together as well as separately. The advantage of using Canadian data rather than U.S. data is that it provides rich variation in the minimum wage. My analysis covers the 1979 – 2016 period. The panel data used in this paper is obtained from the Canadian LFS, CANSIM and Services Canada.

The OLS results imply an economically and statistically significant dis-employment effect for teenagers, while the effect is much smaller for young adults. A 10% increase in the real minimum wage diminishes the employment rate by approximately 1.4 percentage points for teenagers, and by approximately 0.7 percentage points for young adults. Given that on average employment rate was 40% for teenagers and 65% for young adults, the elasticity of demand equals -0.33 and -0.12, respectively. The results of the specifications with lags show that the

[24] The fact that the number of observation in FGLS estimation is smaller than in OLS is due to the data transformation used in FGLS. Thus, I checked if the different number of observation affects the results. In particular, I dropped March of 1979 from the sample for AR(1) and dropped March and September of 1979 for AR(2). The results of the base specification with dropped years does not change the estimates implying that the difference between the OLS estimate and the FGLS estimate is not due to the different sample size, it is due to the different methods of estimation.

teenage dis-employment effect takes from 12 to 18 months to appear, while the effect for young adults occurs only 6 months later. The magnitude of the effects remains unchanged. The results when broken down by gender are very similar; if anything they are slightly larger for males, and this finding holds true for both age categories. The results are robust to choice of the minimum wage measure, the choice of weights, and whether one addresses the potential endogeneity of the minimum wage. Finally, using FGLS as an alternative method for dealing with serial correlation generates more muted coefficient estimates than OLS.

Appendices

Appendix A

Most survey data files, including the LFS, come with probability weights. In such case, the weight represents the inverse of the probability for an observation being chosen from the target population. For instance, an observation that has a weight of 200 represents 200 individuals of the target population. Said differently, the odds of being sampled from that group of 200, assuming a random draw, is 1/200 = 0.005. When conducting data analysis using probability weights, statistical software packages (such as STATA) transform the weight, using the following equation:

$$W_i = \frac{weight_i}{\sum_{i=1}^{n} weight_i} \times n \qquad \text{(A1)}$$

where $weight_i$ is the assigned probability weight given to observation i, and n is the total number of observations in the sample. The resulting normalized weights, i.e. W_i, are very intuitive; they add up to the sample size, and a weight of say 1.5 would mean that the observation counts as 1.5 observations in the regression analysis. This observation, for example, would count three times as much (in the regression) as another observation that has weight of 0.5. The use of such normalized weights can be problematic when dealing with repeated cross sections, as I discuss below. The fact that the unit of observation in this paper is a province at particular moment in time further complicates this issue, particularly if one wants to account for the size of provinces. I therefore provide a discussion of four different approaches to weighting (one of which is not to weight) when using aggregated data where the unit of observation is a province at a moment in time, identifying the strength and weaknesses of each approach.

The first method is to assignment a weight of one to each observation, which is equivalent to using an un-weighting regression approach. This, in turn, means each year counts the same, as does each province within each year. That each year count exactly the same is appealing as it means that the results are representative of the full-time period. Equally weighting all provinces, however, is problematic. It would imply that provinces with small populations, such as Prince Edward Island or Newfoundland and Labrador, would matter equally (regression wise) as the more populated provinces such as Ontario and Quebec.

An alternative approach that accounts for the relative size of the provinces is to create the weights as follows

$$NW1_{p,t} = \sum_{i \in p,t} weight_{i,p,t} \quad \text{(A2)}$$

where $weight_{i,p,t}$ is the probability weight of individual *i* living in province *p* at time *t*. One will be weighting an observation from province *p* in time *t* by the size of its population (as of time *t*). It therefore puts more weights on observations from larger provinces like Ontario. For instance, the teenage population for Ontario and British Columbia, as of March 2016, was 820,500 and 265,900, respectively. As such, the (recent) observation for Ontario will be three times more important in the regression analysis than the (recent) observation for British Columbia. The fact that the teenage population has increased over time in Canada, it was 1,951,703 in March 1996 but grew to 2,391,215 in March of 2016, means that the observations from the most recent year will, as a group, count for 23% more than the group of observations from the first year of my sample. Finally, this approach will also account for changes in the relative size of provinces over time. The teenage population has grown over time in Alberta, whereas it has fallen in Saskatchewan, and the weighting approach will account for this.

A third method of constructing weights is to use the following equation:

$$NW2_{p,t} = \frac{\sum_{i \in p,t} weight_{i,p,t}}{\sum_{i \in t} weight_{i,t}} \tag{A3}$$

where the numerator is an estimated count of the target population in province *p* as of time *t*, and the denominator is a count of the target population as of time *t* for all provinces combined. Larger provinces will still account for more, as was the case in the previous approach, but the fact that the weights in each time period add up to one means that the observations for say 1996 will, as a group, count the same as those from 2016. The same holds true for other years.

The last method constructs the weights using the following approach:

$$NW3_{p,t} = NW2_{p,t} \times n_t \tag{A4}$$

where n_t represents the number of individual observations in the t sample period.[25] Compared to the previous case, the sum of the weights as of time *t* do not add up to 1, but instead add up to the sample size.[26] If one believes that results might be more precise in the years where the sample size is larger, then, one can account for it using these normalized weights. This approach will, as

[25] For the regressions that focus on teenagers, $n_{march\ 2016}$ will simply be the number of individual observation in the March 2016 LFS, after having eliminated non-teenagers from the sample.

[26] Each year counts in the regression according to the sample size at the particular time period. For example, the number of observation in March 2000 equals 8,793, and one year later it equals 9,222. Hence, March 2001 counts 5% more in the regression than March 2000 data.

was the case for the previous two approaches, still account for the relative size of provinces within each year.

Appendix B

The use of panel data raises the very real possibility of serial correlation. Although the Ordinary Least Squares (OLS) estimator will still be consistent and unbiased, the standard errors will be incorrect due to the presence of serial correlation. This causes problems at the inference stage. OLS standard errors are typically too small, and as such, they will usually lead to an over-rejection of the null hypothesis. In the case where clustering is less appropriate, i.e. when there are too few clusters, Feasible Generalized Least Squares (FGLS) approach is a suitable alternative, as it generates appropriate standard errors, while still providing a consistent and unbiased estimator of the parameters.[27] This section provides a brief overview of the approach, and most importantly, how it addresses the serial correlation problem.

For illustrative purposes, I rely on a simplified version of the econometric model used in this paper:[28]

$$ER_{p,t} = \beta_0 + \beta_1\, ln(RMW)_{p,t} + Z_{p,t}\beta_2 + \varepsilon_{p,t} \qquad \text{(B1)}$$

where $ER_{p,t}$ represents the employment rate for 15 – 19 year olds in province p and at time t, while $ln(RMW)_{p,t}$ is the log of the real minimum wage. Finally, $Z_{p,t}$ is a vector of controls, i.e. time and province fixed effects.

[27] Clustering does not change the coefficient estimates, it only corrects the standard errors. The FGLS approach will, however, generate different coefficient estimates than OLS.
[28] The arguments presented below also apply to the equation that includes lagged real minimum wage terms.

For ease of presentation, assume that the error term follows an autoregressive process of order one, i.e.

$$\varepsilon_{p,t} = \rho\varepsilon_{p,t-1} + \eta_{p,t} \tag{B2}$$

where $\eta_{p,t}$ is white noise - it is not correlated with any explanatory variables in the original equation, has a constant variance and its autocovariance equals zero. Lagging equation (B1)

$$ER_{p,t-1} = \beta_0 + \beta_1\, ln(RMW)_{p,t-1} + Z_{p,t-1}\beta_2 + \varepsilon_{p,t-1} \tag{B3}$$

and then multiplying by ρ results in

$$\rho ER_{p,t-1} = \rho\beta_0 + \rho\beta_1\, ln(RMW)_{p,t-1} + \rho Z_{p,t-1}\beta_2 + \rho\varepsilon_{p,t-1}. \tag{B4}$$

Subtracting equation (B4) from equation (B1) generates the following equation

$$(ER_{p,t} - \rho ER_{p,t-1}) = (\beta_0 - \rho\beta_0) + (\beta_1 \ln(RMW)_{p,t} - \rho\beta_1 \ln(RMW)_{p,t-1}) + (Z_{p,t}\beta_2 - \rho Z_{p,t-1}\beta_2) + (\varepsilon_{p,t} - \rho\varepsilon_{p,t-1}) \tag{B5}$$

which simplifies to

$$(ER_{p,t} - \rho ER_{p,t-1}) = \beta_0 (1-\rho) + \beta_1(\ln(RMW)_{p,t} - \rho \ln(RMW)_{p,t-1}) + (Z_{p,t} - \rho Z_{p,t-1})\beta_2 + (\varepsilon_{p,t} - \rho\varepsilon_{p,t-1}). \tag{B6}$$

The last bracketed term in equation (B6), i.e. the new error term, equals $\eta_{p,t}$ which is white noise. As such, there is no serial correlation. Equation (B6) can be rewritten as follows

$$\widetilde{ER}_{p,t} = \alpha + \beta_1 \ln(\widetilde{RMW})_{p,t} + \widetilde{Z_{p,t}}\beta_2 + \eta_{p,t} \tag{B7}$$

where $\widetilde{ER}_{p,t}$ equals

$$\widetilde{ER}_{p,t} = (ER_{p,t} - \rho ER_{p,t-1}), \tag{B8}$$

with $\ln(\widetilde{RMN})_{p,t}$ and $\widetilde{Z_{p,t}}$ similarly defined. Finally the constant is simply

$$\alpha = \beta_0\,(1 - \rho\,). \tag{B9}$$

If one knew ρ, one could simply construct the differenced variables, $\widetilde{ER}_{p,t}$, $\ln(\widetilde{RMN})_{p,t}$ and $\widetilde{Z_{p,t}}$ and estimate equation (B7) by OLS. This approach is referred to as Generalized Least Squares (GLS).

In most cases, and in my case as well, ρ cannot be observed, which requires an adaptation of the above method. The adapted approach, called Feasible Generalized Least Squares (FGLS), necessitates two steps. In the first step, one obtains an estimate of ρ, i.e. $\hat{\rho}$, by estimating equation (B1) using OLS, and then regressing the residuals on the lagged residuals (with no constant), i.e. equation (B2). In the second step, one constructs the differenced variables using $\hat{\rho}$ (instead ρ), and then estimate, using OLS, a modified version of equation (B7), i.e.

$$\overline{\overline{ER_{p,t}}} = \alpha + \beta_1 \overline{\overline{\ln(RMW)_{p,t}}} + \overline{\overline{Z_{p,t}}}\beta_2 + \eta_{p,t} \tag{B10}$$

where $\overline{\overline{ER_{p,t}}}$ equals

$$\overline{\overline{ER_{p,t}}} = (ER_{p,t} - \hat{\rho}ER_{p,t}), \tag{B11}$$

with $\overline{\overline{\ln(RMW)_{p,t}}}$ and $\overline{\overline{Z_{p,t}}}$ similarly defined, and α is defined as in (B11). The approach for dealing with higher order AR processes involves very similar steps.

References

Angrist, J. D., and Pischke, J. (2009), *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton, NJ: Princeton University Press.

Baker, M., Benjamin, D., and Stanger, S. (1999), 'The highs and lows of the minimum wage effect: A time-series cross-section study of the Canadian law.' *Journal of Labor Economics* 17(2), 318–350.

Bell, L. A. (1997), 'The impact of minimum wages in Mexico and Columbia.' *Journal of Labor Economics* 15(3), S102–S135.

Brochu, P., and Green, D. A. (2013), 'The impact of minimum wages on labour market transitions.' *Economic Journal* 123(573), 1203–1235.

Brown, C., Gilroy, C., and Kohen, A. (1982), 'The effect of the minimum wage on employment and unemployment.' *Journal of Economic Literature* 20(2), 487–528.

Burkhauser, R., Couch, K., and Wittenburg, D. (2000), 'A reassessment of the new economics of the minimum wage literature using monthly data from the CPS.' *Journal of Labor Economics* 18(4), 653–680.

Campolieti, M., Fang, T., and Gunderson, M. (2005), 'Minimum wage impacts on youth employment transitions, 1993 – 1999.' *Canadian Journal of Economics* 38(1), 81–104.

Card, D., and Krueger, A. B. (1994), 'Minimum wage and employment: A case study of the fast-food industry in New Jersey and Pennsylvania.' *American Economic Review* 84(4), 772–793.

Card, D., and Krueger, A. B. (1995), *Myth and Measurement: The New Economics of the Minimum Wage*, Princeton, NJ: Princeton University Press.

Currie, J., and Fallick, B. (1996), 'The minimum wage and the employment of youth.' *Journal of Human Resources* 31(2), 404–428.

Dube, A., Lester, T. W., and Reich, M. (2010), 'Minimum wage effects across state borders: Estimates using contiguous counties.' *The Review of Economics and Statistics* 92(4), 945–964.

Dube, A., Lester, T.W., and Reich, M. (2016), 'Minimum wage shocks, employment flows, and labor market frictions. ' *Journal of Labor Economics* 34(4), 663–704.

Goldberg, M., and Green, D. (1999), *Raising The Floor: The Social and Economic Benefits of Minimum Wages in Canada*, Vancouver, BC: Canadian Centre for Policy Alternatives.

Kan, J., and Sharir, S. (1996), 'Minimum-wage and probability-of-getting-a-job effects in a simultaneous equations model of employment and participation: Canada 1975 – 1991.' *Canadian Journal of Economics* 29 (Special issue: Part 1), S53–S56.

Neumark, D., Schweitzer, M., and Wascher, W. (2004), 'Minimum wage effects throughout the wage distribution.' *Journal of Human Resources* 39(2), 425–450.

Neumark, D., and Wascher, W. (2004), 'Minimum wage, labor market institutions and youth employment: A cross-national analysis.' *Industrial and Labor Relations Review* 57(2), 223 – 248.

Schaafsma, J., and Walsh, W. D. (1983), 'Employment and labour supply effects of the minimum wage: Some pooled time-series estimates from Canadian provincial data.' *Canadian Journal of Economics* 16(1), 86–97.

Sen, A., Rybczynski, K., and Van de Waal, C. (2011), 'Teen employment, poverty, and the minimum wage: Evidence from Canada.' *Labour Economics* 18(1), 36–47.

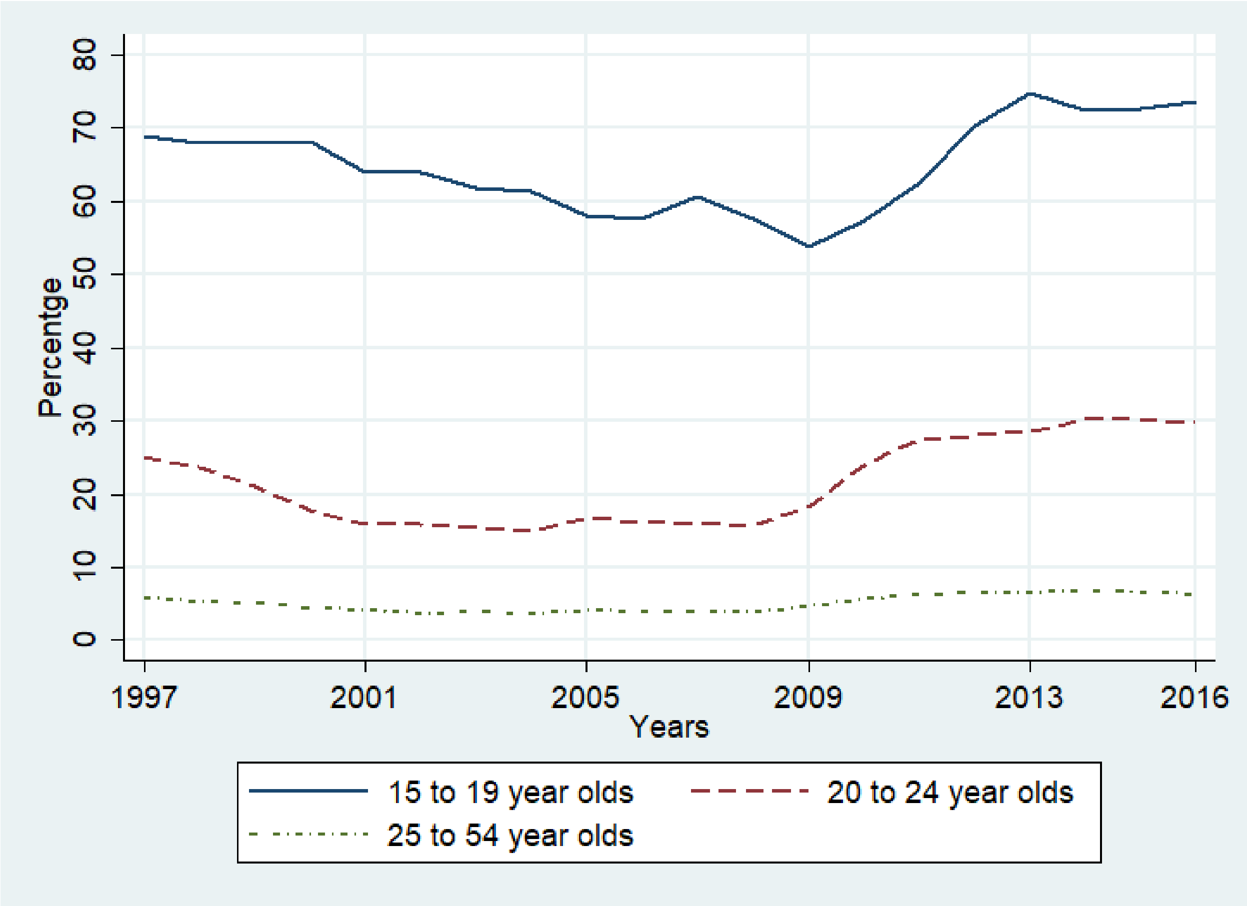
Singell, L. D., and Terborg, J. R. (2007), 'Employment effects of two northwest minimum wage initiatives.' *Economic Inquiry* 45(1), 40–55.

Wellington, A. J. (1989), 'Effects of the minimum wage on the employment status of youths: An update.' *Journal of Human Resources* 26(1), 27–46.

Williams, N. (1993), 'Regional effect of the minimum wage on teenage employment.' *Applied Economics* 25(12), 1517–1528.

Yuen, T. (2003), 'The effect of minimum wages on youth employment in Canada: A panel study.' *Journal of Human Resources* 38(3), 647–672.

Figure 1. Percentage of working individuals who are at-risk, by age categories, 1997 – 2016

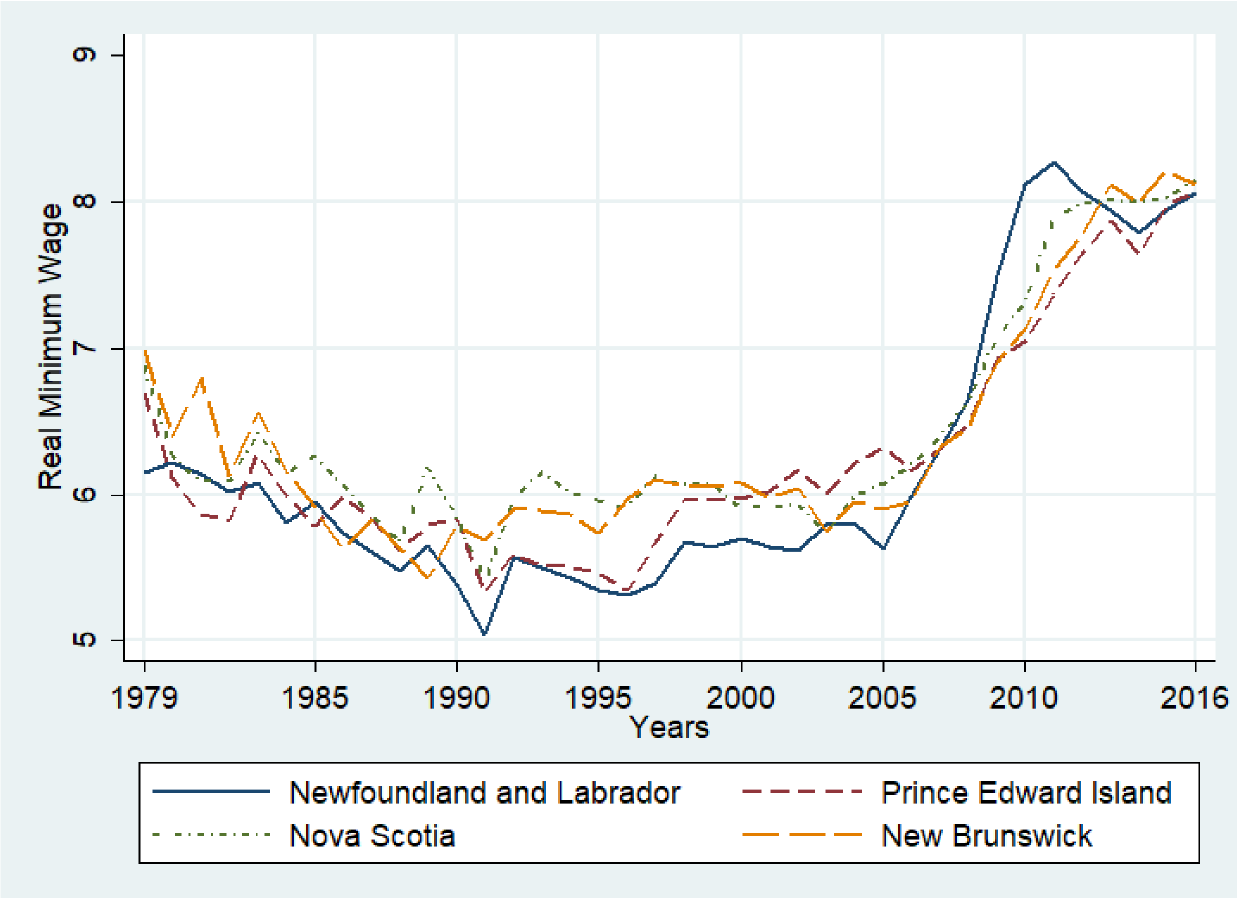


Notes: At-risk is defined as working individuals whose wage is no more than 10% higher than the current minimum wage in the individual's province of residence as of March of each year. Because data on wages in the LFS are only available from 1997 onwards, the figure is constructed from 1997 to 2016.

Figure 2. Percentage of low-skill working individuals who are at-risk, by age categories, 1997 – 2016

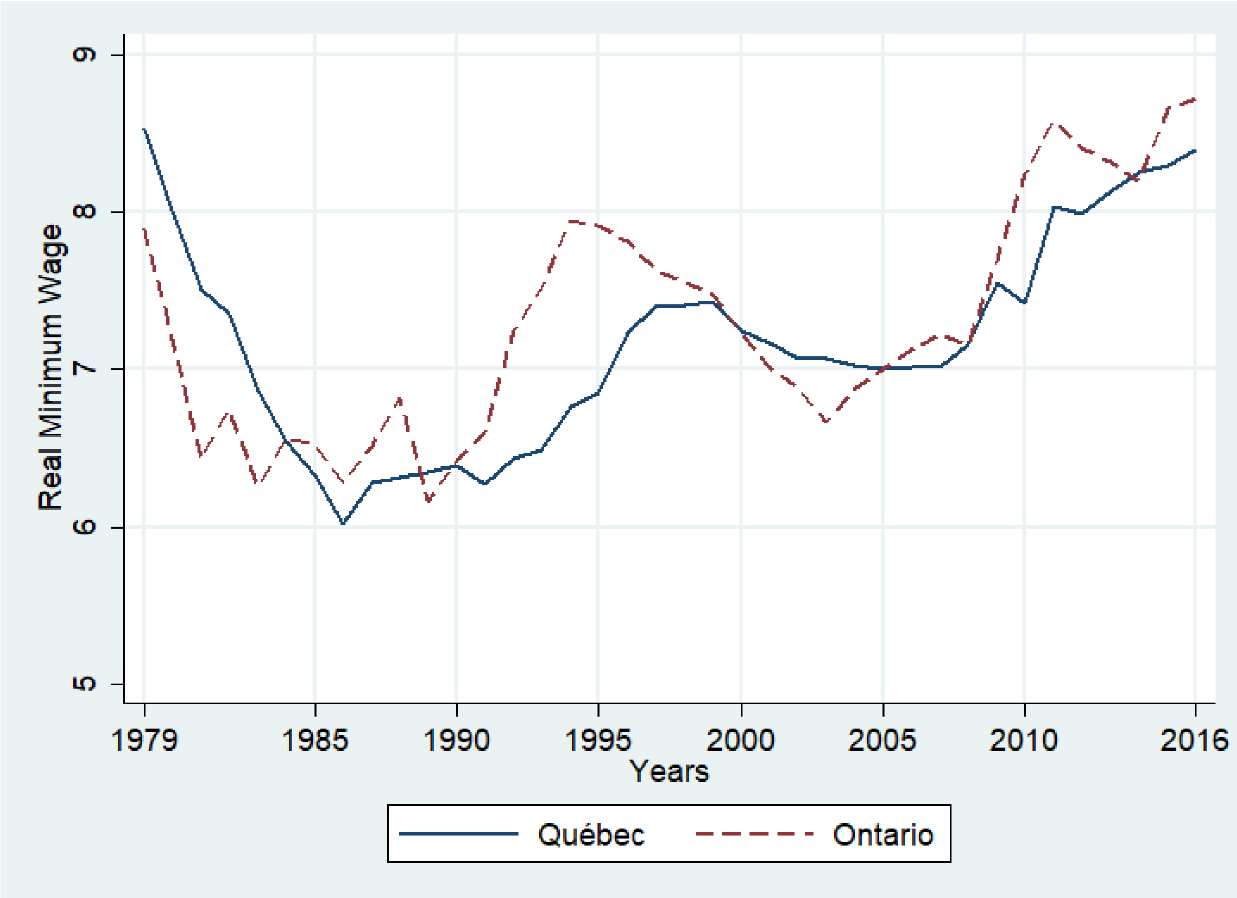
Notes: At-risk is defined as low-skilled (high school education or less) working individuals whose wage is no more than 10% higher than the current minimum wage in the individual's province of residence as of March of each year. Because of data on wages in the LFS are only available from 1997 onwards, the figure is constructed from 1997 to 2016.

Figure 3. Real minimum wage, Eastern Provinces, 1979 – 2016



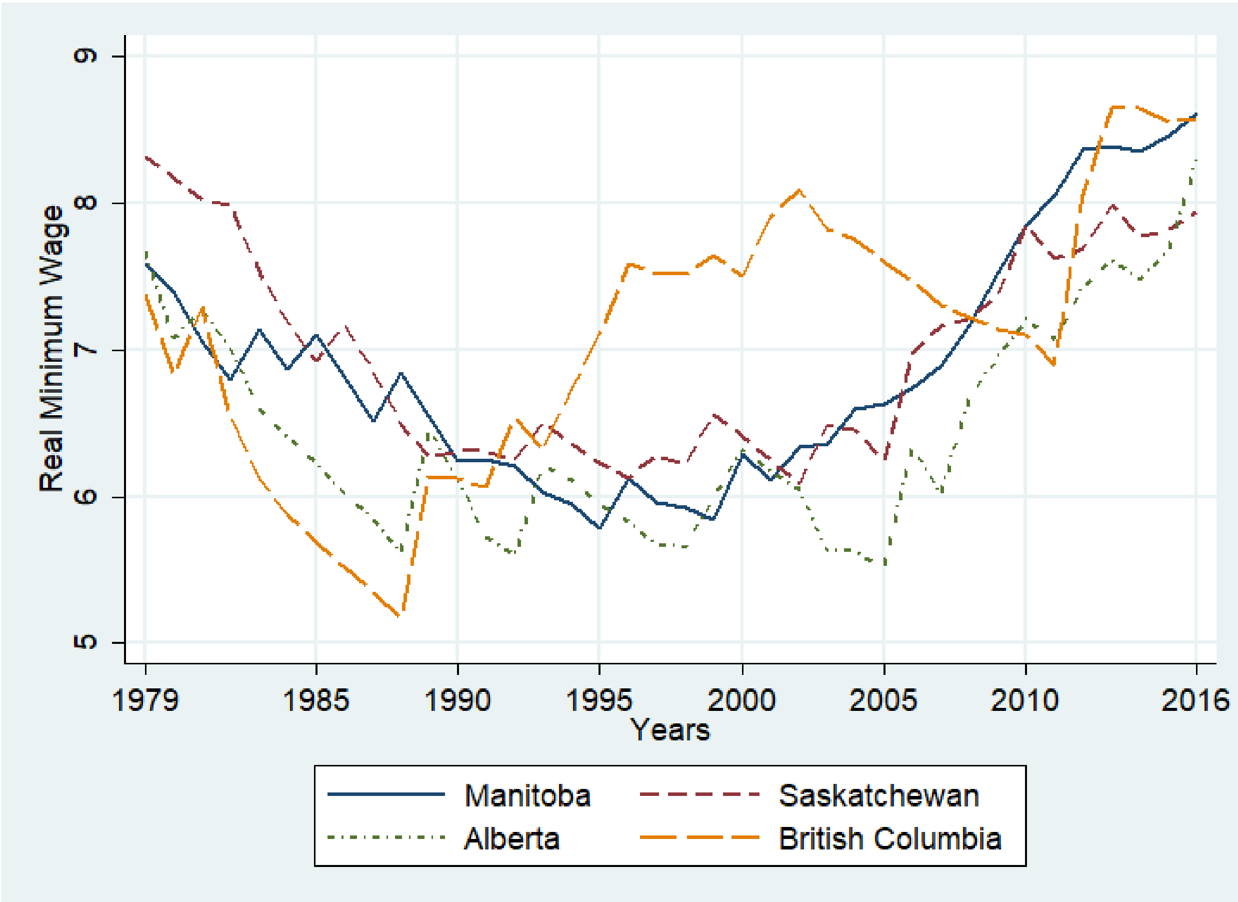
Notes: For ease of presentation, the real minimum wage is computed using March data only.

Figure 4. Real minimum wage, Central Provinces, 1979 – 2016



Notes: For ease of presentation, the real minimum wage is computed using March data only.

Figure 5. Real minimum wage, Western Provinces, 1979 – 2016



Notes: For ease of presentation, the real minimum wage is computed using March data only.

Table 1. OLS regression results for teenagers

Explanatory Variables	(1)	(2)	(3)
Log (real min. wage)	-0.1298	-0.0692	-0.1323**
	(0.1221)	(0.2031)	(0.0457)
Time fixed effect	No	Yes	Yes
Province fixed effect	No	No	Yes
Constant	0.6575	0.5350	0.6667
	(0.2493)	(0.3941)	(0.0910)
R-Squared	0.0472	0.2288	0.7156
Observations	760	760	760

Notes: Dependent variable is the teenage employment rate. All regressions are estimated using OLS with clustered standard errors in brackets. All regressions are weighted where the weights are constructed using equation (A3) in Appendix A. *is 10% significance. **is 5% significance. ***is 1% significance.

Table 2. OLS regression results for teenagers, with lagged real minimum wage terms

Explanatory Variables	(1)	(2)	(3)	(4)	(5)
Log (real min. wage)	-0.1322**	-0.0021	0.0176	0.0035	0.0070
	(0.0457)	(0.0530)	(0.0565)	(0.0559)	(0.0775)
Log (real min. wage) lagged by 6 months		-0.1420*	-0.0300	0.0010	-0.0060
		(0.0764)	(0.0775)	(0.0758)	(0.0946)
Log (real min. wage) lagged by 12 months			-0.1432***	-0.0377**	-0.0215
			(0.0212)	(0.0163)	(0.0172)
Log (real min. wage) lagged by 18 months				-0.1340***	-0.0887**
				(0.0296)	(0.0358)
Log (real min. wage) lagged by 24 months					-0.0584
					(0.0369)
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes
Constant	0.6667	0.6887	0.7117	0.7357	0.7369
	(0.0910)	(0.0958)	(0.0908)	(0.0884)	(0.0820)
R-Squared	0.7156	0.7170	0.7163	0.7165	0.7135
Observations	760	750	740	730	720

Notes: Dependent variable is the teenage employment rate. All regressions are estimated using OLS with clustered standard errors in brackets. All regressions are weighted where the weights are constructed using equation (A3) in Appendix A. *is 10% significance. **is 5% significance. ***is 1% significance.

Table 3. OLS regression results for teenagers, by gender

Explanatory Variables	Males (1)	Females (2)	Males (3)	Females (4)	Males (5)	Females (6)
Log (real min. wage)	-0.1367**	-0.1267**	0.0126	-0.0172	0.0317	0.0030
	(0.0518)	(0.0455)	(0.0501)	(0.0584)	(0.0509)	(0.0644)
Log (real min. wage) lagged by 6 months			-0.1637*	-0.1184	-0.0588	0.0016
			(0.0794)	(0.0756)	(0.0966)	(0.0630)
Log (real min. wage) lagged by 12 months					-0.1345***	-0.1518***
					(0.0367)	(0.0264)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.6449	0.6877	0.6719	0.7044	0.6938	0.7286
	(0.1019)	(0.0892)	(0.1058)	(0.0952)	(0.0998)	(0.0911)
R-Squared	0.7457	0.6478	0.7491	0.6471	0.7465	0.6469
Observations	760	760	750	750	740	740

Notes: The dependent variable for columns (1), (3) and (5) is the male teenage employment rate, while the dependent variable for columns (2), (4) and (6) is the female teenage employment rate. All regressions are estimated using OLS with clustered standard errors in brackets. All regressions are weighted where the weights are constructed for each gender group using equation (A3) in Appendix A. *is 10% significance. **is 5% significance.***is 1% significance.

Table 4. OLS regression results for young adults, with lagged real minimum wage terms

Explanatory Variables	(1)	(2)	(3)
Log (real min. wage)	-0.0611	0.0501	0.0576**
	(0.0349)	(0.0282)	(0.0286)
Log (real min. wage) lagged by 6 months		-0.1239**	-0.0977**
		(0.0489)	(0.0428)
Log (real min. wage) lagged by 12 months			-0.0326
			(0.0236)
Time fixed effect	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes
Constant	0.7760	0.8003	0.7982
	(0.0725)	(0.0830)	(0.0853)
R-Squared	0.7066	0.7086	0.7059
Observations	760	750	740

Notes: Dependent variable is the employment rate for young adults (i.e. 20 – 24 year olds). All regressions are estimated using OLS with clustered standard errors in brackets. All regressions are weighted where the weights are constructed using equation (A3) in Appendix A. *is 10% significance. **is 5% significance. ***is 1% significance.

Table 5. OLS regression results for young adults, by gender

Explanatory Variables	Males (1)	Females (2)	Males (3)	Females (4)	Males (5)	Females (6)
Log (real min. wage)	-0.0750*	-0.0472	0.0733	0.0249	0.0796*	0.0336
	(0.0339)	(0.0397)	(0.0405)	(0.0196)	(0.0402)	(0.0200)
Log (real min. wage) lagged by 6 months			-0.1641**	-0.0815	-0.1366**	-0.0579
			(0.0544)	(0.0454)	(0.0538)	(0.0368)
Log (real min. wage) lagged by 12 months					-0.0333	-0.0302
					(0.0205)	(0.0300)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.8179	0.7336	0.8480	0.7515	0.8473	0.7472
	(0.0747)	(0.0798)	(0.0831)	(0.0906)	(0.8473)	(0.0928)
R-Squared	0.7586	0.5658	0.7607	0.5665	0.7537	0.5678
Observations	760	760	750	750	740	740

Notes: The dependent variable for columns (1), (3) and (5) is the male employment rate for young adults, while the dependent variable for columns (2), (4) and (6) is the female employment rate for young adults. All regressions are estimated using OLS with clustered standard errors in brackets. All regressions are weighted where the weights are constructed for each gender group using equation (A3) in Appendix A. *is 10% significance. **is 5% significance.***is 1% significance.

Table 6. Robustness check

Explanatory Variables	Base, from 1997 onwards (1)	Log (NMW/AMW) (2)	Base, all years (3)	Political IV (4)	Exclusion of recessionary years (5)
Log (real min. wage)	-0.1330	-0.2001	-0.1323**	-0.3490	-0.1996*
	(0.1066)	(0.1279)	(0.0457)	(0.2649)	(0.0975)
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes
Constant	0.6449	0.1793	0.6667	1.0908	0.7866
	(0.2007)	(0.1322)	(0.0910)	(0.5181)	(0.1866)
R-Squared	0.7068	0.7268	0.7156	0.6869	0.6929
Observations	400	400	760	760	430

Notes: In columns (1), (3), (4) and (5), dependent variable is the teenage employment rate. In column (2), the log of the ratio of the nominal minimum wage (NMW) to the average manufactory wage (AMW) is used instead of the log of the real minimum wage. In column (4), political IV (i.e. right-wing and left-wing) is used as an instrument for the real minimum wage. In column (5), the time periods are dropped from the sample where the overall unemployment rate is over 8%. All regressions are estimated using OLS with clustered standard errors in brackets. All regressions are weighted where the weights are constructed using equation (A3) in Appendix A. *is 10% significance. **is 5% significance. ***is 1% significance.

Table 7. Robustness check, weights and FGLS

Explanatory Variables	Base	Weights			FGLS	
		Weight 1	Weight 2	Un-weighted	AR(1)	AR(2)
	(1)	(2)	(3)	(4)	(5)	(6)
Log (real min. wage)	-0.1323**	-0.1357**	-0.1357**	-0.0034	-0.0231	0.0037
	(0.0457)	(0.0522)	(0.0547)	(0.0792)	(0.0377)	(0.0336)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.6667	0.6725	0.6774	0.4161	0.1339	0.0342
	(0.0910)	(0.1039)	(0.1106)	(0.1527)	(0.0270)	(0.0061)
R-Squared	0.7156	0.7117	0.7452	0.8022	0.5713	0.4845
Observations	760	760	760	760	750	740

Notes: Dependent variable is the teenage employment rate. The regressions in columns (1) through (4) are estimated using OLS with clustered standard errors in brackets. Columns (5) and (6) are estimated using FGLS with AR(1) and AR(2) models, respectively. The regressions are weighted using the different weights discussed in Appendix A, except column (4) where weights are not used. In columns (1), (5), and (6), the preferred weights, computed using equation (A3), are used. In column (2) and (3), the weights are constructed using equations (A2) and (A4), respectively. *is 10% significance. **is 5% significance. ***is 1% significance.