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Going back to school takes time: evidence from a negative trade shock

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Abstract

We estimate the impact of a negative trade shock on labour market outcomes and educational choices of workers. We exploit the Canadian lumber exports crisis beginning in 2007 in a quasi-experimental design. We find that the employment probability of forestry industry workers decreased by 4.1 percentage points following the crisis relative to other workers in comparable industries. While one would expect younger forestry workers to return to school in such circumstances, we find that in the first two years following the crisis, unemployed workers did not go back to school. But going back to school takes time, and after 3 to 4 years, we find that education enrollment increases by 2.5 percentage points (p=0.083). This confirms the idea that adjustments towards an increase in education enrollment are gradual, as it is easier to drop out than to enroll. In time of crisis, facilitating a return to education might be a valuable policy intervention.

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1 Introduction

Investing in one's human capital may entail substantial opportunity costs, among which foregone labor income. When this opportunity cost decreases, standard economic models predict that individuals will increase the scope of their investment in education. Estimating the effect of variations in opportunity costs on investments in human capital is an important task, since the long-run effects on individuals' incomes and economic outcomes can be substantial.

Business cycles naturally affect the opportunity cost to invest in education. In periods of recessions, one expects students to increase their investment in human capital, either at the intensive margin — extending the duration of studies or reorienting one's field of study — or at the extensive margin by going back to school. Blom et al. (2015) estimates the impact of the business cycle on the program choice of college students. They find that in periods of recessions, students tend to enroll in programs that have higher expected market returns. Charles et al. (2018) show that the housing boom during the 2000s reduced college attendance among young adults and that this decline was not completely reversed severals years later, providing suggestive evidence that this positive shock may have permanently affected college education in the United States.

In this paper, we focus on the effect of a negative trade shock on workers labour market outcome and educational choices. We exploit the Canadian lumber exports crisis beginning in 2007 in a quasi-experimental design. Between 2007 and 2009, the subprime mortgage crisis caused a substantial slowdown in the U.S. housing market, including in the construction sector. This downturn helped to amplify the Great Recession, a global financial crisis that lasted from the fourth quarter of 2007 to the second quarter of 2009 in the United States. That shock translated into a substantial drop in American imports of Canadian lumber. We use this shock as a natural experiment to estimate the propensity of forestry workers to work part-time vs full-time, become unemployed or inactive, and return to school.

We offer several contributions to the literature. First, we provide empirical evidence on the impacts of a negative labour demand shocks on workers' occupations following the shock. We look at both labour market outcomes and educational choice. To our knowledge, the literature investigating the impact of labour demand shocks on educational choices has mainly focused on positive labour demand shocks. Second, we show that outcome adjustments may vary with respect to time. More specifically, we find that labour market outcomes adjustments materializes rapidly, while educational choices take more time. This directly contributes to our understanding of individuals' situations with respect to occupational choices following a negative labour demand shock. It also suggests that policies could be designed to help workers who wish to return to school to adjust more rapidly. From an administrative standpoint, it is easier to dropout of school than to enroll. Enrollment processes could be streamlined to encourage individuals to invest in their education.

Our main results suggest that the probability of being implored forestry industry decreased by 4.1 percentage points (p.p.) (p=0.023), in addition to an overall decrease of 8.6 percentage points (p=0.000) for workers in the primary and secondary sector. The shock on forestry workers was therefore 1.5 times larger to the overall shock on comparable workers. This more severe shock translated into a higher probability of being unemployed (2.4 p.p., p=0.032) or inactive (1.6 p.p., p=0.237). While one would expect younger forestry workers to return to school in such circumstances, we find that in the first two years following the crisis, these additional unemployed or inactive workers did not go back to school. But, going back to school takes time, and after 3 to 4 years, we find that education enrollment increases by 2.5 percentage points (p=0.083). This confirms the idea that adjustments towards an increase in education enrollment are gradual, as it is easier to drop out than to enroll.

The paper is structured as follows. Section 2 provides an outlook of the recent literature. In section 3 present the historical context of the trade shock suffered by the Canadian forest industry around 2007. Then, we discuss the data and our methodology in section 4 before presenting the results in section 5.

2 Literature

Several papers have studied changes in workers' activity that came along with variations in the price of natural resources. We first present some of the papers that have focused mainly on labour market outcomes, and then present papers that have also look at educational choices.

Davis & Haltiwanger (2001) studied the impact of oil shocks on jobs. Using U.S. data from the Longitudinal Research Database from 1978 to 1988, they estimated a VAR model to measure the impact of oil price variations on job growth in the manufacturing sector, to conclude that oil price shocks were responsible for 20 to 25% of job growth variance. They also document an asymmetric effect: for a shock of the same size, more jobs were lost in a bust than created in a boom. Black et al. (2005a) also find evidence of asymmetry. They studied the impact of the oil crises in the 1970s and 1980s on employment in the coal industry by estimating the differential impacts between companies serving local markets and those producing for export. They found a 6.8% increase in employment during the boom period, and a 7.8% decrease during the bust period. They also estimated that, during the boom periods, 0.174 jobs in local industry were created for every job gained in the coal industry, but 0.349 local jobs were lost during the bust periods. More recently, Marchand (2012) used a similar methodology on Canadian data using variations in oil prices between 1971 and 2006. He found that 0.9 local jobs were created for each oil sector job created, and that local job numbers stagnated, rather than decreased, during recession periods.

In addition to investigating labour market dynamics, two recent articles have looked at trade shocks of the same nature as the one we are studying. Ebenstein et al. (2014) estimated the impact of growth in international trade on the real salaries of American workers. Using two-stage least squares and data from the Current Population Survey Merged Outgoing Rotation Groups[1] they estimated that job changes due to globalization led to real

[1]That is, the Current Population Survey combined with industry-level data and Bureau of Economic

salary reductions of 12 to 17 percentage points.They created a dichotomous measure of their instrument to differentiate occupational switching owing to globalization from other occupational changes. Their results indicate that trade shocks can lead individuals working in the affected industries to change jobs. ancd D. Dorn et al. (2014) studied the impact of increases in imports from China on the American labour market. They used data from the Annual Employee-Employer file (EE) contained in the Social Security Administration's Master Earnings File (MEF) and also employ the two-stage least squares method. They use the rate of penetration of Chinese imports in Western countries other than the United States to instrument the rate of penetration of Chinese imports in the United States. They found that the opening of China had a negative impact on the cumulative wages, cumulative number of hours worked and annual work income of individuals initially working in industries more directly exposed to Chinese competition. Those workers were more likely to change employer or industry, but not to move to a new region. Using a different sample, ancd D. Dorn et al. (2014) came to a conclusion similar to that of Ebenstein et al. (2014), confirming that trade shocks have a significant impact on the labour market.

Chan et al. (2011) made another contribution to our understanding of negative trade shocks on labour demand by describing the characteristics of individuals who lost their jobs during the last three recessions, namely, those in 1980, 1990 and 2008. Compared with the previous recessions, Canadians who lost their jobs during that of 2008 were on average older, had more seniority, were more highly educated and were less likely to come from the manufacturing sector. Yet, in the last recession, individuals who were most likely to become unemployed were man aged 15 to 24, with at most two years of seniority and no university degree, working in the primary sector or in construction, and residing in a Maritime province. They also found that there were fewer jobs lost from recession to recession and that, on average, in the most recent recession, salaries dropped very little. However, this small variation masks great heterogeneity. A quarter of the workers saw their weekly salaries reduced by 23%, while a similar proportion experienced an average salary increase of 18%.

Analysis data on American multinationals.

Nolan & Voitchovsky (2016) also measured the impact of a financial shock on job losses by wage quintile in Ireland following the Great Recession. They find that the shock had little impact on individuals in the two highest quintiles and that those in the three lowest quintiles were more likely to become unemployed.

The recent literature clearly shows the importance of studying the impact of trade shocks, natural resource prices shocks, and of the business cycle's effect on employment and unemployment, but less is known on the impact of these shocks on educational choices. Black et al. (2005b) examined the impacts of salary increases in jobs requiring little human capital on enrollment in education in the United States. They used the strong growth in the coal industry following the oil shocks. Their data was structured around coal reserves per county, which were considered to determine which counties were likely to benefit from increases in coal prices. They estimated that a 10% increase in income per inhabitant in a county where the coal industry was active led to a 5 to 7% decrease in the rate of high school enrollment. They also noted that a 10% increase in the average income per inhabitant seemed to lead to an over 10% increase in dropouts' prospective income. This is in accordance with the hypothesis underlying classical human capital models, which indicate that individuals cease going to school if their expected wage is greater if they drop out rather than complete their diploma (Mincer, 1958; Becker, 1964). Therefore, an increase in the salaries of low-skilled workers leads to a drop in school enrollment.

Cascio & Narayan (2015) estimated the impact of a positive labour demand shock on dropout rate instead of education enrollment rate. They used the discovery and spread of hydraulic fracturing technology as a positive labour demand shock. The technology favors the mining, construction and road transportation sectors, in which most workers are low skilled and male. The spread of this technology has had an impact on the expected wage of low-skilled workers, but no significant impact on the expected wage of highly educated workers. They estimated that a one percentage point increase in male employment in the oil and gas extraction industry increases the high school dropout rate of young men by

1.5 to 2.5 percentage points. Although Black et al. (2005b) and Cascio & Narayan (2015) did not use the same dependant variable (school enrollment rate vs. dropout rate), or the same explanatory variable of interest (income per capita vs. rate of employment in the coal industry), and they measured their results differently (percentage vs. percentage points), they both found that an increase in the expected wages of low-skilled workers had a negative impact on high school attendance.

Using LFS data and the oil price increase from 2001 to 2008, Chan et al. (2015) estimated that an increase in the expected wage of low-skilled workers had no impact on high school enrollment, but that it affected post-secondary enrollment. According to their results, a 10% increase in after-tax real wages led to a 2.6 to 3.5 percentage point reduction in post-secondary enrollment, as well as a 1.4 to 1.9 percentage point decrease in young men who were neither employed nor enrolled in education. The combined effects resulted in a 3.5 to 4.5 percentage point increase in young men with jobs. They found no significant impact on young people's high school enrollment. The hypothesis advanced to explain this result is that young people's inclination to make new educational choices following variations in real wages changed over time. However, this does not explain the difference with Cascio & Narayan (2015)'s findings, which covered the same period as those of Chan et al. (2015).

Finally, Carillo (ming) studies the effect of coffee prices on educational attainment of children and on long-run economic outcomes. He uses variations in the price of coffee and estimates their effect on educational attainment and, in the long run, on incomes. He concludes that young individuals tend to leave school during temporary booms and that such decisions come at the expense of substantial future income. This result is interpreted as indirect evidence of present-bias. In the same vein, Atkin (2016) documents that the arrival of formal jobs during years of substantial expansions in export-manufacturing industries in Mexico led to reduced school attendance and lower educational attainment, although it had no overall impact on labor market income.

To our knowledge, the literature looking at educational choices and labour supply shocks has focused on positive labour demand shocks. In this paper we use data from a similar time frame, but we exploit a negative shock instead and find that educational choices may be adjusting less quickly to negative shocks.

3 Historical shock in the forestry industry and institutional context

The negative shock experienced in the Canadian forestry industry around 2007 was dramatic. Figure 1 reports the market value of sales of manufactured wood products for the three largest Canadian provinces between 1992 et 2015. The drop in the value of sales around 2007 is strikingly sharp. Within the course of one year, the value of shipments declined by 87% in British Columbia, by 74% in Ontario, and by 69% in Quebec. The decrease in Canadian lumber exports was caused by a drop in American demand. Between 2005 and 2010, the number of new houses built in the United States shrank drastically, going from over 2 million down to around 587,000, causing an equally significant decline in Canadian lumber exports (Germain, 2015).[2] Figure 3 shows the evolution of total sales of wood products for the tree largest Canadian provinces. The sharp decline in all all three of them, between 2007 and 2008, is starking.

Between 2004 and 2009, the annual value of Canadian production dropped from by 65.1%, from $16.9 billion to $5.9 billion. The value of annual exports to the United States declined by 72.7%, from $9.6 billion down to $2.6 billion. Moreover, between 2006 and 2010, the volume of annual softwood lumber exports to the United States slid from 47.27 down to 21.8 billion cubic meters, a 55% reduction over 4 years (Figure 2). Notably, around 60% of the production was destined for the American market in 2006, compared with only 41% in 2010.

[2] "Forestry industry" refers to forestry, logging and wood processing. It corresponds to North American Industry Classification System (NAICS 2007) codes 1131, 1132, 1133, 1153, 3211, 3212, 3219, 3221 and 3222.

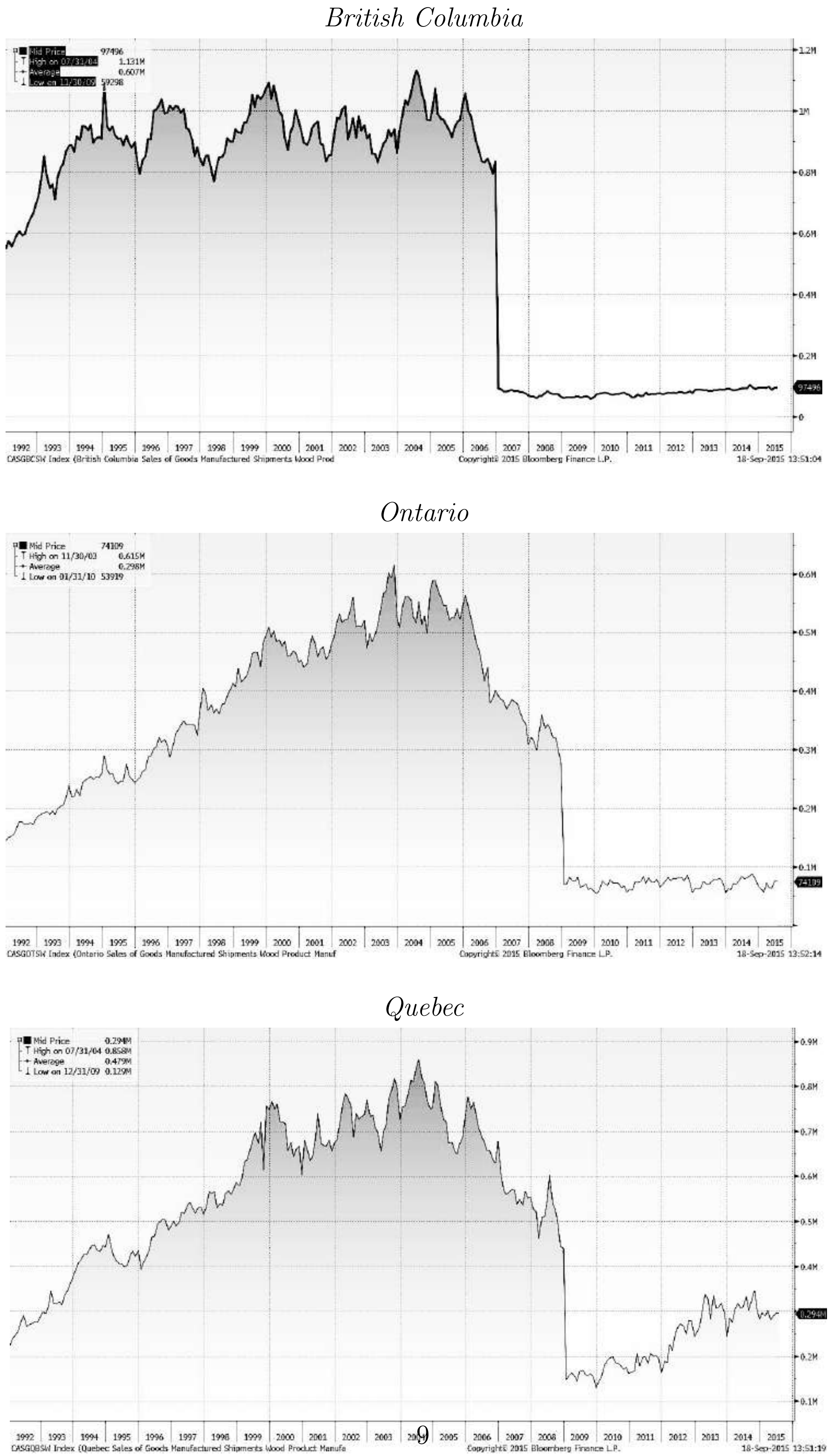

Figure 1: Market value of Sales of Manufactured Wood Products (Bloomberg, L.P., 2017, Canadian lumber exportation, January 2004 to December 2011. Monthly values, in thousands of U.S. Dollars. Consulted on September 18, 2015 using the Bloomberg database.)

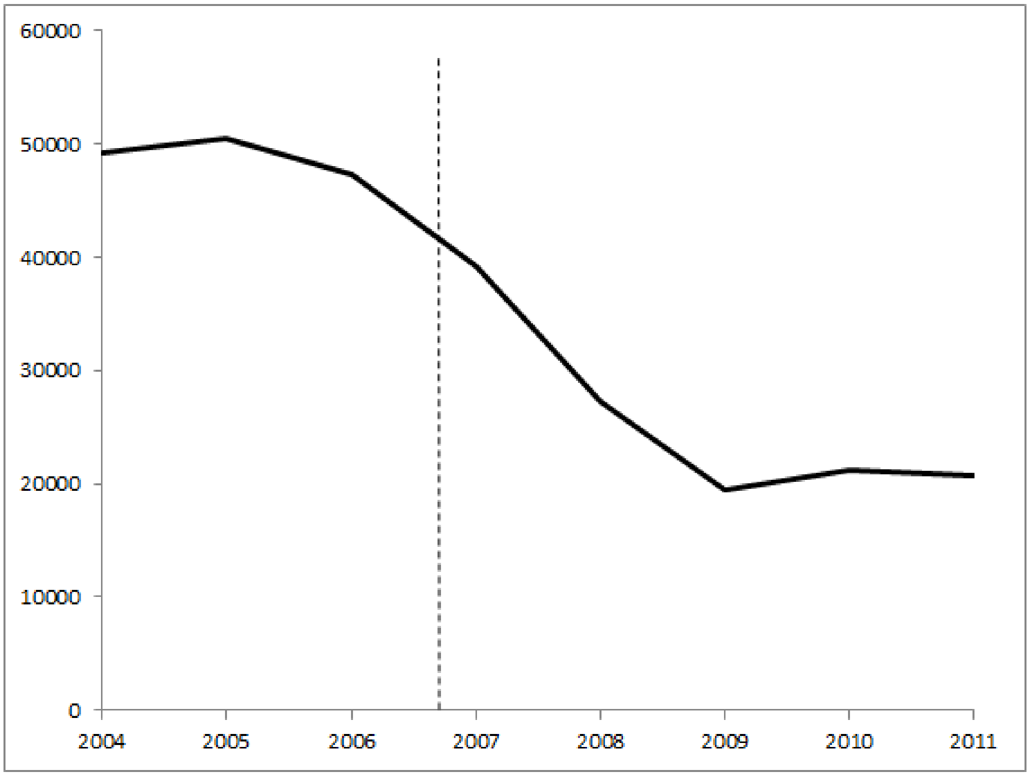

Figure 2: Annual exportation of Canadian lumber to the United States, 2004-2011, in thousands of cubic metres. (Bloomberg, L.P., 2017, Canadian lumber exportation, January 2004 to December 2011. Consulted on May 26, 2017 using the Bloomberg database.)

During the same period, Canadian softwood lumber production decreased from 79.17 to 51.92 million cubic meters, a 35% reduction over 4 years (Figure 3), and approximately 47.7% of sawmill jobs were lost. Moreover, the forestry industry's annual share of the manufacturing sector went from 2.9% to 1.2%. While the largest companies were able to find new markets to survive the shock, many smaller enterprises had to close, including some that were the economic hearts of their regions. In some 200 rural municipalities, the forestry industry accounts for over 50% of the economy (Germain, 2015).[3]

[3]The 2007 crisis was not the first problem that the Canadian forestry industry has had to deal with. In 2002, the softwood lumber dispute led to the imposition of countervailing duty tariffs of 18.73% and anti-dumping duties of 8.43% on Canadian wood exported to the United States, totalling average duties of 27.22%. Yet, previously, no duties had been charged (Carmody, 2006). In 2004, over 81% of annual Canadian wood exports were to the United States, in particular for the construction market.

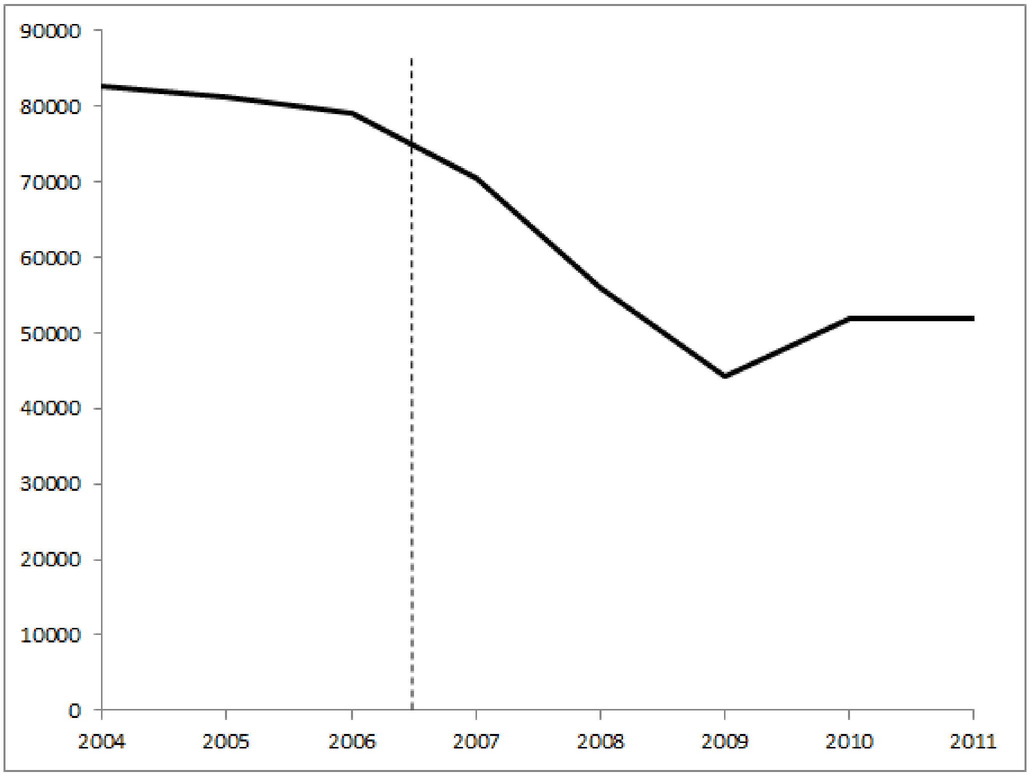

Figure 3: Annual production of Canadian lumber, 2004-2011, in thousands of cubic metres. (Bloomberg, L.P., 2017, Canadian lumber production, January 2004 to December 2011. Consulted on May 26, 2017 using the Bloomberg database.)

Clearly the shock experienced in Canada was major and mainly caused by external factors. We use this dramatic exogenous drop in Canadian lumber production in a quasi-experimental framework.

4 Data and estimation strategy

Our data comes from Statistics Canada's Survey of Labour and Income Dynamics (SLID). SLID participants are selected from the monthly Labour Force Survey (LFS) and therefore share the same survey design.[4] SLID participants are followed for six years, with a new

[4]For more information on the LFS design, refer to the Statistics Canada Publication Methodology of the Canadian Labour Force Survey.

panel starting every three years. Each panel includes, on average, 17,000 households. For this study, we use the 2005 to 2010 panel, which covers the period during which the shock took place in the forestry sector. The SLID's usefulness lies in the fact that it contains a series of variables on human capital, education, income, housing, mobility as well as a number of other socio-demographic characteristics. Data on jobs and education over six years allow us to track the occupations of each individual over the period.

The SLID provides detailed information not only to the individual's main occupation, but also on any other occupation that a person may hold on a monthly basis. Since work is seasonal in the forestry sector, this level of detail allows us to accurately identify all individuals working in the forestry sector whether it be their main occupation or not.

4.1 Methodology

Considering the amplitude of the decreases in exports, production and sales following the subprime mortgage crisis (Figures 2 to 1), we use a difference-in-differences strategy (Blundell & Dias, 2009) to measure the effect of the shock on workers in the forestry industry. We use a simple model with two periods, $t \in \{b, a\}$, *b*efore and *a*fter treatment, respectively. Ideally, we would observe each individual in both states, treated (1) and non-treated (0), at the same time. However, since an individual cannot be in two states simultaneously, we instead compare the treated individuals with comparable individuals who are not treated. Our treated group includes individuals working mainly in the forestry industry prior to the shock, that is, before 2007. The control group includes all other secondary and/or primary sector workers prior to 2007. Unlike most studies on the topic, which have been done using aggregate data at the regional level, we use individual-level data since we are able to accurately identify the occupation of the individual before the shock.

Given Figures 2 and 3, we consider that the shock occurred in January 2007. We estimate the following model:

$$y_{ijt} = \alpha + \theta d_i + \delta I_{t \geqslant 2007} + \gamma d_i I_{t \geqslant 2007} + \beta \mathbf{X}_{it} + \phi_j + \upsilon_i + \epsilon_{ijt}, \tag{1}$$

where y_{ijt} is the occupation of individual i observed in month j of period t. Our dependent variable, y_{ijt}, is a binary variable, one for each of our four occupation variables: employed, unemployed, not in the labour force and enrolled in education. The first three occupations are mutually exclusive. However, an individual can be a student and be employed, unemployed or not in the labour force. We describe the construction and properties of the sample below. In subsection 4.3, we describe the construction of the occupation variables. We represent occupations using binary variables, an approach also used by Chan et al. (2015) in a similar framework.

The indicator variable $I_{t \geqslant 2007}$ marks the timing of the shock and therefore takes the value one when the individual is observed after the shock, and zero otherwise. Variable d_i identifies the treatment status of individual i. It takes the value one if the individual worked in the forestry industry for at least six months per year prior to the shock, in both 2005 and 2006, and zero otherwise. This ensures that we capture individuals who were actively participating to the forestry industry prior to the shock. We test the sensitivity of our results to this assumption in section B.1. Thus, α is the constant, δ captured the average effect of the shock on y for all workers irrespective of their industry, θ captured the average effect of working in the forestry industry, and γ, the average effect of the shock specific to individuals working in the forestry industry. γ is our main parameter of interest, it corresponds to the difference-in-differences estimator.[5]

To ensure that our results are not due to changes in characteristics of the individuals, we also add individual and regional characteristics. Vector $\mathbf{X}$ contains the following individual control variables: age, age-squared, gender, province of residence indicators, a rural indicator, education level, an immigration indicator, membership in a visible minority, mother tongue

[5] Although the dependent variable, y_{it}, is binary, we used a linear probability model to estimate the impact of the shock on forestry industry workers' occupations. Our results are robust to using of a logit or probit model.

(English, French or other), marital status, and whether or not the individual had a disability wholly or partly preventing him or her from working. Given that some forestry industry jobs are seasonal, we also include month-fixed effects (ϕ_j). We use a random effect υ_i model at the individual level, as opposed to a fixed effect model, to recognize the fact that forestry industry workers may have unobservable characteristics that are specific to them and that influence their choice of occupation. For example, they may be less geographically mobile. However, it should be noted that in practice, the coefficient of interest γ was practically identical when using a fixed effect model. ϵ_{ijt} is the error term. Finally, we estimate cluster-robust standard errors at the individual level.

The DID analysis isolates the effect of a treatment under certain conditions. First, for the γ estimator to be unbiased, the two groups must share a common trend over time. We test this condition in section 5.1. Second, the treatment should only affect those who are treated. In reality, the crisis had an impact on many industries, so the effect that we are measuring is the supplementary effect specific to forestry industry workers, that is, the effect of the crisis above and beyond the effect experienced by everyone else.

4.2 Sample and assignment to treatment

For our base sample, we select individuals who were of working age (16-65 years old) in 2005, resided in one of Canada's ten provinces, filed income tax returns and were in the database before and after 2007, that is, the year of the shock. Only primary and secondary sector workers who worked for at least six months in 2005 and 2006 were used. Since our dependent variables capture occupations, we exclude individuals whose occupations could not be identified because they did not answer the relevant survey questions. They accounted for less than 0.001% of our observations. Our final sample contains over 220,000 observations.

We divided the sample into two groups: the "treated" and "non-treated". As mentioned above, an individual is assigned to the treated group if he or she held a job in the forestry industry for at least six months in 2005 and six months in 2006. Since forestry industry jobs are often seasonal (see Appendix A), this restriction is necessary to make sure that the individuals in our treated group did indeed work in the forestry industry before the shock. Table 1 shows the socio-demographic characteristics of the complete sample and of the two groups comprising it.

Table 1 shows that there is a slightly greater proportion of men in the forestry industry than in other primary and secondary sector industries, but even there, the fraction of men is high (0.853 in the forestry industry relative to 0.745 elsewhere). The average age and marital status of both groups are comparable. Relative to the treated group, the non-treated include a greater proportion of immigrants, visible minorities and individuals whose mother tongue is neither French nor English. Since we use individual fixed-effects, differences in occupational choices linked with fixed characteristics are controlled for. We also observe that most of our individuals are located in Ontario, Québec and British Columbia, the three largest provinces in respective order. Individuals working in the forestry industry are also mainly located in these three provinces, but the largest fraction is in Québec, followed by Ontario and British Columbia. Individuals in the treated group are mainly located in Québec (0.37), where there is a strong forestry industry, while individuals in the control group are mainly in Ontario (0.40), which has Canada's largest economy. Moreover, the secondary sector is more prevalent in the treated group than in the control group: 0.74 versus 0.52. We note that the average income was slightly lower for individuals whose main occupation was in the forestry industry. Finally, we observe that individuals in the treated group have a lower level of education: 20.9% have less than a secondary diploma and 33.3% only have a secondary diploma, relative to 16.7% and 28.4% in the control group.

Table 1: Descriptive statistics by treatment status

Characteristics	(1) Sample	(2) Non-treated	(3) Treated
Age	43.728	43.724	43.770
Gender (male=1)	0.782	0.776	0.853
Marital status			
Couple	0.743	0.745	0.729
Single	0.257	0.255	0.271
Immigrant	0.186	0.196	0.079
Visible minority	0.129	0.136	0.046
Mother tongue			
English	0.566	0.573	0.485
French	0.244	0.228	0.419
Other	0.190	0.199	0.096
Level of education			
Less than secondary	0.170	0.167	0.209
Secondary	0.288	0.284	0.333
Postsecondary	0.380	0.382	0.365
University	0.132	0.137	0.075
Undeclared	0.030	0.031	0.018
Province of residence			
Newfoundland and Labrador	0.016	0.017	0.013
Prince Edward Island	0.006	0.007	0.002
Nova Scotia	0.027	0.026	0.036
New Brunswick	0.025	0.023	0.049
Quebec	0.247	0.236	0.372
Ontario	0.384	0.395	0.264
Manitoba	0.038	0.040	0.021
Saskatchewan	0.033	0.035	0.013
Alberta	0.122	0.129	0.042
British Columbia	0.100	0.092	0.189
Modal industry sector i			
Primary	0.471	0.489	0.262
Secondary	0.533	0.515	0.738
Net after-tax income ($)	43,340	43,719	39,769
Disability	0.017	0.016	0.024
Weighted observations (thousands)	206,140	189,475	16,665
Months of participation in survey	64.127	64.000	65.573
Years of participation in survey	5.347	5.336	5.474

Note: The sample contains 220,171 unweighted observations for 3588 individuals. The number of annual observations is weighted and in thousands. "Months of participation" corresponds to the number of months that the individual answered the survey, and "Years of participation" to the number of years during which the individual was observed.

4.3 Occupations

An occupation was attributed to an individual in three stages. First, we identified the monthly employment status (worker, unemployed or not in the labour force). Second, we checked to see whether the individuals who were working were part-time or full-time. Third, we identified whether the individuals were enrolled in education, irrespective of their employment status.

In order to determine frequency of work on a monthly basis (full-time vs. part-time), we use a variable indicating whether the individual was working full-time or part-time for the entire year. Only individuals with the same employment status for 12 months are considered to have been working full-time. When frequency of work on a monthly basis is missing, we use the number of hours worked per month to determine the frequency of work. We define a person who has worked 130 hours or more during the month as having worked full-time, and a person who has worked less than 130 hours during the month as having worked part-time. Lastly, if the information is still missing, we use the number of hours worked per week. An individual who has worked 30 hours or more (less than 30 hours) per week is defined as full-time (part-time).[6]

Our observations also cover the choice of being enrolled in education, but that choice is non-exclusive with respect to the other occupations. We consider an individual as being a student for a given month if he or she was enrolled in secondary school, college (or CEGEP), university, business school or trade school during the month. As a result, we focus on four occupations, of which three are mutually exclusive (employed, unemployed and not in the labour force). We also estimate the impact of the shock on the probability of working full-time and the probability of working part-time.

Table 2 presents the percentage of monthly obervations per occupation for our entire sample (column 1) and for each group before and after the shock (columns 2 to 5). The difference-in-difference estimator without controls is presented in column 6. For the sample

[6] Chan et al. (2015) also suggested a model for analysing occupational choices. They generated five binary variables in relation to occupations: (1) being employed, (2) being enrolled in school, (3) being enrolled in university full-time, (4) being neither employed nor enrolled in school, and (5) being both employed and enrolled in school. Our method is strongly inspired by theirs. However, we make a distinction between being unemployed and not being in the labour force, and between being employed full-time and being employed part-time.

as a whole (column 1), we find that individuals in our sample were employed 90% of the time on a monthly basis, with 83% employed full-time and 5,6% employed part-time. The monthly labour force participation rate is high in part because individuals selected in our sample had to have worked at least six months a year in 2005 and 2006. As a results, our individuals were unemployed only 3.6% of the time, and inactive (not in the labour force) 6.1% of the time. Over our observation period, monthly enrollment in education was around 2.7%.

Table 2: Occupations by treatment status

		Non-treated		Treated		
	(1)	(2)	(3)	(4)	(5)	(6)
Categories	Sample	Before	After	Before	After	DD
Employed	0.903	0.968	0.874	0.970	0.830	-0.045
						(0.019)
						[0.016]
full-time	0.830	0.900	0.798	0.910	0.752	-0.056
						(0.024)
						[0.019]
part-time	0.056	0.053	0.057	0.042	0.070	0,024
						(0,015)
						[0,108]
Unemployed	0.036	0.017	0.043	0.014	0.066	0.025
						(0.011)
						[0.030]
Not in labor force	0.061	0.015	0.083	0.016	0.105	0.020
						(0.014)
						[0.159]
Enrolled in education	0.027	0.028	0.025	0.025	0.039	0.015
						(0.010)
						[0.147]
Weighted observations (thousands)	206,140	63,045	126,429	5,590	11,074	206,140

Note: $N = 220,171$. The number of monthly observations is weighted. This table presents the relative frequencies for each occupation in each sub-group. The occupations were defined on a monthly basis. The difference between "Employed" and the sum of "full-time" and "part-time" corresponds to the fraction of individuals whose work time could not be determined. Column 6 presents the OLS estimate of the treatment effect, with no control variable. For each dependent variable, we present the coefficient, cluster-robust standard errors at the individual level are presented. (between parentheses) and p-value (within brackets).

When we focus on columns 2 to 5, we note a similar pattern, especially prior to 2007. Statistics presented in columns 2 and 4 are very similar, suggesting that our control group is representative of our treated group. Comparing columns 2 to 3, and 4 to 5, we observe a strong drop in the percentage of individuals employed on a monthly basis after the shock in both the treated group and the control group. The difference is greater in the treated group, as can be seen from the DD estimator in column 6.[7] After the shock the treated group was subject to an additional drop of 4.5 percentage points in the percentage of individuals employed compared to the control group. This difference is highly significant (p-value=0.016). The sharp decrease derived mainly from a reduction in full-time employment, which shrank by over 5.6 percentage points. Some workers appear to have switched to part-time employment, but the effect is not statistically significant. Workers who lost their jobs became either unemployed (0.025, p-value=0.030) or left the labour force (0.020, p-value=0.159). On average, very few individuals decided to enroll in education following the shock (0.015, p-value=0.147).

5 Results

Table 3 presents our main results. Each line reports a different regression for each of our six occupations. Columns 1 and 4 present the estimated coefficient on the interaction term (γ) and on the dummy indicator post (δ). Each estimated model also includes the treatment variable, the control variables $\mathbf{X}$, the months fixed effects, and the individual random effects. Cluster-robust standard errors are presented in parentheses in columns 2 and 5. $P-$values are in columns 3 and 6. The coefficient γ corresponds to the average effect of the shock on forestry industry workers relative to workers in other sectors, and the coefficient δ measures the average effect of the shock on all of the workers in our sample, including forestry workers.

We observe that, following the shock, the probability of being employed on a monthly basis for treated individuals was 4.1 percentage points lower than that of other compara-

[7] The estimated equation is the following: $y_{it} = \alpha + \theta d_i + \delta I_{t \geqslant 2007} + \gamma d_i I_{t \geqslant 2007} + \epsilon_{it}$, where the difference-in-differences estimator is γ.

Table 3: Impact of the shock on employment and enrollment in education

Occupation	(1) Interaction (γ)	(2) s.e.	(3) p-value	(4) Post (δ)	(5) s.e.	(6) p-value	R^2
Work	-0.041	(0.018)	[0.023]	-0.086	(0.005)	[0.000]	0.094
full-time	-0.050	(0.022)	[0.022]	-0.091	(0.007)	[0.000]	0.105
part-time	0.022	(0.015)	[0.128]	0.002	(0.004)	[0.614]	0.034
Unemployed	0.024	(0.011)	[0.032]	0.028	(0.003)	[0.000]	0.016
Not in labor force	0.016	(0.014)	[0.237]	0.059	(0.004)	[0.000]	0.095
Enrolled in education	0.014	(0.011)	[0.172]	0.005	(0.003)	[0.085]	0.068

Note: N = 220,171. Each line presents the results of a different regression. In addition to the interaction term and the binary variable $I_{t \geqslant 2007}$, each regression includes the treatment variable, the control variables, the fixed effects (months), and the individual random effects. Cluster-robust standard errors at the individual level are presented.

ble workers, but all workers experienced a decline in employment of 8.6 percentage points. Forestry workers employment probability therefore declined by more than 12 percentage points overall. The additional decrease in employment in the forestry sector came essentially from a reduction in full-time work, that is, a specific reduction of 5 percentage points. Considering that the decline in the probability of being employed after the recession was steeper for full-time workers than for all workers, it is probable that some of them saw their work hours cut down to part-time. Although the treatment's effect on part-time employment seems positive, the effect is not significant. Overall, we observe that forestry industry workers were more heavily impacted by the crisis than workers in other similar industries between 2007 and 2010.

With a view to prescribing government action to help workers in times of crisis, it is important to understand which occupations they move toward. The workers turned mainly toward unemployment (2.4 percentage points) and some left the labour force (1.6 percentage points, not statistically significant). We must recall that the occupations "employed", "unemployed" and "not in the labour force" are mutually exclusive and complete. Educational enrollment's effect on the treated group is 1.4 percentage point, but it is not significant. Now looking at education enrollment, we do not find strong evidence that workers in general returned to education following the crisis, δ equals 0.5 p.p. (p=0.085). However, we find some weak evidence that forestry workers may have been more inclined to return to education, δ equals 1.4 p.p. but the effect is statistically not significant. As mentioned above, while most studies have focused on positive shocks on labour demand, we study the impact of a negative one. Black et al. (2005a) and Marchand (2012) showed that booms and busts may lead to labour market effects not only going in opposite directions, but also of different magnitudes. Our results, combined with those of previous studies on educational choices, are also compatible with the hypothesis that booms and busts my have asymmetric effects, but this time on educational choices.

To identify the industry of our workers, we had to observe their work pattern prior to the shock. The sample used in this analysis was based on workers working at least 6 months in both 2005 and 2006. Relaxing this assumption between 4 to 9 months does not change our main results. Table 8 shows that the number-of-months-of-employment constraint[8] has little impact on the coefficient of interest. For employment, the coefficient ranges between -0.05 and -0.041 (our main estimate). For education, the coefficient ranges between 0.012 and 0.014.

In sum, subsequent to the decrease in exports, the forestry industry suffered greater job losses than other primary and secondary sector industries. The impact, specific to the forestry industry on enrollment in education seems to have been modest but likely higher than for other workers. Educational choices may take time to materialized since one must first decide to go back to school, then apply, and then wait for the term to start. We explore the timing of educational choices below, but before doing so, we first present evidence of the common trend assumption.

[8] This is also valid if we expand the variation to cover 1 to 12 months.

5.1 Common trends

For our estimator γ to be unbiased, we had to posit that the two groups had a common trend. Figure 4 presents the employment rates for the treated and non-treated groups for Canada as a whole.[9]

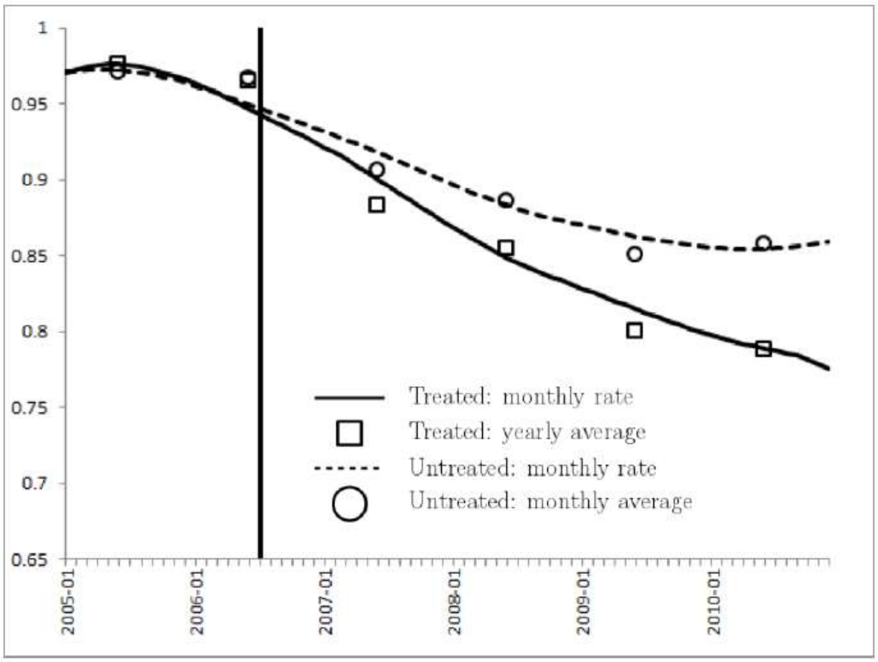

Figure 4: Employment rates trends

Note: The vertical line identifies the date of the shock. The monthly rates were smoothed using the LOWESS method. Annual averages are calculated using the unsmoothed series.

We observe that, overall, the trends were the same between 2005 and 2006. Beginning in 2007, when the shock occurred, the trends began to diverge. In order to test the common trends hypothesis formally, we add a variable for 2006 and an interaction term between that variable and the treatment variable (d_i). We estimate the following equation:

$$y_{ijt} = \alpha + \theta d_i + \tau_1 I_{t=2006} + \tau_2 d_i I_{t=2006} + \delta I_{t\geqslant 2007} + \gamma d_i I_{t\geqslant 2007} + \beta \mathbf{X}_{it} + \phi_j + \upsilon_i + \epsilon_{ijt} \quad (2)$$

[9]Graphs by region are presented in the Appendix. We observed that the effect of the shock was stronger in Québec than in the other provinces.

Table 4 presents the estimated coefficients τ_2 (column (2) and γ (column 4). We find that the common trend assumption holds, since τ_2 is not different from zero (except for part-time employees). Each of the estimated models includes all of the variables presented in Equation (2). The estimated impact of the shock, presented in column (4), is in line with that presented in column (1) of Table 3 above. Thus, our results are robust to the inclusion of an effect specific to the 2006 sub-period.

Table 4: Common trends

Occupation	(1) Interaction (τ_2)	(2) s.e.	(3) p-value	(4) Interaction (γ)	(5) s.e.	(6) p-value	(7) R^2
Work	-0,008	(0,009)	[0,396]	-0,045	(0,019)	[0,018]	0,094
full-time	0,022	(0,018)	[0,217]	-0,039	(0,025)	[0,121]	0,105
part-time	-0,018	(0,010)	[0,070]	0,013	(0,016)	[0,433]	0,035
Unemployed	0,007	(0,007)	[0,265]	0,028	(0,012)	[0,016]	0,017
Not in labor force	0,000	(0,006)	[0,950]	0,017	(0,015)	[0,253]	0,095
Enrolled in education	0,005	(0,008)	[0,518]	0,017	(0,012)	[0,142]	0,068

Note: N = 220,171. The vertical line identifies the date of the shock. The monthly rates were smoothed using the LOWESS method. The annual averages were calculated using the unsmoothed series.

5.2 Gradual effects over time

Although the demand shock was relatively sudden, it is possible that the individuals did not change their occupations immediately. In some cases, the mills may have continued working and accumulating stock before closing their doors or slowing down their operations more substantially. Moreover, the decision to return to education generally has heavy consequences on individuals living in remote areas, often requiring them to move. Access to education also implies an application process that can take several months.

We explored this temporal dimension of occupational choices by testing whether changes in the short term differ from changes in the medium term. To do this, we estimate the following equation:

$$
\begin{aligned}
y_{ijt} = \alpha + \theta d_i \delta_0 I_{t\in\{2007,2008\}} + \delta_1 I_{t\in\{2009,2010\}} \\
+ \gamma_0 d_i I_{t\in\{2007,2008\}} + \gamma_1 d_i I_{t\in\{2009,2010\}} + \beta \mathbf{X}_{it} + \phi_j + \upsilon_i + \epsilon_{ijt}
\end{aligned} \tag{3}
$$

This equation is similar to Equation (1), but it divides the effects of the treatment and the interaction into two sub-periods: the short term and the medium term. We define "short term" as the 2007-2008 period, namely the year when the shock took place and the following year. "Medium term" is defined as the effect of the shock on occupational choices in the two subsequent years, that is, 2009 and 2010.

Table 5: Gradual effects of the forestry industry shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2007 and 2008						2009 and 2010					
	Interaction			Post			Interaction			Post		
	γ_0	s.e.	p-value	γ_1	s.e.	p-value	δ_0	s.e.	p-value	δ_1	s.e.	p-value
Work	-0.029	(0.020)	[0.143]	-0.069	(0.005)	[0.000]	-0.054	(0.023)	[0.018]	-0.106	(0.007)	[0.000]
full-time	-0.041	(0.023)	[0.079]	-0.074	(0.007)	[0.000]	-0.061	(0.027)	[0.024]	-0.11	(0.009)	[0.000]
part-time	0.029	(0.019)	[0.125]	-0.002	(0.004)	[0.654]	0.015	(0.016)	[0.376]	0.006	(0.006)	[0.274]
Unemployed	0.027	(0.012)	[0.027]	0.018	(0.003)	[0.000]	0.022	(0.014)	[0.117]	0.038	(0.004)	[0.000]
Inactive	0.003	(0.017)	[0.871]	0.051	(0.004)	[0.000]	0.032	(0.018)	[0.077]	0.067	(0.005)	[0.000]
Education	0.005	(0.010)	[0.600]	0.006	(0.003)	[0.052]	0.025	(0.014)	[0.083]	0.004	(0.003)	[0.265]

Note: N = 220,171. Each line is a separate regression.

The short and medium term impacts are presented in Table 5. We find that labour market outcomes adjust immediately, employment decreases by 2.9 percentage points between 2007 and 2008, with a larger negative impact on part-time employment. The fraction unemployed rises by 2.7 percentage points, but that of the inactive remains stable. In the medium term, employment decreases even more: by 5.4 percentage points. Full-time employment drops by 6.1 percentage points. Few individuals benefit from an increase in part-time employment (1.5 percentage point, p=0.376). The compensating effect comes from an increase in unemployment (2.2 percentage points, p=0.117) and inactivity (3.2 percentage points, p=0.077).

Enrollment in education does not differ from zero in the short term, but it raises significantly in the medium by 2.5 percentage points (p=0.083). This confirms the idea that adjustments towards an increase in education enrollment are gradual, as it is easier to drop out than to enroll. Table 5 reveals that although few workers in the forestry industry went back to school in the medium term, they were more likely to invest in their education in the medium term relative to other workers who lost their jobs during the financial crisis. One hypothesis is that workers in the forestry industry perceived the shock to be more permanent than workers in other sectors. Younger workers are also more likely to return to school since their lifetime return to education are larger. Furthermore, their school-specific human capital has not depreciated as much and, therefore, the cost of returning in a classroom may be lower to them.

In Table 6 we present the effects of the shock for different sub-groups, namely, workers under 30 years old and those 30 years and over. Unfortunately, given the sample size, we are not able to look at the short term versus medium term effect by age group. The effects on workers under 30 are estimated less precisely because of the low number of observations (544 individuals observed 30,708 times), but the sign and magnitude of the coefficient warrant a discussion.

Results presented in Table 6 suggest that the effect of the shock on employment is equally important for younger workers: 4.5 percentage points compared to 3.9 percentage points for older workers. It is only significant for older workers, but only effects above 10 p.p. could be detected for younger workers. The effect on educational enrollment is not significant for both groups, but the sign of the coefficient suggest that the effect measured in our overall sample, mainly comes from a change in the educational choices of younger workers. The γ coefficient for younger workers is 3.8 compared to 0.5 for older workers. For younger workers, the γ coefficient on employment is almost equivalent in absolute term to the γ coefficient on education. This suggests most young workers returned to school when they loose their job.

Table 6: Heterogenous effects by age group

Occupation	(1) Interaction γ	(2) s.e.	(3) p-value	(4) Post δ	(5) s.e.	(6) p-value	(7) N	(8) R^2
Work								
$<$ 30 years old	-0.045	(0.052)	[0.385]	-0.099	(0.016)	[0.000]	30,708	0.093
$\geqslant$ 30 years old	-0.039	(0.018)	[0.035]	-0.084	(0.005)	[0.000]	189,463	0.100
Education								
$<$ 30 years old	0.038	(0.046)	[0.404]	0.022	(0.014)	[0.103]	30,708	0.118
$\geqslant$ 30 years old	0.005	(0.008)	[0.516]	0.004	(0.002)	[0,087]	189,463	0.013

Note: Each line presents the results of a different regression. In addition to the interaction term and the binary variable $I_{t \geqslant 2007}$, each regression includes the treatment variable, the control variables, the fixed effects (months), and the individual random effects. Cluster-robust standard errors at the individual level are presented.

6 Conclusion

We find that the events following the subprime mortgage crisis reduced the probability of being employed to a greater extent for forestry industry workers in Canada than for those in other primary and secondary sector industries. The probability of being employed after the crisis was 4.1 percentage points lower for the forestry industry than for all other workers in the primary and secondary sectors. This decline mainly impacted full-time employment, 5 p.p., and was offset by an increase in both part-time employment (2.2 percentage points) and unemployment (2.4 percentage points).

Right after the shock, workers did not go back to school immediately (1.4 percentage points, p=0.172), but as of 2009-2010 we find an increase in education enrollment of 2.5 p.p. ($p = 0.083$). We also find some evidence that this effect may have been entirely concentrated among young workers aged less than 30 years old. Although the effects are not statistically significant, in part because the sample size of young forestry workers is very small, the size of our estimated effects suggests that most young forestry workers return to school if they loose their job, and this is also partially true for all other workers in the primary and secondary sector (1 out of 4 return to school).

Together, these findings have potentially important policies implication for society seeking to increase the postsecondary education rate of young adults. Since a vast majority of workers in our analysis were men (about 80%), this finding mainly reflects young male's behaviour. Since male participation rate in postsecondary education is lagging behind that of females in most OECD countries[10], knowing that without a valuable outside option on the labour market young male return to school is key to our ability to design policies that work for them.

In sum, our results show that workers in the forestry industry were more heavily impacted. More lost their jobs, but they were also relatively more likely to go back to school in the medium term. Booms and bust seem to have differential impact on the probability of enrolling in education. Studying the impact on school enrollment when the wood industry bounces back would bring valuable insight, as having access to administrative data providing decent sample sizes.

[10] See, for instance, https://stats.oecd.org/index.aspx?queryid=54741

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A Seasonality of employment in the Canadian forest industry

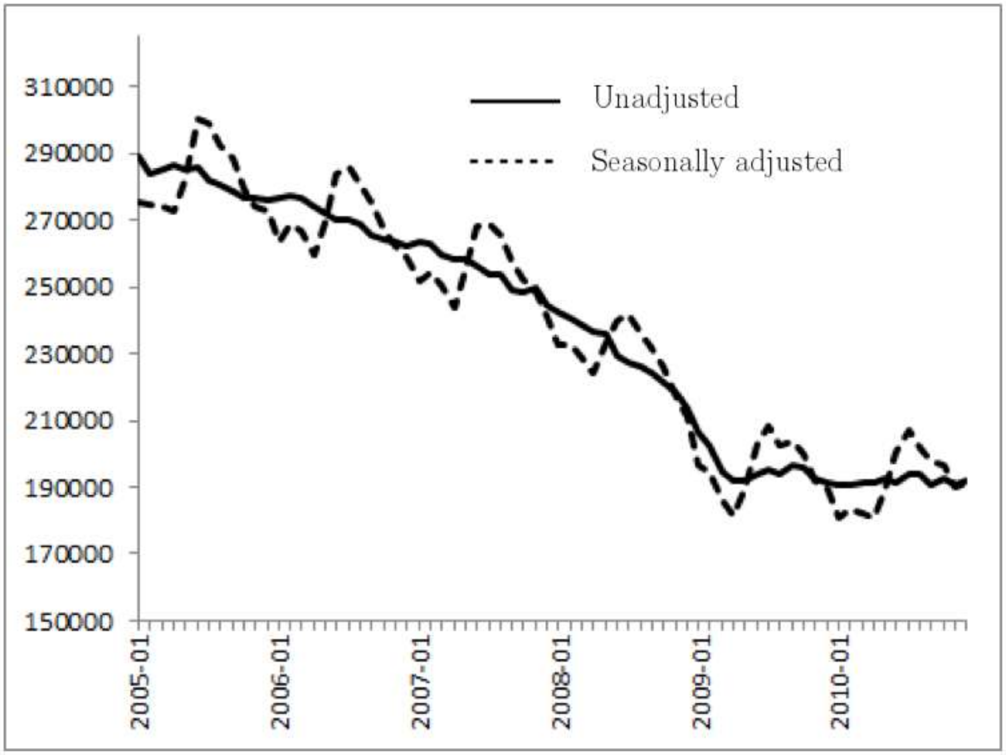

Figure 5: Number of jobs in the Canadian forest industry

Sources :

Statistics Canada. Table 281-0023 —Table 14-10-0201-01 — Employment by industry, monthly, unadjusted for seasonality.

Statistics Canada. Table 281-8047 —Table 14-10-0331-01 — Historical releases of employment and average weekly earnings (including overtime) for all employees by industry, monthly, seasonally adjusted.

B Employment trends by province

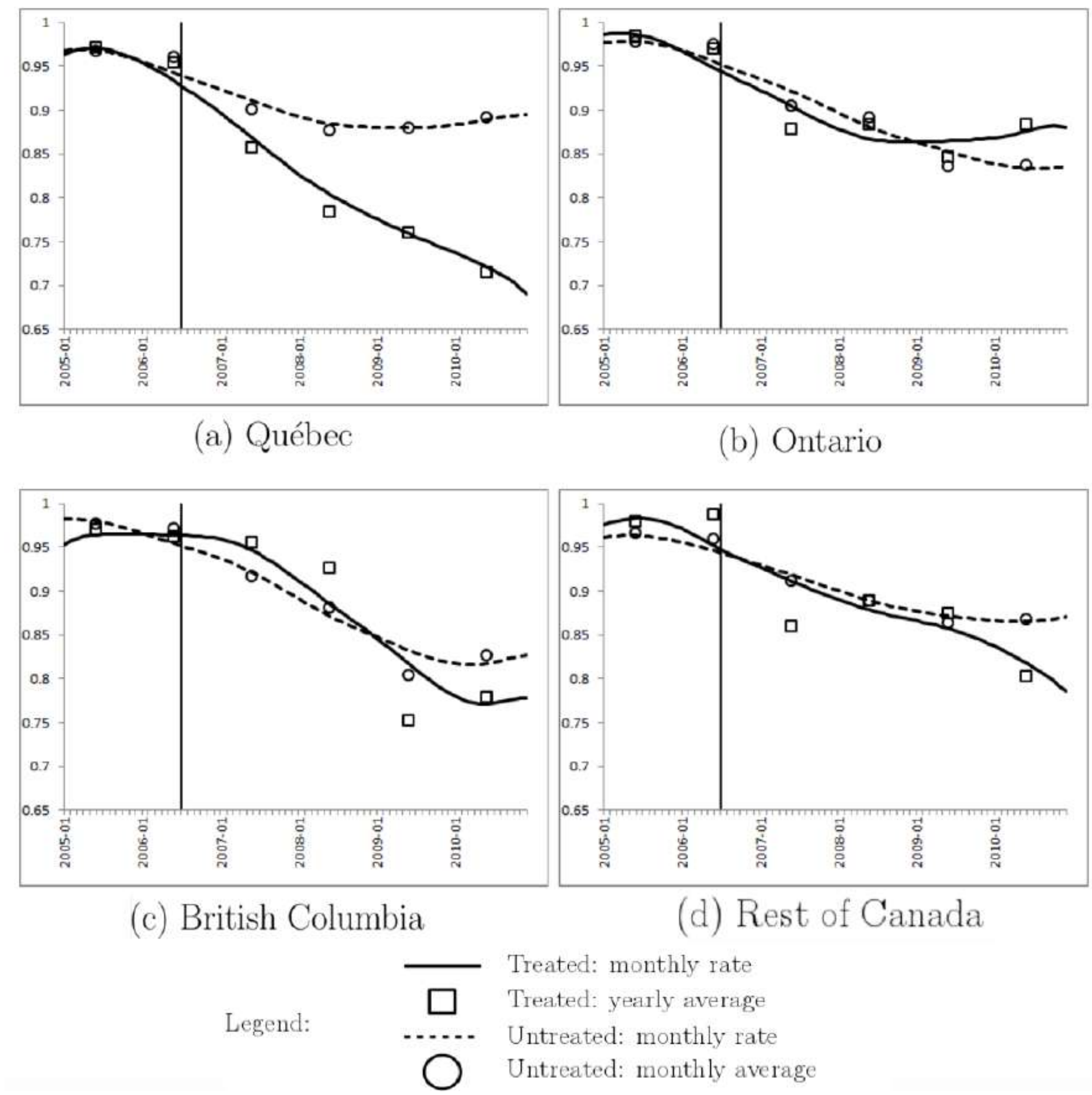

Figure 6: Employment rates by province

Note : $N = 3588$. The vertical line identifies the date of the shock. The monthly rates were smoothed using the LOWESS method. The annual averages were calculated using the unsmoothed series. The unsmoothed rates cannot be reproted for confidentiality reasons.

Table 7: Number of observations remaining after each exclusion (in thousands)

(1) Nonrestricted sample	(2) 16-65 years old in 2005	(3) Declared incomes	(4) Present before and after shock	(5) Declared occupations	(6) Worked at least 6 months	(7) Primary and/or secondary sectors
1 192	1 186	1 185	1 081	1 080	849	221

Note: Unweighted monthly data.

B.1 Month restrictions

In this section, we relax one the restriction that we had previously imposed. We no longer assume that individuals worked a minimum of 6 months per year in the forestry industry in order to belong to the treated group and an equal constraint on the number of months of employment in order to be part of the control group. Table 8 presents the effect of the shock on employment using a 4- to 9-month constraint (columns 1 to 6), with our main results in column 4.

Table 8: Estimated effect of the shock on forestry industry workers by number of months of employment prior to the shock

Occupation	(1) 4 months	(2) 5 months	(3) 6 months	(4) 7 months	(5) 8 months.	(6) 9 months
Work	-0.048	-0.043	-0.041	-0.045	-0.044	-0.050
	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
	[0.006]	[0.015]	[0.023]	[0.013]	[0.016]	[0.009]
R^2	0.091	0.092	0.094	0.099	0.100	0.104
Education	0.012	0.012	0.014	0.012	0.012	0.014
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.012)
	[0.221]	[0.253]	[0.172]	[0.273]	[0.268]	[0.225]
R^2	0.079	0.078	0.068	0.066	0.061	0.061
N	232,002	225,935	220,171	213,048	208,020	201,067
$N individuals$	3,784	3,682	3,588	3,469	3,388	3,272

The treated group contained over 300 individuals when the constraint was 6 months or less, and between 200 and 300 individuals when the constraint was 7 months or more. For each variable, we have presented the coefficients, standard errors (between parentheses) and p-values (between brackets).