Does it Matter Where and What I Study?
Evidence from the Oil Price Crash in Canada*

Constanza Abuin Pascuel Plotkin

Harvard UBC

August 17, 2022

Abstract

We estimate the impact of a labour demand shock on Canadian recently graduated bachelor students. We leverage a unique Canadian administrative data that features links between individuals post-secondary education and their tax-files. We estimate that a standard deviation increase in school-major specific labour demand, increased earnings immediately in a magnitude between 2.3 and 2.6 log points, with persistent and increasing effects throughout the oil shock. Additionally, the labour demand shock had effects on other labour market outcomes such as unemployment or self-employment. In terms of schooling, school-major specific labour demand had a positive effect on dropouts, which remarks the importance of considering the outside option of students when studying school enrollment.

*Abuin: mabuin@g.harvard.edu; Plotkin: pascuel.plotkin@ubc.ca. **Very preliminary version, please do not circulate.**

1 Introduction

Increasing evidence suggests that the choice of majors and universities condition career outcomes[1]. Heterogeneity in formation across majors condition the type of jobs that an individual will be suited for once graduating from a program. Similarly, schools invest resources differently in both the quality of the classes and in the generation of job opportunities for students[2]. Hence, each program generates its own "job network" that facilities the transition between schooling and work. Heterogeneity's in return to majors and schools suggest that individuals must be forward looking when choosing where and what to study as the choice they make at the start of their post-secondary education will influence their job outcome at graduation.

Moreover, career paths are not neutral to either the first job after graduation or the context in which an individual graduates. Students who graduate during recessions are known to have both immediate and persistent negative effects throughout their careers[3]. Yet the question remains on how economic shocks spread throughout specific cohorts. Are all students affected equally within a cohort? What is the role of schools and majors in the spread of a shock?

In this paper we argue that schools and major choices are relevant factors in understanding the impact that an economic shock can have on recently graduated individuals. Specifically, we exploit the sudden oil price crash between 2014 and 2016 that reduced oil prices more than 50 percent over the span of two years. The heterogeneous nature of this shock, along with administrative school enrollment and tax-file data, allows us to build a novel measure of graduates exposure to the shock. A Key feature of our exposure measure, is that it allows for students from each major and school to be impacted differently by

[1]See Altonji, Arcidiacono, and Maurel (2016) for an extensive review.

[2]For example, Zimmerman (2019) shows how elite universities in Chile help students reach top jobs.

[3]There is an extensive literature that shows that graduating in recessions has long-term effects on individuals career (see, e.g., Arellano-Bover, 2020; Kahn, 2010; Schwandt and Von Wachter, 2019). Additionally, Altonji, Kahn, and Speer (2016) and Oreopoulos, Von Wachter, and Heisz (2012) show that these effects are heterogenous across majors.

both geographic and industry specific shocks to the economy. We then provide evidence that the oil price shock had especially negative effects on graduates who's labour demand was particularly negatively affected by the shock. Importantly, our methodology allows to weight the impact of the shock on the whole economy (and not just the oil sector), which permits to study the impact of a sudden labour demand shock on a broad set of graduates.

Exposure to a shock defined at the school-major level is a function of two key elements: a school-major specific component, such as a school's investment in quality (both general and specific to a major) or investment in network, and a sorting component, driven by a higher propensity of certain type of students to enroll (and be admitted) in certain type of schools and majors. Given the geographic nature of the shock, it is likely that students that have higher attachments to provinces where the shock had a stronger impact, will be more affected no matter the school or major where they studied. In this paper, we argue that the geographic sorting of students, although relevant, can not explain the totality of the impact of the shock on recently graduated students. That is, the exposure measure is still a relevant predictor for the effect of the shock on students even when conditioning on the province of origin of these students[4].

An advantage of our data is that it allows to investigate heterogeneities across both majors and universities. Detailed information on both institutions and majors allows me to categorize them in terms of their returns previous to the shock. Hence, we are able to study not only how the shock affected schools given their exposure, but also if high-return schools or majors worked as a shield protecting their graduates from the shock, as has been suggested previously by the literature.

Our results suggest several key findings. First, school-major units present persistence in the labour markets in which their graduates find their first job. That is, over the course of the years, graduates from the same school-major tend to work in similar labour markets.

[4]An intuitive way of understanding geographic selection, is the tendency of students from certain provinces to enroll in specific school-majors and later return to their province of origin once graduated. If the school-major component is irrelevant, then one would expect the entire effect of the shock to be absorbed by the selection of students.

Moreover, these labour markets are relevant predictors of how an unexpected labour demand shock can affect the graduates labour market outcomes. We find that a decrease of the school-major specific labour demand of a standard deviation implied a reduction of between 2.3 and 2.6 log points in earnings of the graduates of that unit. Consistent with the duration of the shock, these results also show persistence over time. Additionally, the evidence suggests that graduates that were more negatively exposed to the shock have a higher probability of reporting positive employment insurance in their first year after graduation, lower probability of filing taxes and a slightly higher probability of being self-employed.

Second, consistent with models that suggest the importance of the outside options in the schooling choices of students, dropouts increased in relative terms in the school-majors that had a positive labour demand shock. This spilled over to the levels of graduation in the following years, where school-majors that were relatively benefited by the shock decreased their relative amount of graduates. These results raise a flag of the potential generation of mismatches between the types of graduates demanded and the available pool of graduates in future cohorts. Additionally, enrollments presented a slightly similar pattern, as they increased in relative terms in the school-majors that were negatively affected by the shock.

Third, consistent with the literature, we find that high-paying majors slightly shielded the effects that the labour demand shock had on graduates, but that this protection was not immediate. Alternatively, graduates from high-paying schools were on average more affected by the labour demand shock over time. Up to our knowledge, this is the first paper to register the role of both majors and institutions separately in the presence of an economic shock.

The paper contributes to growing literature in labor economics that has documented the importance of the macroeconomic cycle at the moment of graduation. Using a panel of administrative schooling data for Canadian graduates similar to ours, Oreopoulos, Von Wachter, and Heisz (2012) document that 'unlucky' cohorts suffer earnings decline that persist up to ten years. The authors highlight the importance of the first job as the key mechanism that marks differences across cohorts. Others have found similar results for the US. Using survey data, Kahn (2010) finds that cohorts who graduate in worse national economies not only have negative persistent earning effects, but also have higher tenure and higher education attainment. Schwandt and Von Wachter (2019) extend the analysis to a more extensive set of cohorts and find similar results. Arellano-Bover (2020) uses data on adults cognitive skills from several countries to show that graduating in a recession can also have a long-term impact on skill-development. Additionally, Altonji, Kahn, and Speer (2016) uses survey data to argue that the major is also a relevant factor when explaining the impacts of a recession across cohorts. This paper contributes to this literature by examining the impact of a an economic shock within cohorts in contrast to these studies who focus on the effects across cohorts. Specifically, our paper studies the importance of schools and major specific labour demand in explaining the propagation of a shock.

This paper also contributes to a second strand of literature related to the choice of colleges and majors. Using survey data from Chile, Hastings et al. (2016) analyze how students form their beliefs and the relation between these beliefs and college enrollment. Kirkeboen, Leuven, and Mogstad (2016) use administrative post-secondary data from Norway to study returns to fields and institutions and find that payoffs are consistent with individuals choosing fields in which they have a comparative advantage. Additionally, both Kirkeboen, Leuven, and Mogstad (2016) and Hastings, Neilson, and Zimmerman (2013) provide casual evidence that the specific choice of degrees or field of studies have a significant impact on short and long-term labor market outcomes. In the same lines, Altonji, Blom, and Meghir (2012) provides evidence of heterogeneity of post-secondary education returns by major, while Chetty et al. (2020) finds evidence of heterogeneity of value-added that each college generates in the US. Zimmerman (2019) and Hoekstra (2009) provide evidence of the importance of attending to ’elite’ colleges on labour market outcomes, remarking the importance of the networks these universities have for individuals when they transition from school to work. This paper, contributes to this literature by showing that school and major decisions are also relevant in determining how individuals will be affected by economic shocks that are heterogeneous by regions and sectors. Additionally, by focusing on schooling outcomes such as dropouts and enrollment, we are able to study how students respond to their school-major specific labour demand shocks.

Lastly this paper also contributes to the literature that studies the effect of commodity price shocks on local economies. A growing strand of literature has shown that these shocks can have disproportionate effects on wages and employment relative to the size of the resource sector (see, e.g., Black, McKinnish, and Sanders, 2005; Marchand, 2012; Feyrer, Mansur, and Sacerdote, 2017; Bartik et al., 2019). Specifically in the Canadian context, Marchand (2015) and Fortin and Lemieux (2015) show that the oil price boom had local spillover effects within regions that focus on extracting activities. Green et al. (2019) study the spillover effects of the oil price boom across Canadian regions and find that the possibility of commuting increased the bargaining power of workers even in non-oil extracting regions. This paper contributes to this literature by showing that resource shocks also have strong effects on recently graduated workers, and that the choice of college and major is not neutral to how these shocks affect them.

The paper is organized as follows: Section 2 describes the administrative data used to estimate the effect of the oil price crash on recently graduates, Section 3 describes the shock and the main empirical strategy used to estimate the key results, Section 4 presents the main results of the paper, Section 5 presents results in terms of the the major and school premium, Section 6 describes the robustness of the findings, and Section 7 provides some discussion and summarizes potential next steps of the project.

2 Data and Sample Construction

In order to estimate the effect of a labour demand shock on graduates we merged multiple data sources: Post Secondary Student Information System (henceforth PSIS), T1 Family File Tax Records (henceforth T1FF), and employment-unemployment data from the publicly available Canadian Labour Force Survey and Survey of Employment, Payrolls and Hours[5]. PSIS is a national survey that provides detailed information on enrolments and graduates for the universe of Canadian public Post-secondary institutions during the period 2009-2017. The data is structured as a repeated cross-section of students and graduates and is known to have administrative data quality[6]. Typical information provided in this survey contains the institution in which the student/graduate was enrolled during the reference year, the location of the institution, the major studied, type of program, year of graduation if applicable as well as demographics of the students such as province of residence at enrollment, and immigration status.

The PSIS was merged with administrative T1FF data, available for the universe of students observed in PSIS who filed taxes at any moment during the years 1992-2017. For the purposes of the research question studied, students tax files were merged only after graduation (i.e. the first year a tax file was merged to a PSIS individual was 2010). The selection of variables available from the T1FF combines information from both T1 and T4 Canadian tax files as well as the Canada Child Tax Benefit, and are composed by a set of income, demographic and geographic variables [7]. Most importantly for the purpose of this paper, T1FF provides information on the 3 digit industries in which an individual worked during the tax year and the geographic location in which the individual filed taxes

[5]Both PSIS and T1FF are part of STATSCAN Education and Labour Market Longitudinal Linkage Platform, and we were able to access them through UBC's Research Data Center.

[6]See for example, Finnie and Qiu (2009)

[7]The T1 General Form, is the main document used to file personal taxes in Canada, and acts as a summary of all the forms completed to report income taxes in the country. T4 slips are a summary of employment earnings (and deductions) earned by the individual during a tax year. Employers who paid employees employment income, commissions, taxable allowances and benefits, fishing income or any other remuneration should provide their employee with at least one T4 slip. The Canada Child Tax Benefit is a tax-free monthly payment made to eligible families who have children under 18 years of age.

from[8].

A summary of the key demographic variables found in the T1FF for the sample are reported in column (1) of Table 1. The mean age for bachelor graduates (the year after graduation) between 2010 and 2017 was 27 years[9]. Approximately 60% of the graduates were females (slightly above the OECD average for 2015 of 58%), and close to 90% of the graduates were Canadian citizens. Interestingly, approximately 10% of the students reported either employment insurance income or self-employment income the year after graduation.

The last key components of data merged were employment and unemployment statistics reported by STATSCAN for provinces and industries. As explained in Section 3, these statistics were used to build a Bartik style instrument, key to my main empirical strategy. Specifically, STATSCAN publishes employment aggregate statistics at the province - 3 digit industry through the Survey of Employment Payrolls and Hours (SEPH). This survey provides a monthly description of the levels of earnings, amount of jobs and hours worked by industries and provinces. Alternatively, unemployment rates at the provincial - 2 digit industry were collected through the Canadian Labour Force Survey[10].

3 Empirical Strategy

To study how an economic shock affects differently graduates given their school and major, one must consider a context in which the effects of the shock are heterogeneous across sectors and regions. The oil price crash that took place at the end of 2014 counted with these features and presents an ideal scenario to study how an unexpected shift in labour

[8]As noted in Green et al. (2019), ideally one would want both the Economic Region of the employer (reported in the T4 slips) and the employee. However for the purpose of my research question, the economic conditions of the labour market in which the individual is located is likely to be more relevant then the economic conditions of the location of the employer.

[9]This number is consistent with what was reported by the National Graduate Survey.

[10]Section A.3 of the Appendix provides further details on the construction of the sample for the main analysis.

demand can affect graduates differently given their schooling choices[11]. In this section, we present an overview and some trends of the oil shock as well as the main empirical strategy used to estimate the effects of the shock on graduates.

3.1 Oil shock and Graduate trends

At the end of 2014 an oversupplied oil market reached a sudden price crash, which was followed by a continuous downward spiral of prices until 2016. Between June 2014 and January 2015, Crude prices were reduced by 56%, trend that continued until reaching the lowest point of the decade in January 2016 at a price of 29 USD per barrel[12]. Some of the main explanations of the oil crash explored in the literature have been a shift in supply (see, e.g., Arezki and Blanchard, 2014; Baffes et al., 2015), revision of expectations (Baumeister and Kilian, 2016), and negative financial bubble (Fantazzini, 2016), yet studying in detail the causes of the oil crash exceeds the scope of this paper.

The oil price crash had a particular strong effect on the Canadian economy given that the fuel exports were representing approximately 29% of the total merchandising exports of the country in 2014[13]. Figure 1 and Figure 2 expose the correlation between international oil prices and Canada's economic performance. While between 2010 and 2014 Canada's GDP grew on average 2.6% per year, between 2015-2016 the average annual GDP growth was driven down to 0.8%. Furthermore, as oil prices started to stabilize at a new equilibrium and even increased progressively between 2017 and 2019, Canada's GDP responded increasing on average 2.4% during the same period. Similarly, the National unemployment rate that had been decreasing since the Great Recession increased 3% between 2015 and 2016, while total employment essentially remained flat during the same period[14].

[11]For some anecdotal evidence on how low oil prices affect graduates, see this New York Times article.

[12]The price per barrel reached a new low in April 2020 with the economic recession propagated by the Covid-19 pandemic.

[13]World Bank estimates based on Comtrade

[14]Total employment for individuals between 25 and 54 years of age grew at an average of 0.6% between

Canadian bachelor graduates were no excuse to this cycle. As presented in Figure 3, during the oil price crash the average real employment earnings of graduates (the year after graduation) declined on average 1% per year, while between 2010 and 2013, and in 2017 the average growth of real earnings was 1.7% and 2% respectively.

Importantly for my research design, the oil price shock had heterogeneous effects across sectors and regions. As Figure 4 shows, employment growth patterns varied across provinces. Taking as a reference 2015 (the first full year with low oil prices), employment, weighted by the graduate presence in each industry, grew 3.8% in British Columbia, while it decreased 1.9% in its oil-intensive neighbour province Alberta. The other main resource province, Saskatchewan decreased its employment 0.4%, while the rest of the country increased their employment, on average, 0.8%.

Similarly, not all industrial sectors were affected equally. Figure 5 shows the distribution of employment growth by 3 digit industries in 2015 at the National level. One can clearly observe the dispersion across different sectors[15]. For instance, the support activities for mining and oil and gas extraction sector reduced its employment by 19%, while the beverage and tobacco product manufacturing sector increased its employment by 7.4%. Exploiting the fact that each school-major has a specific propensity to place students in each labour market, the intersection of geographic and industrial variation allows to identify the effects of an unexpected shock, such as the oil price shock, on graduates given the level of exposure their class had. This is the crucial starting point for the implementation of the main empirical strategy described in the next section.

3.2 Regression Specification

In order to estimate the effect of the oil price crash on graduates, one must first identify those students that were most exposed to the shock. The ideal regression would relate

2009 and 2013, decreased in 2014 0.2%. remained flat between 2014-2015 and grew on average 1.4% between 2017 and 2019.

[15]51 sectors presented positive employment growth, while 39 sectors decreased their employment in 2015.

outcomes such as earnings on the propensity of each graduate to enter a specific labour market and the demand shifts of that specific labour market. Of course this regression is not feasible, given that a graduates propensity to enter a specific labour market is not directly observable and each labour markets demand must be inferred. To overcome this, we leverage on the administrative quality of the data and proceed to construct the distribution of destinations for each school-major unit during the years previous to the oil price crash, where each destination is composed by a 3 digit industry and an Economic Region[16]. This yields a total of 4,960 potential destinations for each of the 692 school-majors and acts as a de-facto propensity of entering each labour market for the graduates who enter the workforce during the oil price crash. Each destination is then matched with an annual employment growth that corresponds to that 3 digit industry and the province the Economic Region corresponds to, yielding an approximation for the labour demand shift of each specific labour market[17]. In essence, the combination of the shift and the share, generates what in the literature has been called frequently as a Bartik instrument, where the variation of the shift comes from the difference of pre-shock exposures of each school-major[18].

A first approach to estimating the effect of the sudden shock on graduates is to estimate a reduced form regression of outcomes of interest on the Bartik instrument described above. Specifically the regression has the following form:

$$\begin{aligned} Y_{l(m,s)t} &= \beta_0 + \beta_1 \xi_{l(m,s)t} + \beta_2 X_{l(m,s)t} + \delta_{mt} + \epsilon_{l(m,s)t} \\ \xi_{l(m,s)t} &= \sum_k z_{l(m,s)k0}\, g_{kt} \end{aligned} \tag{1}$$

Where is $Y_{l(m,s)t}$ is the annual difference between t and $t-1$ of the average residual

[16]Economic Regions are a subprovincial definition constructed by STATSCAN, and are composed by a grouping of complete census divisions. In my sample, there is a total of 76 Economic Regions.

[17]The employment growth is calculated over the totality of the workforce and not only the graduates to avoid the well known reflection problem.

[18]See Goldsmith-Pinkham, Sorkin, and Swift (2020) for an overview of Bartik instruments.

earnings for school-major $l(m, s)$ for the period 2014-2017, $\xi_{l(m,s)t}$ is the Bartik instrument corresponding to each school-major in year t, built using the share (z) of graduates from l that go to destination k during 2010-2013, and the growth (g) at the provincial level for each destination k in time t[19]. To control for major specific time trends, the vector δ_{mt} includes a full set of interactions between year and major fixed effects. Lastly, the regression includes controls for the proportion of graduates of school l in time t that were living at an oil extracting province when enrolling, to account for specific ties to origins.

The underlying assumption of model (1) is that, in the absence of the shock, earnings of graduates more and less affected by the oil price crash would had *evolved* similarly during 2014-2017. Essentially, this assumption is a steady state type of statement where the exogeneity of the instrument is driven by the shares instead of the shifts. Yet the exogeneity of the shock is still relevant in this context, given that the residual earnings may not control for unobserved composition differences across the years within a school-major unit. In other words, although the Bartik instrument's exogeneity is based on the distribution of destinations, the unexpected nature of the shock strengthen the assumption that annual differences in earnings within units are not capturing unobserved differences across cohorts.

However, if certain students from school-majors that were negatively exposed to the oil shock changed their schooling decisions, such as delaying their graduation, compared to those who in relative terms were less affected by the shock, then regression (1) would also be capturing this behaviour in any earnings results. For instance, if high skill students were the ones more keen to delay graduation because they believe their potential first wage has a higher ceiling, then it is likely that any estimated earnings effect would have a positive bias. Alternatively, if lower skilled workers were the ones delaying graduation, because they know they are unlikely to get a good job during a recession, then the estimated effects

[19]Residual earnings allow to control for composition effect. Specifically, these earnings were estimated regressing log average earnings of each school-major l in year t on age, family size fixed effects, family composition fixed effects, marital status, and a full set of interactions of gender-by-immigration status with quadratic age.

would be negatively biased.

Both pre-trends of graduates more and less affected by the oil price shock, and cohorts reaction to the shock are relevant empirical questions by themselves. To further study these patterns, we estimate the following event-study regression model:

$$Y_{it} = \beta_0 + \gamma_t + \delta_l + \sum_{j=2011}^{2017} \beta_j \, \xi_{l,\, 2015} \times 1\{t = j\} + \beta_2 X_i + \epsilon_{it} \tag{2}$$

Where Y_{it} are outcomes at the individual level (earnings the year after graduation, decision to graduate, dropout, self-employment, employment insurance, filling taxes), γ_t are time fixed effects, $\xi_{l,\, 2015}$ is the Bartik instrument corresponding to school-major l in the year 2015, and X_i is a vector of controls at the individual level similar to those used to estimate residual earnings in regression (1)[20]. The Bartik instrument in 2015 reflects the employment demand change in the first full year with low oil prices. Appendix Figure 15 illustrates the sudden change of growth pattern of the Canadian economy. While industrial employment growth weighted by size in 2015 correlated positively with years after the oil price crash, the relationship is inverted when comparing it to the patterns registered before the shock.

Notice that under specification (2), the interaction of the Bartik instrument in 2015 with time fixed effects allows not only for placebo tests before the oil price shock but also allows to estimate the dynamic effect of the shock on graduates outcomes years after the initial crash. Essentially, if the shock had some type of effect on graduates outcomes due to their exposure, one would expect the implicit ranking of exposure generated by the Bartik instrument to explain a differential effect after 2015, but not before[21]. Importantly, to avoid capturing any type of mean reversion of the outcomes due to the 2008-2009 recession,

[20]The event study was normalized using 2014 as the base year. Notice that under this specification, each individual is observed only once when analyzing earnings the year after graduation. In this case, year fixed effects act essentially as cohort fixed effects.

[21]A similar approach has been used recently in the literature to estimate spillover effects of voluntary employer minimum wages (see, e.g., Derenoncourt, Noelke, and Weil, 2021).

outcomes from 2010 were left out of this regression.

As in model (1), the variation exploited is at the school-major level, and hence the regression could be run at the school-major level directly. Yet, the advantage of running the regression at the individual level is that one can control for individual characteristics in a more natural way, avoiding the two step estimation through residuals[22]. In particular, this approach allows to control for province of origin fixed effects and province of origin time trends directly, which helps understand the relative importance of geographical selection into school-majors when studying the effects.

4 Results

4.1 Labour Market Outcomes

Table 2 presents the effect of the labour demand shift on graduates estimated through the lens of model (1). The Bartik instrument has a significant positive effect when using as an outcome both residual and non-residual earnings of graduates from each school-major. More precisely, an increase in 1 standard deviation of the Bartik instrument implies an increase of 2.3 log points of earnings of bachelor graduates one year after graduation. Interestingly, when controlling for the province of origin in the residualized earnings, the effect decreases and is not significantly different from 0 under standard parameters. This remarks the potential importance of geographic selection when analyzing the impact of school-major specific labour demand shocks on graduates.

As in most countries, Canadian tax-files report annual earnings but not wages or time worked. Therefore, one must be cautious when interpreting the estimations, keeping in mind that the results could be a combination of both lower wages and less hours worked.

[22]Additionally, regressing the outcome at the individual level weights the school-major by the number of students. As a robustness, all the specifications were run at the school level and the results were essentially unchanged. These results were not exported from the RDC to avoid overcrowding the outputs to be exported, but are available upon request.

Yet in both cases, the evidence would suggest that a demand shift for certain type of graduates had an effect on their total annual earnings one year after graduation. These results provide a first set of evidence that not all graduates were equally affected by the oil price crash. Specifically, a school-major specific labour demand component is a relevant factor when explaining the impact of the shock on the earnings of the first job of graduates.

As a first approximation to understanding the dynamic effects of the shock, Figure 6 presents the raw mean of log earnings decomposed by quartile of the Bartik instrument in 2015. Graduates from school-majors affected more negatively by the shock were earning, in 2014, on average 10 log points more then those that were in relative terms more benefited by the shock. Yet 3 years later, in 2017, the difference between the two groups was reduced to only 2 log points.

Although these patterns are suggestive of the importance of the labour demand shock on earnings, a regression framework allows to control for observable differences across school-majors and cohorts. Figure 7 illustrates the estimated results of the event-study model (2). Estimations show that the value of the Bartik instrument in 2015 when interacted with years prior to the oil price crash is not statistically significantly different from 0. Earnings of graduates from school-majors that were more exposed to the shock in 2015 were not particularly growing more or less then the earnings of other graduates in previous years. In other words, the evidence supports the parallel trends assumption, key to interpret the effects of the labour demand shock as casual. Interestingly, earnings of graduates who *benefited* in relative terms by the oil price crash, not only grew more during 2015 but posterior cohorts had a persistent and increasing growth over the years up until the end of the sample. An increase in 1 standard deviation of the Bartik instrument implied an increase of 2.5 log points in 2015, 5.4 log points in 2016, and 6.7 log points in 2017, compared to the base year 2014. The persistence and timing registered are consistent with findings by both Green et al. (2019) and Kline (2008) for the Canadian and US oil and gas industry respectively, who find a lag in response of wages to the oil price movements by one or two years.

Table 3 presents the precise estimates with and without province of origin fixed effects and time trends to evaluate the importance of geographic sorting when studying school-major specific labour demand shocks. Specifically, province of origin fixed effects allow to control for time invariant unobserved heterogeneity of individuals across province of origin. For instance, if high-school education has higher quality in certain provinces compared to others, and students from those provinces are more keen to be exposed positively (negatively) to the shock, then this would be accounted for by controlling for province of origin fixed effects. Additionally, incorporating province of origin time trend allows to control for cohort specific effects by province of origin. If the estimated effects are totally driven by geographic sorting, then one would expect the effect of the Bartik instrument to be absorbed by these time trends. In other words, if the Bartik instrument was capturing only differential proportions of students from each province in each school-major, then one would expect the Bartik instrument to have a null effect once accounted for province of origin time trends. Column (1) of Table 3 presents the results without province of origin fixed effects, column (2) presents the same regression but including province of origin fixed effects (the preferred specification, and the one illustrated in Figure 7). Column (3) presents the results when including additionally province of origin time trends. As it can be seen, the Bartik instrument presents a strong and significant effect across all 3 columns. Including province of origin time trend does reduce slightly the effect of the labour demand shock, yet the effect is still relevant, which provides evidence that institution specific networks are important when analyzing labour demand shocks to graduates.

Figure 8 shows estimation results of model (2) using as an outcome a dummy variable for reporting positive employment insurance the year after graduation[23]. Similar to

[23]In Canada, a worker is potentially entitled to earn employment insurance when they were employed in insurable employment, lost a job through no fault of their own, have been without work and pay for at least seven consecutive days in the last 52 weeks, and are looking actively for a job.

the earnings patterns, parallel trends seem to hold up until 2015, when graduates from less negatively exposed school-majors start reporting a relative decrease in employment-insurance compared to 2014. More precisely, an increase in a standard deviation of the Bartik instrument reduces the probability of benefiting from employment insurance by 0.7 percentage points. Columns (1), (2) and (3) of Table 4 show once again that these results are robust to controlling for province of origin fixed effects and time trends.

Finally, Figure 9 and Figure 10 present estimations using as outcomes a dummy variable for filing taxes and self-employment respectively. Interestingly, graduates who's labour demand increased in 2015, presented a higher probability of filling taxes in 2015, but this effect was not persistent over future cohorts. Put in other words, those who were affected *negatively* by the oil price crash had a negative effect on earnings, higher probability of benefiting from employment insurance (and hence likely being unemployed at some time of the year) and lower probability of filing taxes (hence working at all during the year). Finally, the likelihood of reporting self-employment income seems somewhat unresponsive to the labour demand shock (although presents a slightly, but imprecisely estimated, negative relation), which suggests that graduates are not strongly transferring to alternative work arrangements due to the labour demand shock.

4.2 Schooling Outcomes

As it has been discussed before, when studying labour market outcomes of an economic shock on bachelor graduates, one must necessarily take into account the behaviour of students that are soon to become future cohorts of graduates. For instance, if highly exposed students are dropping out of school or delaying graduation, then differences in the evolution of earnings could be capturing a composition effect instead of a direct labour demand effect on those specific students.

Figure 11 presents the estimated response of students dropouts to the labour demand shock. Students who given their school-major were relatively *benefited* by the shock, presented an increase in dropouts. Specifically, an increase of 1 standard deviation of the school-major specific labour demand implied an increase of 0.15 percentage points in the relative probability of dropping out compared to 2014. Given the correlation of the composition of the economic growth in 2015 and posterior years, it is not surprising to find a slightly positive effect in the following years too. Appendix Figure 16 splits the effects by year of study and shows that the strongest effects can be found in the later years of study.

These findings are consistent with models that suggest that the outside option of students is a key driver when making a decision to enroll (or continue to be enrolled) in a program, such as the one proposed in Atkin (2016). Specifically, if the cost of switching majors increases with time of study, and the probability of being hired increases with age or years of study, then it is likely that higher cohorts will be the ones who react the most to an economic shock.

Importantly, changes in behaviours in terms of dropouts does not alter the interpretation of the earnings results for 2015. While changes in dropouts patterns may affect posterior cohorts of graduates, such as those graduating in 2016 (for third year dropouts in 2015), or graduates in 2017 (for second year dropouts in 2015), the relevant question for those in fourth year in 2015 is weather they graduated or not in that year due to the economic shock[24]. Figure 12 shows results for regression (2) using a dummy for graduation as an outcome. As it can be seen, the hypothesis of a null effect can not be rejected in 2015, but there seems to be a negative effect of the bartik instrument on graduation in 2016 and 2017. However, these the results for these years must be taken with caution, as total graduation is also a function of enrollment, which we have shown that likely was reduced for school-majors that were more demanded by the labour market during the shock.

Furthermore, graduation is also a function of initial enrollment to the program. If for example, schools that were relatively more *benefited* by the shock were following an upward trend in first year enrollment, then comparing graduation in 2015 to graduation in 2014,

[24]The average length of a bachelor in Canada is 4 years.

would likely be capturing differences in the amount of students initially enrolled. That is, under null effects on dropouts and invidual decision to graduate, the patterns found in total graduation should map one-to-one the patterns in initial enrollment. Appendix Figure 17 shows precisely this [25]. In 2010, there seems to be a slight increase compared to 2011 in enrolled students in the school-majors that were more demanded during the shock. This difference maps with the slight difference in graduation between 2014 and 2015. Yet when comparing graduation in 2015 and 2016 there is a reduction in graduation which does not translate to a difference in initial enrollment in 2011 and 2012 (4 years before each one). Hence, this difference in graduation patterns in 2015 and 2016 maps with the increase in dropouts and not a change in initial initial enrollment patterns.

Putting these results together, students seem to respond to school-major specific labour demand shocks dropping out more (less) when the demand increases (decreases), which results spills over to the levels of graduation of future cohorts. Therefore, when interpreting the dynamic effects of the shock on graduates labour market outcomes, one must consider the fact that the pool of graduates has been affected by the shock. For instance, if the students who are more keen to modify their dropout status are those who are in the lower distribution of skills within their school-major, then the earnings effects found in 2016 and 2017 could be reflecting a composition effect of graduates across school-majors. Yet the effects of the shock on earnings found in 2015 seem to be independent of any changes in composition. Furthermore, these results also suggest the importance of considering the outside option of individuals when modelling schooling decisions.

[25]The relation between enrollment and the 2015 Bartik instrument takes a steep jump in 2017 which at this phase of the research we can not explain with precision. One possibility, related to the outside option hypothesis, is that enrollment is anti-cyclical, which would explain the reduction in enrollment in the school-majors that were *benefited* during the shock, but also the increase in enrollment in 2017 once oil prices started to normalize again.

5 Heterogeneity

A relevant empirical question that arises from the results exposed in the previous section is if labour demand shocks affect deferentially graduates from certain schools or majors. To study this, we proceed to follow the empirical strategy proposed by Altonji, Kahn, and Speer (2016). A crucial advantage of my data, however, is that it allows to not only estimate returns to majors, but also return to institutions[26]. Specifically, we regress log earnings on major fixed effects, school fixed effects, and a vector of controls for the sample of graduates who entered the labour market between 2010 and 2013. From this regression we then extract the major and school fixed effect and standardize them to be mean zero and a standard deviation of 1. We denote these standardized fixed effects variables β^{Major} and β^{School}.

To estimate the heterogeneous effects by school and major we estimate the following regression model:

$$\begin{aligned} Y_{it} = \beta_0 + \gamma_t + \delta_l + \sum_{j=2011}^{2017} \beta_{j\xi} \left(\xi_{l,\,2015} \times 1\{t=j\}\right) + \sum_{j=2011}^{2017} \beta_{jH} \left(\beta^H \times 1\{t=j\}\right) + \\ + \sum_{j=2011}^{2017} \beta_{jH^\xi} \left(\beta^H \times \xi_{l,\,2015} \times 1\{t=j\}\right) + \beta_2 X_i + \epsilon_{it} \end{aligned} \tag{3}$$

Where $H \in \{Major, School\}$[27]. Under this specification, β_{jH^ξ} reflects the differential effect of the labour demand shock on high-paying vs low-paying schools and majors.

Figure 13 and Figure 14 plot the estimated β_{jM^ξ}, β_{jS^ξ} respectively. In terms of major premiums, the estimated coefficients seem to suggest that if anything, graduates from high paying majors shielded graduates from the shock in the subsequent years to the shock, but

[26]Oreopoulos, Von Wachter, and Heisz (2012) with similar data take a slightly different approach by using a linear regression to predict log earnings based on college attended, major, and controls, to then rank individuals by their predicted earnings. This approach however, does not allow to isolate majors from institutions when analyzing heterogeneous effects.

[27]Importantly, to avoid endogeneity when estimating the heterogeneity school and major premiums, graduates were randomly split in two sample, where one half was used to estimate the school and major premiums, while the other half was used to estimate Regression (3).

not in 2015. Alternatively, when evaluating the differential effects by school premiums, we find that the shock had a stronger effect on graduates from high paying institutions in 2016,2017, but but not in 2015. However, one must be cautious when interpreting the effects by school premium as casual, given that graduates from high paying schools that were more exposed to the shock, seemed to be earning above the 2014 levels even before the shock[28].

6 Robustness

6.1 Strength of the Instrument

All the specifications mentioned up to this moment rely on a Bartik instrument that is based on the destinations of graduates from each school-major unit in the years previous to the shock. However, this instrument is built implicitly on the assumption that this information is actually relevant to predict the counterfactual destinations of graduates in the following years (in the absence of the oil price shock). Yet this might not necessarily be the case for all units. For instance, some school-majors may have strong attachments to certain labour markets (either through networking, or by the profile of students who enter the unit), while other institutions may have a more flexible attachments to the destinations of their graduates.

To distinguish between school-major units that have more and less flexible destinations we must generate a measure of persistence of the destinations across the years used to build the instrument. In essence, this becomes a problem of measuring similarities across distributions in each year. Clearly there is not a unique way to approach this problem, as there are several ways to define similarities across distributions, and of course the results will depend on which features of the distribution are weighted more when studying

[28]At this stage of the research, the relevance of heterogeneous effects by majors and schools is unclear. This is a main focus for the next steps of the project.

similarities[29]. In this paper we use the Hellinger distance which is a type of f-divergence, and has properties that yield interpretation advantages in my context, such as its scale neutrality. Specifically, this measure is bounded between 0 and 1, where a lower value represents two distributions that are more *similar* to each other, while the closer the measure gets to 1, the more *distant* the two distributions are.

To be precise, the Hellinger distance $d(z_{lt}, z_{lt+1})$ between two consecutive years for the same school is defined the following way:

$$d(z_{lt}, z_{lt+1}) = \frac{1}{\sqrt{2}}\sqrt{\sum_{k=1}^{K}(\sqrt{z_{klt}} - \sqrt{z_{klt+1}})^2} \tag{4}$$

Where z_{klt} defines for school-major l in time t the share that the destination k represents of the total possible destinations. Once calculated the distance for each pair of consecutive years, we proceeded to take the average of the measure for each l for the period 2010-2013 and split the sample by the median of the distribution[30]. This yields two groups of school-major units: one that is more *persistent* in the destinations of its graduates and another less *persistent*[31]. Summary stats of the sample split by median of the Hellinger distance can be found in Column (2) and (3) of Table 1[32].

Appendix Figure 19 presents the estimated β_j of Regression (2) split by the median of the Hellinger distance for earnings[33]. As it would be expected, the instrument loses predictive power when the Hellinger distance is higher, resulting in noisier estimations. Additionally, the point estimates of the coefficients in the less *persistent* sample are consistently lower in

[29]For an overview of measures of probability distributions similarity see Tsybakov (2009) Section 2.4 and Pfanzagl (2012) Section 6.1.

[30]The distribution is plotted in Figure 18 of the Appendix.

[31]Notice that by splitting the sample without weights we are assuring a similar number of school-majors above and below the median, but not of students. This exercise was replicated splitting using weights of students to guarantee the same number of students above/below the median instead of school-major units and are available upon request.

[32]As can be seen, more *persistent* school-majors tend to have more students and their graduates tend to earn more.

[33]Appendix Figure 20, 21, 22 replicate the main results for employment insurance, self-employment and filing taxes by Hellinger distance median, respectively.

absolute values post oil-price shock and in some cases not significantly different from 0[34].

In terms of the more standard instrumental variable literature, splitting the sample by the Hellinger distance median allows to study the first stage of the instrument. That is, the difference between both samples can be associated with the relevance of the instrument itself. If the profile of destinations during the pre-shock period is not representative of the potential destinations the school-majors would have had in a counterfactual scenario without the oil price crash during 2014-2017, then it is expected for the coefficients of the Bartik instrument to be noisier and potentially not statistically different from 0.

6.2 Measurement Error

A potential concern when interpreting the findings described in Section 4 is that results are dependant on the measure of employment used. For instance it could be that employment growth of an industry is not necessarily the best measure of demand shifts of that industry if most of the variation in growth is driven by differences in supply instead of demand. To re-enforce the role of the demand, we reproduce all the estimations using the industrial unemployment growth rate instead of employment growth rate to construct the Bartik instrument[35]. Contrasting the main results using the Bartik instrument built with the unemployment rate has the advantage that both measures likely reflect alternative patterns in terms of the labour supply. While a supply driven low employment growth would reflect few people wanting to enter a specific occupation, this would also likely be reflected in a lower unemployment rate in the sector. Alternatively, a higher employment growth driven by supply, would likely also reflect a higher unemployment rate in the sector as well under a relatively inelastic demand[36]. Consequently, if the main findings remain

[34]A joint test for the difference of the coefficients in 2015 of both samples is significant at the 0.1 level.

[35]Notice that unemployment at the industrial level is not defined in a precise way. For the construction of the Bartik instrument, we use STATSCAN publicly available industrial unemplyoment rate, which is based on the workers last job before being unemployed.

[36]An additional advantage is that employment and unemployment measures are constructed using different surveys, as mentioned in Section 2, which allows to discard any survey specific aspects of the results. An important observation, however, is that industrial unemployment rate at the provincial level are only

unchanged under this new instrument it would reinforce that the instrument is indeed capturing labour demand shifts instead of differences in labour supply.

Appendix Figure 23 illustrates unemployment growth across the different provinces in 2015 and shows a quite similar pattern to the employment growth presented in Figure 4. Appendix Table 12, presents the estimated coefficients for Regression (2) using this new measure of labour demand shift. Overall, the main patterns are very similar using unemployment instead of employment. Under this specification, an increase of a standard deviation of the exposure weighted unemployment implied a decrease in earnings of 2.1 log points in 2015, with persistent and increasing effects over time[37]. Importantly, the relation between the Bartik Instrument and the earnings dynamics is inverted given the implications of unemployment on labour demand.

6.3 Functional Form

A different type of concern when interpreting the results can be related to the functional form chosen. It could be, for instance, that the findings depend on the linear function chosen for the Bartik instrument. To re-assure that this is not the case, Appendix Tables 16-18 reproduce the main regressions using as an independent variable a binary variable for above/below the median of the Bartik instrument in 2015. As can be observed, the main results are essentially unchanged when using this type of regression. Under this specification, the graduates that came from school-majors that were more *negatively* affected by the shock, had on average 2.6 log points lower earnings in 2015 compared to the 2014 benchmark.

publicly available at the 2 digit industry, so the two measures are not totally comparable.

[37] Appendix Table 13, Table 15, Table 14 replicate this robustness for employment insurance, filing taxes and self-employment.

7 Discussion and Next Steps

This paper finds that a labour demand shock, such as the oil price crash of 2014-2016 had important effects on Canadian bachelor graduates. In particular, a decrease in school-major specific labour demand implied a decrease in earnings, a decrease in the probability of filing taxes, and an increase in the probability of acquiring employment insurance that persisted over future cohorts. The labour demand shock also had important effects on schooling outcomes, such as dropouts, and graduation levels.

A central next step in this project is to elaborate a model that can rationalize the main findings that were described throughout the paper. A starting point could be a toy model of school and major choice, with many elements taken from Altonji, Arcidiacono, and Maurel (2016). In such a model, individuals would get a utility flow from both their college years and their future jobs once entered the labour market. Importantly, the model would aim to match the key features of my results: (1) the importance of the outside option when deciding to enroll or continue their studies every period during school, (2) differential effects of economic shocks on graduates depending on the school or major (3) potential over-under supply of workers in certain occupations due to the adjustment frictions in education choices.

Feature (3) results particularly important in a context where we find a negative relation between occupation specific demand and graduation levels. This also opens an avenue for future research to understand how specific shocks can have spillover effects over time due to the mismatch generated between graduates and labour demand. Unfortunately, my sample only reaches until 2017, which limits the possibility of studying the persistent effects of mismatches over time. Yet it may be possible that STATSCAN extends the timeline of the data allowing for such an analysis in the future.

Although this paper focuses on the labour demand variation related to the oil price crash, there are several public policies that aim to shift the activity of certain sectors or regions. This paper highlights the potential externalities that these type of policies can have on bachelor students and young workers who just entered the labour market. Given the trade-off that is generated between earnings and schooling attainment, it is crucial for policy makers to take into account the potential consequences that such policies can generate on the future generations of workers.

References

Altonji, Joseph G, Peter Arcidiacono, and Arnaud Maurel. 2016. "The analysis of field choice in college and graduate school: Determinants and wage effects." In *Handbook of the Economics of Education*, vol. 5. Elsevier, 305–396.

Altonji, Joseph G, Erica Blom, and Costas Meghir. 2012. "Heterogeneity in human capital investments: High school curriculum, college major, and careers." *Annu. Rev. Econ.* 4 (1):185–223.

Altonji, Joseph G, Lisa B Kahn, and Jamin D Speer. 2016. "Cashier or consultant? Entry labor market conditions, field of study, and career success." *Journal of Labor Economics* 34 (S1):S361–S401.

Arellano-Bover, Jaime. 2020. "The Effect of Labor Market Conditions at Entry on Workersâ Long-Term Skills." *The Review of Economics and Statistics* :1–45.

Arezki, Rabah and Olivier Blanchard. 2014. "Seven questions about the recent oil price slump." *IMFdirect-The IMF Blog* 22.

Atkin, David. 2016. "Endogenous skill acquisition and export manufacturing in Mexico." *American Economic Review* 106 (8):2046–85.

Baffes, John, M Ayhan Kose, Franziska Ohnsorge, and Marc Stocker. 2015. "The great plunge in oil prices: Causes, consequences, and policy responses." *Consequences, and Policy Responses (June 2015)* .

Bartik, Alexander W, Janet Currie, Michael Greenstone, and Christopher R Knittel. 2019. "The local economic and welfare consequences of hydraulic fracturing." *American Economic Journal: Applied Economics* 11 (4):105–55.

Baumeister, Christiane and Lutz Kilian. 2016. "Understanding the Decline in the Price of

Oil since June 2014." *Journal of the Association of Environmental and resource economists* 3 (1):131–158.

Black, Dan, Terra McKinnish, and Seth Sanders. 2005. "The economic impact of the coal boom and bust." *The Economic Journal* 115 (503):449–476.

Chetty, Raj, John N Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan. 2020. "Income segregation and intergenerational mobility across colleges in the United States." *The Quarterly Journal of Economics* 135 (3):1567–1633.

Derenoncourt, Ellora, Clemens Noelke, and David Weil. 2021. "Spillover effects from voluntary employer minimum wages." *Available at SSRN 3793677* .

Fantazzini, Dean. 2016. "The oil price crash in 2014/15: Was there a (negative) financial bubble?" *Energy Policy* 96:383–396.

Feyrer, James, Erin T Mansur, and Bruce Sacerdote. 2017. "Geographic dispersion of economic shocks: Evidence from the fracking revolution." *American Economic Review* 107 (4):1313–34.

Finnie, Ross and Theresa Qiu. 2009. *Moving through, moving on: Persistence in postsecondary education in Atlantic Canada, evidence from the PSIS*, vol. 72. Citeseer.

Fortin, Nicole M and Thomas Lemieux. 2015. "Changes in wage inequality in Canada: An interprovincial perspective." *Canadian Journal of Economics/Revue canadienne d'économique* 48 (2):682–713.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik instruments: What, when, why, and how." *American Economic Review* 110 (8):2586–2624.

Green, David A, Rene Morissette, Ben M Sand, and Iain Snoddy. 2019. "Economy-wide spillovers from booms: Long-distance commuting and the spread of wage effects." *Journal of Labor Economics* 37 (S2):S643–S687.

Hastings, Justine S, Christopher A Neilson, Anely Ramirez, and Seth D Zimmerman. 2016. "(Un) informed college and major choice: Evidence from linked survey and administrative data." *Economics of Education Review* 51:136–151.

Hastings, Justine S, Christopher A Neilson, and Seth D Zimmerman. 2013. "Are some degrees worth more than others? Evidence from college admission cutoffs in Chile." Tech. rep., National Bureau of Economic Research.

Hoekstra, Mark. 2009. "The effect of attending the flagship state university on earnings: A discontinuity-based approach." *The review of economics and statistics* 91 (4):717–724.

Kahn, Lisa B. 2010. "The long-term labor market consequences of graduating from college in a bad economy." *Labour economics* 17 (2):303–316.

Kirkeboen, Lars J, Edwin Leuven, and Magne Mogstad. 2016. "Field of study, earnings, and self-selection." *The Quarterly Journal of Economics* 131 (3):1057–1111.

Kline, Patrick. 2008. "Understanding sectoral labor market dynamics: An equilibrium analysis of the oil and gas field services industry." .

Marchand, Joseph. 2012. "Local labor market impacts of energy boom-bust-boom in Western Canada." *Journal of Urban Economics* 71 (1):165–174.

———. 2015. "The distributional impacts of an energy boom in Western Canada." *Canadian Journal of Economics/Revue canadienne d'économique* 48 (2):714–735.

Oreopoulos, Philip, Till Von Wachter, and Andrew Heisz. 2012. "The short-and long-term career effects of graduating in a recession." *American Economic Journal: Applied Economics* 4 (1):1–29.

Pfanzagl, Johann. 2012. *Contributions to a general asymptotic statistical theory*, vol. 13. Springer Science & Business Media.

Schwandt, Hannes and Till Von Wachter. 2019. "Unlucky cohorts: Estimating the long-term effects of entering the labor market in a recession in large cross-sectional data sets." *Journal of Labor Economics* 37 (S1):S161–S198.

Tsybakov, Alexandre B. 2009. "Introduction to nonparametric estimation."

Zimmerman, Seth D. 2019. "Elite colleges and upward mobility to top jobs and top incomes." *American Economic Review* 109 (1):1–47.

8 Figures

Figure 1: Oil Prices

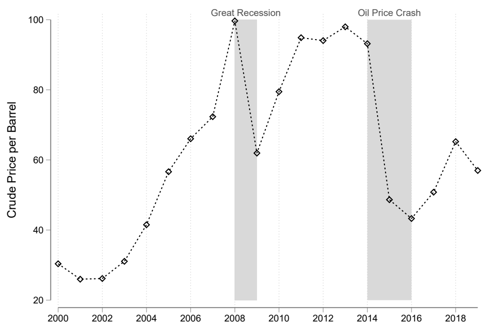
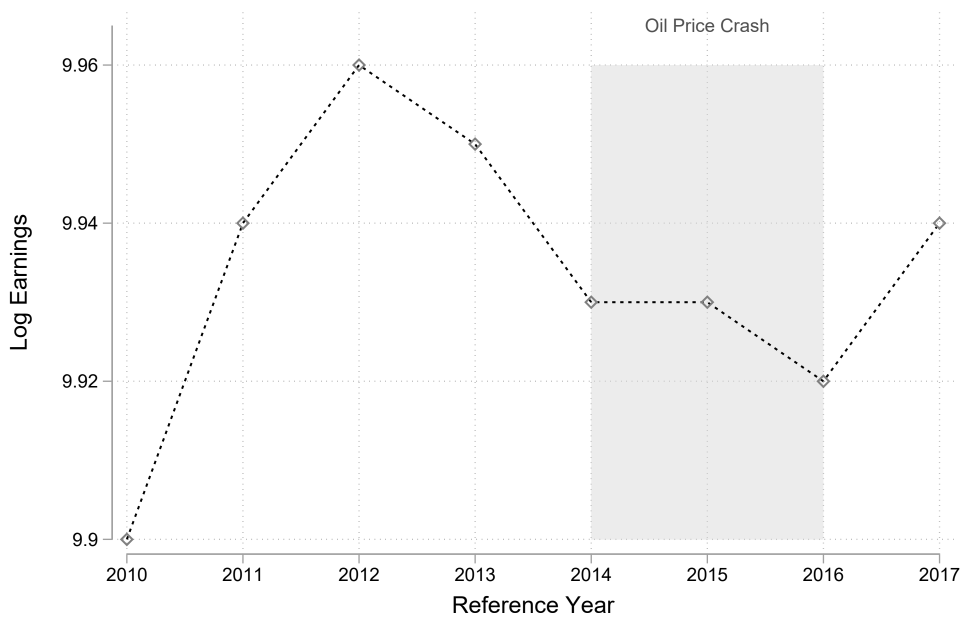


Figure 2: GDP

Note: Figure 1 shows the West Texas Intermediate (WTI) Crude Oil Prices, as published by the St. Louis Fed. The grey areas highlight the Great Recession of 2009-2009 and the oil price crash of 2014-2016. Figure 2 exposes Canada's annual National GDP growth per year.

Figure 3: Graduates Log Earnings Per Year



Note: The figure presents the average log earnings for individuals one year after their graduation. Individuals included are those who once graduated, never study again in the timeline of the sample and graduated from a school-major that had at least 10 graduates per year between 2010 and 2017. Earnings refer to the totality of all employment earnings as reported in the T4 tax File. Log real earnings were CPI deflated using 2009 as a base year. The shaded area highlights the period of the oil price crash.

Figure 4: Employment Growth by Province

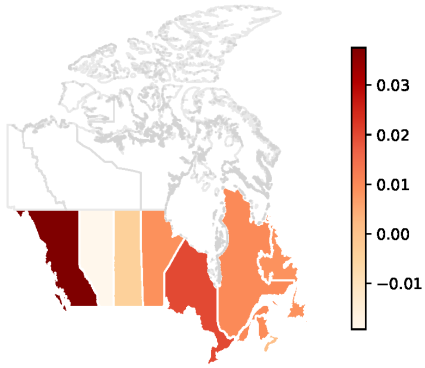
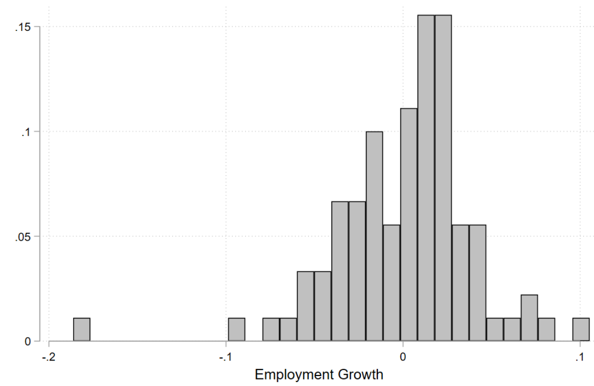
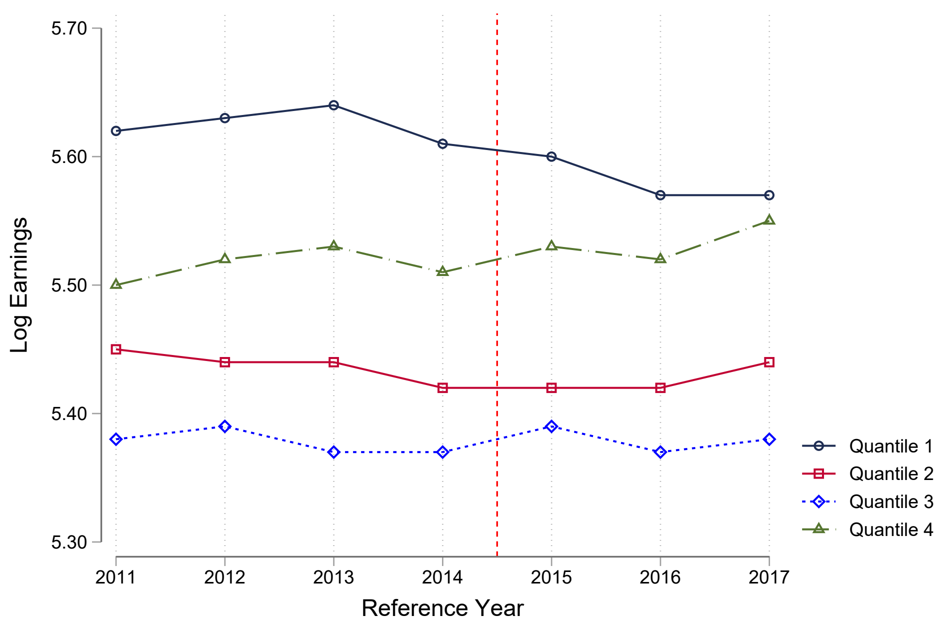


Figure 5: Employment Growth Distribution



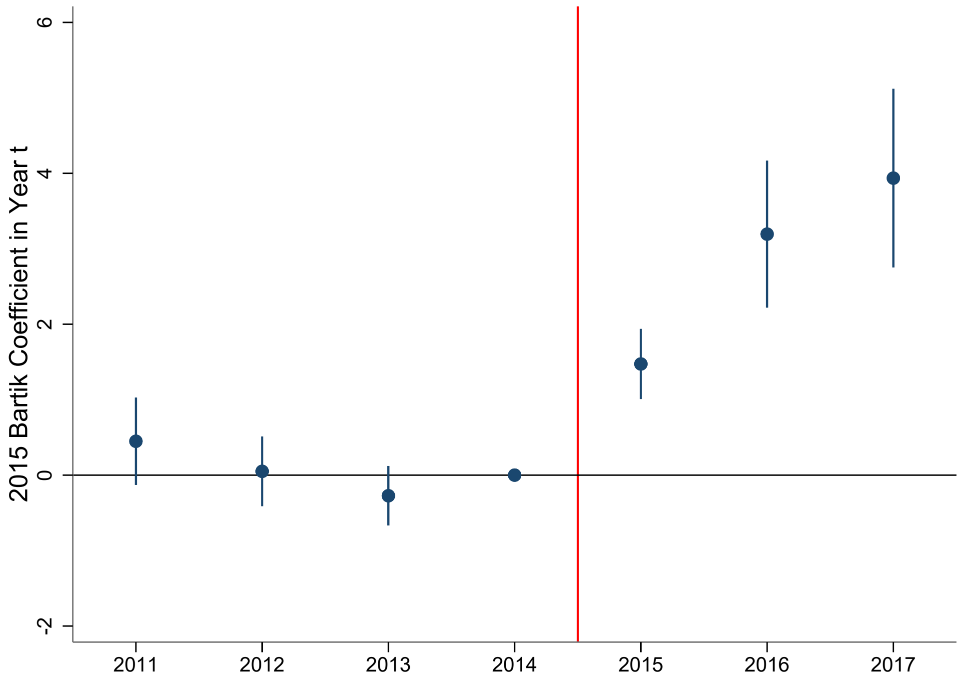
Note: Figure 4 presents the weighted average of employment growth by province in 2015 where the weights represent the number of graduates that entered the labour market in each 3 digit industry between 2010 and 2013. Figure 5 presents a histogram of the 3 digit industry employment growth in 2015 at the National level. Employment growth was collected through publicly available data published by STATSCAN, and was calculated using the Canadian Labour Force Survey.

Figure 6: Earnings by Quartile of Bartik Instrument in 2015



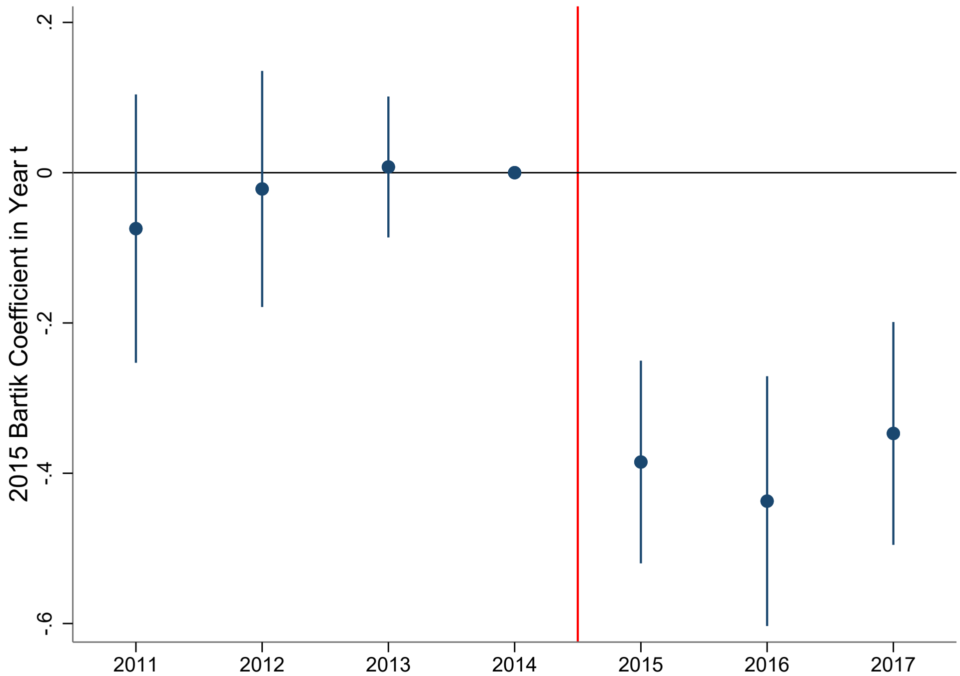
Note: This figure presents trends of real log earnings by quartile of the Bartik instrument in 2015. Individuals included are those who once graduated, never study again in the timeline of the sample and graduated from a school-major that had at least 10 graduates per year between 2010 and 2017. Earnings refer to the totality of all employment earnings as reported in the T4 tax File. Log real earnings were CPI deflated using 2002 as a base year.

Figure 7: Earnings



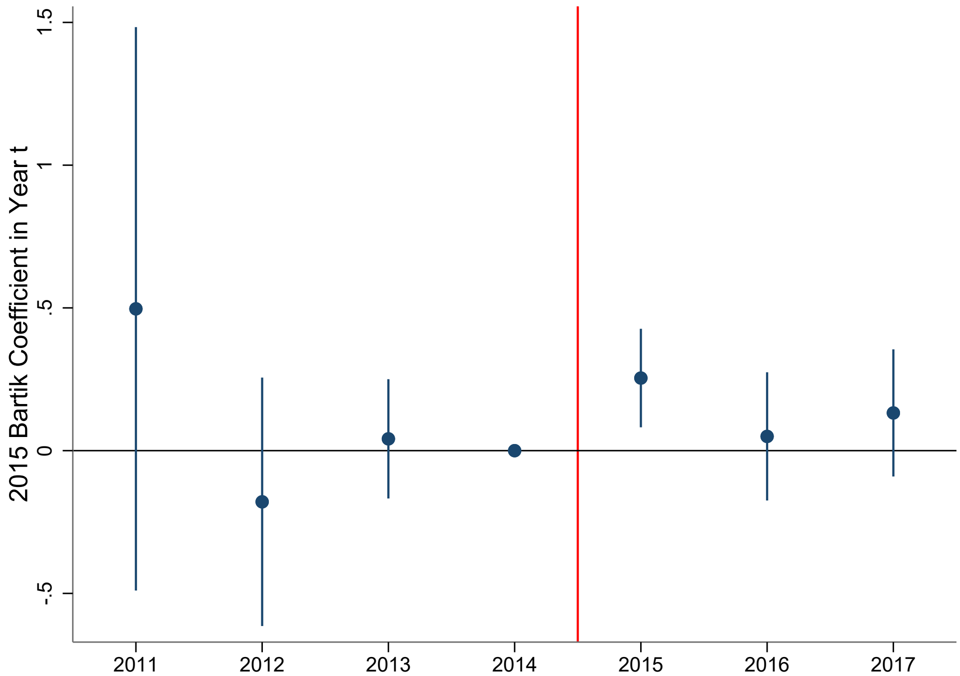
Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample. That is, the plotted coefficients represent each β_j of Regression (2) as presented in Column (2) of Table 3. Standard errors were clustered at the school-major level. Individuals included are those who once graduated, never study again in the timeline of the sample and graduated from a school-major that had at least 10 graduates per year between 2010 and 2017. Earnings refer to the totality of all employment earnings as reported in the T4 tax File. Log real earnings were CPI deflated using 2009 as a base year.

Figure 8: Employment Insurance



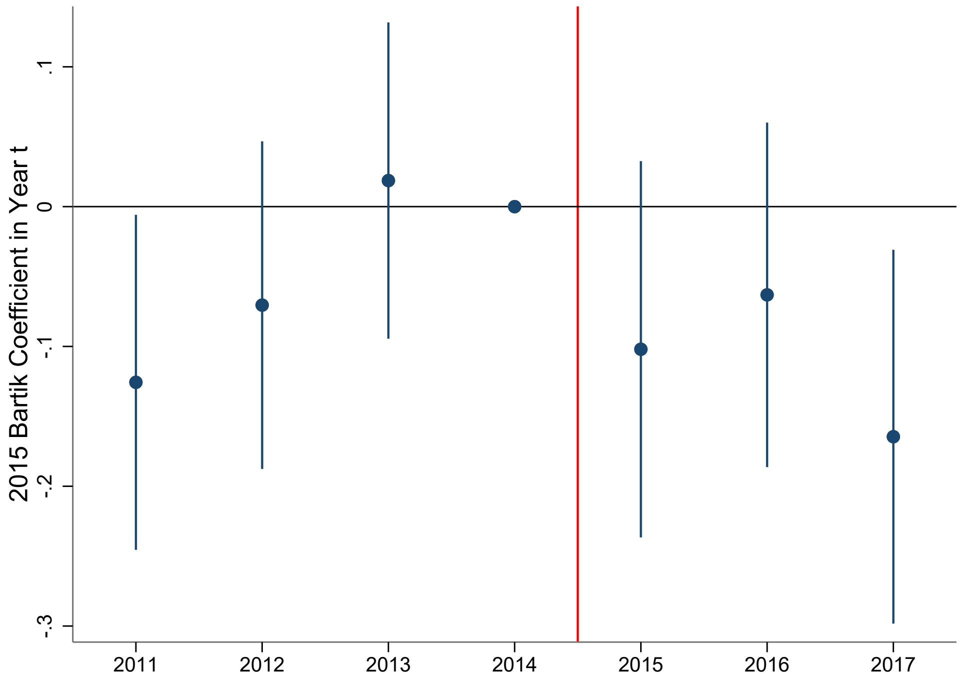
Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample. That is, the plotted coefficients represent each β_j of Regression (2) as presented in Column (2) of Table 4. Standard errors were clustered at the school-major level. Individuals included are those who once graduated, never study again in the timeline of the sample and graduated from a school-major that had at least 10 graduates per year between 2010 and 2017. Employment insurance was derived from Line 119 of the T1 General form.

Figure 9: Filing Taxes



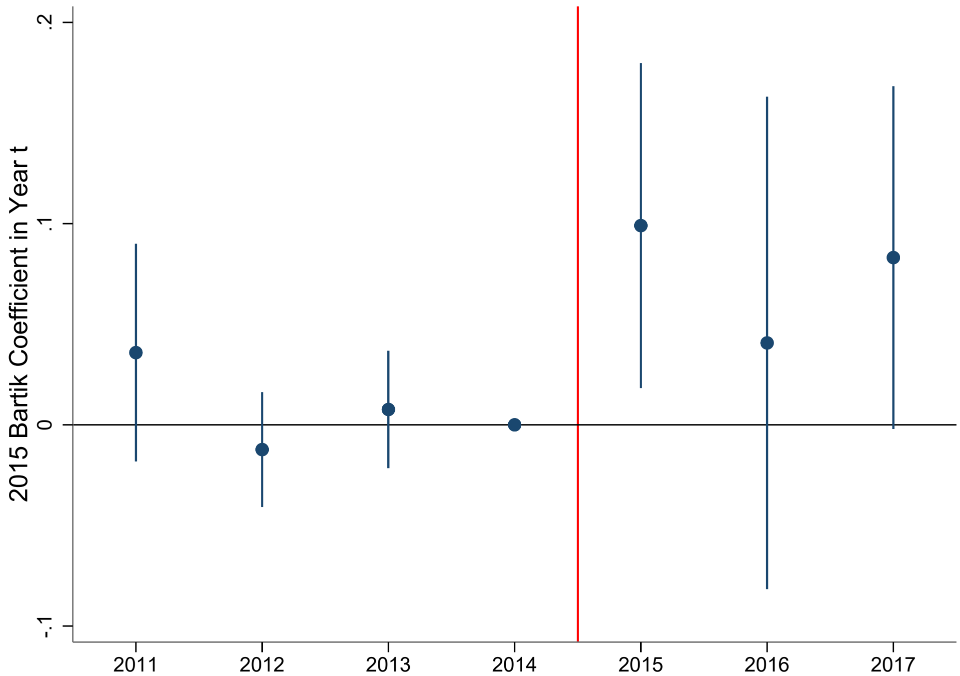
Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample. That is, the plotted coefficients represent each β_j of Regression (2) as presented in Column (2) of Table 5. Standard errors were clustered at the school-major level. Individuals included are those who once graduated, never study again in the timeline of the sample and graduated from a school-major that had at least 10 graduates per year between 2010 and 2017. An individual was considered to file taxes if they were able to be merged with a T1 tax form.

Figure 10: Self-Employment



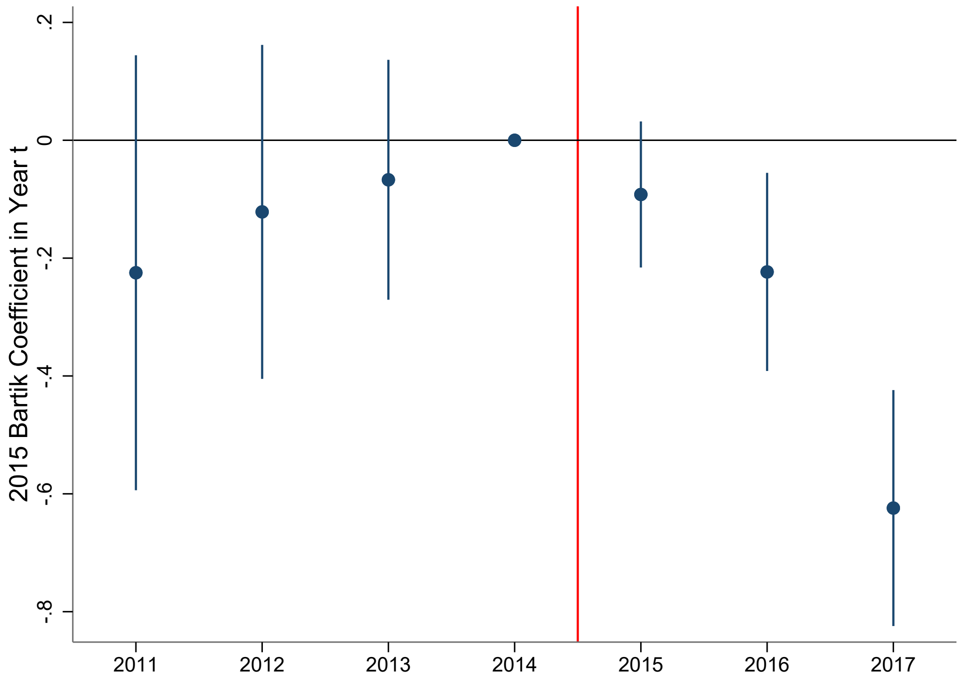
Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample. That is, the plotted coefficients represent each β_j of Regression (2) as presented in Column (2) of Table 6. Standard errors were clustered at the school-major level. Individuals included are those who once graduated, never study again in the timeline of the sample and graduated from a school-major that had at least 10 graduates per year between 2010 and 2017. An individual was considered to have self-employment if they reported positive income in business, professional, commission, farming or fishing. Specifically, this variable was derived from Lines 135, 137, 139, 141 and 143 of the T1 General form.

Figure 11: Dropouts



Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample. That is, the plotted coefficients represent each β_j of Regression (2) as presented in Column (2) of Table 7. Standard errors were clustered at the school-major level. School-majors included had to have at least 10 graduates per year between 2010 and 2017. Dropout was derived from the PSIS census.

Figure 12: Graduation



Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample. That is, the plotted coefficients represent each β_j of Regression (2) as presented in Column (2) of Table 8. Standard errors were clustered at the school-major level. School-majors included had to have at least 10 graduates per year between 2010 and 2017. Graduation was derived from the PSIS census.

Figure 13: Bartik interacted with Major Premium

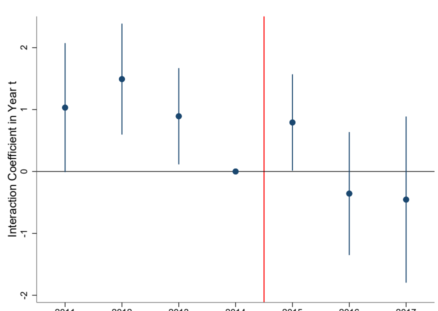
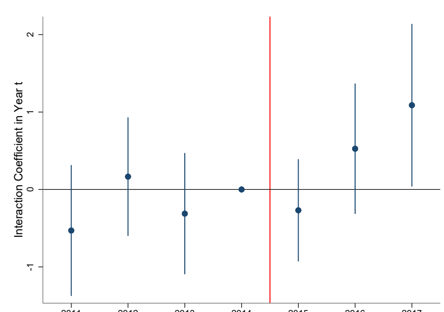


Figure 14: Bartik interacted with School



Note: Figure 13 presents the estimated effects of $\beta_{JM^{\xi}}$ estimated through the lens of Regression (3). That is, the plotted coefficients represent each year of Column (2) of Table 9. Figure 14 presents the estimated effects of $\beta_{JS^{\xi}}$ estimated through the lens of Regression (3). That is, the plotted coefficients represent each year of Column (2) of Table 10. Standard errors were clustered at the school-major level. School-majors included had to have at least 10 graduates per year between 2010 and 2017.

9 Tables

Table 1: Summary Stats

	Total Sample (1)	Above Hellinger Median (2)	Below Hellinger Median (3)
Age	27.04	27.06	27.04
Female	0.60	0.61	0.60
Family Size	2.74	2.72	2.74
Married	0.88	0.89	0.88
Immigrant	0.11	0.08	0.11
Real Employment Income	29,200	23,700	30,400
Number of T4 Slips	1.75	1.78	1.74
Employment Insurance	0.09	0.09	0.10
Self-Employed	0.08	0.09	0.08
Number of Graduates	853,565	160,950	692,620

Note: This Table presents the summary statistics for all the individuals who graduated from a Canadian public institution bachelor program between 2010 and 2017, never studied again during the sample period, and matched with a T1 Tax form during the same period. The summary stats are descriptive for the calendar year after graduation. All individuals included in this sample graduated from a school-major that registered at least 10 graduates per year between 2010 and 2017. Earnings refer to the totality of all employment earnings as reported in the T4 tax File. Real earnings were CPI deflated using 2009 as base year. An individual was considered to have self-employment if they reported positive income in business, professional, commission, farming or fishing. Specifically, this variable was derived from Lines 135, 137, 139, 141 and 143 of the T1. Employment insurance was derived from Line 119 of the T1 General form.

Table 2: Effect of Labour Demand Shift on Graduates Earnings

	Outcome: Difference in Log Earnings				
	(1)	(2)	(3)	(4)	(5)
Bartik Instrument	1.383***	1.794***	2.166**	1.474	1.267
	(0.354)	(0.552)	(0.870)	(0.944)	(0.850)
Residual Earnings	X	✓	✓	✓	✓
Province of Study FE	✓	X	✓	X	✓
Province of Origin FE	X	X	X	✓	✓

Note: This Table presents the estimations of Regression (1) using the Bartik instrument as the independent variable (in a continuous version). Column (1) presents the estimation using as an outcome log earnings, while the rest of the columns present results for residualized log earnings as defined in Section 3. The earnings were calculated for each graduate 1 year after graduation. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. Earnings refer to the totality of all employment earnings as reported in the T4 tax File. Real earnings were CPI deflated using 2009 as base year. For the sample of this regression, the Bartik instrument has a mean of 0.015 and a SD of 0.013. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 3: Dynamic Effect of Labour Demand Shift on Graduates Earnings

	Outcome: Log Earnings								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	0.439	0.449	0.679**	0.599**	0.611**	0.697**	-1.484	-1.457	-0.275
	(0.284)	(0.295)	(0.275)	(0.286)	(0.298)	(0.281)	(0.916)	(0.899)	(1.051)
2012	0.0280	0.0503	0.293	0.199	0.213	0.276	-1.947**	-1.824*	-0.589
	(0.231)	(0.235)	(0.246)	(0.228)	(0.233)	(0.253)	(0.943)	(0.941)	(1.198)
2013	-0.258	-0.273	-0.214	-0.174	-0.192	-0.316	-1.264	-1.241	-0.0733
	(0.200)	(0.201)	(0.235)	(0.202)	(0.202)	(0.233)	(0.863)	(0.855)	(1.039)
Post Oil Price Shock:									
2015	1.485***	1.473***	1.357***	1.600***	1.587***	1.254***	0.254	0.255	1.567*
	(0.239)	(0.237)	(0.299)	(0.246)	(0.244)	(0.319)	(0.778)	(0.770)	(0.932)
2016	3.240***	3.194***	2.771***	3.358***	3.300***	2.752***	2.126**	2.246**	2.259**
	(0.498)	(0.497)	(0.553)	(0.517)	(0.517)	(0.584)	(0.879)	(0.891)	(1.140)
2017	3.960***	3.936***	3.172***	4.094***	4.054***	3.255***	2.692***	2.882***	1.608
	(0.606)	(0.603)	(0.709)	(0.630)	(0.630)	(0.750)	(0.900)	(0.906)	(1.064)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the 2015 Bartik instrument as the independent variable (in a continuous version). Each row presents the estimated coefficients for each β_j. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. Earnings refer to the totality of all employment earnings as reported in the T4 tax File. Real earnings were CPI deflated using 2009 as base year. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 4: Dynamic Effect of Labour Demand Shift on Graduates Employment Insurance Status

	Outcome: Employment Insurance								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	-0.072	-0.074	-0.008	-0.088	-0.091	-0.006	0.113	0.118	0.157
	(0.090)	(0.091)	(0.010)	(0.099)	(0.100)	(0.108)	(0.234)	(0.231)	(0.252)
2012	-0.024	-0.022	-0.017	-0.027	-0.026	-0.008	0.003	0.014	0.068
	(0.080)	(0.080)	(0.091)	(0.084)	(0.084)	(0.093)	(0.307)	(0.303)	(0.355)
2013	0.008	0.008	0.021	-0.010	-0.011	0.011	0.192	0.197	0.305
	(0.048)	(0.048)	(0.064)	(0.049)	(0.049)	(0.070)	(0.184)	(0.185)	(0.225)
Post Oil Price Shock:									
2015	-0.386***	-0.385***	-0.336***	-0.387***	-0.387***	-0.335***	-0.385	-0.380	-0.223
	(0.069)	(0.069)	(0.072)	(0.071)	(0.071)	(0.073)	(0.263)	(0.262)	(0.306)
2016	-0.434***	-0.437***	-0.333***	-0.442***	-0.445***	-0.339***	-0.347	-0.351	-0.210
	(0.085)	(0.085)	(0.089)	(0.089)	(0.089)	(0.093)	(0.257)	(0.256)	(0.309)
2017	-0.345***	-0.347***	-0.199**	-0.363***	-0.365***	-0.241***	-0.163	-0.160	0.274
	(0.076)	(0.076)	(0.080)	(0.078)	(0.078)	(0.080)	(0.260)	(0.259)	(0.319)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the 2015 Bartik instrument as the independent variable (in a continuous version). Each row presents the estimated coefficients for each β_j. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. Employment insurance was derived from Line 119 of the T1 General form. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 5: Dynamic Effect of Labour Demand Shift on Graduates Tax Status

	Outcome: Filing Taxes								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	0.059	0.021	-0.061	0.067	0.032	-0.077	-0.045	-0.097	0.050
	(0.068)	(0.080)	(0.104)	(0.067)	(0.079)	(0.109)	(0.313)	(0.292)	(0.349)
2012	0.120*	0.128*	0.104	0.171**	0.174**	0.173**	-0.435	-0.358	-0.597
	(0.072)	(0.071)	(0.080)	(0.075)	(0.070)	(0.078)	(0.305)	(0.298)	(0.371)
2013	0.027	-0.024	-0.074	0.021	-0.036	-0.105	0.095	0.123	0.220
	(0.062)	(0.062)	(0.071)	(0.064)	(0.064)	(0.074)	(0.241)	(0.228)	(0.300)
Post Oil Price Shock:									
2015	0.183***	0.186***	0.209***	0.183***	0.185***	0.186***	0.184	0.197	0.407
	(0.058)	(0.058)	(0.070)	(0.061)	(0.060)	(0.071)	(0.206)	(0.207)	(0.273)
2016	0.267***	0.103	0.180**	0.276***	0.125	0.215**	0.195	-0.056	-0.130
	(0.071)	(0.081)	(0.090)	(0.075)	(0.083)	(0.092)	(0.241)	(0.240)	(0.331)
2017	0.279***	0.164**	0.181**	0.264***	0.154**	0.155*	0.435	0.336	0.578*
	(0.071)	(0.073)	(0.086)	(0.074)	(0.077)	(0.088)	(0.268)	(0.245)	(0.324)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the 2015 Bartik instrument as the independent variable (in a continuous version). Each row presents the estimated coefficients for each β_j. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. An individual was considered to file taxes if they were able to be merged with a T1 tax form. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 6: Dynamic Effect of Labour Demand Shift on Graduates Self-Employment Status

	Outcome: Self Employment								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	-0.121*	-0.126**	-0.157**	-0.103	-0.107*	-0.130*	-0.322	-0.334	-0.495*
	(0.062)	(0.061)	(0.070)	(0.065)	(0.064)	(0.0747)	(0.226)	(0.223)	(0.267)
2012	-0.069	-0.071	-0.153**	-0.039	-0.041	-0.081	-0.366	-0.371	-0.811***
	(0.060)	(0.060)	(0.066)	(0.064)	(0.063)	(0.067)	(0.235)	(0.235)	(0.278)
2013	0.021	0.019	0.024	0.047	0.044	0.0407	-0.234	-0.232	-0.185
	(0.058)	(0.058)	(0.076)	(0.059)	(0.059)	(0.080)	(0.238)	(0.238)	(0.283)
Post Oil Price Shock:									
2015	-0.102	-0.102	-0.118	-0.056	-0.057	-0.068	-0.561***	-0.559**	-0.762**
	(0.068)	(0.069)	(0.081)	(0.071)	(0.071)	(0.084)	(0.217)	(0.216)	(0.297)
2016	-0.059	-0.063	-0.049	-0.059	-0.063	-0.042	-0.065	-0.066	-0.129
	(0.063)	(0.063)	(0.078)	(0.065)	(0.065)	(0.082)	(0.246)	(0.246)	(0.292)
2017	-0.162**	-0.165**	-0.144*	-0.153**	-0.155**	-0.143	-0.283	-0.272	-0.213
	(0.068)	(0.068)	(0.086)	(0.072)	(0.072)	(0.091)	(0.230)	(0.229)	(0.277)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the 2015 Bartik instrument as the independent variable (in a continuous version). Each row presents the estimated coefficients for each β_j. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. An individual was considered to have self-employment if they reported positive income in business, professional, commission, farming or fishing.Specifically, this variable was derived from Lines 135, 137, 139, 141 and 143 of the T1 General form. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 7: Dynamic Effect of Labour Demand Shift on Students Dropouts

	Outcome: Dropouts								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	0.036	0.036	0.045	0.043	0.043	0.044	-0.011	-0.009	0.036
	(0.028)	(0.028)	(0.037)	(0.031)	(0.031)	(0.042)	(0.041)	(0.040)	(0.036)
2012	-0.012	-0.012	-0.022	-0.010	-0.010	-0.023	-0.027	-0.028	-0.022
	(0.015)	(0.015)	(0.020)	(0.016)	(0.016)	(0.022)	(0.033)	(0.033)	(0.034)
2013	0.008	0.008	-0.001	0.007	0.007	-0.001	0.016	0.015	0.000
	(0.015)	(0.015)	(0.020)	(0.016)	(0.017)	(0.022)	(0.025)	(0.025)	(0.032)
Post Oil Price Shock:									
2015	0.099**	0.099**	0.087***	0.102**	0.102**	0.086**	0.072	0.072	0.094
	(0.041)	(0.041)	(0.032)	(0.045)	(0.045)	(0.034)	(0.091)	(0.091)	(0.100)
2016	0.041	0.041	0.006	0.032	0.032	-0.005	0.109	0.107	0.106
	(0.062)	(0.062)	(0.068)	(0.068)	(0.068)	(0.074)	(0.110)	(0.109)	(0.111)
2017	0.084*	0.083*	0.086**	0.083*	0.083*	0.083*	0.090	0.087	0.094
	(0.044)	(0.043)	(0.043)	(0.047)	(0.047)	(0.046)	(0.127)	(0.123)	(0.117)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the 2015 Bartik instrument as the independent variable (in a continuous version). Each row presents the estimated coefficients for each β_j. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. Dropout was derived from the PSIS census. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 8: Dynamic Effect of Labour Demand Shift on Graduation

	Outcome: Graduation								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	-0.097	-0.225	-0.541**	-0.056	-0.153	-0.405*	-0.314	-0.633	-1.424***
	(0.174)	(0.188)	(0.236)	(0.181)	(0.191)	(0.237)	(0.392)	(0.461)	(0.484)
2012	-0.086	-0.122	-0.271	-0.014	-0.055	-0.168	-0.535*	-0.552*	-0.912***
	(0.143)	(0.144)	(0.179)	(0.148)	(0.148)	(0.179)	(0.315)	(0.322)	(0.350)
2013	-0.067	-0.067	0.109	-0.015	-0.016	0.189	-0.439**	-0.438**	-0.488*
	(0.104)	(0.104)	(0.122)	(0.109)	(0.108)	(0.128)	(0.203)	(0.203)	(0.249)
Post Oil Price Shock:									
2015	-0.116*	-0.092	-0.164*	-0.092	-0.056	-0.131	-0.292	-0.337*	-0.454**
	(0.061)	(0.063)	(0.091)	(0.064)	(0.064)	(0.097)	(0.183)	(0.182)	(0.219)
2016	-0.199**	-0.223***	-0.460***	-0.218**	-0.219**	-0.431***	-0.056	-0.203	-0.604**
	(0.083)	(0.086)	(0.104)	(0.092)	(0.092)	(0.111)	(0.222)	(0.234)	(0.273)
2017	-0.475***	-0.624***	0.634**	-0.528***	-0.637***	0.585*	-0.145	-0.518	1.124
	(0.103)	(0.102)	(0.318)	(0.105)	(0.106)	(0.347)	(0.332)	(0.321)	(0.865)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the 2015 Bartik instrument as the independent variable (in a continuous version). Each row presents the estimated coefficients for each β_j. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. Graduation was derived from the PSIS census. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 9: Heterogeneous Dynamic Effect of Labour Demand Shift on Earnings by Major Premium

	Outcome: Log Earnings		
	(1)	(2)	(3)
2011	1.018*	1.032*	1.053**
	(0.534)	(0.531)	(0.517)
2012	1.474***	1.493***	1.536***
	(0.456)	(0.457)	(0.446)
2013	0.887**	0.893**	1.040***
	(0.399)	(0.396)	(0.399)
Post Oil Price Shock:			
2015	0.788*	0.792**	0.954**
	(0.403)	(0.397)	(0.401)
2016	-0.415	-0.357	-0.162
	(0.510)	(0.506)	(0.493)
2017	-0.510	-0.454	-0.126
	(0.694)	(0.684)	(0.638)
Province of Origin FE	X	✓	✓
Province of Origin Time Trend	X	X	✓

Note: This Table presents the estimations of Regression (3) using the 2015 Bartik instrument as the independent variable (in a continuous version). Each row presents the estimated $\beta_{JM\xi}$. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. Earnings refer to the totality of all employment earnings as reported in the T4 tax File. Real earnings were CPI deflated using 2009 as base year. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 10: Heterogeneous Dynamic Effect of Labour Demand Shift on Earnings by School Premium

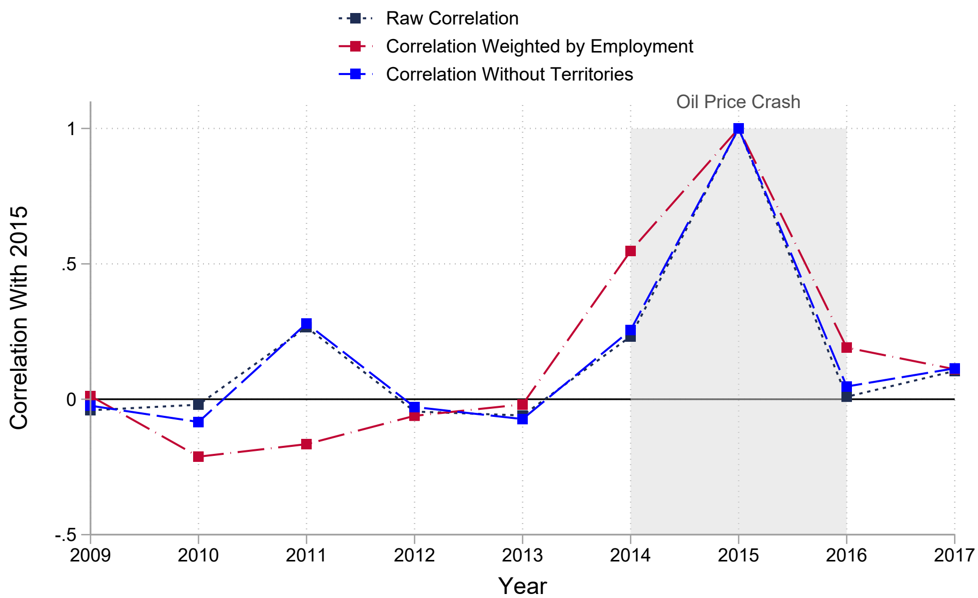
	Outcome: Log Earnings		
	(1)	(2)	(3)
2011	-0.628	-0.530	-0.802*
	(0.425)	(0.430)	(0.437)
2012	0.115	0.166	0.0198
	(0.386)	(0.390)	(0.403)
2013	-0.304	-0.312	-0.447
	(0.400)	(0.399)	(0.403)
Post Oil Price Shock:			
2015	-0.271	-0.269	-0.292
	(0.339)	(0.336)	(0.362)
2016	0.524	0.526	0.445
	(0.427)	(0.429)	(0.416)
2017	1.093**	1.088**	1.135**
	(0.536)	(0.535)	(0.491)
Province of Origin FE	X	✓	✓
Province of Origin Time Trend	X	X	✓

Note: This Table presents the estimations of Regression (3) using the 2015 Bartik instrument as the independent variable (in a continuous version). Each row presents the estimated $\beta_{JS\xi}$. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. Earnings refer to the totality of all employment earnings as reported in the T4 tax File. Real earnings were CPI deflated using 2009 as base year. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

A Appendix

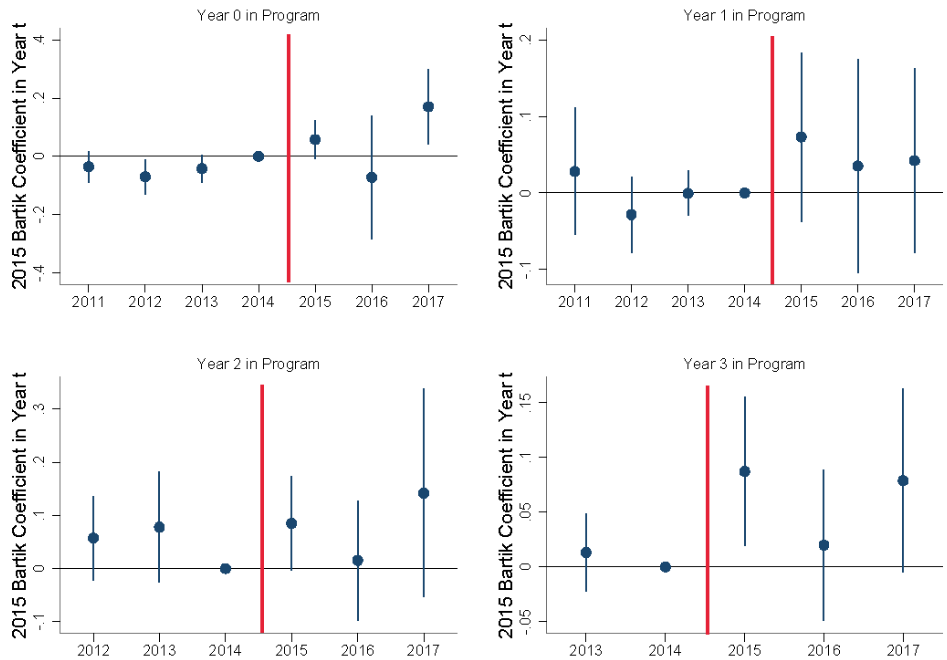
A.1 Figures

Figure 15: Correlation of yearly Industry-Province Growth with 2015 Growth



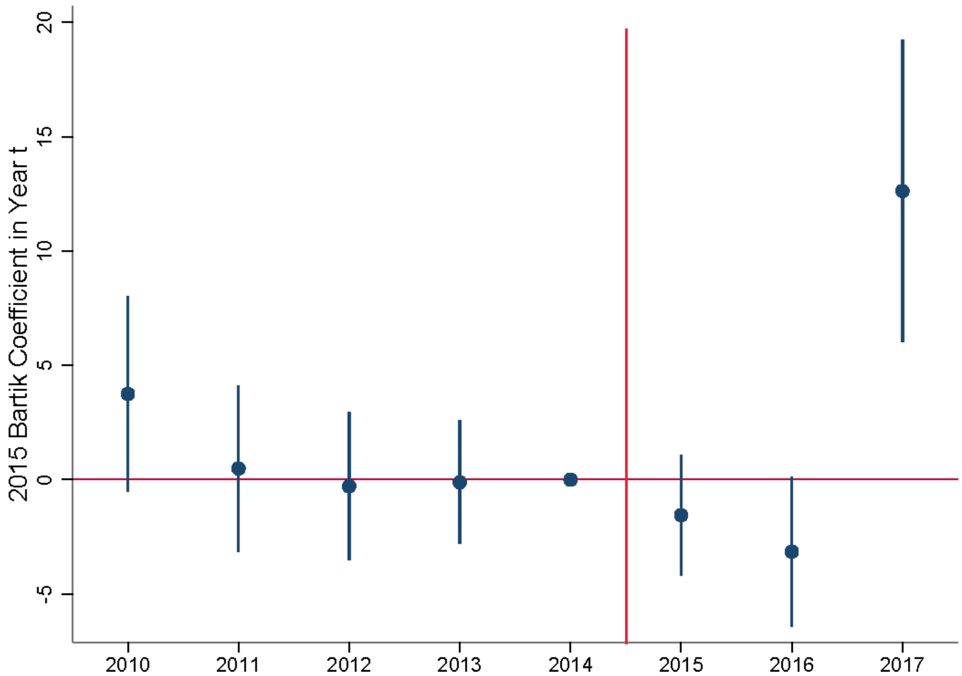
Note: The figure presents the correlation of annual 3-digit industrial employment growth for each year in the sample with 2015. The black line presents the raw correlation. The red line presents the correlation weighted by employment the average level of employment during the whole period. The blue line presents the correlation without including the territories. Employment growth was collected through publicly available data published by STATSCAN, and was calculated using the Survey of Employment, Payrolls and Hours (SEPH).

Figure 16: Dropouts Per Year of Study



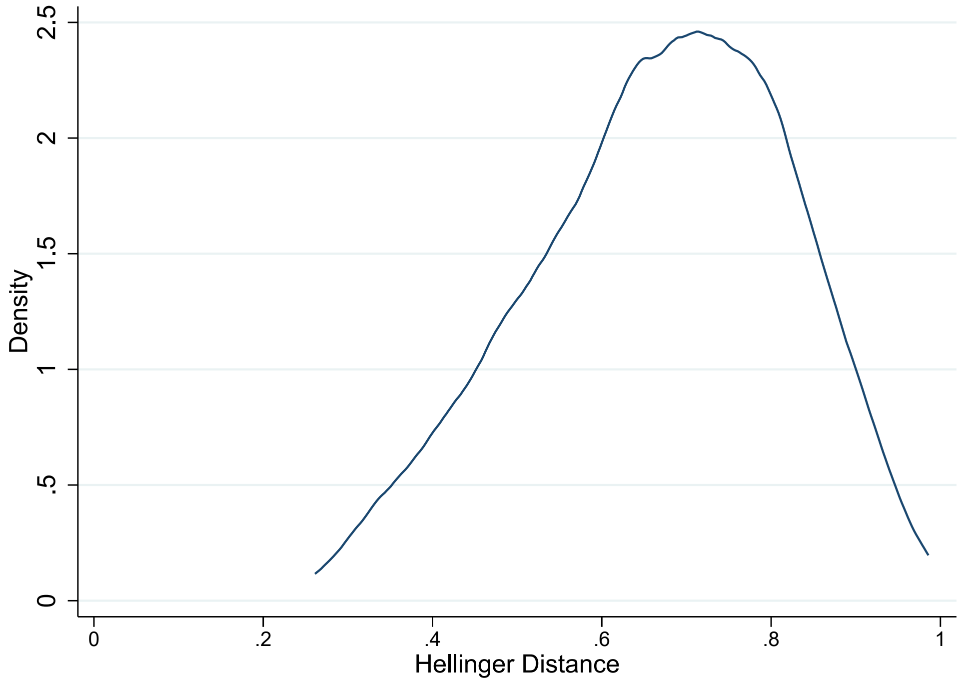
Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample. That is, the plotted coefficients represent each β_j of Regression (2) split by year of study. Standard errors were clustered at the school-major level. School-majors included had to have at least 10 graduates per year between 2010 and 2017. Dropout was derived from the PSIS census.

Figure 17: New Enrollments



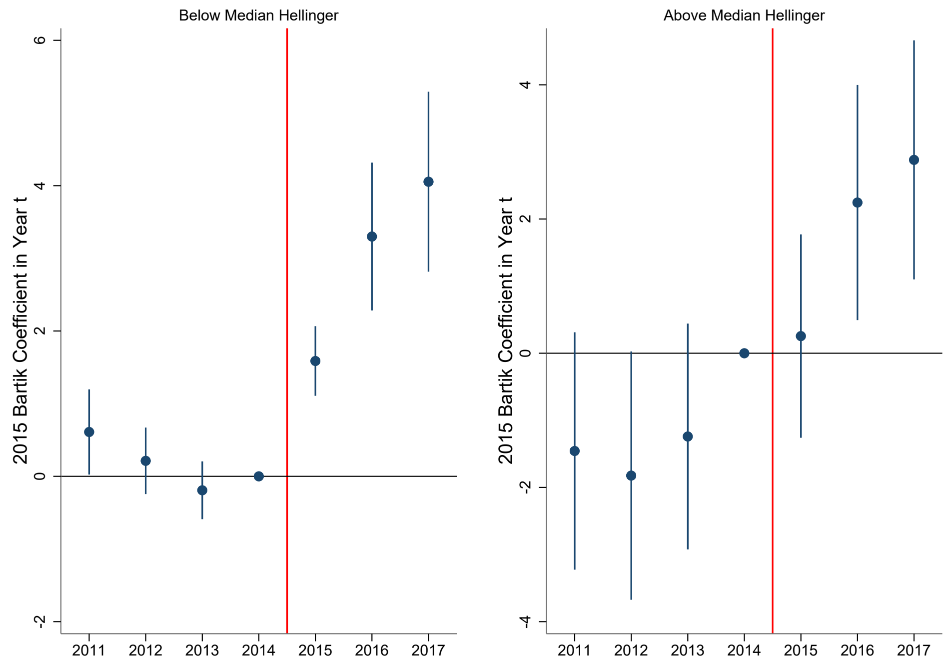
Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample. That is, the plotted coefficients represent each β_j of Regression (2) as presented Column (1) of the Appendix Table 11. Standard errors were clustered at the school-major level. School-majors included had to have at least 10 graduates per year between 2010 and 2017. Enrollments were derived from the PSIS census.

Figure 18: Distribution of Average Hellinger Distance



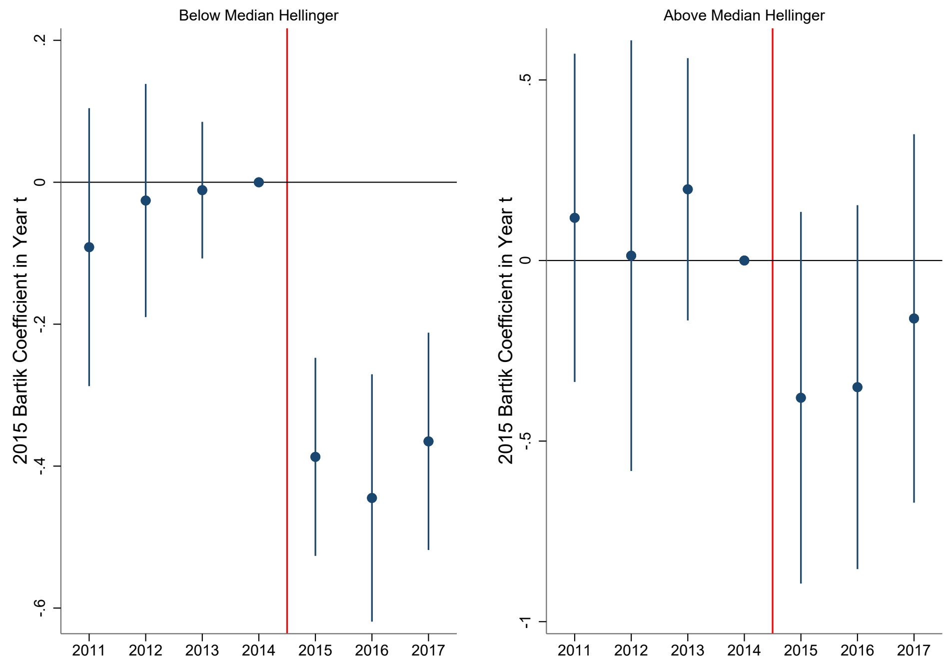
Note: This figure presents the distribution of the average Hellinger Distance across school-majors between 2010 and 2013. Hellinger Distance was calculated as expressed in Equation (4). School-majors included had to have at least 10 graduates per year between 2010 and 2017.

Figure 19: Earnings per Persistence of School-Major



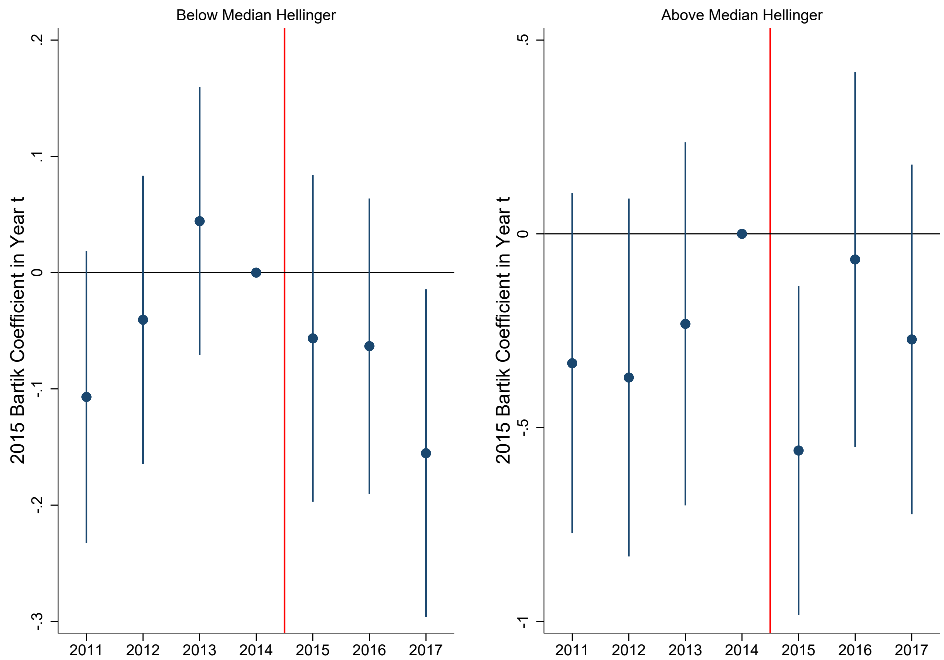
Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample split by Hellinger Distance. That is, the plotted coefficients represent each β_j of Regression (2) as presented in Column (5) and (8) of Table 3. Standard errors were clustered at the school-major level. Individuals included are those who once graduated, never study again in the timeline of the sample and graduated from a school-major that had at least 10 graduates per year between 2010 and 2017. Earnings refer to the totality of all employment earnings as reported in the T4 tax File. Log real earnings were CPI deflated using 2009 as a base year.

Figure 20: Employment Insurance per Persistence of School-Major



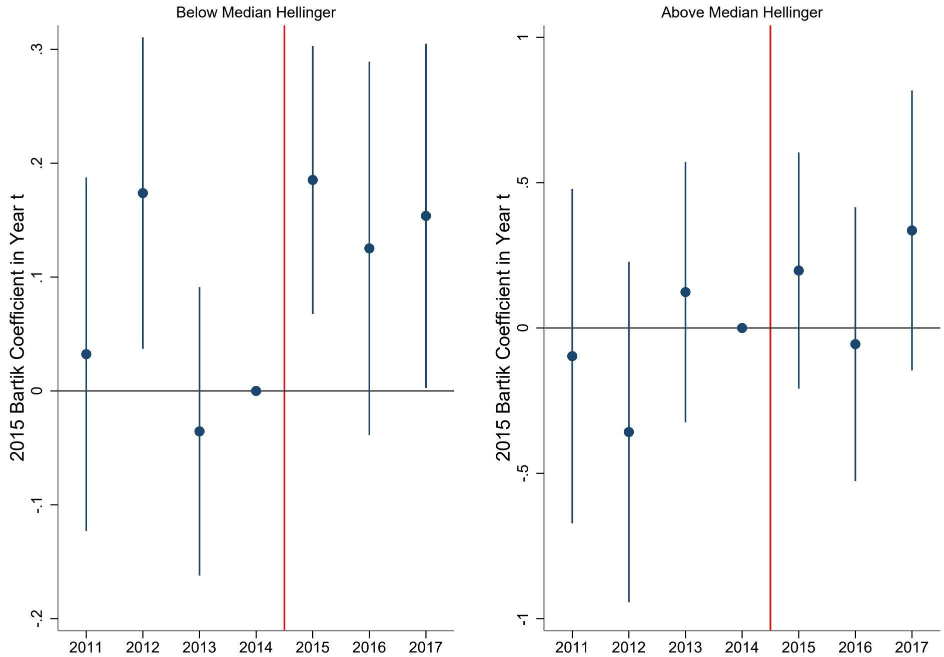
Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample split by Hellinger Distance. That is, the plotted coefficients represent each β_j of Regression (2) as presented in Column (5) and (8) of Table 4. Standard errors were clustered at the school-major level. Individuals included are those who once graduated, never study again in the timeline of the sample and graduated from a school-major that had at least 10 graduates per year between 2010 and 2017. Employment insurance was derived from Line 119 of the T1 General form.

Figure 21: Self-Employment per Persistence of School-Major



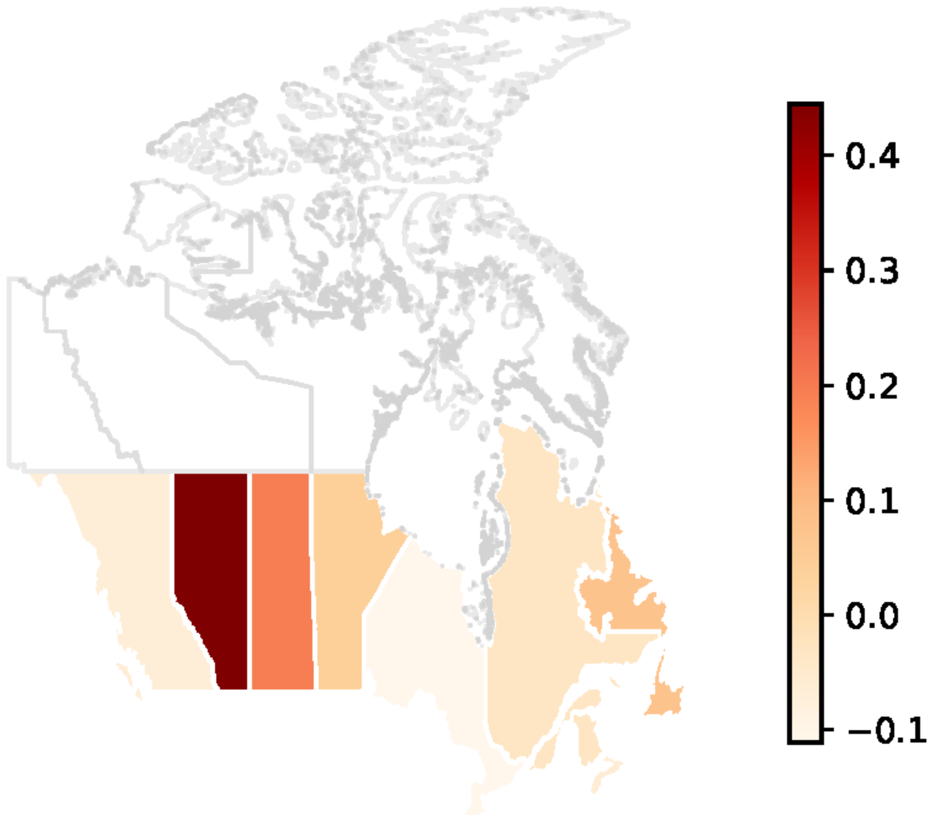
Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample split by Hellinger Distance. That is, the plotted coefficients represent each β_j of Regression (2) as presented in Column (5) and (8) of Table 6. Standard errors were clustered at the school-major level. Individuals included are those who once graduated, never study again in the timeline of the sample and graduated from a school-major that had at least 10 graduates per year between 2010 and 2017. An individual was considered to have self-employment if they reported positive income in business, professional, commission, farming or fishing. Specifically, this variable was derived from Lines 135, 137, 139, 141 and 143 of the T1 General form.

Figure 22: Tax Filing per Persistence of School-Major



Note: This figure presents the estimated coefficients of the interaction of the Bartik instrument in 2015 with each year of the sample split by Hellinger Distance. That is, the plotted coefficients represent each β_j of Regression (2) as presented in Column (5) and (8) of Table 5. Standard errors were clustered at the school-major level. Individuals included are those who once graduated, never study again in the timeline of the sample and graduated from a school-major that had at least 10 graduates per year between 2010 and 2017. An individual was considered to file taxes if they were able to be merged with a T1 tax form.

Figure 23: Unemployment Growth by Province



Note: Figure 4 presents the weighted average of unemployment growth by province in 2015 where the weights represent the number of graduates that entered the labour market in each 2 digit industry between 2010 and 2013. Unemployment growth was collected through publicly available data published by STATSCAN, and was calculated using the Canadian Labour Force Survey.

A.2 Tables

Table 11: Dynamic Effect of Labour Demand Shift on First Year Enrollment

	Outcome: Enrollment		
	(1)	(2)	(3)
2011	0.221	1.997	-2.661
	(1.862)	(1.440)	(4.544)
2012	-0.153	1.459*	-3.502
	(1.661)	(0.852)	(4.459)
2013	0.083	0.696	-1.249
	(1.341)	(0.599)	(3.700)
Post Oil Price Shock:			
2015	-1.555	-0.643	-3.466
	(1.356)	(0.872)	(3.553)
2016	-3.219*	-2.221*	-5.343
	(1.677)	(1.276)	(4.243)
2017	12.470***	15.230***	7.536
	(3.399)	(3.664)	(6.319)

Note: This Table presents the estimations of Regression (2) using the 2015 Bartik instrument as the independent variable (in a continuous version). Each row presents the estimated coefficients for each β_j. The outcome presented in this table is the log of the total enrollment at the school-major level per year. The regression contains now additional controls at the school-major level. Column (1) presents results for the complete sample. Column (2) and Column (3) present results of the sample of schools below and above the median of the Hellinger Distance respectively. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. enrollment was derived from the PSIS census. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 12: Dynamic Effect of Labour Demand Shift on Earnings

	Outcome: Log Earnings								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	-0.095***	-0.096***	-0.077**	-0.112***	-0.113***	-0.083**	0.122	0.119	0.145
	(0.024)	(0.025)	(0.033)	(0.023)	(0.023)	(0.033)	(0.103)	(0.099)	(0.133)
2012	-0.060***	-0.062***	-0.073**	-0.072***	-0.073***	-0.074**	0.110	0.094	0.054
	(0.022)	(0.022)	(0.031)	(0.022)	(0.021)	(0.032)	(0.116)	(0.113)	(0.170)
2013	-0.007	-0.006	0.005	-0.015	-0.013	-0.000	0.101	0.090	0.200*
	(0.020)	(0.020)	(0.030)	(0.020)	(0.020)	(0.032)	(0.088)	(0.087)	(0.111)
Post Oil Price Shock:									
2015	-0.125***	-0.124***	-0.115***	-0.136***	-0.135***	-0.114***	0.009	0.007	-0.031
	(0.028)	(0.028)	(0.040)	(0.028)	(0.028)	(0.042)	(0.084)	(0.080)	(0.120)
2016	-0.328***	-0.327***	-0.279***	-0.322***	-0.319***	-0.270***	-0.416***	-0.428***	-0.387***
	(0.053)	(0.053)	(0.071)	(0.057)	(0.057)	(0.077)	(0.080)	(0.082)	(0.122)
2017	-0.374***	-0.372***	-0.300***	-0.376***	-0.373***	-0.310***	-0.364***	-0.379***	-0.154
	(0.068)	(0.068)	(0.093)	(0.072)	(0.072)	(0.098)	(0.092)	(0.094)	(0.122)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the 2015 Bartik instrument as the independent variable (in a continuous version). The Bartik instrument was built using the 2 digit industrial unemployment growth at the provincial level. Each row presents the estimated coefficients for each β_j. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. Earnings refer to the totality of all employment earnings as reported in the T4 tax File. Real earnings were CPI deflated using 2009 as base year. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 13: Dynamic Effect of Labour Demand Shift on Employment Insurance Status

	Outcome: Employment Insurance								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	0.011	0.011	0.029*	0.011	0.012	0.025	0.006	0.004	0.058*
	(0.010)	(0.010)	(0.016)	(0.011)	(0.011)	(0.016)	(0.031)	(0.031)	(0.035)
2012	0.002	0.002	0.016	0.001	0.001	0.015	0.015	0.014	0.030
	(0.008)	(0.008)	(0.012)	(0.008)	(0.008)	(0.013)	(0.030)	(0.030)	(0.034)
2013	-0.003	-0.003	-0.001	-0.002	-0.002	0.000	-0.021	-0.023	-0.028
	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)	(0.007)	(0.020)	(0.020)	(0.034)
Post Oil Price Shock:									
2015	0.034***	0.035***	0.032***	0.034***	0.034***	0.030***	0.049	0.048	0.054
	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.009)	(0.032)	(0.032)	(0.041)
2016	0.050***	0.050***	0.036***	0.049***	0.049***	0.035***	0.066**	0.065**	0.042
	(0.008)	(0.008)	(0.011)	(0.008)	(0.008)	(0.011)	(0.027)	(0.027)	(0.036)
2017	0.044***	0.044***	0.030***	0.042***	0.042***	0.029***	0.069**	0.069**	0.047
	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.008)	(0.028)	(0.028)	(0.047)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the 2015 Bartik instrument as the independent variable (in a continuous version). The Bartik instrument was built using the 2 digit industrial unemployment growth at the provincial level. Each row presents the estimated coefficients for each β_j. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. Employment insurance was derived from Line 119 of the T1 General form. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 14: Dynamic Effect of Labour Demand Shift on Tax Status

	Outcome: Taxes								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	-0.004	-0.003	0.008	-0.003	-0.003	0.009	-0.006	-0.008	0.005
	(0.006)	(0.007)	(0.012)	(0.006)	(0.008)	(0.012)	(0.027)	(0.028)	(0.043)
2012	-0.009	-0.012	-0.004	-0.009	-0.011	-0.004	-0.009	-0.028	-0.007
	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)	(0.011)	(0.026)	(0.030)	(0.051)
2013	-0.002	-0.001	0.002	-0.001	0.002	0.006	-0.017	-0.030	-0.052
	(0.006)	(0.006)	(0.009)	(0.006)	(0.006)	(0.009)	(0.023)	(0.026)	(0.042)
Post Oil Price Shock:									
2015	-0.016***	-0.013**	-0.014*	-0.015***	-0.011**	-0.012	-0.027	-0.043*	-0.051
	(0.005)	(0.005)	(0.008)	(0.005)	(0.006)	(0.009)	(0.025)	(0.025)	(0.042)
2016	-0.022***	-0.023***	-0.026**	-0.022***	-0.022***	-0.029***	-0.030	-0.037	-0.009
	(0.007)	(0.008)	(0.011)	(0.008)	(0.008)	(0.010)	(0.029)	(0.028)	(0.052)
2017	-0.028***	-0.026***	-0.027***	-0.026***	-0.023***	-0.024***	-0.060**	-0.068***	-0.079**
	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.009)	(0.024)	(0.021)	(0.036)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the 2015 Bartik instrument as the independent variable (in a continuous version). The Bartik instrument was built using the 2 digit industrial unemployment growth at the provincial level. Each row presents the estimated coefficients for each β_j. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. An individual was considered to file taxes if they were able to be merged with a T1 tax form. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 15: Dynamic Effect of Labour Demand Shift on Self-Employment Status

	Outcome: Self-Employment								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	0.005	0.011	0.004	0.004	0.010	0.004	0.013	0.030	0.014
	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.024)	(0.032)	(0.025)
2012	0.008	0.016**	0.008	0.006	0.013	0.006	0.030	0.060*	0.031
	(0.006)	(0.007)	(0.006)	(0.006)	(0.008)	(0.006)	(0.026)	(0.034)	(0.026)
2013	-0.005	-0.007	-0.005	-0.008	-0.010	-0.008	0.027	0.052	0.027
	(0.006)	(0.008)	(0.006)	(0.006)	(0.009)	(0.006)	(0.026)	(0.037)	(0.026)
Post Oil Price Shock:									
2015	0.001	-0.001	0.001	-0.001	-0.002	-0.001	0.031	0.025	0.031
	(0.007)	(0.009)	(0.007)	(0.007)	(0.009)	(0.007)	(0.020)	(0.037)	(0.020)
2016	0.008	0.007	0.008	0.006	0.008	0.006	0.029	0.004	0.029
	(0.006)	(0.008)	(0.006)	(0.006)	(0.008)	(0.006)	(0.025)	(0.039)	(0.025)
2017	0.009	0.013	0.009	0.009	0.014	0.009	0.011	0.019	0.012
	(0.007)	(0.010)	(0.007)	(0.007)	(0.010)	(0.007)	(0.033)	(0.047)	(0.033)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the 2015 Bartik instrument as the independent variable (in a continuous version). The Bartik instrument was built using the 2 digit industrial unemployment growth at the provincial level. Each row presents the estimated coefficients for each β_j. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. An individual was considered to have self-employment if they reported positive income in business, professional, commission, farming or fishing.Specifically, this variable was derived from Lines 135, 137, 139, 141 and 143 of the T1 General form. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 16: Dynamic Effect of Labour Demand Shift on Graduates Earnings

	Outcome: Log Earnings								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	0.003	0.005	-0.021*	-0.004	-0.002	-0.027*	0.048**	0.048**	0.0161
	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.014)	(0.023)	(0.022)	(0.026)
2012	0.014	0.014	-0.007	0.010	0.010	-0.010	0.045**	0.044**	0.015
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.013)	(0.021)	(0.021)	(0.029)
2013	0.025***	0.026***	0.010	0.027***	0.028***	0.015	0.032	0.031	-0.001
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.011)	(0.021)	(0.021)	(0.025)
Post Oil Price Shock:									
2015	-0.026***	-0.026***	-0.019	-0.032***	-0.032***	-0.0196	0.007	0.007	-0.012
	(0.009)	(0.009)	(0.012)	(0.011)	(0.0105)	(0.014)	(0.019)	(0.019)	(0.021)
2016	-0.044***	-0.044***	-0.025*	-0.051***	-0.050***	-0.027*	-0.026	-0.027	-0.022
	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.015)	(0.021)	(0.021)	(0.025)
2017	-0.060***	-0.060***	-0.038**	-0.069***	-0.068***	-0.043**	-0.035	-0.037*	-0.028
	(0.016)	(0.016)	(0.015)	(0.019)	(0.019)	(0.019)	(0.022)	(0.022)	(0.025)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the median of the 2015 Bartik instrument as the independent variable. Each row presents the interaction of a dummy for values under the median of the Bartik instrument in 2015 interacted with each year. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. Earnings refer to the totality of all employment earnings as reported in the T4 tax File. Real earnings were CPI deflated using 2009 as base year. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 17: Dynamic Effect of Labour Demand Shift on Graduates Employment Insurance Status

	Outcome: Employment Insurance								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	0.004	0.004	-0.002	-0.002	0.005	-0.002	-0.002	0.000	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.006)
2012	0.003	0.003	0.001	0.002	0.005	0.002	-0.005	-0.006	-0.005
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.007)	(0.006)	(0.007)
2013	0.001	0.001	0.003	0.003	0.001	0.003	0.001	0.001	0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.005)	(0.006)
Post Oil Price Shock:									
2015	0.005*	0.005*	0.005**	0.005*	0.005	0.005*	0.005	0.005	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
2016	0.001	0.001	0.001	0.001	0.001	0.001	0.003	0.001	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.006)	(0.005)	(0.006)
2017	-0.002	-0.002	-0.002	-0.002	-0.003	-0.002	-0.001	0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.006)	(0.006)	(0.006)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the median of the 2015 Bartik instrument as the independent variable. Each row presents the interaction of a dummy for values under the median of the Bartik instrument in 2015 interacted with each year. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. Employment insurance was derived from Line 119 of the T1 General form. Real earnings were CPI deflated using 2009 as base year. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

Table 18: Dynamic Effect of Labour Demand Shift on Graduates Self-Employment Status

	Outcome: Self Employment								
	Complete Sample			Below Median Hellinger Distance			Above Median Hellinger Distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2011	0.001	0.001	0.004*	0.002	0.000	0.002	0.015**	0.008	0.015**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.006)	(0.005)	(0.006)
2012	-0.000	-0.000	0.002	-0.000	-0.002	-0.000	0.013**	0.006	0.013**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
2013	-0.000	-0.000	0.000	-0.001	-0.002	-0.001	0.006	0.007	0.006
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.006)	(0.005)	(0.006)
Post Oil Price Shock:									
2015	0.003	0.003	0.003	0.001	0.002	0.001	0.013*	0.008	0.013*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)	(0.005)	(0.007)
2016	0.004	0.004	0.001	-0.001	0.004	-0.001	0.010	0.007	0.010
	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.007)	(0.006)	(0.007)
2017	0.007***	0.007***	0.004	0.003	0.006**	0.003	0.015**	0.014**	0.015**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.006)	(0.007)
Province of Origin FE	X	✓	✓	X	✓	✓	X	✓	✓
Province of Origin Time Trend	X	X	✓	X	X	✓	X	X	✓

Note: This Table presents the estimations of Regression (2) using the median of the 2015 Bartik instrument as the independent variable. Each row presents the interaction of a dummy for values under the median of the Bartik instrument in 2015 interacted with each year. Column (1) and (2) present the estimated coefficients with and without province of origin fixed effects, while Column (3) includes Province of Origin Time trends. Columns (4), (5), and (6) repeat the pattern but for the sample of schools below the median of the Hellinger distance measure. Columns (7), (8) and (9) display the results for schools above the median of Hellinger Distance. The Hellinger Distance was calculated as the average of the yearly distance for the period 2010-2013 as described in Section 6. All school-majors included in this sample had to register at least 10 graduates per year between 2010 and 2017. An individual was considered to have self-employment if they reported positive income in business, professional, commission, farming or fishing.Specifically, this variable was derived from Lines 135, 137, 139, 141 and 143 of the T1 General form. Real earnings were CPI deflated using 2009 as base year. Observations and R Square were omitted to comply with the RDC's intermediate outputs privacy rules. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p <0.01.

A.3 Sample Construction

To build the sample for the main empirical strategy, we focused on students who graduated from an undergraduate program between 2009 and 2016. To avoid accounting for students who are in a transition between two different levels of schooling (or between transitioning between programs), most specifications were limited to students who once graduated, never enrolled again in a post-secondary institution during the available period of the sample [38]. When a student was reported being enrolled in more then one program either at the same time or in different periods of the sample, only the program with the latest starting date was kept. Students that started more then one program in the same date were dropped as the exposure definition would not be clear for these cases. Additionally, given that the main variation exploited is at the institution-major level, all units with less then 10 graduates per year were dropped from the sample to avoid the impact of small cells.

A specific concern when studying outcomes reported in the PSIS is the possibility that different institutions have different criteria when reporting outcome variables such as dropouts, graduation or enrollment. To avoid results driven by institutions that behave as outliers in their reporting procedure, all specifications based on PSIS outcomes were trimmed at the 0.1% level. The procedure consisted in identifying the 0.1% of highest reports of the outcome at the institution-major level in any given year, and dropping the observations of these institutions for all years [39].

[38]Exceptions are regressions based uniquely on schooling outcomes such as dropouts, enrollments or decision to graduate.

[39]Note that at maximum, this procedure would drop 0.1% of the institution-major units, and would be less if the same units report in different years were above the 99.9 percentile of the outcome.