Timing is Everything: Labor Market Winners and Losers during Boom-Bust Cycles*

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Abstract

Sectoral expansions and contractions require labor reallocation between declining and booming sectors. Which types of workers gain and lose during these transitions? Using linked employer-employee panel data from Brazil spanning a boom-bust cycle in its oil and gas sector, we find that timing of labor market entry is critical. Only highly educated workers hired at the onset of a boom reap significant earnings and employment benefits. Low-education workers and later entrants experience earnings and employment penalties, reflecting a last-in, first-out pattern. We show the boom induced rapid growth in sector-specific education and a mistimed glut of specialized graduates, dissipating earnings.

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1 Introduction

Economic sectors expand and contract asymmetrically as a result of trade shocks, new technologies, commodity cycles, and policy changes – requiring a continuous process of intersectoral labor reallocation. A major global transition to clean energy, for example, will require widespread exit of workers from fossil fuel industries and entry into renewables (e.g., Hanson, 2023; Rud et al., 2022; Weber, 2020). Labor transitions of this scale involve costly frictions and impose distributional consequences.[1] Some workers may benefit by possessing in-demand skills during a boom, while others will be displaced during busts and left "stranded" if their skills do not match those needed in growing sectors (Braxton and Taska, 2023; van der Ploeg and Rezai, 2020; Von Wachter, 2020).

Previous studies on timing of labor market entry have largely focused on either entry during a boom (e.g., Bütikofer et al., 2022) or a recession (e.g., Von Wachter, 2020; Altonji et al., 2016; Oreopoulos et al., 2012; Kahn, 2010). Much less is known about the individual and distributional consequences of entry timing across a full boom-bust cycle. Which types of workers benefit most from sectoral expansions, and which are most vulnerable to displacement during contractions? What mechanisms drive heterogeneity in outcomes across entry timing and worker type? Answers to these questions will inform the design of policies to manage future booms (e.g., in clean energy sectors) and soften impacts of sectoral declines on workers.

We study the heterogeneous effects of entry timing on workers' labor market outcomes through a longitudinal analysis of labor reallocation into and out of the oil and gas sector in Brazil.[2] During the 2000s and 2010s, Brazil experienced oil booms and busts driven by changes in global energy prices and major domestic oil and gas dis-

[1]Labor reallocation frictions include search and matching costs (Pissarides, 2014), skill loss during unemployment (Jarosch, 2021; Ortego-Marti, 2017), and skill mismatch between declining and expanding sectors (Baley et al., 2022; Şahin et al., 2014; Wasmer, 2006).

[2]Throughout this paper, we use the terms "oil" and "oil-linked" to refer to the oil and natural gas sector, as well as closely linked upstream and downstream sectors.

coveries. These unpredictable developments led to disproportionate expansions and contractions in oil-linked employment relative to the broader economy, providing an ideal context to study the effects of a sector-specific boom-bust cycle on workers.

Using employer-employee linked panel data spanning 2003-2017, we estimate dynamic wage, employment, and earnings effects of exposure to sectoral volatility on workers who enter oil-linked sectors at different points along the boom-bust cycle.[3] We identify effects by estimating event study specifications for cohorts of workers hired into oil relative to closely matched workers who are hired into non-oil sectors in the same year. Rich administrative data allow us to impose strict coarsened exact matching criteria (Iacus et al., 2012), restricting control workers to those with identical previous labor market experience, observable characteristics, and locations.

We find that timing of entry into the oil industry has major consequences for individual labor market outcomes. Among experienced workers hired into oil, the boom-bust cycle only benefited a select few early entrants and left most later entrants stranded. Workers hired into oil-linked sectors at the boom's onset in 2006 enjoy sustained earnings growth in subsequent years relative to matched controls hired into other sectors. Earning premiums for this group persist despite a sectoral downturn in 2008 provoked by the Global Financial Crisis and a broader oil bust beginning in 2014. In contrast, workers hired into oil in later years are much more likely to lose employment during the bust, and are employed an average 20-40% *fewer* months per year by 2017. This negative employment shock results in annual earnings *penalties* for later entrants relative to matched controls. These findings are consistent with a "last-in, first-out" pattern and reveal large inequalities between cohorts.

Inequality in labor market outcomes is even more pronounced when we split the

[3] We analyze three modes of entry into oil-linked or other sectors: (i) *experienced hires*, who voluntarily leave their previous firm and are promptly rehired (i.e., poached); (ii) *new hires*, who attain their first formal job before the age of 30, and who may make educational investments in response to sectoral dynamics; and (iii) *workers hired from unemployment or the informal sector*. In the main text, we focus on experienced hires, for whom it is possible to observe past labor market experience and pre-trends.

sample by workers' educational attainment. Within the 2006 cohort of early entrants, workers with more than secondary schooling capture *all* positive earnings effects across the boom-bust cycle. For later cohorts, education attenuates negative earnings and employment effects of busts, but does not insure against these effects completely. Low-education workers (those with less than secondary schooling) experience negative earnings effects across all cohorts – including early entrants – and thus bear the brunt of the bust. Negative effects for low-education workers are driven by the extensive (employment) margin. For example, low-education workers entering oil in 2006 are employed for 86% fewer months per year in 2017, relative to matched controls that entered other sectors.

Why do highly educated, experienced early entrants capture almost all the earnings and employment benefits of the boom-bust cycle, while low-education workers and later entrants are displaced and stranded? We document worker- and sector-level mechanisms underlying this dynamic. First, we show that firms disproportionately hire experienced, high-education workers to fill knowledge-intensive professional roles at the beginning of boom periods – perhaps to set up production processes – allowing these workers to accumulate on-the-job knowledge that protects them from busts. We document that these workers are significantly less likely to switch occupations or establishments after entering the oil industry. In contrast, low-education workers occupy easy-to-replace roles with little on-the-job knowledge accumulation, making them the margin of adjustment when firms face negative shocks.

At the sector-level, we use data from Brazil's Higher Education Census to show that the oil boom was accompanied by rapid growth in oil-specific degree programs and graduations, and that this growth was strongest near oil industry hubs. Growth was driven by expansion of private-sector technical training programs focused on the oil industry, which increased from 82 graduates in 2003 to 12,177 in 2015, before falling to 8,500 in 2016. This lagged surge in the supply of sector-specific skills increased competition for later entrants, helping to explain monotonically declining returns for high-education new hires over time. Stranded careers thus appear to be accompanied by degrees that are no longer in demand, revealing relatively irreversible human capital investment as a key channel underlying long-run adverse effects.

Our findings are relevant for commodity-dependent countries exposed to high sectoral volatility (van der Ploeg and Poelhekke, 2009), but also connect to literatures on sector-specific labor market shocks (Autor et al., 2014), skill-biased structural change (Buera et al., 2022), and distributional consequences of energy transitions (Michieka et al., 2022; Rud et al., 2022; Sharma and Banerjee, 2021). In particular, this paper contributes evidence of how sectoral booms and busts affect labor market outcomes. Hombert and Matray (2019) study long-term earnings of skilled workers in the French IT sector and find they earn less than similar workers in other sectors due to rapid skill obsolescence. Braxton and Taska (2023) find that technological change shifts skill requirements within occupations over time, and show that displaced workers tend to re-enter the labor market in lower-wage roles. Autor et al. (2014) show how sector-specific declines caused by trade exposure to China lead to negative earnings effects (especially on low-wage workers) in the United States.

We extend this literature by exploiting an especially clear context: cohorts of workers who enter a sector in well-defined ways (e.g., experienced or newly hired) at different times during an exogenous boom-bust cycle. Further, we document that a skill-biased boom provoked rapid growth in sector-specific higher education, adding nuance to previous findings that a booming sector reduces higher education in aggregate (Balza et al., 2021; Charles et al., 2018; Emery et al., 2012).

Our paper contributes novel and nuanced evidence to the literature on the resource curse, which has increasingly shifted from country-level to subnational analyses (Pelzl and Poelhekke, 2021; Cavalcanti et al., 2019; Allcott and Keniston, 2018; Jacobsen and Parker, 2016; Cust and Poelhekke, 2015; Aragón and Rud, 2013), but continues to focus overwhelmingly on places rather than people. Exceptions include Jacobsen et al. (2021), who use longitudinal household survey data from the US to show that workers exposed to the oil boom and bust of the 1980s experienced reduced earnings and delayed retirement. Kovalenko (2022) links Texas school and employment records to measure the effects of fracking booms on education and employment, finding that booms lead to less human capital accumulation, but also to higher earnings. Bütikofer et al. (2022) show that an oil boom in Norway reduced inter-generational earnings mobility among men, but not women. Finally, Guettabi and James (2020) study a recent oil boom in Alaska's North Slope, finding that employment and wage gains were disproportionately captured by migrant workers, rather than local residents.

Our study complements these findings by exploiting rich administrative panel data on the universe of formal workers in Brazil, which allows us to explore heterogeneity in labor market experiences by timing of entry and education across a full boom-bust cycle, as well as detailed worker-level mechanisms related to the skill content of occupations.

2 Related Literature on Mechanisms

How does entry into a boom-bust industry affect workers' labor market outcomes, and why might effects depend on entry timing and educational attainment? Studies show that firms affected by positive profitability shocks (e.g., increased oil prices) often share rents with their employees (Macis and Shivardi, 2016; Card et al., 2014; Guertzgen, 2009). Bargaining models predict that workers with more bargaining power within firms capture higher rent shares, while fairness and risk-sharing models predict more even rent-sharing across worker types (Martins, 2009). It is thus an empirical question whether wage premiums in a booming sector are shared across workers of all education levels, or concentrated among high-skill workers.

Studies have also shown that firms respond to negative shocks by laying off workers of different skill levels asymmetrically (Beuermann et al., 2021). Filling specialized high-skill positions is typically more costly for firms than filling low-skill positions, creating an option value of retaining skilled workers (Dolado et al., 2009; Albrecht and Vroman, 2002).[4] Binding minimum wages may protect low-skill workers' wages during downturns but push more of them into unemployment (Cockx and Ghirelli, 2016). Consequently, firms facing negative shocks may lay off easy-to-replace low-skill workers and retain difficult-to-replace high-skill workers.[5]

It is well documented that workers who enter a sector close to a downturn are exposed to potential labor market penalties (Von Wachter, 2020; Altonji et al., 2016), driven by dislodgement from career ladders and scarring effects of unemployment (Jarosch, 2021). However, mechanisms determining relative returns for early versus later entrants are not well established. Early entrants may earn higher premiums if firms hire workers into more skill-intensive roles at the onset of booms (Modestino et al., 2016), if working in an immature sector entails higher risk (Black and de Meza, 1997), or if early entry avoids direct competition with specialized later entrants. Labor protections that increase with tenure may also favor early entrants by creating seniority bias within firms.

To the disadvantage of early entrants, later skilled entrants may possess more up-to-date human capital (Braxton and Taska, 2023; Hombert and Matray, 2019). In a sector where technology evolves quickly – as in software and energy industries – this may lead firms to favor newer entrants over incumbents. In sum, the theoretical effects of entry timing on labor market outcomes for workers with heterogeneous skill levels are ambiguous. We next describe a context where exogenous and unpredictable sector-specific booms and busts allow us to assess these questions empirically.

[4]High-skill roles may also involve greater accumulation of firm-specific knowledge, conveying asymmetric hold-up power on high-skill workers (Bloesch, 2021).

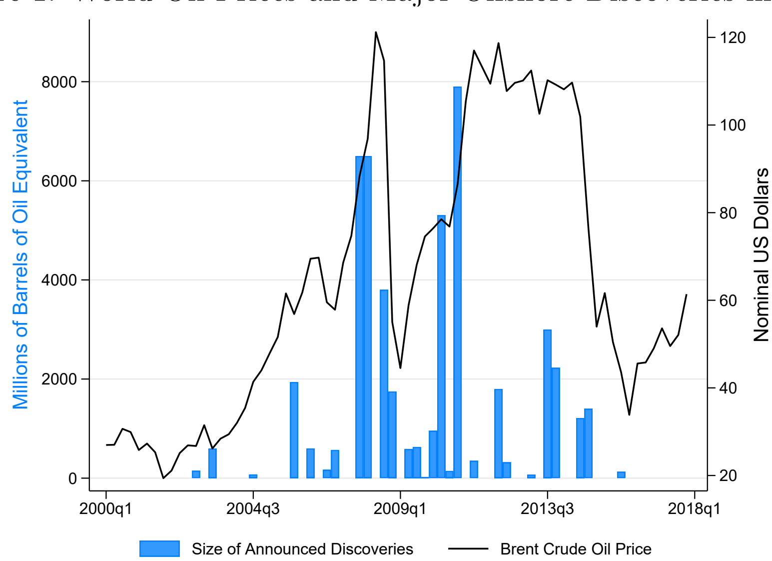
[5]There are indications that this may be changing. A report in the Wall Street Journal, for example, argues that the wave of job cuts in the US during the second half of 2022 was focused on white-collar jobs, marking a departure from previous downturns when blue-collar workers lost their jobs first (Francis and Glazer, 2022).

3 Context

3.1 Oil Boom and Bust in Brazil

Brazil's oil and gas sector presents an ideal context for this study, given the relative importance of oil-related employment in the country's economy and asymmetric shocks that amplified the oil industry's boom and bust dynamics beyond movements in other sectors. Beginning in 2004, Brazil made a series of giant offshore oil and gas discoveries, primarily located in the deepwater Pre-Salt formations off the coast of São Paulo, Rio de Janeiro, and Espírito Santo, with the largest three discoveries each adding over six billion barrels of oil equivalent (Figure 1). Discoveries coincided with a rise of the global oil price, from an average nominal price of US$21 per barrel over the 1990-2003 period to a peak of US$134 in July 2008. Oil prices crashed briefly in late 2008 as a result of the Global Financial Crisis, but recovered quickly and remained above US$100 per barrel until 2014, after which they dropped sharply to US$30 per barrel by 2016.

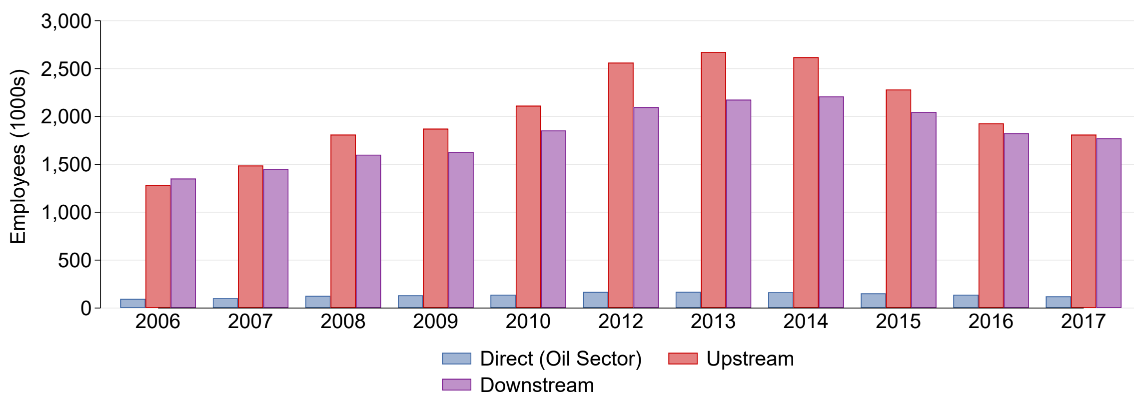
Figure 1: World Oil Prices and Major Offshore Discoveries in Brazil



Note: Brent Crude oil prices are drawn from FRED. Announced discovery volumes are aggregated from a comprehensive list of discovery announcements filed by oil companies with Brazil's *Comissão de Valores Mobiliários* (Katovich, 2023).

Discoveries and high oil prices combined to provoke rapid growth in oil-sector investment during this period. Investments by Petrobras, Brazil's national oil company, increased from USD$4.3 billion in 2000 (constant 2010 values) to USD$59.1billion in 2013 (Petrobras, 2020). The subsequent collapse of world oil prices in 2014 reduced commercial viability of ultra-deep Pre-Salt fields and squeezed operating margins along the oil and gas supply chain. Also in 2014, a corruption scandal (*Lava Jato* in Portuguese) involving Petrobras caused the company to freeze much of its investment portfolio, which fell to to USD$27.3 billion by 2017 (see Appendix A1).

Figure 2: Oil-Linked Employment (2006-2017)



Note: Bars denote thousands of employees in different segments of Brazil's oil sector (direct, upstream, and downstream). Direct, upstream, and downstream sectors are reported in Appendix B3. Formal employment is calculated from RAIS.

Brazil's oil industry is dominated by capital-intensive offshore production and generates relatively little direct employment (Figure 2). Nevertheless, the industry exerts strong upstream and downstream linkages, generating significant oil-*linked* employment (Negri et al., 2010). Using Brazil's Input-Output Matrix (IBGE, 2010), we identify 7-digit industry codes that are tied directly to oil or exhibit strong upstream (e.g., construction of ships or drilling rigs) or downstream (e.g., fabrication of petrochemicals) linkages.[6] As illustrated in Figure 2, employment in Brazil's oil-linked

[6]This process is described in detail in Appendix B1. We identify 14 directly oil-linked sectors, 109 upstream sectors, and 31 downstream sectors, reported in Appendix Table B3.

sectors co-moves with price and discovery shocks.[7] At the peak of the boom in 2013, Brazil's oil-linked sectors accounted for 10.3% of formal employment in the country.

3.2 Education and Labor Market Policies

In the early 2000s, Brazil introduced labor market policies to meet booming demand for workers with oil-relevant skills. Petrobras, together with public-private industry groups, implemented the Program for Mobilization of the National Oil and Gas Industry (Prominp), which facilitated technical training programs and graduated over 80,000 oil-sector professionals between 2007 and 2017, when the program was discontinued (SINAVAL, 2020).

During this period, formal employment contracts were governed by strong labor protections laid out in the *Consolidação das Leis do Trabalho* (CLT). Employers incur significant expenses to lay off a worker without just cause, such as an obligation to pay unemployment insurance proportional to the employees' highest pay-period with the company for employees with more than one year of service and a fine of 40% of the accumulated value of deposits made monthly in the employee's Guarantee Fund for Time of Service (FGTS in Portuguese). Collectively, these rules make it disproportionately expensive for firms to lay off high-earning or senior workers (CLT, 2017). Labor market regulations of this type are comparable to those found in many developing and OECD countries (Betcherman, 2014; Bassanini and Duval, 2006).

4 Data

In our main analysis, we draw on linked employer-employee administrative records on the universe of formal establishments and employees in Brazil from the *Relação*

[7] In Appendix Figure A2, we plot relative employment growth in oil-linked sectors compared to the non-oil economy, documenting that (i) expansions and contractions in oil-linked employment are larger in magnitude than movements in the broader economy, and (ii) direct, upstream, and downstream sectors co-move with each other.

Anual de Informações Sociais (RAIS).[8] We focus on three ways in which a booming energy sector may expand employment: (i) by poaching experienced workers, (ii) by hiring new workers who graduate or age into the labor market, and (iii) by hiring workers from unemployment or the informal sector. Using official data on the reason for job separation, we define experienced hires as those who left their previous job voluntarily and are rehired at a new firm within 4 months. We define new hires as workers aged 30 or less who are hired to their first formal job. We define workers hired from unemployment or the informal sector as those who (i) are hired to their first formal job after the age of 30 (since these likely held previous informal employment), or (ii) are hired in a given year but are missing from RAIS formal employment records for earlier parts of that year and the previous year. For each experienced worker hired in a particular year, we construct a complete 2003-2017 employment trajectory. For new hires and workers hired from unemployment or the informal sector, we construct their complete post-hire employment history.

In Appendix A5, we decompose employment flows into and out of oil-linked sectors by "type of hire" and "cause of separation." This decomposition reveals that workers were primarily hired into oil from the pool of unemployed and informal workers, reducing the scope for crowding out of formal employment in other sectors. Finally, we estimate logit models to explore predictors of being hired into an oil-linked establishment (Appendix B.3). Results indicate that higher-education, male, and older workers are significantly more likely to be hired into oil. Workers hired into oil-linked establishments come from larger firms, and within their previous firms, workers hired

[8]RAIS contains between 40-73 million job-level observations per year over the 2003-2017 period. Data were cleaned using standardized procedures developed by Dahis (2020). While RAIS provides rich labor market data for the universe of formal establishments and employees, it does not report information for the informal sector. If workers do not appear in the RAIS dataset in a particular year, we cannot determine whether they are unemployed, self-employed, or informally employed in that period. In Appendix Figure A3, we draw on nationally representative household survey data from the *Pesquisa Nacional por Amostra de Domicílios* (PNAD) to document that oil-linked sectors exhibit significantly higher rates of formal employment than the Brazilian economy as a whole, suggesting we miss relatively fewer workers by focusing on these sectors. In Appendix Figure A4, we use PNAD to document that formal wages are significantly higher than informal wages, both in oil-linked sectors and the broader economy.

into oil were *not*, on average, among the top earners or top levels of education or management.

5 Empirical Strategy

The aim of our empirical strategy is to estimate causal effects of being hired into the oil and gas industry at particular points along a boom-bust cycle on subsequent wages, earnings, and employment. The primary threat to identification is that workers are not randomly hired into sectors. Rather, they may select or be selected into treatment based on characteristics that correlate with labor market outcomes. To minimize this source of bias, we first implement coarsened exact matching (CEM) to identify cohorts of comparable workers, some of whom (the "treated") are hired into an oil-linked sector, while others ("controls") are hired into other sectors in the same year.[9]

We match workers hired into oil-linked sectors with workers hired into other sectors within each year-cohort separately. We match exactly on education, sex, a non-white race indicator, and labor market outcomes over a two-year retrospective matching window, including previous establishment, previous occupation category (low/high skill white collar and low/high skill blue collar), previous wage bin (0-1, 1-2, 2-3, 3-5, 5-10, 10-20, >20 minimum wages), previous age bin (e.g. $\leq$ 16, 16-20... 56-60, >60), and destination municipality. By matching exactly on previous establishment, we account for heterogeneity in productivity captured at the establishment level. By matching on destination municipality, we account for idiosyncratic spatial shocks. The retrospective matching window constrains the sample to experienced workers who are on similar labor market trajectories and who made similar past choices for

[9] We opt for CEM over other matching procedures due to CEM's: (i) transparent implementation that achieves exact matches on categorical variables (including establishment and municipality); (ii) *ex-ante* imposition of balance across observables, wherein choosing the balance criterion for one covariate does not affect balance across other covariates; (iii) customizable bins that respect context-sensitive cutoffs, such as education levels; (iv) retention of all matched observations in sample, rather than 1-to-1 pairs (Iacus et al., 2012).

particular employers and sectors. We present baseline descriptive statistics on full and matched samples of experienced workers in Appendix Table B8.

For newly hired workers, we are unable to observe pre-hire characteristics. Thus, we match exactly within each cohort on education, sex, a non-white race indicator, municipality of hire, first wage (using the same bins described above), first establishment size (defined by micro (<10 employees), small (10-49), medium (50-249), and large (>249) establishments), and age (using finer two-year intervals). We present baseline descriptive statistics on full and matched samples of newly hired workers in Appendix Table B9. We summarize sample sizes and match rates for experienced and newly hired workers in Appendix Table B22.[10]

5.1 Dynamic Difference-in-Differences

We identify dynamic causal effects of being hired into a boom-bust sector by comparing outcomes (e.g., hourly wages, months employed per year, annual formal earnings) for experienced or new workers hired into an oil-linked sector in a particular year t with outcomes for closely matched workers hired into other sectors in year t. Specifically, for worker i in cohort c in year t, let E_{ic} be the period when i is treated by entering an oil-linked sector as an experienced or a new hire. Then let $K_{ict} = t - E_{ic}$ be the number of years before or after this event. We regress individual-level outcome Y_{ict} on $\mathbb{1}(K_{ict} = k)$ relative year indicators. We include individual and year fixed effects, δi and λ_t, cluster standard errors at the individual level, and weight observations by the CEM matching weight:

[10] The number of experienced workers hired into oil ranges from 15,347 in 2006 to 43,659 in 2014. In our preferred specification, between 10-26% of treated workers match with controls and are retained in sample for estimation. The number of workers obtaining their first formal job in oil ranges from 72,582 in 2006 to 84,554 in 2014, with between 25-51% matched. In general, matched sub-samples tend to exhibit slightly higher average wages and education levels relative to full unmatched samples, since individuals with higher education and wages are more likely to retain formal employment across the retrospective window and survive the matching procedure. In Section 7, we implement looser matching criteria to retain more workers in sample and find that results are qualitatively similar.

$$Y_{it} = \delta_i + \lambda_t + \sum_{k \neq -1} [\mathbb{1}(K_{it} = k)]\beta_k + \epsilon_{it} \quad (1)$$

We estimate this specification separately for the cohorts 2006, 2008, 2010, 2012, and 2014 (thus omitting the c subscript) to assess how timing of entry relative to the boom and bust cycle affects outcomes. This strategy avoids common pitfalls in event studies with staggered treatment timing, where recent studies have shown that two-way fixed effects specifications may produce biased estimates (Goodman-Bacon, 2021; Sun and Abraham, 2021; de Chaisemartin and D'Haultfœuille, 2020). Our specifications reduce these concerns by focusing on a series of single-event studies with not-yet-treated controls.[11]

To explore heterogeneity across education level, we re-estimate event studies separately for low, medium, and high education workers (defined as workers with less than high school, high school complete, and more than high school, respectively). For outcomes that apply only to employed workers (i.e., hourly wage or occupation), we drop unemployed worker-year observations from the dataset prior to estimation. For outcomes where post-hire unemployment is itself an outcome of interest (i.e., annual formal earnings and months employed per year), we preserve the full balanced sample. Continuous outcomes are transformed using the inverse hyperbolic sine function.

5.2 Identification

In an ideal experimental setting (i.e., workers are randomly hired into oil-linked establishments), coefficient estimates of β_k from Equation 1 would identify the average treatment effect (ATE) of being hired into an oil-linked establishment k years after treatment. In practice, both workers and employers may make job-matching choices

[11] New hires are not treated prior to hire by definition. Among experienced hires, our retrospective matching procedure restricts the sample to individuals who have not previously changed jobs for two-years prior to period t. To address potential bias from heterogeneous treatment effects across groups, we re-estimate event studies for experienced hires using Callaway and Sant'Anna (2021)'s *csdid* estimator as a robustness check, and find that results are nearly identical.

based on observable and unobservable characteristics that are correlated with labor market outcomes (e.g., ability, motivation, or risk preferences). Exact matching on (i) sex, race, education, age bin, destination municipality, and (ii) previous occupation type, wage bin, and establishment for two years prior to being hired into a new job captures most of the information a prospective employer would have access to when deciding whether or not to hire a new employee. Moreover, workers' unobserved preferences and risk attitudes are at least partly reflected in observed past choices for employers and sectors of the economy, and comparing experienced hires with each other (where both chose to leave the same employer, but each for a new job in different sectors) reduces concerns over such selection-into-treatment. Inclusion of individual fixed effects absorbs time-invariant worker characteristics, including unobservables such as ability insofar as these are time-invariant.[12]

Upon dropping unmatched control and treated observations that do not share common support under this matching procedure, the estimand obtained from Equation 1 is the average treatment effect in the matched sample (ATM). In Appendices B.4 and B.7, we present descriptive statistics for full and matched samples to evaluate the generalizability of ATM estimates.

Compared to matched workers who were hired into other sectors in the same year, workers hired into oil-linked sectors are exposed to asymmetric and difficult-to-anticipate labor market shocks driven by exogenous and unprecedented offshore discoveries and large changes in global energy prices. Revelation of the *Lava Jato* corruption at Petrobras, which deepened Brazil's oil investment bust, was also unanticipated. The unpredictability of oil sector developments during this period reduces concerns that systematically different types of workers may have self-selected into oil.

In Section 7 we address the concern that the composition of entrants hired into oil-linked sectors may change over the course of the boom-bust cycle. Workers hired

[12]The matching strategy is weaker for new hires and workers hired from unemployment or the informal sector, as we are unable to observe pre-hire labor market characteristics or verify pre-trends for these groups. As such, results for these groups should be interpreted less causally than results for experienced hires.

into oil in 2006 may be more forward-looking or risk-loving than laggards who enter the sector after observing its growth. The booming sector may also draw in workers with progressively lower productivity or sector-specific efficacy, as in Young (2014). Endogenous changes in cohort composition over time could therefore compromise our ability to causally interpret differences in outcomes across cohorts. To reduce these concerns, we estimate a robustness check that restricts samples to workers who share common support on observables across cohorts, and find results are largely unchanged.

6 Results

We first present our main results, in which we focus on wages, employment, and earnings of workers who enter oil-linked establishments as experienced hires. We then discuss results for other modes of entry into oil-linked sectors (new hires and hires from unemployment or informality). We show results for cohorts of workers hired in 2006, 2008, 2010, 2012, 2014, relative to matched workers hired into other sectors in the same year.[13]

6.1 Experienced Hires

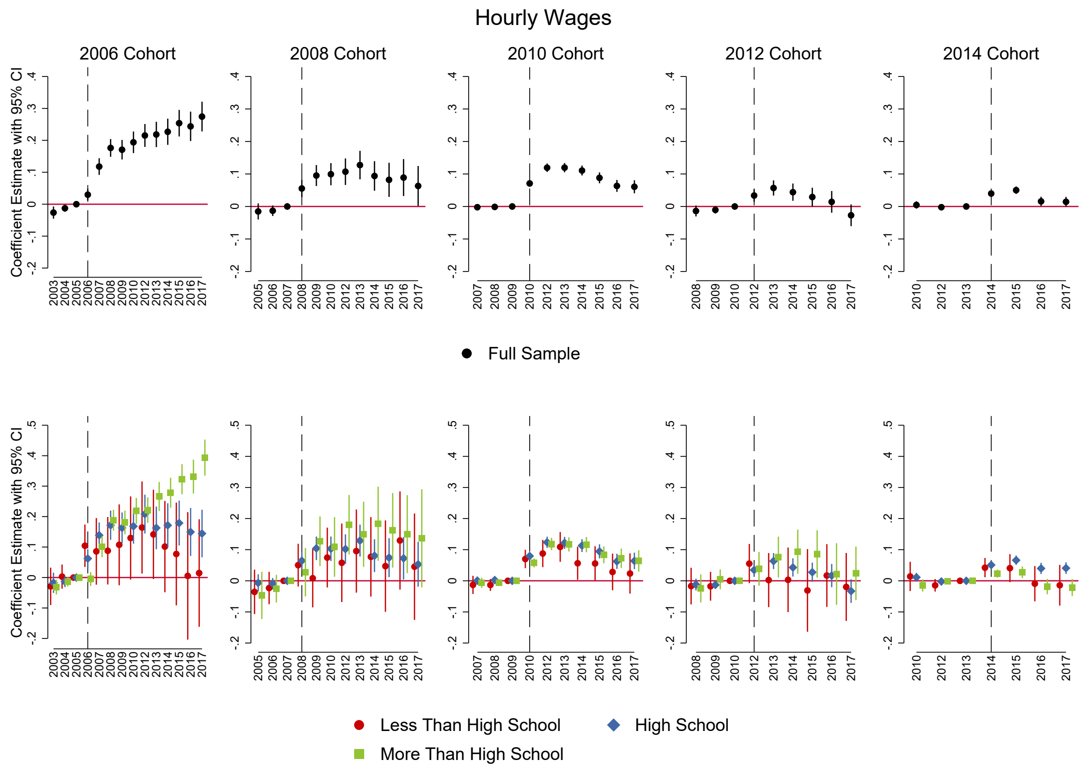
For each of five cohorts, the following figures report dynamic treatment effect estimates and 95% confidence intervals ranging from three years prior to being hired into an oil-linked establishment until 2017. In the bottom row of subfigures, effects are disaggregated by education. Coefficient estimates, standard errors, and sample descriptives corresponding with figures in this section are reported in Appendix B.5.

To assess effects on *wages*, we limit the sample in Figure 3 to workers employed in a given year. Coefficient estimates are statistically insignificant in the three years preceding entry into oil, supporting the identifying parallel pre-trends assumption.[14]

[13]Even years are reported for brevity. Detailed 7-digit industry codes are only available from 2006 onward, limiting our ability to precisely identify oil-linked workers prior to this year. Year 2011 is omitted due to missing data.

[14]Only the $t-3$ period for the full 2006 cohort is significant, but the magnitude of -0.026 is very

Figure 3: Hourly Wages After Hire into Oil-Linked Sector



Note: Event studies regress hourly wages on year indicators centered around year of hire into an oil-linked establishment ($t-1$ omitted), relative to being hired into an non-oil establishment. Wages are deflated to constant 2018 BRL and transformed using inverse hyperbolic sine. Standard errors are clustered at the individual level, individual and year fixed effects are included, and CEM matching weights are applied. This specification keeps only employed individuals. Sample: experienced hires. Workers match on wage and age bins, education, sex, race, occupation category, and establishment during a two-year matching window prior to being hired, as well as destination municipality. Corresponding regressions are reported in Appendix Table B10.

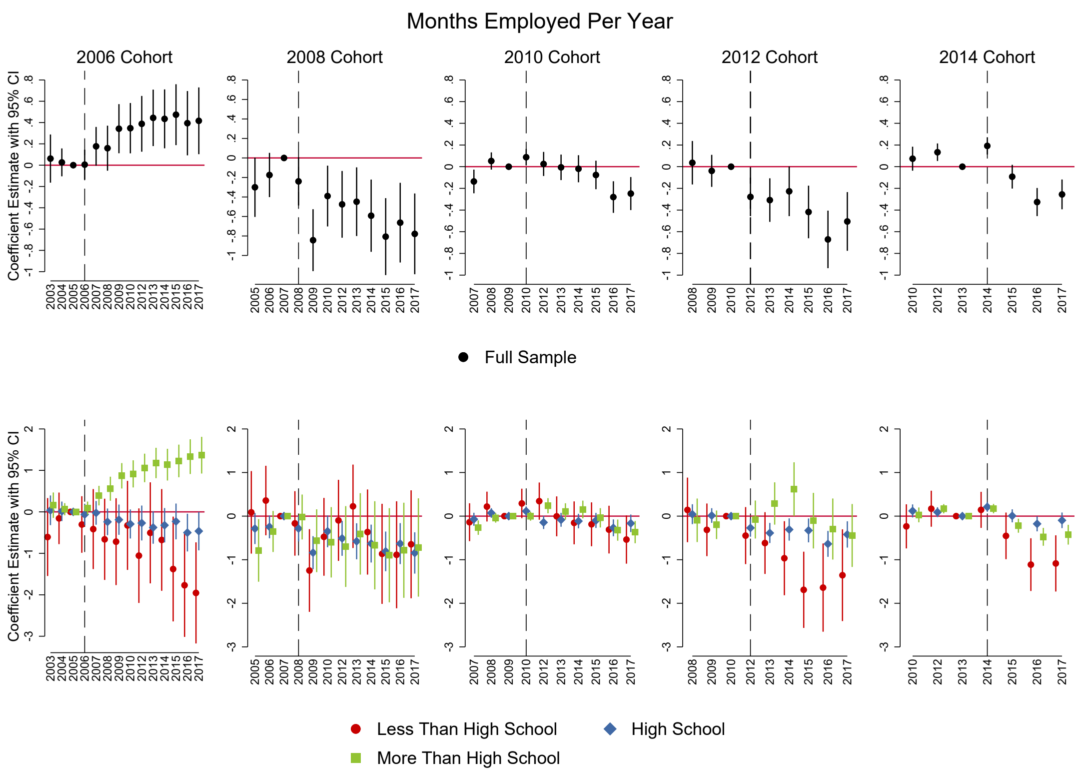
In the year of being hired, treated workers in all cohorts experience significant positive effects on wages, ranging from 3% for the 2006 cohort to 7% for the 2010 cohort.[15] For the 2006 cohort, we observe a growing hourly wage premium for workers hired into oil-linked firms, which rises to +32% by 2017 and appears unaffected by the oil bust. In contrast, subsequent cohorts do not experience the same persistent wage growth

small compared to the treatment effect.

[15]Semi-elasticities may be interpreted as the percentage change in wages upon switching from control to treated. For instance, $100 \times (e^{(0.03)} - 1) = 3.05\%$ for the 2006 cohort; $100 \times (e^{(0.071)} - 1) = 7.36\%$ for the 2010 cohort.

after their entry into oil. Wage premiums for later cohorts grow to approximately +13% by 2013, then turn downwards (but remain non-negative) with the onset of the bust in 2014.[16] Evidently, wage benefits from oil only persist for *early* entrants. The bottom graphs show that wage premiums in the 2006 cohort are driven by gains among high-education workers, whose wages are 48% higher by 2017 than those of matched controls in other sectors.

Figure 4: Months Employed Per Year After Hire into Oil-Linked Sector



Note: See also Figure 3. Months employed ranges from 0-12. This specification retains all treated individuals and matched counterfactuals in sample, with a value of zero months employed ascribed to workers who do not appear in RAIS during a given year. Corresponding regressions are reported in Appendix Table B11

[16]Treatment effects for oil-linked workers are not driven by confounding developments (e.g., booms, busts, or catch-up) in other sectors. As shown in Appendix Figure A2, employment in other sectors co-moves with oil – growing between 2006 and 2013 and declining thereafter – but to a much lesser magnitude. Consequently, effect estimates for oil-linked workers may be interpreted as a lower bound for true treatment effects.

Because wage results are conditional on employment, we next analyze the extensive margin of *employment*, retaining all matched workers in the sample and computing an outcome equal to the number of months in a year where a worker holds a formal job.[17] Results reported in Figure 4 contrast sharply with the wage premiums in Figure 3: being hired into oil has a significant negative effect on subsequent formal employment for all cohorts hired after 2006. Again the 2006 cohort stands out: they are employed for 52% *more* months than matched workers by 2017. These positive results are driven completely by high education workers, who are employed for 293% more months than their former colleagues hired into other sectors by 2017, despite the oil bust. Subsequent cohorts experience significantly negative employment outcomes, with negative effects on months employed of -54% for the 2008 cohort, -22% for the 2010 cohort, -40% for the 2012 cohort, and -23% for the 2014 cohort by 2017. Negative employment effects of being hired into oil are worst for low-education workers, who are especially likely to lose their jobs during busts.[18]

We capture the combined effect of wages and employment in *annual formal earnings*, which is summed across formal jobs and imputed as zero when a worker does not appear in RAIS.[19] As shown in Figure 5, annual formal earnings for the 2006 cohort of experienced hires grow dynamically through 2017, despite the 2014 oil bust. Earnings gains for this group are entirely captured by high-education workers, who earn 117% more than matched controls in 2010 and 397% more in 2017. Inequality in outcomes with later cohorts and with less-educated workers is stark: low-education

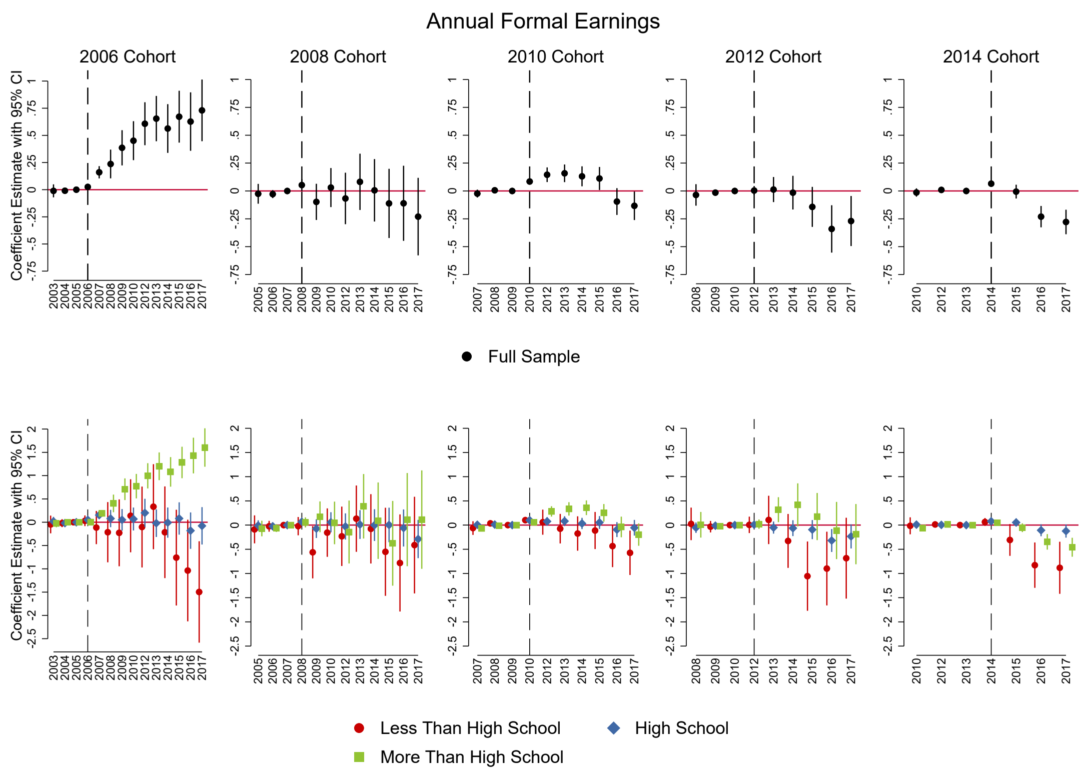
[17]Employment is reported in RAIS at the monthly level, making this the finest available continuous measure of employment intensity.

[18]The employment experience of the 2008 cohort in Figure 4 is noteworthy as it reveals persistent negative effects of bad entry timing. Workers hired into oil in 2008 entered just as the Global Financial Crisis provoked a brief but deep crash in oil prices. This crisis did not affect the already-established 2006 cohort, but led to significant job-loss among the new 2008 cohort, who are employed for 57% fewer months in 2009 relative to matched workers in other sectors. Low-education workers bear the brunt of firms' adjustment to the 2008-9 price crash: they are employed 71% fewer months per year than matched controls in 2009.

[19]For both treated and controls we thus underestimate potential earnings outside formal employment, which may range from zero while unemployed to, on average, half of formal wages in the informal sector based on representative survey data (see Appendix Figure A4).

workers hired into oil in 2006 never experience positive earnings during boom periods and experience significantly negative effects on earnings after 2013 (-78% by 2017). Later cohorts experience at best small temporary gains, which turn negative as the 2014 bust sets in. Worst off are low-education workers hired in 2014, who earn 59% less by 2017.

Figure 5: Annual Earnings After Hire into Oil-Linked Sector



Note: See also Figure 3. Annual earnings refers to total earnings across all formal jobs. Earnings are transformed using the inverse hyperbolic sine transformation and deflated to constant 2018 BRL. This specification keeps all matched workers, whether formally employed or not, in a strongly balanced panel. In periods where individuals do not appear in the panel, they are ascribed a value of zero formal earnings. Corresponding tables are reported in Appendix Tables B12-B15.

We conclude that only highly educated early entrants persistently gain from and throughout the oil-linked boom and bust. All other workers at best earn more temporarily and are eventually left worse off than matched workers who joined other sectors. Many later entrants appear unable to find employment after their jobs disappear during the oil bust, reminiscent of the experience of US workers displaced by competition from China (e.g., Autor et al., 2014).

6.2 New Hires and Hires from Informality/Unemployment

The experienced hires analyzed above already had jobs and predetermined skills before entering oil. However, the boom may also trigger an endogenous response from students, who could choose degree programs to acquire skills relevant to the booming sector. Thus, we next examine effects of entry into oil on new hires, who are under 30 and start their first formal job. For completeness, we also look at workers hired from unemployment or informality.[20]

We report the results for new hires in Appendix A.2. New hires into oil prior to 2014 earn higher wages relative to matched controls, but the magnitude of their wage premium is less than half of that for experienced hires. Turning to employment and annual earnings, we find that entry into oil leaves workers no better off, or significantly worse off than matched controls. Moreover, we no longer find that high-education workers earn more during boom years, indicating that firms do not favor recently educated workers over older, experienced workers. Combined with the results for experienced hires, this suggests that on-the-job knowledge accumulation, rather than formal training, may account for gains enjoyed by experienced early entrants.

Among workers hired from unemployment or informality (results reported in Appendix A.3), we find that wage premiums in oil are initially positive but converge rapidly to zero during the bust for all cohorts. Early entrants' wage premiums are also driven by high-education workers, which includes workers with experience gained at unobserved informal jobs or prior formal employment. Magnitudes of wage premiums among these workers are much smaller than those for experienced workers hired

[20] As shown in Appendix A5, workers hired from unemployment or informality constitute the largest source of employment growth for the expanding oil sector. Nevertheless, these workers are highly heterogeneous and do not allow observation of pre-trends.

directly from another firm, suggesting formal labor market experience is valued and may correlate with productivity. High education does protect previously unemployed or informal workers from displacement, and middle-education workers (those with completed secondary education) are most likely to lose their jobs during the bust.

Thus, among workers who obtained their first formal job or were hired from unemployment or informality, we find that exposure to the oil sector again led to stranded careers. Among these groups, high-education early entrants do not exhibit the dynamic earnings growth enjoyed by experienced high-education early hires, suggesting there was a strong and persistent labor market premium for *experienced* skilled workers at the beginning of the boom. We examine potential mechanisms underlying these patterns in Section 8.

7 Robustness Checks

In this section, we test the sensitivity of results to alternative definitions of oil-linked sectors, model specifications, and estimators.

Keep only directly oil-linked workers

We re-estimate event studies using only directly-linked sectors (e.g., petroleum extraction and support activities) and looser matching criteria to retain more treated workers in the sample. We report results from this specification in Appendix C.1. Coefficient estimates under this specification are larger than under our preferred specification, but do not change our conclusions qualitatively, suggesting our preferred estimates are a lower bound for effects of joining the oil-linked sector. This is intuitive, as workers with closer ties to the booming and busting sector experienced the same trends as our broader sample, but to an exaggerated degree.

Keep only workers within 100 kilometers of a shipyard

Brazil is a large country with spatially concentrated hubs of offshore oil activity, which we proxy using the location of shipyards (which serve as assembly nodes in the oil supply chain) (PortalNaval, 2020). We re-estimate event studies with matched samples limited to experienced hires or those newly-hired into destination municipalities that are within 100km of a shipyard, and report results in Appendix C.2. Coefficient estimates in this robustness check are several times larger than those in our main specifications, but reflect the same trends. This finding is again intuitive: workers closer to oil hubs feel effects of oil boom and bust more strongly.

Omit publicly-employed workers

Could positive effects on specific subgroups of workers be explained by disproportionate entry into public employment (e.g., Petrobras, Brazil's national oil company), which conveys job stability and may not respond to market signals? In Appendix C.3, we re-estimate event studies omitting publicly-employed workers (which constitute approximately 5% of treated workers) from the sample. Results remain largely unchanged.

Restrict samples to workers who are comparable across cohorts

The progression of Brazil's oil boom could induce changes in the composition of cohorts entering the oil sector over time, compromising cross-cohort comparisons. We re-estimate event study specifications using sub-samples of each cohort that share common support with the baseline 2006 cohort. Specifically, we preserve in sample only individuals from the 2006 cohort and subsequent cohorts who match exactly on education, sex, nonwhite indicator, and age bins. For new hires, we also match on first-job wage bins and firm size bins. For experienced hires, we also match on previous job wage bins and firm size bins. We report results in Appendix C.4. Results are similar to our preferred specifications, confirming that differences in outcomes across cohorts are not driven by observable changes in cohort composition.

Implement Callaway and Sant'Anna (2021) csdid estimator

By estimating event studies separately for each cohort using not-yet-treated controls, we avoid bias from inclusion of already-treated units that plagues two-way fixed effects estimation with staggered treatment timing (Goodman-Bacon, 2021). Nevertheless, dynamic (e.g., effects that grow over time post-treatment) and heterogeneous (e.g., effects that differ across treated groups) treatment effects may still introduce bias into our ATT estimates (de Chaisemartin and D'Haultfœuille, 2020). To address this threat, we re-estimate using the *csdid* estimator proposed in Callaway and Sant'Anna (2021). As reported in Appendix C.5, results closely resemble our preferred specification in sign, significance, and magnitude.

8 Mechanisms

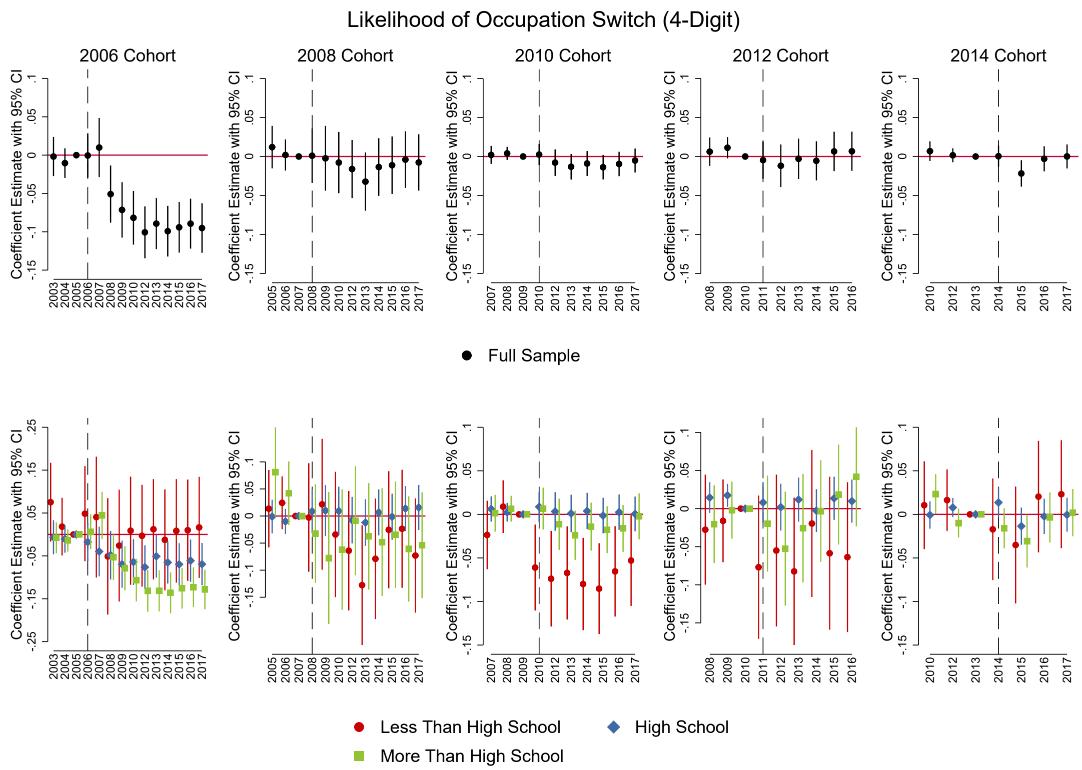
8.1 Job stability in Knowledge-Intensive Roles

Why do high-education experienced hires in 2006 capture such dramatic shares of overall earnings from the boom, and weather busts so well? We first assess whether these workers avoid negative shocks by retaining jobs and occupations at the oil-linked firms that originally hired them, or by possessing transferable skills that allow them to "jump ship" to other sectors during downturns.

Figure 6 plots the effects on experienced workers of being hired into oil on an indicator for occupation switching. Results show that high-education hires into oil in 2006 are significantly less likely to switch away from the occupation they were originally hired into. Appendix Figure A12 plots analogous results for an indicator of establishment switching and shows high-education hires into oil in 2006 are also significantly less likely to switch establishments.[21]

[21] In Appendix Figures A16 and A17, we report results from analogous specifications for new hires. Results suggest that high-education new hires into oil – in contrast to experienced workers – are more likely to switch occupations and establishments after their initial hire. This result is consistent with findings for Canada in Oreopoulos et al. (2012).

Figure 6: Probability of Occupation Switch
after Hire into Oil-Linked Sector (Experienced Hires)

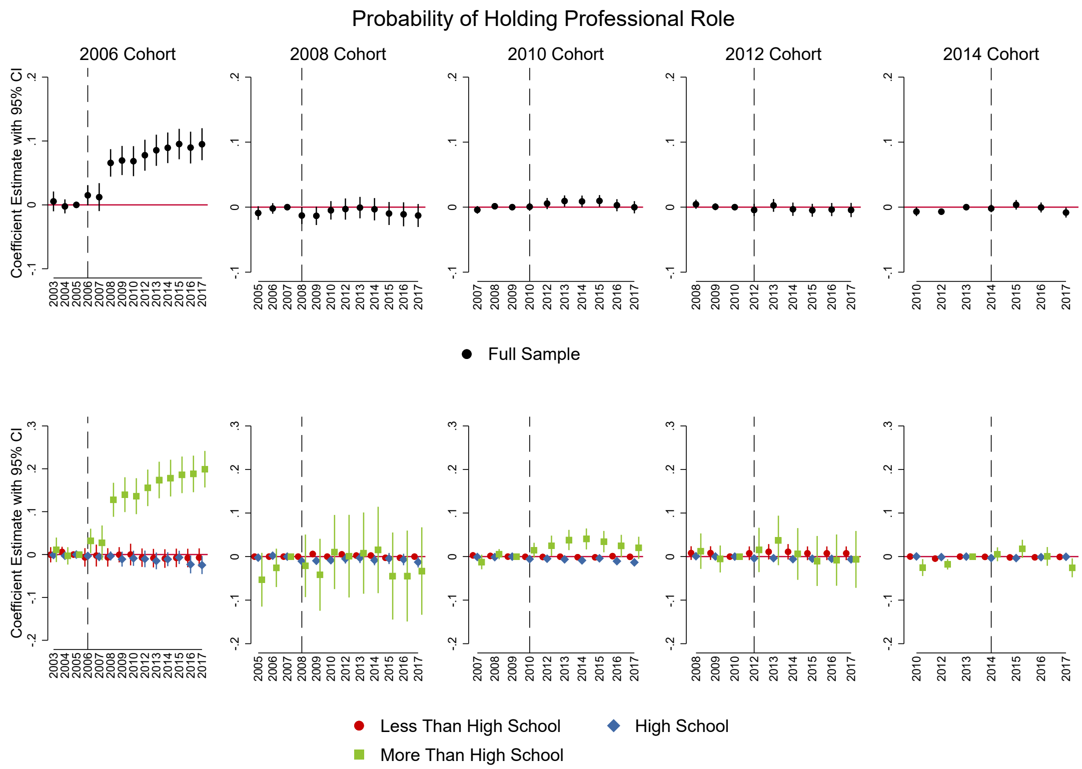


Notes: Outcome is an indicator assuming a value of zero in each period the worker holds the same 4-digit occupation code in their primary job as the one they were originally hired into, and a value of one when they hold a different occupation code. Sample is limited to employed workers.

Earnings premiums for high-education early entrants thus appear related to their ability to stay in the same job and occupation. Why do firms retain these workers during downturns? One possibility is that seniority-biased labor regulations bind, creating a first-in, last-out dynamic. Alternatively, high-education early entrants may accumulate valuable knowledge and skills on the job, as in Gathmann and Schönberg (2010) and Burdett et al. (2020). If labor regulations drive outcomes, we would expect early low-education entrants to weather the post-2013 bust better than later low-education entrants. As shown in Figure 4, however, low-education early entrants lose jobs to an equal or greater extent than later entrants, suggesting seniority does not protect them.

To assess on-the-job knowledge accumulation, we regress an indicator for holding a professional role (e.g., "researcher", "scientist", "engineer", "analyst") on relative time indicators around being hired into oil (Figure 7). Results show that workers hired in 2006 are significantly more likely to hold a professional role in subsequent years, with this effect driven by high-education workers.[22]

Figure 7: Probability of Occupying Professional Role
after Hire into Oil-Linked Sector (Experienced Hires)



Notes: Professional roles are defined as CBO occupation codes beginning with 2, including "researcher", "scientist", "engineer", and "analyst". Outcome is a binary indicator for "professional role," which is regressed on individual and year fixed effects and relative time indicators around year of being hired into oil. The sample is limited to employed workers.

[22] In Appendix Figure A13, we estimate analogous specifications for managerial occupations (e.g., "leader," "director," or "manager") and find workers hired into oil in 2006 (and to a lesser extent in 2010) are significantly *less* likely to hold managerial roles, with this effect again driven by high-education workers. Appendix Figures A15 and A14 report corresponding results for new hires and show null effects.

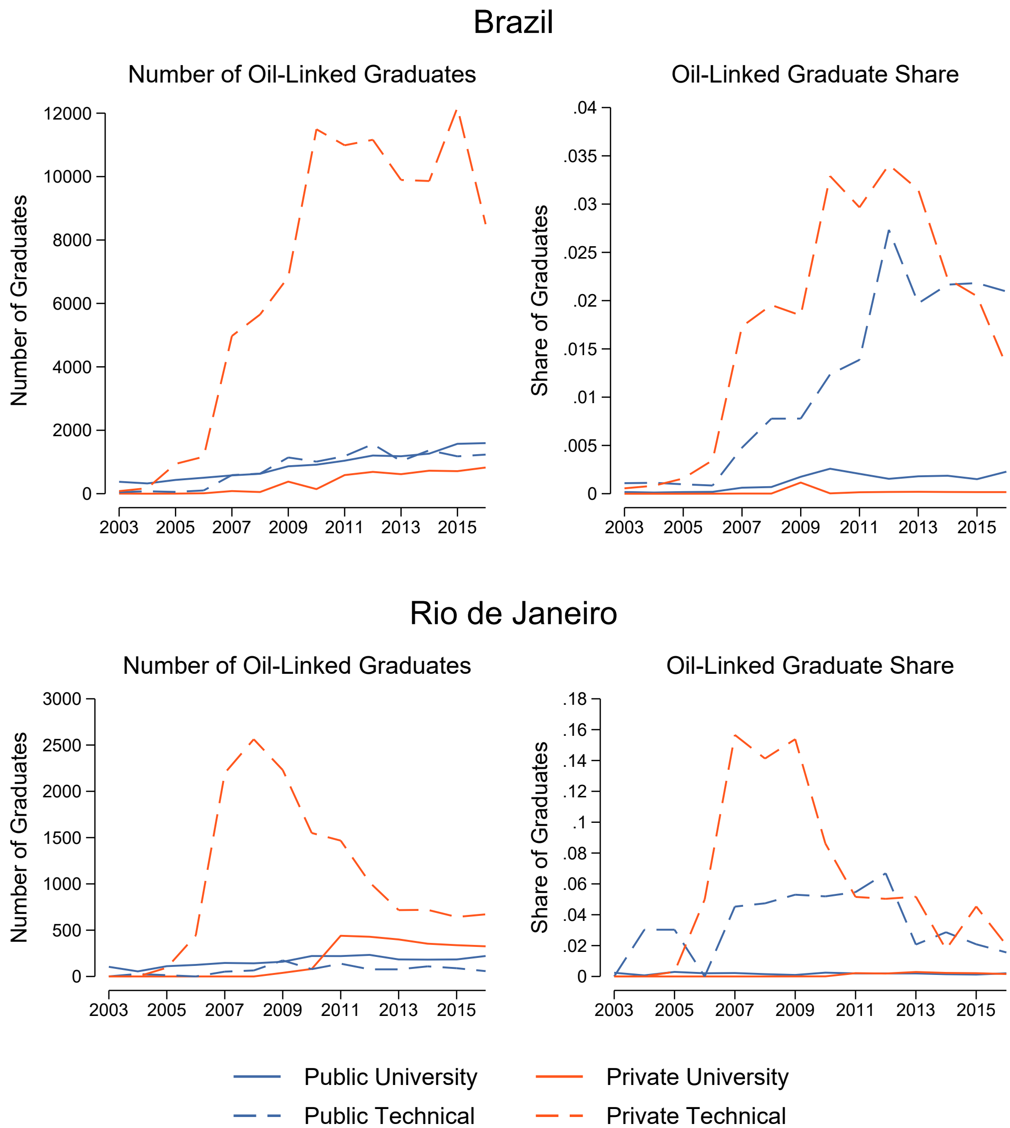
Taken together, these findings provide evidence that high-education early entrants with prior formal labor market experience disproportionately enter professional roles and retain these positions across the boom and bust cycle, enabling on-the-job accumulation of skills and experience that makes them sufficiently valuable to firms to retain them through downturns. In contrast, low-education hires do not occupy knowledge-intensive roles that would allow them to accumulate on-the-job skills, and are thus more likely to lose their jobs during the bust. This dynamic corroborates Modestino et al. (2016)'s documentation of "downskilling," over the business cycle.

8.2 Lagged Sector-Specific Higher Education Response

The education premium enjoyed by early entrants into oil-linked sectors is more muted and less persistent for later entrants. In this section, we show that a plausible explanation for this decline is an endogenous response of human capital investment by both the demand side (students) and the supply side (degree-programs), which combine to create a glut of skilled oil workers. This may affect new hires more than experienced hires, as the latter's prior experience places them in a segmented labor market relative to new entrants.

To assess these dynamics in the context of Brazil's oil boom and bust, we draw on data from Brazil's Higher Education Census, which reports the number of graduates at the institution-degree-year level for the universe of higher education institutions between 2003-2016. Using 6-digit degree-area (i.e., major) codes, we classify 24 out of 1,104 total degree programs as oil-linked based on contextual knowledge, and sum the number of graduates from public/private and university/technical programs to the municipality-year level. We describe this process in more detail and list oil-linked degree programs in Appendix Table B26.

Figure 8: Number and Share of Oil-Linked Graduates



Note: Number and share of graduates are calculated from Brazil's Higher Education Census (2003-2016). Oil-linked majors are defined in Appendix Table B26. University degrees typically take 4-6 years to complete; technical degrees typically take 1-2 years. Rio de Janeiro state is selected as an example since it is the center of Brazil's oil industry.

Figure 8 shows the number of graduates from oil-linked higher education degree programs each year between 2003-2016. The figure reports results for Brazil as a whole, and then for the state of Rio de Janeiro, where the country's oil sector is most prominent. The number and share of oil-linked higher education graduates in Brazil increased sharply from 2006 onward, corresponding with the oil boom, and peaked around 2010-12. The increase was most dramatic in private technical-training, which increased from 82 graduates (0.1% of total graduates in this category) in 2003 to 11,493 (3.3%) in 2010 and 12,177 (2%) in 2015, before falling to 8,500 (1.3%) in 2016. Public technical graduates also grew dramatically, from 49 (0.1%) in 2003 to 1,564 (2.7%) in 2012, before declining to 1,234 (2.1%) by 2016. A clear contrast between technical and university degrees is that technical programs are sufficiently short-term for students to react to the oil bust. University programs take 4-6 years to complete, leading many university students who enrolled during boom years to graduate during unfavorable bust years. Rio de Janeiro's boom in oil-linked higher education preceded the national boom by approximately three years, likely due to stronger early-boom signals in this state.

Growth in oil-linked graduations corresponded with expansion of oil-linked post-secondary degree programs. For Brazil as a whole, the number of oil-linked public university programs grew from 24 in 2003 to 75 in 2016. Private university programs grew from 1 in 2003 to 33 in 2016. Technical programs fluctuated even more dramatically. Private oil-linked technical programs grew from 12 in 2003 to 181 in 2012, then fell to 143 by 2016. Public technical programs grew from 7 in 2003 to 73 in 2014, then declined to 68 by 2016 (see Appendix Figure A18). Evidently, technical programs responded pro-cyclically to the oil boom and bust, while university programs continued to expand despite the 2014 downturn. In Rio de Janeiro, oil-linked private technical programs increased from 4 in 2003 to 28 in 2009, then declined to 11 by 2016. Similar trends hold in other states affected by the oil boom and bust (Appendix Figure A19).

We estimate a difference-in-differences specification to test whether oil-linked graduations increased more in municipalities near oil industry hubs (proxied by shipyards, which are supply-chain nexuses for oil inputs) during boom years. We regress outcome y_{mt} (number of graduates transformed using the inverse hyperbolic sine function, or share of STEM graduates in oil-linked majors in municipality m in year t) on a proxy for oil industry presence (municipality centroid within 50km of a shipyard), an indicator for the boom period (years 2006-2013), the interaction of these two terms, and state fixed effects, with standard errors clustered at the municipality-level:

$$y_{mt} = \beta Close_m + \gamma Boom_t + \delta(Close_m \times Boom_t) + \mu_s + \epsilon_{mt} \tag{2}$$

We report results in Table 1. The difference-in-differences interaction term of oil-proximity and oil boom period is significantly positive, indicating that oil-linked graduations increased most where the oil sector is most important (near shipyards) during the boom. Disaggregating effects across degree-program categories, we find that effects are driven by private technical training programs. The share of total STEM graduates earning oil-linked degrees is also higher during oil boom years and increases most near shipyards during the boom for technical training programs. These results provide evidence that students specialized in oil-relevant skills in response to Brazil's oil boom, increasing competition for later entrants into oil-linked sectors.

9 Conclusion

How does the timing of entry into a sector relative to sector-specific expansions and contractions affect workers' careers? Using rich employer-employee linked panel data from Brazil, we measure dynamic labor market outcomes of workers hired into oil-linked sectors at specific points in the boom-bust cycle, relative to closely matched workers hired into other sectors in the same year. We find that timing of entry into the oil industry has lasting impacts: only workers who enter at the beginning of a boom period earn substantial earnings premiums over the course of the boom-bust cycle. For most later entrants, the decision to enter the oil-linked sector results in significant and persistent employment and earnings penalties.

Table 1: Effects of Oil Boom on Number and Share of Oil-Linked Graduates

	Number of Graduates from Oil-Linked Degree-Programs				
Variables	**Total**	**Pub. Uni.**	**Priv. Uni.**	**Pub. Tech.**	**Priv. Tech.**
<50km from Shipyard	0.382	0.257	0.095	0.073	0.278
	(0.099)	(0.063)	(0.052)	(0.048)	(0.081)
Boom Year (2006-2013)	0.197	-0.001	0.001	0.032	0.184
	(0.018)	(0.008)	(0.004)	(0.009)	(0.016)
Near × Boom	0.415	0.032	0.019	0.048	0.522
	(0.158)	(0.095)	(0.075)	(0.072)	(0.144)
State FEs	YES	YES	YES	YES	YES
Observations	16,600	16,600	16,600	16,600	16,600
ihs(Pre-Boom DV Mean)	0.073	0.045	0.001	0.007	0.029
R-squared	0.074	0.076	0.037	0.014	0.067

	Share of STEM Graduates in Oil-Linked Degree-Programs				
Variables	**Total**	**Pub. Uni.**	**Priv. Uni.**	**Pub. Tech.**	**Priv. Tech.**
<50km from Shipyard	-0.007	0.002	0.000	-0.001	0.009
	(0.004)	(0.001)	(0.000)	(0.006)	(0.009)
Boom Year (2006-2013)	0.014	0.001	0.000	0.004	0.027
	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)
Near × Boom	0.010	-0.001	0.000	0.008	0.065
	(0.007)	(0.001)	(0.001)	(0.009)	(0.017)
State FEs	YES	YES	YES	YES	YES
Observations	16,600	16,600	16,600	16,600	16,600
Pre-Boom DV Mean	0.0076	0.0004	0.0001	0.0010	0.0009
R-squared	0.011	0.015	0.007	0.017	0.042

Note: Table reports coefficient estimates and standard errors from regression of number or share of oil-linked graduates in a municipality-year pair on an indicator of that municipality's proximity to a shipyard (<50km), an indicator of whether the year falls during Brazil's oil boom period (2006-2013), an interaction of those indicators, and state fixed effects. Standard errors are clustered at the municipality level and number of graduates is transformed using inverse hyperbolic sine. Degrees are split by: public (federal, state, or municipal)/private (*particular*), and university (*bacharelado* or *licenciatura* degrees)/technical (*tecnólogo* degrees). Share of graduates refers to the share of total STEM (*exatas*) graduates in that specific category who earn an oil-linked degree. Pre-boom dependent variable means refer to values in 2005.

Further, we show sectoral volatility generates significant inequality *within* worker cohorts. Highly educated, experienced early entrants capture almost the entirety of earnings benefits across the boom-bust cycle. These workers disproportionately transition into knowledge-intensive professional roles within firms, enabling on-the-job skill formation that conveys job and occupation-stability even during busts. Low-education workers – occupying easy-to-replace roles with little on-the-job knowledge accumulation – constitute firms' margin of adjustment to downturns. They experience disproportionate job loss during busts and subsequently re-enter the formal labor market at lower rates.

Finally, we document rapid growth in graduation rates from oil-related higher education programs following the oil boom, which may explain declining wage premiums for later entrants into oil-linked sectors. Growth in sector-specific skills may have benefited firms, but for graduates, investment in sector-specific human capital yielded relatively low returns and resulted in a persistent mismatch of skills in the post-bust economy.

These findings are particularly relevant for energy and commodity sectors, and raise questions for future research on energy transitions. The clean energy transition promises to be marked by a decline in fossil fuel employment and growth in renewable energy and critical mineral and metal sectors. Will displacement of workers from fossil fuel sectors follow the same "last-in, first-out" pattern we document here, with low-education workers the most adversely affected? Have early entrants into clean energy industries already positioned themselves to capture most of the labor rents from these sectors' expansion, or will the pace of technological advancement favor later entrants with more up-to-date human capital? Finally, will the surge in education programs to train renewable energy workers deliver on their promise of high labor market returns, or will endogenous entry of specialized workers bid down premiums? We leave these important questions for future research.

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Online Appendix

Timing is Everything: Labor Market Winners and Losers during Boom-Bust Cycles

Erik Katovich, Dominic Parker, and Steven Poelhekke

February 7, 2023

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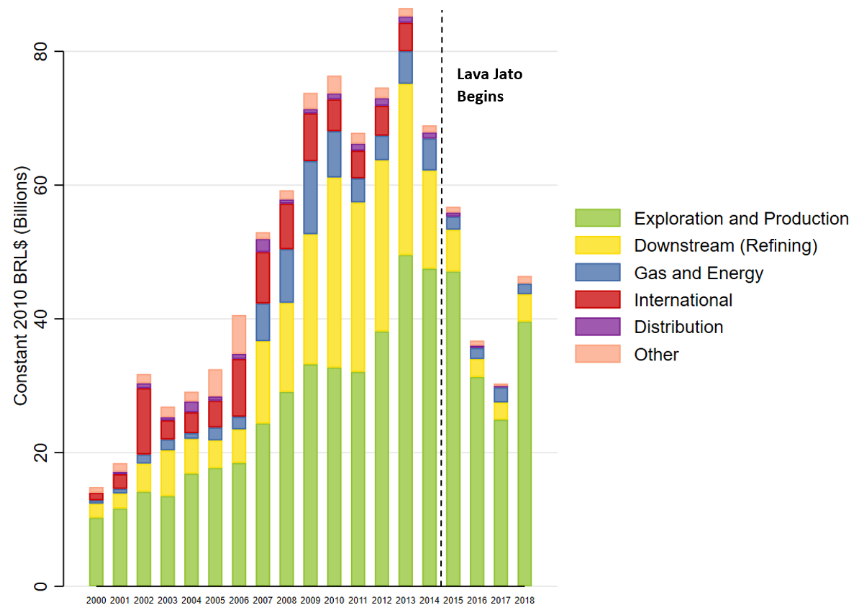
A Supplementary Figures

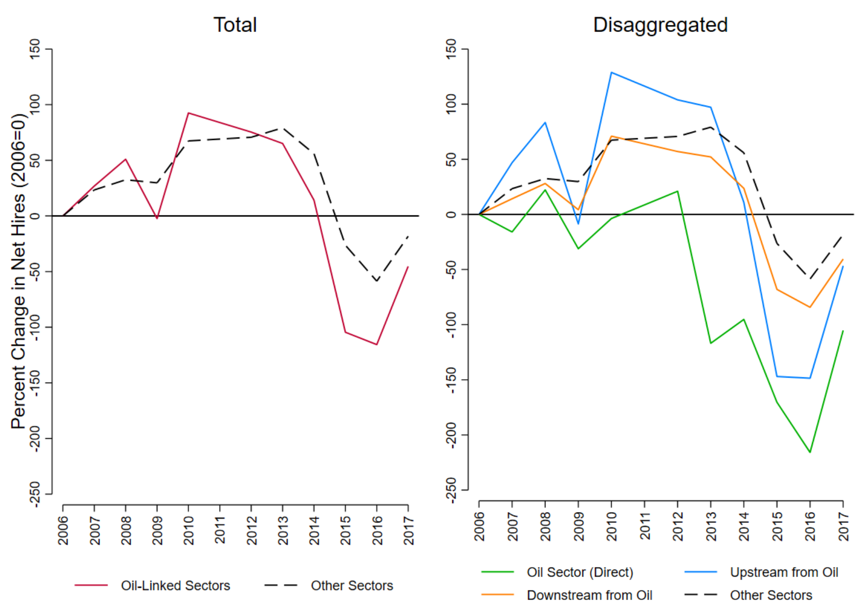
A.1 Descriptive Figures

Figure A1: Petrobras: Annual Investment by Category (2000-2018)



Source: Petrobras (2020)

Figure A2: Percent Change in Net Hires (Oil-Linked and Other)



Source: RAIS (2006-2017)

Figure A3: Formal Employment in Oil-Linked Sectors Relative to Total

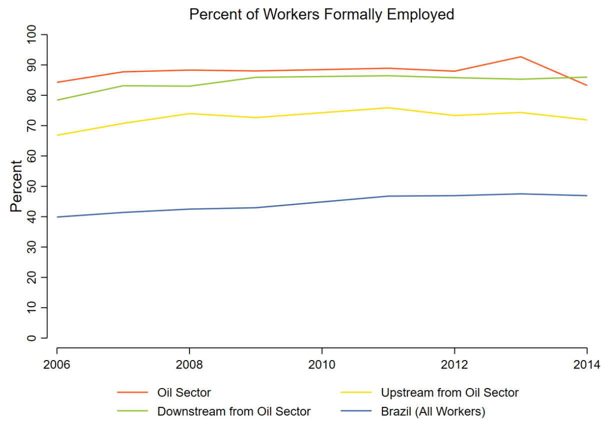
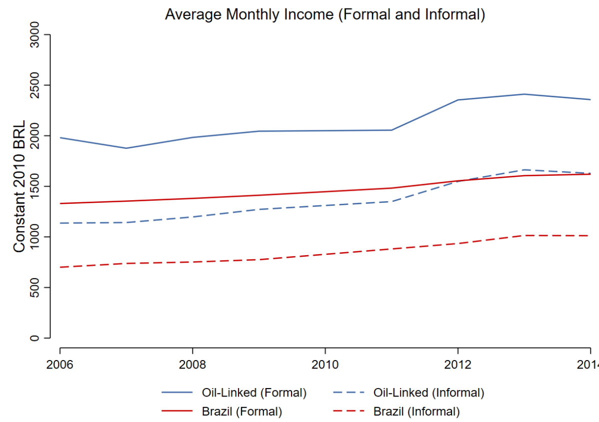
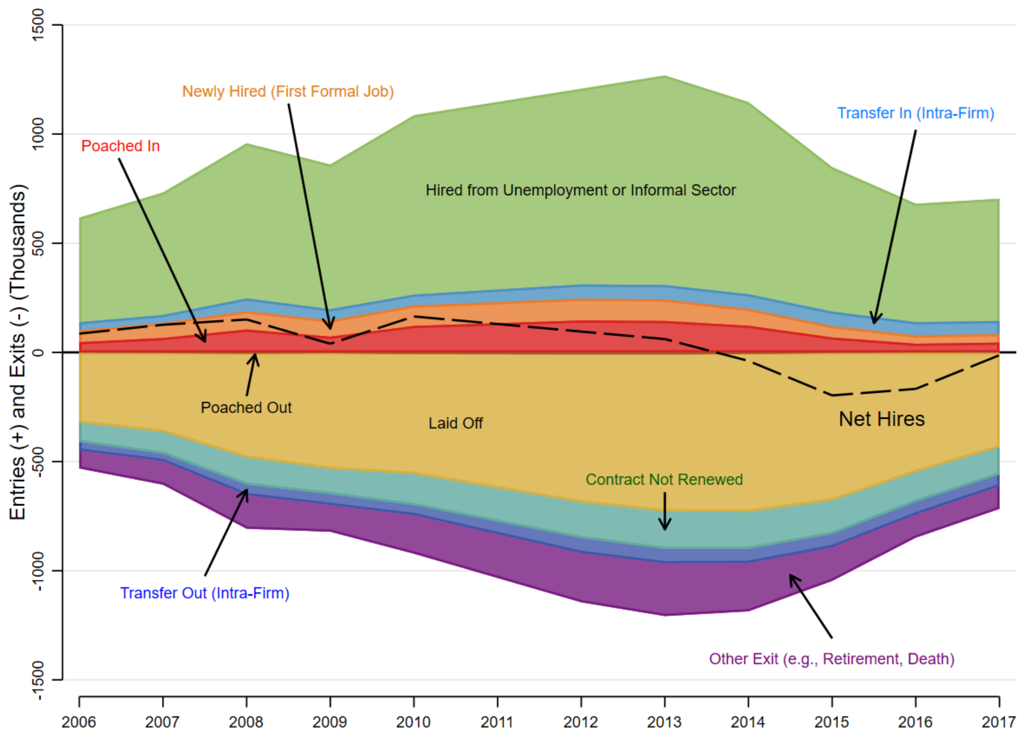


Figure A4: Average Monthly Earnings for Formal and Informal Workers



Note: Data are drawn from Brazil's *Pesquisa Nacional por Amostra de Domicílios* (PNAD), an annual nationally representative household survey. PNAD includes both formal and informally employed workers, allowing us to compute comparative statistics for formal sectors (corresponding to data available in the RAIS formal employment registry), and informal sectors (unobserved in RAIS). Figure A3 shows the percentage of workers in oil-linked sectors (direct, upstream, and downstream) with formal employment, relative to the average rate of formality for workers in Brazil as a whole. Figure A4 shows earnings for formal versus informal workers in oil-linked sectors, relative to formal and informal workers for Brazil as a whole.

Figure A5: Disaggregated Job Flows Into and Out of Oil-Linked Sector

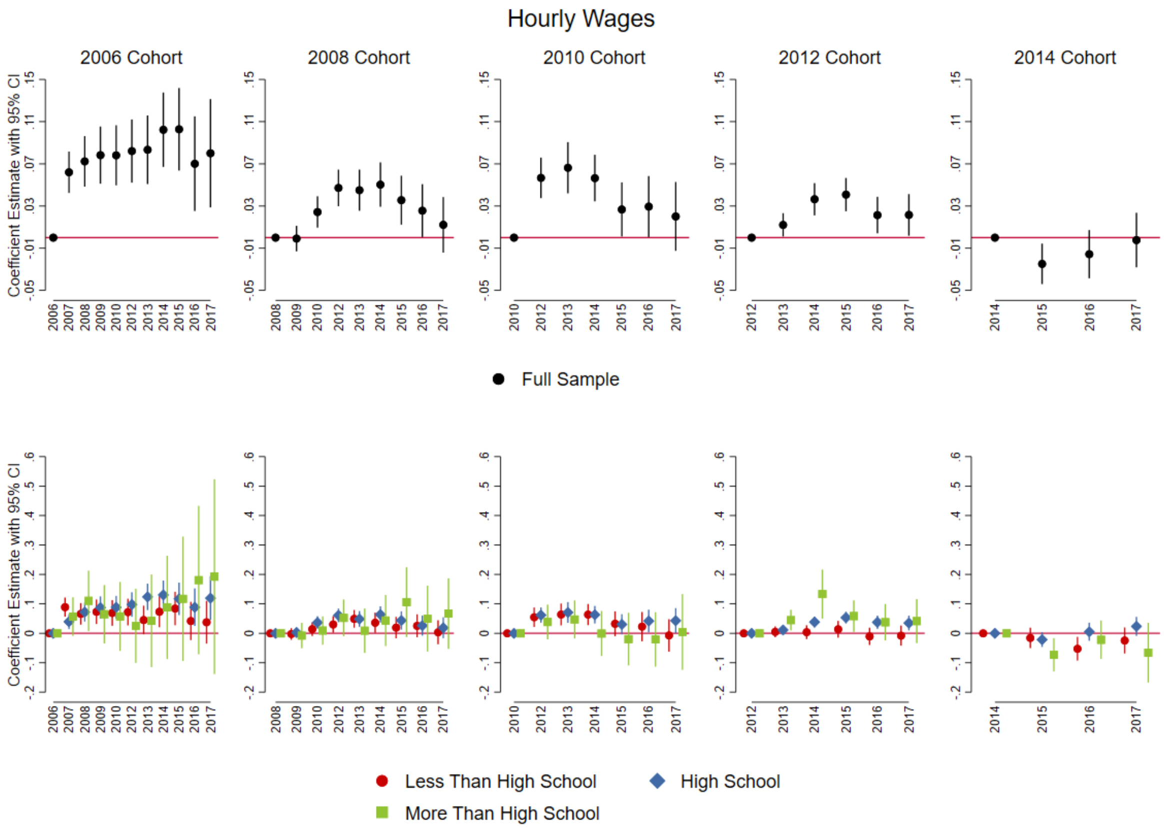


In this figure, we disaggregate employment flows into and out of oil-linked sectors using "type of hire" and "cause of separation" recorded at the job-year level in RAIS. Job flow categories into and out of oil-linked sectors (direct, upstream, and downstream) are mutually exclusive and comprehensive. Categories include: hired into oil from other existing jobs, defined as workers who left a previous non-oil job voluntarily (*recisão sem justa causa por iniciativa do empregado*) and were rehired (*reemprego*) within four months into an oil-linked firm; new hire (*primeiro emprego*) into oil, defined as workers who are hired in their first formal job at an oil-linked firm; hire from informality or unemployment into oil, defined as (i) workers who were laid off from their previous job (*recisão com/sem justa causa por iniciativa do empregador*) and rehired into an oil-linked firm, or (ii) any worker who is rehired into an oil-linked firm after 5 or more months without formal employment; and transfers into oil (*Transferência/movimentação do empregado/servidor, com/sem ônus para o cedente*), defined as workers who were transferred between establishments within a firm to an oil-linked establishment; hired out of oil, defined analogously to hires into oil; layoffs from oil (*recisão sem justa causa por iniciativa do empregador*; contract not renewed (*término de contrato*); other exits, e.g., retirements or deaths (*aposentadoria* and *falecimento*); and intra-firm transfers out of oil. Small numbers of other types of entry and exit (*cessão, redistribuição, mudança de regime*, etc.) are grouped into transfers-in and other exits, respectively.

The boom and bust is shown by the dashed line, which tracks net formal employment growth in oil-linked sectors. Net annual growth grew from 86,096 workers in 2006 to 164,817 in 2010, then declined steadily to 2014, when oil-linked sectors lost 38,708 formal jobs. The nadir occurred in 2016, when oil-linked sectors lost 166,747 jobs, driven by a sharp drop in new entries relative to exits. The dip in net employment growth in 2009 reflects the 2008-2009 bust in world oil prices. The figure reveals that most workers were hired into oil-linked sectors from the pool of unemployed workers and the informal sector. This suggests there is relatively little scope for crowding out of formal employment in other sectors, in contrast to what standard Dutch Disease theories predict. To the best of our knowledge, we are the first to track worker flows by origin into and out of oil-linked sectors during a boom and bust. From 2006-2014 an average of 185 thousand workers per year entered the oil sector as new hires or as experienced hires from other existing jobs. We focus on these groups of workers in the main text because they approximate the notion of labor reallocation in standard Dutch diseases models.

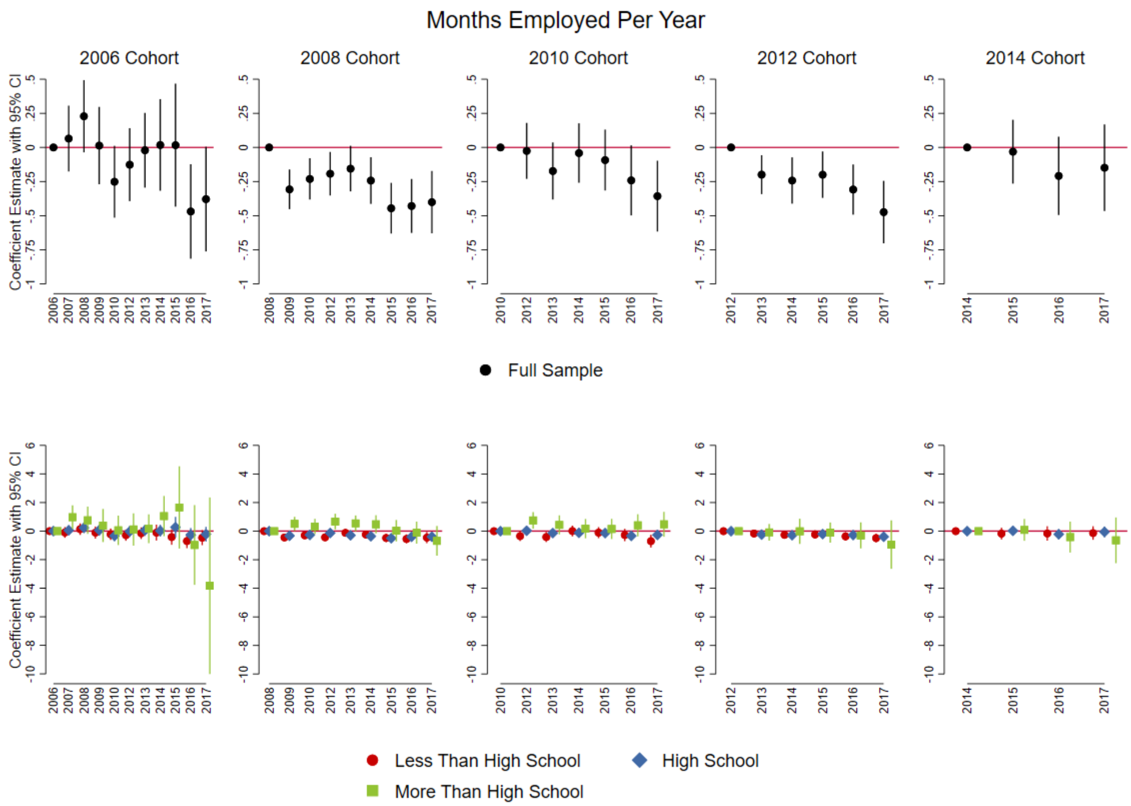
A.2 Results: New Hires

Figure A6: Hourly Wages After New Hire into Oil-Linked Sector



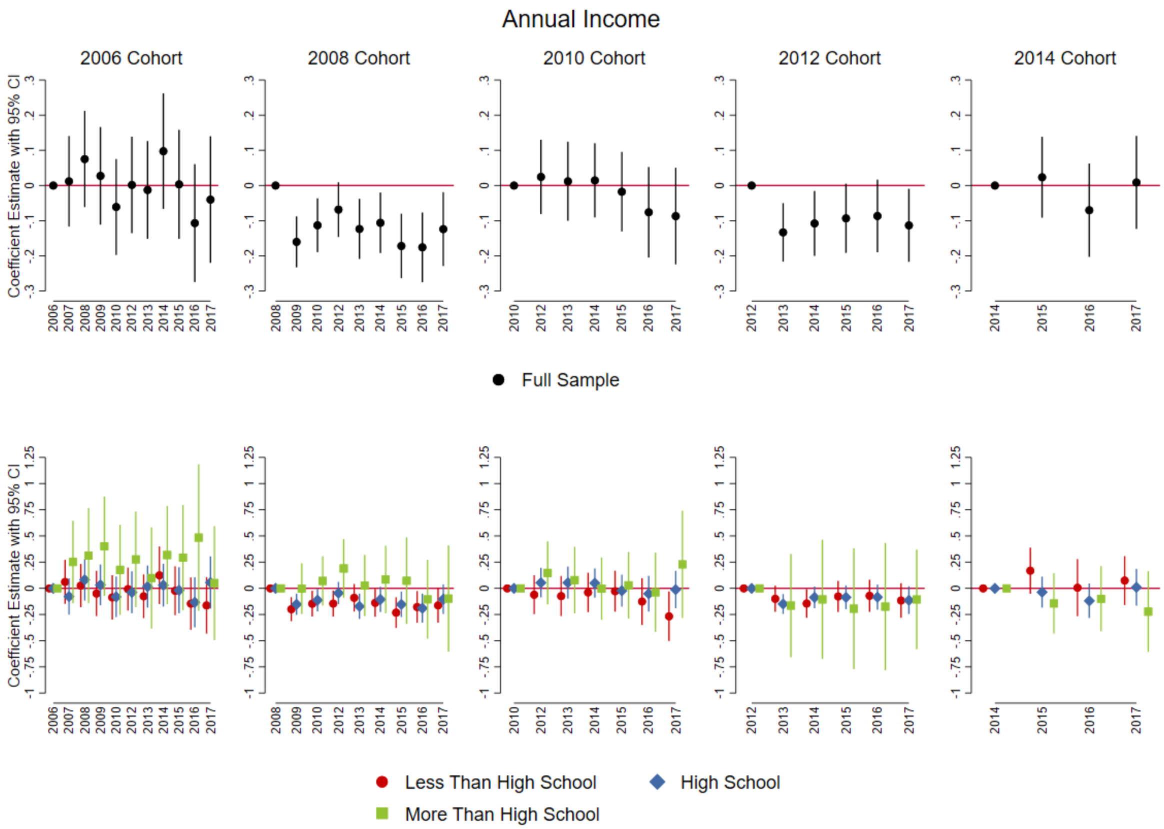
Note: Event studies regress hourly wages on relative time indicators centered around new hire into an oil-linked establishment (t omitted). Wages are deflated to constant 2018 BRL and transformed using inverse hyperbolic since. Standard errors are clustered at the individual level, and individual and year fixed effects are included. This specification keeps only employed individuals. Treated individuals (newly hired into oil-linked sector in year t) are compared to individuals newly hired into other sectors in year t who matched on age, education, sex, race, municipality, and wage and firm size bins in their first job. New hires are defined as workers who are hired into their firm formal job. Corresponding tables are reported in Appendix Table B16.

Figure A7: Months Employed Per Year After New Hire into Oil-Linked Sector



Note: See also note to Figure A6. Months employed ranges from a minimum of zero if the individual never appeared in formal employment registries during a year, to 12 if the individual was employed each month. This specification keeps all treated individuals and matched controls, whether formally employed or not, in a strongly balanced panel. Corresponding tables are reported in Appendix Table B17.

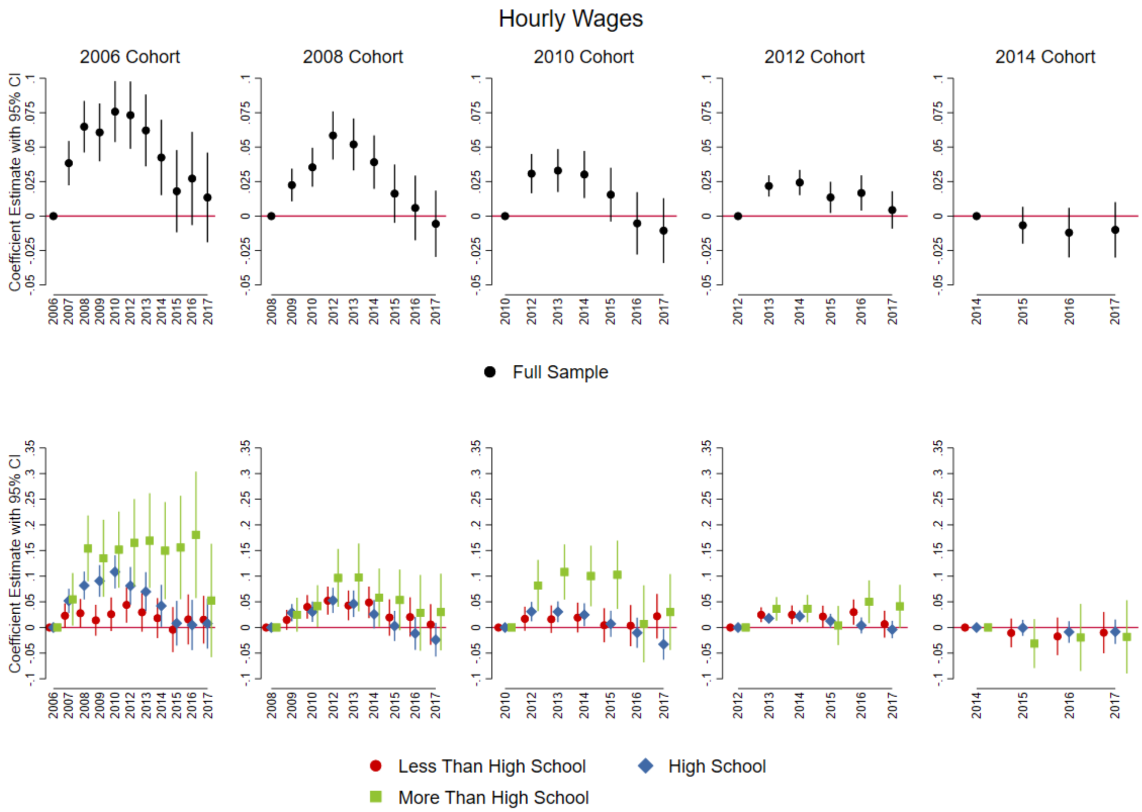
Figure A8: Annual Earnings After New Hire into Oil-Linked Sector



Note: See also note to Figure 3. Annual earnings refers to total formal earnings across all formal jobs. Earnings are transformed using the inverse hyperbolic sine transformation and deflated to constant 2018 BRL. This specification keeps all matched experienced hires, whether formally employed or not, in a strongly balanced panel. In periods where individuals do not appear in the panel, they are ascribed a value of zero formal earnings for this period. Corresponding tables are reported in Appendix Table B18-B21.

A.3 Results: Hired from Unemployment or Informal Sector

Figure A9: Hourly Wages After Hire from Unemployment/Informality into Oil-Linked Sector

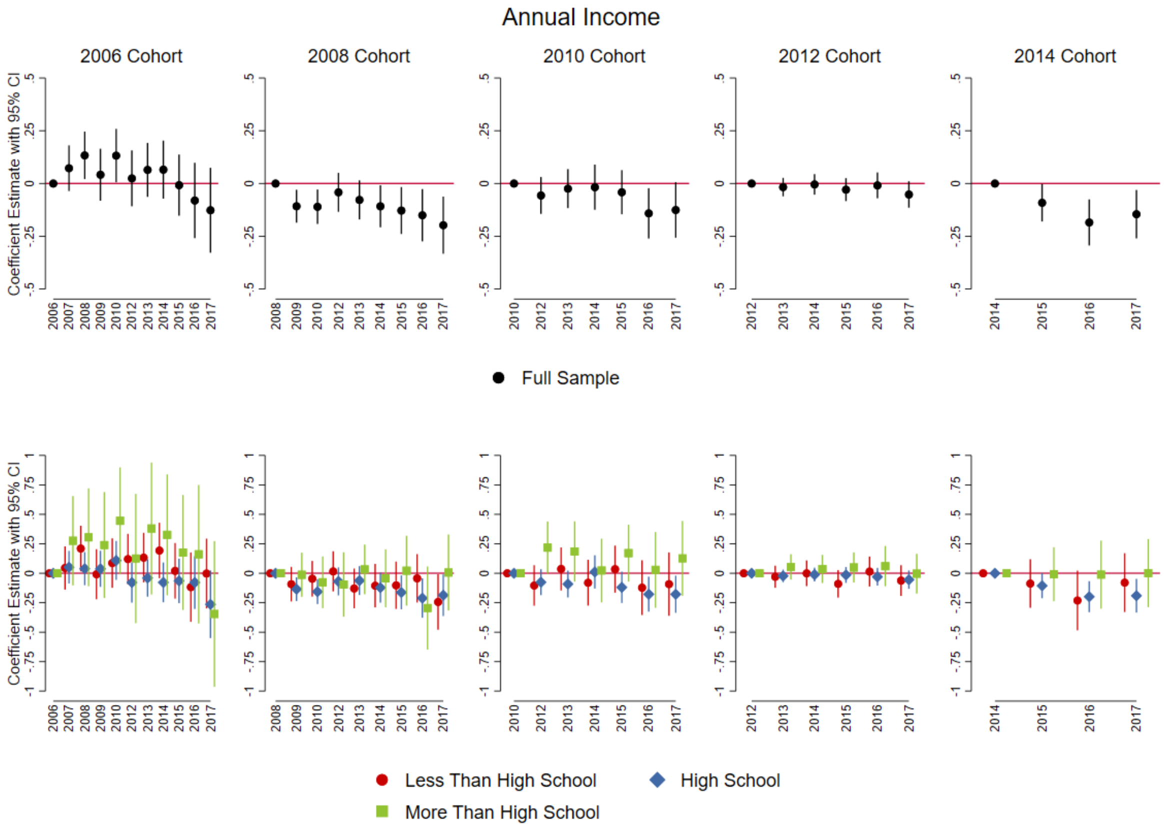


Note: Event studies regress hourly wages on relative time indicators centered around hire from unemployment or informality into an oil-linked establishment (t omitted). Wages are deflated to constant 2018 BRL and transformed using inverse hyperbolic since. Standard errors are clustered at the individual level, and individual and year fixed effects are included. To analyse effects at the intensive margin, this specification keeps only employed individuals. Treated individuals (hired from informality or unemployment into oil-linked sector in year t) are compared to individuals hired from similar conditions into other sectors in year t who matched on age, education, sex, race, municipality, and wage and firm size bins in their first job. Hires from unemployment or informality are defined as workers who are (i) hired to their first formal job (*primeiro emprego*) after the age of 30, or (ii) hired in year t and missing from RAIS formal employment records for the entirety of year $t - 1$.

Figure A10: Months Employed Per Year After Hire from Unemployment/Informality into Oil-Linked Sector

Note: Months employed ranges from a minimum of zero if the worker never appeared in formal employment registries during a year, to 12 if the individual was employed each month in at least one formal job. This specification keeps all treated individuals and their matched counterfactuals (whether formally employed or not) in a strongly balanced panel.

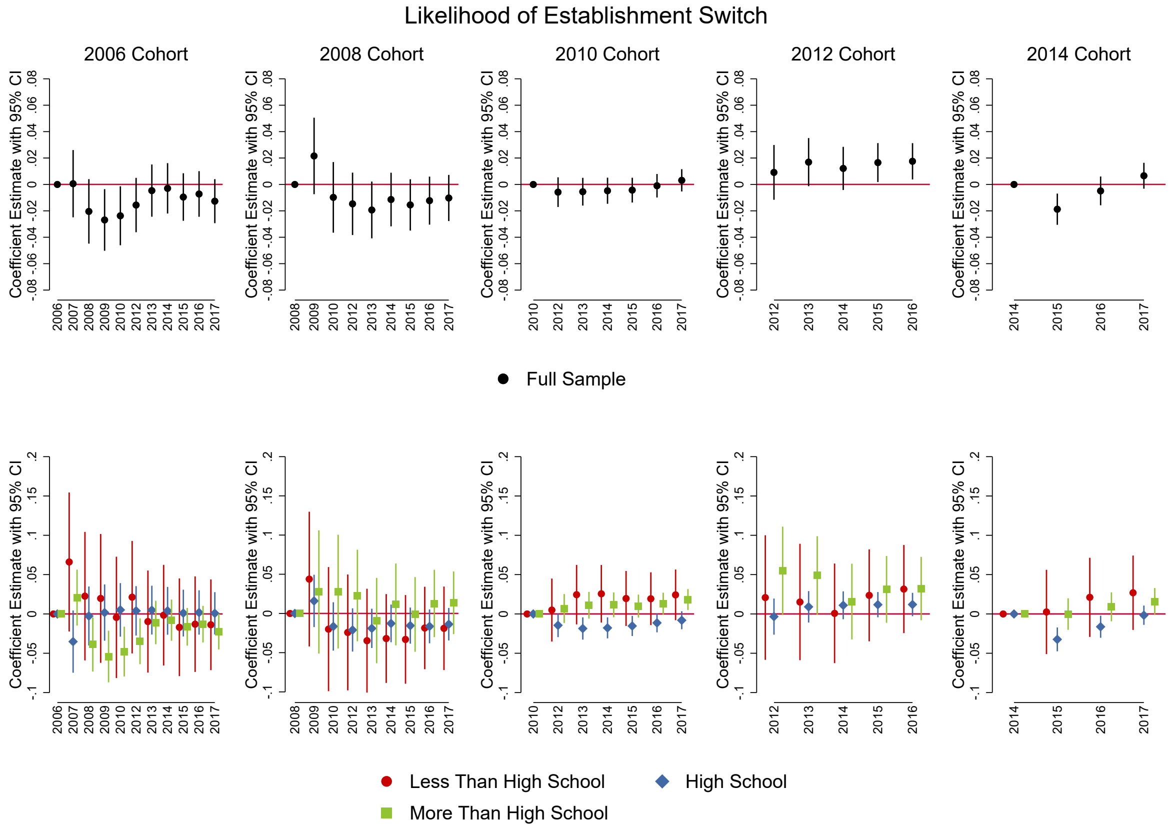
Figure A11: Annual Earnings After Hire from Unemployment/Informality into Oil-Linked Sector



Note: Annual earnings refers to total formal earnings for each worker across all formal jobs. Earnings are transformed using the inverse hyperbolic sine transformation and deflated to constant 2018 BRL. This specification keeps all treated individuals and their matched counterfactuals, whether formally employed or not, in a strongly balanced panel. In periods where individuals do not appear in the panel, they are ascribed a value of zero formal earnings for this period.

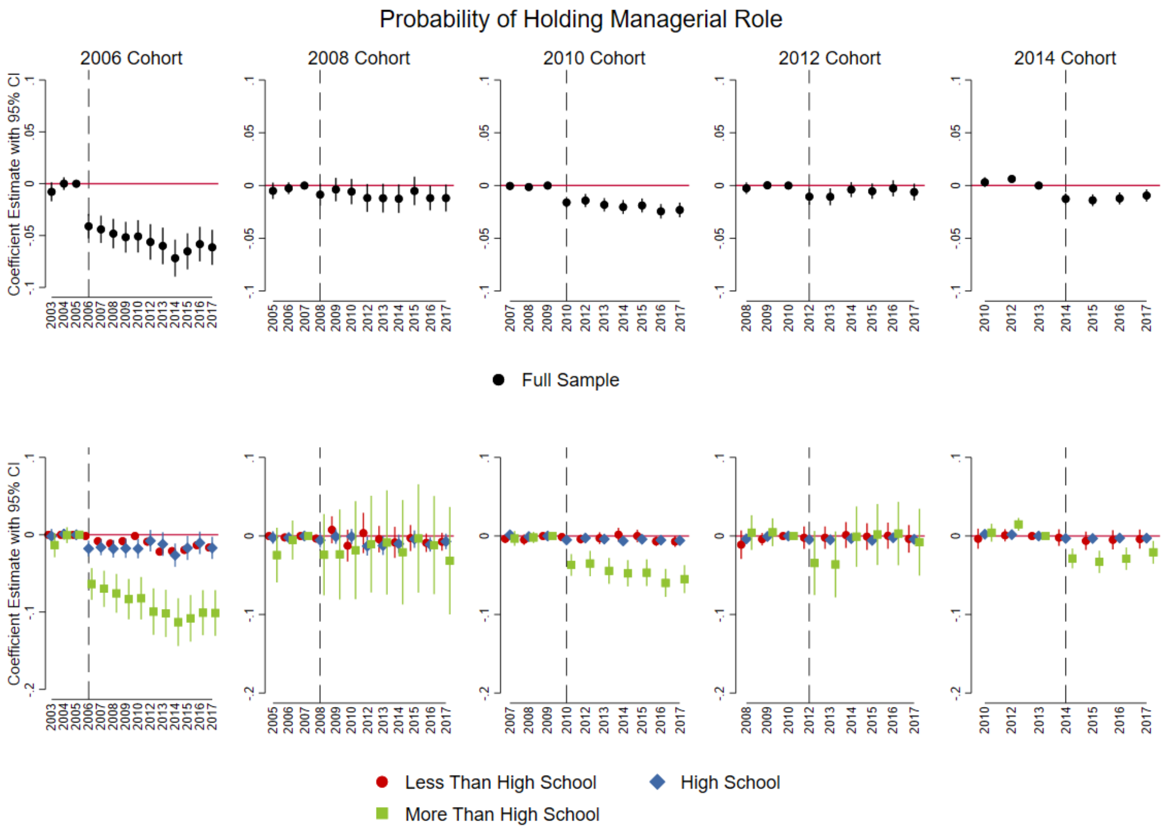
A.4 Results: Mechanisms

Figure A12: Establishment Switching after Hired into Oil-Linked Sector (Experienced Hires)



Notes: Specifications are analogous to those described in Figure 7. Here, the outcome is an indicator assuming a value of zero in each period the worker holds a job in the same establishment they were originally hired into, and a value of one in each period they hold a job in a different establishment.

Figure A13: Managerial Roles after Hired into Oil-Linked Sector (Experienced Hires)



Notes: Managerial roles are defined as CBO occupations with codes beginning with 1. These roles are primarily described as "leader", "director", or "manager". Binary outcomes are regressed on individual and year fixed effects and relative time indicators around year of being hired into oil (baseline $= t-1$). Standard errors are clustered at the individual level.

Figure A14: Professional Roles after New Hire into Oil-Linked Sector

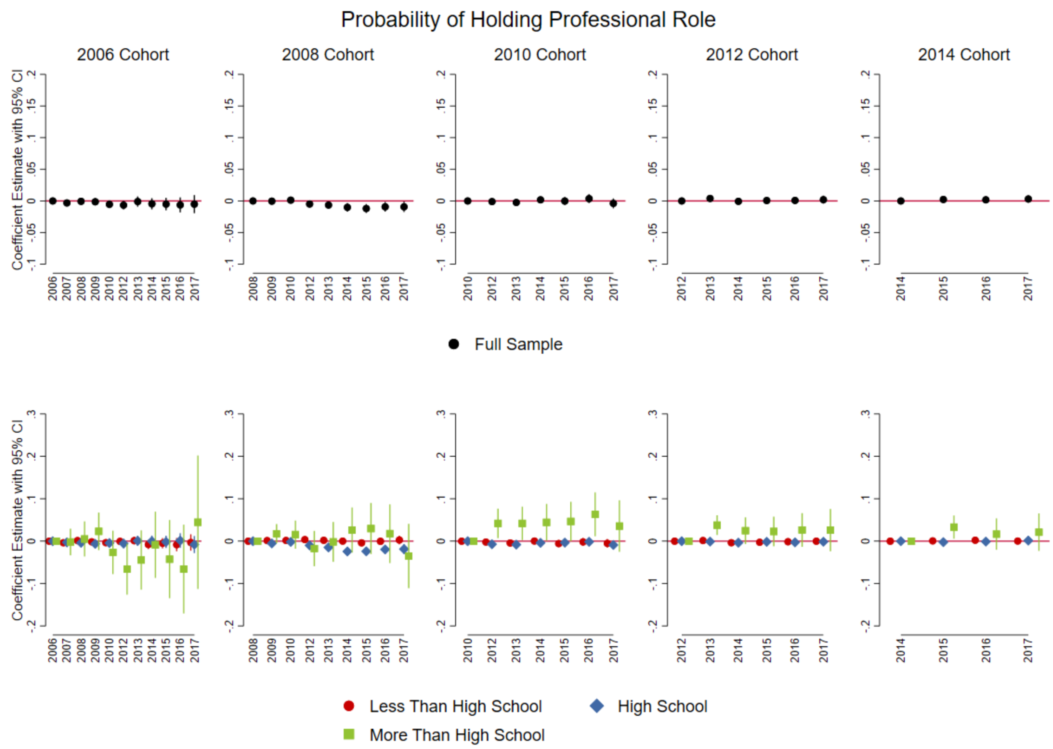


Figure A15: Managerial Roles after New Hire into Oil-Linked Sector

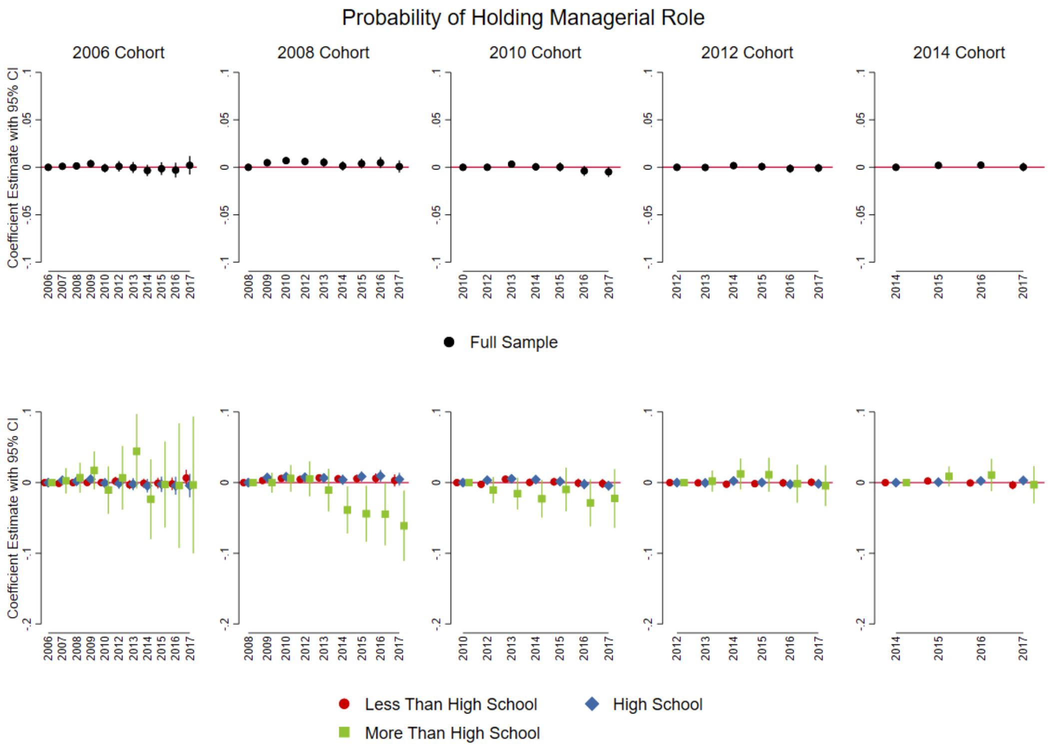


Figure A16: Occupation Switching after New Hire into Oil-Linked Sector

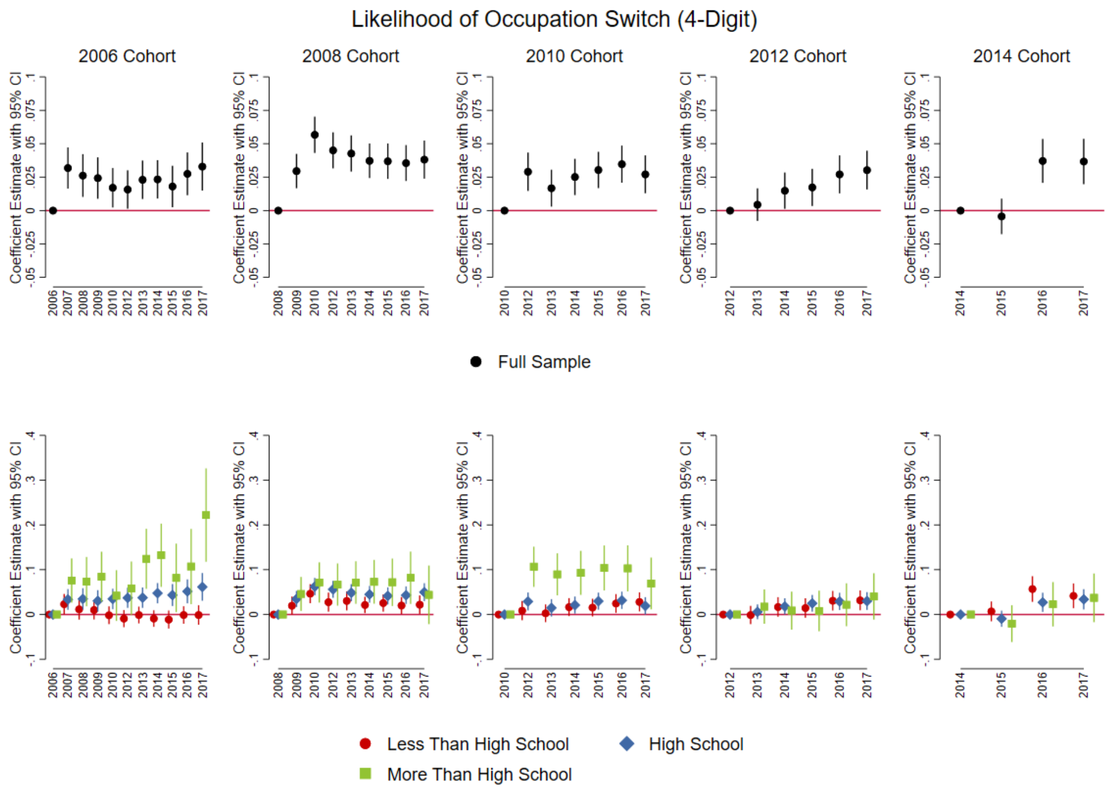
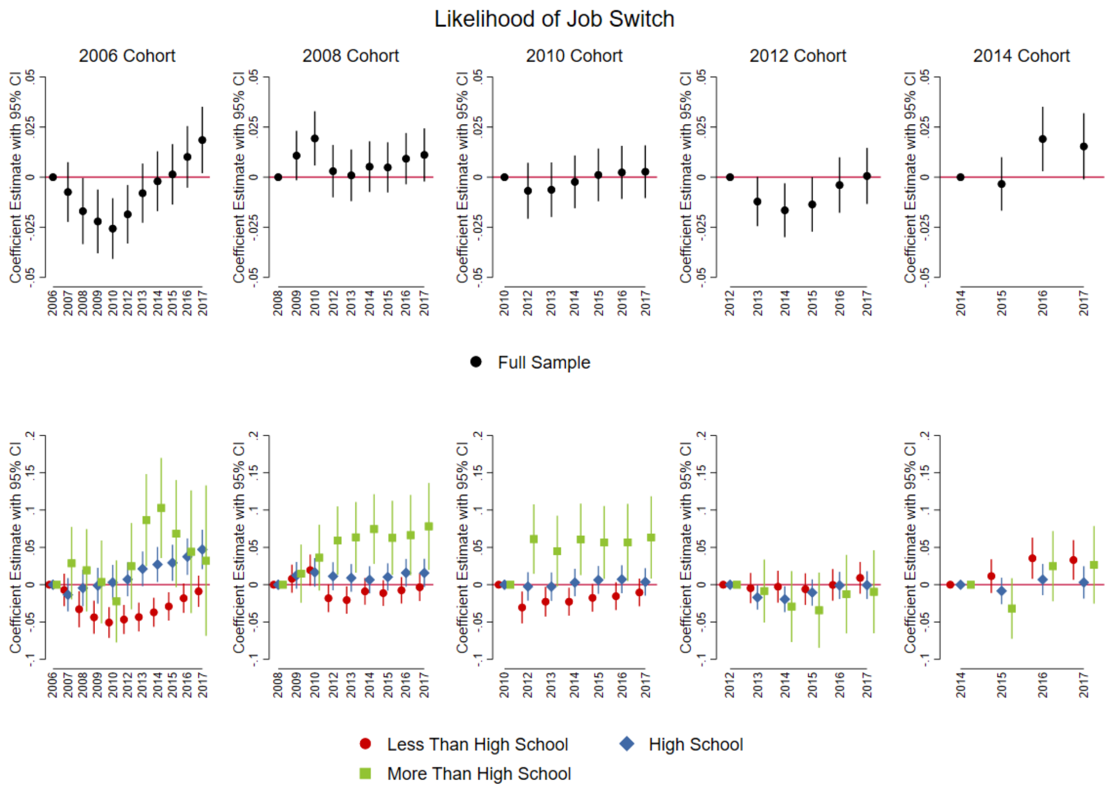


Figure A17: Establishment Switching after New Hire into Oil-Linked Sector



A.5 Oil-Linked Higher Education

Figure A18: Number of Oil-Linked Degree Programs

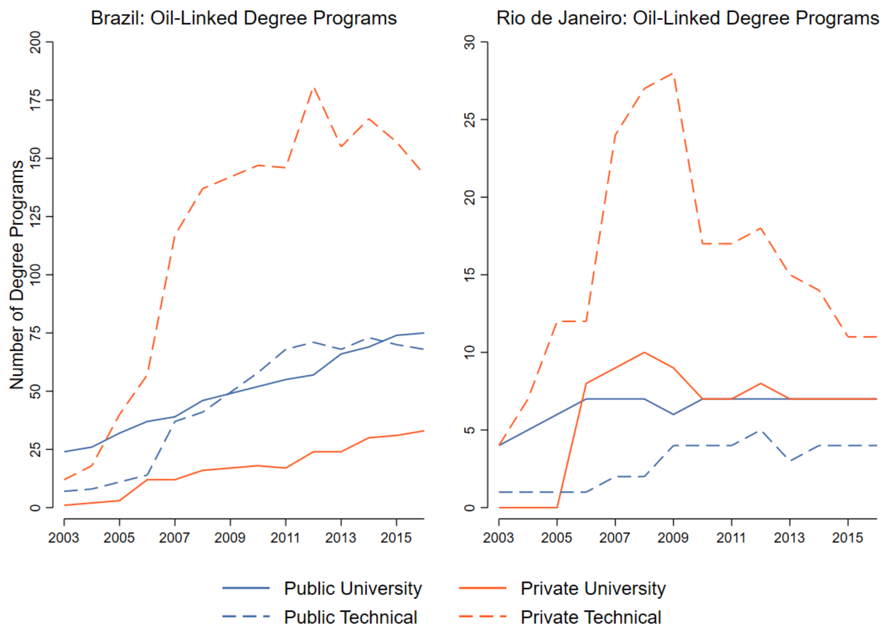
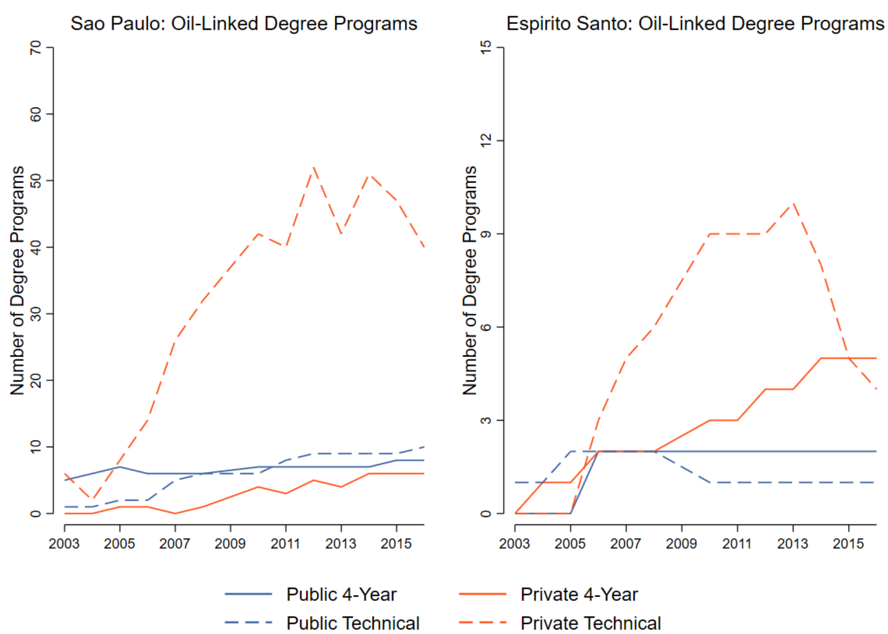


Figure A19: Oil-Linked Degree Programs (São Paulo and Espírito Santo)



B Supplementary Tables

B.1 Identifying Oil-Linked Sectors

We use Table 11 (Technical Coefficients of National Inputs) from Brazil's 2010 Input-Output Matrix (67 activities × 127 products), published by the *Instituto Brasileiro de Geografia e Estatística* (IBGE), to identify the top fifteen product categories located upstream and downstream from activity-code 0680 (Oil and Gas Extraction and Support Activities). We report these product categories in Appendix Table B1.

We translate product codes reported for each of these upstream and downstream activities into 2-digit CNAE 2.0 code roots, which is the activity classification system reported in RAIS. Each CNAE 2.0 code root is associated with numerous CNAE 2.0 subclasses, the finest available level of activity classification. For each CNAE 2.0 subclass, we manually inspect the activity description in order to assign the subclass to one or more of three oil-linked categories: direct oil-link (e.g., oil and gas extraction), upstream oil-link (e.g., fabrication of machinery for petroleum prospecting and extraction), or downstream oil-link (e.g., fabrication of petrochemical products). To check sensitivity to these definitions, we use stricter and looser assignment rules in robustness checks. In Appendix Table B2, we present examples of the translation of oil-linked I-O product codes into oil-linked CNAE 2.0 activity codes. In our preferred definition, we identify 14 directly oil-linked CNAE 2.0 subclasses, 109 upstream oil-linked subclasses, and 31 downstream oil-linked subclasses. We report the full set of oil-linked subclasses in Appendix Tables B3-B5.

Table B1: Input-Output Leontief Coefficients (Level 67 Product Codes): Direct Oil Ties and Top Upstream/Downstream Sectors

Oil Sector	**Leontief Coefficient**
Oil Extraction and Support Activities	1.068
Upstream Sectors	
Legal, Accounting, and Consulting Services	0.055
Land Transportation of Cargo	0.039
Petroleum Refining and Coke Plants	0.032
Fabrication of Machines and Mechanical Equipment	0.027
Production of Pig Iron, Alloys, Steel, and Steel Pipes	0.023
Storage and Logistics	0.021
Construction	0.021
Maintenance, Repair, and Installation of Machines and Equipment	0.020
Production of Organic and Inorganic Polymers and Resins	0.018
Architecture, Engineering, and R&D	0.018
Aquatic Transportation	0.017
Fabrication of Metal Products, Except Machines and Equipment	0.014
Non-Real Estate Rentals and Intellectual Property Management	0.011
Downstream Sectors	
Petroleum Refining and Coke Plants	0.411
Land Transportation of Cargo	0.088
Production of Organic and Inorganic Polymers and Resins	0.053
Electrical Energy and Utilities	0.047
Extraction of Non-Ferruginous Metals	0.045
Metallurgy of Non-Ferruginous Metals and Metal Casting	0.035
Extraction of Coal and Non-Metallic Minerals	0.029
Fabrication of Non-Metalic Mineral Products	0.029
Production and Refining of Sugar	0.029
Air Transportation	0.028
Production of Biofuels	0.027
Aquatic Transportation	0.027
Fabrication of Cellulose and Paper Products	0.026
Fabrication of Pesticides, Disinfectants, and Paints	0.026

Table B2: Translating 4-Digit IO Product Codes (Level 67) to 7-Digit CNAE 2.0 Activity Subclasses (Selected Examples)

IO Sector	SCN Code	CNAE Roots	CNAE 2.0 7-Digit Subclasses (Upstream Oil-Linked)	CNAE 2.0 7-Digit Subclasses (Non Oil-Linked)
Fabrication of Machines and Equipment	2800	28	Motors and Turbines, Except for Aircraft and Road Vehicles Hydraulic and Pneumatic Equipment, Except Valves Valves and Registers Industrial Compressors Industrial Ball Bearings Transmission Equipment, Except Ball Bearings Industrial Furnaces for Thermal Installations Industrial Stoves and Furnaces Lifting and Transport Machinery for People Lifting and Transport Machinery for Cargo Machinery for Industrial Refrigeration and Ventilation Machinery for Sewage and Environmental Cleanup Machine Tools Machinery for Petroleum Prospecting and Extraction Machinery for Metallurgical Industries	Compressors for Non-Industrial Uses Air Conditioning Machinery for Non-Industrial Uses Writing and Calculating Machinery for Offices Machines for General Uses Not Elsewhere Specified Tractors for Agriculture Irrigation Equipment for Agriculture Machines for Agriculture, Except Irrigation Machines for Mineral Extraction, Except Petroleum Tractors, Except for Agriculture Earth Moving, Planing, and Paving Machines Machines for Food, Drink, and Tobacco Production Machines for Textile Production Machines for Leather and Shoe Production Machines for Paper and Cardboard Production Machines for Plastic Production Machines for Industrial Uses Not Elsewhere Specified
Infrastructure Projects	4180	41, 42, 43	Construction of Pipelines, Except Water and Sewage Construction of Ports (Maritime and Riverine) Assembly of Metallic Structures Industrial Assembly Drilling and Test Boring Installation and Maintenance of Electrical Equipment Installation of Hydraulic, Sanitary, and Gas Equipment Installation and Maintenance of HVAC Systems Installation of Fire Prevention Systems Installation of Marine Navigation Systems Thermal, Acoustic, and Vibration Control Systems Project Management Services Operation and Supply of Transport and Lifting Equipment	Construction of Buildings Real Estate Development Construction of Highways and Railroads Painting and Signaling for Highways and Airports Construction of Special Art Projects Street, Plaza, and Sidewalk Projects Construction of Dams and Reservoirs for Energy Generation Construction and Maintenance of Energy Transmission Networks Construction and Maintenance of Telecommunication Networks Construction of Water and Sewage Sytems Irrigation Projects Construction of Sporting and Recreation Facilities Civil Engineering Not Elsewhere Specified Demolition of Buildings and Structures Preparation of Building Sites Earth Planing and Moving Other Site Preparation Services Installation of Billboards Installation and Maintenance of Elevators and Escalators Assembly and Installation of Public Lighting and Signaling Systems Other Installations Not Elsewhere Specified Water-Proofing in Civil Engineering Projects Installation of Doors, Windows and Roofs Plaster and Stucco General Painting Services Application of Resins (Interior and Exterior) Other Construction Finishing Services Foundation Laying Assembly and Disassembly of Scaffolding Masonry Drilling of Wells for Water

Note: Classification of CNAE 2.0 7-digit Subclasses as "oil-linked" or "non oil-linked" is based on text descriptions and contextual knowledge of each subclass. These classifications are informed by detailed descriptions of oil-linked upstream and downstream sectors provided by Oliveira (2010) and IPEA (2010).

Table B3: CNAE 2.0 Oil-Linked Subclasses

Subclass	**Subclass Description**	**D**	**US**	**US Coef**	**DS**	**DS Coef**
0600001	Extraction of Petroleum \& Natural Gas	1	0	1.068	0	1.068
0600003	Extraction \& Processing of Tar S\&s	1	0	1.068	0	1.068
0910600	Oil \& Nat. Gas Extract. Support Activ.	1	0	1.068	0	1.068
6911701	Legal Services	0	0	0.055	0	0.000
6911703	Industrial Property Management	0	0	0.055	0	0.000
6920601	Accounting Services	0	0	0.055	0	0.000
6920602	Account. \& Tax Consult. \& Audit.	0	0	0.055	0	0.000
7020400	Management Consulting	0	0	0.055	0	0.000
4911600	Rail Transport of Cargo	0	0	0.039	1	0.088
4930201	Road Transport of Cargo (Municipal)	0	0	0.039	1	0.088
4930202	Road Transport of Cargo (Inter-Munic.)	0	0	0.039	1	0.088
4940000	Pipeline Transport	0	1	0.039	1	0.088
1910100	Coke Plants	1	0	0.032	1	0.411
1921700	Fab. of Refined Oil Products	1	0	0.032	1	0.411
1922501	Formulation of Fuel Products	1	0	0.032	1	0.411
1922502	Refining of Oil Lubricants	1	0	0.032	1	0.411
1922599	Fab. of Other Petroleum Products	1	0	0.032	1	0.053
2811900	Fab. of Motors/Turbines (ex. Vehicles)	0	1	0.027	0	0.000
2812700	Fab. of Hydraulic \& Pneumatic Equip.	0	1	0.027	0	0.000
2813500	Fab. of Valves \& Registers	0	1	0.027	0	0.000
2814301	Fab. of Industrial Compressors	0	1	0.027	0	0.000
2815101	Fab. of Industrial Ball Bearings	0	1	0.027	0	0.000
2815102	Fab. of Transmission Equip.	0	1	0.027	0	0.000
2821601	Fab. Indust. Furnaces for Therm. Plants	0	1	0.027	0	0.000
2821602	Fab. of Industrial Stoves \& Furnaces	0	1	0.027	0	0.000
2822401	Fab. of Mach. for Transp./Elev. Ppl.	0	1	0.027	0	0.000
2822402	Fab. of Mach. for Transp./Elev. Cargo	0	1	0.027	0	0.000
2823200	Fab. of Machines for Industrial HVAC	0	1	0.027	0	0.000
2824101	Fab. of Indust. Air Conditioning Equip.	0	0	0.027	0	0.000
2825900	Fab. of Mach. for Sewage/Enviro. Treat	0	1	0.027	0	0.000
2840200	Fab. of Machine-Tools	0	1	0.027	0	0.000
2851800	Fab. of Mach./Equip. for Oil Prospect.	1	0	0.027	0	0.000
2861500	Fab. of Machines for Metallurg. Indust.	0	1	0.027	0	0.000
2411300	Prod. of Pig Iron	0	1	0.023	0	0.035
2412100	Prod. of Iron Alloys	0	1	0.023	0	0.035
2421100	Prod. of Semi-Finished Steel Products	0	1	0.023	0	0.035
2422901	Prod. of Steel Sheets	0	1	0.023	0	0.035
2422902	Prod. of Special Steel Sheets	0	1	0.023	0	0.035
2423701	Prod. of Steel Tubes (without Seams)	0	1	0.023	0	0.035
2423702	Prod. of Long Steel Sheets, ex. Tubes	0	1	0.023	0	0.035
2424501	Prod.s of Steel Wires	0	1	0.023	0	0.035
2424502	Prod. of Specialized Steel Products	0	1	0.023	0	0.035
2431800	Prod. of Steel Tubes (with Seams)	0	1	0.023	0	0.035
2439300	Prod. of Other Steel \& Iron Tubes	0	1	0.023	0	0.035
5212500	Loading \& Unloading of Cargo	0	1	0.021	0	0.000
5231101	Admin. of Port Infrastructure	0	1	0.021	0	0.000
5231102	Operation of Port Terminals	0	1	0.021	0	0.000
5232000	Maritime Activity Management	0	1	0.021	0	0.000
5239700	Aquatic Transport. Support Activities	0	1	0.021	0	0.000
5250804	Logistic Org. of Cargo Transport.	0	1	0.021	0	0.000

Note: Subclass refers to CNAE 2.0 Subclass. Subclass descriptions are abbreviated. D = Direct Oil; US = Upstream; US Coef. = Upstream Leontief Coefficient; DS = Downstream; DS Coef. = Downstream Leontief Coefficient. Direct, Upstream, and Downstream classifications are first made using Input-Output relationships (5-digit SCN codes) reported in Table B1. Each SCN code is translated into a 2-digit CNAE 2.0 code root using the official SCN/CNAE 2.0 Conversion Table from IBGE. Each 2-digit CNAE 2.0 code root is associated with multiple 7-digit subclasses. We manually assign selected CNAE 2.0 Subclasses as "oil-linked" using contextual knowledge and text descriptions of each subclass (Oliveira, 2010; IPEA, 2010). This process is illustrated in Table B2.

Table B4: CNAE 2.0 Oil-Linked Subclasses Cont'd.

Subclass	Subclass Description	D	U	U Coef.	D	D Coef.
4223500	Constr. of Pipe. (ex. Water/Sewage)	0	1	0.021	0	0.000
4291000	Port \& Maritime Projects	0	1	0.021	0	0.000
4292801	Construction of Metallic Structures	0	1	0.021	0	0.000
4292802	Industrial Construction Projects	0	1	0.021	0	0.000
4312600	Perforations \& Drilling	0	1	0.021	0	0.000
4321500	Electrical Install. \& Maint.	0	1	0.021	0	0.000
4322301	Hydraulic, Sanitary, \& Gas Install.	0	1	0.021	1	0.000
4322302	Install. \& Maint. of HVAC Systems	0	0	0.021	0	0.000
4322303	Install. of Fire Prevention Systems	0	1	0.021	0	0.000
4329102	Install. of Maritime Navigation Syst.	0	1	0.021	0	0.000
4329105	Treat. for Heat, Noise, Vibrat. Cont.	0	1	0.021	0	0.000
4399101	Project Management	0	1	0.021	0	0.000
4399104	Supply of Transport \& Elev. Equip.	0	1	0.021	0	0.000
3311200	Maint. \& Repair of Tanks (ex. Vehicles)	0	1	0.020	0	0.000
3312102	Maint. \& Repair of Measurement Instr.	0	1	0.020	0	0.000
3312104	Maint. \& Repair of Optical Instr.	0	0	0.020	0	0.000
3313901	Maint. \& Repair of Eletrical Generators	0	1	0.020	0	0.000
3313902	Maint. \& Repair Batteries (ex. Vehic.)	0	1	0.020	0	0.000
3313999	Maint. \& Repair of Other Electr. Mach.	0	1	0.020	0	0.000
3314701	Maint. \& Repair of Non-Elect. Motors	0	1	0.020	0	0.000
3314702	Maint. \& Repair Hydr./Pneum. Equip.	0	1	0.020	0	0.000
3314703	Maint. \& Repair of Industrial Valves	0	1	0.020	0	0.000
3314704	Maint. \& Repair of Compressors	0	1	0.020	0	0.000
3314705	Maint. \& Repair Indust. Transm. Equip.	0	1	0.020	0	0.000
3314706	Maint. \& Repair of Thermal Machines	0	1	0.020	1	0.000
3314707	Maint. \& Repair of HVAC Machines	0	0	0.020	0	0.000
3314708	Maint. \& Repair of Transp./Elev. Equip.	0	1	0.020	0	0.000
3314713	Maint. \& Repair of Machine Tools	0	1	0.020	0	0.000
3314714	Maint. \& Repair of Oil Prospect. Equip.	1	0	0.020	0	0.000
3314718	Maint. \& Repair Metal. Machines	0	1	0.020	0	0.000
3317101	Maint. \& Repair Ships/Floating Struct.	0	1	0.020	0	0.000
3321000	Install. of Industrial Machines	0	1	0.020	0	0.000
2014200	Fab. of Industrial Gases	0	1	0.018	1	0.053
2022300	Fab. of Interm. Plastics, Resins, Fibers	0	1	0.018	1	0.053
2021500	Fab. of Basic Petrochemical Products	1	0	0.018	1	0.053
2031200	Fab. of Thermoplastic Resins	0	1	0.018	1	0.053
2032100	Fab. of Thermosetting Resins	0	1	0.018	1	0.053
2033900	Fab. of Elastomeres	0	1	0.018	1	0.053
7111100	Architectural Services	0	0	0.018	0	0.000
7112000	Engineering Services	0	1	0.018	0	0.000
7119701	Cartog., Topog., \& Geo. Services	0	1	0.018	0	0.000
7119702	Geological Studies	0	1	0.018	0	0.000
7119703	Tech. Design Services Architect./Eng.	0	1	0.018	0	0.000
7119704	Workplace Safety Services	0	1	0.018	0	0.000
7119799	Other Eng. \& Architect. Service	0	1	0.018	0	0.000
7120100	Tests \& Technical Analyses	0	1	0.018	0	0.000
7210000	Exp. R&D in Phys. \& Nat. Sciences	0	1	0.018	0	0.000
5011401	Maritime Cargo Transport	0	1	0.017	0	0.027

Note: Subclass refers to CNAE 2.0 Subclass. Subclass descriptions are abbreviated. D = Direct Oil; US = Upstream; US Coef. = Upstream Leontief Coefficient; DS = Downstream; DS Coef. = Downstream Leontief Coefficient. Direct, Upstream, and Downstream classifications are first made using Input-Output relationships (5-digit SCN codes) reported in Table B1. Each SCN code is translated into a 2-digit CNAE 2.0 code root using the official SCN/CNAE 2.0 Conversion Table from IBGE. Each 2-digit CNAE 2.0 code root is associated with multiple 7-digit subclasses. We manually assign selected CNAE 2.0 Subclasses as "oil-linked" using contextual knowledge and text descriptions of each subclass (Oliveira, 2010; IPEA, 2010). This process is illustrated in Table B2.

Table B5: CNAE 2.0 Oil-Linked Subclasses Cont'd.

Subclass	**Subclass Description**	**D**	**U**	**U Coef.**	**D**	**D Coef.**
5012201	Maritime Cargo Transp. (Long-Dist.)	0	1	0.017	0	0.027
5030101	Maritime Navigation Support	0	1	0.017	0	0.027
5030102	Port Navigation Support	0	1	0.017	0	0.027
2511000	Fab. of Metallic Structures	0	1	0.014	0	0.000
2513600	Fab. of Heavy Boilers	0	1	0.014	0	0.000
2522500	Fabricatoin of Vapor Boilers	0	1	0.014	0	0.000
2531401	Prod. of Forged Steel Products	0	1	0.014	0	0.000
2531402	Prod. of Forged Iron Alloys	0	1	0.014	0	0.000
2532201	Prod. of Stamped Metal Products	0	1	0.014	0	0.000
2532202	Powder Metallurgy	0	1	0.014	0	0.000
2539000	Machining \& Welding Services	0	1	0.014	0	0.000
2539001	Machining \& Turning	0	1	0.014	0	0.000
2539002	Treatment \& Coating of Metals	0	1	0.014	0	0.000
2543800	Fab. of Tools	0	1	0.014	0	0.000
2592601	Fab. of Draw Metal Prod. (Stand.)	0	1	0.014	0	0.000
2592602	Fab. of Drawn Metal Prod. (Non-Stand.)	0	1	0.014	0	0.000
2599302	Metal Cutting \& Folding Services	0	1	0.014	0	0.000
7719501	Rental of Ships w.o. Crew (ex. Rec.)	0	1	0.011	0	0.000
7732201	Rental of Machines \& Equip. Constr.	0	1	0.011	0	0.000
7739001	Rental of Mach./Equip. for Petrol. Extr.	1	0	0.011	0	0.000
7739002	Rental of Scientific Equip.	0	0	0.011	0	0.000
7740300	Mgmt. Intangible Non-Financ. Assets	0	0	0.011	0	0.000
3011301	Construction of Large Ships	1	1	0.000	0	0.000
3511500	Electrical Energy Gen. (Deactivated)	0	0	0.000	1	0.047
3511501	Electrical Energy Generation	0	0	0.000	1	0.047
3511502	Coord. \& Control of Elect. Gen.	0	0	0.000	1	0.047
3512300	Electrical Energy Transmission	0	0	0.000	0	0.047
3513100	Wholesale Electr. Energy Comm.	0	0	0.000	0	0.047
3514000	Electricity Distribution	0	0	0.000	0	0.047
3520401	Prod. of Gas	0	0	0.000	1	0.047
3520402	Dist. of Fuel Gas to Urban Util.	0	0	0.000	0	0.047
2219600	Fab. of Rubber Products	0	0	0.000	1	0.024
2221800	Fab. of Plastic Tubes \& Sheets	0	0	0.000	1	0.024
2222600	Fab. of Plastic Packaging	0	0	0.000	1	0.024
2223400	Fab. of Plastic Tubes for Constr.	0	0	0.000	1	0.024
2229301	Fab. of Plastic Art. for Domest.	0	0	0.000	1	0.024
2229302	Fab. of Plastic Products for Industr.	0	0	0.000	1	0.024
2229303	Fab. Plast Prod. Constr. (ex. Tubes)	0	0	0.000	1	0.024
2229399	Fab. of Plast Prod. Other Use	0	0	0.000	1	0.024
1931400	Fab. of Ethanol	0	0	0.000	1	0.027
1932200	Fab. of Biofuels (ex. Ethanol)	0	0	0.000	1	0.027

Note: Subclass refers to CNAE 2.0 Subclass. Subclass descriptions are abbreviated. D = Direct Oil; US = Upstream; US Coef. = Upstream Leontief Coefficient; DS = Downstream; DS Coef. = Downstream Leontief Coefficient. Direct, Upstream, and Downstream classifications are first made using Input-Output relationships (5-digit SCN codes) reported in Table B1. Each SCN code is translated into a 2-digit CNAE 2.0 code root using the official SCN/CNAE 2.0 Conversion Table from IBGE. Each 2-digit CNAE 2.0 code root is associated with multiple 7-digit subclasses. We manually assign selected CNAE 2.0 Subclasses as "oil-linked" using contextual knowledge and text descriptions of each subclass (Oliveira, 2010; IPEA, 2010). This process is illustrated in Table B2.

B.2 Oil-Linked Shipyards

Table B6: Oil-Linked Shipyards (PortalNaval, 2020)

Shipyard Name	Region	State	Municipality	CEP
Construção e Montagem Offshore - CMO	NE	PE	Ipojuca	55590-972
Estaleiro Atlantico Sul	NE	PE	Ipojuca	55590-970
Vard Promar	NE	PE	Ipojuca	55590-000
Enseada Indústria Naval - Unidade Paraguaçu	NE	BA	Maragojipe	44420-000
Estaleiro Jurong Aracruz	SE	ES	Aracruz	29198-046
Terminal de Serviços e Logística da Barra do Furado	SE	RJ	Quissama	28735-000
Estaleiro Cassinu	SE	RJ	São Gonçalo	24430-620
Navegação São Miguel	SE	RJ	São Gonçalo	24430-500
Estaleiro Alianca	SE	RJ	Niterói	24110-200
Equipemar	SE	RJ	Niterói	24110-205
Estaleiro Brasa	SE	RJ	Niterói	24040-005
Estaleiro Mauá – Ponta D'Areia	SE	RJ	Niterói	24040-290
Mac Laren Oil	SE	RJ	Niterói	24040-260
RENAVE e ENAVI	SE	RJ	Niterói	24110-200
UTC Engenharia	SE	RJ	Niterói	24110-814
Vard Niteroi	SE	RJ	Niterói	24050-350
EISA	SE	RJ	Rio de Janeiro	21920-630
Inhauma	SE	RJ	Rio de Janeiro	20936-900
Brasfels S.A.	SE	RJ	Angra dos Reis	23905-000
Estaleiro Detroit Brasil	S	SC	Itajaí	88311-550
Estaleiro Itajai	S	SC	Itajaí	88305-620
Estaleiro Oceana	S	SC	Itajaí	88311-045
Estaleiro Keppel Singmarine Brasil	S	SC	Navegantes	88375-000
Estaleiro Navship	S	SC	Navegantes	88375-000
RG Estaleiro ERG	S	RS	Rio Grande	96204-040
Estaleiro do Brasil	S	RS	São José do Norte	96225-000

B.3 Predicting Hire into Oil-Linked Sectors

Table B7: Predictors of Being Hired into Oil-Linked Sector (Logit)

Covariates	New Hires	Experienced Hires	Experienced Hires
Education	0.023	0.047	0.053
	(0.001)	(0.001)	(0.001)
Female	-1.54	-1.46	-1.47
	(0.003)	(0.003)	(0.003)
Nonwhite	0.187	0.175	0.175
	(0.002)	(0.002)	(0.002)
Age	0.048	0.029	0.030
	(0.001)	(0.001)	(0.001)
Age Squared	-0.001	-0.0003	-0.0003
	(0.000)	(0.000)	(0.000)
Wage in Previous Job		0.0001	
		(0.000)	
Previous Firm Size		0.033	
		(0.000)	
Wage Rank in Previous Firm			-0.267
			(0.004)
Education Rank in Previous Firm			-0.166
			(0.005)
Occupation Rank in Previous Firm			-0.475
			(0.008)
2007 (years relative to 2006)	0.153	0.093	0.097
	(0.006)	(0.006)	(0.006)
2008	0.273	0.241	0.248
	(0.006)	(0.006)	(0.006)
2009	0.206	0.0142	0.0204
	(0.006)	(0.006)	(0.006)
2010	0.330	0.151	0.162
	(0.005)	(0.006)	(0.006)
2011	0.451	0.095	0.134
	(0.006)	(0.006)	(0.006)
2012	0.470	0.128	0.173
	(0.005)	(0.005)	(0.005)
2013	0.419	0.080	0.127
	(0.005)	(0.005)	(0.005)
2014	0.351	-0.030	0.016
	(0.006)	(0.006)	(0.006)
2015	0.240	-0.222	-0.180
	(0.006)	(0.006)	(0.006)
2016	0.119	-0.311	-0.273
	(0.007)	(0.007)	(0.007)
2017	0.074	-0.236	-0.195
	(0.007)	(0.007)	(0.007)
State FEs	Y	Y	Y
Observations	40,712,468	23,042,525	23,042,525

Note: Marginal effects from logit models are reported with heteroskedasticity-consistent robust standard errors in parentheses. Estimates are obtained by regressing a binary indicator that takes a value of 1 if a worker was hired as a new or experienced worker into an oil-linked establishment on worker-level covariates and year and state fixed effects. Column 1 uses a pooled cross-sectional sample of all newly hired formal workers in Brazil between 2006-2017. Columns 2 and 3 use a pooled cross-sectional sample of all experienced hires between 2006-2017. For experienced workers, previous employment characteristics are observed and can therefore be included in regressions. Rank variables (wage, education, and occupation) are computed for each experienced worker's previous firm, such that the highest paid employee at the firm would have a wage rank of 1. Ranks are normalized to a 0-to-1 scale. Occupation rank is based on workers' occupation falling into categories ranging from manager or professional (highest), to technician (mid-rank), to worker (low-rank). Year fixed effects are reported relative to the omitted base year (2006).

B.4 Descriptive Statistics

Table B8: Descriptive Statistics: **Experienced Hires**

		Starting Wage	Education	Age	Female	Nonwhite	n
	Population (Treated)	4,312 (4457.5)	6.90 (1.63)	32.51 (8.38)	0.13 (0.34)	0.28 (0.45)	15,347
2006	Population (Control)	2,580 (3795.5)	6.58 (1.78)	31.39 (8.04)	0.33 (0.47)	0.30 (0.46)	294,342
	Matched (Treated)	6,210 (6037.2)	7.75 (1.33)	31.55 (6.45)	0.18 (0.38)	0.19 (0.39)	2,461
	Matched (Control)	7,653 (9220.4)	7.94 (1.24)	30.76 (5.71)	0.23 (0.42)	0.17 (0.37)	10,201
	Population (Treated)	3,171 (3453.9)	6.43 (1.56)	32.64 (8.57)	0.10 (0.30)	0.39 (0.49)	14,760
2008	Population (Control)	1,928 (2305.0)	6.31 (1.68)	31.52 (8.12)	0.30 (0.46)	0.34 (0.47)	243,331
	Matched (Treated)	3,041 (3647.6)	6.81 (1.16)	31.13 (6.91)	0.08 (0.28)	0.34 (0.47)	1,437
	Matched (Control)	2,530 (3717.6)	6.97 (0.97)	29.87 (5.76)	0.10 (0.29)	0.31 (0.46)	4,961
	Population (Treated)	4,181 (5053.3)	6.87 (1.52)	32.56 (8.51)	0.13 (0.34)	0.40 (0.49)	41,437
2010	Population (Control)	2,522 (3510.2)	6.73 (1.64)	31.78 (8.28)	0.35 (0.48)	0.36 (0.48)	662,855
	Matched (Treated)	5,255 (6619.4)	7.31 (1.26)	31.65 (7.12)	0.14 (0.35)	0.38 (0.48)	10,767
	Matched (Control)	4,572 (6638.2)	7.50 (1.18)	30.35 (6.09)	0.24 (0.43)	0.31 (0.46)	54,024
	Population (Treated)	3,217 (3414.1)	6.56 (1.51)	33.35 (8.52)	0.11 (0.32)	0.48 (0.50)	22,371
2012	Population (Control)	2,069 (2240.0)	6.50 (1.59)	32.83 (8.39)	0.34 (0.48)	0.40 (0.49)	369,713
	Matched (Treated)	3,075 (3692.3)	6.86 (1.09)	32.42 (6.92)	0.09 (0.28)	0.48 (0.50)	2,899
	Matched (Control)	2,447 (3377.7)	6.98 (0.87)	31.55 (6.25)	0.14 (0.35)	0.44 (0.50)	11,327
	Population (Treated)	3,932 (4728.5)	6.94 (1.46)	32.24 (8.51)	0.15 (0.36)	0.48 (0.50)	43,659
2014	Population (Control)	2,542 (3286.9)	6.86 (1.56)	32.25 (8.80)	0.41 (0.49)	0.42 (0.49)	869,401
	Matched (Treated)	4,852 (6038.9)	7.34 (1.20)	31.63 (7.13)	0.17 (0.37)	0.47 (0.50)	10,805
	Matched (Control)	4,775 (6690.3)	7.61 (1.12)	31.06 (6.44)	0.28 (0.45)	0.40 (0.49)	66,213

Note: Table reports means and standard deviations (in parentheses) for the full population of formal workers who were hired as experienced workers from employment in other jobs (poached) in a given year, as well as for matched subsamples. “Treated” refers to workers who were hired into an oil-linked establishment; “control” refers to all other workers hired into other sectors from employment in other jobs. Monetary values are deflated to constant 2018 $BRL. Poached is defined as voluntary exit from previous firm and rehire at a new firm within 4 months. Coarsened exact matching criteria are: education, sex, non-white race indicator, occupation category, age bin, previous establishment, previous wage bin during a two-year matching window prior to poach, and destination municipality. While matching procedure does not always appear to balance raw sample means between treated and control groups, inclusion of matching weights in regression analyses ensures proper balancing.

Table B9: Descriptive Statistics: **New Hires**

		Starting Wage	Education	Age	Female	Nonwhite	n*
2006	Population (Treated)	1,491 (2153)	5.44 (1.90)	26.15 (8.75)	0.13 (0.34)	0.47 (0.50)	72,582
	Population (Control)	1,238 (1661)	5.97 (1.80)	26.18 (8.95)	0.44 (0.50)	0.50 (0.50)	3,169,213
	Matched (Treated)	1,298 (1540)	6.01 (1.54)	23.22 (6.19)	0.13 (0.34)	0.39 (0.49)	3,592
	Matched (Control)	1,173 (1215)	6.41 (1.22)	21.56 (4.29)	0.25 (0.44)	0.33 (0.47)	15,953
2008	Population (Treated)	1,642 (2541)	5.76 (1.78)	26.01 (8.68)	0.15 (0.36)	0.49 (0.50)	99,771
	Population (Control)	1,277 (1679)	6.11 (1.74)	26.21 (8.94)	0.46 (0.50)	0.52 (0.50)	3,757,139
	Matched (Treated)	1,423 (2125)	6.15 (1.44)	23.93 (6.98)	0.15 (0.36)	0.46 (0.50)	9,184
	Matched (Control)	1,175 (1217)	6.45 (1.10)	22.33 (5.34)	0.28 (0.45)	0.46 (0.50)	80,985
2010	Population (Treated)	1,799 (2651)	5.95 (1.69)	26.42 (9.03)	0.15 (0.36)	0.53 (0.50)	106,114
	Population (Control)	1,361 (1754)	6.26 (1.67)	26.37 (9.14)	0.48 (0.50)	0.56 (0.50)	4,007,616
	Matched (Treated)	1,468 (1643)	6.38 (1.32)	24.06 (7.16)	0.15 (0.36)	0.50 (0.50)	6,228
	Matched (Control)	1,301 (1403)	6.58 (1.12)	22.49 (5.73)	0.26 (0.44)	0.47 (0.50)	26,556
2012	Population (Treated)	1,956 (3032)	6.17 (1.63)	25.72 (9.03)	0.18 (0.38)	0.59 (0.49)	108,924
	Population (Control)	1,410 (1700)	6.36 (1.58)	25.90 (9.55)	0.49 (0.50)	0.47 (0.50)	3,906,395
	Matched (Treated)	1,841 (3265)	6.46 (1.32)	24.13 (8.04)	0.18 (0.39)	0.59 (0.49)	11,143
	Matched (Control)	1,364 (1909)	6.63 (0.97)	21.68 (6.31)	0.33 (0.47)	0.55 (0.50)	91,778
2014	Population (Treated)	1,959 (3307)	6.27 (1.53)	25.50 (9.28)	0.19 (0.39)	0.58 (0.49)	84,554
	Population (Control)	1,490 (1821)	6.47 (1.58)	25.81 (9.77)	0.49 (0.50)	0.48 (0.50)	3,422,596
	Matched (Treated)	1,613 (2170)	6.60 (1.12)	23.14 (7.45)	0.21 (0.41)	0.59 (0.49)	4,745
	Matched (Control)	1,415 (2306)	6.71 (0.92)	20.77 (5.65)	0.37 (0.48)	0.58 (0.49)	26,758

Note: Table reports means and standard deviations (in parentheses) for the full population of formal workers who were newly hired in a given year, as well as for matched subsamples. "Treated" refers to workers who were hired into an oil-linked establishment; "control" refers to all other hired workers. Monetary values are deflated to constant 2018 $BRL. A new hire is defined as a worker who is hired to their first formal job and is 30 or younger. Coarsened exact matching criteria are: education, sex, non-white race indicator, municipality, age bin, and wage and firm size bins in first job. While matching procedure does not always appear to balance raw sample means between treated and control groups, inclusion of matching weights in regression analyses ensures proper balancing.

*Matching is performed on a random subsample of 20% of the full population of new hires. Thus, when evaluating matched workers as a share of the population, note that the matching success rate is five times larger than suggested by reported sample sizes.

B.5 Regression Tables (Experienced Hires)

Table B10: Experienced Hires: **Hourly Wages**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2003	-0.026	0.01	-	-	-	-	-	-	-	-
2004	-0.013	0.006	-	-	-	-	-	-	-	-
2005	(base)	-	-0.015	0.013	-	-	-	-	-	-
2006	0.03	0.009	-0.013	0.008	-	-	-	-	-	-
2007	0.118	0.013	(base)	-	-0.002	0.005	-	-	-	-
2008	0.176	0.014	0.055	0.014	-0.001	0.003	-0.014	0.009	-	-
2009	0.171	0.016	0.095	0.016	(base)	-	-0.011	0.006	-	-
2010	0.194	0.017	0.099	0.017	0.071	0.005	(base)	-	0.005	0.006
2012	0.215	0.018	0.107	0.021	0.119	0.007	0.034	0.01	-0.002	0.003
2013	0.218	0.02	0.127	0.022	0.119	0.007	0.057	0.012	(base)	-
2014	0.227	0.021	0.094	0.023	0.111	0.008	0.044	0.014	0.04	0.004
2015	0.254	0.021	0.082	0.027	0.088	0.009	0.029	0.015	0.05	0.006
2016	0.244	0.023	0.089	0.029	0.063	0.009	0.014	0.017	0.016	0.007
2017	0.274	0.024	0.063	0.031	0.061	0.01	-0.027	0.017	0.014	0.008
n	12,563		6,357		64,302		14,095		76,333	
n×t	158,323		78,868		758,754		164,345		793,605	
N	309,689		258,091		704,292		392,084		913,060	
DV Mean	36.82		14.29		22.87		13.42		25.14	
Adj. R^2	0.842		0.678		0.808		0.681		0.788	

Note: Table reports coefficient estimates, standard errors in parentheses, and sample statistics corresponding with Figure 4, Panel 1. Hourly wages are deflated to constant 2018 $BRL and transformed using inverse hyberbolic sine, then regressed on relative time indicators around year of being hired into an oil-linked establishment, with $t-1$ period omitted. Worker and year fixed effects are included; standard errors are clustered at the matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. For hourly wages, the sample is restricted to employed individuals. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

Table B11: Experienced Hires: **Months Employed per Year**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2003	0.062	0.115	-	-	-	-	-	-	-	-
2004	0.026	0.067	-	-	-	-	-	-	-	-
2005	(base)	-	-0.301	0.155	-	-	-	-	-	-
2006	0.005	0.072	-0.175	0.116	-	-	-	-	-	-
2007	0.177	0.093	(base)	-	-0.136	0.056	-	-	-	-
2008	0.159	0.108	-0.240	0.126	0.052	0.041	0.036	0.102	-	-
2009	0.342	0.118	-0.843	0.162	(base)	-	-0.039	0.075	-	-
2010	0.347	0.120	-0.391	0.159	0.088	0.039	(base)	-	0.074	0.057
2012	0.388	0.133	-0.476	0.175	0.025	0.057	-0.278	0.091	0.133	0.041
2013	0.444	0.135	-0.449	0.180	-0.006	0.060	-0.308	0.103	(base)	-
2014	0.435	0.141	-0.592	0.189	-0.019	0.064	-0.227	0.117	0.192	0.041
2015	0.474	0.146	-0.807	0.201	-0.076	0.067	-0.418	0.124	-0.092	0.056
2016	0.394	0.154	-0.663	0.208	-0.28	0.074	-0.671	0.135	-0.326	0.066
2017	0.416	0.160	-0.778	0.211	-0.248	0.078	-0.505	0.138	-0.256	0.070
n	12,158		6,095		61,763		14,095		65,709	
n×t	169,779		85,330		864,682		197,330		919,926	
N	309,689		258,091		704,292		392,084		913,060	
DV Mean	11.57		10.13		10.84		11		11.02	
Adj. R^2	0.373		0.287		0.321		0.343		0.423	

Note: Table reports coefficient estimates, standard errors in parentheses, and sample statistics corresponding with Figure 5, Panel 1. Months employed per year are regressed on relative time indicators around year of being hired into an oil-linked establishment, with $t-1$ period omitted. Worker and year fixed effects are included; standard errors are clustered at the matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. For brevity, each column reports coefficient estimates from every other year for a specific cohort. One pre-period is reported for each cohort to evaluate pre-trends. All matched workers (employed & unemployed) are retained in sample. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

Table B12: Experienced Hires: **Annual Formal Earnings**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2003	-0.011	0.030	-	-	-	-	-	-	-	-
2004	-0.009	0.009	-	-	-	-	-	-	-	-
2005	(base)	-	-0.026	0.045	-	-	-	-	-	-
2006	0.026	0.013	-0.028	0.018	-	-	-	-	-	-
2007	0.16	0.029	(base)	-	-0.023	0.018	-	-	-	-
2008	0.237	0.068	0.053	0.027	0.006	0.006	-0.036	0.049	-	-
2009	0.386	0.083	-0.098	0.083	(base)	-	-0.015	0.012	-	-
2010	0.451	0.092	0.030	0.089	0.085	0.008	(base)	-	-0.014	0.019
2012	0.607	0.101	-0.067	0.118	0.146	0.034	0.004	0.020	0.009	0.006
2013	0.654	0.106	0.082	0.129	0.158	0.040	0.013	0.057	(base)	-
2014	0.563	0.114	0.006	0.143	0.131	0.046	-0.015	0.077	0.065	0.009
2015	0.672	0.122	-0.112	0.158	0.112	0.053	-0.143	0.092	-0.006	0.032
2016	0.627	0.137	-0.111	0.172	-0.095	0.061	-0.341	0.108	-0.231	0.049
2017	0.73	0.145	-0.230	0.177	-0.133	0.065	-0.27	0.115	-0.278	0.056
n	12,158		6,095		61,763		14,095		65,709	
n×t	169,779		85,330		864,682		197,330		919,926	
N	309,689		258,091		704,292		392,084		913,060	
DV Mean	76064.82		27280.15		46162.49		27112.43		50684.74	
Adj. R^2	0.367		0.280		0.336		0.348		0.466	

Note: Table reports coefficient estimates, standard errors in parentheses, and sample statistics corresponding with Figure 6, Panel 1. Annual formal earnings are deflated to constant 2018 $BRL, transformed with inverse hyperbolic sine, then regressed on relative time indicators around year of being hired into an oil-linked establishment, with $t-1$ period omitted. Worker and year fixed effects are included; standard errors are clustered at the matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. All matched workers (employed & unemployed) are retained in sample. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

Table B13: Experienced Hires: **Annual Formal Earnings (Less Than High School)**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2003	-0.048	0.097	-	-	-	-	-	-	-	-
2004	-0.020	0.043	-	-	-	-	-	-	-	-
2005	(base)	-	-0.089	0.147	-	-	-	-	-	-
2006	0.031	0.058	-0.025	0.057	-	-	-	-	-	-
2007	-0.114	0.181	(base)	-	-0.062	0.072	-	-	-	-
2008	-0.214	0.329	-0.022	0.096	0.035	0.025	0.025	0.171	-	-
2009	-0.227	0.366	-0.562	0.275	(base)	-	-0.033	0.060	-	-
2010	0.138	0.399	-0.156	0.255	0.102	0.034	(base)	-	-0.015	0.089
2012	-0.103	0.442	-0.232	0.312	0.060	0.132	0.005	0.086	0.013	0.030
2013	0.333	0.465	0.132	0.349	-0.074	0.156	0.107	0.255	(base)	-
2014	-0.215	0.501	-0.077	0.365	-0.174	0.181	-0.328	0.284	0.064	0.041
2015	-0.759	0.523	-0.552	0.463	-0.112	0.195	-1.055	0.365	-0.307	0.168
2016	-1.037	0.555	-0.783	0.511	-0.434	0.222	-0.898	0.388	-0.828	0.239
2017	-1.497	0.554	-0.413	0.508	-0.573	0.234	-0.684	0.425	-0.883	0.274
n	595		485		2,986		765		1,878	
n×t	8,297		6,790		41,804		10,710		26,292	
N	102,533		95,733		194,036		120,835		215,044	
DV Mean	16,782.5		17,846.7		15,777.2		18,337.6		19,138.2	
Adj. R^2	0.371		0.278		0.313		0.307		0.429	

Note: Table reports coefficient estimates, standard errors in parentheses, and sample statistics corresponding with Figure 6, Panel 2. Annual formal earnings for subsample of workers with less than complete secondary education are deflated to constant 2018 $BRL, transformed with inverse hyperbolic sine, then regressed on relative time indicators around year of being hired into an oil-linked establishment, with $t-1$ period omitted. Worker and year fixed effects are included; standard errors are clustered at the matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. All matched workers (employed & unemployed) are retained in sample. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

Table B14: Experienced Hires: **Annual Formal Earnings (High School Complete)**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2003	0.018	0.049	-	-	-	-	-	-	-	-
2004	-0.018	0.016	-	-	-	-	-	-	-	-
2005	(base)	-	-0.009	0.055	-	-	-	-	-	-
2006	0.052	0.025	-0.025	0.021	-	-	-	-	-	-
2007	0.154	0.043	(base)	-	0.006	0.025	-	-	-	-
2008	0.080	0.095	0.069	0.032	0.011	0.009	-0.054	0.055	-	-
2009	0.051	0.118	-0.074	0.099	(base)	-	-0.013	0.014	-	-
2010	0.069	0.126	0.059	0.106	0.1	0.012	(base)	-	0.010	0.025
2012	0.200	0.154	-0.028	0.138	0.076	0.045	0.009	0.023	0.004	0.009
2013	-0.021	0.151	0.011	0.152	0.081	0.052	-0.051	0.064	(base)	-
2014	-0.008	0.165	-0.001	0.168	0.033	0.060	-0.064	0.084	0.078	0.012
2015	0.081	0.177	0.003	0.182	0.053	0.068	-0.094	0.101	0.054	0.043
2016	-0.180	0.199	-0.060	0.196	-0.094	0.079	-0.319	0.121	-0.107	0.063
2017	-0.077	0.205	-0.288	0.202	-0.055	0.083	-0.234	0.127	-0.123	0.070
n	4,641		4,670		35,366		11,184		36,700	
n×t	64,830		65,380		495,124		156,576		513,800	
N	132,673		124,471		349,400		212,235		483,765	
DV Mean	22,895.6		19,597.4		19,943.7		21,503.0		22,620.5	
Adj. R^2	0.329		0.273		0.325		0.348		0.453	

Note: Table reports coefficient estimates, standard errors, and sample stats corresponding with Figure 6, Panel 2. Annual formal earnings for workers with complete secondary education are deflated to constant 2018 $BRL, transformed with inverse hyperbolic sine, then regressed on relative time indicators around year of being hired into oil-linked establishment, with $t-1$ omitted. Worker and year fixed effects are included; standard errors clustered at matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. For brevity, each column reports every other coefficient estimate for a specific cohort. One pre-period is reported to evaluate pre-trends. All matched workers (employed & unemployed) are retained in sample. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

Table B15: Experienced Hires: **Annual Formal Earnings (More than High School)**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2003	-0.027	0.041	-	-	-	-	-	-	-	-
2004	0.000	0.010	-	-	-	-	-	-	-	-
2005	(base)	-	-0.071	0.082	-	-	-	-	-	-
2006	0.004	0.014	-0.062	0.041	-	-	-	-	-	-
2007	0.19	0.037	(base)	-	-0.07	0.028	-	-	-	-
2008	0.404	0.096	0.056	0.053	-0.012	0.008	0.006	0.135	-	-
2009	0.708	0.119	0.171	0.162	(base)	-	-0.023	0.023	-	-
2010	0.774	0.134	0.045	0.224	0.057	0.010	(base)	-	-0.06	0.031
2012	0.996	0.138	-0.143	0.331	0.282	0.055	0.019	0.049	0.013	0.008
2013	1.2	0.152	0.389	0.339	0.334	0.071	0.319	0.132	(base)	-
2014	1.08	0.162	0.091	0.402	0.358	0.077	0.418	0.227	0.049	0.010
2015	1.283	0.172	-0.377	0.446	0.253	0.093	0.177	0.248	-0.054	0.046
2016	1.432	0.195	0.113	0.490	-0.039	0.109	-0.112	0.301	-0.347	0.082
2017	1.604	0.210	0.113	0.518	-0.196	0.118	-0.188	0.317	-0.458	0.100
n	6,922		940		23,411		2,146		27,131	
n×t	96,652		13,160		327,754		30,044		379,834	
N	74,483		37,887		160,856		59,014		214,251	
DV Mean	116,809		70,315.9		89,645.7		59,474.3		90,830.8	
Adj. R^2	0.362		0.279		0.327		0.345		0.484	

Note: Table reports coefficient estimates, standard errors, and sample stats corresponding with Figure 6, Panel 2. Annual formal earnings for workers with > secondary education are deflated to constant 2018 $BRL, transformed with inverse hyperbolic sine, then regressed on relative time indicators around year of being hired into an oil-linked establishment, with $t-1$ omitted. Worker and year fixed effects are included; standard errors are clustered at the matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. All matched workers (employed & unemployed) are retained in sample. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

B.6 Regression Tables (New Hires)

Table B16: New Hires: **Hourly Wages**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2006	(base)	-	-	-	-	-	-	-	-	-
2007	0.036	0.006	-	-	-	-	-	-	-	-
2008	0.072	0.008	(base)	-	-	-	-	-	-	-
2009	0.068	0.008	0.012	0.005	-	-	-	-	-	-
2010	0.08	0.009	0.042	0.006	(base)	-	-	-	-	-
2012	0.1	0.010	0.059	0.007	0.048	0.006	(base)	-	-	-
2013	0.106	0.011	0.058	0.008	0.05	0.007	0.015	0.004	-	-
2014	0.103	0.012	0.056	0.008	0.055	0.008	0.031	0.005	(base)	-
2015	0.089	0.013	0.043	0.009	0.048	0.009	0.026	0.007	-0.006	0.006
2016	0.062	0.014	0.03	0.010	0.038	0.010	0.015	0.007	-0.010	0.007
2017	0.062	0.016	0.025	0.011	0.026	0.011	0.017	0.008	0.009	0.008
n	93,818		135,750		122,162		137,333		109,205	
nxt	666,401		798,751		624,650		611,985		345,068	
N	3,241,795		3,856,910		4,113,730		4,015,319		3,507,150	
DV Mean	7.17		7.12		8.13		8.79		9.53	
Adj. R^2	0.676		0.665		0.650		0.726		0.690	

Note: Table reports coefficient estimates, standard errors in parentheses, and sample statistics corresponding with Figure 7, Panel 1. Hourly wages are deflated to constant 2018 $BRL and transformed using inverse hyberbolic sine, then regressed on relative time indicators around year of new hire into an oil-linked establishment, with period t as baseline. Worker and year fixed effects are included; standard errors are clustered at the matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. For hourly wages, the sample is restricted to employed individuals. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

Table B17: New Hires: **Months Employed per Year**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2006	(base)	-	-	-	-	-	-	-	-	-
2007	0.007	0.073	-	-	-	-	-	-	-	-
2008	0.089	0.079	(base)	-	-	-	-	-	-	-
2009	0.023	0.082	-0.277	0.061	-	-	-	-	-	-
2010	0.024	0.080	-0.162	0.062	(base)	-	-	-	-	-
2012	-0.054	0.083	-0.186	0.067	-0.096	0.062	(base)	-	-	-
2013	-0.047	0.087	-0.238	0.070	-0.058	0.066	-0.217	0.059	-	-
2014	-0.029	0.088	-0.23	0.071	-0.048	0.066	-0.283	0.062	(base)	-
2015	-0.125	0.114	-0.242	0.074	-0.122	0.070	-0.258	0.069	-0.376	0.066
2016	-0.224	0.104	-0.371	0.082	-0.151	0.076	-0.315	0.074	-0.575	0.078
2017	-0.029	0.118	-0.325	0.086	-0.171	0.080	-0.375	0.080	-0.429	0.081
n	94,511		137,222		123,639		139,349		112,145	
nxt	680,825		817,327		641,779		630,572		358,570	
N	3,241,795		3,856,910		4,113,730		4,015,319		3,507,150	
DV Mean	5.20		5.30		5.20		5.30		5.50	
Adj. R^2	0.346		0.370		0.366		0.427		0.364	

Note: Table reports coefficient estimates, standard errors in parentheses, and sample statistics corresponding with Figure 8, Panel 1. Months employed per year are regressed on relative time indicators around year of new hire into an oil-linked establishment, with period t as baseline. Worker and year fixed effects are included; standard errors are clustered at the matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. All matched workers (employed & unemployed) are retained in sample. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

Table B18: New Hires: **Annual Formal Earnings**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2006	(base)	-	-	-	-	-	-	-	-	-
2007	0.004	0.040	-	-	-	-	-	-	-	-
2008	0.069	0.041	(base)	-	-	-	-	-	-	-
2009	0.020	0.044	-0.144	0.029	-	-	-	-	-	-
2010	0.075	0.043	-0.082	0.030	(base)	-	-	-	-	-
2012	0.052	0.044	-0.083	0.032	-0.066	0.036	(base)	-	-	-
2013	0.073	0.045	-0.094	0.032	-0.061	0.034	-0.13	0.028	-	-
2014	0.073	0.046	-0.077	0.034	-0.054	0.033	-0.122	0.030	(base)	-
2015	0.036	0.051	-0.123	0.036	-0.09	0.038	-0.129	0.033	-0.2	0.033
2016	-0.003	0.053	-0.13	0.041	-0.082	0.041	-0.15	0.035	-0.264	0.039
2017	-0.015	0.059	-0.154	0.040	-0.11	0.041	-0.17	0.037	-0.169	0.041
n	94,511		137,222		123,639		139,349		112,145	
nxt	680,825		817,327		641,779		630,572		358,570	
N	3,241,795		3,856,910		4,113,730		4,015,319		3,507,150	
DV Mean	6,794		7,019		7,715		7,715		8,980	
Adj. R^2	0.299		0.294		0.264		0.270		0.240	

Note: Table reports coefficient estimates, standard errors in parentheses, and sample statistics corresponding with Figure 9, Panel 1. Annual formal income is deflated to constant 2018 $BRL, transformed using inverse hyberbolic sine, then regressed on relative time indicators around year of new hire into an oil-linked establishment, with period t as baseline. Worker and year fixed effects are included; standard errors are clustered at the matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. All matched workers (employed & unemployed) are retained in sample. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

Table B19: New Hires: **Annual Formal Earnings (Less Than High School)**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2006	(base)	-	-	-	-	-	-	-	-	-
2007	0.024	0.066	-	-	-	-	-	-	-	-
2008	0.14	0.065	(base)	-	-	-	-	-	-	-
2009	0.055	0.070	-0.2	0.048	-	-	-	-	-	-
2010	0.154	0.066	-0.136	0.051	(base)	-	-	-	-	-
2012	0.112	0.069	-0.122	0.054	-0.072	0.061	(base)	-	-	-
2013	0.108	0.069	-0.075	0.053	-0.007	0.065	-0.117	0.050	-	-
2014	0.153	0.072	-0.096	0.057	0.015	0.059	-0.124	0.055	(base)	-
2015	0.105	0.080	-0.175	0.059	-0.066	0.069	-0.146	0.061	-0.275	0.057
2016	0.030	0.080	-0.041	0.068	-0.016	0.076	-0.083	0.061	-0.469	0.073
2017	0.079	0.088	-0.181	0.066	-0.064	0.072	-0.174	0.064	-0.25	0.077
n	35,522		45,789		36,737		44,042		36,977	
nxt	257,118		271,637		190,403		198,311		115,009	
N	1,219,971		1,354,170		1,287,639		1,224,211		1,074,898	
DV Mean	4,468		4,535		4,649		4,630		4,422	
Adj. R^2	0.256		0.248		0.207		0.184		0.153	

Note: Table reports coefficient estimates, standard errors in parentheses, and sample statistics corresponding with Figure 9, Panel 2. Annual formal earnings for subsample of workers with less than complete secondary education are deflated to constant 2018 $BRL, transformed using inverse hyberbolic sine, then regressed on relative time indicators around year of new hire into an oil-linked establishment, with period t as baseline. Worker and year fixed effects are included; standard errors are clustered at the matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. All matched workers (employed & unemployed) are retained in sample. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

Table B20: New Hires: **Annual Formal Earnings (High School Complete)**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2006	(base)	-	-	-	-	-	-	-	-	-
2007	-0.015	0.052	-	-	-	-	-	-	-	-
2008	0.007	0.055	(base)	-	-	-	-	-	-	-
2009	-0.017	0.060	-0.149	0.039	-	-	-	-	-	-
2010	0.004	0.061	-0.067	0.041	(base)	-	-	-	-	-
2012	-0.004	0.062	-0.063	0.041	-0.108	0.048	(base)	-	-	-
2013	0.040	0.061	-0.13	0.044	-0.142	0.041	-0.181	0.036	-	-
2014	-0.001	0.062	-0.083	0.045	-0.132	0.042	-0.167	0.040	(base)	-
2015	-0.023	0.068	-0.091	0.049	-0.147	0.048	-0.147	0.043	-0.206	0.045
2016	-0.008	0.071	-0.211	0.052	-0.156	0.050	-0.211	0.047	-0.21	0.050
2017	-0.114	0.080	-0.153	0.053	-0.18	0.053	-0.183	0.050	-0.155	0.052
n	53,347		83,447		79,361		86,074		67,780	
nxt	390,602		502,728		414,042		389,987		218,539	
N	1,022,482		1,289,402		1,474,166		1,478,128		1,238,914	
DV Mean	5,691		5,899		5,883		6,200		6,623	
Adj. R^2	0.289		0.267		0.238		0.213		0.195	

Note: Table reports coefficient estimates, standard errors in parentheses, and sample statistics corresponding with Figure 9, Panel 2. Annual formal earnings for subsample of workers with complete secondary education are deflated to constant 2018 $BRL, transformed using inverse hyberbolic sine, then regressed on relative time indicators around year of new hire into an oil-linked establishment, with period t as baseline. Worker and year fixed effects are included; standard errors are clustered at the matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. All matched workers (employed & unemployed) are retained in sample. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

Table B21: New Hires: **Annual Formal Earnings (More Than High School)**

	2006		2008		2010		2012		2014	
Year	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
2006	0.000	-	-	-	-	-	-	-	-	-
2007	-0.022	0.125	-	-	-	-	-	-	-	-
2008	-0.020	0.136	0.000	-	-	-	-	-	-	-
2009	-0.009	0.139	0.145	0.084	-	-	-	-	-	-
2010	-0.029	0.133	0.093	0.094	0.000	-	-	-	-	-
2012	-0.008	0.142	0.003	0.100	0.217	0.095	0.000	-	-	-
2013	0.030	0.150	0.031	0.098	0.218	0.111	0.095	0.080	-	-
2014	-0.050	0.157	0.055	0.097	0.148	0.100	0.120	0.082	0.000	-
2015	-0.130	0.197	-0.061	0.114	0.172	0.101	0.035	0.091	0.111	0.100
2016	-0.419	0.269	-0.146	0.149	0.106	0.120	-0.058	0.099	0.113	0.113
2017	-0.174	0.202	0.016	0.124	0.157	0.148	-0.083	0.103	0.066	0.124
n	5,642		7,986		7,541		9,233		7,388	
nxt	33,105		42,962		37,334		42,274		25,022	
N	260,282		317,018		340,212		322,458		313,782	
DV Mean	20,495		22,310		22,573		29,936		29,497	
Adj. R^2	0.380		0.379		0.360		0.443		0.386	

Note: Table reports coefficient estimates, standard errors in parentheses, and sample statistics corresponding with Figure 9, Panel 2. Annual formal earnings for subsample of workers with more than complete secondary education are deflated to constant 2018 $BRL, transformed using inverse hyberbolic sine, then regressed on relative time indicators around year of new hire into an oil-linked establishment, with period t as baseline. Worker and year fixed effects are included; standard errors are clustered at the matched worker level. Regressions are weighted to account for coarsened exact matching weights generated by CEM package in Stata. All matched workers (employed & unemployed) are retained in sample. n reports the number of matched individuals in that cohort sample; n×t reports number of observations in panel. N reports total number of hired workers in that cohort. DV Mean reports mean of dependent variable in $t-1$ period. p<0.01, p<0.05, p<0.1

B.7 Sample and Matching Statistics

Table B22: Sample Sizes for **Main Specification**

Experienced Hires					
	Before Matching		After Matching		
Cohort	Treated	Control	Treated	Control	% of Treated Matched
2006	15,347	294,342	2,461	10,201	16.0
2008	14,760	243,331	1,437	4,961	9.7
2010	41,437	662,855	10,767	54,024	26.0
2012	22,371	369,713	2,899	11,327	13.0
2014	43,659	869,401	10,805	66,213	24.7
New Hires					
	Before Matching		After Matching		
Cohort	Treated	Control	Treated	Control	% of Treated Matched
2006	72,582	3,169,213	3,592	15,953	24.7
2008	99,771	3,757,139	9,184	80,985	46.0
2010	106,114	4,007,616	6,228	26,556	29.3
2012	108,924	3,906,395	11,143	91,778	51.2
2014	84,554	3,422,596	4,745	26,758	28.1

Table B23: Sample Sizes for **Robustness I** (Direct Oil Link, Loose Match)

Experienced Hires					
	Before Matching		After Matching		
Cohort	Treated	Control	Treated	Control	% of Treated Matched
2006	3,463	306,226	2,074	12,040	59.9
2008	1,429	256,662	683	5,673	47.8
2010	4,914	699,378	3,515	43,621	71.5
2012	2,178	389,906	1,180	14,986	54.2
2014	4,868	908,192	3,388	67,831	69.6
New Hires					
	Before Matching		After Matching		
Cohort	Treated	Control	Treated	Control	% of Treated Matched
2006	4,851	3,236,944	638	9,441	65.8
2008	5,903	3,851,007	741	19,623	62.8
2010	5,333	4,108,397	731	15,558	68.5
2012	8,183	4,007,136	1,262	26,892	77.1
2014	6,256	3,500,894	806	22,252	64.4

Table B24: Sample Sizes for **Robustness II** (Near Oil Industry Hubs)

Experienced Hires					
	Before Matching		After Matching		
Cohort	Treated	Control	Treated	Control	% of Treated Matched
2006	4,317	51,734	1,073	2,251	24.9
2008	3,376	39,443	333	742	9.9
2010	11,021	116,239	3,255	10,115	29.5
2012	5,765	65,909	804	2,338	13.9
2014	12,279	158,965	3,609	14,807	29.4
New Hires					
	Before Matching		After Matching		
Cohort	Treated	Control	Treated	Control	% of Treated Matched
2006	9,958	475,655	546	2,171	27.4
2008	15,915	551,406	1,674	12,410	52.6
2010	19,425	634,144	1,245	4,667	32.0
2012	23,017	619,495	2,752	17,780	59.8
2014	17,538	547,854	1,116	5,666	31.8

Table B25: Sample Sizes for **Robustness III** (Common Support with 2006 Cohort)

Experienced Hires					
	Before Matching		After Matching		
Cohort	Treated	Control	Treated	Control	% of Treated Matched
2006	15,347	294,342	1,924	8,375	12.5
2008	14,760	243,331	1,254	4,596	8.5
2010	41,437	662,855	8,282	43,879	20.0
2012	22,371	369,713	2,355	9,902	10.5
2014	43,659	869,401	7,766	50,085	17.8
New Hires					
	Before Matching		After Matching		
Cohort	Treated	Control	Treated	Control	% of Treated Matched
2006	72,582	3,169,213	2,413	12,887	16.6
2008	99,771	3,757,139	7,125	68,121	35.7
2010	106,114	4,007,616	4,728	21,409	22.3
2012	108,924	3,906,395	6,873	62,398	31.5
2014	84,554	3,422,596	2,944	16,624	17.4

B.8 Oil-Linked Higher Education Degrees

Public higher education institutions are those classified as federal, state, or municipal; private institutions are those classified as private (for- or non-profit) and special. Universities are considered to be those institutions that award bachelors degrees (*bacharelado*) and full and short licensures (*licenciatura plena e curta*). Technical training institutions are those that award technician degrees (*tecnólogo*). To ensure consistency across the 2003-2016 panel, we exclude categories that are only defined in some years, including profession-specific degrees (*específico da profissão*) and short course specializations. In all cases, we include both in-person and distance learning options.

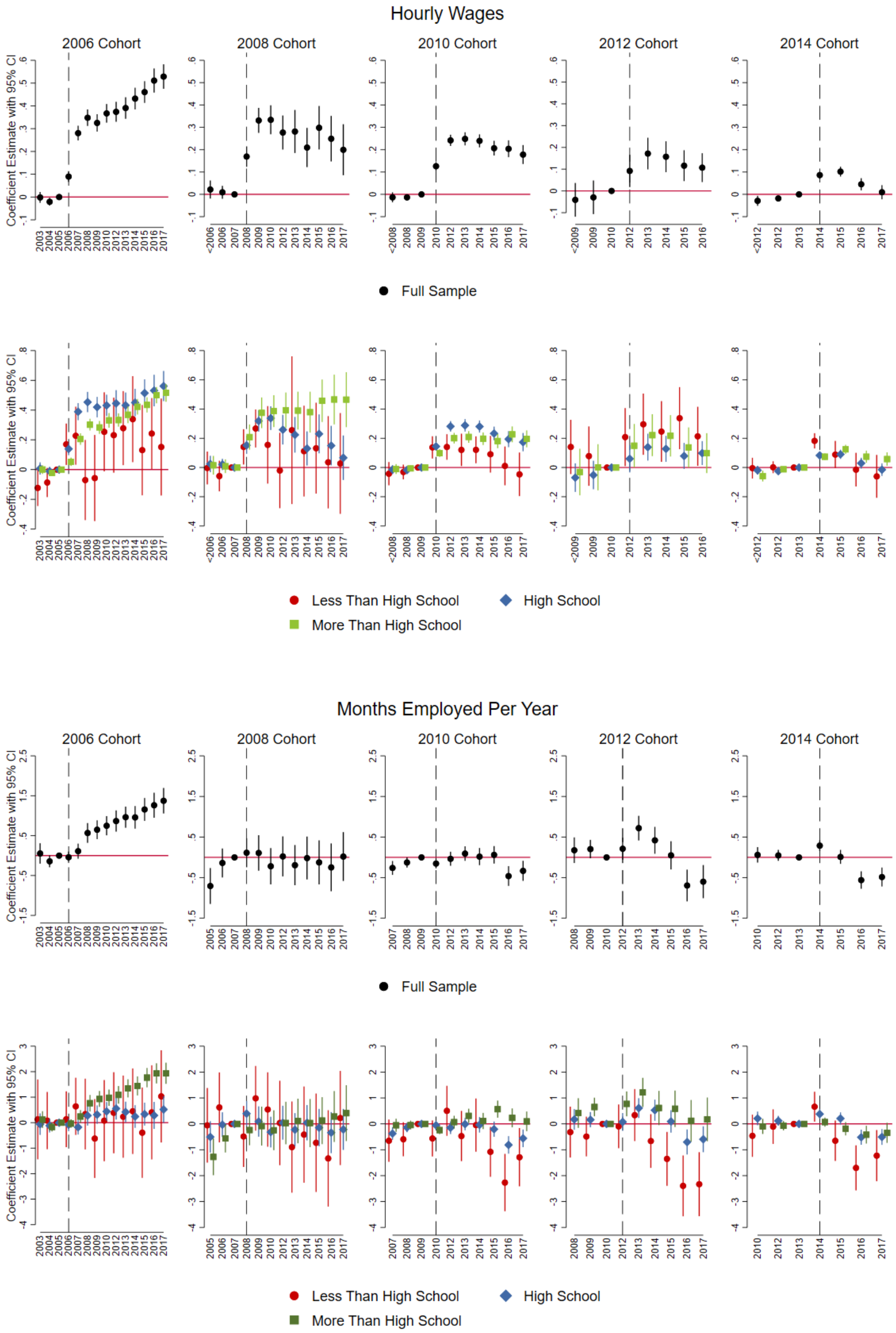
Table B26: Oil-Linked Majors

Oil-Linked Majors	
Petroleum Engineering	Environmental Management
Geological Engineering	Naval maintenance
Naval Engineering	Petrochemical Maintenance
Shipbuilding	Mining & Extraction
Shipbuilding (non-motorized)	Marine Navigation
Naval Construction	Operation of Ships
Environmental Control	Paleontology
Water Pollution Control	Petrology
Extraction of Petroleum & Gas	Processing of Petroleum & Petrochem.
Geoscience	Petroleum Refining
Geophysics	Environmental Cleanup
Geology	Environmental Protection Tech.

C Robustness Checks

C.1 Direct Oil Links Only

Figure C1: Robustness: Experienced Hires, Hired into Directly Oil-Linked Firms (Loose Match)



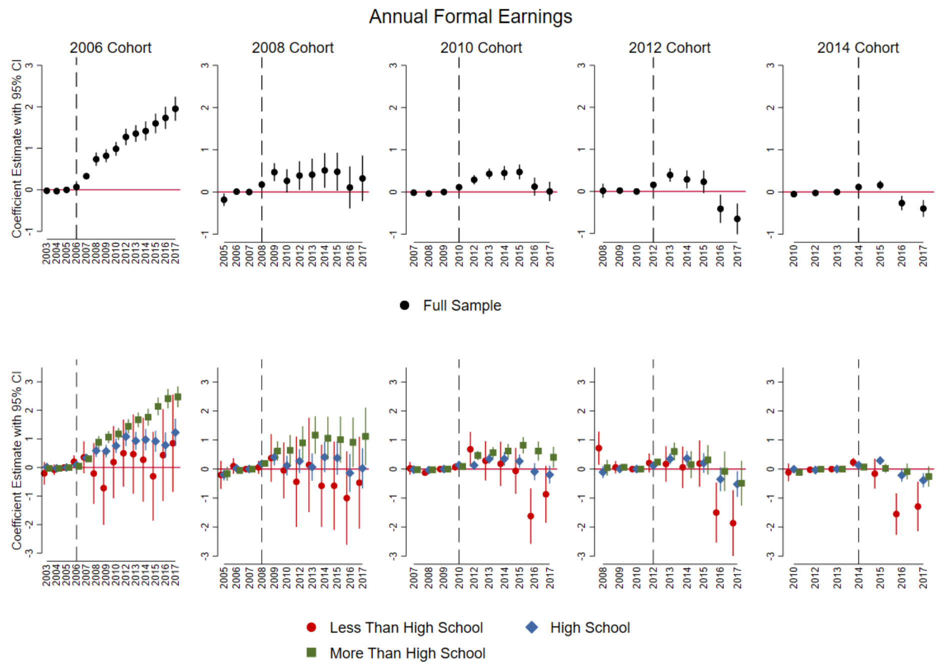
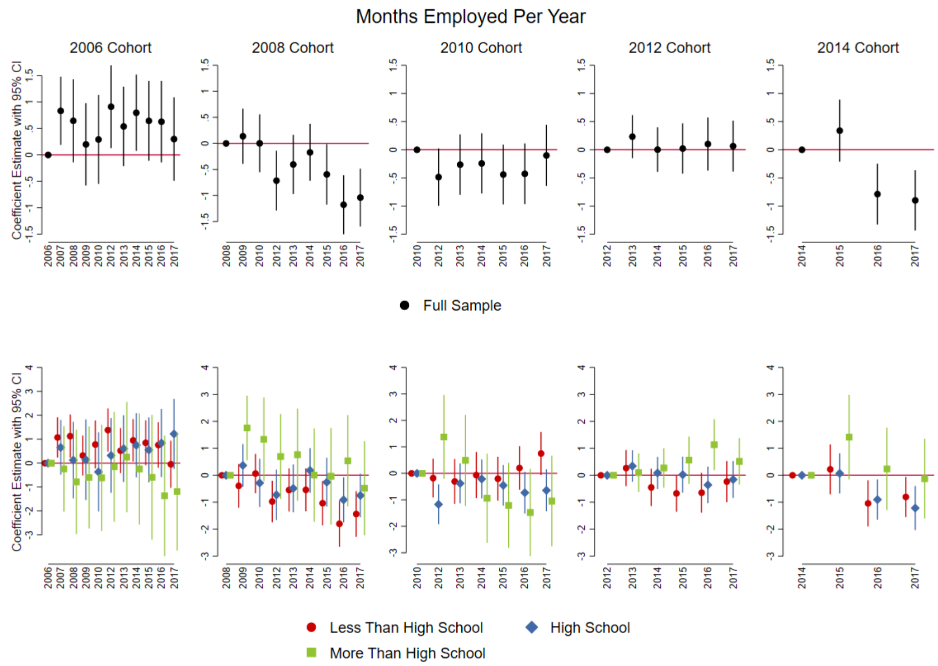
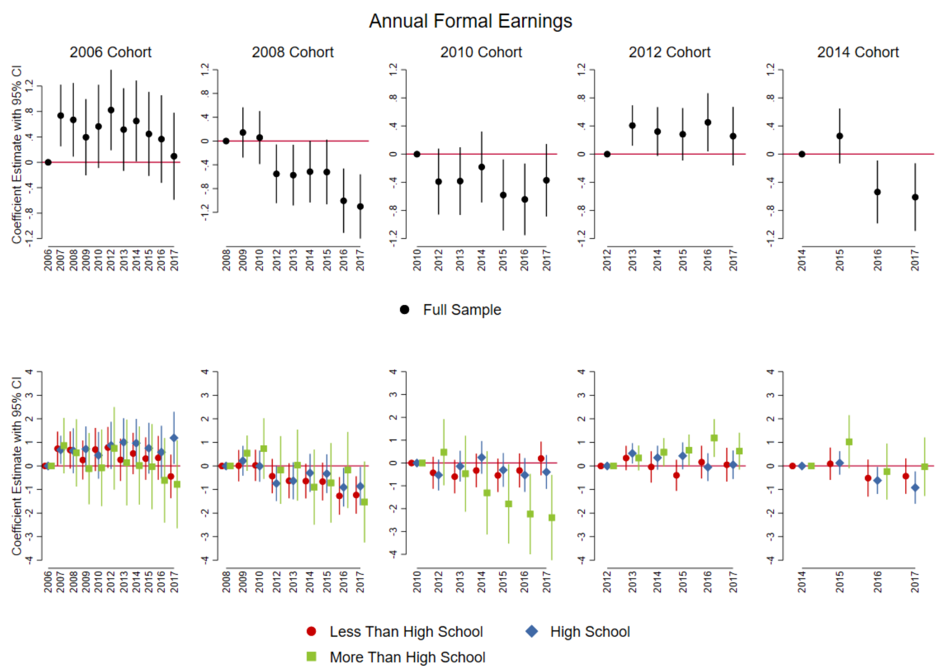


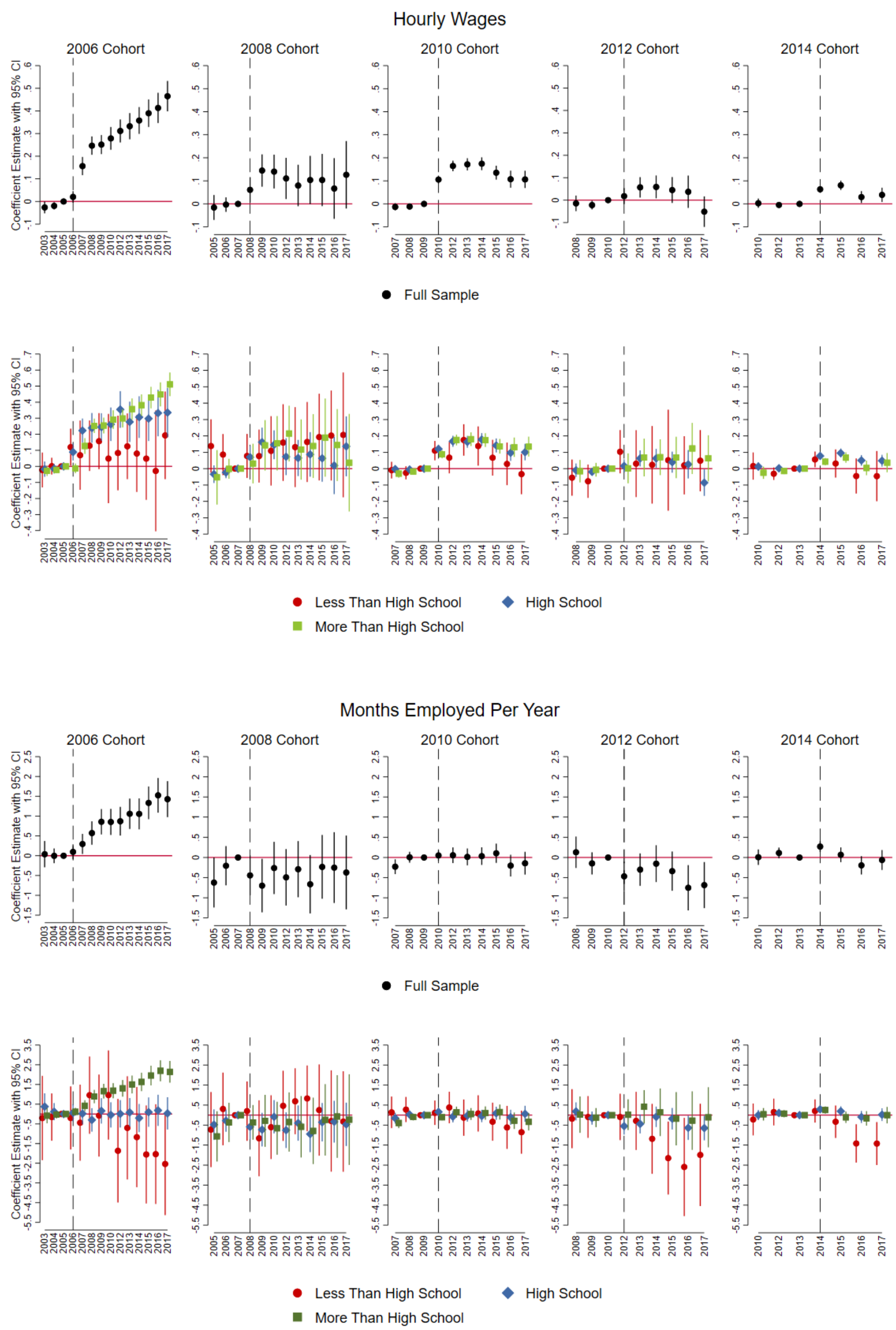
Figure C2: Robustness: New Hires, Hired into Directly Oil-Linked Firms (Loose Match)


Months Employed Per Year
2006 Cohort
2008 Cohort
2010 Cohort
2012 Cohort
2014 Cohort
Coefficient Estimate with 95% CI
Full Sample
Less Than High School
High School
More Than High School


Annual Formal Earnings
2006 Cohort
2008 Cohort
2010 Cohort
2012 Cohort
2014 Cohort
Coefficient Estimate with 95% CI
Full Sample
Less Than High School
High School
More Than High School

C.2 Hired within 100km. of Shipyard

Figure C3: Robustness: Experienced Hires, Hired into Oil-Linked Firms (<100km. from Shipyard)



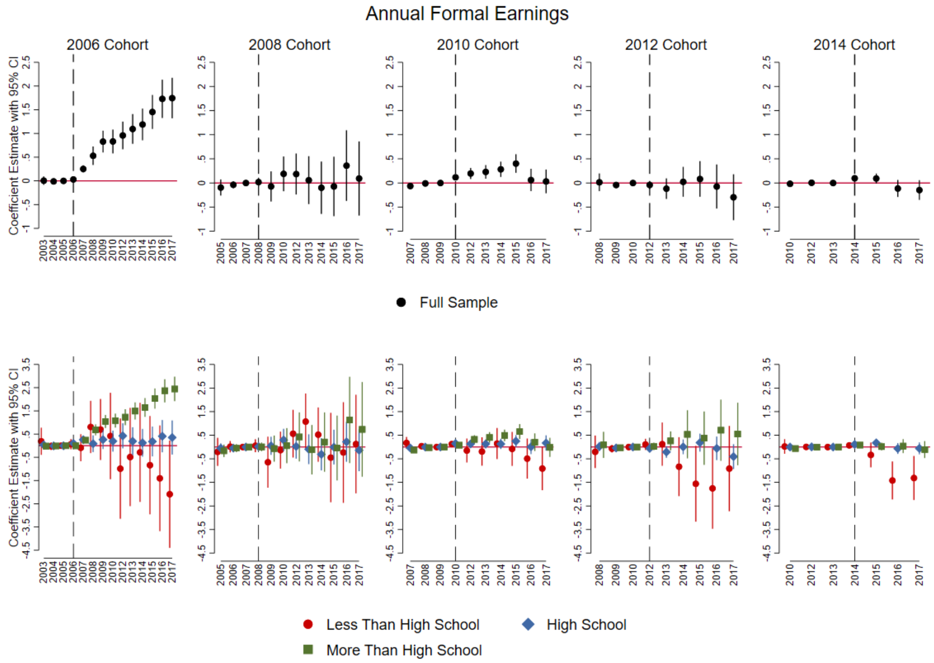
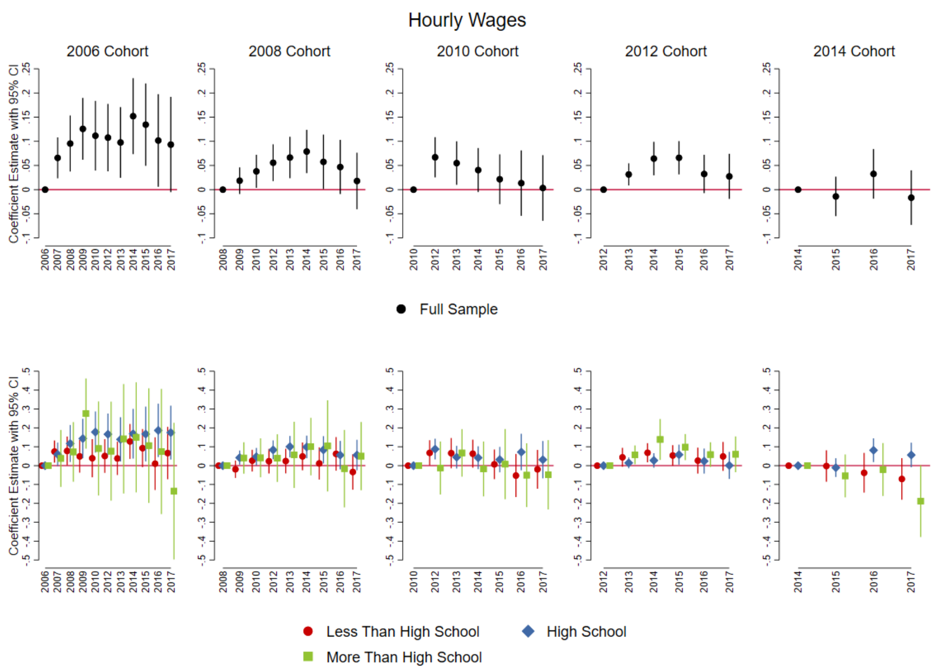
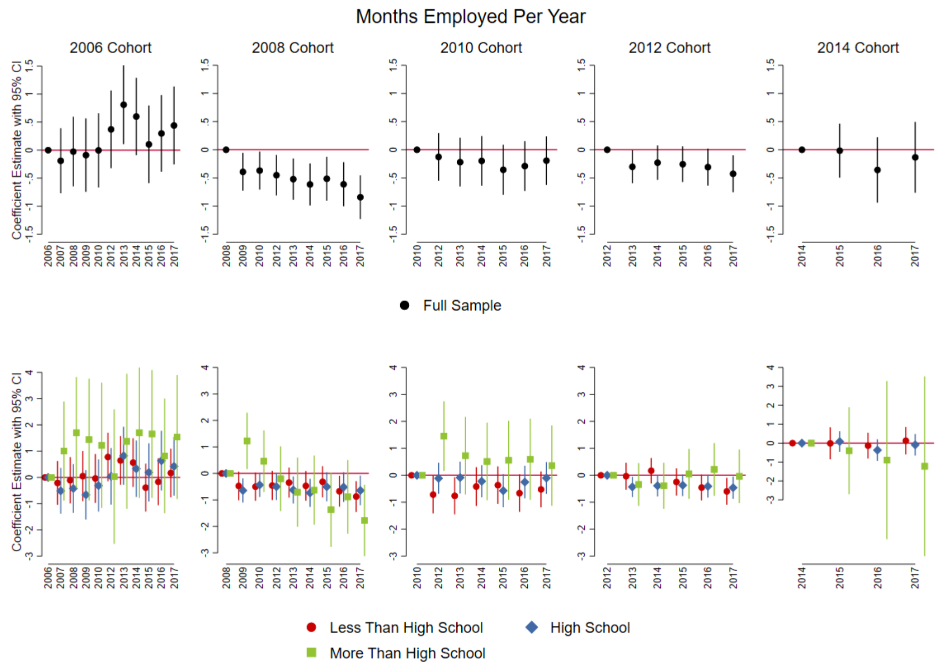
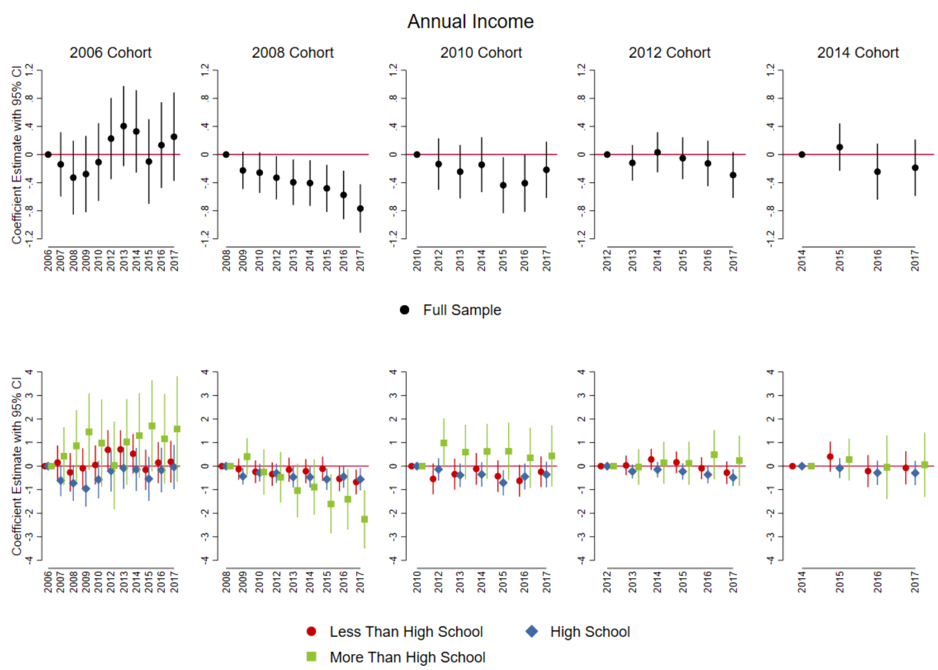


Figure C4: Robustness: New Hires, Hired into Oil-Linked Firms (<100km. from Shipyard)

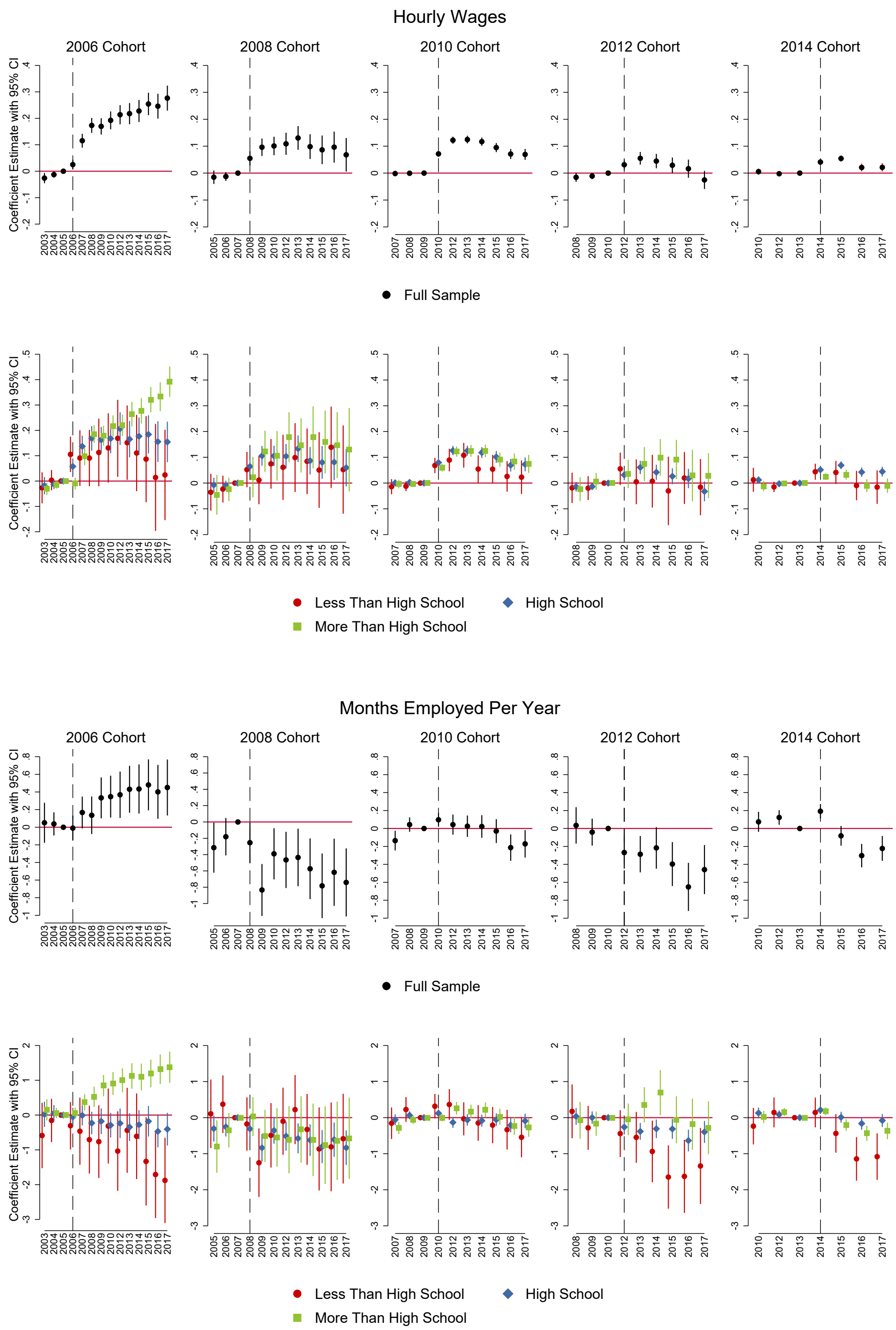



Months Employed Per Year
2006 Cohort
2008 Cohort
2010 Cohort
2012 Cohort
2014 Cohort
Coefficient Estimate with 95% CI
Full Sample
Less Than High School
High School
More Than High School


Annual Income
2006 Cohort
2008 Cohort
2010 Cohort
2012 Cohort
2014 Cohort
Coefficient Estimate with 95% CI
Full Sample
Less Than High School
High School
More Than High School

C.3 Omitting Public Employees

Figure C5: Robustness: Experienced Hires, Hired into Oil-Linked Firms (Private Sector Only)



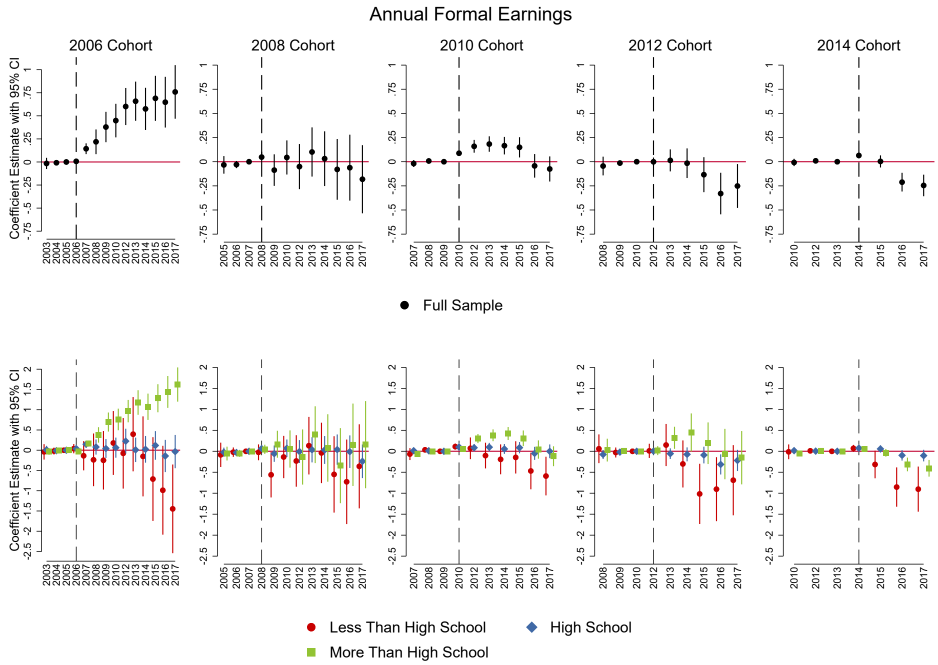
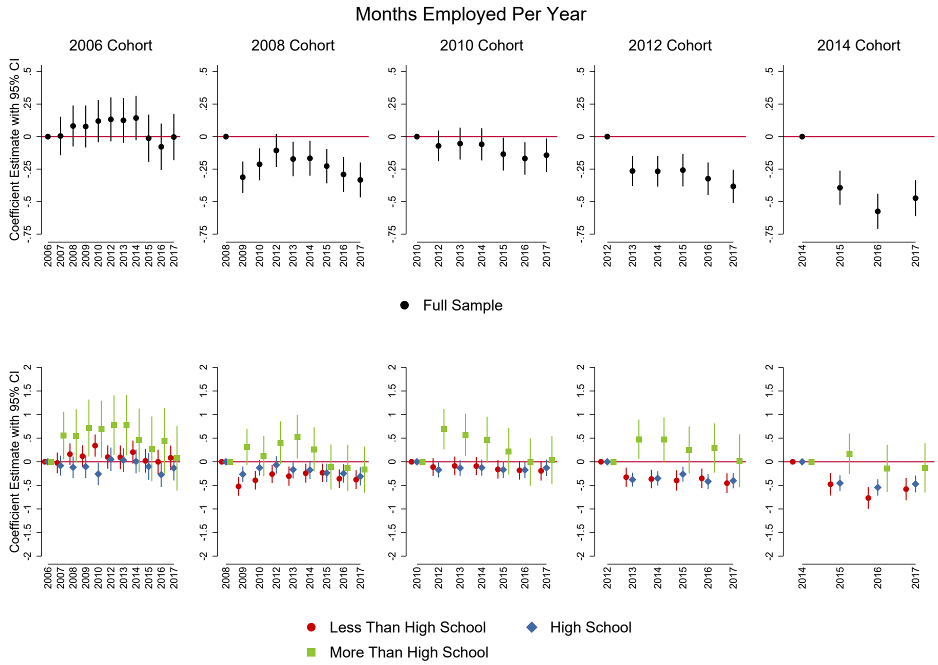
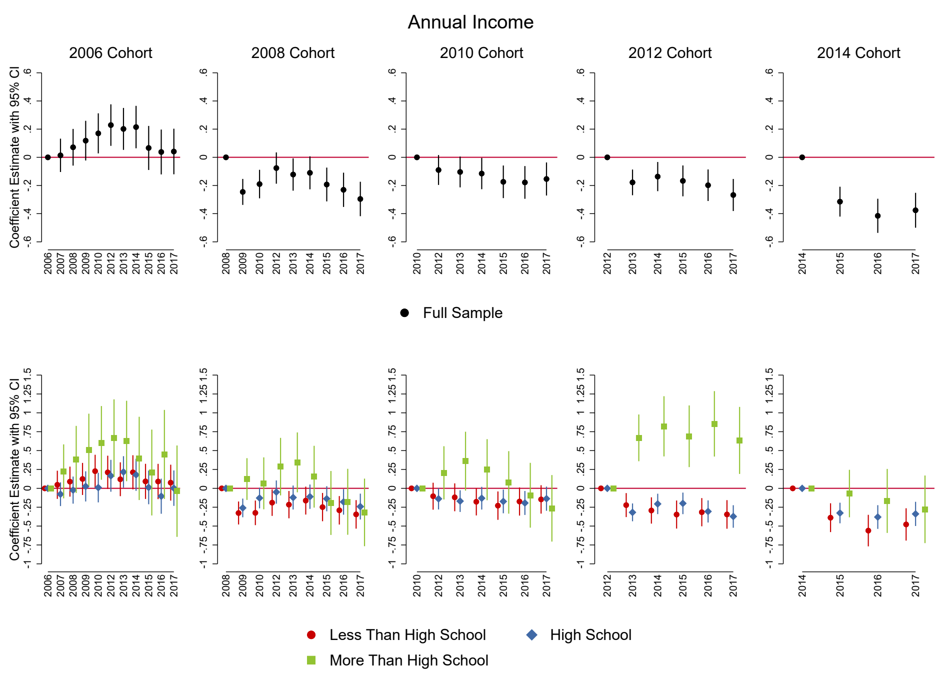


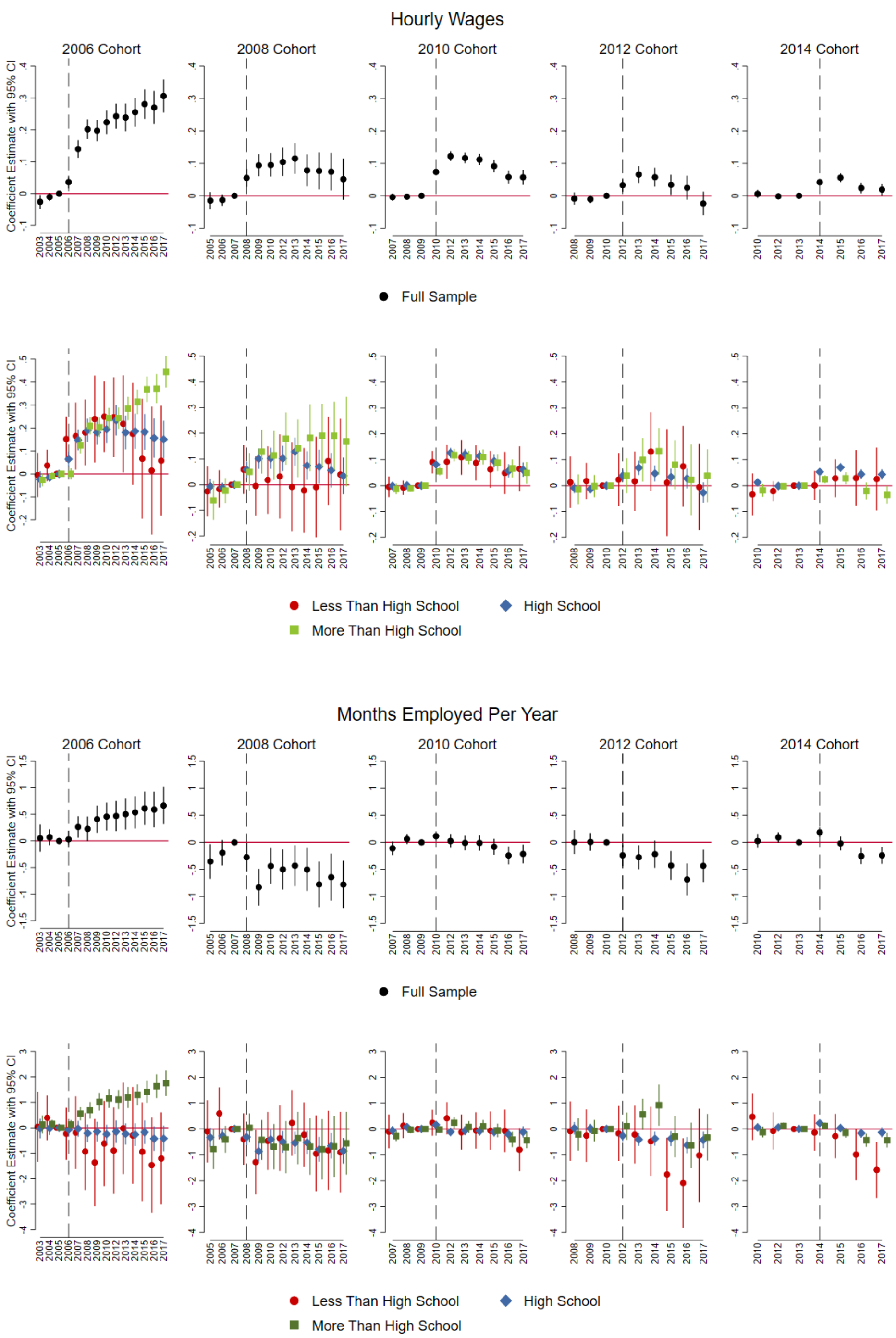
Figure C6: Robustness: New Hires, Hired into Oil-Linked Firms (Private Sector Only)


Months Employed Per Year
2006 Cohort
2008 Cohort
2010 Cohort
2012 Cohort
2014 Cohort
Coefficient Estimate with 95% CI
Full Sample
Less Than High School
High School
More Than High School


Annual Income
2006 Cohort
2008 Cohort
2010 Cohort
2012 Cohort
2014 Cohort
Coefficient Estimate with 95% CI
Full Sample
Less Than High School
High School
More Than High School

C.4 Common Support Across Cohorts

Figure C7: Robustness: Experienced Hires, Hired into Oil-Linked Firms (Common Support Across Cohorts (Baseline = 2006))



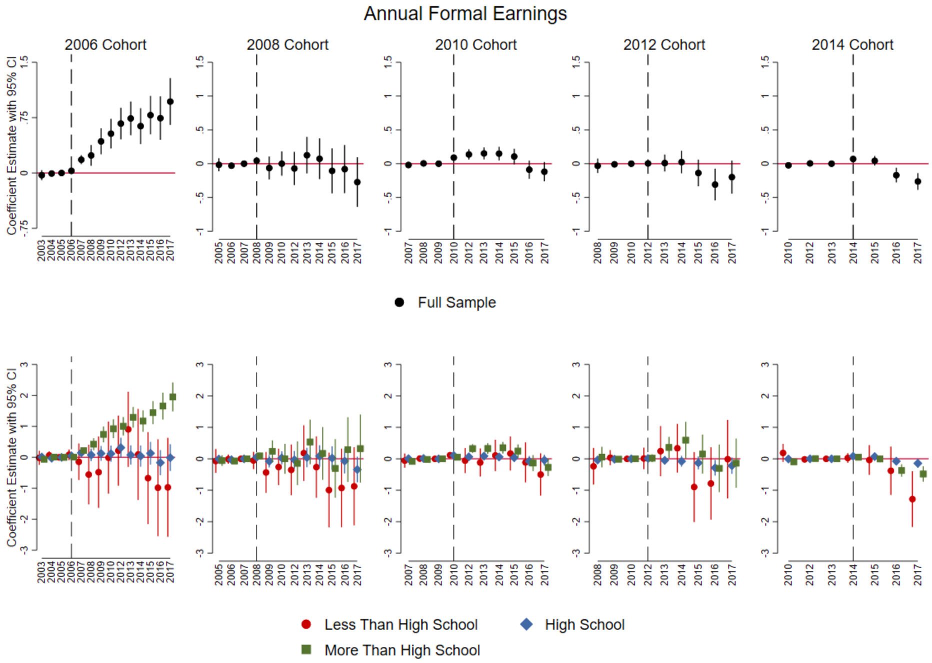
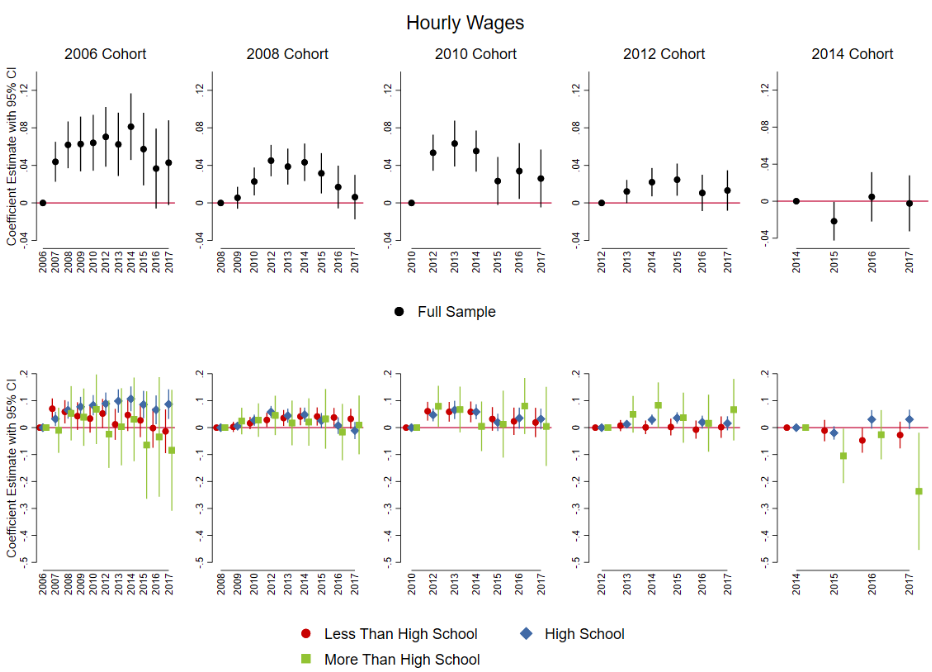
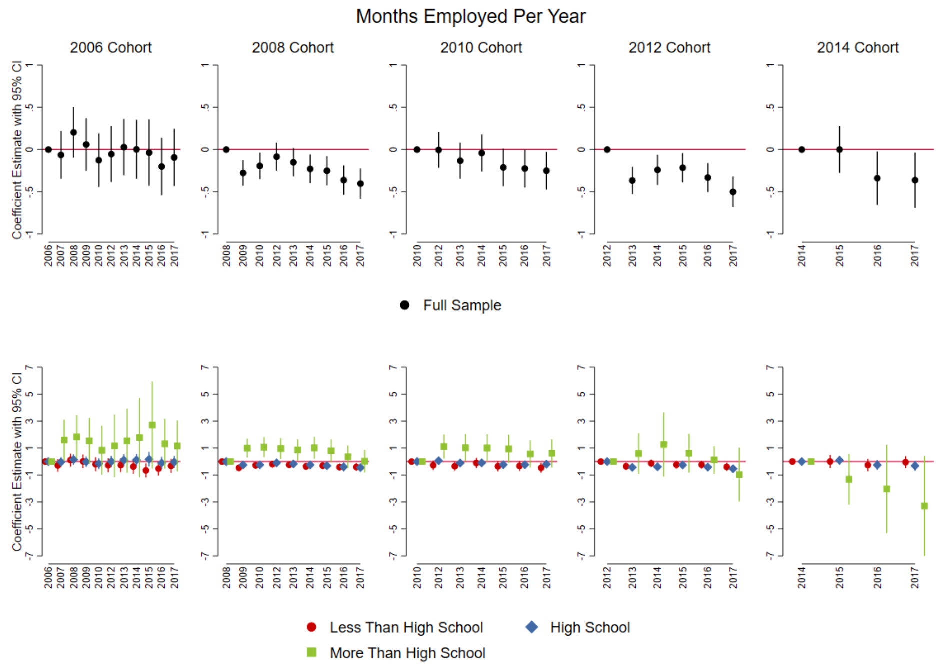
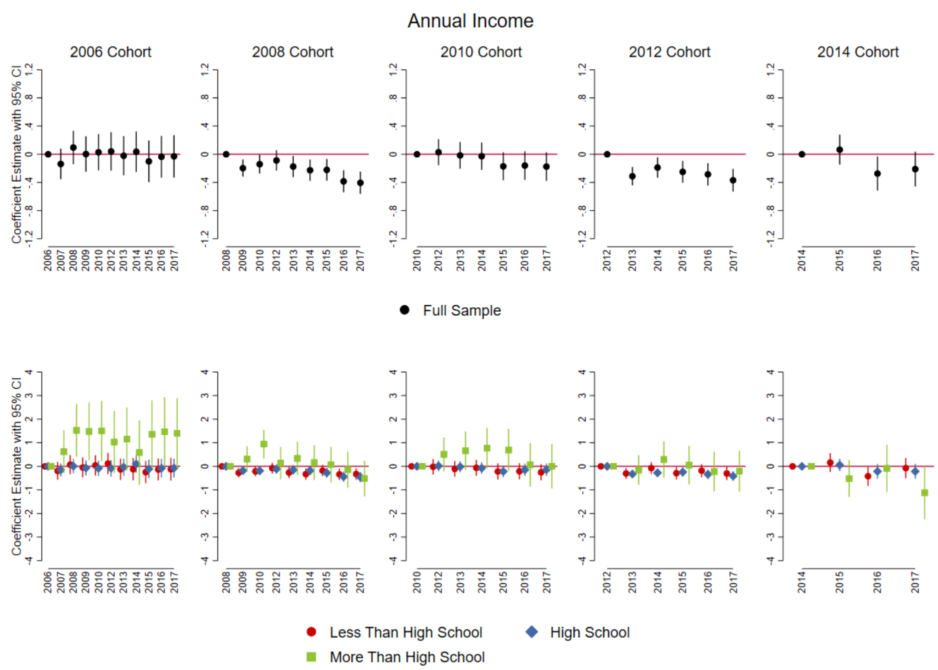


Figure C8: Robustness: New Hires, Hired into Oil-Linked Firms (Common Support Across Cohorts (Baseline = 2006))

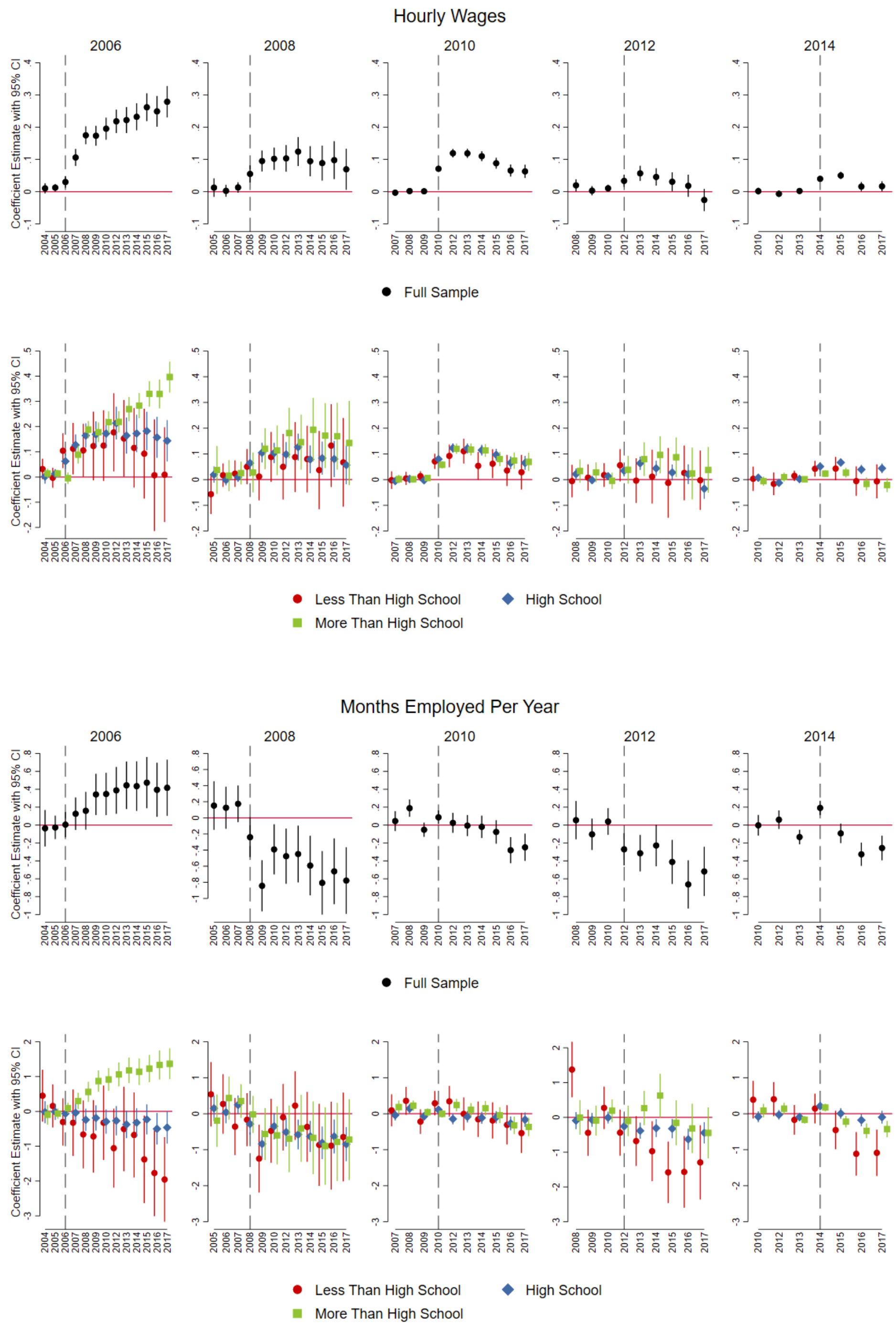


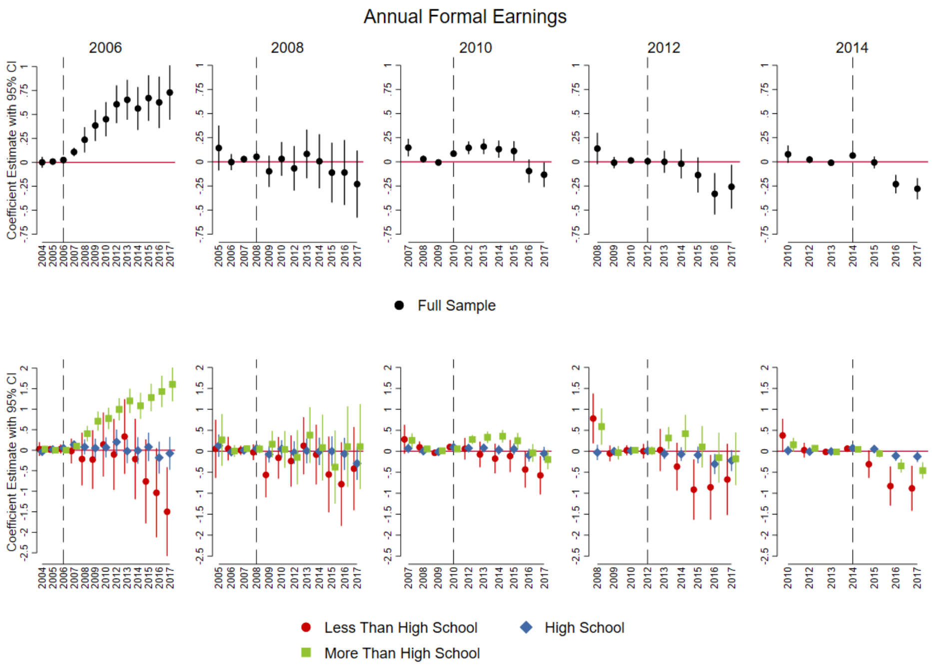

Months Employed Per Year
2006 Cohort
2008 Cohort
2010 Cohort
2012 Cohort
2014 Cohort
Coefficient Estimate with 95% CI
Full Sample
Less Than High School
High School
More Than High School


Annual Income
2006 Cohort
2008 Cohort
2010 Cohort
2012 Cohort
2014 Cohort
Coefficient Estimate with 95% CI
Full Sample
Less Than High School
High School
More Than High School

C.5 Callaway and Sant'Anna (2021) *csdid* Estimator

Figure C9: Robustness: Callaway and Sant'Anna (2021) *csdid* estimator





Annual Formal Earnings
2006
2008
2010
2012
2014
Coefficient Estimate with 95% CI
Full Sample
Less Than High School
High School
More Than High School