Working Papers | 97

28.10.2022

The Labor-market Effects of Service Offshoring

A SYNTHETIC CONTROL APPROACH WITH HIGH-DIMENSIONAL MICRODATA

Otto Kässi
Etla Economic Research, Finland
otto.kassi@etla.fi

Suggested citation:
Kässi, Otto (28.10.2022). "The Labor-market Effects of Service Offshoring: A Synthetic Control Approach with High-dimensional Microdata".

ETLA Working Papers No 97.
http://pub.etla.fi/ETLA-Working-Papers-97.pdf

Abstract

I use novel high-quality survey data on firms' international sourcing activities combined with firm-level financial and linked employer–employee data to study the effect of services offshoring on wages and employment. To overcome the endogeneity related to reverse causality and omitted variables, I use microsynth, a variation of the synthetic control method specially developed for high-dimensional microdata. I find that offshoring firms pay higher wages for both high-skilled and low-skilled workers, and employ fewer FTE workers compared with a synthetic control, but these effects take several years to appear.

Tiivistelmä

Palveluiden ulkoistamisen työmarkkinavaikutukset

Tarkastelen palvelu-ulkoistuksen vaikutuksia työllisyyteen ja yritysten maksamiin palkkoihin suomalaisella aineistolla. Tutkimus perustuu Eurostatin vuonna 2011 tekemään Global Value Chains -kyselytutkimukseen. Kyselyn vastaajajoukoksi oli valittu edustava otos suomalaisia yrityksiä. Tunnistan kyselytutkimuksen perusteella yritykset, jotka ryhtyivät ostamaan ulkoistettuja palveluita ulkomailta vuosien 2009–2011 aikana.

Keskeinen haaste ulkoistuspäätöksen tuottavuusvaikutusten identifioimisessa on, että ulkoistajayritykset eroavat ei-ulkoistajayrityksistä monilla eri tavoilla. On esimerkiksi mahdollista, että ulkoistajayritykset ovat kannattavampia tai niiden odotukset tulevaisuudesta ovat positiivisempia jo ennen ulkoistusta. Ratkaisen tämän haasteen hyödyntämällä synteettisen kontrollin menetelmää ei-ulkoistajien tilastollisen vertailuryhmän muodostamiseen.

Tulosten perusteella ulkoistaminen korottaa yrityksissä maksettuja palkkoja, mutta ulkoistajayritykset työllistävät vähemmän ihmisiä. Näiden vaikutusten ilmenemiseen menee kuitenkin useita vuosia.

Ph.D. (Econ.) **Otto Kässi** is a Researcher at Etla Economic Research and a Research Associate at Oxford Internet Institute (University of Oxford).

VTT **Otto Kässi** on Elinkeinoelämän tutkimuslaitoksen tutkija sekä Research Associate Oxfordin yliopiston Oxford Internet Institutessa.

Acknowledgements: This research is done as a part of "Reigniting Growth through Innovation" project funded by Business Finland. I am grateful for Anne Kovalainen and the seminar participants at Etla for various useful comments.

Kiitokset: Tutkimus on toteutettu osana Business Finlandin rahoittamaa "Reigniting Growth through Innovation" -hanketta. Olen kiitollinen Anne Kovalaiselle sekä Etla-seminaarin osallistujille lukuisista hyödyllisistä kommenteista.

Keywords: Service offshoring, Offshoring

Asiasanat: Palveluiden ulkoistaminen, Ulkoistaminen

JEL: F14, C33, J31

1 Introduction

The effect of offshoring on domestic firms has been and remains a hot topic in economic policy discussion. While offshoring could allow firms to tap into sources of skilled workers at low cost (Manning, 2014), workers at home might worry about losing employment opportunities and increased competition from abroad.

The offshoring of manufacturing activities has been studied at length in economic research. The effects of offshoring are theoretically ambiguous: increased competition can benefit home workers by increasing productivity or hurt them via increased competition (see, e.g., Baldwin and Robert-Nicoud, 2014; Grossman and Rossi-Hansberg, 2006, 2008). The existing empirical evidence suggests that the offshore purchase of intermediate goods increases wages, at least for the college-educated workforce (see, e.g., Feenstra & Hanson, 1999). There is much less evidence on the effects of services offshoring, where tasks are the object being traded instead of goods. Indeed, goods and services are traded very differently. Goods usually need to cross borders, while services are intangible. Moreover, in contrast to trade in goods, trade agreements do not regulate trade in services, so there are fewer barriers to service trade.

Trade in services is still low compared with trade in goods (Baldwin and Dingel, 2021), but it has grown more rapidly (Berlingieri et al., 2021; Amiti and Wei, 2009). Recent information and communication technologies (see, e.g., Kässi and Lehdonvirta, 2018; Lehdonvirta et al., 2018; Baldwin and Dingel, 2021) have transformed many jobs across the skill spectrum into "anywhere-jobs" (Kakkad et al., 2021), which are much easier to offshore.[1] The Covid-19 pandemic has

[1] Blinder and Krueger (2013) found that roughly 25% of US workers work occupations with a hght potential for offshoring. More recently, Ozimek (2021) has shown that the offshorability measure created by Blinder and Krueger

further accelerated this trend (Stephany et al., 2020). Finally, global differences in wages are much higher than those in the prices of goods, creating stronger arbitrage incentives (Baldwin, 2019). While the labor-market effects of offshoring manufacturing have been widely documented (e.g., Autor et al., 2014; Ebenstein et al., 2014; Goos et al., 2014; Hummels et al., 2014), it is unclear whether their results generalize to trade in services.

The existing evidence on services offshoring is still relatively scarce. Generally, it is associated with shifts in employment toward higher-educated workers (Becker et al., 2013; Crino, 2010) doing more non-routine and interactive tasks (Becker et al., 2013). On the other hand, the evidence of the total employment effects of the increased offshoring of services in firms is mixed. Kovak et al. (2021) find positive employment effects, whereas Amiti and Wei (2008) find small negative ones. Kerr et al. (2020) use a similar linked employer–employee data set to that used in this paper to study the effects of both goods and services trade on the level of the whole economy. According to their findings, offshoring reduces the routine work performed within firms, but their results do not shed light on the wage and employment effects of offshoring.

Business and management literature offers a complementary view on how firms' internal personnel and capital needs adjust to offshoring. Manning (2014) reviews the challenges that firms need to overcome and ways to overcome these challenges. This literature highlights the various operational challenges that offshoring firms face and the need to find ways of mitigating them, which usually takes time. Thus, any effects of offshoring usually take a long time to emerge.

has no predictive power on changes in the number of people employed in the occupations in 2019. Instead of offshoring potential, this paper studies the labor-market effects of realized offshoring events.

This paper uses a synthetic control method (Abadie and Gardeazabal, 2003; Abadie et al., 2010) to study the effects of offshoring on firms' employment and wage outcomes. The offshoring choice of the firm depends on a variety of observable and non-observable characteristics, which may also affect the firm-level outcomes. I utilize the synthetic control method to overcome this endogeneity due to omitted variables. The synthetic control method allows me to form a data-driven donor pool of non-outsourcing firms that I compare with firms that start outsourcing in the sample period. More concretely, I study how the employment and wages of a college-educated and a non-college-educated workforce evolved between 2012 to 2019 in firms that started buying outsourced services in 2011. These firms are compared with a synthetic control firm whose trajectories of capital stock, personnel, wages, share of college-educated workers, and labor productivity evolved in tandem with the offshoring firms from 2002 to 2009.

Additionally, I provide estimates on how the offshoring of low-skill tasks and high-skill tasks affects high- and low-skilled workers separately. Extensive offshoring literature pioneered by Grossman and Rossi-Hansberg (2008) has postulated that offshored tasks and home tasks with the same skill level are complementary, and thus, offshoring increases the productivity of the workers who do similar tasks to the offshored ones. However, thus far, only limited evidence exists in favor of this assumption.

The traditional synthetic control method applies in the context of a single treated unit and a relatively small number of control units (see, e.g., Abadie, 2003). The data used in this paper consists of hundreds of treated firms (i.e., firms that started service offshoring in a single year) matched to potentially hundreds of non-treated firms. This high-dimensional setting renders the traditional synthetic control method unusable. Instead, I resort to the microsynth framework, a modified version of the synthetic control method developed to bring high-dimensional, micro-level data into the traditional synthetic control framework (Robbins and Davenport, 2021; Robbins et al., 2017). Using microsynth, I can form a synthetic control unit where the pre-treatment observations are matched across all outcome variables and continuous time-varying control variables. The synthetic control method accounts for time-varying unobservable confounders and, thus, tackles endogeneity from omitted variable bias in a straightforward fashion.

A related but distinct issue is the endogeneity due to reverse causality. More concretely, if the decision to offshore is triggered by an anticipation of future changes in demand for firms' goods or productivity, the synthetic control method would be biased. To mitigate this concern, I also present results from an alternative specification where we split the pre-treatment period into two parts: early pre-treatment and late pre-treatment. I only perform matching using data from the early pre-treatment period and demonstrate no differences between the treatment and control groups in the late pre-treatment period. Assuming that anticipation effects would be reflected in late pre-treatment period outcomes, this is evidence against endogeneity due to reverse causality.

As an additional caveat, we note that service offshoring could take very different forms across different firms. Further, my data lacks a measure for the value of the offshoring project, so my estimates are not interpretable as elasticities. Nonetheless, my data does have information on the types of services being outsourced, which allows us to study heterogeneity for different types of outsourced services.

I find that offshoring increases both high-skilled and low-skilled workers' wages while decreasing employment relative to the control group of non-offshoring companies. In the long run, offshoring firms pay approximately three percent higher wages than the synthetic control group. The long-run effect of offshoring on employment is roughly 11 percentage points. Moreover, I find that offshoring firms employ marginally fewer low-skilled workers compared with the synthetic control group.

A sub-sample analysis of the offshoring of high-skill and low-skill tasks separately indicates that the effects of the former almost entirely drive the effects of offshoring on firm outcomes. I find that, in general, only a tiny minority of the offshoring firms offshore low-skill tasks, and the effects of offshoring low-skill tasks are mostly statistically indistinguishable from zero.

The rest of the paper is structured as follows. Section 2 reviews the microsynth framework, and Section 3 describes the data. Section 4 presents the main results and sensitivity analyses, and Section 5 concludes.

2 A review of the microsynth framework

The synthetic control methodology is based on the idea that one can estimate weights for non-treated units so that the pre-treatment values of outcomes follow each other. The microsynth framework expands on the standard synthetic control method along various dimensions. It allows for multiple treated units and jointly incorporates multiple outcome variables, making it particularly useful for the application at hand. In this section, I present a review of the microsynth framework and discuss how I apply it in the current setting.

Let Y_{ijt} denote the observed value of outcome i at time t for firm j. There are a total of I separate outcomes, so that $i \in (1, \dots, I)$. T years are divided into two portions: years $(1, \dots, T_0)$ are pre-intervention and $(T_0 + 1, \dots, T)$ are post-intervention years, $t \in (1, \dots, T_0, T_0 + 1, \dots, T)$. There is total of J_0 non-treated firms of a total of J firms so that $j \in (1, \dots, J_0, J_0 + 1, \dots, J)$.

Now, each observed outcome has the form

(1)

$$Y_{ijt} = Y_{ijt}(0) + \alpha_{ijt} D_{jt},$$

where D_{jt} is the treatment indicator, getting the value 1 if firm j has started buying offshored services in year t and retains value 1 after that. For years, $t > T_0$, $Y_{ijt}(0)$ is the unobserved counterfactual for the treated units. The treatment effect averaged across the treatment group reads as

$$a_{it}^* = \frac{1}{J - J_0} \sum_{j=J_0+1}^{J} a_{ijt}, \tag{2}$$

where $t \in (T_0 + 1, \dots, T)$ and $i \in (1, \dots, I)$. To estimate a_{it}^*, it is necessary to calculate $Y_{it}^*(0)$, which is unobservable. The microsynth estimation framework boils down to choosing a set of weights $(w_1, \dots, w_{J_0})$ (with each firm in the control group receiving a non-negative weight), so that for every outcome i and period t, the weighted firms in the control group sum up to their respective sums across the treated group, or

$$\sum_{j=1}^{J_0} w_j Y_{ijt} = \sum_{j=J_0}^{J} Y_{ijt} \tag{3}$$

for each combination of outcomes and years $t < T_0$. The weights are scaled so that

$$\sum_{j=1}^{J_0} w_j = J - J_0, \tag{4}$$

which implies that the synthetic control weights add up to the number of firms in the treatment group.

If there exists a vector of weights that satisfies (3) and (4), the counterfactual outcome values can be approximated by

$$\hat{Y}^*_{it}(0) = \sum_{j=1}^{J_0} w_j Y_{ijt}, \tag{5}$$

where $t \in (T_0 + 1, \dots, T)$.

Therefore, the average treatment effect across the treatment region can be approximated by

$$\hat{a}^*_{it} = \frac{1}{J - J_0} \sum_{j=J_0+1}^{J} Y_{ijt} - \sum_{j=1}^{J_0} w_j Y_{ijt}\,, \tag{6}$$

where $t \in (T_0 + 1, \dots, T)$.

So far, the model setup described in Equations (1)–(6) is exactly analogous to the standard synthetic control method of Abadie et al. (2010). Robbins et al. (2017) showed that the validity and asymptotic unbiasedness results of Abadie et al. (2010) readily generalize to a situation where Y_{ijt} is a matrix of all outcome variables in all pre-treatment periods for firm j, that is,

$$\boldsymbol{Y}_j \equiv \left(Y_{1j1}, \dots, Y_{1jT_0-1}, Y_{2j1}, \dots, Y_{2jT_0-1}, Y_{Ij1}, \dots, Y_{\mathrm{I}jT_0-1}\right). \tag{7}$$

Using the definition in Equation (7), a matrix version of Equation (3) can be expressed as:

$$\sum_{j=1}^{J_0} w_j \boldsymbol{Y}_j = \sum_{j=J_0}^{J} \boldsymbol{Y}_j. \tag{8}$$

The weight vector w_j, exactly solving (8), is calculated numerically. The solution boils down to solving a set of weights w_j and Lagrange multipliers $\boldsymbol{\Lambda}'$ that minimize the objective function

$$\sum_{j=1}^{J_0} G(w_j) - \boldsymbol{\Lambda}' \left(\sum_{j=1}^{J_0} w_j \boldsymbol{Y}_j - \sum_{j=J_0}^{J} \boldsymbol{Y}_j \right). \tag{9}$$

The function $G(w_j)$ is a calibration function that regulates the behavior of weights. Robbins et al. (2017) defined the calibration function as $G(w_j) = \frac{J-J_0}{J} \times (w_j - 1)^2$, when $w_j \geq 0$ and $+\infty$ otherwise. This function has an implicit regularizing effect on the vector $\boldsymbol{w}$; it chooses the weights so that a minimal number of elements have a positive weight.[2] Minimizing the set of positive weights reduces the risk of overfitting, an inherent risk in synthetic control discussed in Abadie (2021)

The main analytical difference between microsynth and the standard synthetic control is that the function to be minimized is different. Instead of a function akin to Equation (9), the standard synthetic control method minimizes a sum of squared errors between treatment and synthetic control groups.

In practice, there are no guarantees that a vector of weights that solves Equation (8) always exists. In such cases, the microsynth algorithm returns a vector of weights that most closely satisfies (8). The estimates presented throughout this paper are from models where Equation (8) is exactly solved or where the pre-treatment values of the treatment and control units match exactly.

[2] For discussion on alternative calibration functions, see Robbins et al. (2017).

In addition to an estimate for the effect of offshoring, $\widehat{\boldsymbol{a}}_{it}^{*}$, statistical inference also necessitates an estimate for the uncertainty related to the quantity $\widehat{\boldsymbol{a}}_{it}^{*}$.[3] In this paper, I follow a bulk of previous literature and use a permutation test for calculating the distribution of $\widehat{\boldsymbol{a}}_{it}^{*}$ under the null hypothesis of $\boldsymbol{a}_{it}^{*} = [0, \dots ,0]$. In practice, I perform the permutation test by assigning $D_{jt} = 1$ to randomly selected $J - J_0$ firms and re-estimating $\widehat{\boldsymbol{a}}_{it}^{*}$ on the placebo sample. Repeating this approach P times generates a distribution of parameter vectors $\widehat{\boldsymbol{a}}_{it,p}^{*}$ $(p \in (p_1, \dots , P))$ under the null hypothesis of zero treatment effects. Comparing the values of $\widehat{\boldsymbol{a}}_{it}^{*}$ to the quantiles of $\widehat{\boldsymbol{a}}_{it,p}^{*}$ enables the calculation of *p*-values related to parameter estimates.

I will next make some general remarks pertinent to the application at hand. First, as discussed by Abadie (2021), the synthetic control method is not inherently unbiased. The degree of bias depends on how well the weighted control units follow the time paths of treated units. If the pre-treatment fit is poor, the performance of the synthetic control estimate will be poor. However, matching on several outcomes improves the fit. Including more outcomes acts analogously to increasing the pre-intervention period length and reduces the maximum bias related to the synthetic control. Intuitively, having several outcomes as matching variables introduces additional moments that are matched between the treatment and control groups in the pre-treatment years.

In my specific setting, the treatment variable is a binary variable that gets a value of 1 if a firm has started buying services abroad between 2009 and 2011. The control group consists of firms that do not offshore any services. Our matrix of outcomes consists of personnel (log), average (log) salaries of college-educated and non-college-educated workers, the share of college-educated workers, and labor productivity, estimated using a Cobb-Douglas production function.

[3] Note that since we are studying the effect of offshoring on multiple outcomes, $\boldsymbol{a}_{it}^{*}$ is a vector.

Additionally, since firms with highly heterogeneous capital stocks can pay similar wages and have equal numbers of people employed, I include capital stock levels as an additional matching variable.

There is extensive literature from Olley and Pakes (1996) on estimating production functions. This literature highlights that capital and personnel stock are strategic variables that depend on their (unobserved) productivity. The microsynth framework presented here conveniently sidesteps this issue by ensuring that the treatment and control groups are precisely matched on both capital and labor stocks and labor productivity.

A related issue, also highlighted in Olley and Pakes (1996), is that the entry and exit of firms are partly determined by factors that are unobservable to we researchers. This is a problem for synthetic control, which requires complete observations for all firms and years. Thus, my results on the effects of offshoring should be seen as the effects of offshoring on established firms. For example, the estimation method excludes "born global" firms that have built their business models on global services from their inception.

3 Data and descriptive statistics

3.1 Dataset construction

The Finnish survey data I use in this paper was collected as a part of the "Global Value Chains" (GVC) survey administered by Statistics Finland and Eurostat.[4] The survey sampling frame consisted of companies employing over 100 people and a representative random sample of

[4] See Eurostat (2013) for details.

companies employing 50–99 people. The survey sampling frame covered all industry and service sectors. The response rate for the survey was 82%.[5]

I operationalize the offshoring variable by using a survey question which probed whether the company started offshoring some of its activities outside of Finland during 2009–2011. The respondents were additionally asked about the type of service they had offshored during that period. The survey does not allow me to pinpoint the exact year when the offshoring started.[6] I assume that the treatment year is 2011 for all treated firms in my baseline specification. I also demonstrate in Section 4 that the results are not sensitive to changing this year.

The services categories and their associated skill requirements are listed in Table 1. Unfortunately, the data does not provide a classification for the skill requirement of each task. Instead, we have manually classified the offshored tasks into *high-skill tasks* and *low-skill tasks* according to the typical educational requirements.

Table 1: Offshored task classifications

The type of tasks being offshored	Skill requirement
The firm's core functions	High
Distribution and logistics	Low
Sales, marketing, marketing, telemarketing, and after-sales services	Low
ICT services	High
Administrative and management functions	Low

[5] Kerr (2020) use an earlier wave of the same survey.

[6] Thus, if a firm already offshored some service before 2009, the offshoring variable would get the value 0 for that firm.

Engineering and other technical services	High
Research and development	High

I link the GVC survey data to two additional datasets. First, the annual panel of financial statements contains information on the value added, capital stock, and personnel of each of the firms in the survey. The synthetic control method requires complete observations, so I drop all the firms with missing financial information.

The annual salaries and worker-skills data are based on the linked employer–employee data. For each year, I take all the workers employed at the surveyed firm at the end of the year and calculate their average incomes by education group. I exclude workers whose educational information is not recorded in the data.

The matching variables used for creating the synthetic control group are the following:

- High-skilled workers' average income (log): the average income of workers with college education or a higher level of education (in logs)
- Low-skilled workers' average income (log): the average income of workers with a lower level of education than college education (in logs)
- The share of high-skilled workers: the share of workers with more than a college education as a share of the personnel in the company
- Personnel: the number of full-time-equivalent (FTE) employees during a year (in logs)
- Capital stock divided by personnel: the book value of capital stock per employee (in logs)
- Labor productivity: value added divided by employees (in logs)

To limit the effect of anomalous observations, we winsorize all the monetary values at a 1% level.

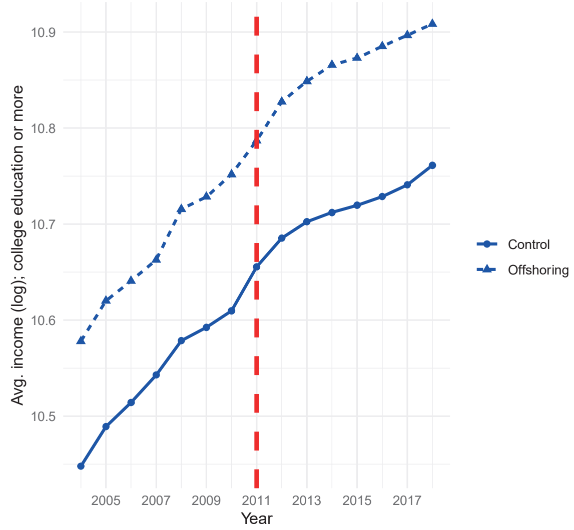
3.2 Descriptive statistics

Table 2 lists the sample sizes used in the analysis. The total sample size in the survey is 1673, but as explained in the previous section, the synthetic control method requires complete observations. Excluding missing values reduces the sample size to 973. In the survey, 21% of the firms reported that they started offshoring between 2009 and 2011, 2% of the companies reported offshoring low-skill tasks, and 13% reported only offshoring high-skill tasks. The low- and high-skill offshoring shares do not add up to 21% because some firms offshore both high- and low-skill tasks simultaneously.

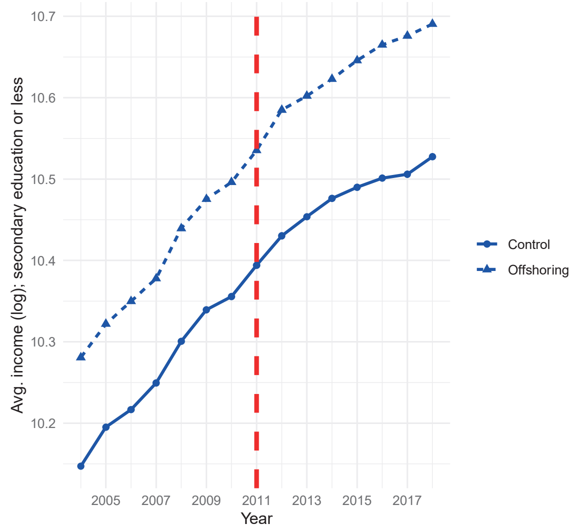
Table 2. The sample sizes used in the analysis

Number of firms in the offshoring survey	1653
Number of complete observations	985
Share of firms that began offshoring in 2011	21%
Share of firms that began offshoring low-skill tasks in 2011	2%
Share of firms that began offshoring high-skill tasks in 2011	13%

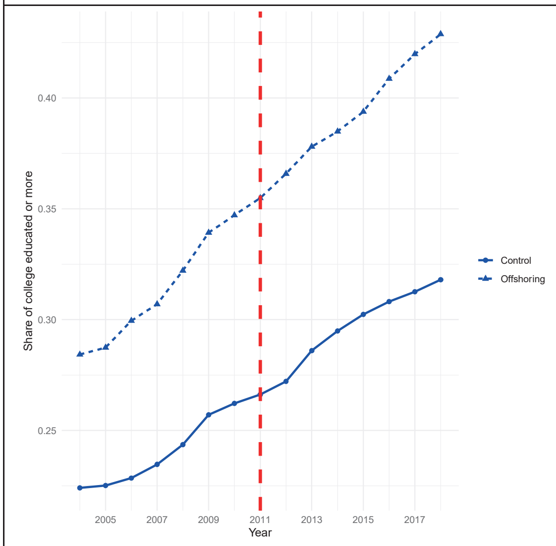
Figure 1 plots the time paths for the variables of interest for offshoring and non-offshoring firms. A few general remarks come to mind. First, the firms that bought offshored services during 2009–2011 tend to pay higher wages, employ more high-skilled labor, and have higher capital stocks than their peers. Second, both types of firms' personnel were on a decreasing trend from 2007 onward. Third, the offshoring firms show slightly lower labor productivity than non-offshoring firms, but these time series are also extremely noisy. Figure 1 also suggests that classical difference in differences would likely result in biased estimates due to diverging pre-trends.



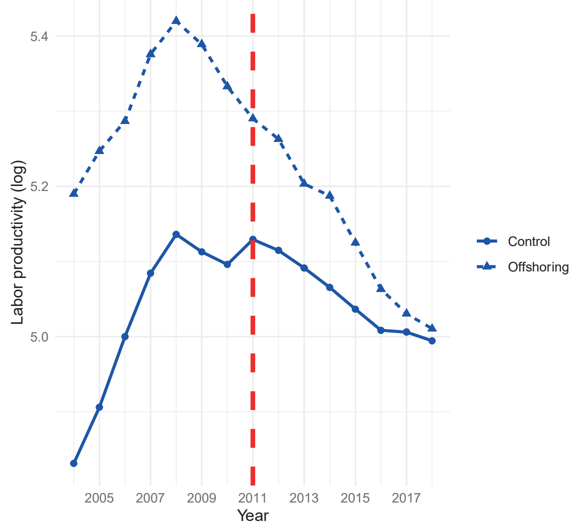
(a) High skill avg. income (log)



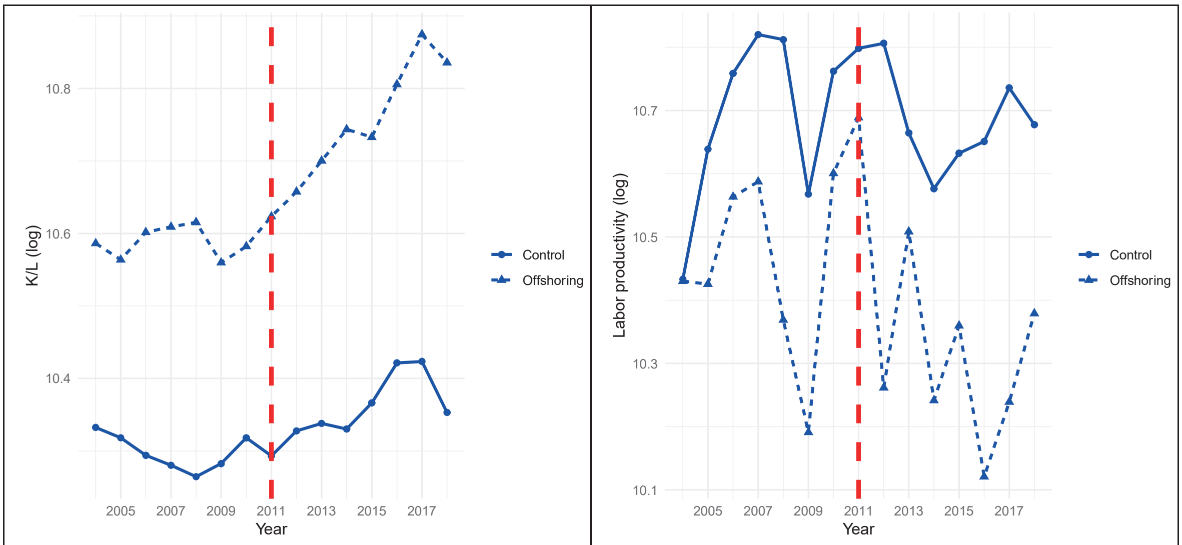
(b) Low skill avg. income (log)



(c) Share of high-skill workers



(d) Personnel (log)



(e) Capital stock divided by personnel

(f) Labor productivity (log)

Figure 1. A time series for the variables used in the synthetic control analysis. Dashed lines correspond to the group of firms that started offshoring abroad in 2009–2011; the solid lines correspond to those that did not start offshoring; and I red dashed line corresponds to the year 2011.

4 Results

4.1 The main results: The effects of offshoring on wages and employment

I begin by discussing the effects of offshoring on wages and employment in the full sample using data from 2003–2009 for building the synthetic control unit.

Figure 2 reports the results of this specification. The left column of Figure 2 (parts a.1–f.1) plots the levels of treatment and control groups. The right column of Figure 2 (parts a.2–f.2) presents the difference between the two. The gray lines in parts a.2–f.2 also present the results of counterfactual outcomes, which are based on treatment permutations, as discussed in Section 2. The dashed lines in parts a.2–f.2 correspond to the 0.025th, and 0.975th percentiles of the distribution of permutation draws. If the difference lies outside the 0.025th and 0.975th percentiles of the permutation distribution, the difference is significant at a 5% risk level.

According to parts a.1 and b.1 of Figure 2, the average salaries of high-skilled and low-skilled workers have grown in both offshoring firms and the synthetic control group. Moreover, part a.2 demonstrates that the incomes of high-skilled workers grow quicker in the offshoring firms compared with those in the synthetic control. This difference is statistically significant from 2013 onwards at a 5% risk level. Part b.2 plots the difference for low-skilled workers. In this group, the growth picks up later and is only statistically significant from 2016 (five years after offshoring took place).

Part c.2 of Figure 2 indicates that the differences between the offshoring and synthetic control groups in the share of high-skilled workers have remained at zero. The exception to this is 2018, the final year in the sample. While this difference is statistically significant, the point estimate – 0.019 log points – is economically rather small. Transformed to FTE workers, the point estimate of 0.019 implies that offshoring firms employ roughly 2.8 more workers with a college education (or even more) when compared with the synthetic control.

Simultaneously, according to part d.2 of Figure 2, the offshoring firms' personnel has contracted quicker than in the synthetic control. While only statistically discernible from zero after 2016, the differences are economically substantial. For instance, according to part d.2, the difference in employment in 2018 was 19%. When the difference in log-points is transformed back to levels, this corresponds to roughly 33 FTE workers.

Part e.2 of Figure 2 indicates that there are no differences in capital stock between the treatment and control firms in any year after offshoring. Finally, part f.2 of Figure 2 shows that annual changes in labor productivity differences are noisy, and there are no statistically discernible differences between the treatment and synthetic control groups.

The fact that offshoring does not seem to result in productivity improvements is slightly surprising. Nonetheless, the period under consideration coincides with stagnant productivity growth in Finland (see, e.g., Fornaro et al., 2021; Dai et al., 2022). Moreover, as evidenced by Figure 1f, the annual changes in labor productivity within firms are relatively noisy, which increases the risk that the synthetic control fails to detect any effects from the noise. Additionally, there exists a large amount of literature showing that firm productivity is both highly persistent within firms and highly variable between firms (for a review, see Syverson 2011).

Part a of Table 3 reports the point estimates of the results. In Table 3, *short-term* refers to an average over the years [t + 1, …, t+3] (i.e., the years 2012–2014) and *long-term* refers to observation from the year 2018. The full period corresponds to the average over [t+1, …, t+7]. It is plausible that the differences in the year 2018 capture the differences between offshoring firms and the synthetic control group after they have finished adjusting their organization and building the necessary international infrastructures for offshored services.

I find that generally, there are no differences between the offshoring group and the synthetic control in the short term. In the long term, the annual difference in high-skilled workers' incomes between the offshoring and the synthetic control groups is approximately 3.1%, while the difference in low-skilled workers' incomes between the two groups is of comparable magnitude (3.3%). The estimates for the difference in the full period are mostly not discernible from zero. Moreover, parts a.2 and b.2 of Figure 2 do not indicate a mean reversion in the wages of offshoring firms. Therefore, it seems more likely that, on average, the wage effects of offshoring take years to emerge.

In the long term, the offshoring firms employ 19% fewer full-time-equivalent workers than the synthetic control. However, analogously to earnings, the short-term differences are not statistically significant at conventional risk levels. Additionally, like earnings differences, the differences in the averages over the full period are not discernable from noise.

Finally, the share of high-skilled workers is 2 percentage points larger in the offshoring group compared with the control group in the long term. No other statistically significant differences emerge from panel "a" of Table 3.

4.2 Balance diagnostics: Industry distribution

As explained above, the synthetic control group is only formed using the continuous time-varying characteristics of firms.[7] Therefore, comparing the time-invariant characteristics of the synthetic control and the treatment group provides a natural diagnostic check for match quality.

I report the industry distributions of both groups in Figure 3. Figure 3 also includes 95% confidence intervals based on a block bootstrap. I have taken 250 bootstrap resamples of firm identifiers (one firm identifier corresponds to one block in the data) and re-estimated the synthetic control model. The confidence intervals are calculated as the 0.025th and 0.975th percentiles of the industry share distributions of bootstrapped synthetic control estimates. Figure 2 shows that the two distributions match rather well. The only statistically discernible difference between the

[7] I have not used the time-invariant background characteristics as match variables for two reasons. First, the sample size in many industry cells is relatively small. Second, recent literature (e.g., Kaul et al., 2015; Klößner et al., 2018; Kuosmanen et al., 2021) has raised the concern that using time-invariant covariates as matching variables in synthetic control might lead to numerically unstable estimates.

treatment and control group at a 5% risk level is for industry NACE code C (manufacturing). When tested jointly, using a chi-square test for homogeneity, I fail to reject the null hypothesis that the industry distributions differ between the synthetic control group and the offshoring group.

4.3 The results from an alternative matching period

In this section I report the results from a model where I have performed the matching for 2003–2008 instead of 2003–2011. This analysis serves three purposes. First, the offshoring variable is based on whether the firm started offshoring a particular service sometime between 2009 and 2011. In the previous subsection, I assumed that the offshoring event always occurred in 2011. If the results are not sensitive to changing the matching period from 2003–2011 to 2003–2008, this suggests that the results are not sensitive to the exact year of outsourcing.

Second, while the synthetic control method can plausibly tackle endogeneity due to omitted variables, it is sensitive to reverse causality. That is, if a firm observes a shock that results in an offshoring decision later in time, the synthetic control method might be biased. However, showing that the results are robust to changing the matching period suggests that there were no such shocks during 2008–2010.

Third, following Abadie et al. (2010), splitting the pre-intervention period in two allows me to test for the possible risk of overfitting. If the fit during 2008–2010 is poor, it is evidence of overfitting.

I report the results of this exercise in both Figure 4 and panel "b" of Table 3. Comparing the results reported in the previous subsection shows that the two specifications result in almost identical estimates. Moreover, the fact that no differences between the treatment and control groups emerge during 2008–2010 suggests that there is no excessive noise due to overfitting.

4.4. The results by offshoring skill level

To study the differences between types of tasks being offshored, I perform the synthetic control estimation separately for high-skill and low-skill offshored tasks. The primary motivation for this exercise stems from Grossmann and Rossi-Hansberg's (2008) framework. Their central assumption is that offshoring a particular type of task is analogous to factor-augmenting technical change. Thus, for instance, offshoring high-skill tasks should increase the demand for high-skilled workers at home and increase their share of employment and income.

The empirical estimates in Table 3, panel "c", repeat the analysis from Section 4.1 but only for firms that only offshored high-skill tasks. Panel "d" only reports the results for low-skill offshoring.

Comparison between panels "a" and "c" in Table 3 indicates that the results reported in the previous sections seem to be driven by high-skill offshoring. No statistically significant differences appear in panel "d," while the results of panel "c" are comparable to those reported in the previous sections. The minimal results in panel "d" might primarily be related to small sample sizes. Only 2% of the firms in the sample offshored low-skill tasks, as reported in Table 2.

Taken at face value, the results for the offshoring of high-skill tasks broadly conform to Grossman and Rossi-Hansberg's theoretical setup. The offshoring of high-skill tasks seems to increase the salaries of both high-skilled and low-skilled workers while increasing the relative employment share of high-skilled workers (due to the share of high-skilled workers increasing while total employment decreases). According to Grossman and Rossi-Hansberg, this is a result of offshored high-skill work being complementary to high-skill work undertaken at home, which increases high-skilled workers' productivity within the firm.

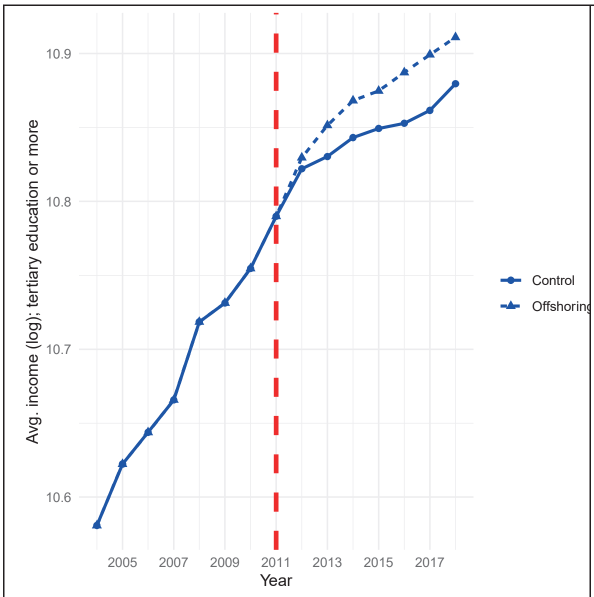
4.5. The results using an alternative control group

Another potential issue with the construction of the treatment variable is that some of the control group firms might be treated after the treatment time. In practice, this could happen if a firm in the control group starts offshoring sometime after 2011.

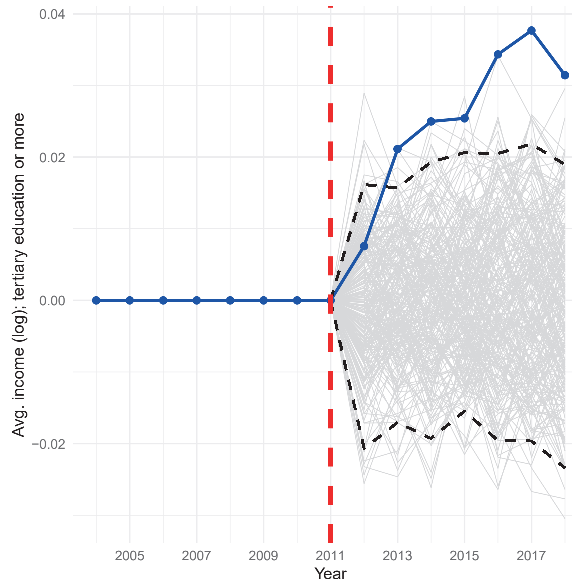
I address this by proxying post-2011 offshoring using the "external services" variable from firms' financial statements. This variable captures both services offshored from abroad and domestically outsourced services. Moreover, in some cases, expenses such as rents and occasional equipment maintenance costs might be classified as *external services*. Thus, while external services might capture other expenses in addition to offshoring/outsourcing, if a firm starts offshoring some of its services, this should be associated with a discrete jump in external services expenses.

I filter out possible post-treatment time offshoring events by first finding all firms who do not report starting offshoring between 2009 and 2011 and whose expenditure on external services per worker has increased by more than 50% after 2011 compared with the pre-2009 external services per worker expenditure. I then exclude these firms from the donor pool of synthetic control units and re-estimate the synthetic control weights.

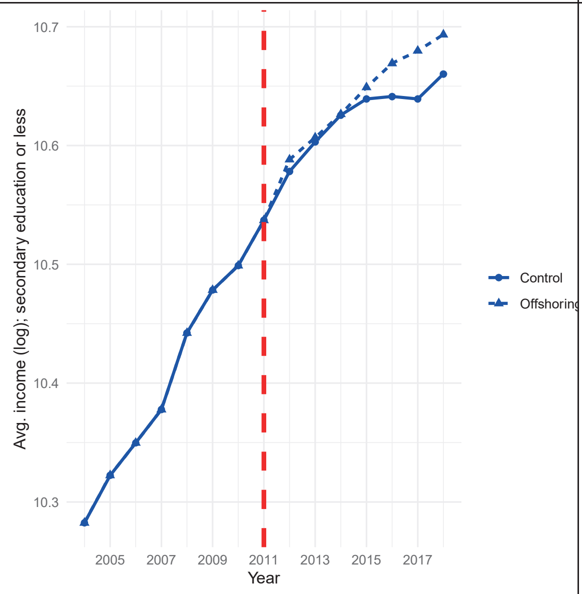
This filtering is costly for the sample size and results in the yearly observations decreasing from 985 to 579. Nonetheless, panel "f" of Table 3 shows that the estimates using the filtered donor pool for constructing the synthetic control are almost identical to the main estimates.



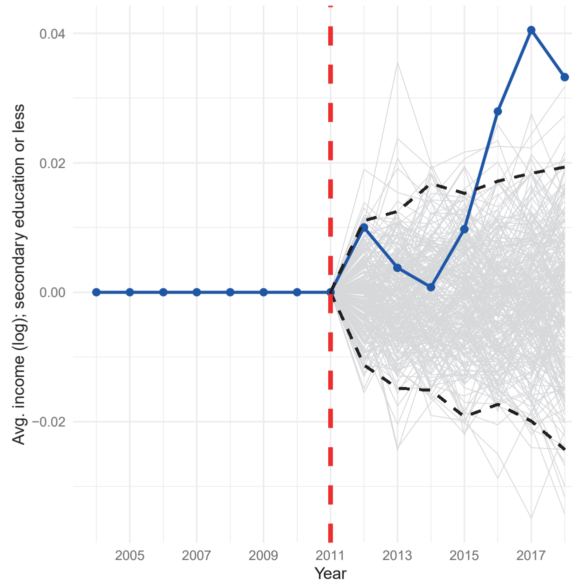
(a.1) High skill avg. income (log)



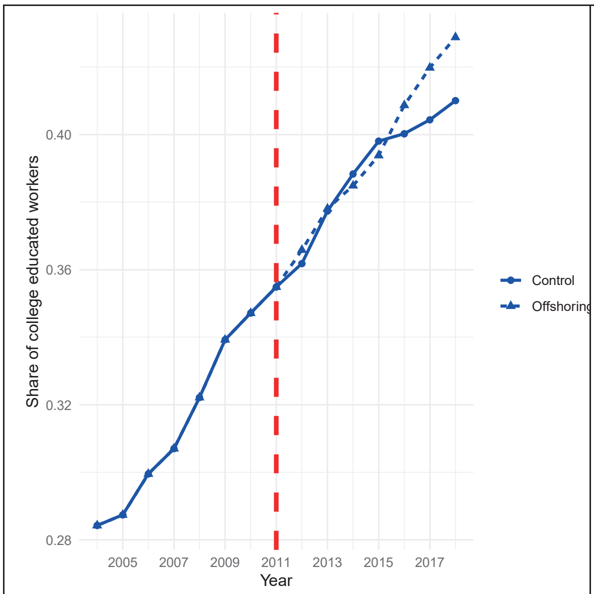
(a.2) Difference: High skill avg. income (log)



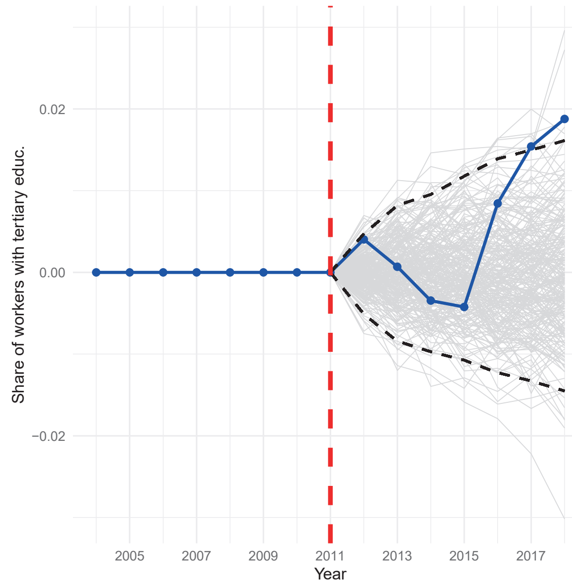
(b.1) Low skill avg. income (log)



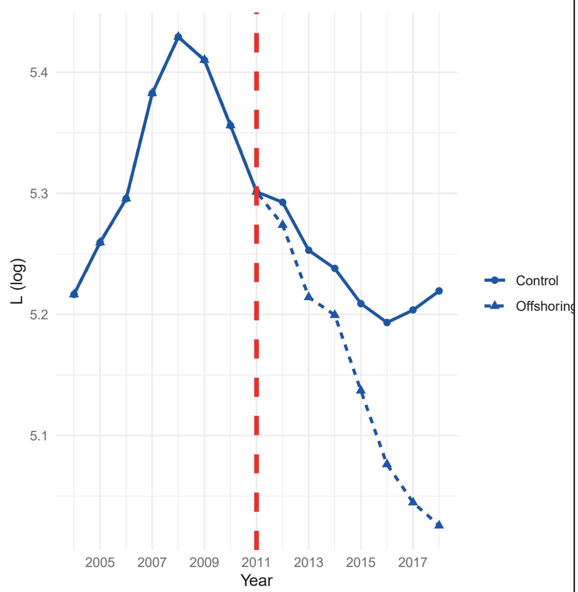
(b.2) Difference: Low skill avg. income (log)



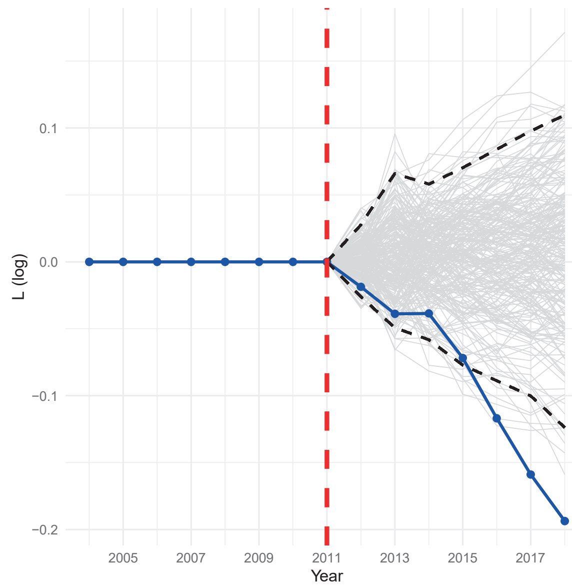
(c.1) Share of high-skill workers



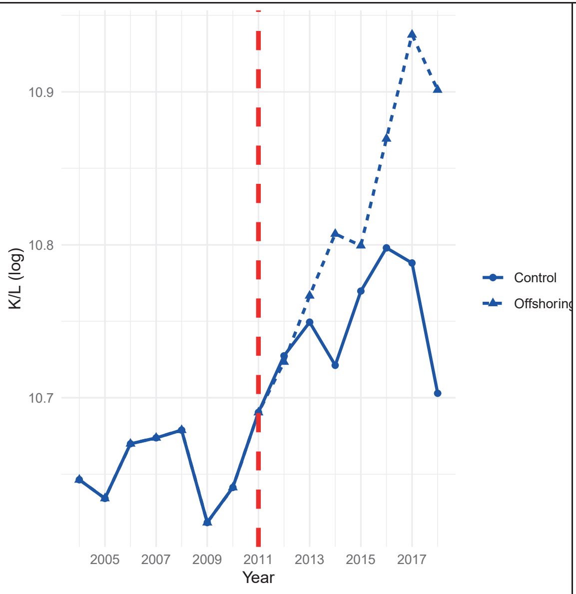
(c.2) Difference: Share of high-skill workers



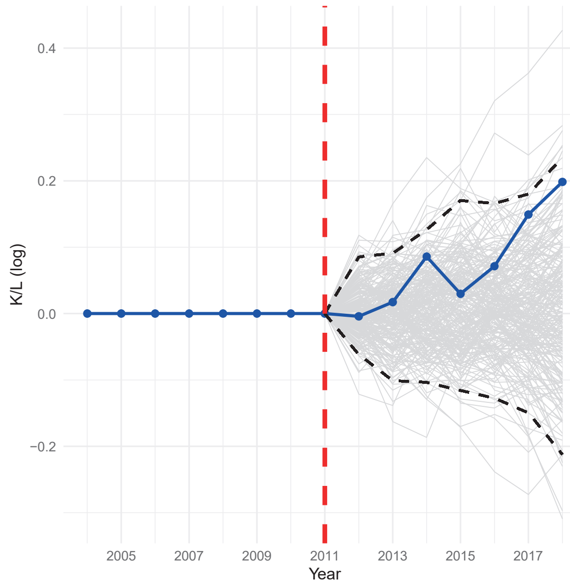
(d.1) Personnel (log)



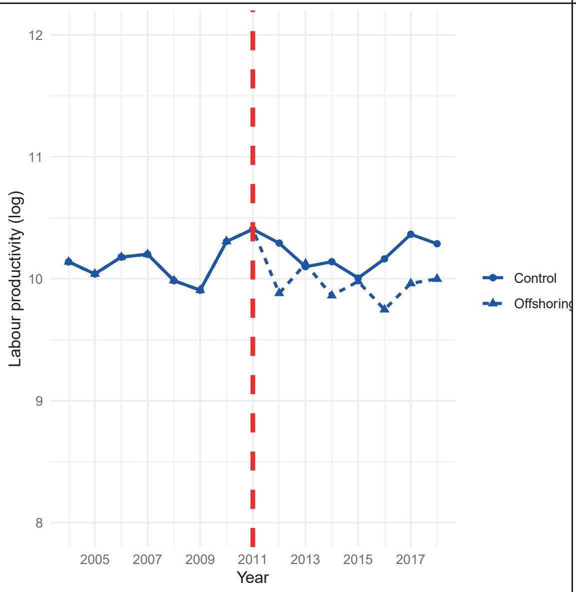
(d.2) Difference: personnel (log)



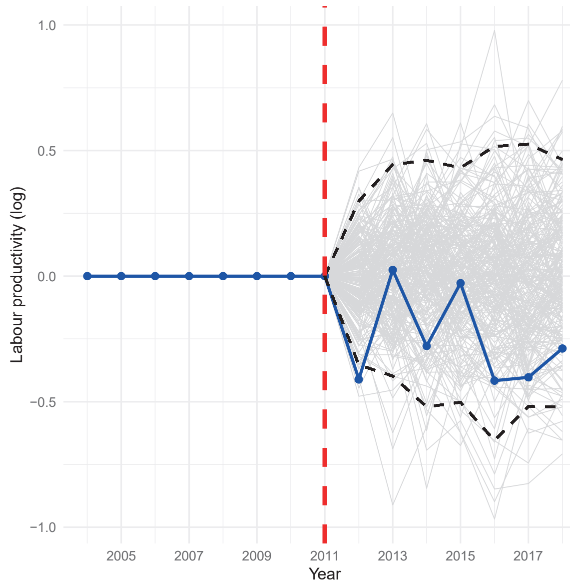
(e.1) Capital stock divided by personnel (log)



(e.2) Difference: Capital stock divided by personnel (log)



(f.1) Labor productivity (log)



(f.2) Difference: Labor productivity (log)

Figure 2. A comparison between the offshoring firms and the synthetic control in levels (a.1–f.1) and differences between the two (a.2–f.2). The red vertical line corresponds to the year 2011, which is the treatment date. In a.1–f.1, the solid line is the synthetic control and the dashed line is the

offshoring group. In parts a.2–f.2, the light gray lines correspond to 250 permutation draws and the black dashed lines are the 0.025^{th} and 0.975^{th} percentile of the permutation draws.

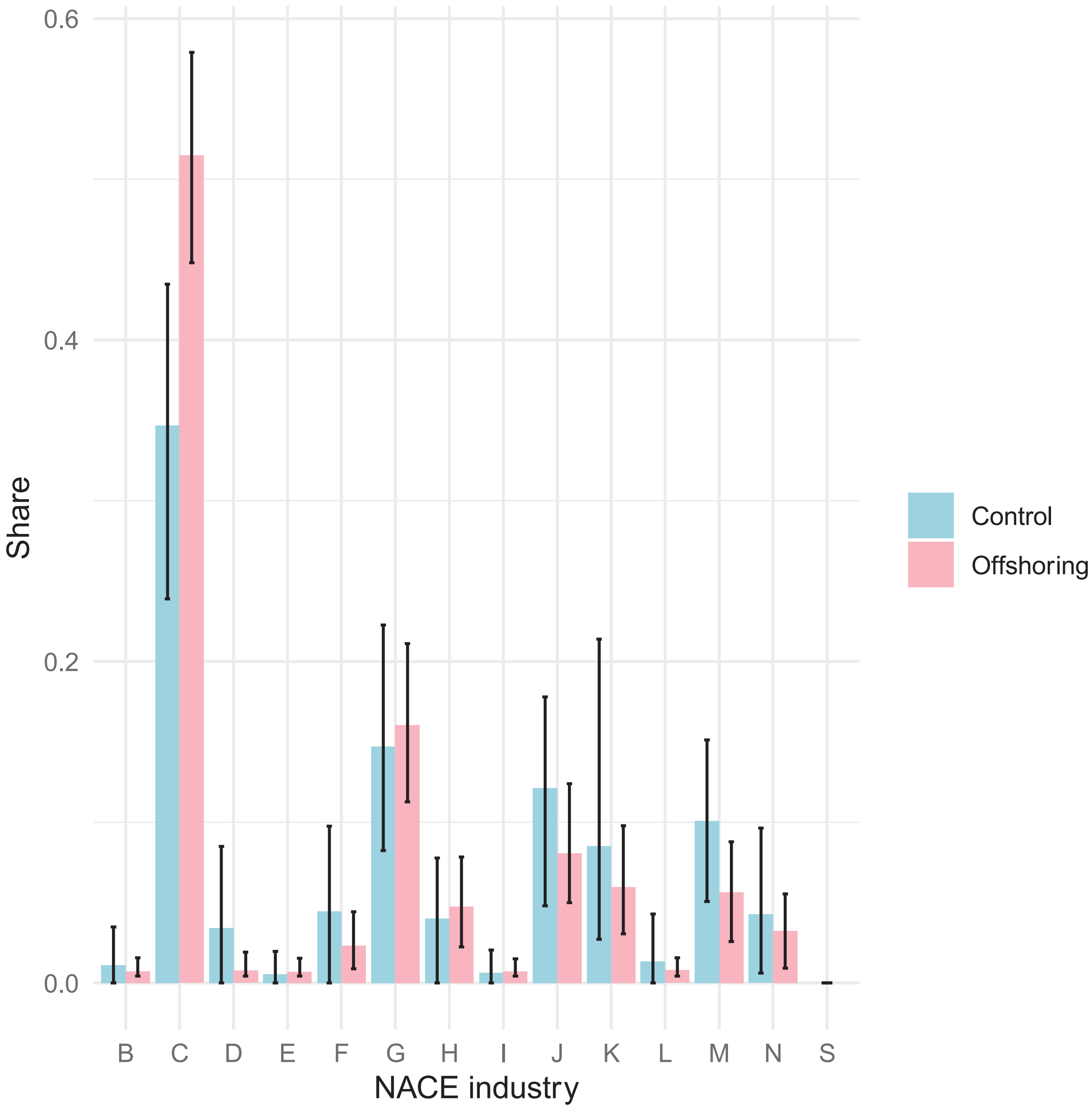
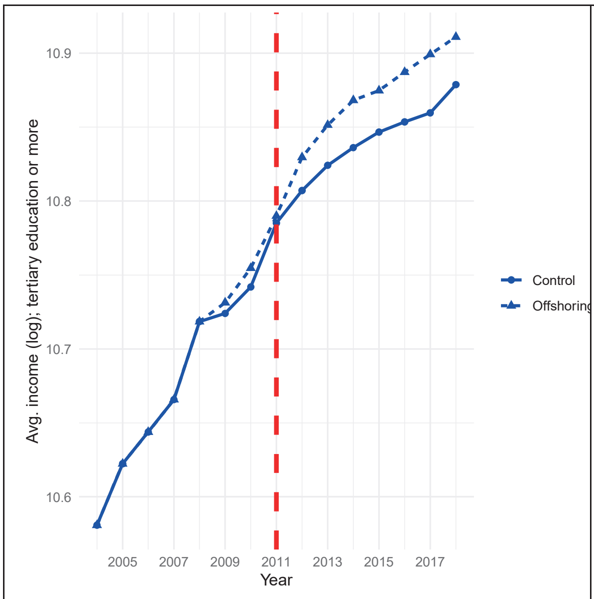
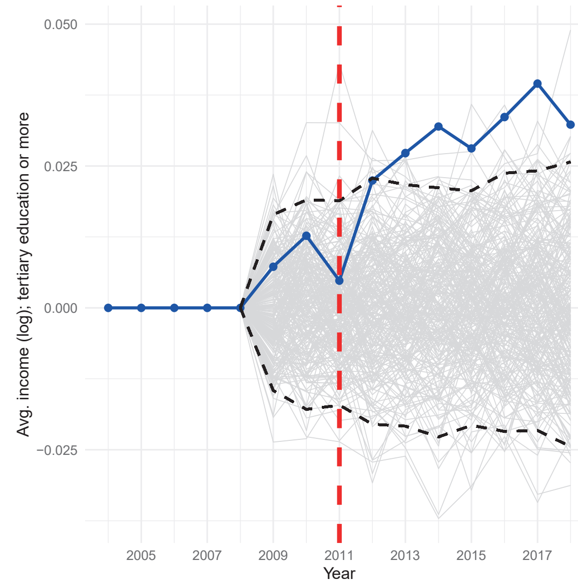


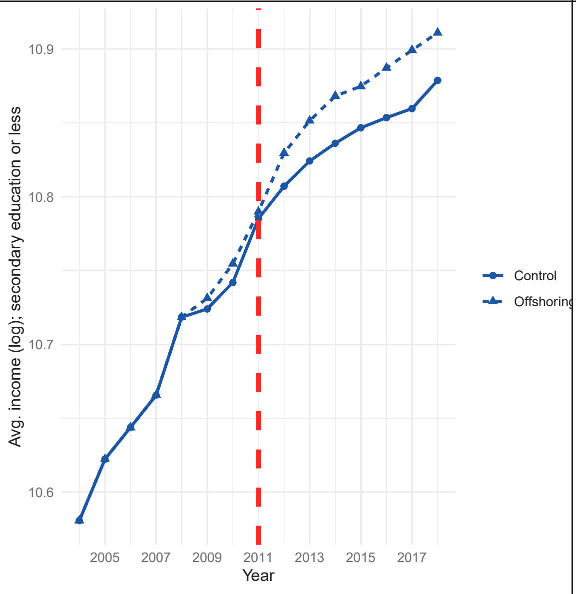
Figure 3. A comparison between the industry distribution (1-digit NACE, 2008) between the treatment and synthetic control groups. Confidence intervals are calculated by block bootstrap.



(a.1) High skill avg. income (log)

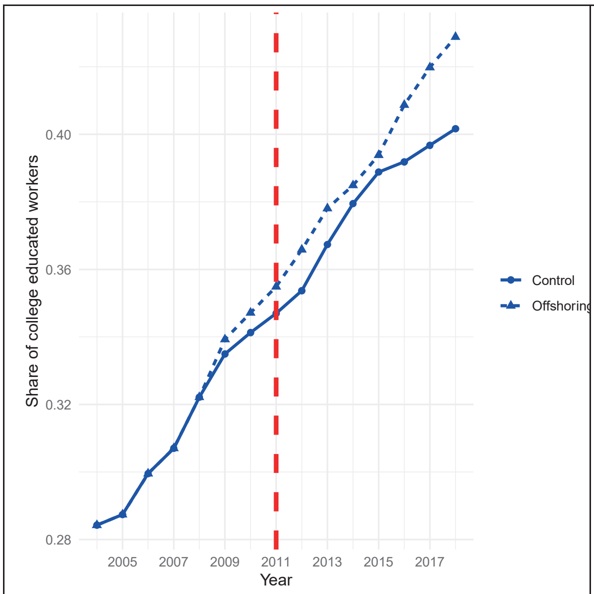


(a.2) Difference: High skill avg. income (log)

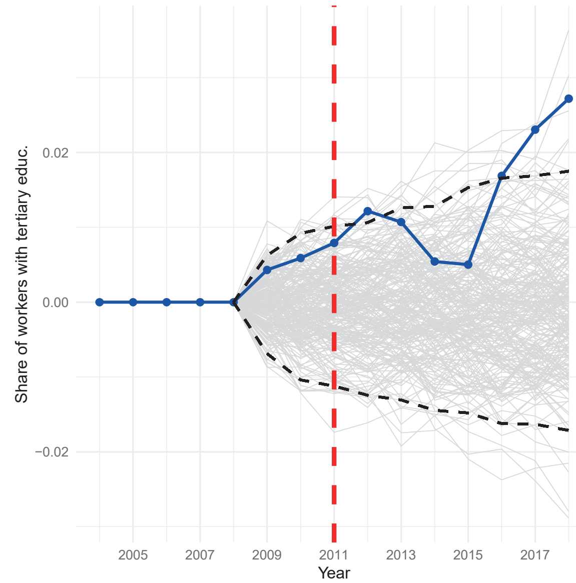


(b.1) Low skill avg. income (log)

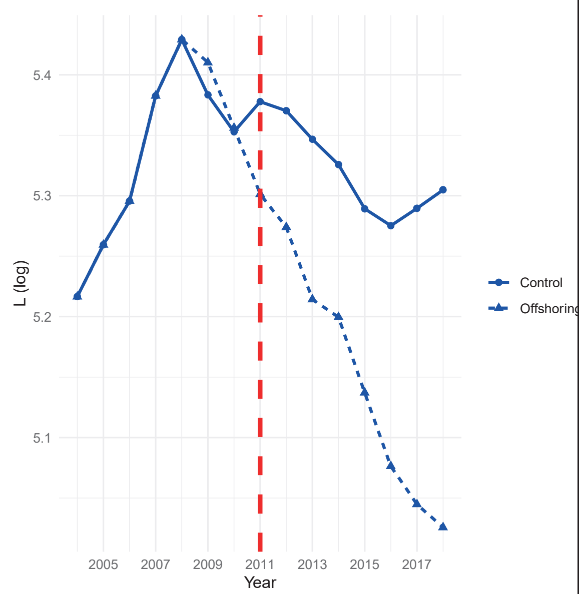
(b.2) Difference: Low skill avg. income (log)



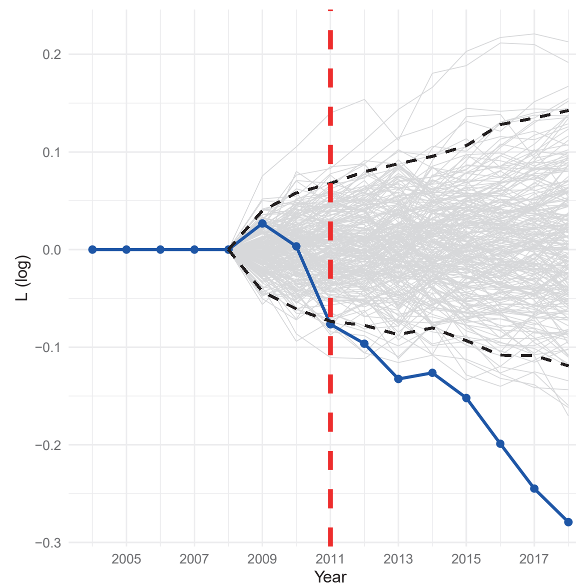
(c.1) Share of high-skill workers



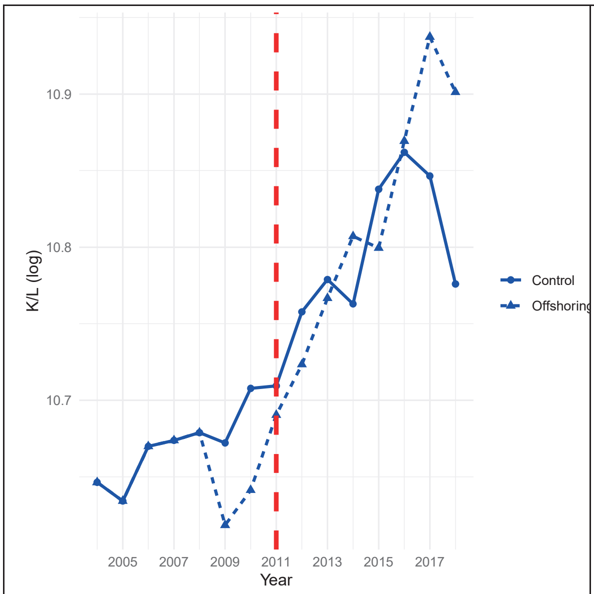
(c.2) Difference: Share of high-skill workers



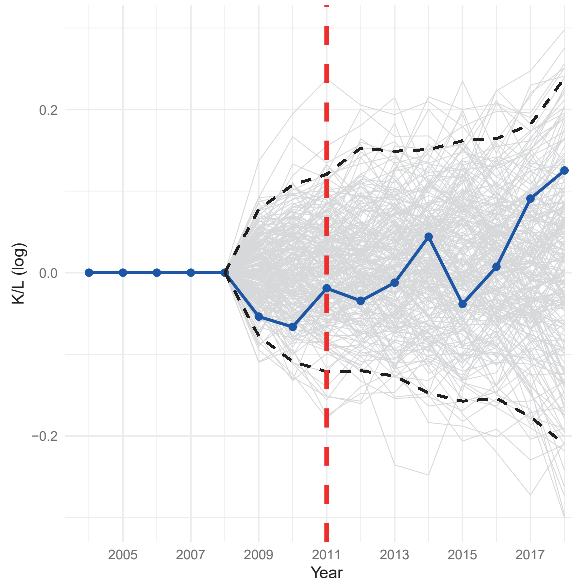
(d.1) Personnel (log)



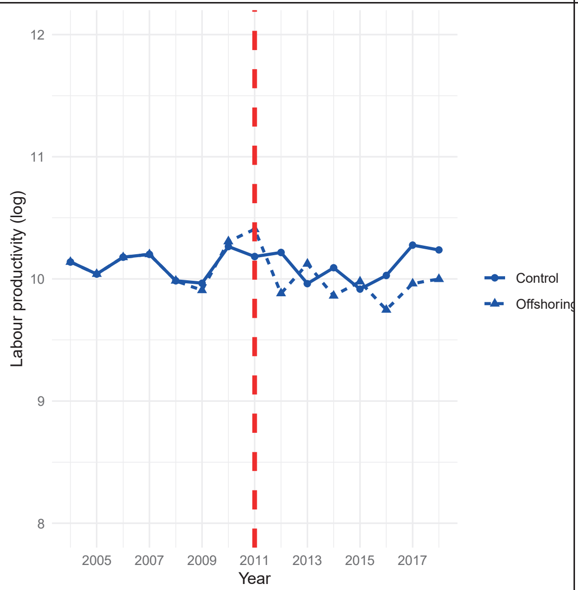
(d.2) Difference: personnel (log)



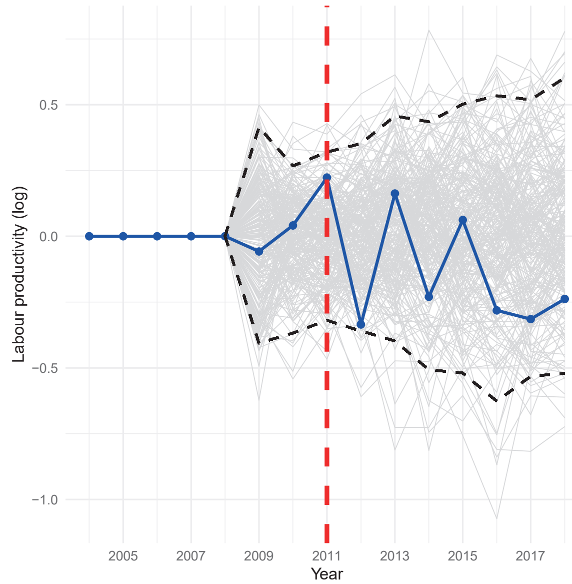
(e.1) Capital stock divided by personnel (log)



(e.2) Difference: Capital stock divided by personnel (log)



(f.1) Labor productivity (log)



(f.2) Difference: Labor productivity (log)

Figure 4. A comparison between the offshoring firms and the synthetic control in levels (a.1–f.1) and differences between the two (a.2–f.2) using alternative matching periods. The red vertical line corresponds to year the 2011, which is the treatment date. In a.1–f.1, the solid line is the synthetic control and the dashed line is the offshoring group. In a.2 – f.2, the light gray lines correspond to

250 permutation draws and the black dashed lines are the 0.025th and 0.975th percentile of the permutation draws.

(a) Main specification

	Short term	Long term	Full time period
Average earnings, high skill	0.013	0.031	0.023
	[0.27]	[0]	[0.14]
Average earnings, low skill	0.004	0.033	0.016
	[0.56]	[0]	[0.31]
Share of high-skilled workers	0	0.019	0.005
	[0.98]	[0.0083]	[0.71]
Personnel	-0.024	-0.19	-0.08
	[0.41]	[0]	[0.22]
Capital stock	0.025	0.2	0.068
	[0.74]	[0.058]	[0.53]
Labor productivity	-0.166	-0.29	-0.225
	[0.71]	[0.26]	[0.54]

(b) Matching period: years 2003–2008

	Short term	Long term	Full time period
Average earnings, high skill	0.015	0.032	0.022
	[0.39]	[0]	[0.25]
Average earnings, low skill	0.014	0.044	0.023
	[0.35]	[0]	[0.22]
Share of high-skilled workers	0.007	0.027	0.011
	[0.37]	[0.0082]	[0.28]
Personnel	-0.057	-0.28	-0.116
	[0.49]	[0]	[0.31]
Capital stock	-0.02	0.13	0.004
	[0.58]	[0.29]	[0.81]
Labor productivity	-0.028	-0.24	-0.088
	[0.9]	[0.35]	[0.77]

(c) Only high-skill tasks

	Short term	Long term	Full time period
Average earnings, high skill	0.006	0.021	0.016
	[0.75]	[0.11]	[0.4]

(d) Only low-skill tasks

	Short term	Long term	Full time period
Average earnings, high skill	-0.014	0.0088	-0.007
	[0.71]	[0.69]	[0.85]

Average earnings, low skill	0.004	0.033	0.019	-0.015	-0.018	-0.021
	[0.65]	[0]	[0.36]	[0.68]	[0.85]	[0.61]
Share of high-skilled workers	0.005	0.02	0.009	0	-0.037	-0.015
	[0.44]	[0.008]	[0.32]	[0.99]	[0.17]	[0.58]
Personnel	-0.019	-0.13	-0.065	-0.049	-0.17	-0.093
	[0.54]	[0.048]	[0.3]	[0.3]	[0.33]	[0.34]
Capital stock	0.049	0.18	0.085	-0.02	-0.13	-0.058
	[0.55]	[0.18]	[0.44]	[0.9]	[0.75]	[0.87]
Labor productivity	-0.365	-0.29	-0.286	-0.288	-0.76	-0.551
	[0.33]	[0.32]	[0.44]	[0.47]	[0.28]	[0.48]

(e) Filtered control group

	Short term	Long term	Full time period
Average earnings, high skill	0.016	0.026	0.022
	[0.38]	[0.12]	[0.25]
Average earnings, low skill	0.004	0.032	0.017
	[0.76]	[0.033]	[0.45]
Share of high-skilled workers	0.005	0.016	0.008
	[0.67]	[0.082]	[0.45]
Personnel	-0.021	-0.22	-0.09
	[0.61]	[0]	[0.31]
Capital stock	0.063	0.28	0.131
	[0.74]	[0.033]	[0.43]
Labor productivity	-0.549	-0.21	-0.468

	[0.32]	[0.57]	[0.35]

Table 3. The estimation results. Notes: the values refer to the difference between the treatment and synthetic control groups; *p*-values that are based on permutation tests are listed in brackets; *short term* corresponds to average of years [t+1, …. t+3] and *long term* corresponds to [t+7]; panel (a) is the main specification.

5 Discussion and conclusions

This paper studied the wage and employment effects of offshoring services using a synthetic control framework and firm-level microdata. I find that, in general, offshoring increases wages of all workers within the firm. In the long term, offshoring firms pay roughly 3% more than the non-offshoring synthetic control group, but this effect only appears gradually, after 3–4 years of offshoring.

Concurrently with the increase in wages, I also find a negative employment effect. Offshoring firms employ 19% fewer workers in the long term than the synthetic control. Transformed to full-time-equivalent workers, this implies that the offshoring firms employed 23 fewer FTE workers compared to the control, a relatively stark effect. Moreover, the offshoring firms employ relatively fewer low-skilled workers compared with the synthetic control.

In forming the synthetic control group, I ensured that the offshoring firms' and synthetic control group's capital stock and labor productivity match exactly. No statistically significant differences between offshoring firms and the synthetic control group emerge along these dimensions. This suggests that there are no changes after offshoring that could be driving some of the wage or employment effects observed.

Having zero effects on productivity is rather surprising given that one of the main, often-quoted motivations for outsourcing is cost savings. Potential explanations for there being zero effects include noisy productivity measurements and that productivity within firms in general tends to be very persistent (Syverson, 2011). Moreover, the Finnish economy as a whole faced stagnant productivity throughout the observation period (Fornaro et al., 2021).

Existing literature has highlighted offshoring as a potential engine for polarization between high-skilled and low-skilled workers within offshoring firms (see, e.g., Becker et al., 2013; Crino, 2010) or offshoring countries (Baldwin, 2019). The findings in this paper only give tentative support to the former: the effect of offshoring on the incomes of workers with low and high levels of education is almost identical, and the share of high-skilled workers only increases marginally. This contradicts some of the previous empirical evidence from the US (Crino, 2010) and Germany (Becker et al., 2013), which have found that offshoring strongly favors high-skilled workers. One probable explanation for this is that Finland's collective wage-setting regime mandates minimum raises within industries and effectively reduces wage inequality within firms.

While I do not find that offshoring leads to increasing wage polarization within firms, my results imply that offshoring reduces employment within firms. The point estimate for the difference in employment between the treatment and control group is 19% based on my preferred specification. Transformed to FTE workers, this implies that a non-offshoring firm employed 28 fewer workers compared with its non-offshoring synthetic comparison unit.

In summary, my results suggest that offshoring can result in relatively large job losses in the home countries. The results of this paper also indicate that these effects might take years to emerge, which could explain why many analysts have failed to find large effects of offshoring. While past developments are no guarantee for the future, rapidly growing offshoring could result in unemployment. The results of this paper conform to the theoretical predictions developed by Grossman and Rossi-Hansberg (2008). A central building block is the assumption of the complementarity of high-skilled workers at home and offshored high-skill work. According to my results, the offshoring of high-skill tasks disproportionately increases the demand for high-skill work and earnings in the offshoring firm, which supports Grossman and Rossi-Hansberg's assumption.

My results also resonate with the findings of management scholars such as Manning (2014). He emphasized that while offshoring gives access to a large skilled workforce at a relatively low cost, offshoring also comes with considerable coordination challenges and necessitates investments in flexible global infrastructures. Consequently, the positive or negative effects of offshoring on firms, as with most other risky investments, are uncertain and usually take years to materialize. Indeed, my results only emerge several years after the offshoring decision.

The final takeaway from this paper is methodological. I show how microsynth, a variation of the synthetic control method, can be successfully applied to a high-dimensional setting with economic microdata and the special considerations that this type of data entails.

References

Abadie, A., "Using synthetic controls: Feasibility, data requirements, and methodological aspects," *Journal of Economic Literature*, 59:2 (2021), 391–425.

Abadie, A., & Gardeazabal, J., "The economic costs of conflict: A case study of the Basque Country," *American Economic Review*, 93:1 (2003), 113–132.

Abadie, A., Diamond, A., & Hainmueller, J., "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program," *Journal of the American Statistical Association*, 105:490 (2010), 493–505.

Amiti, M., & Wei, S. J., "Service offshoring and productivity: Evidence from the US," *World Economy*, 32:2 (2009), 203–220.

Amiti, M., & Wei, S. J., "Does service offshoring lead to job losses? Evidence from the United States" (pp. 227–243), in *International Trade in Services and Intangibles in the Era of Globalization* (University of Chicago Press, 2009).

Athey, S., & Imbens, G. W., "The state of applied econometrics: Causality and policy evaluation," *Journal of Economic Perspectives*, 31:2 (2017), 3–32.

Autor, D. H., Dorn, D., Hanson, G. H., & Song, J., "Trade adjustment: Worker-level evidence," *Quarterly Journal of Economics*, 129:4 (2014), 1799–1860.

Baldwin, R., & Robert-Nicoud, F., "Trade-in-goods and trade-in-tasks: An integrating framework," *Journal of international Economics*, *92*:1 (2014), 51–62.

Baldwin, R., *The Globotics Upheaval: Globalisation, Robotics, and the Future of Work* (Oxford University Press, 2019).

Baldwin, R., & Dingel, J. I., "Telemigration and development: On the offshorability of teleworkable jobs" (pp. 150-179), in *Robots and AI* (Routledge, 2021).

Becker, S. O., Ekholm, K., & Muendler, M. A., "Offshoring and the onshore composition of tasks and skills," *Journal of International Economics*, 90:1 (2013), 91–106.

Berlingieri, G., Ornelas, E., & Marcolin, L., "Service offshoring and export experience," (2021), https://www.freit.org/EIIT/2020/selected/berlingieri.pdf

Blinder, A. S., & Krueger, A. B., "Alternative measures of offshorability: a survey approach," *Journal of Labor Economics*, 31:S1(2013), S97–S128.

Crino, R., "Service offshoring and white-collar employment," *Review of Economic Studies*, 77:2 2010), 595–632.

Dai, S., Kuosmanen, N., Kuusi, T., Kuosmanen, T., Liesiö, J., & Maczulskij, T., "Misallocation of labor and capital in Finland's business sector." (2022) https://julkaisut.valtioneuvosto.fi/handle/10024/164172

Ebenstein, A., Harrison, A., McMillan, M., & Phillips, S., "Estimating the impact of trade and offshoring on American workers using the current population surveys," *Review of Economics and Statistics*, 96:4 (2014), 581–595.

Fornaro, P., Kuosmanen, N., Kuosmanen, T., & Maczulskij, T., "Labor productivity and reallocation in Finland in 2000–2018," (2021) https://julkaisut.valtioneuvosto.fi/handle/10024/163665.

Eurostat, "Collaboration in Research and Methodology for Official Statistics: Project report on Global Value Chains," (2013) https://ec.europa.eu/eurostat/cros/content/global-value-chains_en (accessed 2022-06-14).

Feenstra, R. C., & Hanson, G. H., "The impact of outsourcing and high-technology capital on wages: estimates for the United States, 1979–1990," *Quarterly Journal of Economics*, 114:3 (1999), 907–940.

Goos, M., Manning, A., & Salomons, A., "Explaining job polarization: Routine-biased technological change and offshoring," *American Economic Review*, 104:8 (2014), 2509–2526.

Grossman, G. M., & Rossi-Hansberg, E., "The rise of offshoring: It's not wine for cloth anymore," *Proceedings - Economic Policy Symposium - Jackson Hole*, Federal Reserve Bank of Kansas City, pages 59-102.

Hummels, D., Jørgensen, R., Munch, J., & Xiang, C., "The wage effects of offshoring: Evidence from Danish matched worker-firm data," *American Economic Review*, 104:6 (2014), 1597–1629.

Grossman, G. M., & Rossi-Hansberg, E., "Trading tasks: A simple theory of offshoring," *American Economic Review*, 98:5 (2008), 1978–1997.

Kakkad, J., Palmou, C., Britto, D., & Browne, J., "Anywhere Jobs: Reshaping the Geography of Work. Tony Blair Institute of Global Change" (2021) (https://institute.global/policy/anywhere-jobs-reshaping-geography-work).

Kerr, S., Maczulskij, T., & Maliranta, M., "Within and between firm trends in job polarization: the roles of globalization and technology," *Journal of Economic Geography*, 20:4 (2020), 1003–1039.

Kovak, B. K., Oldenski, L., & Sly, N., "The labor market effects of offshoring by US multinational firms," *Review of Economics and Statistics*, 103:2 (2021), 381–396.

Kässi, O., & Lehdonvirta, V., "Online labour index: Measuring the online gig economy for policy and research," *Technological Forecasting and Social Change*, 137 (2018), 241–248.

Lehdonvirta, V., Kässi, O., Hjorth, I., Barnard, H., & Graham, M., "The global platform economy: A new offshoring institution enabling emerging-economy microproviders," *Journal of Management*, 45:2 (2019), 567–599.

Manning, S., "Mitigate, tolerate or relocate? Offshoring challenges, strategic imperatives and resource constraints," *Journal of World Business*, 49:4 (2014), 522–535.

Olley, G. S., & Pakes, A., "The dynamics of productivity in the telecommunications equipment industry," *Econometrica*, 64:6 (1996), 1263–1297.

Ozimek, A., "Overboard on Offshore Fears," (2019) https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3777307.

Robbins, M. W., Saunders, J., & Kilmer, B., "A framework for synthetic control methods with high-dimensional, micro-level data: Evaluating a neighborhood-specific crime intervention," *Journal of the American Statistical Association*, 112:517 (2017), 109–126.

Robbins, M. W., & Davenport, S., "Microsynth: synthetic control methods for disaggregated and micro-level data," *Journal of Statistical Software*, 97 (2021), 1–31.

Stephany, F., Dunn, M., Sawyer, S., & Lehdonvirta, V. "Distancing bonus or downscaling loss? The changing livelihood of US online workers in times of COVID-19," *Tijdschrift voor economische en sociale geografie*, 111:3 (2020), 561–573.

Syverson, C., "What determines productivity?" *Journal of Economic literature*, 49:2 (2011), 326–365.

Elinkeinoelämän tutkimuslaitos

ETLA Economic Research

ISSN-L 2323-2420
ISSN 2323-2420 (print)
ISSN 2323-2439 (pdf)

Publisher: Taloustieto Oy

Tel. +358-9-609 900
www.etla.fi
firstname.lastname@etla.fi

Arkadiankatu 23 B
FIN-00100 Helsinki