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ABSTRACT

Offshoring and Skill-Biased Technical Change in the Context of US Protectionism*

We discuss the effects of offshoring on the labor market in a matching model with endogenous adjustment of educational skills. We carry out a comparative statics analysis and show that offshoring leads to a restructuring of the economy through skill-biased technical change (SBTC) where overall welfare is improved. In a policy exercise we show that, if offshoring were to be opposed by a protectionist agenda, labor market flexibility can bring about the same welfare gain. In addition, we offer an empirical analysis aimed at verifying the correlation be- tween offshoring and SBTC in US manufacturing industries in recent years. Our results show that different offshoring strategies affect SBTC differently. In particular, the evidence suggests that while high-skill offshoring strategies open the skill gap, low-skill offshoring strategies tend to work in the opposite direction.

JEL Classification: F66, J64, F16, F17

Keywords: offshoring, skills, skill-biased technical change

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1 Introduction

History does not repeat itself but it certainly rhymes. In recent times the US has moved from a currency war under the Obama administration, to a trade war under President Trump's first term in office. Hopefully, this will not evolve into a major military conflict as history has shown many a time through this sequence of related events. Trumponomics, as it came to be known, might as well have been called Reaganomics 2.0. Indeed, lower taxes, together with higher government spending and debt, a dose of deregulation, and a strong push for protectionist trade policies, get as close as possible to the philosophy behind US economics nowadays.

In this paper we set out to analyze the implications of offshoring strategies for the labor market in general, with a particular focus on skill-biased technical change (SBTC hereafter) and the increasing protectionist trend in present-day US policy. With that end in mind, we offer both theoretical and empirical applications concerning US manufacturing industries in the last couple of decades. SBTC can be defined as a shift in the production technology favoring skilled over unskilled labor, thus increasing its relative productivity and relative demand. In the last three decades the wages of high skilled workers have soared significantly relatively to those of unskilled labor, in spite of a major increase in the relative supply of skills.[1]

Estimates of the offshoring effects on SBTC can vary depending on the assumptions and the data, of course. For instance, using US data, Feenstra and Hanson (1996) find that offshoring explains approximately 19–21% of the increase in the nonproduction wage share in the eighties.[2,3] Berman et al. (1994) argue that this last variable is better than the share of nonproduction labor in employment when accounting for SBTC, if one does not want to underrepresent the shift in demand toward skilled labor. Notice that the generalized rise in the relative wages of nonproduction workers might always induce substitution away from this kind of labor.

Slaughter (2000), on the other hand, fails to produce any strong evidence in support of a positive relationship between multinational activities and skill upgrading during the 1977–1994 period. If anything, international activities such as offshoring tend to have small effects on the US relative labor demand, in spite of the increase of such activities in the past 20 years. Head and Ries (2002), in turn, follow up with a similar framework for the Japanese economy, and find significant evidence that vertical specialization by multinationals contributes to skill upgrading.

The previous results are reinforced by Canals (2006), who is able to account for

[1] See, most prominently, Berman et al. (1994, 1998), Acemoglu (2002), or Card and DiNardo (2002).

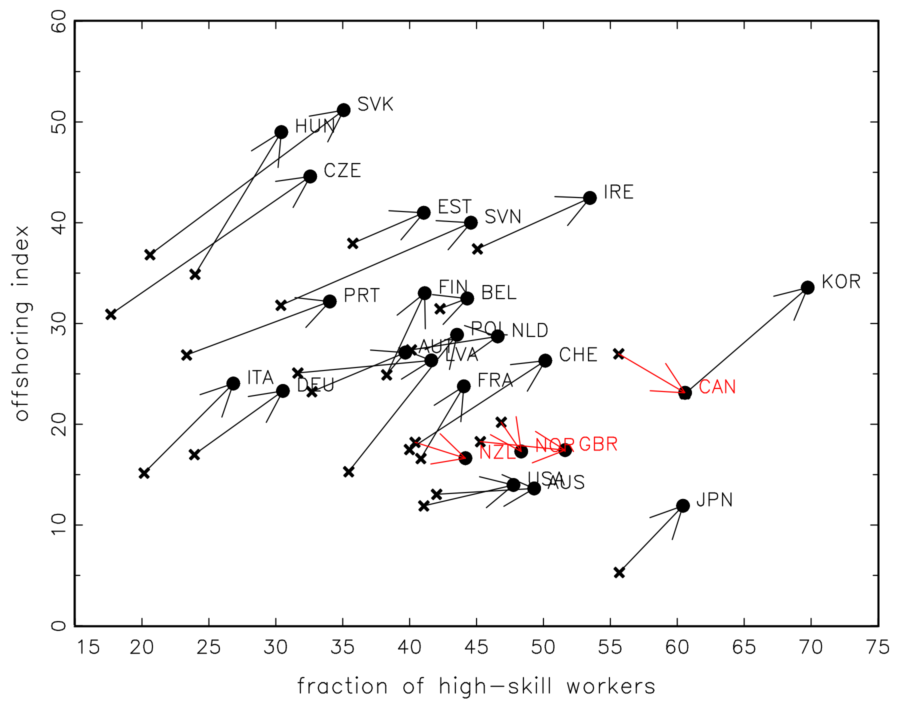
[2] See the errata to their 1996 paper, which revises the original estimated contributions downwards (from 31%).

[3] The change in this variable over the 1979–1990 period was in the order of 39%.

around one tenth of the wage gap as a result of offshoring practices in the US during the eighties and nineties. Alternatively, and more recently, Hummels et al. (2014) find that offshoring in Denmark has considerably different wage effects across educational levels, raising high-skill wages while reducing low-skill ones. Even when SBTC and the wage gap are not exactly the same thing, they bear a strong correlation if SBTC is proxied by the share of the wage bill going to nonproduction (skilled) labor.

For the present paper we use a matching model with endogenous skill requirements where employers create both high and low-skill vacancies and where the distribution of skill requirements across these vacancies is endogenous, as is the schooling decision of workers. The endogenous skill distribution of workers allows us to account for the dynamic reaction of agents to the changes in the economy, thus improving the modelling approach of Albrecht and Vroman (2002) or Agnese and Hromcová (2016), on which we base our present study. To get an idea of the natural adjustment of workers to the offshoring phenomenon and to competition and globalization in general, we present data for a group of highly developed countries.

Figure 1: Offshoring trends (1995–2011) and high-skill shares (2000–2017)

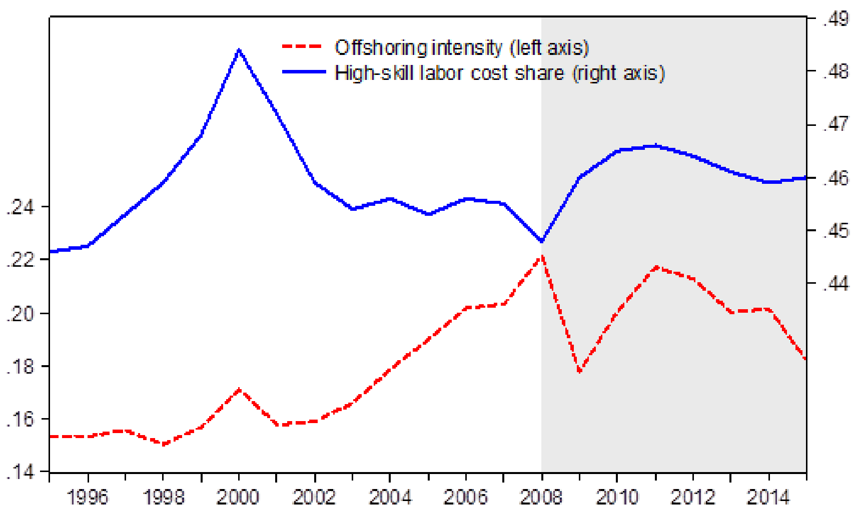


Source for offshoring index (vertical axis) is OECD Input-Output Database (2018), for skill levels (horizontal axis) is OECD Education data. Note: low-skill is below secondary and post-secondary levels and high is tertiary (OECD); moreover, the data point pairs correspond to the education level at t+10 and offshoring index at time t, namely, first point is 2005 edu level and 1995 offsh, last point is 2017 edu level and 2007 offsh. Arrows are created as an OLS regression line over all available points for each country (highskill(t+10),offindex(t)); × is the beginning of the regression line, and ● is the end of the regression line.

In order to produce a measure of offshoring we rely on an intermediate imports index as proposed by Feenstra and Hanson (1996). The rationale is that the higher the volume of intermediate trade the higher the offshoring intensity, as inputs previously produced in the home country are now being imported back from low-wage countries. Figure 1 shows, with a few exceptions, a positive relationship between offshoring and the fraction of high-skill workers in the countries' populations, what is commonly referred to as skill upgrading.[4]

Figure 2 shows the evolution of the variables discussed above for the US manufacturing sector as a whole. SBTC, as proxied by the labor costs of high skilled workers in the total labor cost bill, has lately experienced a slight increase, whereas the intensity of offshoring has been sliding down, maybe as a result of the uncertainty surrounding the last financial crisis. As we will see later, this relapse in the growth of offshoring practices might have prevented a steeper rise in the skill gap and in wage inequality.[5] It is certainly the case that the current protectionist rhetoric is bound to keep offshoring intensity on a downward trend.

Figure 2: Technical change and offshoring, US manufacturing 1995–2015



Source for offshoring measure in US manufacturing are own calculations based on OECD Input-Output Database rev. 3 & 4.; labor costs data are taken from STAN Database rev. 4.

The objective of the paper is to assess the impact of offshoring on the domestic economy and discuss the potential effects of protectionist behavior on the part of the

[4] Offshoring is measured as imported content in exports. We have 28 developed countries: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Japan, Korea, Latvia, Netherlands, Norway, New Zealand, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK and USA. Some are not displayed because of the overlapping arrows (Denmark, Spain, Sweden).

[5] Feenstra and Hanson (1996) proxy SBTC with the nonproduction workers share of the industry wage bill (as do Berman et al., 1994), which they calculate from the NBER database. Their last value for year 1990 stands at around 43 percent whereas our first value for 1995 is close to 44.6 percent.

US government. In particular, we will focus on the unemployment rate, wage inequality, output, and welfare (both overall and by workers' skills). Further, we will evaluate an alternative policy that can lead to the same post-offshoring welfare levels, once we assume that offshoring has been prevented by a protectionist bias in US trade policy, as is currently the case. Finally, we will carry out an empirical analysis aimed at understanding the relationship between SBTC and offshoring—at which point it will be sensible to discuss the different types of offshoring (both high- and low-skill) and how they contribute to SBTC.

Our paper contributes to the previous literature by emphasizing the positive effects of offshoring strategies. In the theoretical part we rely on the previous literature of matching models, as developed by Albrecht and Vroman (2002), Rogerson et al. (2005), and Davidson et al. (2008), while we use a special case of the model developed in a related paper by Hromcová and Agnese (2018). We perform a comparative statics analysis where we discuss the potential labor market effects of offshoring in the context of the US economy. We show that, to some extent, offshoring can lead to a restructuring of the economy through SBTC and that, in spite of increasing wage inequality, overall welfare is improved. We also demonstrate that the same welfare results can be achieved if we allow for a mild increase in labor flexibility. This scenario is suggested as a policy option to compensate for the recent US protectionist trend, yet the truth be told, it still exhibits lower productivity and lower total output, even when relative wages and employment outcomes might seem more attractive from the policy-making perspective.

We also undertake a short empirical analysis of the US manufacturing industries in recent years (1995-2015) by drawing mainly on the pioneering works by Feenstra and Hanson (1996, 1999). Here we aim at assessing the contribution of offshoring strategies, both of high and low-skill activities, to SBTC in the years after the last global crisis. Our estimations show that offshoring is truly a complex phenomenon and, as such, must account for the distinctive effects of high- and low-skill activities separately, as their effects go in opposite directions. The evidence suggests that high-skill offshoring opens the skill gap while low-skill offshoring closes it, and that the pull of high-skill offshoring is stronger—these joint effects resulted in the reduction of the skill gap in recent years as both offshoring measures have experienced a downward trend.

The remainder of the paper is organized as follows. The model and its main properties are briefly discussed in section 2. A short comment on the calibration is found under section 3. The comparative statics analysis is discussed at length in section 4, where we not only go over the labor market effects of offshoring, but we also suggest a policy alternative to offset the negative effects of the recent protectionist drift in US policy. Section 5 offers our empirical analysis and delves into the relationship between SBTC and high- and low-skill offshoring. Final remarks are summarized in section 6.

2 Model

We use an extended version of the model in Albrecht and Vroman (2002), which we developed in Hromcová and Agnese (2018), and that we adapt here for the case of offshoring and policy making. For our present analysis we focus on one of the two possible equilibria discussed at length in the previous references. The main features of the model are outlined in the next paragraphs while additional details can be found in the appendix.

We consider two types of agents, workers, and firms.[6] Workers are infinitely lived and of measure one, and are characterized by their position in the distribution of the cost of skills acquisition function. Besides, each worker is indexed by $x \, \epsilon \, [0, 1]$, his opportunity cost of remaining low-skill, and those who acquire skills have, potentially, higher productivity levels than those who do not. The cost of acquiring skills is described by a monotonic function, cost(x), which satisfies

$$\frac{d\text{cost}(x)}{dx} < 0 \text{ and } \text{cost}(1) = 0.$$

The worker whose opportunity cost of remaining low-skill is the highest, the one indexed by $x = 1$, becomes high-skill at zero cost, whereas the cost for the worker with $x = 0$ is the largest.

Workers are assumed to be risk neutral and thus they maximize their expected discounted income, wages, or unemployment benefits, at a positive rate r. Consumption is equal to the expected income in each period, so saving is not possible. After the skill decision is made, a fraction q of workers remains low-skill, L, and the others become high-skill, H. Such a decision is a one-time action submitted at the start of the model.

On the firm's side, there is free entry and each firm employs one worker when active. A vacancy can be opened at an exogenous cost c, which includes the hiring costs, but also the firing costs that firms will potentially face in the future. Firms place vacancies of both skill types, producing a fraction ϕ of low-skill vacancies and a fraction $1 - \phi$ of high-skill vacancies, and such a distribution is endogenous. Further, if a firm hires a worker to occupy a low-skill vacancy the level of output is y_L, and if it hires a worker to fill a high-skill vacancy then the level of output is y_H. As a result, high-skill firms are more productive than their low-skill counterparts, thus $y_H > y_L$. Finally, all firms maximize their discounted profits at a positive rate r.

As in Albrecht and Vroman (2002), high-skill workers are allowed to take both types of jobs but low-skill workers can only fill a vacancy that matches their skills. Given that the decision of skill acquisition is endogenous and that the purpose of education is

[6] A description of how the model works for one type of worker can be found in Rogerson et al. (2005) and Williamson (2010).

to increase one's status, the equilibrium where high-skill workers accept low-skill jobs ceases to exists once SBTC starts to play out. Therefore, in our analysis below we will deal solely with the case where high-skill workers can only land a job in high-skill firms.[7]

If a worker is employed, he gets a wage corresponding to the type of vacancy and the type of skills he has. A worker of type L (H) working in a job of type L (H) will get a wage w_L (w_H), where $w_H > w_L$. If a worker is unemployed he is entitled to an exogenously given unemployment benefit b, and any worker can refuse the job if his reservation wage is not met. Moreover, jobs are lost at an exogenous rate δ.

Firms and workers meet according to a matching technology $M(u, v)$ where u represents unemployed workers (unemployment rate) and v vacancies. In this process an endogenously determined fraction γ of unemployed workers will be low skilled. In addition, arrival of jobs to workers happens at a rate $\frac{M(u,v)}{u}$ and arrival of workers to employers at a rate $\frac{M(u,v)}{v}$. If we define market tightness as $\theta = \frac{v}{u}$, we can rewrite the job arrival rate to workers as $m(1, \frac{v}{u}) = m(\theta)$ and the workers' arrival rate to firms as $\frac{\frac{M(u,v)}{u}}{\frac{v}{u}} = \frac{m(\theta)}{\theta} = z(\theta)$.

If the match succeeds, the employed worker's expected utility is W_L or W_H, and the active firm's expected profits are J_L or J_H. The utility of the worker comes from earning the wage w_L when low skilled, and the wage w_H when high skilled. The firm's profits stem from the difference between production and incurred costs, to wit, wages and search, or $y_i - w_i - c$, and $i = L, H$.

As in Okazawa (2013), the skill choice of workers depends on the comparison between its cost and the wage differential between low and high-skill workers. The worker whose cost of skill acquisition is $\text{cost}(x)$ chooses to be high-skill if the wage gap is higher than the cost, i.e.

$$w_H - w_L > \text{cost}(x), \tag{1}$$

the worker on the threshold will be indifferent to remain low skilled or to become high skilled

$$w_H - w_L = \text{cost}(x^*). \tag{2}$$

Therefore, all workers with $0 < x < x^*$ will be low skilled and the ones with $x^* \leq x < 1$ will become high skilled. This implies that the fraction of the labor force that remains

[7] Albrecht and Vroman (2002), Agnese and Hromcová (2016), and Hromcová and Agnese (2018), analyze the cases where high-skill workers accept low-skill jobs. In these papers, two types of equilibria are considered: the equilibrium with cross-skill matching (CSM) and the equilibrium with ex post segmentation (EPS). CSM is reached when high-skill workers and low-skill vacancies are matched, whereas EPS kicks in when these potential matches do not meet. Both equilibria, CSM and EPS, can potentially coexist. Due to the characteristics of our study, we focus on the EPS equilibrium only, and the description of the economy is in line with this premise.

low skilled, q, will be determined by the threshold value x^*, i.e.

$$q = x^*. \tag{3}$$

Both workers and firms take into account that the match can be broken with probability δ. If the match does not succeed, an unemployed worker's expected utility is U_L or U_H, and the expected profits of a vacant firm are V_i, $i = L$ or H. In this case, a worker's utility comes from earning the unemployment benefits b, whereas the firm's (negative) profits come from financing a vacancy, $-c$ (hiring and firing costs mainly). A new match between workers and firms can occur with probabilities that depend on the matching process.

There is something to bargain over if the value of working is higher than the value of unemployment, $W_H > U_H$ and $W_L > U_L$, and when the value of the job is higher than the value of the vacancy, $J_H > V_H$ and $J_L > V_L$. Wages are set to maximize the weighted surplus of workers and firms in a Nash bargaining process

$$\max_{\{w_i\}} \left[W_i(w_i) - U_i\right]^{\beta} \left[J_i(y_i - w_i - c) - V_i\right]^{1-\beta}, \; i = L, H \tag{4}$$

where the weighting parameter β represents the bargaining power of workers.

Moreover, workers may experience spells of employment and unemployment. In each period, a number of low- and high-skill workers are employed, that is E_L and E_H, respectively. When the flow of workers into and out of each employment state coincide, the steady-state equilibrium is achieved. Last, utility and profit maximization problems are characterized by Bellman equations. Appendix A goes briefly over the equilibrium conditions, Bellman equations, and expressions for the unemployment rates and output.

Our main concerns in the present paper have to do with SBTC and welfare. We define the former as the labor costs of high-skill workers in the total labor cost bill, S_H,

$$S_H = \frac{E_H w_H}{E_H w_H + E_L w_L}. \tag{5}$$

Total welfare depends on the skill distribution, the number of employed individuals, the values of work and unemployment, and the initial welfare cost incurred by workers acquiring higher skills. Welfare of the average low- and high-skill workers, Ω_L and $\overline{\Omega_H}$, are defined as follows

$$\begin{aligned} \Omega_L &= \frac{E_L W_L + (q - E_L) U_L}{q}, \text{ and} \\ \overline{\Omega_H} &= \frac{E_H \left[W_H - \overline{\text{cost}(x)}\right] + (1 - q - E_H)\left[U_H - \overline{\text{cost}(x)}\right]}{1 - q} \end{aligned}$$

where

$$\overline{\text{cost}(x)} = \frac{1}{1-x^*}\int_{x^*}^{1} \text{cost}(x)dx.$$

Overall welfare, Ω, is the weighted sum of the other two,

$$\Omega = q\Omega_L + (1-q)\,\overline{\Omega_H}.$$

3 Calibration

We calibrate the model to fit US yearly data during 1995–2015. In the given period, jobs last on average approximately 5 years, implying that the rate at which the employment relationship is broken is $\delta = 0.2$. Agents discount the future at a constant rate, which we set at $r = 0.05$. The bargaining power of workers is set to be the same as that of the firms, $\beta = 0.5$, as is usually suggested in the literature. We assume that the matching function has a Cobb-Douglas form as in Albrecht and Vroman (2002), thus

$$M(u,v) = 2\sqrt{uv}.$$

Further, in the baseline case the value of the output in a low-skill firm is set to $y_L = 1$, and the output produced in a high-skill firm is assumed to be $y_H = 1.2$. Under such parameters, unemployment benefits amount to about 40% of previously perceived wages, or $b = 0.4$. Moreover, the cost of opening a vacancy is set to $c = 0.05$, which amounts to approximately 7% of total output. This leads to an unemployment rate of around 5–6%—roughly the US average in our period of analysis.

We take the quadratic shape of the cost of acquiring skills function,

$$\text{cost}(x) = \lambda\,(1-x)^2\,.$$

The value of the parameter λ is such that, in the initial equilibrium, 65% of the labor force is low skilled and 35% is high skilled, so $\lambda = 1.5$. This skill distribution corresponds to the one found in the initial year of our period under examination.

4 Comparative statics

Offshoring can be seen as a source of skill-biased technical change (Feenstra and Hanson, 1996, 1999; Head and Ries, 2002). In the context of our analysis, this is modeled as a change in the productivity gap that is consistent with a change in the labor costs of high-skill workers in the total labor cost bill, S_H, as defined above. We calibrate our model for a range of sensible values of the productivity gap and then proceed to discuss the general effects of offshoring.

4.1 The effects of offshoring

To study the effects of offshoring we allow for a sequence of changes in the productivity gap that result in changes in the nonproduction wage share—S_H in (5)—that are consistent with the SBTC hypothesis. As discussed in the introduction, the resulting change in the nonproduction wage share during the eighties was found to be within the 19–21% interval (see Feenstra and Hanson, 1996, and errata, 1996).[8] We take this estimate as a reference for our numerical exercise below.

In our model, (exogenous) changes in the productivity gap will induce a corresponding reaction in wages. As implied by (2) and (3) above, a higher wage gap will subsequently prompt more workers to acquire new skills, resulting in a lower q share. Depending on the direction of the changes in the productivities of high- and low-skill workers we will be faced with different possibilities.

We propose three scenarios, namely, #1 offshoring raises y_H and lowers y_L, #2 offshoring raises both y_H and y_L, but raises y_H more, and #3 offshoring raises both y_H and y_L, but raises y_L more.[9] At any rate, cases #1 and #2 implicitly assume that offshoring has a bias for high skilled workers (e.g. high-skill offshoring). The reason we offer three distinctive scenarios stems from the somewhat heterogeneous evidence the literature has been able to produce so far, and the apparent lack of a clear pattern as to how offshoring affects productivity levels (see the OECD review by Olsen, 2006). Suffice to say that much depends on both sector and firm-specific characteristics.

Table 1 departs from a 20% productivity gap baseline (first row) and moves away from there in all three scenarios. We believe this is a large enough change to see how the model works, while keeping in mind that, according to Feenstra's and Hanson's estimations, the real impact of offshoring upon SBTC will be roughly one fifth of its change. For our comparative statics analysis, scenarios #1 and #2 (high-skill bias) generate the same changes in S_H once we open the productivity gap.[10]

Under offshoring #1 we observe a mild increase of the unemployment rate which is the result of two significant changes—a stark rise of low-skill unemployment and a noticeable drop of high-skill unemployment. In terms of relative wages and welfare the results show the same pattern. Overall, for our parameters and assumptions we see a substantial sectoral reshuffling within the economy, although we must not forget that

[8] Feenstra and Hanson (1999) find a slightly lower effect as they work with other variables in their specifications—offshoring explains a 15% increase in the relative wage of nonproduction workers while expenditures in high-technology capital such as computers, for example, can explain as much as 35%.

[9] This third possibility, even when incompatible with the SBTC hypothesis, will still be of interest as we will show in a later section.

[10] Consecutive expansions of the productivity gap yield additional 20% changes in S_H.

only a fraction of it is due to offshoring.

Under offshoring #2 we get a significant drop of the unemployment rate, mainly driven by a salient drop in high-skill unemployment which more than compensates the soft increase of low-skill unemployment. Restructuring is far less disturbing now as the welfare of both low- and high-skill workers show an upward trend. Beyond the similarities in S_H, q, and ϕ, the differences between #1 and #2 stem from the fact that, for the latter, a vacancy is relatively cheaper for both types of firms (thus higher profits are expected), the market is tighter, and conditions in general are better for all workers.

Finally, under offshoring #3, we see that unemployment, both total and by skills, remains barely unchanged, yet the opportunity cost in terms of welfare is noteworthy. This result is clearly not consistent with the SBTC hypothesis, as low skilled workers are relatively better off, and can only be thought of if productivity-improving shocks have a bias in favor of that kind of workers. In this context, and for this particular case, we can assume that offshoring has a bias for low skilled workers (e.g. low-skill offshoring), so offshoring strategies will eventually have a positive productivity effect on them.[11]

Our results above suggest a kind of policy governments should strive for, if they want to help the economy toward a more advisable outcome. Indeed, productivity and offshoring-enhancing measures are welcome even when they lead to SBTC, but especially when productivity levels of both high and low-skill workers are improved. Notice that the SBTC hypothesis holds under scenarios #1 and #2, although it is only under #2 that productivity goes up for all skills and should therefore be preferred. In fact, the empirical evidence presented in a later section seems to point to the fact that this scenario is the likeliest when allowing for both high and low-skill offshoring, implying the stronger positive effects of the former. In other words, offshoring tends to improve the productivity levels of those involved and, thus, to change the "skill gap" accordingly—that is to say, high- (low-)skill offshoring tends to raise the productivity of high (low) skilled workers.

The next section offers a short counterfactual exercise based on our comparative statics exercise for the US in Table 1, but mainly focusing on scenario #2. In other words, if such scenario is the most advisable but an anti-offshoring agenda prevails, then we might as well wonder what other mechanism policy makers can rely on to obtain, approximately, the same welfare result.

[11] For our empirical analysis below, we will distinguish between high and low-skill offshoring in a more explicit way.

Table 1: Effects of offshoring under different scenarios

							unemployment (u)			wages (w)			welfare (Ω)		
	y_L	y_H	S_H	q	ϕ	Y	u	u_L	u_H	w_L	w_H	$\frac{w_H}{w_L}$	Ω	Ω_L	$\overline{\Omega_H}$
Baseline	1.00	1.20	0.385	0.65	0.55	1.009	0.056	0.053	0.063	0.916	1.096	1.196	18.90	17.78	20.99
Offshoring #1	0.97	1.23	0.462	0.60	0.50	1.013	0.057	0.057	0.057	0.886	1.129	1.274	18.97	17.15	21.66
(high-skill bias)	0.93	1.27	0.551	0.53	0.44	1.026	0.058	0.064	0.052	0.845	1.171	1.386	19.21	16.33	22.51
	0.87	1.33	0.662	0.45	0.37	1.058	0.059	0.076	0.046	0.784	1.233	1.571	19.82	15.11	23.73
	0.78	1.42	0.789	0.35	0.28	1.130	0.061	0.100	0.040	0.694	1.324	1.907	21.21	13.30	25.52
Offshoring #2	1.02	1.28	0.462	0.60	0.50	1.065	0.055	0.055	0.055	0.934	1.180	1.264	19.94	18.09	22.66
(high-skill bias)	1.04	1.39	0.551	0.53	0.45	1.142	0.053	0.058	0.048	0.951	1.286	1.353	21.40	18.38	24.77
	1.06	1.54	0.662	0.44	0.39	1.266	0.050	0.063	0.041	0.966	1.440	1.490	23.77	18.61	27.79
	1.08	1.77	0.789	0.32	0.31	1.483	0.046	0.072	0.033	0.978	1.668	1.704	27.92	18.73	32.29
Offshoring #3	1.02	1.21	0.371	0.66	0.56	1.023	0.055	0.051	0.063	0.936	1.105	1.181	19.17	18.17	21.15
(low-skill bias)	1.04	1.22	0.356	0.67	0.57	1.038	0.054	0.050	0.064	0.956	1.114	1.165	19.46	18.56	21.31
	1.06	1.23	0.340	0.69	0.58	1.053	0.053	0.048	0.065	0.976	1.123	1.151	19.74	18.96	21.47
	1.08	1.24	0.324	0.70	0.59	1.068	0.053	0.047	0.065	0.995	1.131	1.136	20.03	19.35	21.62
	1.10	1.25	0.308	0.71	0.60	1.084	0.052	0.046	0.066	1.015	1.140	1.122	20.33	19.74	21.77

Notes: Offshoring with high skill bias(#1, #2) is an expansion in the $y_H - y_L$ gap consistent with the same change in S_H, the nonproduction wage share; q is the share of low-skill workers, ϕ is the share of low-skill vacancies, u is the unemployment rate, Y is output, w are wages, Ω is total welfare, Ω_L $(\overline{\Omega_H})$ is average welfare of low- (high-) skill workers.

4.2 Offshoring, welfare, and labor flexibility

Welfare and inequality concerns over the offshoring phenomenon are not new to the literature, although the relation to labor markets and their resilience is less evident.[12] We turn now to a policy experiment that, in our view, could potentially achieve the welfare results under the best offshoring scenario, that is, offshoring #2 in Table 1, but now assuming that offshoring strategies can be hindered by protectionism.

In the light of the recent US protectionist policy agenda and its trade war with China, we believe it would be sensible for the US to pursue a harmonizing policy which is at the same time both achievable and not very disagreeable with the population at large. As we have shown in another place (Agnese and Hromcová, 2016), increased labor market flexibility can significantly help in achieving this result (see also Jung and Mercenier, 2014).

What can be done to achieve the same improvement in welfare levels that stem from offshoring–induced productivity-related shocks?[13] To answer this question we calibrate the model for different levels of the exogenous cost c, which we have assumed to include all costs involved in opening a vacancy, as well as firing costs. We will aim at the same welfare level as in the previous exercise, using total welfare Ω for case #1 and low-skill welfare Ω_L for case #2. The reason we rule out Ω_L under #1 is that, for that particular scenario, such parameter goes down with offshoring.

Table 2 reports our findings on cases #1 and #2 only, as these are the most likely to occur. We contend that, for case #1, it would only take a minor reduction of what we refer to as vacancy costs (e.g. firing and hiring costs) to take the economy to the same welfare level as before. Allowing for a meager rollback of around 5% is shown to be enough as well as politically feasible. However, for case #2, in order to achieve the same welfare for low-skill workers it will be necessary to go for a major cut of 20%—which is perhaps not completely enticing politically, especially when the US labor market is among the most flexible already.

Bear in mind that, in both counterfactual exercises, increased flexibility can restore welfare but at the expense of productivity and output growth, even when wage inequality is reduced. Also, let it not be forgotten that, as in the previous exercise, offshoring is but a fraction of SBTC.

[12] See, among others, Ebenstein et al. (2014), Görg and Görlich (2015), Hummels et al. (2013), and the earlier contributions by Feenstra and Hanson (1996, 1999).

[13] Again, as in the exercise above, we must keep in mind that only a fraction of it is due to offshoring activities.

Table 2: Offshoring, welfare, and labor flexibility

							unemployment (u)			wages (w)			welfare (Ω)		
	y_L	y_H	S_H	q	ϕ	Y	u	u_L	u_H	w_L	w_H	$\frac{w_H}{w_L}$	Ω	Ω_L	$\overline{\Omega_H}$
Baseline	1.00	1.20	0.385	0.65	0.55	1.009	0.056	0.053	0.063	0.916	1.096	1.196	18.90	17.78	20.99
Offshoring #1	0.97	1.23	0.462	0.60	0.50	1.013	0.057	0.057	0.057	0.886	1.129	1.274	**18.97**	17.15	21.66
Flexibility instead of offshoring															
$c_{\downarrow}^{5\%}$	1.00	1.20	0.386	0.65	0.55	1.010	0.055	0.051	0.061	0.919	1.099	1.196	**18.97**	17.85	21.07
Offshoring #2	1.02	1.28	0.462	0.60	0.50	1.065	0.055	0.055	0.055	0.934	1.180	1.264	19.94	**18.09**	22.66
Flexibility instead of offshoring															
$c_{\downarrow}^{20\%}$	1.00	1.20	0.387	0.65	0.55	1.016	0.050	0.047	0.055	0.929	1.111	1.196	19.24	**18.09**	21.38

Notes: See note under previous table; c stands for exogenous cost of opening a vacancy (hiring and firing costs).

5 Empirical analysis

5.1 Estimation

We now intend to provide empirical evidence on the effect of offshoring on SBTC within the US manufacturing sector, as was assumed by our model above. In particular, we analyze the change in the high-skill labor costs share resulting from the change in offshoring-related activities. For that, we estimate a reduced-form equation as in Feenstra and Hanson (1996, 1999) and Head and Ries (2002) with the high-skill labor costs share as dependent variable and offshoring intensity, among others, as explanatory variables—our offshoring measure is calculated from Input-Output tables.[14]

In order to produce a measure of offshoring we rely on an intermediate imports index as first proposed by Feenstra and Hanson (1996). As stated in the introduction, the rationale is that the higher the volume of imported inputs the higher the offshoring intensity, as these inputs are now being imported from subsidiaries in low-wage countries. We use a narrow version of the measure, which means that imported inputs come from the same industry abroad. We believe this makes more sense when working with aggregated data as we do.

The idea behind this simple exercise is to determine the qualitative and quantitative effect of both high and low-skill offshoring on SBTC in recent years. We do this by estimating a share equation, as typically done in the literature, and by running a set of counterfactuals. Following Head and Ries (2002) we estimate the share of high-skill costs in total variable costs as a linear function of the logs of input prices and quasi-fixed factors. As in there, we do not include wages as regressors as we assume that there is no exogenous variation across industries, and we also expand the estimable equation by our high- and low-skill offshoring measures.

We thus run a time-series regression for the US manufacturing sector in a single reduced-form equation, namely:

$$S_{H_t} = f \begin{pmatrix} off_t^H & off_t^L & Y_t & K_t/Y_t \\ + & - & + & + \end{pmatrix}$$

where we expect a positive (negative) effect of high- (low-)skill offshoring, and also a positive effect from the scale and capital intensity coefficients.[15] SBTC is proxied in two ways: high-skill labor costs (total compensation of employees), S_H^L, and high-skill

[14] Appendix B shows the definitions of the variables along with their sources, and Appendix C goes over the classification of manufacturing industries based on their R&D intensities—this classification is then employed to distinguish between high and low-skill offshoring measures.

[15] According to Agnese (2012), different types of offshoring can affect occupations differently; meaning that relocated activities tend to show a positive synergy with other related activities that stay behind, thus giving place to skill upgrading in the relocating firms.

wages and salaries, $S^w_{H_t}$, both as shares of the total.

Table 3 shows the results of the estimation under OLS and IV and for both the alternative dependent variables. Our estimations show the expected signs for high-skill (+) and low-skill (-) offshoring on SBTC. However, both coefficients turn out significant for the OLS estimations alone. Figure 5 shows how our single-equation estimation under model (i) tracks SBTC during 1996–2015—model (i) seems to offer the best results in terms of goodness of fit and significance of the coefficients.[16]

Table 3: SBTC regressions, US manufacturing 1996–2015

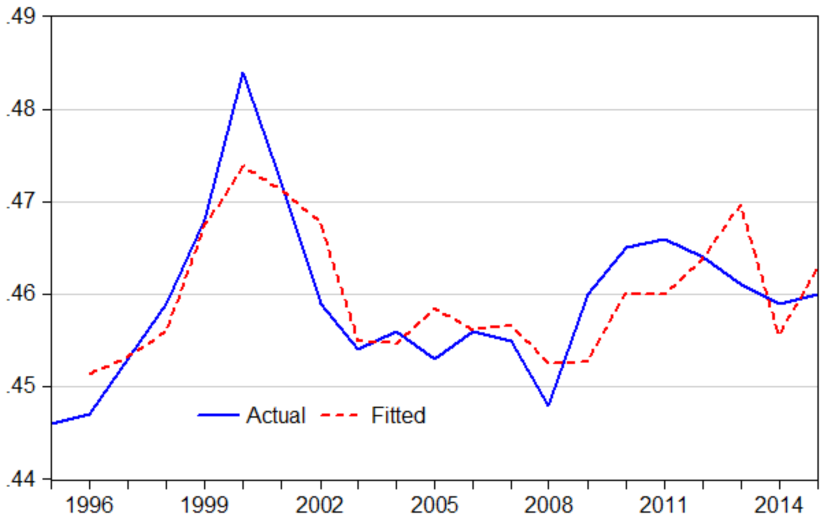
Method	(i) OLS	(ii) IV	(iii) OLS	(iv) IV
Dep. variable	$S^L_{H_t}$	$S^L_{H_t}$	$S^w_{H_t}$	$S^w_{H_t}$
cnt	-0.023 [0.821]	0.021 [0.903]	0.017 [0.894]	0.020 [0.926]
Dep. variable$_{t-1}$	0.609 [0.002]	0.516 [0.027]	0.524 [0.027]	0.494 [0.097]
off^H_{t-1}	1.267 [0.016]	1.207 [0.132]	1.125 [0.058]	1.191 [0.224]
off^L_{t-1}	-0.773 [0.025]	-0.734 [0.147]	-0.637 [0.101]	-0.679 [0.283]
K_t/Y_t	0.105 [0.034]	0.115 [0.076]	0.119 [0.052]	0.125 [0.080]
ΔY_t	0.221 [0.017]	0.213 [0.098]	0.218 [0.036]	0.226 [0.120]
$\overline{r}^2$	0.529	0.483	0.391	0.389
$F-stat$	[0.006]	[0.115]	[0.047]	[0.190]
$J-stat$		[0.977]		[0.757]

Note: p-values in brackets; offshoring regressors not in logs, so coefficients are semi-elasticities.

We now turn our attention to our set of counterfactuals, aimed at throwing more light on the recent contribution of offshoring strategies to SBTC in US manufacturing industries.

[16] We have worked with the deflators of value added and input prices as instruments, as well as their lags. Further, notice that the first lag of the endogenous variable is highly significant in all specifications and that the value added variable only enters in differences; in addition, the offshoring regressors only enter with one lag. Appendix D exhibits the partial regression plots (leverage plots) of the regressors in specification (i)—these plots simply turn a multivariate regression into a collection of univariate regressions involving the residuals of alternative regressions, with the goal to highlight the direction of the correlation between the variables.

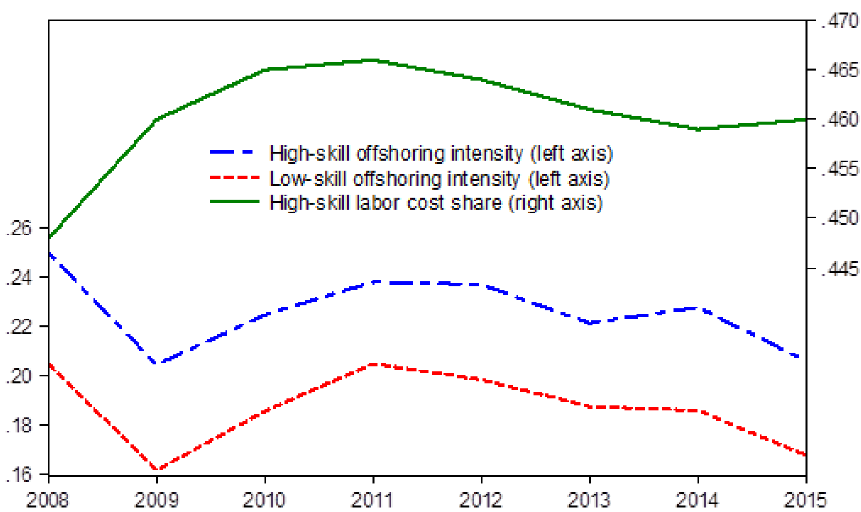
Figure 5: SBTC, actual and fitted values



5.2 Counterfactuals

Figure 6 shows our main variables and their paths in our simulation period. This after-crisis period goes from 2008 to the end of the sample, and right at the start in 2008 shows a low value of the SBTC variable which coincides with a peak in both the high and low-skill offshoring indices. We use the estimated model above to calculate the contribution of the offshoring intensities to SBTC in 2008–2015. With that purpose in mind, we fix the offshoring variables, one at a time, to the simulation's starting year, and then solve the model accordingly. Once we do this we are able to recover the simulated trajectory of the high-skill labor cost share (e.g. SBTC) and, hence, determine the contribution of the exogenous variable to the change in the endogenous one.

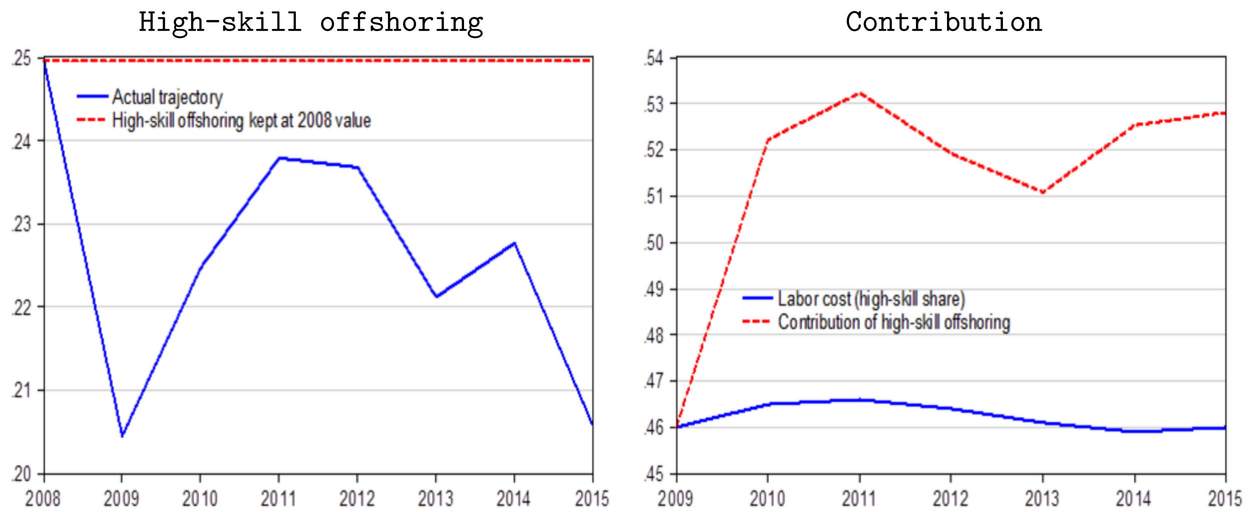
Figure 6: SBTC and offshoring intensities, 2008–2015



5.2.1 High-skill offshoring

Figure 7 on the left shows the high-skill offshoring intensity index fixed to its 2008 value along with its actual trajectory, while the figure on the right shows the contribution of such a variable to the change in the SBTC variable after solving the single-equation model. As shown there, the actual fall in the high-skill offshoring index has contributed to a reduction of the high-skill labor cost share of approximately 7 percentage points, which is a nontrivial figure. Unlike a comparative statics exercise our simulation here takes account of the dynamics occurring within the subsample 2008–2015, and therefore the final effect on SBTC is the result of this summation of effects.

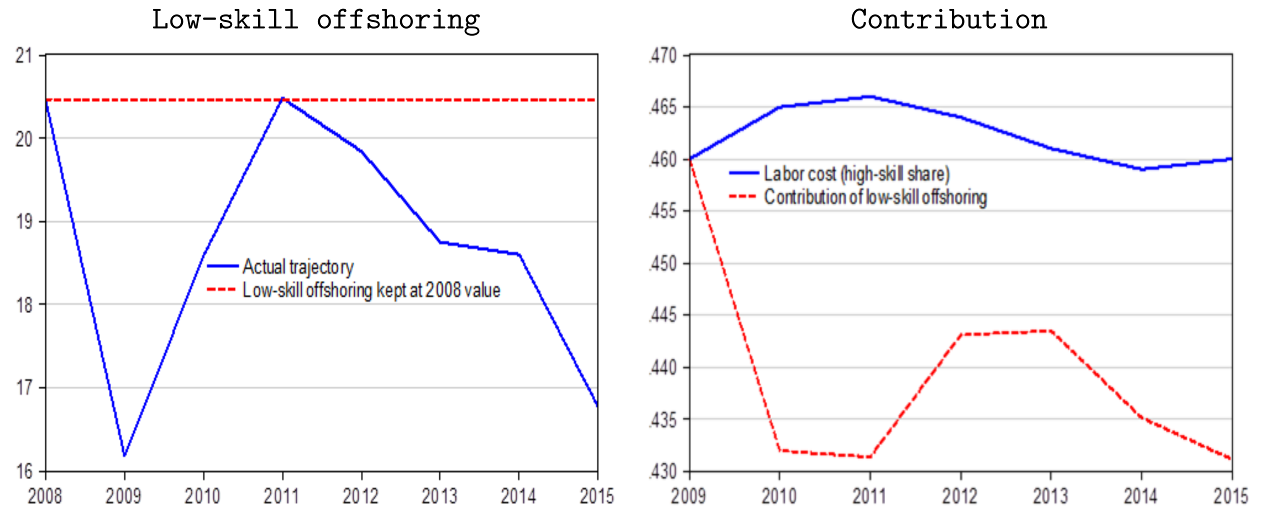
Figure 7: High-skill offshoring and contribution to SBTC



5.2.2 Low-skill offshoring

Figure 8 on the left shows, in turn, the low-skill offshoring intensity index fixed to its 2008 value with its actual trajectory, and to the right the contribution to the SBTC when solving the model. The actual fall in the low-skill offshoring index has contributed to an increase of the high-skill labor cost share of approximately 3 percentage points. Again, as before, this dynamic simulation accounts for the dynamics taking place during 2008–2015.

Figure 8: Low-skill offshoring and contribution to SBTC



5.2.3 Joint contribution and summary of results

Figure 9 shows the joint contribution of both types of offshoring on SBTC. Overall, high-skill offshoring is driving the SBTC in the US in recent years—in particular, the effect of a drop in both offshoring variables has led to a net drop of around 4 percentage points.

Table 4 summarizes our counterfactual exercise. The first two columns show the values of the offshoring measures in 2008 and 2015, which correspond to the starting and final values of the simulation period. The next columns exhibit, respectively, the change, in percentage points (p.p.), in offshoring intensity for that period, the simulated contribution in terms of the SBTC, as drawn from our previous analysis, and the estimated contribution per 1 p.p., which is simply the ratio between the previous two.

A little caveat is in order. The signs under the column referring to the contribution to SBTC, should be understood as how SBTC would have changed under the hypothesized path of the exogenous offshoring variables—see the gaps at the end of the simulations on Figures 7, 8, and 9, under contribution. Notice that, for instance, the contribution of high-skill offshoring to SBTC in Figure 7 is approximately +7 p.p., meaning that, had this measure remained at its 2008 value, then the high-skill cost share would have been 7 p.p. higher than what it actually was. The same applies to low-skill offshoring but in the opposite direction. In reality, though, both offshoring measures went down, which implies that, curiously enough, their impact on SBTC took an unexpected turn.

All in all, SBTC has been very sensitive to the changes in offshoring in the years after the crisis, especially concerning high-skill offshoring, which roughly doubles the contribution of low-skill offshoring. Respectively, their estimated contributions per

1 p.p. during 2008–2015 were -1.59 and +0.81, and the joint contribution is equal to -0.78 p.p. per 1 p.p.

Figure 9: Offshoring and joint contribution to SBTC

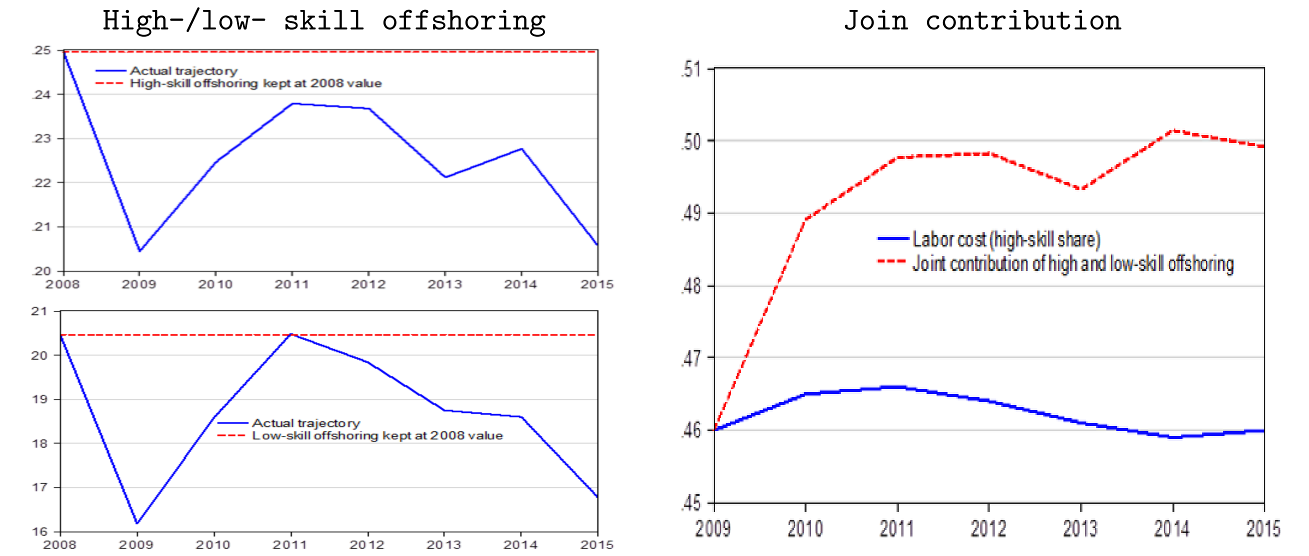


Table 4: Offshoring contribution to SBTC, summary

	2008	2015	Δoff^{*}	Sim. cont. to SBTC**	Est. cont. per 1 p.p.
off^{H}	24.96	20.57	-4.39	$\simeq$ 7	-1.59
off^{L}	20.46	16.77	-3.69	$\simeq$ -3	0.81
total				$\simeq$ 4	-0.78

Note: *in percentage points, **actual minus simulated, in p.p. (see Figs. 7, 8, 9).

6 Final remarks

We have used a matching model to carry out a comparative statics analysis of the effects of offshoring on labor market outcomes while allowing for an endogenous adjustment of skills. We have shown that, to some degree, offshoring can help in the direction of a restructuring of the economy through SBTC and that, in the end, overall welfare is improved. If, however, offshoring practices were to be blocked by a protectionist agenda, as is the trend in US trade policy nowadays, we argue that the resulting welfare losses could be offset by increased labor flexibility.

We have also produced empirical evidence that is consistent with the idea that offshoring is a major driver behind SBTC, as also shown by previous literature. By analyzing the effects of high- and low-skill activities separately, we are able to produce new evidence which lends force to the idea that offshoring is such a complex phenomenon. These results suggest that high-skill offshoring opens the skill gap and low-skill offshoring closes it, and this is consistent with the fact that offshoring tends to increase the productivity of the workers and activities most at hand; in other words, high- (low-)skill offshoring raises the relative productivity of high- (low-)skill activities and workers.

The data clearly show that, in recent years, and possibly because of the global crisis, both types of offshoring have been on the decline. Given that high-skill offshoring in particular has a stronger pull, the overall effect on SBTC has been that of a reduction in the skill gap. In the current context of protectionist US policy and the trade war with China, the welfare losses may be exacerbated if offshoring practices and trade in general are hampered, as we believe they will be. Our word of advice would be that, if such a trend is politically unavoidable, perhaps some attention should be paid to other harmonizing policies such as increased labor flexibility, that might compensate for the welfare loss.

References

[1] Acemoglu, Daron, 2002. Technical Change, Inequality, and the Labor Market, *Journal of Economic Literature* 40, 7–72.

[2] Agnese, Pablo, 2012. Employment effects of offshoring across sectors and occupations in Japan, *Asian Economic Journal* 26, 289–311.

[3] Agnese, Pablo and Hromcová, Jana, 2016. Low-skill Offshoring and Welfare Compensation Policies, *Economic Modelling* 52, 408–426.

[4] Albrecht, James and Vroman, Susan, 2002. A Matching Model with Endogenous Skill Requirements, *International Economic Review* 43, 283–305.

[5] Berman, Eli, Bound, John, and Griliches, Zvi, 1994. Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufacturers, *Quarterly Journal of Economics* 109, 367–397.

[6] Berman, Eli, Bound, John, and Machin, Stephen, 1998. Implications of Skill-Biased Technological Change: International Evidence, *Quarterly Journal of Economics* 113, 1245–1279.

[7] Canals, Claudia, 2006. What Explains the Widening Wage Gap? Outsourcing vs. Technology. *La Caixa Working Paper Series* 01/2006.

[8] Card, David, and DiNardo, John, 2002. Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles, *Journal of Labor Economics* 20, 733–783.

[9] Davidson, Carl, Matusz, J. Steven, and Shevchenko, Andrei, 2008. Outsourcing Peter to pay Paul: High-skill Expectations and Low-skill Wages with Imperfect Labor Markets, *Macroeconomic Dynamics* 12, 463–479.

[10] Ebenstein, A., Harrison, A., McMillan, M. and Phillips, S., 2014. Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys, *Review of Economics and Statistics* 96, 581–595.

[11] Feenstra, Robert C. and Hanson, Gordon H., 1996. Globalization, Outsourcing, and Wage Inequality, *American Economic Review* 86, 240–245.

[12] Feenstra, Robert C. and Hanson, Gordon H., 1996. Errata to Globalization, Outsourcing, and Wage Inequality.

[13] Feenstra, Robert C. and Hanson, Gordon H., 1999. The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the US, *Quarterly Journal of Economics* 114, 907–940.

[14] Görg, Holger and Görlich, Dennis, 2015. Offshoring, Wages, and Job Security of Temporary Workers, *Review of World Economics* 151, 533–554.

[15] Head, Keith, and Ries, John, 2002. Offshore Production and Skill Upgrading by Japanese Manufacturing Firms, *Journal of International Economics* 58, 81–105.

[16] Hromcová, Jana, and Agnese, Pablo 2018. Globalization, Welfare, and the Attitudes toward Higher Education, *Economic Modelling, forthcoming.*

[17] Hummels, David, Munch, Jakob R., and Xiang, Chong, 2013. Education and Labor Market Policies in an Offshoring Global Economy, in: Nordic Economic Policy Review: Globalization, Labour Market Institutions and Wage Structure, Copenhagen: Nordic Council of Ministers.

[18] Hummels, David, Jørgensen, Rasmus, Munch, Jakob R., and Xiang, Chong, 2014. The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data, *American Economic Review* 104, 1597–1629.

[19] Jung, Jaewon, and Mercenier, Jean, 2014. On Modeling Task, Skill and Technology Upgrading Effects of Globalization with Heterogeneous Labor, *Economic Modelling* 39, 49–62.

[20] OECD Economic Outlook 103, 2018.

[21] OECD Employment protection dataset (2013)

[22] OECD Input-Output Database 2012.

[23] Okazawa, Ryosuke, 2013. Skill-biased Technical Change, Educational Choice, and Labor Market Polarization: the U.S. versus Europe, *Journal of Economic Inequality* 11, 321–342.

[24] Olsen, Karsten, 2006. Productivity Impacts of Offshoring and Outsourcing: A Review, *OECD Science, Technology and Industry Working Papers*, 2006/01.

[25] Rogerson, Richard, Shimer, Robert and Wright, Randall, 2005. Search-Theoretic Models of the Labor Market: A Survey, *Journal of Economic Literature* 43, 959–988.

[26] Slaughter, Matthew J., 2000. Production Transfer within Multinational Enterprises and American Wages, *Journal of International Economics* 50, 449–472.

[27] Williamson, Stephen D., 2010. Notes on Search. Washington University in St. Louis, 1–38.

Appendix A. Bellman equations and welfare definitions

A1. Steady state equilibrium flows and matching

In steady state, low-skill workers that were working, E_L,

$$E_L = q - \gamma u, \tag{6}$$

and lose their jobs, equal the low-skill unemployed, $q - E_L$, that find a job (right-hand side)

$$\delta E_L = P_L \left(q - E_L\right), \tag{7}$$

with P_L the probability that a low-skill worker will match with a low-skill firm. On the other hand, high-skill workers that were working, E_H,

$$E_H = 1 - q - \left(1 - \gamma\right) u, \tag{8}$$

and lose their jobs, equal the high-skill unemployed, $1 - q - E_H$, that find a job (right hand side)

$$\delta E_H = P_H \left(1 - q - E_H\right), \tag{9}$$

with P_H the probability that a high-skill worker will match with either a low or a high-skill firm. The probability that a low-skill worker will match with a low-skill firm is

$$P_L = \phi m(\theta), \tag{10}$$

and the probability for a high-skill worker to match with high skill firm is

$$P_H = \left(1 - \phi\right) m(\theta). \tag{11}$$

By rewriting (7) and (9), and using (6), (8), (10) and (11), we get the expressions for the unemployment rate and the fraction of low-skill vacancies (as in Albrecht and Vroman, 2002)

$$u = \frac{\delta\left(\gamma + q - 2\gamma q\right)}{\gamma\left(1 - \gamma\right)\left[m(\theta) + 2\delta\right]}, \tag{12}$$

$$\phi = \frac{\left(1 - \gamma\right) q m\left(\theta\right) + \delta\left(q - \gamma\right)}{m\left(\theta\right)\left(\gamma + q - 2\gamma q\right)}. \tag{13}$$

Unemployment rates for each type of workers depend on the skill distribution, q, and the share of unemployed for each type, γ, and $(1 - \gamma)$

$$u_L = \frac{\gamma u}{q} \text{ and } u_H = \frac{\left(1 - \gamma\right) u}{1 - q}.$$

A2. Workers

The following Bellman equations state that the discounted value of working (left-hand side) must be equal to the flow of net income (first item on the right hand side) and the expected loss from changing the employment status (second item on the right-hand side)

$$rW_i = w_i - \delta(W_i - U_i), \ i = L, H \tag{14}$$

where r is the discount rate. The analogous equations for the unsuccessful match hold—the discounted value of being unemployed must be equal to the flow of net income (unemployment benefits) and the expected gain from finding a job, namely

$$\begin{aligned} rU_L &= b + \phi m(\theta)\left(W_L - U_L\right), && (15) \\ rU_H &= b + (1-\phi)m(\theta)\left(W_H - U_H\right). && (16) \end{aligned}$$

A3. Firms

When the match is successful the Bellman equations for the active firms take the following form

$$rJ_i = (y_i - w_i - c) - \delta\left(J_i - V_i\right), \ i = L, H \tag{17}$$

where the discounted value of the job must be equal to the flow of profits earned by the active firm and the expected loss from changing the labor market status (becoming inactive). The corresponding Bellman equations for the inactive firms are

$$\begin{aligned} rV_L &= -c + z(\theta)\gamma\left(J_L - V_L\right) && (18) \\ rV_H &= -c + z(\theta)(1-\gamma)\left(J_H - V_H\right) && (19) \end{aligned}$$

where the discounted value of the vacancy must be equal to the flow of income lost by maintaining the vacancy open and the expected gain from switching to the active status. There is free entry into the market, and new firms enter while the value of the vacancy is positive. No more firms enter when the value of the vacancy decreases to zero; the free entry condition can be then expressed as

$$V_L = 0 \text{ and } V_H = 0. \tag{20}$$

A4. Wages

Wages for each type of match can be obtained by processing (14), (17) and (20), and by plugging them into (4)

$$w_i = \beta(y_i - c) + (1-\beta)\, rU_i,\ \ i = L, H. \tag{21}$$

Finally, the condition for the equilibrium to exist is that high-skill workers are matching only with high-skill jobs

$$y_L - c \leq rU_H. \tag{22}$$

Total output depends on the productivity and employment of each type of worker

$$Y = E_L y_L + E_H y_H.$$

Appendix B. Empirical analysis, data sources and definitions

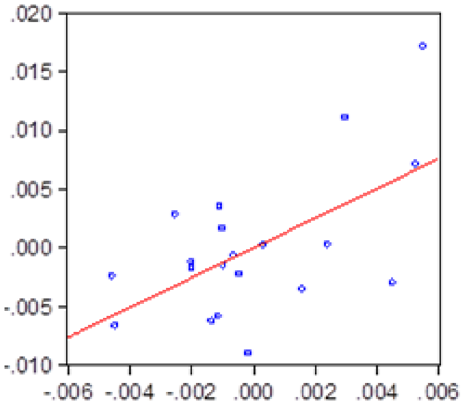
Variable	Name of variable as found in the data	Database
S_H^L or S_H^w	High-skill labor costs (compensation of employees) or wages and salaries, share	STAN Database rev. 4.
off^H	Import content in exports (share), high and medium-high-technology industries	Own calculations, OECD I-O Database rev. 3 and rev. 4.
off^L	Import content in exports (share), low and medium-low and technology industries	Own calculations, OECD I-O Database rev. 3 and rev. 4.
Y	Value added, volumes, US mill 2010	STAN Database rev. 4.
K	Net capital stock, volumes, US mill 2010	STAN Database rev. 4.

Appendix C. Classification of manufacturing industries based on R&D intensities (ISIC rev. 3)

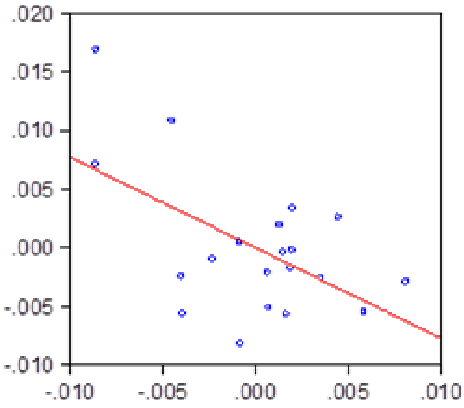
High and medium-high-technology industries	Low and medium-low and technology industries
Chemicals and chemical products	Food products, beverages and tobacco
Machinery and equipment, nec	Textiles, textile products, leather and footwear
Computer, Electronic and optical equipment	Wood and products of wood and cork
Electrical machinery and apparatus, nec	Pulp, paper, paper products, printing & publishing
Motor vehicles, trailers and semi-trailers	Coke, refined petroleum products and nuclear fuel
Other transport equipment	Rubber and plastics products
	Other non-metallic mineral products
	Basic metals
	Fabricated metal products
	Manufacturing nec; recycling

Appendix D. Leverage plots

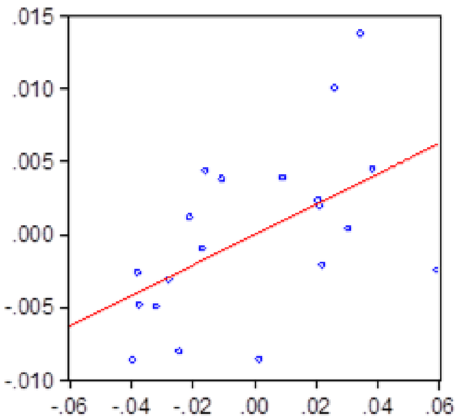
High-skill offshoring $\left(off^{H}_{t-1}\right)$



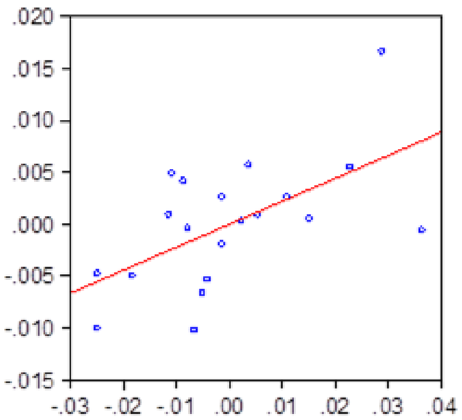
Low-skill offshoring $\left(off^{L}_{t-1}\right)$



Capital/value added (K_t/Y_t)



Value added, growth (ΔY_t)



Note: regressions of the residuals of OLS estimation (i) above on the residuals of auxiliary estimations between the exogenous k-th variable and a vector of the remaining variables.