Does Offshoring Still Play a Role in the Decline in Manufacturing Employment?

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Abstract – Government authorities and the media regularly show great interest in offshoring due to its role in manufacturing employment's decline, in particular. However, it remains difficult to quantify company offshoring given that it can be defined in multiple ways. This article updates the literature's previous research while proposing a new and improved methodological framework for identifying offshoring, based on machine learning methods applied to INSEE's *Chaînes d'activité mondiales* (CAM) survey. Our analysis, which covers 1995–2018, shows that the number of offshoring companies has decreased slightly following the global financial crisis of 2009. We show that offshoring is procyclical and describe the characteristics of the offshored jobs and offshoring companies. A causal econometric estimate of the annual average number of jobs offshored indicates offshoring's continuing macroeconomic influence on the dynamics of French manufacturing employment.

JEL: F23, F66
Keywords: offshoring, manufacturing, global value chains, supervised learning

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Since 1974, the manufacturing sector has fallen dramatically in France. It accounted for just 3.2 million jobs in 2018, compared with 5.8 million in 1974. Part of this decline can be ascribed to offshoring, a phenomenon whereby companies transfer capital or jobs to regions that give them a competitive advantage. Although offshoring does not affect the tertiary sector to the same extent as the manufacturing sector, certain service activities in the tertiary sector are also offshored, e.g. call centres.

Since the early 1990s and the "Hoover" affair (Chanteau, 2003),[1] offshoring has been a repeatedly discussed phenomenon, making it a "public problem", as defined by Gusfield (2009). However, it remains difficult to quantify. Despite this, many studies have already demonstrated that offshoring accounts for the loss of only around several tens of thousands of jobs each year, with figures varying depending on estimates. Offshoring is therefore nowhere near the only reason for the de-industrialisation of French employment (Demmou, 2010), which can also be explained by increased productivity or the outsourcing of certain tertiary sector operations.

However, its impact on the economy may outweigh the direct job losses it causes. Jennequin *et al.* (2017) show that, at local level, offshoring can cause asymmetric shocks that destabilise the local economy. The ensuing fragmentation of value chains can also constitute a vulnerability for all downstream sectors, as Gerschel *et al.* (2020) demonstrated using the example of the shock generated by the COVID-19 pandemic in China.

Quantifying the scale of offshoring therefore continues to constitute a scientific barrier to understanding our economies, which the COVID-19 pandemic revealed to be dependent on international value chains. This is nevertheless a complex task that hinges on the methods and definitions adopted, and the fact that the methods and definitions adopted by previous studies differ makes it difficult to make geographical, sectoral and time comparisons. The aim of this article is to contribute to this literature by quantifying offshoring's economic impact in France between 1995 and 2018 using updated and standardised methods.

Section 1 of the article sets out the literature on offshoring and its contribution to the decline in manufacturing employment. Section 2 introduces the data used, namely the INSEE *Chaînes d'activité mondiales* (CAM) survey. This survey asks a sample of companies about any offshoring undertaken between 2009 and 2011. We also use accounting and customs data. We construct an offshoring detection model and use the data from the CAM survey for the three-year period 2009–2011 to derive estimates for that model. We then use this model to quantify the annual number of relocations[2] over the 1995–2018 period – assuming that the offshoring predictors are constant (Section 3). Our findings are presented in Section 4. These include the evolution of offshoring, the most significantly affected sectors and company size categories, and the most frequent offshoring destinations. Section 5 focuses on estimating offshored employment and describing the characteristics of these jobs.

1. Literature Review

1.1. Definition-related Challenges

Many different approaches are used to understand offshoring, due to multiple possible definitions as much as multiple methodologies adopted.

Offshoring is a concept open to various interpretations. Fontagné & Lorenzi (2005) therefore strictly define offshoring as "the closure of a unit of production in France, followed by a reopening abroad in order to re-import goods to the national territory for a lesser cost and/or to continue to participate in export markets with this new unit of production". Under this definition, offshoring consists of the closure of an establishment, the downsizing of its workforce employed in France, and the creation or consolidation of a subsidiary abroad.

However, a broader definition is necessary to take outsourcing into account. This has been a feature of certain business strategies for several decades and consists of a production company transferring and entrusting certain activities to a supplier or subcontractor. This aspect has been incorporated by Aubert & Sillard (2005), who define offshoring as the "substitution of domestic production by foreign production resulting from the arbitration of a producer who gives up producing in the country of origin to produce or subcontract abroad". This is the definition explicitly used in the questionnaire for INSEE's CAM survey. That questionnaire defines activity

1. In 1993, Hoover, a subsidiary of the US Maytag group, transferred the operations of its facility in France to a factory in Scotland, which resulted in the loss of 600 jobs. The incident received widespread media coverage and has been firmly established in France as the benchmark example for offshoring (Chanteau, 2003).

2. In this article, we will focus only on relocations that correspond to offshoring behaviour (thus excluding changes in already offshored production sites or reshoring behaviour).

offshoring as the "total or partial transfer of the activity from France to another country, where the activity was previously carried out by the company itself or by another company (a subcontractor, for example)". This article applies this definition, for practical purposes.

1.2. Methodological Challenges

Demmou (2010) suggests that relocations be quantified by measuring the impact of commercial trade on manufacturing employment: this would be done by estimating the effects of trade balance variations on manufacturing employment for the trade in question. However, she obtains relatively divergent results depending on whether she applies an accounting approach, which she considers to be a lower bound (foreign trade would explain 13% of manufacturing job losses between 1980 and 2007, equivalent to 9,000 manufacturing job losses per year), or an econometric approach (changes in foreign trade would explain 39% of manufacturing job losses), which is a "fairly inaccurate estimate", according to the author.

Other econometric approaches use macroeconomic or sectoral data to quantify the effect of offshoring: Malgouyres (2018) measures the effects of international trade on employment and demonstrates that, between 2001 and 2007, 13% of manufacturing job losses can be explained by competing Chinese imports, representing a loss of 90,000 jobs in the manufacturing sector and 190,000 jobs in other sectors.

Aubert & Sillard (2005) identify offshoring on the basis of establishment-level data: they detect offshoring whenever a given establishment's employment declines or disappears and that establishment's group more frequently imports goods previously produced in France. Similarly, the method used in this article is based on identifying "presumptions of offshoring". We replicate the method put forward by Aubert & Sillard (2005) for comparison purposes. We have also used other indirect quantification methods based on an analysis of changes in imports (De Gimel, 2005) or of changes in the workforce of non-domestic subsidiaries (Drumetz, 2004).

These authors may follow differing approaches, yet they all conclude that offshoring's macroeconomic impact is relatively minimal in terms of both offshored jobs and operations. According to Aubert & Sillard (2005), approximately 95,000 manufacturing jobs were eliminated in France between 1995 and 2001 as a result of offshoring overseas, which equates to an average of 13,600 jobs per year (or up to 19,300 according to their worst-case scenario). This figure is only 6,600 per year according to Fontagné & D'Isanto (2013), who define offshoring more restrictively.

Leading forecasts available for France estimate the annual number of job losses resulting from offshoring to fall between 6,000 and 13,500 (Table 1). Although this might suggest that offshoring's macroeconomic impact is limited, these jobs are likely to be in a specific region or business sector and therefore their loss triggers asymmetric shocks, disrupting global value chains even more as they become increasingly complex.

Table 1 – **Main studies estimating the number of French company relocations**

Study	Method	Coverage and period	Findings
Aubert & Sillard (2005)	Presumptions of offshoring based on workforce downsizing and increase in imports	Industry (1995–2001)	13,600 jobs per year
Demmou (2010)	Macroeconomic approach		9,000 jobs per year
Bonnal & Bouba-Olga (2011)	Analysis of investment and divestment operations in France	2009–2010	7,250 jobs per year
J. Arthuis (2005)	Estimates based on personal interviews extrapolated using sector-specific imports	2006	8,000 jobs
Fontagné & D'Isanto (2013)	Use of CAM statistical survey	2009–2011, companies with more than 50 employees	6,600 jobs per year
Lécrivain & Morénillas (2019)	Use of CAM-PME statistical survey	SMEs with more than 50 employees, 2014–2016	300 jobs per year
Chanteau (2008)	Documentary monitoring (Bref Rhône-Alpes print magazine, Bodacc (Official Civil and Commercial Advertising Newsletter, weekly surveys))	Rhône-Alpes, 1993/1997/2003	0.15 % of establishments per year

It is unfortunate that the same method has not been reproduced with regularity as this would have made it possible to monitor offshoring trends over time. Comparability is restricted by the sheer number of methods and scopes forming the basis for estimates. Equally, since minimal comparisons exist between methods under a given scope, those methods cannot be calibrated according to their tendency to overestimate or underestimate the phenomenon of offshoring.

2. Data

2.1. The CAM Survey and Offshoring Measurements

INSEE's 2011 *Chaînes d'activité mondiales* (CAM) survey questioned a sample of approximately 6,500 companies about any offshoring operations they may have carried out between 1 January 2009 and 31 December 2011.[3] The survey covers legal units (companies) that are active, commercial and operational as at 31 December 2012, employ at least 50 workers at the end of 2008, are based in France and carry out a principal activity classified in the sectors corresponding to sections B to N (excluding K) of the Nace Rev.2 nomenclature, i.e. all manufacturing, construction and trade activities, plus most other service activities, with the exception of finance and insurance activities.

The survey defines offshoring as a "transfer of national production abroad [capable of] taking various forms: a transfer to a subsidiary based abroad; a transfer to a company belonging to another group, which is not a subsidiary and is based abroad; a transfer to a company based abroad that does not belong to the offshoring company's group; a transfer from a domestic subcontractor to a non-domestic subcontractor". Although this definition is somewhat broad as it includes subcontracting, unlike the definition used by Fontagné & Lorenzi (2005), it is still a less extensive definition than that used by certain authors, such as Arthuis (1993), who includes "non-localisation".

Descriptive statistics on activities offshored between 2009 and 2011 as measured by the CAM survey are presented in Fontagné & D'Isanto (2013): 4.2% of the legal units included in the sample relocated between 2009 and 2011. These authors argue that large enterprises, exporting companies, companies in the manufacturing and information and communication sectors and companies with subsidiaries abroad offshore their activities more often than other types of companies.

2.2. Additional Data

We additionally rely on data from three other sources in order to obtain annual information about company characteristics, namely INSEE's *Fichier approché des résultats d'Esane* (FARE), annual structural statistics of companies from the ESANE scheme with accounting information derived from French company tax returns, consistent with the information provided in the *Enquête sectorielle annuelle*; customs data relating to French company imports;[4] and ILO (International Labour Organization) data concerning average wages in various countries.

Drawing inspiration from the work of Aubert & Sillard (2005), we calculate rates of change in various company characteristics over the three-year period 2009–2011.

We end up with four groups of explanatory variables:

- Ratios reflecting change in accounting variables and the rate of change in employment (over the three-year period);
- Ratios reflecting change in customs variables (over the three-year period);
- Size (3 categories) and sector (5 categories) dummies[5] (prior to the three-year period);
- (Prior) wage ratios comparing the average wage in France with the average wage in the country from which the legal unit imports the most (total or specific) goods after the three-year period.

Figures I to III show the distribution of the three explanatory variables with the greatest explanatory power in the models estimated in Section 3.

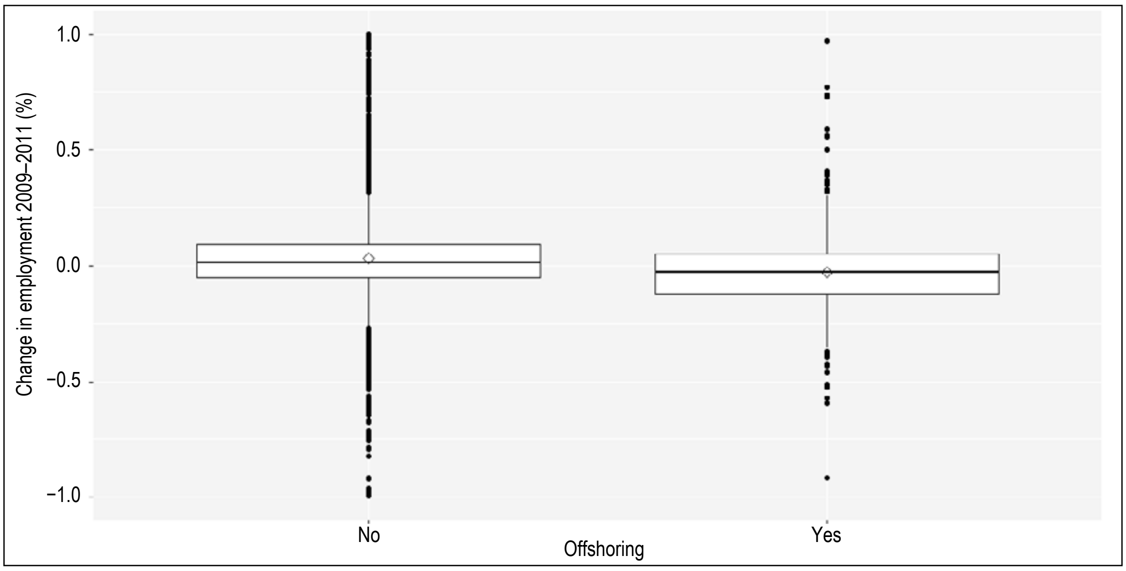
In line with the intuition of Aubert & Sillard (2005), Figure I reveals that companies that have offshored activities exhibit a negative employment trend, on average, whereas the average trend for companies that have not offshored is slightly positive. Similarly, the first and third quartiles and the median of the distribution of

3. Question S2Q3. We group cases of planned yet incomplete offshoring together with cases of offshoring not being carried out.

4. This data is inherently deficient for studying offshoring: a number of intra-European flows are incorrectly recorded despite various adjustments having been made. The methodological challenge of this article is to bypass this limitation by combining the customs variables with other explanatory variables. This combination of variables is what will enable offshoring to be predicted with greater accuracy. For customs variables, we distinguish between imports of specific goods and total imports of goods: specific goods are defined as goods that correspond to the company's principal activity.

5. BE (manufacturing)/FZ (construction)/GI (trade, transport, hotels and restaurants)/JKL (information and communication, finance, real estate)/ MN (professional, technical, scientific and administrative and support service activities).

Figure I – **Rate of change in employment according to the existence of offshoring**



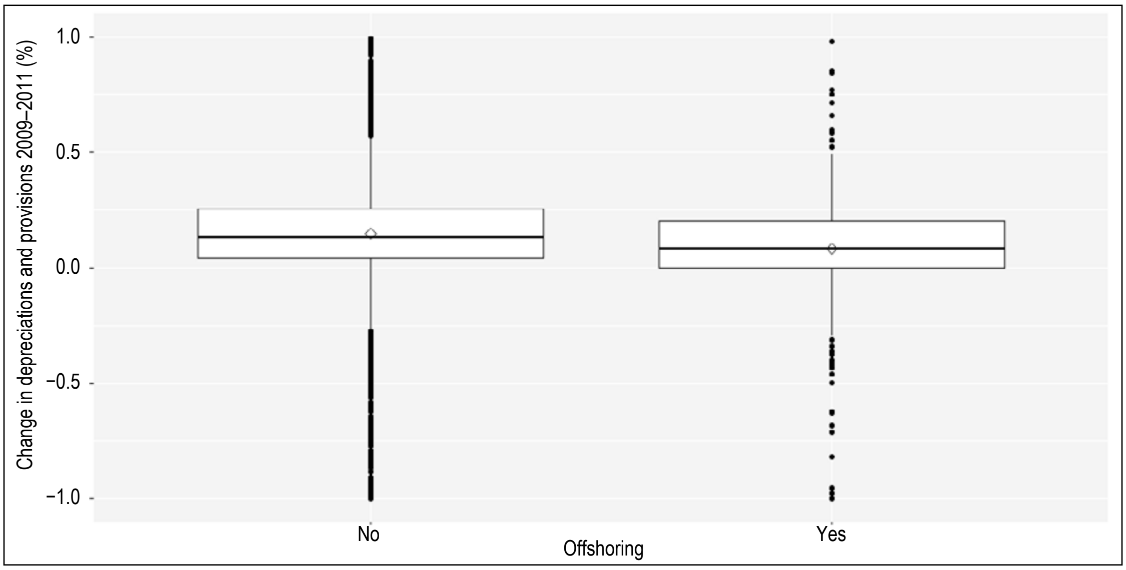
Note: Figures I, II and III are box plots illustrating the distribution of explanatory variables. A rectangle is drawn between the first and third quartiles and intersected by the median. The "box" thus produced is completed by a segment, the ends of which represent the upper and lower adjacent values of distribution.
Source: CAM survey, FARE, INSEE.

changes in employment are higher for companies that have not offshored than for those that have, even if there is an overlap between the two distributions.

On average, companies that offshored some of their activities in 2009–2011 see their depreciation, amortisation and provisions increase by less than other companies (Figure II). In accounting, depreciation and amortisation are used to account for the wear and tear, ageing and usage of an asset (a machine or vehicle, for example). To streamline an asset's potential renewal, a deduction corresponding to this wear and tear is booked against the asset's value each year. Similarly, provisions record the depreciation of inventoried equipment and are deducted from the income statement. One possible reason for depreciation, amortisation and provisions increasing less for offshoring companies could be weakened investment in material assets ahead of the offshoring of certain activities.

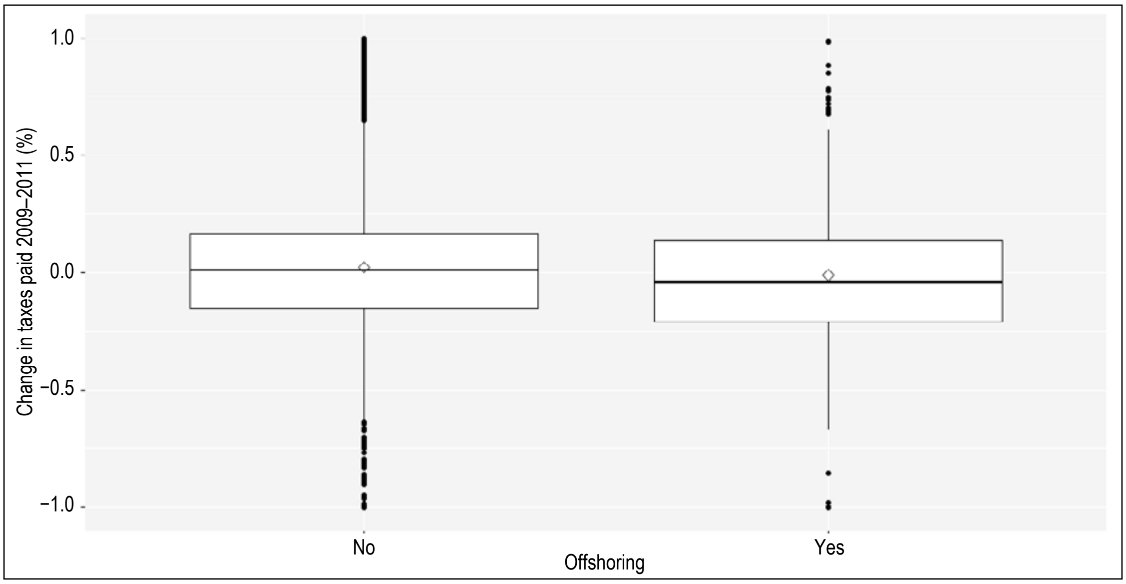
Similarly, on average, taxes paid in France fall for companies that have offshored, whereas they rise modestly for non-offshoring units (Figure III). This can be explained by the reduced volume of production in France in the wake of offshoring.

Figure II – **Rate of change in depreciations and provisions according to the existence of offshoring**



Source: CAM survey, FARE, INSEE.

Figure III – **Distribution of changes in taxes paid in France (%) according to the existence of offshoring**



Source: CAM survey, INSEE.

Table 2 shows the conditional correlations (calculated *via* logistic regression) between the existence of offshoring and some explanatory variables used in the models presented in Section 3. The fact that the learning models include possible non-linear effects explains the non-significance of the logistic regression coefficients for certain prediction variables.

So, although we cannot use logistic regression to identify potential causal effects, it does make it possible to describe offshoring companies in the CAM survey sample accurately: these are the companies for which, all things being equal, we observe an increase in production, financial investment and staff numbers, as well as a decrease in imports, production-related taxes and tangible assets. The positive correlations between the act of offshoring and changes in the number of employees and production volumes sold, which might seem counter-intuitive, can be explained by offshoring companies generally being developing organisations with funds to invest. This idea is explored further in Section 4.2.

3. Offshoring Detection Strategy and Model

Here, we propose a strategy that involves calibrating a model for predicting offshoring based on data on relocations that have actually been observed. Once calibrated, the model is used to predict offshoring over periods during which we do not observe relocations. We compare the performance of different models in order to select the most accurate one.

3.1. Looking Beyond Aubert & Sillard

By virtue of its microeconomic approach and scale, Aubert & Sillard's study (2005) has now become the benchmark for quantifying offshoring in France. Using their model, the authors can detect a "presumption of offshoring" whenever a company sees a decline in employment of more than 25% accompanied by increasing imports of specific goods (in proportion to the shutdown of production in France).

We can test the relevance of their offshoring identification model on companies that responded to

Table 2 – **Logistical model: conditional correlations with existence of offshoring**

Variable	Correlation	p value
Change in production sold	+	<0.0001
Change in financial investment	+	0.0007
Change in number of employees (natural persons)	+	0.0022
Change in value added	-	0.044
Change in imports of specific goods	-	0.43
Change in production taxes	-	0.81
Change in tangible assets	-	0.96

the CAM survey. In Figure IV, each dot corresponds to a company in the CAM survey. Dark grey dots indicate offshoring units and light grey dots indicate non-offshoring units. The axes correspond to the two explanatory variables used by Aubert & Sillard (2005): presumptions of offshoring according to their model therefore appear in the lower right quadrant.

Contrary to the assumptions made by Aubert & Sillard (2005), many companies have actually managed to offshore activities without experiencing a decline in employment and an increase in their imports of specific goods. There are several possible reasons for this:

- Our evaluation focuses on companies, and offshoring is most frequently carried out by companies with multiple establishments. A company may well have offshored an establishment and yet have recruited staff in other establishments, leading to a positive trend in total employment;

- The underlying global economic depression between 2009 and 2011 is certainly a factor in the decline in employment, including for non-offshoring companies;

- Imports of specific goods may not increase after offshoring if this corresponds to a production link that is not a feature of the company's principal activity. They also may not increase if the specific imports are consequently handled by a French subcontractor whose business with the offshoring company does not appear in the customs data.

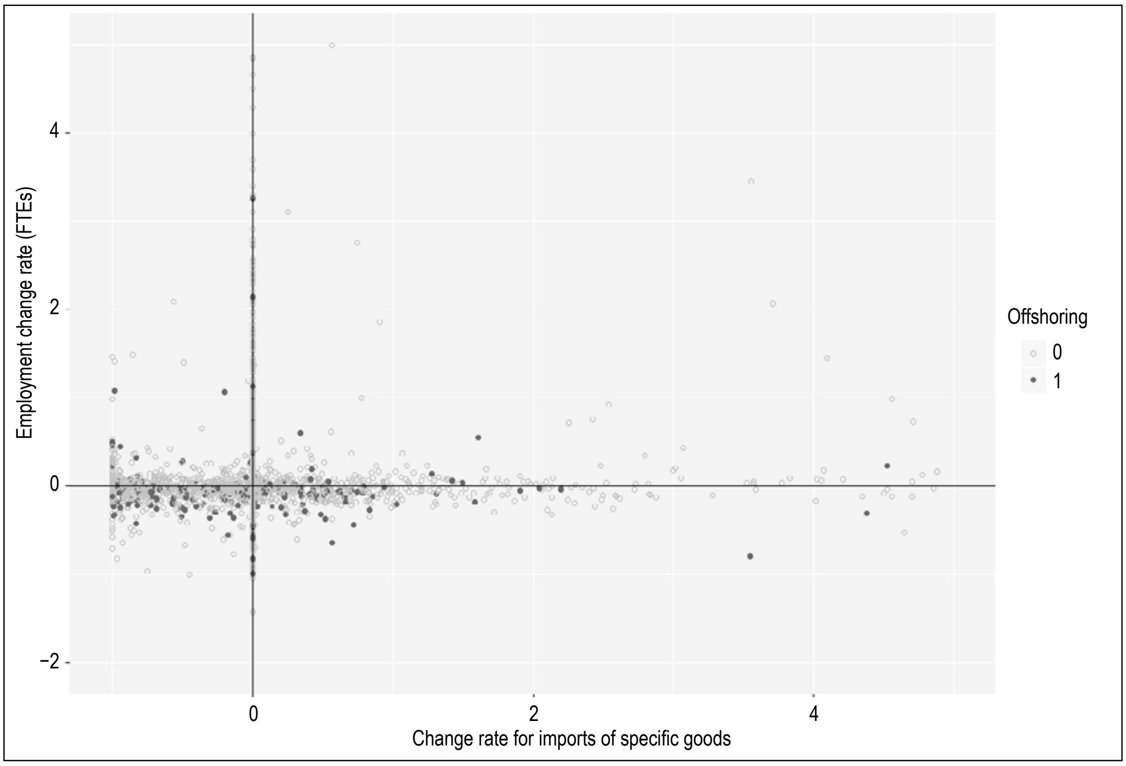
While this graphical representation does not necessarily render the method used by Aubert & Sillard (2005) invalid, the development of the statistical models described below does allow for a more granular analysis and a more accurate prediction of offshoring.

3.2. Model Selection

The data on actual offshoring provided by the CAM survey makes it possible to extend the methodology of Aubert & Sillard (2005) and apply it to other explanatory variables (presented in Section 2.2).

The CAM survey's offshoring variable is used here as an explained variable in order to train the prediction models. These models can be used to apply the results from the three-year period (2009–2011) to a longer period. The CAM survey's sampling method, which has been designed to be representative of the

Figure IV – **Offshoring according to changes in employment and imports of specific goods (2009–2011)**



Coverage: Companies in mainly commercial sectors, excluding agriculture and finance, employing at least 50 workers at the end of 2008.
Source: CAM survey, INSEE.

coverage,[6] goes some way to justifying such a generalisation.

We are therefore creating an offshoring detection model based on numerous potential explanatory variables, the influence of which on offshoring will be estimated using a range of prediction models. We have selected the following models:

- logistic regression, with an additional log-logistic link function (to capture asymmetry effects) and stepwise AIC selection of explanatory variables;

- random forest, with 1,000 trees and 20 variables randomly retained for the selection of each node (from 30 explanatory variables);

- XGBoost forest model (boosting on CART, learning rate of 1, consideration of unequal sample composition in terms of offshoring, maximum tree depth of 20, a single boosting iteration, sub-sample of 0.63, and 3,000 trees launched in parallel);

- implementation of the method used by Aubert & Sillard (2005), with thresholds being multiplied (rather than arbitrarily selecting a single threshold as in their initial methodology) – which makes it possible to estimate optimal thresholds.

These algorithms were configured by comparing their predictive performance. For the sake of simplicity, we have only selected the algorithm with the best performance within each model family.

To estimate each of these models, we divide the CAM survey sample into two sub-samples. The first sub-sample, which comprises 90% of the legal units that responded to the survey, is used to select the model. This is also divided into two samples (a "learning" sample, comprising 80% of these legal units, and a test sample, comprising the remaining 20%) in such a way that both of them have the same proportion of offshoring legal units. The models are estimated or "trained" using the learning sample, and their predictive performance is compared using the test sample. The second sub-sample is known as the validation sample (10% of legal units that responded to the survey). This is kept for the purpose of making unbiased estimates of the prediction scores for the model ultimately selected. All the explanatory variables presented in Section 2.2 are used as inputs for each model.

Figure V shows the relative performance of these models using ROC curves,[7] and Table 3 shows the Areas Under the Curve (AUC) in connection with this.

The random forest model has the largest AUC, covering most of the convex hull of the ROC curves: this is the model with the best predictive performance. As such, we use this model from this point onwards in the article.[8] Incidentally, the specificity of the FARE 2008 data means we have to create a random forest with several fewer variables for the 2008–2010 and 2006–2008 three-year periods, but the AUC for this falls only by a few percentage points (see the second column of Table 3).

Figure V demonstrates that the model proposed by Aubert & Sillard (2005) was well founded, but could be improved. Although the dotted line associated with their model is indeed higher than the first bisector (AUC score: 0.54), its predictive performance is below that of models which include more explanatory variables and allow those variables to be freely combined. Our

6. Stratified sampling is used: 213 strata obtained by cross-referencing sector and workforce class, with "systematic" random sampling within each stratum. Legal units with more than 250 employees were surveyed comprehensively because of their economic relevance (they account for 61.3% of the units in the sample).

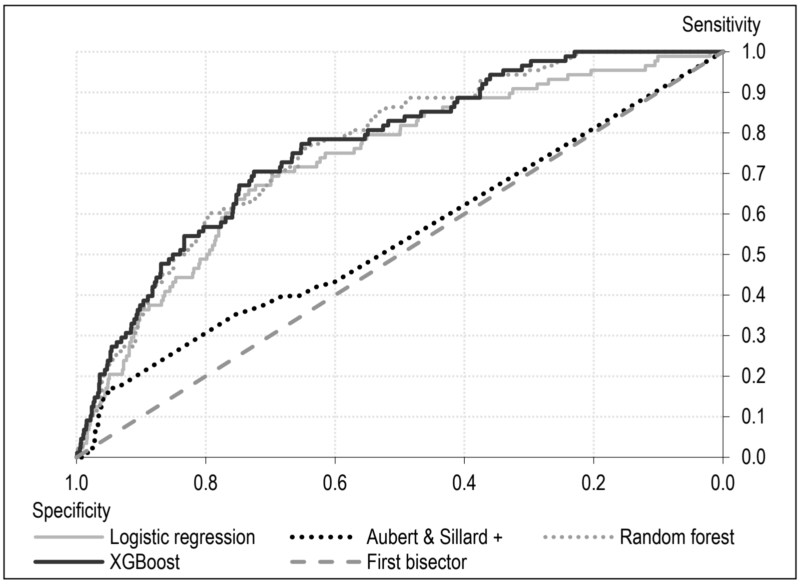
7. ROC (receiver operating characteristic) curves are graphs that make it possible for the predictive performance of different models to be compared. In Figure V, each model is represented by a curve. At this stage, each model returns a probability of offshoring for each company in the test sample. Based on the discriminatory threshold used (above which offshoring is determined, and below which no offshoring is determined), the model will have varying levels of specificity and sensitivity (i.e., the ratio of true negatives to true negatives and false positives, and the ratio of true positives to true positives and false negatives). In the lower left quadrant: maximum specificity and zero sensitivity. The discriminatory threshold is set at 1, so there are no positives (and therefore no false positives, so a specificity value of 1). In the upper right quadrant: the sensitivity value is 1 and the specificity value is zero. The discriminatory threshold is set at 0. The challenge therefore lies in selecting a discriminatory threshold and a model that strike an acceptable balance between specificity and sensitivity. Curves closest to the upper-left corner will provide the best prediction results. The area under the ROC curve (AUC) is a score that varies from 0 to 1 and quantifies this predictive performance. Preferred AUC values are those that exceed 0.5 (the first bisector corresponds to the pure chance model).

8. Subsequently, some of the results will use prediction percentage confidence intervals, established using the infinitesimal jackknife method: see Wager et al. *(2014) and Mentch & Hooker (2016).*

Table 3 – **Predictive performance of models (AUC values)**

	AUC	AUC (2008 model)
Logistic regression (cloglog, stepwise)	0.73	0.73
Random forest	0.80	0.78
XGBoost	0.78	0.77
Aubert & Sillard's method	0.54	0.54

Figure V – **ROC curves for predicting offshoring**



Note: To achieve a specificity of 0.8, the logistic regression model predicts offshoring with a sensitivity value of 0.5.
Source: INSEE, FARE and CAM – DGDDI, Customs.

selected model therefore predicts offshoring more effectively than theirs.

3.3. External Validity Tests

The selection of our model is therefore based on offshoring observed between 2009 and 2011. Use of this model to predict offshoring over the entire 1995–2018 period is predicated on a strong assumption that the offshoring predictors are constant. However, the underlying general economic conditions between 2009 and 2011 are unusual in that this period is a recession, during which offshoring patterns are potentially idiosyncratic. Yet when this study was carried out, there were no data available to make comparisons with other periods: the CAM 2020 survey, which would go on to cover offshoring in 2018–2020, was not yet available. We are therefore forced to retain our prediction models which were estimated during a period of underlying global economic depression, meaning we run the risk of incorrectly extrapolating unusual characteristics from the learning sample (termed “overfitting” in machine learning literature). The validity at other points in time (external validity) of the random forest model we have selected can be tested to some extent.

First, we compare the offshoring company sample derived using our model with the actual offshoring database maintained by the information monitoring company, Trendeo. This database is largely incomplete as it is constructed using documentary monitoring of the daily and regional press. Despite this, we can assume that every relocation recorded in this database is genuine (even if definition-related issues still remain) and check how many of these relocations our model predicted. Over the 2009–2018 period (the common base shared by our study period and the Trendeo database), our random forest model correctly recorded 78% of the relocations identified by Trendeo as offshoring. This is a reassuring outcome for the purposes of calculating the macroeconomic flows associated with offshoring (Section 4) because large enterprises inevitably account for a significant proportion of the aggregated values.

Second, we are using the 2016 CAM-PME survey, a special version of the CAM survey which covers only SMEs with more than 50 employees. By using this sample to estimate our random forest model, our predictions are limited to just 20% of actual relocations (compared with a peak of 42% using 2011 CAM data, see Section 3.4). The AUC score calculated using this CAM-PME sample is only 0.58.

These two tests therefore provide mixed results: our model’s predictive performance based on the Trendeo database is good, but that performance is average at best when the CAM-PME database is used. How do we interpret this? Some of the variations in performance are likely to be associated with the size of the companies: our model manages to recognise the most obvious instances of large manufacturing sites being offshored, which were reported by the press and therefore appear in the Trendeo database. However, it has a harder time detecting instances of SME offshoring, which are recorded by CAM-PME. This size-related effect is certainly compounded by a cyclical effect, linked to changes in the underlying general economic conditions between 2009–2011 and 2014–2016 (periods over which companies were questioned in the CAM and CAM-PME surveys, respectively), and it is impossible to distinguish between them.[9]

3.4. The Random Forest Model Selected

Figure VI shows two importance scores for the different explanatory variables in the random forest.[10] The higher the score, the more the variable contributes to the identification of offshoring. In descending order of contribution, the variables are: change in employment (natural persons); originating country for imports of specific goods *ex post*; change in depreciation, amortisation and provisions; change in taxes paid in France; and business category.

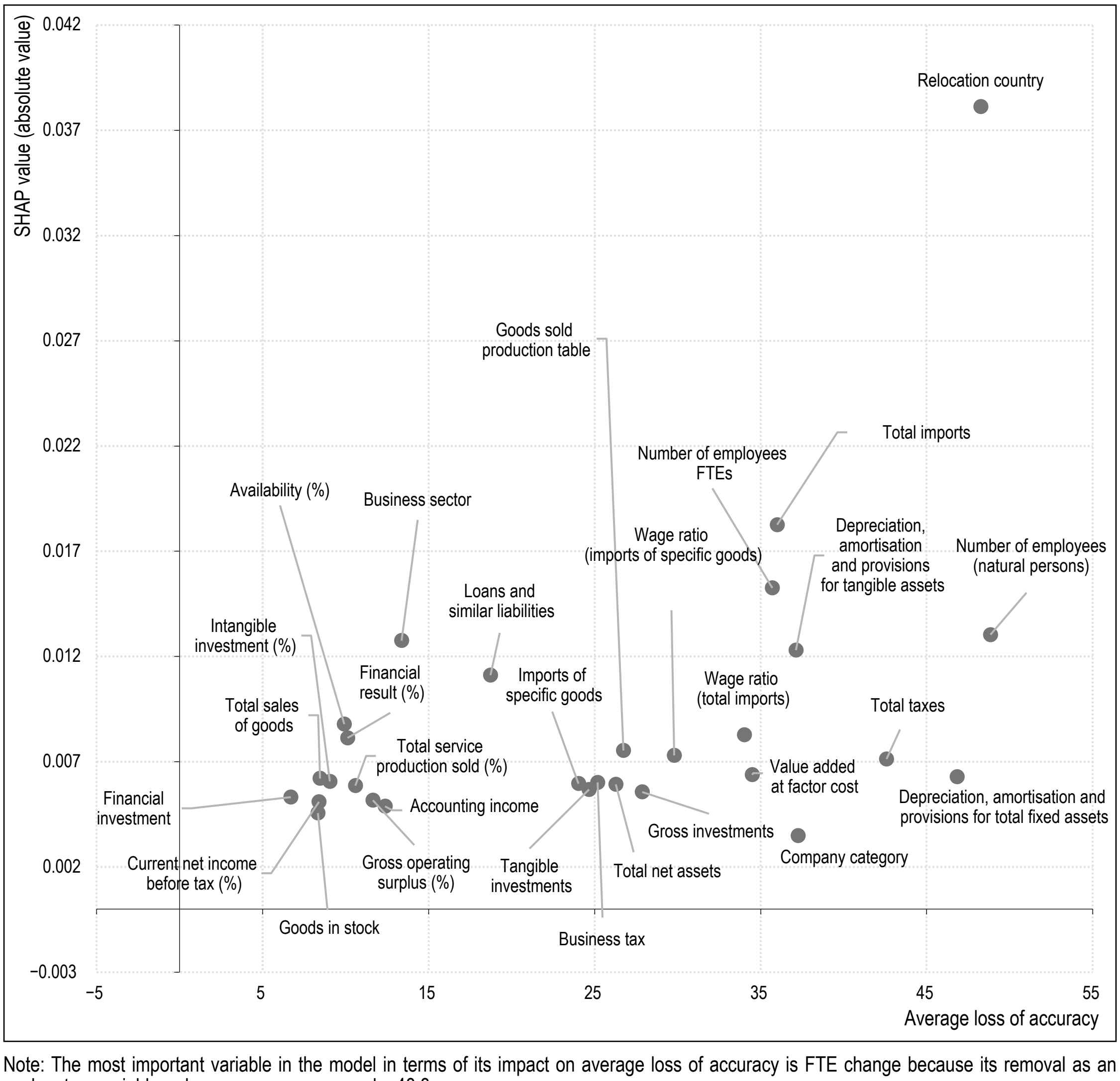
The random forest model does however struggle to predict offshoring with certainty (none of the estimated probabilities for offshoring exceeds 0.6). In addition, when using the test sample, the model predicts that many relocations have occurred for companies when this is not the case (false positives).

We therefore look at the following three scenarios to determine whether a company has offshored its activities. With a view to estimating the correct number of relocations (i.e., 6.1% of companies

9. In this respect, predictive machine learning methods are no substitute for cyclical official statistics surveys. That was somewhat the premise of this article: to overcome the lack of annual offshoring surveys by extrapolating results from a one-off survey (CAM). The external validity tests carried out on Trendeo and especially CAM-PME demonstrate the challenges inherent in such a premise.

10. The score depicted on the horizontal axis indicates the predictive quality loss if the variable were removed from the set of explanatory variables. The score depicted on the vertical axis is the SHAP value, which indicates each variable's contribution to the forecasting output.

Figure VI – **Importance of explanatory variables in the random forest**



Note: The most important variable in the model in terms of its impact on average loss of accuracy is FTE change because its removal as an explanatory variable reduces average accuracy by 48.8.
Source: INSEE, FARE and CAM – DGDDI, Customs.

in the test sample), the central scenario sets the probability threshold above which a company will be considered to be an offshoring company. This is therefore a plausible scenario in terms of predicting the number of relocations. However, it is liable to overfitting. Two additional scenarios are introduced, one to predict 50% fewer relocations (low scenario), and one to predict 50% more relocations (high scenario), both in the test sample. The probability thresholds above which offshoring is considered to have occurred are 0.154 for the low scenario, 0.217 for the central scenario and 0.285 for the high scenario.[11]

The percentages of correct predictions among predictions of offshoring are higher in the low scenario (Table 4). We will therefore use this method when we need to obtain more precise information about the characteristics of offshoring (in terms of sector, company size, etc.), without attempting to estimate the exact number of relocations.

Table 5 shows different prediction quality scores under the three scenarios: the high scenario manages to return 42.0% of actual relocations, albeit at the expense of a loss of specificity, whereas the low scenario offers a high level of specificity (97.5%), but returns fewer actual relocations (17.0%).

4. Predicted Offshoring Results

4.1. Manufacturing Relocations, Primarily to Europe

Using the variables in the model, each company is assigned a probability of offshoring over the three-year periods[12] starting from 1995–1997 and concluding with 2016–2018, by means of the random forest model. A presumption of offshoring or no offshoring is then assigned depending on the (low/central/high) scenarios and their confidence intervals, which have different offshoring prediction thresholds.

The number of relocations in a given year is calculated as the average of presumed relocations over the three three-year periods that include that year.

Over the 1995–2018 period, an annual average of approximately 1,000 companies are estimated to have offshored in the central scenario – either by closing one of their production sites in order to shift production outside of France, or by substituting foreign production for a domestic subcontractor (Figure VII). The low and high scenarios frame this estimate (approximately 500 companies offshoring each year in the low scenario, and 1,750 companies in the high scenario). We also see a decline in annual offshoring volume (−25%) following the 2009 crisis (the annual average is 980 over the 1995–2005 period, and 730 over the 2010–2018 period).

Three quarters of these companies are SMEs, approximately one quarter are intermediate-sized enterprises (ISEs), and large enterprises (LEs) account for less than 1% of the companies

11. For the model based on the three-year periods of 2006–2008 and 2008–2010, the thresholds are 0.225 (central scenario), 0.294 (low scenario), and 0.150 (high scenario).

12. The evaluation follows a three-year cycle to mirror the CAM survey's design: the question featuring in the survey questionnaire (and on which the prediction models are trained) asks companies about the occurrence of any offshoring in the last three years.

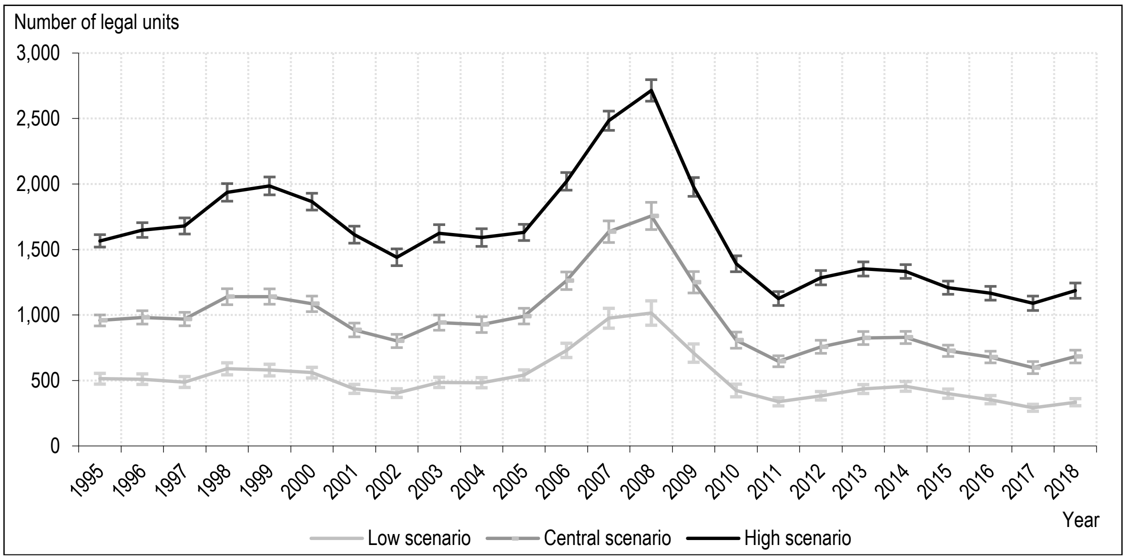
Table 4 – **Prediction model confusion matrix (in total percentages)**

	Lack of offshoring in practice	Actual offshoring in practice
Estimation of non-relocation in the low scenario	90.7	2.1
Estimation of relocation in the low scenario	6.0	1.1
Estimation of non-relocation in the central scenario	88.7	4.0
Estimation of relocation in the central scenario	5.4	1.8
Estimation of non-relocation in the high scenario	85.9	6.9
Estimation of relocation in the high scenario	5.0	2.1

Table 5 – **Model prediction quality scores (in percentages)**

	Low scenario	Central scenario	High scenario
Sensitivity	93.8	94.3	94.5
Specificity	35.0	30.5	23.2
Average accuracy	91.8	90.5	88.0
Kappa score	18.2	22.5	19.5
F1 score	95.7	95.0	93.4

Figure VII – **Annual breakdown of legal units predicted to have offshored activities**



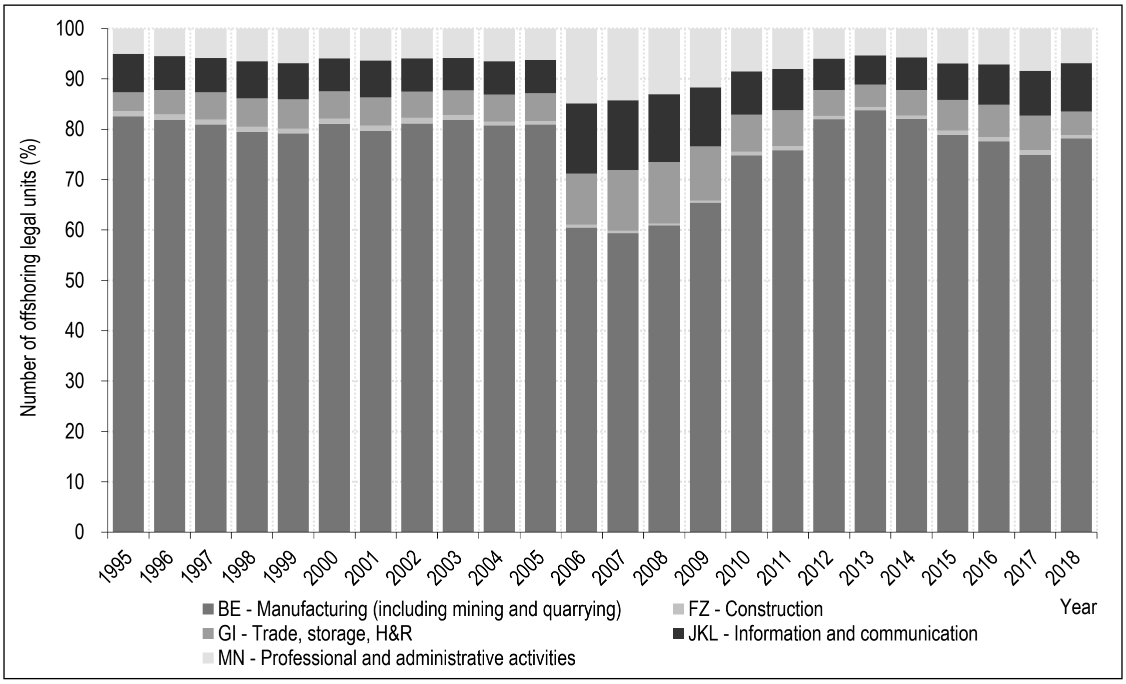
Source: INSEE, FARE and CAM – DGDDI, Customs.

predicted to be offshoring their activities. If we weight each company by its employment, each category (SMEs, ISEs, LEs) accounts for a third, on average, over the 1995–2018 period.

Figure VIII provides a sectoral breakdown of companies predicted to have offshored their activities, for the low scenario.[13] It comes as no surprise that manufacturing accounts for a significant proportion of predicted relocations. This is the sector most affected by the extension of global value chains. Hanson (2017) shows that the phenomenon of offshoring affects a small number of sectors within the manufacturing industry. One example is the auto industry, which has been continually adapting to a rapidly changing international market since the late 1990s. This adaptation has notably led to an internationalisation of value chains across different hubs in North America, Europe and

13. In this scenario, the probability that the company predicted to have offshored its activities has actually done so is higher than in the other two scenarios, which means that the sectoral breakdown is more reliable.

Figure VIII – **Sectoral breakdown of offshoring legal units (low scenario)**



Source: INSEE, FARE and CAM – DGDDI, Customs.

East Asia. Production then combines part and component manufacturing in low-wage countries with assembly in high-wage countries. Despite the rising trend in offshoring within the sector between 2000 and 2016, a large proportion of relocations to countries with low production costs is undertaken by a handful of manufacturing groups. Head & Mayer (2019) show that the five groups with the highest levels of offshoring account for half of all relocations during that period.

Alongside this manufacturing weight, which partly reflects the internationalisation of value chains, a number of relocations occur in sectors that are traditionally not associated with offshoring: professional activities (such as consultancy services), administrative and support service activities, information and communication. This finding can be explained to some extent by the CAM survey's broad definition of offshoring. Service offshoring has boomed since the early 2000s. Pisani & Ricart (2016) identify a total of 79 academic studies on service offshoring, published between 1990 and 2014. This type of offshoring can exhibit specific characteristics that differ from manufacturing offshoring. Doh *et al.* (2009) use US data to demonstrate that, contrary to expectations, a country is more likely to be a location to which services are offshored if the average wage in that country is high. The level of education and the similarities in culture between the countries of origin and destination are also key factors in any decision to offshore services

A very limited number of relocations have been recorded in sectors for which it would initially appear counter-intuitive: construction, trade, storage, and accommodation and food service activities. While a risk of error in the model's prediction cannot be ruled out, it is worth noting that 1% of the companies reporting to have offshored between 2009 and 2011 in the CAM survey belong to the construction sector and 16% fall under trade, storage or accommodation and food service activities. These cases can be explained by the survey's broad definition of offshoring, which incorporates certain cross-border economic effects in addition to changes in subcontractors (in favour of non-domestic producers).

Although we are unable to use the model to directly ascertain the countries to which activities are offshored, they can be deduced by observing trends in the offshoring companies' import flows. We will assume that the company has offshored its activities to the country in which its imports of specific goods have increased the most over the study period (maximum imports). Figure IX shows the significance of each geographical area in total predicted relocations over the study period, normalised by the value of recorded import flows.

A high proportion of relocations are to countries that border France: Germany, Belgium and Italy. By contrast, Eastern European countries account for a low proportion of offshoring – the fact that these countries joined the EU in 2004 or 2007 does not appear to have resulted in an increase in the rate of offshoring over the study period. Europe is the most popular offshoring destination for all periods: in 2018, more than half of all relocations were to Europe. Europe's dominance here is partly explained by the CAM survey's broad definition of offshoring, which likely includes cross-border economic effects. This finding thus provides context for the proportion of countries with low production costs within the offshoring data, particularly for manufacturing offshoring.

Relocations to Africa (including Northern Africa) are relatively minimal. There is a steadily increasing pattern of offshoring to the Middle East, Central Asia, South Asia and South-East Asia over the same period, with these regions accounting for almost a fifth of relocations, in terms of value, in 2018.

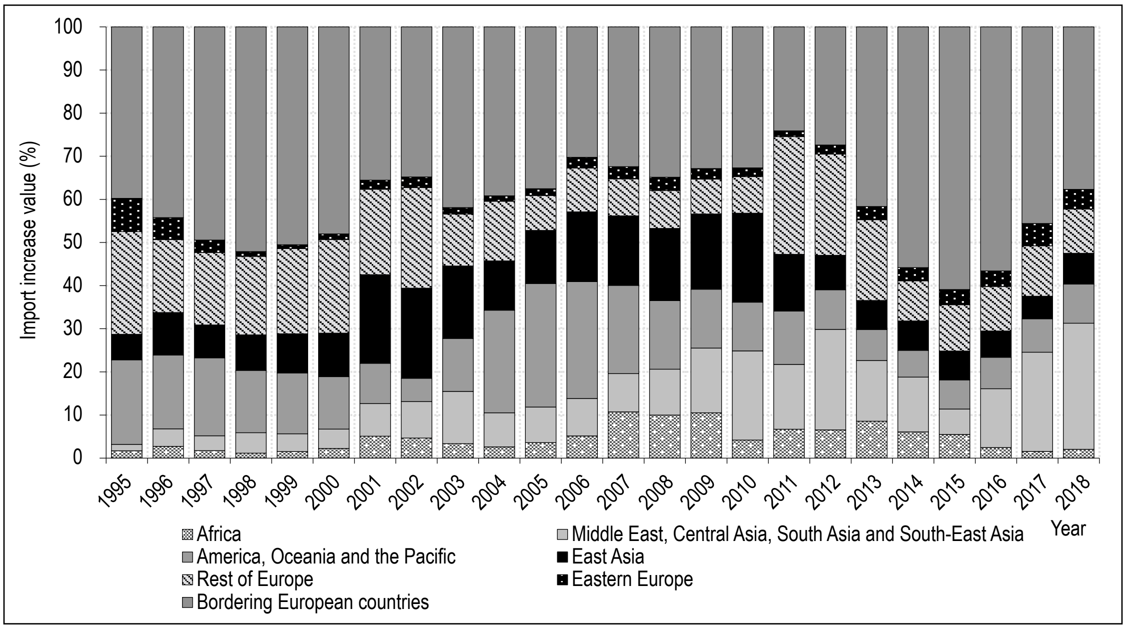
Pierce & Schott (2016) attribute much of US manufacturing's decline to the outsourcing of activities to China. Aubert & Sillard (2005) demonstrated that, between 1995 and 2001, China accounted for an average of 14.1% of manufacturing relocations, compared with 6.9% for the US. We observe similar values over this period when we widen the coverage. However, we see a downward trend for the proportions for East Asia (where China is dominant) and America (where the US is dominant), these regions accounting for only a fringe minority of relocations in 2018.

Figure X presents this information at individual country level (rather than aggregated geographical area level), aggregating all offshoring flows over the 1995–2018 period. The US and China rank among the top offshoring destinations over this period, but Germany and Belgium also feature.

4.2. Is Offshoring a Procyclical Phenomenon?

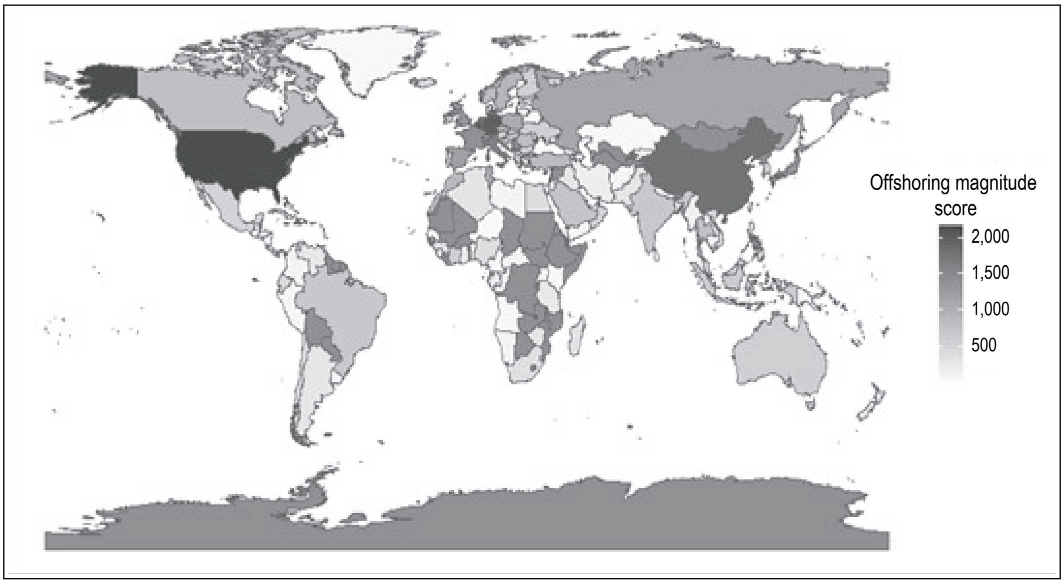
Offshoring (for which Figure VII shows the general trend) increases between 1998 and

Figure IX – **Breakdown of geographical areas from which maximum imports of specific goods increased for offshoring legal units (low scenario)**



Note: the categories are read from bottom to top for each year (from Africa at the bottom to bordering European countries at the top).
Source: INSEE, FARE and CAM – DGDDI, Customs.

Figure X – **Economic magnitude of offshoring (*via* maximum imports of specific goods) 1995–2018**



Source: INSEE, FARE and CAM – DGDDI, Customs.

2000 (strong growth years) and between 2006 and 2008 (strong GDP growth until Q3 2008). In contrast, periods of slowdown in GDP correlate with periods in which there are low levels of offshoring: 2002 and 2009–2010. These two factors therefore indicate offshoring's potentially procyclical nature.

Suggestions that offshoring may be procyclical are also raised in the literature. For example, Zlate (2016) shows that the output and value added of Mexican *maquiladoras* (plants in Mexico) correlate strongly with the US manufacturing cycle when observing the period between 1990 and 2007.

To test offshoring's procyclical nature, we compare the changes in offshoring (central scenario) with changes in the margin and investment rates (Figure XI). Over the 1995–2009 period, the correlation of our offshoring series is 0.70 with an investment rate of 0.70 and a margin rate of 0.35, confirming the assumption that offshoring is procyclical over this period.

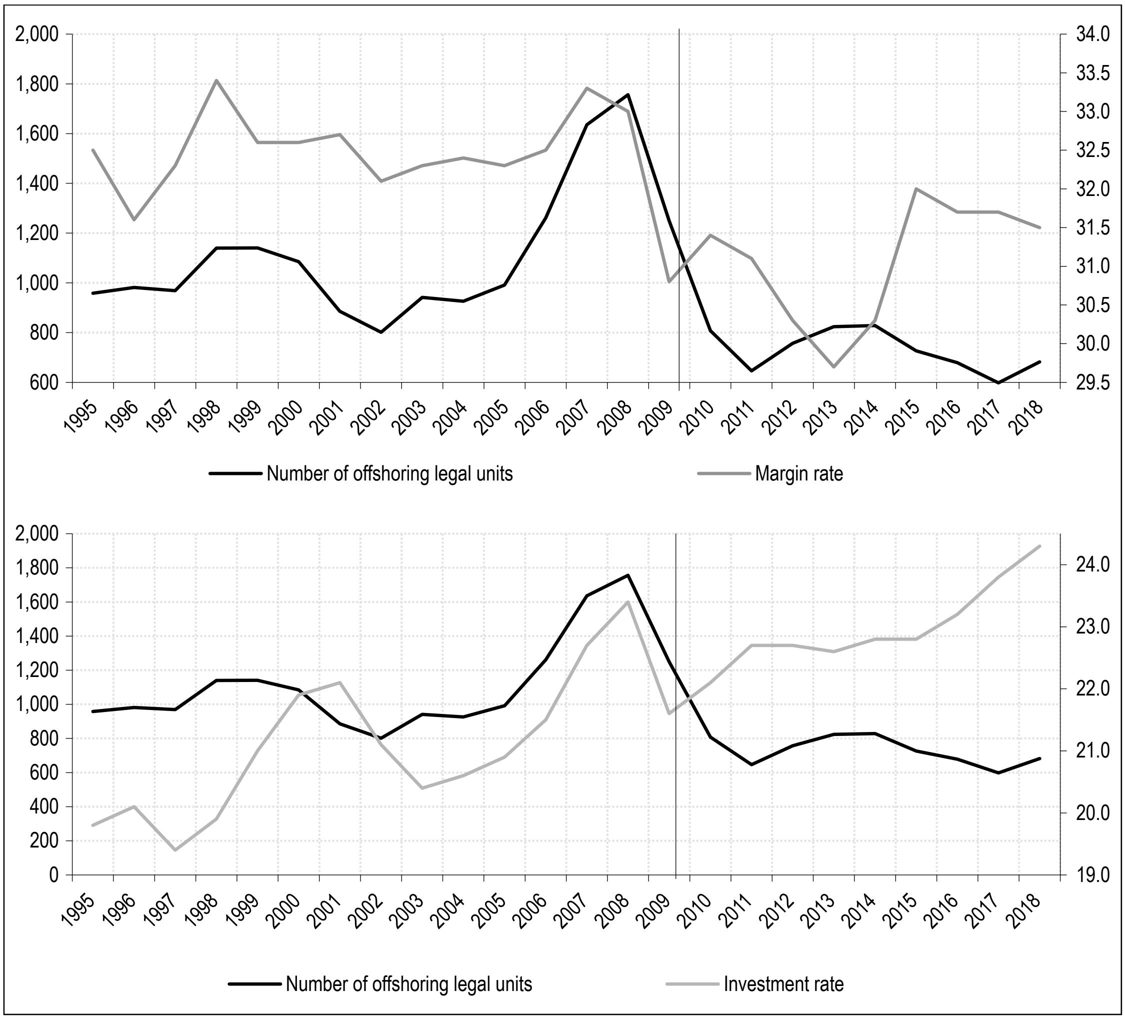
These correlations change in the aftermath of the crisis in 2008–2009: the investment rate picks up and the margin rate recovers, but offshoring stagnates. The correlations invert (−0.35 and −0.66, respectively), which indicates a change in company behaviour. There are several possible explanations for this, such as a sustained phase of debt reduction measures introduced by companies, thereby heightening their reluctance to invest abroad, or more intense price competitiveness within France over the period in question (wage moderation and competitiveness policies such as the CICE competitiveness and employment tax credit).

Offshoring requires the investment of substantial cash flows in a new "production mix", as defined by Schumpeter (1911). Building a new production site overseas requires time, funds and forward planning. These three elements are in short supply during a turning point in the cycle, a period that is also marked by radical uncertainty[14] when we observe the example of the 2008 crisis. A differing interpretation could be that companies tend to abandon native subcontractors and turn to subcontractors abroad during a crisis. This is what Chilimoniuk-Przezdziecka (2011) suggests. During economic booms, companies prefer internal restructuring measures to external ones (which include offshoring).

In the light of our findings, this behaviour is more than offset by the discontinuation of offshoring that requires a minimum level of investment. Furthermore, it is uncertain whether this subcontracting cost optimisation behaviour is amplified during a crisis: use of non-domestic subcontractors can be fully justified during

14. *Knight (1921) introduces a distinction between risk, where the probability of each possible event can be measured, and uncertainty, where it is impossible to quantify probabilities in that same manner. Uncertainty is deemed to be radical whenever it is impossible to produce a list of possible events linked to a risk.*

Figure XI – **Time-series comparison of offshoring, investment rate and margin rate**



Source: INSEE, FARE and CAM – DGDDI, Customs.

periods of strong economic performance, for the same cost-related reasons.

5. What Kind of Jobs Are Offshored?

5.1. Observing Job Losses Linked to Offshoring

Our evaluation at legal unit level,[15] following on from before, is a necessary yet inadequate step: necessary, because the CAM survey collects information at legal unit level, which means that the offshoring prediction models had to be designed starting from that level, and inadequate, because a number of large enterprises may have offshored only one of their establishments, or only a fraction of their activities. The aim of this section is to filter down to establishment and job level in order to quantify the number of jobs affected by offshoring with greater granularity (again drawing inspiration from Aubert & Sillard (2005)).

We rely on the *Déclarations annuelles de données sociales* (DADS – Annual Declarations of Social Data) for this purpose. With this database, it is possible to identify all establishments and positions[16] that form each legal unit recognised by our model as having offshored its activities. For all establishments affected, and drawing inspiration from Aubert & Sillard (2005), we presume that an establishment has been offshored if:

- the establishment existed in *t* but no longer exists in *t*+2;

- the establishment has lost more than 25% of its jobs, measured in full-time equivalents (FTEs),[17] between *t* and *t*+2 (threshold applied by Aubert & Sillard (2005) as it was below one standard deviation of the mean variation in employment).

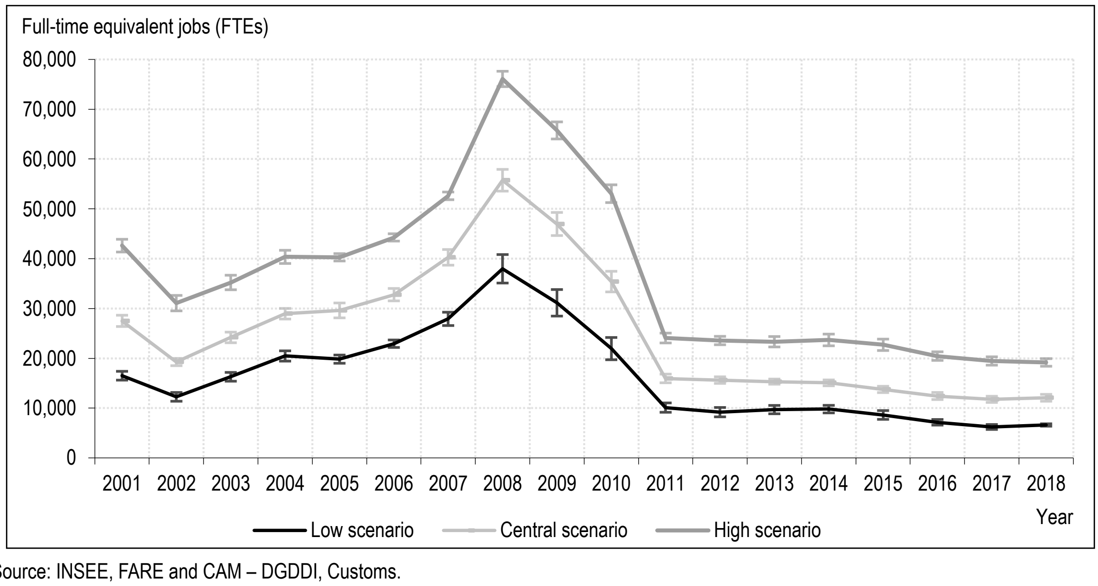
We identify these establishments while considering any changes in SIREN numbers and the phenomenon of "economic continuity" (whereby an establishment and its workforce are taken over by another legal unit, as defined by Picart (2008)).

All jobs for establishments that disappear are deemed to have been offshored. For establishments that have lost more than 25% of their FTEs,[18] each of the jobs existing in *t* is deemed to be *x*% offshored (where *x* is the percentage of jobs eliminated between *t* and *t+2*). *x* therefore carries a weighting function. This method ensures that the number of offshored jobs matches the number of jobs lost between *t* and *t*+2 exactly (rather than using a calculation based on jobs not found in *t+2*, since jobs could well have been replaced in the intervening period).

Figure XII shows the change in the number of jobs eliminated as a result of offshoring between

15. A legal unit is a legal entity under public or private law. This entity is identified by a SIREN number. Establishments are identified by a SIRET number and are production units that are geographically distinct yet legally subordinate to their legal unit. A legal unit may include multiple establishments.
16. The DADS database enables us to draw a distinction between "ancillary" and "non-ancillary" positions; we have included only the latter in this article. Non-ancillary positions are positions for which a defined annual threshold for remuneration and work duration is exceeded.
17. Here, we calculate FTEs in the standard way, in the DADS, omitting positions classed as ancillary and temporary work.
18. In reality, the number of offshored jobs is relatively insensitive to the 25% threshold: most establishments identified as offshored lost their entire workforce.

Figure XII – **Number of jobs predicted to have been offshored**



Source: INSEE, FARE and CAM – DGDDI, Customs.

2001 and 2018 in our three scenarios.[19] In the central scenario, offshored employment has been trending downwards over the last decade: while the average number of jobs eliminated each year between 2001 and 2018 was 25,000, only 12,000 jobs were eliminated in 2018. However, this figure disregards any jobs that may have been created at the same time and does not consider that people whose jobs have been offshored may find another job. Furthermore, this figure reflects only job losses in the company affected (and not jobs that have been lost at the company's suppliers, customers or subcontractors).

In the manufacturing sector, Aubert & Sillard (2005) identified an annual average of 13,600 jobs offshored between 1995 and 2001 (and as many as 19,400 by adjusting their model's parameters). Our results are of a similar scale, albeit with a slightly more comprehensive coverage.

5.2. Using Propensity Score Matching to Estimate Causal Job Losses

The advantage of the previous method lies in its ability to identify specific positions that have been offshored (see Section 5.3. for a study of their characteristics). Nevertheless, it does have two inherent risks of bias. First is a risk of overestimation, because the method ascribes all job losses observed over the period to offshoring, which is not necessarily the case for all of them. Second is a risk of underestimation, because the number of *ex post* jobs may have started to increase again as a result of offshoring during the period in question.

Another initial way to estimate the number of jobs offshored is to use another CAM survey question, which asks employers reporting activity offshoring to indicate the number of positions they believe they have offshored.[20] This approach is what leads Fontagné & d'Isanto (2013) to conclude that approximately 20,000 jobs in France were offshored over the three-year period 2009–2011, but they caution against overinterpreting this finding on the basis of the information reported. This translates to an average of 20.1 jobs eliminated per offshoring company.

There is a second different way to estimate the number of jobs offshored, which consists of adopting a causal econometric evaluation framework, drawing inspiration from Hijzen *et al.* (2011). Using a double-difference method, these authors compare companies that have made foreign investments with comparable companies (identified using a matching method) that have not. One of the challenges here lies in finding companies that can be considered "comparable". However, the CAM survey makes it possible to identify not only companies that have offshored activities, but also those that have only considered doing so. When asked about possible offshoring between 2009 and 2011, 4.2% of companies (weighted data) answered "yes", 3.1% answered "no, but it had been considered" and 92.7% answered "no, and it had not been considered".

Our identification strategy is therefore to compare companies that have offshored activities with those that have considered offshoring activities but did not follow through with it. Some of the unobserved characteristics are therefore controlled (a previous desire to offshore activities).[21] Once these unobserved characteristics have been controlled, the act of having offshored activities remains correlated with observed structural characteristics (business sector, size) and with other, more context-specific, characteristics associated with the perception of the barriers to be overcome in order to offshore activities[22] (information available in the CAM survey).

To aid comparability of the two samples – companies that have offshored activities and companies that have considered doing so – we carry out matching based on the propensity score. Several matching methods will be examined to check the robustness of results. In the six methods proposed, we match companies that share the same structural characteristics and/or consider three barriers to be of equal importance

19. There are several potential breaks in the series, which render studying the changes in the curve more complex:
- In 2008: transition from FICUS to FARE. We previously noticed accounting approximations for a number of variables (such as financial investment). Additional transition from Naf_rev1 to Naf_rev2 (more detailed, particularly for customs data): imports of specific goods were identified less effectively (overestimation, because all potential Naf_rev2 codes are retained);
- In 2003: transition from Naf 1993 nomenclature to Naf_rev1 (same concern for approximation in the activity/product codes, although the change is less significant);
- In 2001: change in the way FTEs are calculated in the DADS. Approximation of the employee identifier in the DADS: continuity of activity is less readily identified, and fewer jobs are counted per establishment (the two effects act at cross purposes). This major break is a good reason for not observing data prior to 2001 in our retrospective estimates.
20. The question concerns the number of positions and not the number of FTEs.
21. Unobserved factors persist to some extent (for example, the macroeconomic or regulatory environment of the country being considered as an offshoring destination, which can influence the ultimate ability to offshore activities or not).
22. Fourteen different barriers are listed in question 2.10 of the CAM survey questionnaire. We will focus on three of these barriers, because they have a significantly different impact on offshoring companies compared with companies that are considering offshoring but have not followed through: the"risk of patent infringements and/or non-compliance with intellectual property rights", the "need to be in close contact with existing clients", and the "considerable general difficulties in view of the expected gains". Companies that ultimately did not offshore activities are therefore more likely to answer that they had faced these constraints than those that did: this is why these variables are included in the propensity score calculation.

in their offshoring plan (see Footnote 21). This strictly corrects for sector and size-related mismatches (over-representation of manufacturing companies and LEs or ISEs among offshoring companies) as well as mismatches linked to differing perceptions of the barriers to offshoring. Table 6 shows the cumulative gains in standardised proportional differences between initial and matched samples for these different matching methods (the higher the gain, the greater the similarity of the samples compared *ex post* with regard to the controlled characteristics).

The unmatched double-difference estimate forecasts an average loss of 38 jobs per relocation. The over-representation of large enterprises and manufacturing companies among companies that have offshored activities is therefore uncontrolled. However, like manufacturing companies, large enterprises tend to experience sharper falls in employment over the period. Whichever method is selected, matching leads to a more conservative estimate of job losses per relocation. The more precise the match with respect to the control variables, the more this estimate decreases: an exact match results in an average loss of 16 jobs per relocation.

The selection of the method to be used is the result of a trade-off between internal and external validities. The more precise the match, the greater the internal validity of the estimate. However, the more precise the match, the more likely it is that the counterfactual sample will consist of the same companies, drawn multiple times, which exposes the sample to a risk of overfitting.

Depending on the trade-off required between internal and external validities, a range of values can be calculated for the average job losses per offshoring company (between 16 for exact matching and 34 for 1:3 matching with replacement). This range makes it possible to validate the methodology specified in Section 5.1 on the basis of results. This methodology estimates the average job losses per relocation to be 29 (value within the range).

By comparing this range with the number of companies predicted to be offshoring their activities in Section 4.1, the number of jobs offshored in 2018 would be between 11,000 and 23,000, depending on the matching method used (12,000 jobs were predicted based on the DADS). Figure XIII shows the different possible series of offshored jobs, according to the method selected.

5.3. Offshored Jobs: Victims Over-represented Among the Most Stable

In addition to estimating the number of jobs affected by offshoring, precisely identifying affected jobs *via* the DADS (see the method described in Section 5.1) means that their characteristics and locations can be studied.

The French departments most exposed to offshoring are those with major cities – not least because they have the highest proportions of manufacturing jobs (Figure XIV). Offshoring due to cross-border economic reasons is evident in the French border departments to the north and east of the country.

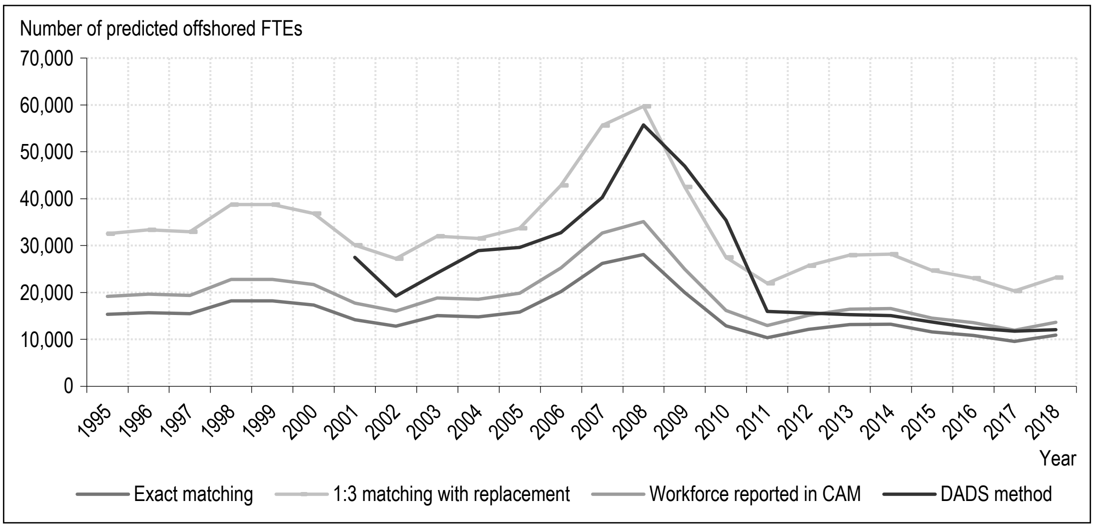
Stable jobs are slightly over-represented among offshored jobs (Table 7). Permanent contracts apply to 91% of offshored jobs, compared with 87% when we consider general coverage (i.e., CAM survey coverage). Full-time employment is also slightly more likely to be offshored (92%, compared with 87% for the general population). Engineers and technical company managers

Table 6 – **Comparison of different methods for estimating job losses associated with offshoring**

Method	Estimated average job losses per offshoring legal unit (ATT)	Cumulative gains in standardised proportional differences (matching quality)
1:1 matching without replacement (double differences)	−27 ***	< 0
1:1 matching with replacement (double differences)	−25 ***	+26
1:2 matching with replacement (double differences)	−29 ***	+28
1:3 matching with replacement (double differences)	−34 ***	+29
Exact matching on size and sector (double differences)	−24 ***	+35
Integral exact matching (double differences)	−16 *	+41
Double differences without matching	−38 ***	/
Reported response in CAM (number of offshored positions)	−20	/
Estimation *via* the DADS (see Section 5.1)	−29	/

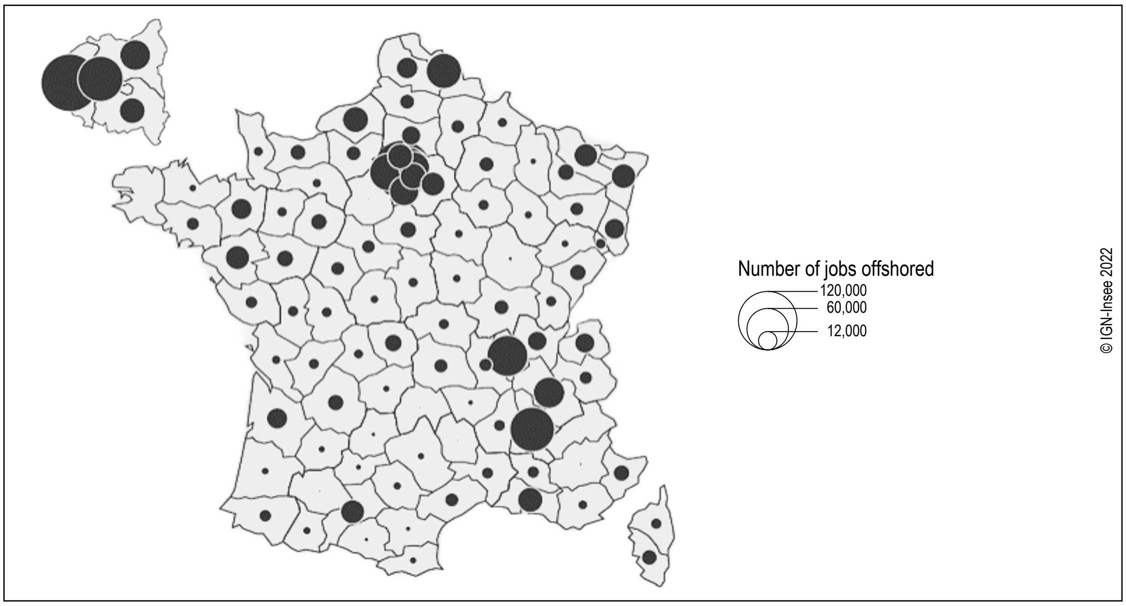
Note: 1:N matching signifies that *N* legal units in the control sample (legal units that have not offshored activities but have expressed a desire to do so) are drawn for each legal unit in the processing sample (legal units that have offshored activities).

Figure XIII – **Number of jobs predicted to be offshored by estimation method**



Source: INSEE, FARE and CAM – DGDDI, Customs.

Figure XIV – **Distribution of positions eliminated as a result of offshoring, by French department**



Source : INSEE, FARE and CAM – DGDDI, Customs.

are slightly over-represented among offshored jobs (13%, compared with 10% for the general population) and the same is true of skilled manufacturing workers (19%, compared with 13% for the general population). These over-representations are explained to some extent by the highly manufacturing nature of relocations and the characteristics of the companies that decide to offshore their production.

* *
*

Offshoring continues to be an economic phenomenon that is shaping the evolution of manufacturing employment in France. While offshoring appears to have declined since the 2009 crisis (down 25% between the periods of 1995–2005 and 2010–2018), the reindustrialisation observed in 2017–2018 has not halted the rate of relocations. Offshoring is touted as a major and ever-present problem in public discussions and its quantification is a major academic challenge.

We propose a new methodology for quantifying relocations in this article, inspired by the current literature. Data from INSEE's CAM survey makes it possible to identify actual offshoring at the turn of the 2010s. This data is combined

Table 7 – **Characteristics of employees who have lost a job due to offshoring (%)**

Variables	Categories	General coverage	Offshored positions
Occupation category	37 – Business and administration professionals	8	9
	38 – Engineers and technical company professionals	10	13
	46 – Administration and business associated professionals	8	9
	47 – Technicians	7	10
	48 – Supervisors, overseers	4	4
	54 – Corporate administrative clerks	9	8
	55 – Sales employees	8	4
	56 – Personal services employees	2	1
	62 – Skilled manufacturing workers	13	19
	63 – Skilled artisanal workers	4	2
	64 – Drivers	5	2
	65 – Skilled workers in maintenance, storage and transport	4	3
	67 – Less skilled manufacturing workers	6	9
	68 – Less skilled artisanal workers	4	1
	Other category	9	10
Age group	Aged 0–25	11	7
	Aged 26–35	28	26
	Aged 36–45	29	30
	Aged 46–55	24	29
	Aged 56 and over	8	8
Status	Full-time	87	92
	Part-time	13	8
Employment contract	Permanent	86	91
	Temporary	7	5
	Other type of contract	6	5
Gender	Male	67	67
	Female	33	33

Note: Skilled manufacturing workers account for 19% of offshored positions, compared with 13% of positions in the general coverage.
Source: INSEE, FARE and CAM – DGDDI, Customs.

with customs and tax data to construct models to predict offshoring. Estimating these models enables us to estimate the number of companies that have offshored their activities each year over the 2001–2018 period, the scale of which confirms the findings in the literature.

Offshoring's impact on the decline in manufacturing employment is certainly less quantitative than qualitative, which is also why it merits inclusion on the political agenda. The baseline figure of 10,000 jobs offshored each year must be assessed in connection with the number of manufacturing jobs – and any comparison cannot afford to ignore the relevant counterfactual (would the companies have gone bankrupt without any relocations whatsoever?). Qualitative impact can be assessed by studying the characteristics of employees whose jobs have been relocated: the most stable are generally affected. Offshoring therefore plays a role in the "destabilisation of the stable" movement described by Castel (2013). Given that relocations primarily occur in the manufacturing sector, they undermine a certain archetype of salaried manufacturing employment: workers more likely to be on a permanent contract, more likely to be working on a full-time basis, and more likely to be skilled.

The various external validity tests (in which our results are compared against the Trendeo or CAM-PME databases) suggest that we should be wary of too hastily making sweeping generalisations based on the results, especially in connection with SMEs covered in our study (SMEs with more than 50 employees). Limiting the data we use to a single year of the CAM survey runs the risk of overfitting the model to the macroeconomic conditions of 2009–2011: matching these conditions too precisely could result in the analysis failing to adapt to data taken from other years. Future versions of the CAM survey, which are scheduled for completion every three years starting in 2020, will make it possible to calibrate our offshoring prediction models with greater accuracy and relevance.

The construction of long offshoring data series remains an interesting support tool for making decisions. Although this does not enable us to make very short-term predictions about changes in offshoring (as FARE database accounting information is made available several years after the period to which it relates), it does enable us to evaluate policies aimed at boosting competitiveness on an *ex post* basis. Long series also enable microeconomic and macroeconomic determining factors behind offshoring to be examined in greater depth. ☐

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