Japan and her dealings with offshoring: An empirical analysis with aggregate data*

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October 26th, 2009

Abstract

First moves towards a real understanding of offshoring date back to very recent times, with employment and productivity effects occupying much of the literature around the subject. In particular for Japan, the studies conducted so far focus on the disaggregate level and put the stress on the productivity side alone. Here I carry out both the analyses of the employment and productivity effects at the aggregate level of the industry, covering the years 1980-2005. Moreover, I consider all industries within the economy and take account of both materials and services offshoring. My results suggest that we should expect, on average, a positive effect of services offshoring and a negative effect of materials offshoring on employment. However, the effects are rather negligible and only amount to a 1.5 to 2 percent loss of the change in employment. On the other hand, positive effects on the growth rate of productivity are found as a result of both types of offshoring, with larger effects from services. In particular, the average offshoring industry has higher productivity growth rates: 1.4 to 1.98 additional percentage points for services and 0.48 to 0.64 for materials.

Keywords: offshoring, Japan, employment, productivity

JEL Classification: F16, J23, O47

****Acknowledgments:** I am grateful to Fundación BBVA for financial support through project grant 162/06. Also, I am indebted to Professors Raymond, Ricart, and Sala for their helpful comments, unrelenting encouragement, and inexhaustible patience. Thanks go also to Professor Ashish Arora, who commented on an earlier draft of this paper, and to the people at the 3^{rd} Annual International Research Conference on Offshoring, held at Duke University, April 2009.

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1 Introduction

It is now no secret that Japan has been lagging behind for the past twenty years, running into an uncertain post-bubble era that seems to stretch to unknown horizons. Many have been the hypotheses thrown into the debate, few have been the definitive answers. Explanations range from those related to low productivity rates and demographic changes, to those identifying monetary factors as main determinants of the current state of affairs. This has practically left in the shadows the increasingly important subject of offshoring, which can have practical consequences for the competitiveness of the local firms and industries. It is certainly not my goal to pursue an answer to the mystery of the present slump. Rather, it is the effects of this "new" offshoring hype over this particular economy that I will be looking into. Particularly, I am interested in the employment and productivity effects.

I will try to find an answer to the following questions. Is offshoring to be seen as a real threat to the economy's employment level? Are we to expect any improvement in the productivity of industries after offshoring takes place? To answer these questions we should first revisit some commonplace definitions of offshoring and decide how to address its measurement. According to the comprehensive report "Offshoring and employment. Trends and impacts" (OECD, 2007), offshoring in the strict or narrow sense refers to business activities being relocated to subsidiaries abroad, while offshoring in the broad sense applies to relocation through third-party providers. These are also known as in-house offshoring and offshore outsourcing, respectively.

How to proxy this phenomenon then, either in its narrow or broad form? It has been lately suggested that an extensive and rigorous way to do it is by looking at the trade data and the changes in intermediate goods and services imports (Feenstra and Hanson, 1996a, 1996b, 1997, 1999). Presumably, it is the import content of intermediate trade (inputs) what best proxies offshoring and gives us a clue to understanding its economic implications. We shall see that for our industry level analysis this works just fine. But why are these economic implications really important?

The most recent and heated discussions about economic policy worldwide have to do with offshoring. The mainstream media is repeatedly warning about the dangers to come in this seemingly new business practice, despite its being nothing but a reformulation of the good old idea of comparative advantages developed by Adam Smith and later by David Ricardo. Thus seen, offshoring poses as much threat to 21^{st} century workers as industrial revolution to farm laborers back in the 19^{th} century. Indeed, agricultural activities have not disappeared, but witty entrepreneurs have often moved production far-off in the search for cheaper labor.

Although it seems reasonable to think of adjustment costs in the short run for workers and firms, one would expect the sectorial composition (rather than the quantity) of the economy's workforce to change in the future. This has been the story of capitalism since such form of economic organization exists. In the words of Blinder (2006), "the world as a whole cannot lose from increases in productivity" that are a natural result of trade and offshoring. Eventually, better paid and higher value-added jobs will open in the "relocating" economy due to economic scarcity.

This is not to deny the possible short-run layoffs or the implied dynamics the employers have to face when dealing with the decision to go abroad. But in the end these frictions should fade away as comparative advantages eventually turn out in increased social welfare, and the entrepreneurs finally succeed in making the most out of them (hopefully without much government interference). Hence, we should be thinking about offshoring as causing as much harm to an economy's labor market as international trade might also bring about. As we shall see here, offshoring and trade (intermediate trade, in particular) can be seen interchangeably.

Simply put, widespread fears on the subject usually revolve around the millions of jobs soon to be relocated from developed economies into developing ones, with a significant welfare cost in the former due to "employment destruction". However, these media reports as well as the surveys conducted by consulting firms so far tend to overlook the brighter side of the story. Gains in terms of employment and productivity for local firms not only are possible, but most expected. For instance, productivity gains could translate into price discounts and a boost in domestic demand, thus affecting employment positively. In fact, in a time when Japan is wavering on the verge of multiple futures and doubts start assailing the population on prospects for a possible recovery, offshoring might as well be the answer.

I therefore undertake the study of the Japanese economy for the 1980-2005 period, using dynamic panel estimation for aggregate data. As we will see, the little evidence that has been collected for Japan refers alone to the disaggregate level. Our empirical analysis then represents a robustness check on these studies and their conclusions, since it is undertaken at the industry level. To carry out such endeavor I make use of the Japan Industrial Productivity database (JIP), which covers 108 industries or branches of activities. This is an exhaustive database with data on manufacturing industries, services industries, and other varied activities.

The empirical research presented here is divided in two, as in Amiti and Wei (2006). First, I take a look at the demand side of the labor market and focus on the effects of offshoring on total employment, rather than on the relative employment among workers of different skills or their relative wages (as in Feenstra and Hanson, 1996a, 1996b, and 1999, for instance). We shall see that some of the later efforts are now looking into the direct effects with more interest (Amiti and Wei, 2005 and 2006, and Cadarso *et al.*, 2008). And second, I deal with the direct effects of offshoring on total factor productivity, while considering two possible ways of measuring the latter. My results suggest: (1) that the total employment loss during 1980-2005 due to offshoring was negligible (around 1.5 to 2 percent in the total increase); and (2) that the average offshoring industry enjoys higher productivity growth rates, with larger effects when services activities and not goods (material inputs) are relocated (from 1.4 to 1.98 additional percentage points in the former case and from 0.48 to 0.64 in the latter).

An outline of the paper is the following. In Section 2 I review a group of selected works, both at the aggregate and disaggregate level. Section 3 is devoted to analyze the details of measuring offshoring properly, and to the econometric methodologies underlying our subsequent analysis. Section 4 goes over the data, an introductory statistical analysis, and the results of the set of estimated equations regarding the employment and productivity effects of offshoring. Section 5 finally concludes the paper.

2 The story so far

Much has been said about offshoring in recent times, less indeed has been produced in terms of sound and unambiguous empirical evidence. However, this relatively scarce literature has taken a drastic step forward since the mid 1990s, hardly to go unnoticed. Table 1 compiles the details of most of the works discussed in the next few sections.

Contributions to the subject of offshoring and its interplay with labor markets split into studies undertaken at different levels of aggregation. Highly aggregated (e.g. industry) works came in first place, with the focus on the US economy and the trade and productivity-related literature.[1] Later on, with the labor market at the center of attention, several aggregate as well as disaggregate studies began to come to light. This implied some loss of homogeneity in the empirical definition of offshoring and the little tangible consensus in the econometric approaches. As for the results, even though some broad conclusions can be drawn, much is yet to be said about the real impact of offshoring on labor markets. A shortened review based on the information in table 1 is what comes next.

2.1 First steps and breakthrough

The first contributions tried to explain the changes in the skill composition of the employed workforce or the underlying relative wages through variables other than productivity. Wage inequality among workers of different skills, or shifts from nonskilled toward skilled labor, could thus be explained by this "new" phenomenon. However, these studies found no decisive evidence of offshoring being a major driver of these relative changes. Berman *et al.* (1994), Krugman (1995), Lawrence and Slaughter (1993), Leamer (1994), Siegel and Griliches (1992), and Slaughter (1995, 2000), present research efforts on similar lines.

[1] See the references cited in the next paragraph.

Table 1: Empirical evidence (selected works)

Work (year)	Country	Sample	Sector[a]	Period	F-H index[b]	Analytical framework[c]	Dependent variable	Effect	OSS[d]
Siegel and Griliches (1992)	US	392 industries	M	1959-1986	✓	Correlation analysis	-	0	0
Berman *et al.* (1994)	US	450 industries	M	1959-1987	0	Translog cost, share eq.	Relative employment	0	0
Slaughter (1995, 2000)	US	32 industries	M	1977-1989	0	Translog cost, share eq.	Relative employment	0	0
Feenstra and Hanson (1996a)	US	450 industries	M	1959-1987	✓	Translog cost, share eq.	Relative employment	✓	0
Feenstra and Hanson (1996b)	US	450 industries	M	1972-1990	✓	Translog cost, share eq.	Relative employment	✓	0
Feenstra and Hanson (1999)	US	447 industries	M	1979-1990	✓	Translog cost, share eq.	Relative employment	✓	0
Amiti and Wei (2006)	US	450 industries	M & S	1992-2000	✓	Cobb-Douglas PF, LD	Prducty. & Emplmnt.	✓, 0	✓
Canals (2006)	US	27 industries	M & S	1980-1999	✓	Translog cost, share eq.	Relative wages	✓	0
Crinò (2010)	US	58 occupations	M & S	1997-2006	✓	Logit, Probit	Transition probabilities	✓	✓
Girma and Görg (2004)	UK	19,000 est.	M	1980-1992	0	Reduced form/PF	Offshoring/Productivity	✓	✓
Amiti and Wei (2005)	UK	78 industries	M & S	1995-2001	✓	LD	Employment	0	✓
Criscuolo and Leaver (2005)	UK	35,000 plants	M & S	2000-2003	✓	PF	Productivity	✓	✓
Hijzen *et al.* (2005)	UK	50 industries	M	1982-1996	✓	Translog cost, share eq.	Relative employment	✓	0
Egger *et al.* (2003)	Austria	38,000 workers	M	1988-2001	✓	Multinomial logit	Transition probabilities	✓	0
Egger and Egger (2003, 2005)	Austria	21 industries	M	1990-1998	✓	General equilibrium	Relative employment	✓	0
Strauss-Kahn (2004)	France	50 industries	M	1977-1993	✓	Translog cost, share eq.	Relative employment	✓	0
Geishecker and Görg (2005)	Germany	1,612 workers	M	1991-2000	✓	Wage equation	Relative wages	✓	0
Görg and Hanley (2005)	Germany	80 plants	Elec.	1990-1995	✓	LD	Employment	✓	✓
Cadarso *et al.* (2008)	Spain	93 industries	M	1993-2003	✓	LD	Employment	✓, 0	0
Ekholm and Hakkala (2006)	Sweden	20 industries	M & S	1995-2000	✓	Translog cost, share eq.	Relative employment	✓, 0	0
Hakkala *et al.* (2007)	Sweden	15,000 firms	M & S	1990-2002	0	LD	Employment	0	0
Head and Ries (2002)	Japan	1,070 firms	M	1971-1989	0	Translog cost, share eq.	Relative employment	✓	0
Tomiura (2005)	Japan	118,300 firms	M	1998	0	Survey/Reduced form	Offshoring intensity	-	0
Hijzen *et al.* (2006)	Japan	12,564 firms	M	1994-2000	0	PF	Productivity	✓	0
Ito *et al.* (2007)	Japan	5,500 firms	M	2006	0	Survey	-	-	✓

[a]: M is manufacturing, S services, and Elec. electronics.; [b]: Feenstra-Hanson index or similar; [c]: PF is production function and LD labor demand; [d]: offshoring of services.
Note: the column labeled “effect” refers to the effect of the offshoring variable on the dependent variable (✓ stands for significance and 0 for non-significance).

Feenstra and Hanson (1996a, 1996b, 1997, 1999) produced evidence for the first time in favor of a shift towards skill-intensive activities within domestic industries due to offshoring. Their rationale was: if firms respond to import competition from low-wage countries by moving nonskilled-intensive activities abroad, then trade has to shift employment toward skilled workers in the domestic economy. Therefore, it is the composition of trade, and the share of intermediate inputs in particular, what matters in the end for wages and employment. In their own words, "trade in intermediate inputs can have an impact on wages and employment that is much greater than for trade in final consumer goods" (2001, p.1). As we shall see, offshoring can best be proxied using a measure that takes account of intermediate trade.

All these efforts described offshoring as a factor-biased technological change, in the sense that high-skilled employment results favored after offshoring takes place, precisely because low-skill activities are more prone to go offshore due to potential labor cost gains. Under this perspective, offshoring might just bring about an increase in the skill-intensity of production that comes with an increase in the wage rate for high-skilled relative to low-skilled labor. Feenstra and Hanson argue that if certain activities at the lower end in terms of skill intensity in the US are offshored to Mexico, where they can be said to be in the upper end of the scale, then skill intensity goes up in both countries. Consequently, an increased demand for high-skill workers in both countries is accompanied by a rise in their relative wages, and offshoring becomes a form of factor-biased technological change.

Feenstra and Hanson also contend that previous calculations might have underestimated the real extent of offshoring. In their 1996b paper, for example, estimations suggest that offshoring can explain up to 31 percent of the increase in the nonproduction wage share during the 1980s for 450 US manufacturing industries. Nonproduction employment is usually seen as a proxy for skilled labor whereas production employment represents most faithfully nonskilled labor. One must be very careful though in defining the skill of workers, since this might disguise some important information. The 1999 paper produced smaller numbers; there, offshoring accounted for 13 to 23 percent of the shift toward nonproduction labor, which is still a significant proportion.

2.2 Aggregate evidence

Aggregate evidence,[2] other than the previously mentioned, comprises a group of works inspired by Feenstra and Hanson's primeval analysis. They rely on their index or some of its variants to some extent.[3] Functional as it may seem at first, aggregation might yet hide some empirical nuisances. In effect, it is to expect that within the same industry there

[2]Whenever I refer to aggregate evidence it is the industry level what I have in mind.

[3]See here, for instance, Campa and Goldberg (1997), Egger and Egger (2003), and Hummels *et al.* (2001), for similar measures of offshoring. Horgos (2009) presents a comparative study of all these.

can be firms that engage in offshoring more often than others. On another level, there are sectors which can offshore more than others. Conveniently, these phenomena are known as aggregation or sector bias. On another theoretical ground it is also possible to expect a bias in production factors since, as argued before, certain kind of labor (e.g. unskilled) is more prone to be relocated.[4] Let us now go over some of the most significant works in a very brief manner.

Egger and Egger (2003) use a panel of 20 Austrian manufacturing industries engaged in offshoring towards East Europe for the period 1990-1998. They find a change of relative employment by about 0.08 to 0.12 percent in favor of high-skilled workers. The fact that the low-skilled labor market is unionized, they argue, emphasizes the change in employment due to offshoring.

Egger and Egger (2005) again dig up the case for Austria, using a panel of 21 industries in the 1990s. And again they find a positive effect of offshoring towards high-skill workers. This time they employ a general equilibrium model and find much larger effects because of the important role of intersectoral spillovers which are now being considered. These spillover effects may be of two kinds. First, offshoring practices by certain industry which might cause an impact on another due to input-output linkages, and second, national labor flows across industries. The authors can therefore avoid a substantial underestimation of the labor market effects of offshoring.

Strauss-Kahn (2004) draws on data from 50 French manufacturing industries during 1977-1993. She asserts that offshoring explains 11 to 15 percent of the drop in the share of unskilled workers in manufacturing employment during 1977-1985, and 25 percent of the decline during 1985-1993. It is theoretically more appropriate to rely on relative wage changes though, since it results from the cost-minimization problem of firms usually embedded in a (translog) cost function. The focus on relative employment rather than relative wages responds to particularly inflexible aspects of the labor market under study, as it is the case of most continental European countries. As a conclusion, the author reasons that globalization has manifested itself through a significant decline in the within industry share of unskilled workers for France.

Ekholm and Hakkala (2006) present evidence for 20 industries from Sweden in the 1995-2000 period. Their results hint at an important contribution of offshoring in the shift of relative labor demand away from the group of workers with upper secondary education. This is only significant when considering offshoring to low-income countries but not to high-income ones.

Cadarso *et al.* (2008) employ data from 93 Spanish manufacturing industries for the 1993-2003 period. They suggest that the effect of offshoring varies depending on the indus-

[4] For theoretical contributions on sector bias see especially Arndt (1997, 1998, 1999). For factor bias see Feenstra and Hanson (1996a, 1996b, 1997, 1999). Krugman (2000) and Leamer (1998) present studies on relative factor prices adjustments due to either sector or factor bias.

try's characteristics and the country of origin. Their estimation implies a negative effect on labor which turns out significant for medium and high-tech industries (when offshoring comes from Central and Eastern European countries) while it is nonsignificant for other countries and low-tech sectors.

Hijzen *et al.* (2005) analyze 50 British manufacturing industries during 1982-1996, and discover a strong negative impact on the demand for unskilled labor. They are able to use information directly linked to occupational classifications, as opposed to the standard division between production and nonproduction workers, which corresponds to the basic nonskilled-skilled classification.

Amiti and Wei (2005) conduct a research that takes up the case of the UK with data from 69 manufacturing industries and 9 service industries during 1995-2001. They find no evidence of offshoring of materials and services having a negative effect on total employment, while estimating a conventional labor demand function. In their companion paper, Amiti and Wei (2006) corroborate this for the US economy using 96 industries in 1992-2000. However, when the economy is decomposed into 450 industries a negative effect on employment is detected. Further, they find a positive effect of offshoring on productivity, ranging from 11 to 13 percent of productivity growth being accounted for by services offshoring and from 3 to 6 percent by materials offshoring. Two points are worth stressing about both works by these authors: first, their methodology detours from the translog cost estimation employed up to those days, and second, they consider services offshoring empirically for the first time.

Canals (2006) uses data in a sample of 27 US industries (18 manufactures, and 9 services), over the period 1980-1999, and finds out that offshoring explains 28 percent of the observed wage change. She carries out an accounting decomposition which is analogous to the growth decomposition within the productivity literature. The wage gap can then be explained by shifts in offshoring, shifts in biased technological change other than offshoring, and total technological change.

At this level of aggregation we can summarize the results as follows (see table 1). For continental Europe there is evidence on both offshoring being a source of (biased) technological change (Egger and Egger, 2003 and 2005; Strauss-Kahn, 2004; Ekholm and Hakkala 2006) and a source of employment loss (Cadarso *et al.*, 2008). However, the latter is dependent on the technology level of the industries involved domestically and the destination countries. For the UK and US there is evidence in favor of offshoring as a factor biased change (see Hijzen *et al.*, 2005, and Canals, 2006, respectively) yet not as a significant source of employment loss (Amiti and Wei, 2005 and 2006). Moreover, positive productivity effects of offshoring are also found for the US (Amiti and Wei, 2006). It must be observed too, that with the exception of both works by Amiti and Wei, the case for services offshoring is not covered.

2.3 Disaggregate evidence

Disaggregate evidence allowed researchers to get rid of the aggregation-sector bias and thus provide a clearer picture of the phenomenon.[5] While it might indeed prove helpful, allegedly allowing a more in-depth analysis, disaggregate evidence very often focuses on a narrow part of the economy. Especially in later times, disaggregate studies have been developed in order to cope with the employment and productivity effects of offshoring. Here are some of the most representative.

Egger *et al.* (2003) use data on Austrian male workers (around 38,000) over the period 1988-2001. They offer an approach for studying the transition probabilities of employment into other sectors, accounting for intermediate steps into the pool of unemployed, or out of the labor force. The results prove that international factors are important for labor market turnover, especially for what they call industries with a comparative disadvantage (net importing industries). They remark that increases in imports, terms of trade and, more importantly, the share of offshoring in total trade, negatively affect the probability of staying in or changing into the manufacturing sector.

Geishecker and Görg (2005) carry out the study for the German manufacturing sector including 1612 individuals during the period 1991–2000. They come to the conclusion that only low-skilled workers employed in low-skill intensive industries experience reductions in their real wages following fragmentation activity in those industries. The wage elasticity points that a one percentage point increase in fragmentation intensity (offshoring) leads to a reduction in average wages by 3.6 percent. On the contrary, high-skilled workers in the high-skill-intensive industries might expect a rise of 2.7 percent in average wages due to a one-percentage point increase in fragmentation.

Görg and Hanley (2005) employ data on 80 plants for the Irish Electronics sector in the period 1990-1995. They find that a fall of 0.27 percent in employment can be explained by a 1 percent increase of offshoring. They also report significant individual effects of materials and services offshoring, with stronger effects from the former. Respectively, elasticities are -0.20 and -0.15.

Hakkala *et al.* (2007) use data on 15,000 Swedish firms during 1990-2002. Their results reveal that there exists no clear difference between foreign and domestic firms, or between multinational and nonmultinational firms, as regards wage elasticities.

Girma and Görg (2004) study 14,000-19,000 establishments in the UK manufacturing sector, for the period 1980-1992. The authors take account of the decision to go offshore and the effect of such decision on the establishments' productivity. They find that there is strong persistence in the offshoring decision and that foreign establishments offshore more than domestic ones. Also, they find that offshoring has significant positive effects on

[5] Here I refer to everything below the industry level (at whatever classification). That is, firms, plants, establishments, or individual workers.

productivity.

Criscuolo and Leaver (2005) use establishment data for both the manufacturing and services sectors in the UK (35.000 plants approximately) during a short span, 2000-2003. They determine that a 10 percentage point increase in (services) offshoring intensity is associated with a 0.37 percentage point increase in total factor productivity. This effect comes mainly from firms that are domestic and nonglobally engaged.

Crinò (2010) presents highly disaggregated data on 58 white-collar occupations in 144 US industries for the 1997-2002 period. He shows that services offshoring is skill-biased because, against common perception, it raises employment among high-skilled occupations and lowers employment among medium- and low-skilled ones. He also proves that the tradability of occupations is negatively related to services offshoring, thus favoring highly complex non tradable jobs.

We can see that also at the disaggregate level the evidence provides with proof for the effects of offshoring on the labor markets (table 1). For continental Europe it is again possible to dig up both the relative effects (Geishecker and Görg, 2005) and the direct effects (Görg and Hanley, 2005) upon employment. Others, however, do not find a significant direct effect on employment (Hakkala *et al.*, 2007).[6] Further, evidence about the effects on labor turnover has also been produced (Egger *et al.*, 2003). Positive effects of offshoring on productivity are obtained for the UK (Girma and Görg, 2004; Criscuolo and Leaver, 2005), whereas some evidence on labor turnover due to offshoring is found for the US (Crinò, 2010). Apparently, services offshoring is here more present than in aggregate studies, but it is still far from receiving the deserving attention.

2.4 What's with Japan?

Japan's offshoring little tale remains in the shadows, as it is the case for much of the subject so far and much of Japan's puzzling performance in the 1990s. The following are some papers that have seen the light very recently and need to be looked at with a keen eye.

To my knowledge, the first step towards an understanding of the dealings of Japan with offshoring and its effects on the labor market is the research by Head and Ries (2002). The authors present evidence of 1070 multinational firms in the manufacturing sector for 1971-1989, that supports the direct relation between multinational activity and domestic skill upgrading. Results in a set of different specifications and samples show that changes in overseas employment shares can explain a 0.9 percentage point increase of the roughly 10 percentage point increase in the share of nonproduction workers. On other accounts, they show that increasing domestic skill intensity proves to dwindle as investment shifts eventually towards higher-income countries.

[6] Significant direct effects refer to negative short-run effects of offshoring in terms of employment. Nevertheless, we will see that for the case of Japan this might be otherwise.

Another contribution at the firm level is Tomiura (2005), who considers a survey from 1998 of 118,300 firms in all manufacturing industries. Surprisingly, nearly 98 percent did not offshore any of their production overseas. The extensive nature of the sample employed in this study bears some limitations though, as made explicit by the author. First, offshoring of services is not covered, and second, only manufacturing firms are considered. The interest relies then in the determinants of offshoring for the individual firm, among which we find several firm-level characteristics. The endowment of human skills and the experience with FDI are found to be of high importance. In the same line, more productive firms and those whose products are more labor-intensive display a more extensive offshoring intensity.

A recent paper by Hijzen *et al.* (2006) focuses on the productivity side, while covering 12,564 manufacturing firms in the years 1994-2000. Indeed, positive productivity effects have been consistently exposed in most of the works that undertook that task, as previously reviewed.[7] A one percent increase in offshoring intensity, these authors assert, would raise productivity growth by 0.17 percent. Further, for the average offshoring firm this would imply a 1.8 percent increase in annual productivity growth. They also find that the potential extent for productivity improvements depends negatively on the initial level of productivity of the firm. Thus, they suggest that "offshoring may be an effective channel in restoring the competitiveness of less productive firms" (p.5). And also, "that specializing in skill-intensive production stages through offshoring generates higher growth in productivity due to larger learning-by-doing effects" (p.7). On the same grounds, they find multinationals to be more important offshorers than purely domestic firms.

Ito *et al.* (2007) analyze a survey from 2006, including more than 5,000 large-sized firms from all manufacturing industries. Their main results indicate that offshoring is more present now than five years ago: sampled firms engaged in offshoring went from 15 percent in 2001 to 20 percent in 2006. Moreover, production-related tasks take most of the offshoring pie, while services offshoring is still of a rather narrow scope. Also according to these data, offshoring for Japanese firms is mainly restricted to own affiliates within East Asia.

We can see that the evidence for Japan consists of firm-level studies displaying the expected qualitative conclusions that abound elsewhere in the literature. Namely, that a factor biased technological change might occur when offshoring takes place, favoring high-skilled workers domestically (Head and Ries, 2002), and that productivity gains are surely to be expected as a result of offshoring (Hijzen *et al.*, 2006). Tomiura's work, however, raises important questions around the subject and its significance for the Japanese economy. In

[7] The story of employment is somehow left apart in works concerning productivity issues. However, a caveat is in order. Employment creation in the shortest run (if any) as a result of productivity gains is usually understood as taking place in a different sector or industry. Certainly, when firms become more productive they can produce with less (not more), be that capital or labor, while workers are faced with the real threat of unemployment. In the longer run, though, offshoring firms are faced with the scale effect. That is, offshoring-related productivity increases can make firms more efficient and competitive after a while, increasing the demand for their output and exerting a positive effect on labor. See Olsen (2006) for a complete account of the offshoring and productivity story.

spite of the latter, I believe it proper to set out the case at a more aggregate level based on a simple reason: it has never been undertaken. This, I suspect, might prove to be a robustness check on the previous Japanese evidence. Moreover, other several features put the current research aside from the other works. First, I take the whole economy and not just one sector; second, I take account of services offshoring; and third, I estimate the direct effects of offshoring on employment.

3 Measurement and estimation issues

How to define offshoring when it comes to empirics? In other words, how to proxy its theoretical definition quantitatively? Roughly speaking, offshoring can be measured either directly or indirectly. Nevertheless, the lack of reliable direct data should make us consider indirect measures to a greater extent.[8] The indices on intermediate trade I discuss below have so far proved to be reliable proxies.

3.1 Indirect indicators

A benchmark contribution is Feenstra and Hanson (1996a, 1996b, 1997, 1999). There, offshoring is defined as the share of imported intermediate inputs in the total purchase of nonenergy inputs. They combine US import data from the four-digit SIC (Standard Industrial Classification) with data on material purchases from the *Census of Manufactures*. The census data crisscross the trade between industries of the same level and provides the base for estimating the share of intermediate inputs in every industry. For a given industry i at time t, multiplying the shares of input purchases from each supplier industry times the ratio of imports to total consumption in the supplier industry, and then adding over, turns out in their offshoring intensity measure. More formally, this can be written as follows:

$$OS_{it} = \sum_j \left(\frac{I_{jt}}{Q_t}\right)^i \left(\frac{\Pi_{jt}}{D_{jt}}\right) \tag{1}$$

where I_j is purchases of inputs j by industry i, Q is total inputs (excluding energy) used by i, Π_j is total imports of goods j, and D_j their domestic demands. This formula provides an index of the offshoring intensity at the industry level. It estimates the import content of intermediate trade of industries which, in turn, proxies their offshoring intensities. Specifically, the first term in (1) stems from the census data (or Input-Output tables), while the second term, which is an economy-wide import share, is obtained from the trade data.

[8] Kirkegaard (2007) breaks down the different sources to measure offshoring into three empirical hierarchies. The lowest tier encompasses all the estimations and projections by consulting companies (Forrester, 2004, and McKinsey, 2003, for instance). Second-class data belong to the estimates elaborated by the press, mostly resorting to public and verifiable sources. And finally, the indirect measures we discuss here place at the top of this ranking.

Conveniently, this expression serves as a measure for both the traditional offshoring of materials and the more fashionable offshoring of services.[9] Besides, it is useful to split offshoring into its narrow and broad measures. The narrow measure restricts to imported intermediate inputs from the same two-digit industry whereas the broad measure includes all other industries as well. In particular, when $i = j$ we have that the equation in (1) becomes the narrow measure. Also the difference between the broad and narrow measures, which represents all imported intermediate inputs from outside the two-digit purchasing industry, stands as an alternative when it comes to capturing the true nature of offshoring. Other indices used in the literature are: the imported inputs in total output ratio (see for instance Egger and Egger, 2003), or the vertical specialization index, which accounts for the imported inputs content of exports (see here Campa and Goldberg, 1997, and Hummels *et al.*, 2001).

A common drawback to all measures relying on import shares is that offshoring does not necessarily imply an increase of imports, and vice versa. If a local exporting firm decides to move part of its production abroad and continues exporting it from a foreign country this would not translate into a drop in imports to the parent firm. Rather, it would represent a fall of its exports. Likewise, a rise in a country's imports due to more favorable terms of trade should not be linked in any fashion to an expansion of offshoring from local firms. Another disadvantage of this particular index is that the second term in (1), the import penetration of inputs, is usually taken as equal for every industry.

The rationale for using this kind of indices should be clear: importing trade stands for an important amount of intra and inter firm trade nowadays, from which offshoring could be proxied. Upon availability of imported intermediate inputs data, equation (1) can readily be reduced to:

$$OS'_{it} = \sum_j \left(\frac{\eta_{jt}}{Q_t}\right)^i \tag{1'}$$

where OS'_{it} is the offshoring intensity index expressed directly as the ratio of total purchases of imported intermediate inputs to the total use of nonenergy inputs. The numerator in (1'), η, represents the imported intermediate inputs which correspond to the diagonal element of import-use matrices. Most of times it is not possible to use such simple expressions as (1') in an extensive time period. Input-Output tables are periodically published around every five years and remain one of the few direct sources of η; this is why it is usually estimated through trade data, as in (1). Therefore, and due to the structure of our data, the statistical and econometric analysis of the following sections relies on a broad measure drawn from equation (1) above.

[9] Amiti and Wei (2005, 2006) elaborate on this index as to account for both types of offshoring at the industry level.

3.2 Analytical framework: Employment

To study the direct effects of offshoring on employment I depart from a Cobb-Douglas technology for the industry (Amiti and Wei, 2006). Thus, omitting subscripts, we have:

$$Y = A(t)K^{\alpha}L^{\beta} \tag{2}$$

with K and L being equal to capital and labor services respectively, Y the value added, and A the time-dependent technology shifter. Also accepting that the industries can be represented as a single cost-minimizing firm (that is, min $rK + wL$), from our knowledge of the production function we can derive the cost function; hypothetically:

$$C(w, r, Y) = \phi r^{\frac{\alpha}{\alpha+\beta}} w^{\frac{\beta}{\alpha+\beta}} Y^{\frac{1}{\alpha+\beta}} \tag{3}$$

ϕ being a constant, r and w the factor prices (the interest rate and wages, for instance), and Y output. As we can see, the cost function and the production function are both sides of the same coin. With exogenous input prices, the production function and the cost function contain virtually the same information.

It must be remembered at this point that, particularly in former efforts, it was most appealing to specify a translog cost function allowing for more substitution possibilities among inputs. This provided with a more flexible framework as regards cross elasticities that led to the estimation of a factor-share equation.[10] We should keep in mind though, that the original debate was all about explaining the wage gap (e.g. the wage skill premium) or the shifts in relative employment of both nonskilled and skilled labor, due essentially to some form of technological change (see Berman *et al.*, 1994, and Feenstra and Hanson, 1996b, most representatively). Some of the current efforts, however, try to disentangle a more direct incidence of offshoring on total employment as in, for example, Amiti and Wei (2005, 2006) or Cadarso *et al.* (2008), who implicitly assume a Cobb-Douglas technology. In this way we have that cost minimization, which entails the optimal demand for inputs given a certain level of output, is characterized by the conditional demand for labor augmented by other factor prices.

Following Hamermesh (1993), minimizing total costs in (3) using Shephard's lemma (Hicks, 1939; Samuelson, 1947; Shephard, 1953) yields the factor demand functions for K and L. For the labor factor we have, in general form:

$$L = \Gamma(w, p, Y) \tag{4}$$

where the demand for labor depends on wages w, other factor prices p, and an output measure Y. Among input prices other than r, we can identify, following Amiti and Wei

[10] See Appendix A.

(2005, 2006), the price of foreign labor services. These pose as a substitute for domestic labor and enter the labor equation:

$$L = \Gamma(w, p^{'}, p^{os}, Y) \tag{5}$$

where $p^{'}$ is a vector of factor prices other than those of foreign services (p^{os}). Since data on p^{os} are often hard to get, these authors propose the offshoring intensity indices as an *inverse proxy* of the price of these imported intermediate inputs.

$$L = \Gamma(w, p^{'}, Y, OSS, OSM) \mid A(OSS, OSM) \tag{6}$$

where OSS and OSM are the services and manufacturing offshoring indices, and A is the technology shifter dependent on offshoring. Here Amiti and Wei (2005, 2006) identify three channels through which offshoring comes to affect the labor demand. First, a possible substitution effect between labor and prices of imported inputs (services or materials); a drop in the latter or, equivalently, an increase in the offshoring indices, would lead to a fall in the demand for labor. Second, a possible short-run productivity effect of offshoring to impact negatively on employment. And third, the scale effect (or long-run productivity effect) which might affect labor positively, provided firms are more efficient and competitive in the longer run due to previous productivity gains.

Log-linearizing and adding the subscripts to the previous formulation, we obtain a widely used equation in the recent literature:

$$\begin{aligned} \ln L_{it} &= \beta_o + \beta_1 \ln L_{it-1} + \beta_2 OSS_{it} + \beta_3 OSM_{it} + \beta_4 \ln w_{it} + \beta_5 \ln p^{'}_{it} + \beta_6 \ln Y_{it} \\ &\quad + \delta_i d_i + \delta_t d_t \end{aligned} \tag{7}$$

Labor is regressed on its lagged value and a set of other explanatory variables, where the subscript i stands for industry and t for time. The introduction of the lagged dependent variable on the right-hand side is justified since we can reasonably suppose that labor does not adjust automatically to changes in the other variables. Or, what is the same, that the level of employment might deviate from its steady state when the adjustment takes place (see Cadarso *et al.*, 2008, and Görg and Hanley, 2005). Explanatory variables include, respectively: the services and materials offshoring intensity indices, OSS and OSM, real average wages w, other factor prices $p^{'}$ (such as r), and an output measure Y. Here we can use the output (either volume or value), the capital stock, or some measure of R&D investment. Industry and year fixed effects also enter the equation through the dummy variables, d_i and d_t. For the benefit of clarity, error terms are omitted here and in the following section.

Introducing lags of both OSS and OSM into equation (7) would allow us to account for the longer run scale effects of offshoring. The signs of the coefficients would eventually tell the final effect on employment. The simple methodology undertaken here is only concerned with the direct effects of offshoring within industries, while no industrial spillovers are taken account of.[11] Therefore, the expected signs of the coefficients β_2 and β_3 are inconclusive, since it is not clear whether the scale effects are large enough to outweigh the substitution and productivity effects *within the same industry.* As stated before, the output may be increased (and employment with it) in response to offshoring-related productivity gains. Moreover, we expect that.$\beta_4 < 0$ (a downward-sloping labor demand), and $\beta_5 > 0$ (if inputs are gross substitutes). Notice too that no restrictions are imposed on the coefficients as to comply with the constant returns to scale (CRS) hypothesis, since this is not found to hold on several specifications of the production function.

A couple of remarks by Amiti and Wei (2006) need be recapped. First, relying on the assumption of perfect mobility of labor across industries, we have that wages are exogenously determined. If that is not the case though, then wages are endogenous. Provided that these potential rents are unchanged over time, we can assume that they would be absorbed by the industry fixed effects (δ_i), so the results would still be unbiased. Second, the price of other inputs (such as imported inputs and the rental on capital) are considered as a function of time, so they are captured by the time fixed effects (δ_t). And lastly, these authors prefer the use of the output variable as a control, which supposes a strong endogeneity problem. Even though this is conventional in most empirical work, the estimated equation remains of doubtful interpretation as the coefficient on the real wage variable represents a partial elasticity and not a total elasticity (Webster, 2003).[12] For this reason, the exogenously determined capital stock variable is made explicit in our final estimating equation with no output variables:

$$\ln L_{it} = \theta_o + \theta_1 \ln L_{it-1} + \theta_2 OSS_{it} + \theta_3 OSM_{it} + \theta_4 \ln w_{it} + \theta_5 \ln K_{it} + \delta_i^* d_i + \delta_t^* d_t \qquad (8)$$

Notwithstanding the previous assumptions in the last few paragraphs, the estimation of the panel in equation (8) in their static or dynamic forms still entails potential endogeneity problems due to the offshoring variables. A potential bias in OLS estimates is expected and should make us consider the implementation of instrumental variables techniques.[13]

[11] For this see Egger and Egger (2005), who claim that the final effect of offshoring could be strongly underrepresented if spillover effects are not being considered.

[12] Webster (2003) carries on: "A total elasticity includes the full effects on employment, once the effects on intermediate variables such as output have been worked through. Partial elasticities are the effects if one or more of these intermediate variables are artificially held constant. Partial elasticities are artificial 'thought experiments', as in real life it is not possible to control most variables." (p. 135, footnote 5).

[13] In addition to the estimation of equation (8), I also present in the appendix some estimations of the conditional and unconditional labor demand functions, as defined for instance in Amiti and Wei (2006). These alternative expressions employ, respectively, the quantity and price of output as control variables.

3.3 Analytical framework: Productivity

Productivity can be measured in multiple ways. Fundamentally, it can be either measured as a ratio of a volume measure of output to a volume measure of input, or as a measure depending on all types of inputs. In this way it is possible to distinguish between labor and capital productivity on the one hand (a single-factor measure), and total factor productivity (TFP) on the other (that is, a multi-factor measure). Different measures of outputs and inputs and, thus, of productivity, reflect different representations of the same production process in a particular industry (Zheng, 2005). We are interested in calculating two of these widely used measures of the TFP for Japan and then estimate the direct effect of offshoring. This is the usual two-stage estimation methodology.

First we have a generalization of the gross value added (or net output) representation of the production function. Gross value added is obtained by deducting intermediate consumption from gross output; at factor costs it includes: wages, consumption of fixed capital, and pre-tax profits. Supposing a Cobb-Douglas technology and omitting subscripts, such an output measure can be represented by:

$$Y_V = F(K, L, t) = A^{'}(t)\ K^{\alpha} L^{\beta} \tag{9}$$

where gross real value added Y_V depends on labor L, capital K, and the Hicks-neutral and time-dependent technological parameter $A^{'}(t)$.

Additionally, we can consider the gross output-based measure, which is a representation of the production function augmented by the consumption of materials and services inputs:

$$Y_O = G(K, L, M, S, t) = A^{''}(t)\ K^{\gamma} L^{\delta} M^{\lambda} S^{\mu} \tag{10}$$

where gross real output Y_O depends on labor L, capital K, materials inputs M, services inputs S, and the neutral technological shifter $A^{''}(t)$.

Taking logarithms and differentiating both expressions with respect to time we get, through Euler's theorem, the contributions of the growth in inputs to the growth in output:

$$\dot{Y}_V = \zeta_K \dot{K} + \zeta_L \dot{L} + \dot{\tau}_V \tag{11}$$

$$\dot{Y}_O = \eta_K \dot{K} + \eta_L \dot{L} + \eta_M \dot{M} + \eta_S \dot{S} + \dot{\tau}_O \tag{12}$$

where $\dot{X} = \frac{\partial \ln X}{dt}$ is the growth rate for any variable in (11) and (12), $\zeta_h = \frac{\partial F}{\partial Z_h}\frac{Z_h}{F}$ and $\eta_h = \frac{\partial G}{\partial Z_h}\frac{Z_h}{G}$ are the elasticities of output to the different inputs (Z_h), and $\dot{\tau}_V = \frac{\partial \ln F}{\partial t} = \dot{A}'$ and $\dot{\tau}_O = \frac{\partial \ln G}{\partial t} = \dot{A}''$ are the changes in the Hicks-neutral residuals (e.g. technical progress). Under the simplifying assumptions of CRS and perfect competition in the market of both output and inputs, these equations can deliver the growth in the TFP:

$$\dot{\tau}_V = \dot{Y}_V - s_K\dot{K} - s_L\dot{L} \tag{13}$$

$$\dot{\tau}_O = \dot{Y}_O - s'_K\dot{K} - s'_L\dot{L} - s'_M\dot{M} - s'_S\dot{S} \tag{14}$$

Because of the competitive equilibrium assumption in particular, equations (13) and (14) also imply the equivalence between factor income shares and output elasticities. That is, $s_h \equiv \frac{p_h Z_h}{p_V Y_V} = \zeta_h$ and $s'_h \equiv \frac{p_h Z_h}{p_O Y_O} = \eta_h$, with p_h the price or return to inputs, and p_V and p_O the prices of real value-added and real gross output respectively. Each input is thus paid its marginal product.[14]

In order to keep consistency with the previous section, the CRS hypothesis is here relaxed. To account for non-constant returns (non-CRS) I follow Liu and Li (2008) decomposition approach,[15] which would imply modifying the output growth equations (11) and (12) as to adjust for the economies of scale effect. As seen in both these equations, when CRS apply, output growth can be decomposed into the weighted sum of input growth and technical progress. However, in the presence of non-CRS, Euler's equations can now be rewritten in general terms as follows:[16]

$$\dot{Y} = \xi\,\Sigma_h \frac{\xi_h}{\xi}\dot{Z}_h + \dot{A} \tag{15}$$

where ξ_h is the output elasticity to input Z_h, ξ is the sum of these elasticities ($\Sigma_h\,\xi_h$), and $\dot{A}$ is the technical progress. When production is CRS, $\xi = 1$, and equation (15) reduces to $\dot{Y} = \Sigma_h\,\xi_h\dot{Z}_h + \dot{A}$, which is a generalization of (11) and (12). By subtracting and adding $\Sigma_h\,\frac{\xi_h}{\xi}Z_h$ and rearranging terms, equation (15) then becomes:

$$\dot{Y} = (\xi - 1)\Sigma_h \frac{\xi_h}{\xi}\dot{Z}_h + \Sigma_h \frac{\xi_h}{\xi}\dot{Z}_h + \dot{A} \tag{16}$$

Equation (16) shows that output growth can now be decomposed into three components: the adjusted economies of scale effect, the weighted sum of input growth, and technical progress. This decomposition can be applied to the decomposition of productivity growth as well. As before, subtracting the growth in inputs to the growth in output yields the unobservable residual term:

[14] Generally speaking, for a production function with a single input Z a simple productivity measure is given by $\frac{Y}{Z}$. When considering multiple inputs, the TFP can be defined as $TFP = \frac{Y}{\Psi}$. If we take logarithms and differentiate with respect to time we get: $\dot{TFP} = \dot{Y} - \dot{\Psi}$. We have that $\dot{\Psi}$ is the Divisia index (Jorgenson and Griliches, 1967), and also that $\dot{\Psi} = \Sigma\frac{p_h Z_h}{pY}\dot{Z}$, which corresponds to the subtracting terms in the right-hand side of (13) and (14), namely: $\Sigma_h\,s_h\dot{Z}_h$ and $\Sigma_h\,s'_h\dot{Z}_h$.

[15] Other references of interest are the work by Kee (2004) and the methodological review by Van Beveren (2007), which go over the different alternatives when classical hypotheses do not hold.

[16] See Liu and Li (2008) for the formal derivation.

$$\dot{TFP} = (\xi - 1)\Sigma_h \frac{\xi_h}{\xi}\dot{Z}_h + \dot{A} \tag{17}$$

which is the sum of the first and last terms in equation (16). Hence, the TFP growth has two components: the adjusted economies of scale effect and technical progress. Notice that when CRS are present $\dot{TFP} = \dot{A}$, as in Solow (1957). Therefore, as argued by Liu and Li, "as long as the parameters of the production function can be estimated", equation (16) "can be used for the empirical estimation of the sources of output growth" and, by extension, equation (17) can be used to extract the sources of productivity growth. Estimating expressions (11) and (12) and then using (16) and (17) to account for non-CRS, we get both adjusted measures of productivity growth ($\dot{TFP}$), that is, $\dot{\tau}'_V$and $\dot{\tau}'_O$. These are two common measures of productivity growth widely used in the literature.[17]

Once I construct the series $\dot{\tau}'_V$ and $\dot{\tau}'_O$ I am able to estimate the effects of offshoring directly. We should remember, though, that since the TFP growth measures are estimated relying on the real values of inputs and output, the cost-saving motive usually attached to offshoring is therefore left out of the analysis. Adding subscripts, the second stage reduced-form estimating equation is simply:

$$\dot{TFP}_{it} = \varphi_1 \dot{TFP}_{it-1} + \varphi_2 OSS_{it} + \varphi_3 OSM_{it} + \lambda_i d_i + \lambda_t d_t \tag{18}$$

where $\dot{TFP}$ is one of the three measures of TFP growth discussed so far: $\dot{\tau}'_V$, $\dot{\tau}'_O$, or $\dot{\tau}_{JIP}$. Additionally, we have the lagged dependent variable which would account for the persistence of TFP growth over time, our offshoring indices (OSS and OSM), and industry and year fixed effects (d_i and d_t). We expect the coefficients associated to both OSS and OSM to be positive independently of the TFP measure considered. According to Amiti and Wei (2006) offshoring can increase productivity either due to compositional or structural changes. First, relocating inefficient parts of the production process to another country could increase the productivity of the remaining workers. And second, due to the access to new inputs, productivity increases are also likely, yet with larger effects arising from services offshoring.

As with employment, potential endogeneity of offshoring is also present in equation (18). Either more productive industries self select into offshoring or, conversely, industries that expect a fall in productivity growth increase their levels of offshoring in the hope of increasing their productivity (Amiti and Wei, 2006). Here again, instrumental variables

[17] See Griliches (1996) and Hulten (2001) for a bibliographical survey and Zheng (2005) for a review of the main indices (which are not considered here) that can be derived from the production function using a nonparametric approach. According to this author, these indices can account for the technological change of a more general nature (e.g. non-neutral Hicks). For instance, in a production function like $Y = H(AK, L)$, the residual affects capital but not labor; in $Y = H(K, AL)$ it affects labor but not capital. These two cases can be described as Hicks-biased, and would account for a rotation of the isoquant curves (instead of a shift, which is our case). For our purposes here, the derivation of our productivity measures in equation (17) through the parametric estimation of (11) and (12) will suffice.

should be considered.[18]

One final word need be said. The analysis in this section stands aside from the debate over whether value added or gross output are more appropriate in measuring output and productivity.[19] The simple methodology laid out here[20] is in the spirit of Hayashi and Prescott's (2002) benchmark contribution to the understanding of Japan's poor TFP performance in the 1990s. In their own words, treating TFP as exogenous (as I do here) would account well for the Japanese lost decade of growth.

4 Empirical analysis

4.1 Descriptive statistics

4.1.1 Data

The JIP database (2006, 2008) provides a comprehensive source for a wide set of variables through a relatively long time period and for the whole Japanese economy. It has been compiled in a joint project by the RIETI (Research Institute of Economy, Trade & Industry), Hitotsubashi University, and the Economic and Social Research Institute (ESRI), all based in Japan. Two versions have been released up to this point, comprising annual data for the period 1970-2005 and covering a total of 108 activities from both the manufacturing and services sectors. Strictly speaking, this classification does not correspond exactly to the industry classification usually found elsewhere (e.g. ISIC, rev. 3, or the EU KLEMS project), yet stands as a faithful approximation.[21]

The database includes data on 54 manufacturing activities, 42 services activities, plus 12 activities which belong into other varying industries of the economy (the primary sector plus energy). Table 2 lists all the activities that make up the JIP database, separated into three sectors: manufacturing, services, and other.

4.1.2 Materials and services offshoring

To estimate the offshoring index I employ the definition in (1) above, resorting exclusively to the JIP database. This is a positive feature since the Feenstra and Hanson-type index necessarily takes data from intermediate inputs and trade, which usually stem from different sources.

[18] More, including a R&D or human capital variable in (18) would be useful to tackle a potential omitted variable bias.

[19] Zheng (2005) states that, at the industry level, the value-added productivity measure might be more sensitive to offshoring than its gross output counterpart. See the example therein provided (pp. 16-17).

[20] Hijzen *et al.* (2006) also adopt this two-step estimation procedure for Japan. Although they assume both CRS and non-CRS, their study is conducted at the firm level.

[21] For a detailed description about this database, including the concordance with other industry classifications, see Fukao *et al.* (2007).

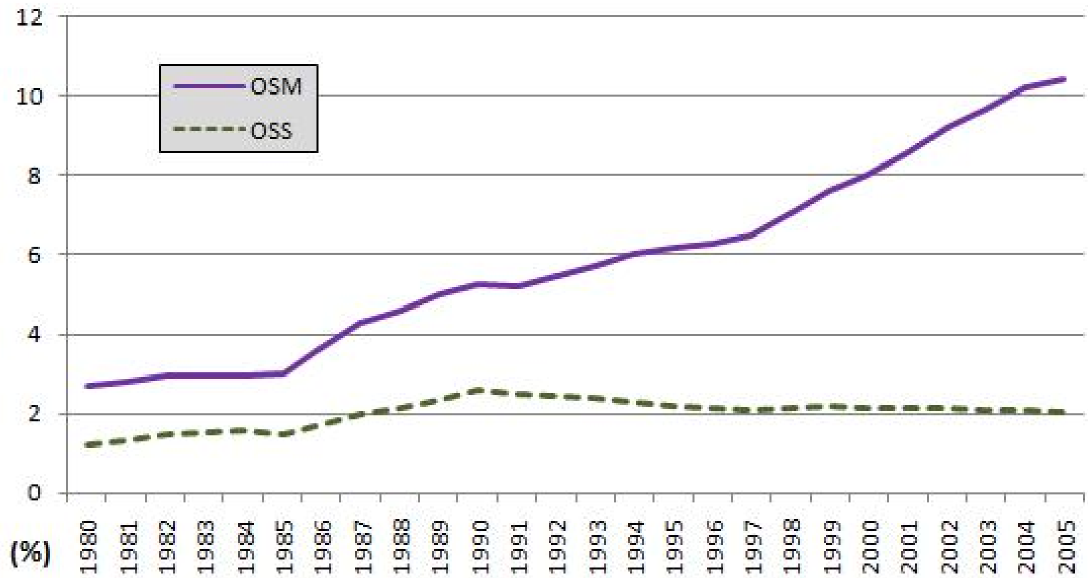
Table 2: JIP database, economic branches of activity

JIP code	*Manufacturing*	*JIP code*	*Services*	*JIP code*	*Other*
008	Livestock products	067	Wholesale	001	Rice, wheat production
009	Seafood products	068	Retail	002	Miscellaneous crop farming
010	Flour and grain mill products	069	Finance	003	Livestock and sericulture farming
011	Miscellaneous foods	070	Insurance	004	Agricultural services
012	Animal foods & fertilizers	071	Real estate	005	Forestry
013	Beverages	072	Housing	006	Fisheries
014	Tobacco	073	Railway	007	Mining
015	Textile products	074	Road transportation	062	Electricity
016	Lumber and wood products	075	Water transportation	063	Gas, heat supply
017	Furniture and fixtures	076	Air transportation	064	Waterworks
018	Pulp, paper, and other paper	077	Other transportation	065	Water supply for industrial use
019	Paper products	078	Telegraph and telephone	066	Waste disposal
020	Printing, and plate making	079	Mail		
021	Leather and leather products	080	Education (private and non-p)		
022	Rubber products	081	Research (private)		
023	Chemical fertilizers	082	Medical (private)		
024	Basic inorganic chemicals	083	Hygiene (private and non-p)		
025	Basic organic chemicals	084	Other public services		
026	Organic chemicals	085	Advertising		
027	Chemical fibers	086	Rental of office equipment		
028	Miscellaneous chemical pdts.	087	Automobile maintenance		
029	Pharmaceutical products	088	Other services for businesses		
030	Petroleum products	089	Entertainment		
031	Coal products	090	Broadcasting		
032	Glass and its products	091	Information and Internet ss.		
033	Cement and its products	092	Publishing		
034	Pottery	093	Video and sound		
035	Miscellaneous ceramic	094	Eating and drinking places		
036	Pig iron and crude steel	095	Accommodation		
037	Miscellaneous iron and steel	096	Laundry, beauty services		
038	Smelting non-ferrous metals	097	Other services for individuals		
039	Non-ferrous metal products	098	Education (public)		
040	Metal products	099	Research (public)		
041	Miscellaneous metal products	100	Medical (public)		
042	General industry machinery	101	Hygiene (public)		
043	Special industry machinery	102	Ss. ins. & ss. welfare (public)		
044	Miscellaneous machinery	103	Public administration		
045	Office and industry machines	104	Medical (non-profit)		
046	Electrical and ind. apparatus	105	Ss. Ins. & ss. welfare (non-p)		
047	Household electric appliances	106	Research (non-profit)		
048	Electronics, computer eqpmnt.	107	Other (non-profit)		
049	Communication equipment	108	Activities not classified		
050	Measuring instruments				
051	Semiconductor and circuits				
052	Electronic parts				
053	Miscellaneous machinery				
054	Motor vehicles				
055	Motor vehicle parts				
056	Other transportation eqpmnt.				
057	Precision machinery eqpmnt.				
058	Plastic products				
059	Miscellaneous industries				
060	Construction				
061	Civil engineering				

Source: JIP database (2006, 2008). RIETI, Hitotsubashi University, and ESRI, Japan.

From (1) we have that the index on materials offshoring is the import content in all materials inputs. Hence, the first term is the input purchases of material j by industry i at time t, as a share of that industry's total use of materials inputs. The second term is a global measure of the import penetration of the referred input j which, even though is time-varying, it remains fixed across industries or branches of activities. This implies the assumption that all industries carry out the importing of these materials with the same intensity. The same reasoning applies to the construction of the services offshoring index.[22]

Figure 1: Materials and services offshoring (%)



Note: Japan's materials and services offshoring indices (OSM, OSS) according to formula (1). Broad measures, weighted by industry value-added (JIP database). See also tables 3 to 5 below.

Figure 1 and table 3 show the evolution of materials and services offshoring according to formula (1), weighted by industry value added. Tables 4 and 5 present a breakdown of manufacturing and services activities.[23] These offshoring indices do not account for the region of origin of the imported intermediate inputs, since these data were unavailable.

[22] In order to come up with the offshoring indices I used the Input-Output tables in section 1.4 of JIP, and the final demand tables in section 1.7, both at constant prices (2000). The import figures had to be linearly interpolated; only years 1980, 1985, 1990, 1995, and 2000 were available. As a result, the econometric analysis below starts in 1980. Due to a possible aggregation bias (which underlies the whole empirical analysis), the measurement errors of the offshoring index, and the potential endogeneity of this variable in the econometric analysis below, it is important to note that any conclusions should be interpreted with caution.

[23] The average annual growth rates in these tables are calculated using a compound annual growth rate index (CAGR). This can be expressed as follows: $CAGR = \left(\frac{ending\ value}{beginning\ value}\right)^{\left(\frac{1}{\#\ of\ years}\right)} - 1$

Table 3: Offshoring intensity, whole economy

Year	OSM (%)	annual g.r. (%)	OSS (%)	annual g.r. (%)
1980	2.72	-	1.22	-
1981	2.84	4.54	1.33	8.70
1982	2.97	4.34	1.47	10.95
1983	2.99	0.92	1.54	4.73
1984	2.98	-0.28	1.56	1.18
1985	3.03	1.70	1.46	-6.71
1986	3.68	21.41	1.75	20.33
1987	4.28	16.16	1.97	12.27
1988	4.62	7.92	2.15	9.18
1989	5.03	8.89	2.35	9.46
1990	5.26	4.60	2.61	10.80
1991	5.24	-0.34	2.52	-3.33
1992	5.50	4.87	2.44	-2.96
1993	5.75	4.63	2.41	-1.59
1994	6.03	4.76	2.31	-3.80
1995	6.21	3.08	2.17	-6.21
1996	6.29	1.21	2.13	-1.99
1997	6.50	3.43	2.12	-0.52
1998	7.08	8.88	2.14	0.99
1999	7.63	7.73	2.18	1.93
2000	8.04	5.37	2.13	-2.16
2001	8.60	6.94	2.14	0.29
2002	9.20	7.08	2.14	-0.02
2003	9.68	5.19	2.10	-1.93
2004	10.22	5.55	2.08	-0.58
2005	10.45	2.23	2.04	-2.30
	avg. annual g.r. (%)	5.31		1.98
	up until 1989	6.35		6.77
	1990 to 2005	4.38		-1.53

Table 4: Offshoring intensity, manufacturing industries

Year	OSM (%)	annual g.r. (%)	OSS (%)	annual g.r. (%)
1980	3.52	-	1.43	-
1981	3.92	9.51	1.51	6.21
1982	4.42	11.70	1.68	10.47
1983	4.62	4.97	1.77	4.87
1984	4.73	2.26	1.80	1.66
1985	4.89	2.72	1.67	-6.96
1986	5.74	13.78	1.95	17.12
1987	6.46	12.97	2.14	9.99
1988	6.67	4.89	2.32	8.51
1989	7.09	7.43	2.52	8.52
1990	7.27	1.35	2.70	6.78
1991	7.38	-0.29	2.47	-8.65
1992	7.61	2.05	2.35	-4.65
1993	8.19	6.16	2.30	-2.00
1994	8.81	8.84	2.20	-4.43
1995	9.01	3.37	2.05	-6.66
1996	8.88	-2.09	2.03	-1.28
1997	8.89	0.65	2.04	0.49
1998	9.43	5.41	2.06	1.37
1999	10.03	5.41	2.13	3.02
2000	9.88	-1.75	2.18	2.10
2001	10.31	4.36	2.21	1.34
2002	10.48	1.63	2.23	0.73
2003	10.54	0.96	2.27	1.62
2004	10.61	2.06	2.29	0.35
2005	10.40	-1.83	2.28	-1.11
	avg. annual g.r. (%)	4.26		1.82
	up until 1989	7.26		5.87
	1990 to 2005	2.26		-1.06

Table 5: Offshoring intensity, services industries

Year	*OSM (%)*	*annual g.r. (%)*	*OSS (%)*	*annual g.r. (%)*
1980	2.61		1.17	
1981	2.66	2.51	1.29	10.26
1982	2.71	1.27	1.45	12.23
1983	2.70	-0.66	1.51	4.26
1984	2.66	-1.38	1.53	1.08
1985	2.67	0.28	1.44	-5.90
1986	3.28	23.25	1.75	20.31
1987	3.85	17.41	1.97	11.74
1988	4.21	9.07	2.14	8.79
1989	4.61	9.65	2.33	8.99
1990	4.85	5.45	2.60	11.76
1991	4.77	-1.60	2.62	0.76
1992	5.04	5.02	2.59	-0.99
1993	5.23	3.81	2.56	-0.80
1994	5.41	3.42	2.48	-3.03
1995	5.61	3.74	2.32	-6.21
1996	5.72	2.00	2.26	-2.49
1997	5.99	4.76	2.22	-1.72
1998	6.61	10.48	2.23	0.22
1999	7.14	8.02	2.26	1.84
2000	7.62	6.52	2.17	-4.21
2001	8.19	7.19	2.16	-0.18
2002	8.87	8.16	2.14	-0.81
2003	9.43	6.00	2.06	-4.00
2004	10.00	5.83	2.03	-1.48
2005	10.32	3.03	1.97	-2.88
	avg. annual g.r. (%)	5.44		2.01
	up until 1989	5.86		7.11
	1990 to 2005	4.83		-1.74

Three things are worth commenting on these tables. First, materials offshoring, proxied by its import content in the industries' total use of materials, is expectedly more predominant.[24] Second, the annual rate of growth of services offshoring is, on average, surprisingly smaller than that of materials in the whole sample period. Due to an ever-increasing globalized world where technologies abound and change fast for the better, one should have expected the opposite to be true, since services offshoring certainly entails a higher value-added process. In particular, this is what happened in the period before the bubble crisis and the lost decade, when the rates of growth were approximately equal. Finally, it is to stress the slowdown in both indices' growth rates, but especially in services offshoring, during the lost decade and up until recent times. The average annual growth rate for services offshoring was in fact negative in any case during that period. A possible explanation, which adds to that of the domestic crisis, is the loss of appeal for services offshoring to be hosted in neighboring Asian countries. This might be due to a relative loss of competitiveness that

[24]This is true both for the whole and when separating between manufacturing and services industries. Remember that the OSM and OSS indices are not directly comparable because the denominators are not the same. Still, I believe they do provide with a closer approximation to both phenomena: services and materials offshoring. Here we have the import content of inputs (either services or materials) in terms of the total use of these same inputs (foreign and domestic). Other studies propose to set this share in terms of the total use of all inputs (services and materials, foreign and domestic) just to derive an index of total offshoring. Even though my stance makes the latter impossible, I believe it stands closer to measuring the real extent of offshoring because services and materials offshoring are intrinsically very different phenomena.

comes with the catch-up process in those fast-growing countries.[25]

The numbers presented in tables 4 and 5 are much in line with those in table 3, yet the separation in types of activities allows now for an additional interpretation. The average growth rate of offshoring intensity, for both materials and services, is slightly higher for the services industries during the whole period. If we focus on the 1980s alone, we can see that the growth rate for materials offshoring is higher in the manufacturing sector, whereas that of services offshoring is higher in the services sector. Contrarily, during the 1990-2005 period the growth rate of materials is higher in the services sector, while that of services is less negative in the manufacturing sector.

4.1.3 A lost decade of growth

Using data from 1970 to 2005 I estimate the output elasticities in (11) and (12). Then I combine this information with equations (16) and (17) and get both TFP growth rates adjusted by the economies of scale effect. Equations (11) and (12) were estimated through a panel considering fixed effects and cross-section weights. Using data from 1970 adds certainly more information to the estimation, yet the $\dot{TFP}$ measures that I obtain this way are not much different from those that I would get if I were to carry out the estimation from 1980. Further, the database was filtered as to be left only with those industries where their labor shares delivered a sensible result (e.g. they were less than 1). As a result, I am left with 83 industries out of a total of 108.

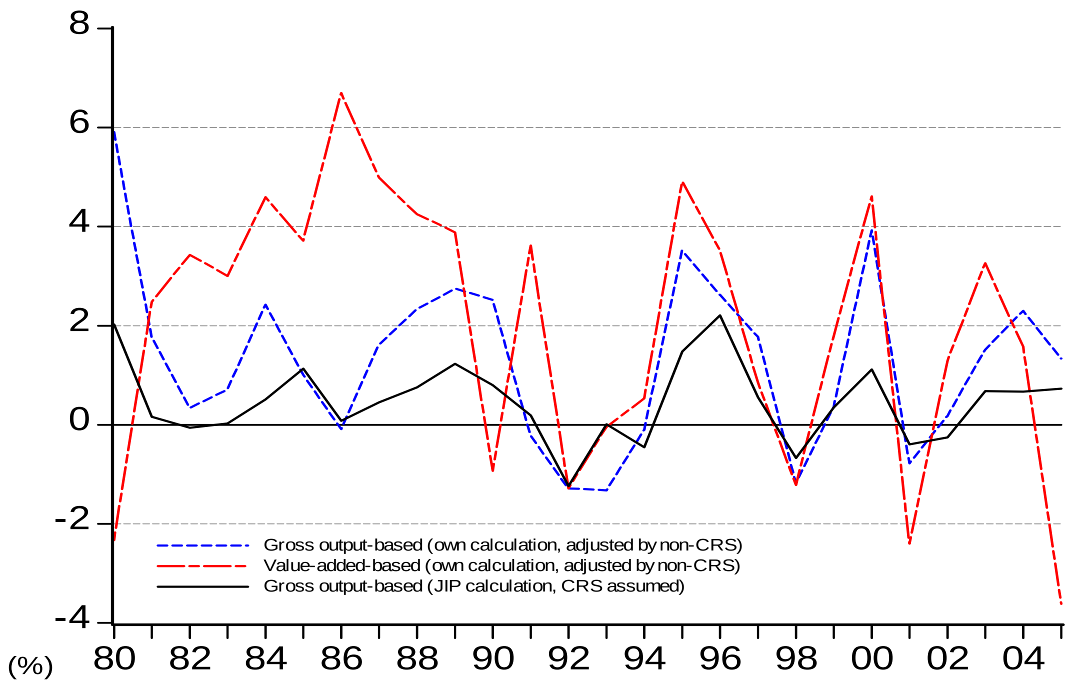
Figure 2 below displays, for the 1980-2005 period, our value-added-based and gross output-based productivity measures as well as the one calculated by the JIP (Fukao *et al.*, 2004, 2007), which is also a gross output measure (e.g. it takes account of intermediate inputs). Yet noticeable at first glance, we must mention the rather pessimistic performance in the annual growth rates of the TFP during the 1990s, as compared to previous years. This is attenuated in the JIP measure, which portrays a less volatile pattern. Notice too that while both measures calculated in this paper are adjusted by non-CRS, the other is not. Another difference is that, despite being the same data, the JIP's methodology addresses the estimation of the TFP growth from an industry by industry perspective which makes use of specific input indices (see Jorgenson and Griliches, 1967, and Gollop and Jorgenson, 1980).[26] In spite of these differences, the correlation coefficients with the JIP measure for 1980-2005 are 0.63 (value-added) and 0.68 (gross output).[27]

[25] Ito *et al.* (2007) stress the preference for large-sized Japanese firms to have their relocation processes being channeled into the region while following an in-house (captive) strategy.

[26] For instance: "the index of capital input is derived by the aggregation of several types of assets, structures, and equipment. The labor input index is an aggregate of the number of workers cross-classified by sex, age, employment status, and educational attainment" (Fukao *et al.*, 2007).

[27] If we extend this to 1970-2005, the coefficients become 0.47 and 0.61. See that the correlation with our gross output-based measure is in both cases logically higher since the JIP measure is of the same nature. Also, the correlation between our measures is 0.60 (1980-2005) and 0.75 (1970-2005).

Figure 2: Total factor productivity, growth rate (%)



Note: mean values across 83 industries (due to data cleaning).

The use of labor and capital indices which accounted for the quality of labor and capacity utilization is said to come as a sophistication over previous estimations on the Japanese TFP (Fukao *et al.*, 2004). However, due to the aggregation entailed by our approach and the assumed exogeneity of the TFP variable, I simply use the number of workers and the real capital stock as the input variables. The three TFP measures are later used to determine the effects of offshoring. Complementing figure 2, table 6 summarizes some information in a comparative manner. There the sample is split into two subsamples.

Table 6: TFP growth rates compared (%)

	Whole economy			Manufacturing			Services		
Period	τ'_V	τ'_O	τ'_{JIP}	τ'_V	τ'_O	τ'_{JIP}	τ'_V	τ'_O	τ'_{JIP}
1980-1989	3.47	1.87	0.63	4.22	2.21	1.23	2.02	1.16	-0.50
1990-2005	1.03	0.94	0.36	0.68	0.82	0.40	1.03	0.73	0.16
1980-2005	1.97	1.30	0.46	2.04	1.35	0.72	1.41	0.89	-0.09

Note: means of $\dot{\tau}'_V$ (value-added), $\dot{\tau}'_O$ (gross output), and $\dot{\tau}'_{JIP}$ (JIP), on 83 industries.

Of particular interest is the difference between the TFP growth rates of the manufacturing and services industries. For some authors it was the TFP of the latter industries which suffered more dearly, especially during the 1990s (see for instance Ahearne and Shinada, 2005, Caballero *et al.*, 2008, Hattori and Miyazaki, 2000, and the Cabinet Office, 2002). Others however state the opposite, that the downturn in the TFP growth rate was more serious in manufacturing (see here Fukao *et al.*, 2004, Kawamoto, 2004, Miyagawa, 2003, and Yoshikawa and Matsumoto, 2001). The evidence presented here sides with the findings of the latter authors.[28] See however that while the JIP measure went up for services in the 1990s as shown in table 6, the other two measures actually went down, yet less drastically than in the manufacturing sector. Fukao and Kwon (2006) provide an explanation on why the TFP slowdown in the manufacturing sector was more pronounced. Seemingly, the average TFP level of the exiting firms was higher than that of staying firms, whereas the entry effect and the reallocation effect were positive yet very small. As they put it, "this low metabolism seems to have slowed down the TFP growth of the manufacturing sector."[29]

Among all the works referred in the previous paragraph, it is interesting to note that only Kawamoto (2004) does not assume CRS. His estimations are yet very similar to the ones presented here.[30] Accordingly, it would be illustrative to know how much of a difference the assumption of CRS makes for our estimations of the TFP growth. Using this time equations (11) to (12) and again taking the number of workers and the real capital stock (and not the indices as in the JIP) for the input variables, I directly derive the TFP growth measures $\dot{\tau}_V$and $\dot{\tau}_O$ from (13) and (14). Surprisingly, I find that both these measures imply slightly larger values for the whole sample period (2.10 and 1.68 percent) than with $\dot{\tau}'_V$and $\dot{\tau}'_O$ (1.97 and 1.30 percent, in table 6). This finding goes counter to the lower values of the CRS-JIP measure. It seems to suggest that the difference between both our measures and JIP's is mainly due to the consideration of certain features of the input variables, and not the CRS hypothesis. As already stated, the JIP's measure adjusts for the quality of labor and the capacity utilization of capital.

However, if we take the subsample that accounts for the lost decade of growth (1990-2005), a gap is seen between $\dot{\tau}_V$ and $\dot{\tau}'_V$ (the difference between $\dot{\tau}_O$ and $\dot{\tau}'_O$ being of no significance). Respectively, the averages across industries for 1990-2005 were 0.78 and 1.03 percent, which means that the value-added measure with CRS might present us with a somewhat more pessimistic scenario.[31] In what is left of the paper I will be sticking to the TFP measures as originally estimated ($\dot{\tau}'_V$and $\dot{\tau}'_O$, adjusted by non-CRS) along with the one estimated by the JIP.

[28] All the references from this paragraph are taken from Fukao and Kwon (2006), table 1, pp. 198-199.

[29] This low metabolism of firms might also be related to what has come to be known as the "zombie firms" hypothesis (see the final paragraph of this section).

[30] His paper presents the following estimations: 1.9 percent for 1980-1998 for the whole private sector, 2.8, 1.7, and 1.6 percent for 1980-1990 for the durable-manufacturing, non-durable manufacturing, and services sectors respectively, and 1.4, 1.9, and 2.1 percent for 1990-1998.

[31] Correlation coefficients were, 0.99 between $\dot{\tau}_V$ and $\dot{\tau}'_V$, and 0.91 between $\dot{\tau}_O$ and $\dot{\tau}'_O$. Appendix B presents graphically the differences between our measures with and without CRS being assumed.

Even though the study presented in this section is not an attempt to go into the details of the causes that brought the lost decade into being, some final observations are in order. The "zombie firms" hypothesis has been put forward on occasions, mainly to explain the important decline in the TFP as measured by many different estimates. Seemingly, unproductive firms ("the zombies") keep on running due to bad loans practices encouraged by permissive banks. This, consequently, prevents more productive companies from gaining market share (Ahearne & Shinada, 2005) since the competitive outcome where “zombies” lay off workers and lose their share no longer holds (Caballero *et al.*, 2008, and Kobayashi, 2007). More, the Japanese government helped in delivering a noncompetitive outcome during the 1990s through its soaring debt and large bailouts targeting a financial sector already damaged by the bubble crisis (Agnese and Sala, 2009). In more general terms and following Fukao and Kwon (2006), we can distinguish between those who find the disappointing performance of the 1990s in a lack of effective demand and a liquidity trap-deflation cycle (Yoshikawa, 2003, and Fukao, 2003), from those who identify supply-side factors as major determinants (Hayashi and Prescott, 2002).

4.2 How good are the offshoring measures?

To answer this question I carry out a decomposition analysis over time (1980-2005) and at the country level in a rather conventional way. The analysis involves following the "within" and "between" exercise to account for variations in, respectively, the industries' offshoring intensity and their shares in total production.[32] Decomposing the variance turns out helpful in isolating the changes in the offshoring intensities within industries from the changes in the production shares between them. Thus, it is easy to see what proportion of the change in the index is due to either a change in real offshoring or a change in the industries' relative weights in the economy. The country index (tables 3 to 5) might as well be picking up structural influences that have nothing to do with offshoring.

Therefore, to see to what extent the index describes the phenomenon accurately, I move on to extract the sources of growth using the following expression:

$$\Delta\Phi^{80-05} = \Delta\sum_{i}^{n}\theta_i\delta_i = \sum_{i}^{n}\overline{\theta}_i\Delta\delta_i + \sum_{i}^{n}\overline{\delta}_i\Delta\theta_i \quad ; \quad \Phi = OSM, OSS$$

where the change in the offshoring index at the country level (Φ) is decomposed, throughout industries (i), into the change in the offshoring intensity (the within term) and the change in the share of total production (the between term). The former fixes the structural component of industries, also the share of industry output to total output (θ), to focus on the change in the offshoring intensity (δ). The latter, contrariwise, fixes the offshoring component, thus

[32] See Hummels *et al.* (2001), Strauss-Kahn (2004), and Horgos (2009), who also undertake decomposition analyses along these lines.

capturing the contribution of the structural component to the change in the index. A bar over the variables defines the mean for the period under study.

Table 7 breaks down the sources of growth for the index during the whole sample and in two subsamples (1980-1990 and 1990-2005).

Table 7: Sources of growth of the offshoring index

Whole economy (table 3)	*Within*	*Between*	*Total* (w+b)	*Within/Total*
OSM				
1980-1990	2.53	0.01	2.54	99.5%
1990-2005	5.25	-0.07	<u>5.19</u>	101.3%
1980-2005	**7.79**	**-0.07**	**7.73**	**100.9%**
OSS				
1980-1990	1.37	0.01	1.38	99.0%
1990-2005	-0.51	-0.06	<u>-0.57</u>	90.2%
1980-2005	**0.84**	**-0.03**	**0.81**	**103.5%**
Manufacturing (table 4)				
OSM				
1980-1990	3.82	-0.07	3.75	101.8%
1990-2005	4.03	-0.91	<u>3.13</u>	129.0%
1980-2005	**8.09**	**-1.21**	**6.88**	**117.6%**
OSS				
1980-1990	1.28	0.00	1.28	99.7%
1990-2005	-0.44	0.02	<u>-0.42</u>	104.0%
1980-2005	**0.81**	**0.05**	**0.85**	**94.3%**
Services (table 5)				
OSM				
1980-1990	2.29	-0.04	2.24	102.0%
1990-2005	5.24	0.24	<u>5.47</u>	95.7%
1980-2005	**7.52**	**0.19**	**7.72**	**97.5%**
OSS				
1980-1990	1.42	0.01	1.43	99.1%
1990-2005	-0.55	-0.09	<u>-0.64</u>	85.6%
1980-2005	**0.85**	**-0.06**	**0.79**	**107.4%**

Note: numbers were rounded. Disaggregate results across industries are available on request.

With the exception of the last column, all numbers are the increases and drops in the indices, in percentage points, that could be derived from tables 3, 4, and 5. The column labeled "within" captures the change in the index that is due to changes in the offshoring intensities of industries alone, while the column labeled "between" seizes the change in the index that corresponds to a change in the production shares. The contributions of each component are summed up under "total", and refer to the total change, in percentage points, in the indices shown before. For instance, during 1980-2005, the increase in the OSM index for the whole economy was 7.73 percentage points (see table A3), of which 7.79 correspond to a change in the offshoring intensity and -0.07 to a change in the structural component. Lastly, the "within/total" column focuses on the proportion of the change in the index that is exclusively explained by a change in offshoring intensity.

In general, we can see that the changes in the offshoring intensity across all branches of activities account for most of the growth in overall offshoring, as shown in tables 3, 4, and 5. The structural components have hardly any incidence on the indices, especially prior to the "lost decade". After 1990 the ratios in the last column behave less consistently and deviate a bit from the 100 percent benchmark. Naturally, we should expect the economic turmoil in the 1990s to produce some changes in the sector composition of the Japanese economy.[33] All in all, for every categorization the index performs acceptably well for the whole sample yet less smoothly during the fading 1990s.

4.3 Econometric analysis

Having determined the suitability of the index, I now proceed to gauge the effects on the Japanese economy relying on panel data analysis. Panel studies advantage simple cross-section data studies in one important aspect: cross-section surveys do not provide enough information about earlier time periods (Bond, 2002). On the other hand, purely aggregated time series analyses might obscure the microeconomic dynamics and make the underlying aggregation bias even more severe. As opposed to these techniques, panels offer a wider scope to examine the heterogeneity in adjustment dynamics between firms or industries (Bond, 2002). Table 8 provides the summary statistics of the main variables.

Table 8: Summary statistics, 1980-2005 (means across 83 industries)

	Variable	*Observations*	*Mean*	*Max.*	*Min.*	*Std. dv.*
Offshoring	OSS_{it} (%)	2158	2.13	25.11	0.54	1.34
indices	OSM_{it} (%)	2158	8.03	114.12	0.62	12.58
Productivity	τ'_{Vit} (%)	2158	1.97	126.16	-120.39	13.49
growth	τ'_{Oit} (%)	2158	1.30	35.45	-29.32	5.19
rates	τ_{JIPit} (%)	2158	0.46	34.42	-36.41	5.20
Inputs and	L_{it} (workers)	2158	554,525	7,285,919	1,767	983,149
output	H_{it}*	2158	1,067,583	13,959,645	3,358	1,876,792
	K_{it} (real, million yen)	2158	8,436,522	123,477,018	60,968	15,885,311
	Y_{it} (real, million yen)**	2158	3,406,296	38,767,333	34,133	5,121,855
Prices	w_{it} (avg., real, million yen)	2158	5.15	34.84	0.33	3.38
	p^{Y}_{it} (2000 = 1)***	2158	1.06	5.93	0.42	0.32

*: 1000 workers × total annual working hours; **: gross value-added (factor prices); ***: price deflator.

[33] Coincidentally, it is argued that the three-sector hypothesis has taken longer to manifest in Japan (see Balassa and Noland, 1988). Whereas for other developed economies the shift from the secondary (manufacturing) to the tertiary (services) sector has long taken place, for Japan it seemingly started out during the 1990s.

As stated before, the potential effects of offshoring basically come down to disentangling the gains and losses in terms of employment and productivity. The analysis below is therefore divided accordingly, and follows the methodology developed in sections 3.2 and 3.3. But prior to that, some general remarks might be useful.

Under our industry setting we should expect, *a priori*, that we are dealing with a heterogeneous dataset in the sense that there are perceptible differences between estimated cross-sections (e.g. different constants) that could be exploited.[34] Heterogeneity bias usually implies the inclusion of either fixed or random effects which can capture these differences better than a pooled estimation. However, since we are dealing with dynamic panels where we assume a large number of cross-sections (N) compared to the number of periods (T), the OLS and fixed effects estimators are inconsistent. In particular, whereas the former tends to overestimate the autoregressive coefficient the latter tends to underestimate it.

Moreover, in our case it also becomes important to address the endogeneity of the offshoring variable, since it might not be random which industries engage more in this practice. If the same industries engage in offshoring all over the sample then industry fixed effects would do the work. This is hardly the case though and, on top of that, the endogeneity of the offshoring variable is further magnified due to the presence of measurement errors.

Hence, for the reasons stated in the last two paragraphs I deem it necessary to rely on GMM estimation. To remove the permanent industry-specific effects from our final estimating equations,[35] I need to transform the variables either into first-differences (Arellano and Bond, 1991) or orthogonal deviations (Arellano and Bover, 1995). Potential measurement problems underlying the offshoring index would lead us to opt for the latter, since first-differencing tends to amplify such problems through larger variances.[36]

Therefore, to study the effects of offshoring on both employment and productivity I present several estimations based on the GMM estimator (both in first differences and orthogonal deviations). When possible, the coefficients of all specifications are reparametrized to show the total effects concentrated in period t. Joint Wald tests are presented along the estimations to ensure that this is possible and the coefficients do not cancel out. More, some of these specifications include time dummies to control for period specific shocks common to all industries. These time dummies are also used (no transformation involved) as additional instruments to the specific ones used in the final equations. For the labor demand in equation (8) I use period-specific (predetermined) instruments and exogenous ones. Specifically, they involve all valid lags of the dependent variable from $t-2$ to T on the one hand, and the first two lags of real wages and capital, $w_{it-1}, w_{it-2}, K_{it-1}, K_{it-2}$, all in logs, on the

[34] Enough to see the variance of some of the variables displayed in table 8 above.

[35] These are equation (8) in section 3.2 for the employment analysis and equation (18) in section 3.3 for the productivity analysis.

[36] Another method would be system GMM, which combines the estimation of an equation in first differences with an equation in levels. However, this approach is not undertaken here for it was not available while running our regressions in Eviews.

other hand.[37] For the TFP equation I use the lags of the dependent variable from $t-2$ to T, as well as the first two lags of other explanatory variables. Finally, the validity of the instrument sets and of the overidentifying restrictions is tested using the conventional Sargan test. The consistency of the GMM estimates also depends on the absence of serial correlation in the errors. In this regards, the $m2$ statistic proposed by Arellano and Bond (1991) tests for the absence of second-order serial correlation in the residuals.

4.3.1 Employment effects

To capture the employment effects of offshoring I estimate the labor demand equation in (8) using the GMM estimator. Our variables of interest are OSS and OSM, and since these are not transformed into logarithms, they should be interpreted as semi-elasticities. Table 9 in the next page shows the equations estimated by difference GMM (GMM-DIF) and GMM in orthogonal deviations (GMM-OD), with and without a full set of year dummies. As for the assumed GMM weighting, all four equations are estimated with the Arellano-Bond 2-step estimator, which updates weights once.[38]

Notice that all the equations are characterized by a large persistence coefficient, indicating a strong inertia in the industries' aggregate level of employment. The Wald test for the lagged employment coefficient being equal to 1 (unit root) is strongly rejected in all cases. Related to this, Agnese and Sala (2009) estimate a system of structural equations for Japan consisting of a labor demand and a labor supply equations.[39] Even though offshoring is not considered there, the labor demand equation appears with a high autoregressive coefficient (0.89). Also to note is the similarity between the estimated coefficients, or short-run elasticities, of the real wages. In the present work this elasticity ranges between -0.02 and -0.03, while in the previously referred paper is approximately -0.04. This would imply a long-run elasticity of 0.37 in the work by Agnese and Sala (see p.432) and values around the 0.4-0.6 range, as can be deduced from table 9.[40] One final resemblance lies in the fact that the capital variable in levels does not enter the labor demand equation. For all specifications in table 9 I fail to reject the Wald of both the current and lagged coefficients of capital being jointly non-significant, so the variable enters in differences. This means that what we have as $\Delta \ln K_{it}$ is the real investment.[41]

[37] This strategy is employed by Layard and Nickell (1986) who estimate a labor demand function similar to (8) in a dynamic (unbalanced) panel of 1031 observations (140 firms, years 1976-1984).

[38] The standard errors for the two-step estimator may not be reliable (see Arellano and Bond, 1991).

[39] Their dataset contains data at the country level from the OECD Economic Outlook, which is used to carry out a time-series analysis for the years 1972-2006.

[40] From equation (8) we have that the long-run elasticity of employment to a change in real wages can be simply expressed as: $\varepsilon_w^{LR} = \dfrac{\hat{\theta}_4}{1-\hat{\theta}_1}$

[41] Agnese and Sala (2008) study the harming effects of a sharp decline in real investment in Japan. Their simulations suggest that this has been decisive in explaining the sudden upsurge in the unemployment rate during the 1990s, perhaps as a practical consequence of comparatively lower productivity rates.

Table 9: Labor demand, GMM estimation

(83 industries, 1980-2005)

Dependent variable: ln L_{it}

	(1)	(2)	(3)	(4)
	GMM-DIF	**GMM-DIF**	**GMM-OD**	**GMM-OD**
ln L_{it-1}	0.95†	0.95†	0.95†	0.95†
	(0.001)	(0.01)	(0.001)	(0.005)
ln w_{it}	-0.03†	-0.02†	-0.03†	-0.03†
	(0.001)	(0.009)	(0.001)	(0.002)
Δ ln w_{it}	-0.07†	-0.06†	-0.10†	-0.10†
	(0.001)	(0.01)	(0.002)	(0.01)
OSS_{it} / 100	**1.02†**	**0.92**	**1.03†**	**0.53‡**
	(0.07)	(0.71)	(0.06)	(0.25)
Δ *OSS_{it} / 100*	-0.50†	*	-0.59†	*
	(0.03)		(0.13)	
OSM_{it} / 100	**-0.26†**	**-0.14**	**-0.33†**	**-0.23‡†**
	(0.01)	(0.14)	(0.01)	(0.13)
Δ *OSM_{it} /100*	-0.46†	*	-0.47†	*
	(0.03)		(0.03)	
ln K_{it}	*	*	*	*
Δ ln K_{it}	0.27†	0.20†	0.21†	0.17†
	(0.004)	(0.06)	(0.01)	(0.06)
Joint tests (Wald):				
ln L_{it-1} = 1	$\chi^2(1)$ = 2,440	$\chi^2(1)$ = 13.07	$\chi^2(1)$ = 2,912	$\chi^2(1)$ = 73.25
	p-value = 0.00	*p-value* = 0.00	*p-value* = 0.00	*p-value* = 0.00
ln w_{it} + ln w_{it-1} = 0	$\chi^2(1)$ = 503.2	$\chi^2(1)$ = 9.59	$\chi^2(1)$ = 1,013	$\chi^2(1)$ = 142.3
	p-value = 0.00	*p-value* = 0.00	*p-value* = 0.00	*p-value* = 0.00
***OSS_{it}* + *OSS_{it-1}* = 0**	$\chi^2(1)$ = 131.6	-	$\chi^2(1)$ = 276.9	-
	p-value = 0.00		*p-value* = 0.00	
***OSM_{it}* + *OSM_{it-1}* = 0**	$\chi^2(1)$ = 115.2	-	$\chi^2(1)$ = 461.3	-
	p-value = 0.00		*p-value* = 0.00	
ln K_{it} + ln K_{it-1} = 0	$\chi^2(1)$ = 0.90	$\chi^2(1)$ = 2.16	$\chi^2(1)$ = 1.28	$\chi^2(1)$ = 1.98
	p-value = 0.34	*p-value* = 0.14	*p-value* = 0.25	*p-value* = 0.16
Sargan test:	$\chi^2(76)$ = 90.19	$\chi^2(53)$ = 68.65	$\chi^2(76)$ = 82.49	$\chi^2(53)$ = 66.24
	p-value = 0.18	*p-value* = 0.07	*p-value* = 0.28	*p-value* = 0.10
***m*2 test:**	z = -16.83	z = -1.63	z = 0.38	z = 1.68
	p-value = 0.00	*p-value* = 0.10	*p-value* = 0.70	*p-value* = 0.10
Period dummies	**no**	**yes**	**no**	**yes**
s.e.	0.05	0.05	0.04	0.04
Adj. r^2	0.05	0.11	0.96	0.96
observations	1,992	2,075	1,992	2,075

*: strongly non-significant, individually or jointly (variable removed).

Note: all specifications estimated with Eviews and based on equation (8). GMM-DIF is the Arellano-Bond (1991) estimator in first differences and GMM-OD the Arellano-Bover (1995) estimator in orthogonal deviations. Both are estimated using the 2-step method by Arellano and Bond (1991), so the standard errors may not be reliable. Results from 1-step estimations with the GMM-DIF were rather similar. The offshoring indices (%) are divided by 100 so as to interpret the semi-elasticities directly. Standard errors in parentheses and †, ‡, and ‡† the usual levels of significance: 1%, 5%, and 10%; Δ is the difference operator.

With the exception of the capital variable, all other variables enter the equations both in levels and differences.[42] This means that the short-run elasticities (or semi-elasticities, for the offshoring variables) can be directly read from the estimated coefficients of the variables in levels. This reparametrization is made possible because the coefficients of the current and lagged variables (easily) pass the Wald tests of joint significance. But prior to analyzing the effect of offshoring on employment it is necessary to spend a word on our misspecification tests, also reported in table 9.

Under the null hypothesis that the over-identifying restrictions are valid, the Sargan statistic is distributed as a $\chi^2(k-p)$, where k is the instrument rank and p the number of estimated coefficients. Thus, not rejecting the Sargan test is indicative of the exogeneity of the instruments used. Notice that for the regressions without period dummies, (1) and (3), these tests are easily passed, yet when period dummies are included, like in (2) and (4), these tests are only passed at the margin. As for the $m2$ statistic, specification (1) seems to suffer of autocorrelation of second order in the residuals, so the estimates are not consistent. As for the rest the null hypothesis is rejected, and in particular for (3), it is strongly rejected.[43] Let us now take a closer look at the offshoring coefficients, since these are the focus of our work.

All labor demand equations show a positive effect of services offshoring and a negative effect of materials offshoring. This is not counterintuitive at all, since both types of offshoring entail very different processes. The dissimilarities go from radically different managerial strategies to different business relations with providers or local partners, as well as a rather disparate perception on the degree of customer satisfaction. Services offshoring very often includes more dynamic activities involving more highly trained workers. In this sense, relocating services activities abroad might turn into positive employment effects domestically, by way of complementing and expanding other activities already undertaken at home. In particular for Japan, Ando and Kimura (2007) suggest that as a result of offshoring, domestic employment can be expanded since these operations are usually "complementary to the rest of the value added chain". Remember that our setting does not allow for spillovers effects between industries, so both the positive and negative effects should be thought as taking place within the same industry.[44]

For instance, specification (1) shows that services and materials offshoring have short-run semi elasticities of 1.02 and -0.26 respectively. That is, an increase of 1 percentage point

[42] Adding the lagged variable in differences would not change things dramatically in any of the specifications.

[43] An option to perform this test directly in Eviews was not available. For this reason I had to reestimate all models adding the residuals lagged two periods, both as explanatory variable and instrument. Perhaps under the hypothesis of no correlation the t statistic of the added variable is distributed as $N(0,1)$, but this has not been proved. As presented here, the test then remains of doubtful interpretation.

[44] For an analysis of offshoring from a general equilibrium perspective see Egger and Egger (2005), who explicitly account for spillovers, and Mitra and Ranjan (2007), who develop a theoretical model to study the impact of offshoring on sectoral and economywide rates of unemployment.

in any of the offshoring variables explains, on average, a change of 1.02 and -0.26 percent in employment. In turn, long-run elasticities are 20.4 and -5.2. The same reasoning applies to the rest of the specifications. Table 10 below sums up the information on the elasticities of employment to offshoring, both in the short (ε_{SR}) and long run (ε_{LR}).

Table 10: Short and long run elasticities (offshoring)

	(1)		**(2)**		**(3)**		**(4)**	
	OSS	*OSM*	*OSS*	*OSM*	*OSS*	*OSM*	*OSS*	*OSM*
ε_{SR}	1.02	-0.26	0.92	-0.14	1.03	-0.33	0.53	-0.23
ε_{LR}	20.4	-5.2	18.4	-2.8	20.6	-6.6	10.6	-4.6

Note: as calculated from table 9; elasticities on (2) are not statistically significant.

Remember from table 3 the different evolution in both offshoring indices. For our period of analysis we can see that while OSS raised, on average, from 1.22 to 2.04 percent (0.82 percentage points), OSM went from 2.72 to 10.45 percent (7.73 percentage points). Combining this information with the long-run elasticities in the second line of table 10, and with the change in employment, it is possible to quantify the effects of both kinds of offshoring on the Japanese labor market. To do that I will only focus on the long-run elasticities as estimated from specifications (3) and (4). In (2) the coefficients are not statistically significant and specification (1) shows signs of second-order correlation in the residuals. Notice, however, that the elasticities calculated from (1) and (3) are rather alike.

According to the JIP database, the level of employment in Japan for our restricted sample of 83 industries grew, on average, about 18 percent during 1980-2005 (around 100,000 workers). Multiplying the estimated long-run elasticities times the average change in the offshoring variables,[45] and expressing that as a proportion of the average change in employment, allows us to get an idea of the size of the effect of offshoring on employment.

From the estimation in (3), this implies an increase, on average, of around 1,000 workers due to services offshoring and a loss of 2,900 workers due to materials offshoring. The net average loss is of approximately 1,900 workers during 1980-2005. From (4) I estimate an average increase of about 500 workers due to services offshoring and a loss of 2,000 due to materials offshoring, totaling a net average loss of nearly 1,500. Since both total magnitudes are negative they should be interpreted as the number of jobs that fail to open due to offshoring. Indeed, they only represent a small fraction of the total increase in employment: between 1.9 percent in specification (3) to 1.5 in (4).[46]

[45] These changes must be divided by 100 to keep consistency with the variable as entering the estimated equation.

[46] Recall that this analysis, due to its very characteristics, omits both the possible spillover effects between industries, and the fact that some of them may, individually, be experiencing different effects of offshoring to those depicted here. An industry by industry analysis to solve for this aggregation problem is certainly in the research agenda.

Table 11: **Average employment effects of offshoring**

	(3)		(4)	
	Δ workers	**%**	**Δ workers**	**%**
OSS	951	0.9	489	0.5
OSM	-2,872	-2.8	-2,001	-2.0
Total	-1,921	-1.9	-1,512	-1.5

Note: average employment increase was 101,425 workers (or 18%).

Table 11 goes over the offshoring-induced changes in Japanese employment in more detail. As can be seen from the table, the relative impact of OSS and OSM is minor, both individually and overall. Aggregating these figures, our estimations suggest that, during 1980-2005, the total loss of jobs as a result of offshoring was negligible. Estimated figures range from 160,000 in specification (3) to 125,000 in (4) or, which is the same thing, from 1.9 to 1.5 percent of the total growth in employment.

As a robustness analysis I present a summary of additional estimations in Appendix C. As a first robustness check I substitute in the output variable, volume or price, for the capital variable, which gives respectively the conditional or unconditional version of the labor demand, as in Amiti and Wei (2006). Another check comes after replacing the dependent variable "employed persons" by "hours worked", as in Cadarso *et al.* (2008). In line with the results obtained in table 9, all the additional estimations suggest an overall positive effect of services offshoring and an overall negative effect of materials offshoring on domestic employment.

4.3.2 Productivity effects

To see if offshoring has any effect on productivity growth I estimate the reduced-form equation in (18) relying once again on GMM estimation. As argued before, our variables of interest are believed to be determined endogenously. One more time, OSS and OSM ought to be understood as semi-elasticities, for these variables are not transformed into logarithms. Table 12 below shows different alternative specifications estimated with the GMM-OD estimator alone (Arellano-Bond 2-step). The reason for this is that both the offshoring and productivity variables are probably measured with errors. As observed earlier, taking first differences (GMM-DIF estimator) to remove the permanent industry-specific effects tends to amplify such problems through larger variances.

In order to avoid omitted variables biases I follow Fariñas and Martín (2009) and try to control for human capital intensity. For this I use the share of high-skill workers that comes with the JIP database.[47] Further, following Hijzen *et al.* (2006) I control for the

[47] The JIP database offers data by industry on six different occupations: (1) professionals and technical workers, (2) managers and officials, (3) clerical and related workers, (4) sales workers, (5) service workers,

R&D expenditure, which is a natural driver of the productivity growth. Since this variable does not come with the JIP, I decide to use a proxy instead. This is the investment in information technologies (as a share of GDP); particularly, the real value of the investment in software by industries. We should expect both these controls to have a positive effect on the TFP growth rate.

Table 12: TFP growth, GMM estimation
(83 industries, 1980-2005)

Dependent variable: $\Delta\ \tau'_{Oit}$

	(1')	(2')	(3')	(4')	(5')	(6')
	GMM-OD	**GMM-OD**	**GMM-OD**	**GMM-OD**	**GMM-OD**	**GMM-OD**
$\Delta\ \tau'_{Oit-1}$			0.009		0.008	0.008
			(0.01)		(0.01)	(0.01)
OSS_{it} / 100	**0.32**	**0.66‡†**	**0.73‡†**	**0.84‡†**	**0.93‡†**	**0.86‡†**
	(0.36)	(0.40)	(0.42)	(0.46)	(0.51)	(0.51)
OSM_{it} / 100	**0.02**	**0.08‡**	**0.07‡†**	**0.08‡**	**0.07‡†**	**0.06**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
H_K		0.09	0.08	0.07	0.05	0.05
		(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
$\Delta\ H_K$		-1.42†	-1.39†	-1.36†	-1.31†	-1.32†
		(0.27)	(0.26)	(0.24)	(0.23)	(0.24)
R&D				0.09	0.10	0.07
				(0.15)	(0.16)	(0.16)
Δ *R&D*						-0.22
						(0.20)
Period dummies	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**
Sargan (p-value):	0.51	0.32	0.33	0.32	0.35	0.32
Adj. r^2	0.10	0.09	0.09	0.08	0.08	0.09
observations	2,075	1,660	1,660	1,660	1,660	1,660

Note: all specifications estimated with Eviews and based on equation (18). GMM-OD is the Arellano-Bover (1995) estimator in orthogonal deviations (Arellano-Bond 2-step). Results from 1-step estimations with the GMM-DIF or using τ_{VAit} and τ_{JIPit} as dependent variables were ambiguous. Results without period dummies were also not significant. The offshoring indices (%) are divided by 100 so as to interpret the semi-elasticities directly. Standard errors in parentheses and †, ‡, and ‡† the usual levels of significance: 1%, 5%, and 10%; Δ is the difference operator, H_K the share of high-skill workers, and *R&D* the share of software investment in GDP.

All reduced-form equations in table 12 are run on our output-based TFP growth variable ($\dot{\tau}'_O$). The other two measures ($\dot{\tau}'_{VA}$ and $\dot{\tau}'_{JIP}$) do not produce satisfying results, as neither do the specifications without period dummies. Also, the explanatory variables enter the regressions both in levels and differences. However, the control variables are not significant even though the null fails to be rejected at the margin for our human capital variable in (2') and (3'). Lagged terms of offshoring are not included since these are strongly non-significant, thus suggesting an immediate effect upon productivity.

and (6) production process workers and laborers. Our human capital variable is set equal to the sum of the first two categories, which are those occupations usually involving a higher degree of specialization.

Notice that both coefficients of services and materials offshoring appear with a positive sign, yet for the former the effect is significantly larger. According to the definitions of our variables, a 1 percentage point expansion in services offshoring would bring about an increase in the TFP growth rate ranging from 0.66 to 0.93 percent. On the other hand, for materials offshoring it goes from 0.06 to 0.08 percent.[48] These results are consistent with those by Hijzen *et al.* (2006), who find that productivity growth would rise by 0.17 percent. Their study is from 12,564 Japanese manufacturing firms during 1994-2000. And the offshoring variable includes both the value of subcontracting at arm's length and the purchases of intermediate inputs from a firm's foreign affiliates. However, their broad measure does not account for the differences between services and materials inputs.

As done by these authors, we can multiply the means of services and materials offshoring from table 8 times the estimated coefficients from table 12. The results, summarized in table 13, suggest that for the average offshoring industry, the average annual TFP growth is from 1.4 to 1.98 percentage points higher than had it not engaged in services offshoring. For materials offshoring this goes from 0.48 to 0.64 additional percentage points. Hijzen *et al.* (2006), in turn, find that offshoring firms show a higher average TFP growth by 1.8 percentage points.

Table 13: Average productivity effects of offshoring

	(2')	(3')	(4')	(5')	(6')	Hijzen *et al.* (2006)
OSS	1.40	1.55	1.79	1.98	1.83	1.80
OSM	0.64	0.56	0.64	0.56	0.48	
in percentage points						

Note: means of OSS and OSM are 0.02 and 0.08 respectively (table 8).

5 Conclusions

Usual fears around offshoring entail, above all, the loss of domestic jobs that are now being imported in greater numbers. It is true that as even more services become tradable (especially with the exponential growth of communications and Internet), more jobs will be at risk of being moved abroad. But this argument loses sight of the other side of the story, namely, that new jobs might be created locally due to a productivity boost or in response of economic scarcity. We have seen in this paper how offshoring might be employment-friendly (e.g. services offshoring) and how this innovative practice might hold the key as regards productivity improvement, something Japan is desperately in need for.

In order to provide a full-fledged account of the issue for Japan, this paper first reviews the main literature and finds its applicability to our special case, then analyzes the

[48] The values from (1') are not considered since it is to expect some bias due to an omitted variables problem.

measurement issues to assess the phenomenon adequately, and finally offers an econometric analysis for the whole economy during the period 1980-2005. Manufacturing as well as services industries are here considered, and both materials and services offshoring are brought into the analysis. The data show materials offshoring to be of much greater importance than services offshoring, in spite of the communications revolution tapping in every corner of the globe. Moreover, with the ghost of the lost decade still looming over the economy, services offshoring remains on rather modest levels. Enough to say that its growth rate was slightly higher than that of materials' during the 1980s, just to recede during the 1990s in a considerable proportion (in fact, the average annual rate was negative during the 1990s and onwards).

The results of the econometric analysis suggest a positive employment effect of services offshoring which explains between 0.5 to 1 percent of the average rise in employment. Materials offshoring, oppositely, appears with a negative sign, and the effect on employment goes from 2 to 3 percent of jobs that fail to open out of the average increase in employment. The net negative effect is around 1.5 to 2 percent approximately, which is a rather negligible figure. However, this should be taken with care, because no spillover effects among industries have been considered. Moreover, we must not forget about the aggregation of our analysis, which might be hiding some relevant information on the real effect of offshoring on particular industries. In general, the results presented here are robust to the different specifications of the dynamic labor demand, whether it refers to control variables or the dependent variable.

On the productivity side the results are also encouraging. Positive effects of both types of offshoring are found. The effect, for the average offshoring industry, goes from a 1.40 to an almost 2 percentage point increase in the annual average TFP growth rate, for services offshoring. For materials offshoring the numbers are smaller, and imply an increase of 0.48 to 0.64 percentage points. These results are similar to those obtained by Hijzen *et al.* (2006) for Japan.

The empirical work laid out in this paper points to the direction of potential gains due to offshoring, both in terms of employment and productivity. As seen here, the realization of the principle of comparative advantages does not escape our analysis if we consider offshoring as a particular form of trade. However, one is left to wonder how much it will take for policy-makers to really comprehend this fact and stop hindering the natural process of profit-seeking and efficiency-seeking. Or perhaps we are hopeless against the interventionist wave that spreads like gunpowder these days. But in any case, hope dies last.

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A Appendix: The translog cost function

First moves towards laying a suitable framework for offshoring are found in the cost function originally proposed by Berman *et al.* (1994). Typically assuming a translog cost function where firms minimize costs in choosing their inputs, the next step is to derive and estimate a factor-share equation. The translog, or transcendental logarithmic function, is basically a standard specification for modeling cost and production functions allowing for very flexible functional forms. Generally, with C being total costs, x a vector of prices of multiple inputs (q), and y a vector of the given levels of multiple outputs, we have:

$$\begin{aligned} C(x,y) &= \min_q x\,q \\ s.t.\ q &\in Z(y) \end{aligned}$$

with $Z(y)$ the total input requirements for the given $y's$. In this way, the translog function takes the form:

$$\begin{aligned} \ln C\,(x,y) &= \alpha_0 + \Sigma_i^m \alpha_i \ln y_i + \Sigma_i^n \beta_i \ln x_i \\ &+ \frac{1}{2}\Sigma_i^m \Sigma_j^n \alpha_{ij} \ln y_i \ln y_j + \frac{1}{2}\Sigma_i^m \Sigma_j^n \beta_{ij} \ln x_i \ln x_j + \Sigma_i^m \Sigma_j^n \gamma_{ij} \ln y_i \ln x_j \quad \text{(A1)} \end{aligned}$$

which is an extension or more general expression of the Cobb-Douglas (cost) function.[49] The first line of (A1) is none other than the Cobb-Douglas, while the second line allows for wider substitution possibilities between inputs and outputs. Using Shephard's lemma, first differentiating the cost function yields the share cost equation for each input. Specifically, the lemma states that if $C(x,y)$ is differentiable, there is a unique vector S such that $\frac{\partial C(x,y)}{\partial x_i} = S_i$. From (A1) it can be obtained:

$$\frac{\partial C(x,y)}{\partial x_i} = S_i = \frac{x_i\,q_i}{C} = \beta_i + \Sigma_j^n \beta_{ij} \ln x_j + \Sigma_i^m \gamma_{ij} \ln y_j \quad \text{(A2)}$$

This specification is further augmented with other control variables, the offshoring index being one among them, and Feenstra and Hanson's being especially of widespread use. Particularly, the index aims at capturing the elasticity of substitution of domestic value added in relation to imported intermediate inputs. A common representation for the industry, as found for instance in Berman *et al.* (1994) and Feenstra and Hanson (1996a, 1996b, 1999), would be something like:

$$\Delta S_{it}^* = \beta_0 + \beta_1 \Delta(OS_{it}) + \beta_2 \Delta \ln(y_{it}) + \beta_3 \Delta \ln(k_{it}) + \beta_4 \Delta(Z_{it}) \quad \text{(A3)}$$

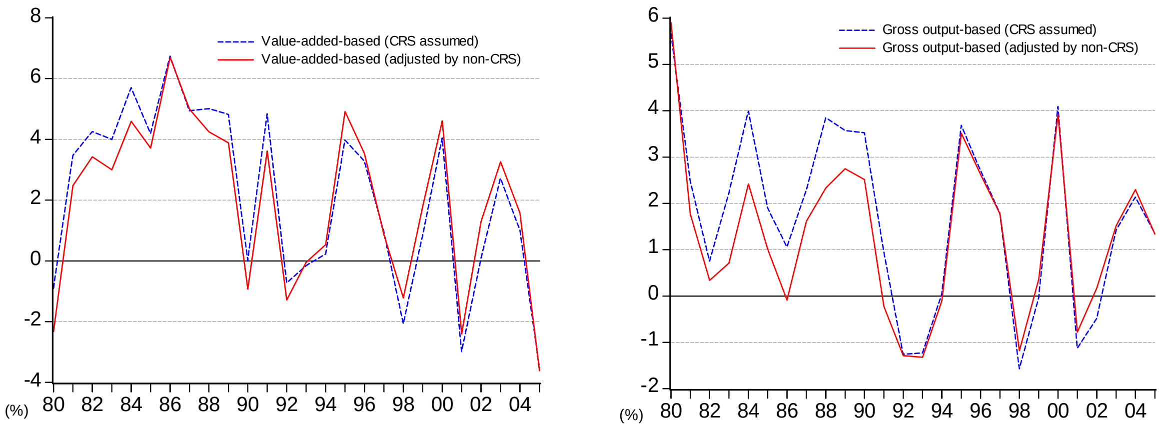
which is usually a regression of the change in the share of nonproduction wages in the industry's wage bill (S_{it}^*) on the structural (output and capital, among others) and control variables. Nonproduction and production labor are usually used as proxies of skilled and nonskilled employment. Through this it is possible to analyze the effects of offshoring on the relative changes between two (or more) skills of labor. Provided there are only two levels of skills which are identified, a second equation would turn out redundant.

[49] Also, a second order Taylor's series expansion of certain function, in this case a cost function.

B Appendix: CRS or non-CRS in Japan?

Figure B1 shows our TFP value-added and gross-output based measures, both considering CRS ($\dot{\tau}_V$ and $\dot{\tau}_O$) and non-CRS ($\dot{\tau}'_V$ and $\dot{\tau}'_O$). For both charts the measure displaying CRS delivers a more optimistic estimation prior to 1990 and a more pessimistic one after that.

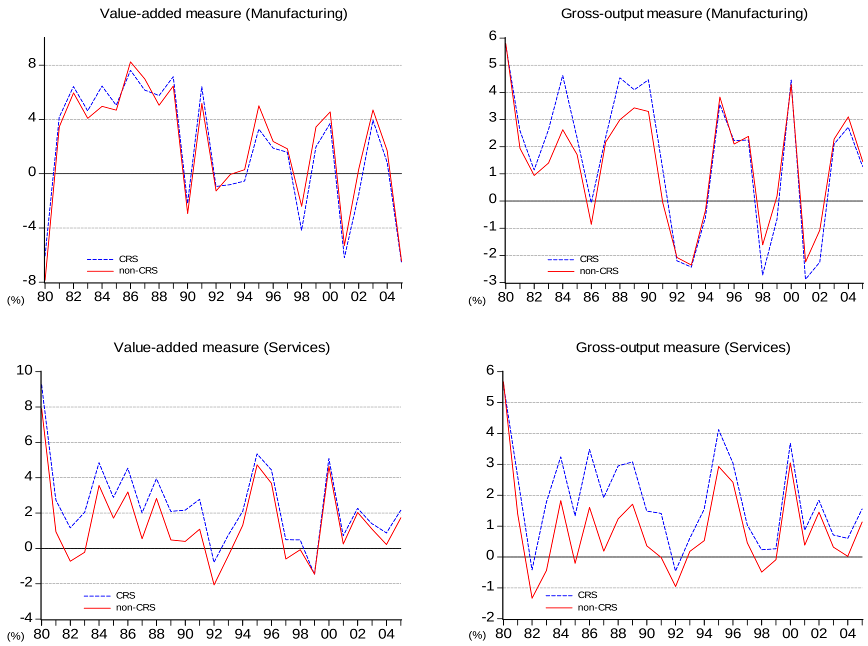
Figure B1: TFP growth rates compared (%), whole economy



Note: mean values across 83 industries (own calculations).

Additionally, figure B2 exhibits the TFP growth rates separated by sector (CRS and adjusted by non-CRS). Here, the steeper downfall in manufacturing is very clearly seen.

Figure B2: TFP growth rates compared (%), manufacturing and services



Note: mean values of restricted samples (own calculations).

C Appendix: additional labor demand estimations

Dependent variable: **ln L_{it}**				
	GMM-DIF	**GMM-DIF**	**GMM-OD**	**GMM-OD**
ln L_{it-1}	0.89†	0.88†	0.88†	0.89†
	(0.003)	(0.01)	(0.005)	(0.008)
ln w_{it}	-0.09†	-0.09†	-0.10†	-0.08†
	(0.003)	(0.01)	(0.005)	(0.008)
Δ ln w_{it}	-0.11†	-0.09†	-0.12†	-0.13†
	(0.004)	(0.01)	(0.002)	(0.01)
OSS_{it} / 100	**0.88**†	*	**0.44**‡	**0.28**
	(0.10)		(0.19)	(0.25)
Δ OSS_{it} / 100	-0.38†	*	*	*
	(0.09)			
OSM_{it} / 100	**-0.34**†	**-0.18**	**-0.39**†	**-0.32**†
	(0.05)	(0.11)	(0.04)	(0.12)
Δ OSM_{it} /100	-0.34†	*	*	*
	(0.04)			
ln Y_{it}	0.06†	0.09†	0.08†	0.06†
	(0.003)	(0.02)	(0.004)	(0.009)
Δ ln Y_{it}	0.08†	0.05†	0.07†	0.08†
	(0.004)	(0.01)	(0.005)	(0.01)
Sargan (p-value):	0.39	0.18	0.37	0.07
Period dummies	**no**	**yes**	**no**	**yes**
observations	1991	2073	2073	2073

Note: see table 8 and footnote of table 9 for definitions.

Dependent variable: **ln L_{it}**				
	GMM-DIF	**GMM-DIF**	**GMM-OD**	**GMM-OD**
ln L_{it-1}	0.94†	0.95†	0.95†	0.95†
	(0.001)	(0.008)	(0.001)	(0.004)
ln w_{it}	-0.02†	*	-0.02†	*
	(0.001)		(0.003)	
Δ ln w_{it}	-0.06†	-0.08†	-0.09†	-0.09†
	(0.001)	(0.005)	(0.004)	(0.008)
OSS_{it} / 100	**0.95**†	*	**1.02**†	**0.29**
	(0.09)		(0.11)	(0.24)
Δ OSS_{it} / 100	-0.42†	*	-0.48†	*
	(0.09)		(0.16)	
OSM_{it} / 100	**-0.37**†	**-0.18**‡†	**-0.37**†	**-0.12**‡†
	(0.03)	(0.11)	(0.01)	(0.07)
Δ OSM_{it} /100	-0.57†	-0.67‡	-0.42†	*
	(0.06)	(0.34)	(0.07)	
ln p^{Y}_{it}	0.02†	0.05†	0.01†	0.05†
	(0.005)	(0.01)	(0.005)	(0.004)
Δ ln p^{Y}_{it}	0.11†	*	0.14†	*
	(0.007)		(0.006)	
Sargan (p-value):	0.35	0.11	0.34	0.12
Period dummies	**no**	**yes**	**no**	**yes**
observations	1992	1992	1992	2073

Note: see table 8 and footnote of table 9 for definitions.

Dependent variable: ln H_{it}

	GMM-DIF	GMM-DIF	GMM-OD	GMM-OD
ln H_{it-1}	0.95†	0.87†	0.95†	0.92†
	(0.002)	(0.02)	(0.002)	(0.01)
ln w_{it}	-0.04†	-0.04†	-0.03†	-0.04†
	(0.001)	(0.01)	(0.001)	(0.005)
Δ ln w_{it}	-0.06†	-0.05†	-0.10†	-0.10†
	(0.002)	(0.007)	(0.004)	(0.009)
OSS_{it} / 100	**0.31**†	**1.65**‡	**0.14**‡†	*
	(0.08)	(0.81)	(0.07)	
Δ *OSS_{it} / 100*	*	-1.16‡	*	*
		(0.54		
OSM_{it} / 100	**-0.28**†	*	**-0.36**†	**-0.11**
	(0.01)		(0.02)	(0.08)
Δ *OSM_{it} /100*	-0.55†	*	-0.58†	*
	(0.04)		(0.07)	
ln K_{it}	*	0.08†	*	0.04†
		(0.02)		(0.01)
Δ ln K_{it}	0.20†	0.28†	0.16†	0.19†
	(0.006)	(0.06)	(0.01)	(0.06)
Sargan (p-value):	0.07	0.08	0.18	0.08
Period dummies	**no**	**yes**	**no**	**yes**
observations	1992	1992	1992	2075

Note: see table 8 and footnote of table 9 for definitions.