How Many US Jobs Might be Offshorable?

Alan S. Blinder

To date, more political heat than intellectual light has been shed on the phenomenon that has come to be called 'offshoring' – that is, the migration of employment from the United States (and other rich countries) to other (mostly poorer) countries.[1] This unfortunate situation may be inevitable, given the political sensitivity of the subject and the thinness of the factual base.[2] For example, no one really knows how many US jobs have been offshored to date, although the patchy evidence seems to point to a small number outside of manufacturing.[3] Naturally, we know much less about the potential for offshoring in the future.

It would be nice to know more – or at least to have some reasonable ballpark estimates. For example, the implications for public policy are probably quite different depending on whether offshoring will eventually affect 3 million American jobs, 30 million or 90 million. A few guesstimates of the number of jobs that might be vulnerable to offshoring have been made; several are discussed below. But they are rough, reach disparate conclusions and are typically not comprehensive – that is, they do not cover the totality of jobs. This paper remedies the last of these three shortcomings and, I hope, at least mitigates the first two.

---

[1] To clarify terminology that is often confused, 'offshoring' refers to movement of jobs to other countries, whether or not that movement is within the same firm or to a different firm. In the latter case, it is also 'outsourcing'; but much outsourcing is purely domestic.

[2] Regarding some of the politics, see Mankiw and Swagel (2006). Regarding the lack of data, see for example National Academy of Public Administration (2006) or Sturgeon *et al.* (2006).

[3] See, for example, the compendium of estimates in National Academy of Public Administration (2006), Chapter 4.

Alan S. Blinder is the Gordon S. Rentschler Memorial Professor of Economics and Public Affairs at Princeton University, and Co-Director of Princeton's Center for Economic Policy Studies, which he founded in 1990. The author is grateful to Yanliang Miao for diligent and insightful research assistance, to assistance from the staff at O*NET and to Princeton's Center for Economic Policy Studies for financial support. The author has also benefited from helpful inputs from David Autor, Alan Krueger, Frank Levy and Aurora Medina-Ng.

More specifically, and subject to many caveats that will be developed later, this paper provides a ranking of all occupations in the 2004 US workforce by their 'offshorability'. It then uses this index to offer several new, and hopefully more accurate, estimates of the number of jobs that are potentially vulnerable to offshoring. It also shows, as Blinder (2006) had speculated, that the degree of 'offshorability' of an occupation is virtually uncorrelated with either its educational requirements or its current median wage.

Antecedents

In an earlier paper (Blinder 2006), I argued that the migration of service-sector jobs from the US and other rich countries to other (mostly poorer) nations, while a minor phenomenon to date, is likely to become a major one in the coming decades – perhaps extensive enough to constitute a 'new industrial revolution'. While the movement of manufacturing jobs abroad is a decades-old story, the phenomenon of service sector offshoring is a relatively new wrinkle that has been enabled by two major developments of fairly recent vintage: stunning advances in computerised telecommunications technology (e.g. the internet), and the entry of several 'new' countries (principally India and China) into the global economy since the 1990s, and especially in this decade.

In thinking about the potential for offshoring, I argued, it is critical to distinguish between two very different sorts of services, which I labelled *personally delivered* (or just 'personal') and *impersonally delivered* (or just 'impersonal'). The first category encompasses a bewildering variety of jobs, ranging from janitors and child care workers on the low-wage end to surgeons and Chief Executive Officers on the high-wage end. Similarly, the second category includes both low-end jobs such as call centre operators and high-end jobs such as scientists. The key attribute on which to focus, I argued, is not the job's skill or its educational requirements, but rather whether the service 'can be delivered [to its end user] electronically over long distances with little or no degradation in quality' (Blinder 2006). Impersonal services such as data entry and writing computer code can be so delivered – with ease. Personal services such as driving a taxi or arguing a case in court cannot. Thus, in large measure, only impersonal services are tradable – and thus potentially vulnerable to offshoring. Personal services, which require physical presence and/or face-to-face contact with end users, are not.

The distinction between personal and impersonal services is closely related but not identical to the one emphasised by Autor *et al.* (2003) – namely, how rule-based (and thus how susceptible to computerisation) a task is. Other things being equal, jobs that can be broken down into simple, routinisable tasks are easier to offshore than jobs requiring complex thinking, judgement and human interaction. However, a wide variety of complex tasks that involve high levels of skill and a great deal of human judgement can also be offshored with modern telecommunication facilities. Think, for example, of statistical analysis, computer programming, manuscript editing and security analysis, to name just a few. I believe the personal/impersonal distinction is more germane to the offshoring issue than is the question of routinisability – although the two criteria do overlap.[4]

Of course, the distinction between personal and impersonal services is really a continuum, not a sharp dichotomy. Data entry may fall at one extreme (completely impersonal) while child care falls at the other (completely personal), but in between lies a vast array of occupations. For example, the services of an architect or a college professor probably can be delivered electronically over long distances, but we believe that the quality of those services is degraded notably when that happens. The central objective of this paper is to create an empirical counterpart to the conceptual continuum, and then to use that continuum to estimate the potential outer limits of offshoring. Precisely where to draw the line between jobs that are too personal to be moved offshore and those that are not is far from clear, however (and is also less important). So several alternatives will be presented. But one thing is certain: since information and communications technology (ICT for short) keeps getting both better and cheaper, the scope for offshoring will increase inexorably. Wherever we draw the line this year, it will be further out next year.

In Blinder (2006), I was either brave or foolish enough to offer a 'ballpark figure of the number of US jobs threatened by offshoring'. The reason was simple, and was stated in the Introduction: the appropriate policy responses (if any) to this problem probably depend on how many jobs

[4] For more on this debate, see Blinder *et al.* (2006).

might be susceptible to offshoring. My brave-but-crude guesstimate of the number of potentially offshorable jobs was 42–56 million, of which 14 million are in manufacturing and 28–42 million (a large range, to be sure) are in the various non-manufacturing ('service', for short) sectors. In round numbers, the total represents roughly 30–40% of all the jobs in the US at present.[5] That is a very large number. But remember: I was guesstimating the number of jobs that might be offshorable, not the number that actually would be offshored. For a wide variety of reasons, the latter will surely be much smaller than the former – just as millions of production jobs in manufacturing are still located in the US despite decades of offshoring. One main purpose of this paper is to reassess and refine my original crude guesstimate. In so doing, I ask whether a number as large as 30–40% of the US workforce is at all believable.

There are several reasons to wonder. First, I based the crude offshorable/non-offshorable classification only on the industry of employment. For example, I judged educational and health care services to be mostly immune to offshoring, while manufacturing jobs are vulnerable. In some cases, that is sound reasoning – for example, political considerations make government jobs highly unlikely to be offshored. But in many other cases, the offshorability of a job depends much more on the occupation than on the industry. For example, I believe I was correct to classify the health care sector as mostly non-offshorable. After all, very few doctors and even fewer nurses will ever see their jobs performed from abroad (or so I assume).[6] But there are a number of specific services within the vast health care sector that can be, and to some extent already have been, offshored. Think, for example, of medical transcription, handling health care records and processing health insurance claims.

At the other end of the spectrum, I made the standard assumption that essentially all manufacturing jobs are potentially offshorable. However, the jobs of top managers and their close assistants are probably not in much danger of moving offshore. Nor are most jobs in advertising, sales and marketing. The offshorability of a particular job, it seems to me, depends much more on the occupation than on the industry of employment – which is how I approach the question in this paper.

[5] The 30–40% figure includes manufacturing jobs. The service jobs that are potentially vulnerable to offshoring amounted to about 20–30% of total US employment in 2004.
[6] See Levy and Yu (2006) for a discussion of offshoring of radiology, which they view as an urban myth.

Second, I made no effort in Blinder (2006) – and no pretence – to be precise. For example, I used only the coarsest one-digit industrial classification. A more serious estimate needs to dig much deeper into the details. In this study, I use six-digit occupation codes, as explained below.

Third, a number of other studies of the potential for offshoring have yielded quite different, and often much lower, estimates than mine,[7] as demonstrated by the following examples.

- A series of well-publicised studies by Forrester Research, beginning in 2002, predicted that about 3.4 million US service jobs would be lost to offshoring by 2015.[8] That is a very small number in a workforce of over 140 million jobs. Notice, however, that, unlike my estimates or those that follow, Forrester's is projecting actual offshoring, not potential offshorability. The latter is a multiple of the former.

- A well-known paper by the McKinsey Global Institute (2005), based on detailed studies of eight 'representative sectors' in rich countries around the world, estimated that only about 11% of worldwide private-sector service employment might potentially be offshored to developing countries within about the next five years. On this basis (excluding government service jobs), my earlier estimate would translate to about 31–47% of US private-sector service jobs – three or four times as much. That's quite a discrepancy. Notice, however, three features of McKinsey's estimates. First, its time frame is only five years; I think we need to look ahead much further than that (more on this below). Second, its analysis applies only to job losses to developing countries (a minor point). Third, it included rich countries from around the world, while I believe the potential for offshoring is substantially greater in English-speaking countries than in non-English-speaking countries. Each of these adjustments leads to a lower estimate. But, that said, the gap between McKinsey's 11% and my 31–47% seems far too great to be explained away by such 'details'.

---

[7] Such differences are, of course, hardly surprising when one is speculating about the future rather than analysing data from the past.
[8] See, for example, McCarthy (2004).

- Looking at occupations rather than at industries, Bardhan and Kroll (2003) estimated that about 11% of all US jobs in 2001 were vulnerable to offshoring. This 11% figure compares directly to my 30–40%. One main reason for the large difference is that Bardhan and Kroll restricted themselves to 'occupations where at least some [offshore] outsourcing has already taken place or is being planned'. In my view, service-sector offshoring is in its infancy at present, and is mostly a prospective phenomenon. We must look ahead.

- Jensen and Kletzer (2006) employed a creative but questionable methodology that used geographical concentration in the US to estimate how 'tradable' each occupation was in 2000. (I will have more to say about this methodology below.) They estimated that 38% of US workers were in 'tradable occupations' – a number that is very close to my high-end estimate of 40%.

- Van Welsum and Vickery (2005) based their estimates of offshorability for a variety of OECD countries on the intensity of ICT use by industry. Their estimate for the US in 2002 was about 20% of total employment.

Ground rules

This paper seeks to sharpen my previous – admittedly crude – estimate of potential offshoring of US employment. But, before going further, I need to clarify some of the ground rules.

First, the task is to estimate the number of jobs that are potentially offshorable, meaning that Americans performing those jobs face potential competition from, say, Indian or Chinese workers. As just suggested, only a fraction of these offshorable jobs will actually be moved offshore.

Second, I am trying, in a loose sense, to forecast offshorability some unspecified number of years into the future, perhaps a decade or two. As mentioned earlier, we can be quite confident that ICT will continue to improve year after year. It also seems a safe bet that the number of well-qualified workers in China, India and elsewhere who are effectively integrated into the global economy will increase dramatically over time. For example, while there are already reports of shortages of Indian workers with the skills required by such industry leaders as Infosys, Tata Consulting and Wipro (and consequent upward pressure on wages), the number of Indians who can in principle be trained for such jobs over the next two decades is enormous. So we clearly need to look ahead rather than focus myopically on the present.

Third, however, the projections that underlie this paper are based on what might be called extrapolating normal technological progress, not on any breakthrough technologies that are highly conjectural at this point. More concretely, I assume that the electronic communications technologies we have today (telephone, internet, videoconferencing, voice recognition systems, etc.) will improve steadily, and perhaps dramatically, over time. But I assume that we do not experience dramatic breakthroughs into areas and methods not presently foreseen – no 'beam me up, Scotty', if you will. For example, one day, Princeton students may get their Economics 101 lectures from a true-to-life hologram of a professor who is actually in Bangalore, where he earns a fraction of my salary. While that strikes me as within the realm of the possible, I certainly don't know that it will ever happen. So, for purposes of this paper, I assume that college teaching (and many other such) jobs are not offshorable. This example and others like it illustrate one important respect in which the estimates of offshorability in this paper, large as they are, are actually conservative. We know that some college teaching is delivered by television already. With better ICT, why can't the broadcast originate in India?[9] But I assume it will not.

Fourth, and in a similar vein, I make no attempt to forecast future changes in the occupational distribution of US employment – even though we know there will be some large ones. For example, while the US Bureau of Labor Statistics (BLS) projects that total US employment will grow by 13% from 2004 to 2014, its projected growth rates across the major occupations – which I define arbitrarily as those employing at least 250,000 people in 2004 – range from over 50% (e.g. home health aids and medical assistants) to as low as –36% (e.g. file clerks and sewing machine operators).[10] But I ignore such projections and focus on the mix of jobs that actually existed in 2004. So the specific question addressed in this paper

[9] The higher education example is also driven by Baumol's disease, which predicts tha the relative costs of personally-delivered services will rise inexorably. The relative cost of delivering college education is rising year after year, which will push colleges and universities into an increasingly desperate search for cost-saving innovations.

[10] The BLS employment projections can be found at www.bls.gov.

is this: How many of the 2004 US jobs are, or might become, potentially offshorable within, say, a decade or two?

Fifth, this paper creates and presents a two-digit 'offshorability' index number for each of 817 occupations. But the scale is ordinal, not cardinal. For example, by assigning an index number of 100 to keyboard data entry and an index number of 95 to medical transcription, I do not mean to imply that transcription is 5% less offshorable than data entry – whatever that might mean. I only mean to assert that data entry is more offshorable than medical transcription. The reader should therefore not think that, say, the 'distance' between 95 and 100 is, in any meaningful sense, smaller than the distance between 95 and 87. Nor should such numbers be interpreted as probabilities that various occupations will in fact be offshored.

Sixth, and finally, the rankings presented below are largely subjective rather than objective. I would have preferred, and originally set out to create, a purely objective ranking – as Kletzer (2006) did. But I concluded that this was impossible to do in any sensible way. Nonetheless, as a point of reference, I present an alternative, purely objective, ranking of occupations in three 'cross-checks' below, where I compare it with my preferred subjective ranking. As will be seen, the correlation between the two is quite low.

This last issue merits further discussion. Subjective rankings have some obvious and serious shortcomings. Among the most important of these are the facts that subjective judgements are probably not replicable, and that they run the danger that the analyst might (even subconsciously) rig the data to conform to his or her beliefs. So I started out by trying to use the O*NET data (described in the next section) to develop a strictly objective index of offshorability – meaning that any subjective judgements that went into it were at least not mine. I even had a role model for this task: Kletzer's (2006) creative attempt to use geographical concentration of employment to measure how 'tradable' each occupation is. But I quickly encountered two huge problems.

One was that Kletzer's mechanical classification procedure leads to some results that are plainly wrong, if not indeed bizarre – the sorts of decisions that 'only a computer could make'. For example, lawyers and judges rank among her most tradable occupations (rated '96% tradable', just below computer programmers); and even such demonstrably non-tradable occupations as farmer and postmaster/postmistress are ranked as

'65% tradable'.[11] At the other end of the spectrum, her objective procedure classifies such eminently offshorable occupations as data entry keyers, telephone operators and billing clerks as virtually impossible to move offshore ('7% tradable').[12] I point out these examples not to criticise Kletzer, whose approach is both clever and objective, but to illustrate the kinds of results that a mechanical procedure – devoid of human judgement – can produce.

My own hopes of using the job descriptions in the O*NET database to create a more reasonable objective ranking of occupations were quickly dashed by considerations such as the following. Two key defining characteristics of jobs that cannot be offshored are (a) that the job must be performed at a specific US work location (e.g. working on a farm or at an amusement park) and (b) that the job requires face-to-face personal communication and/or contact with end users of the service (e.g. a taxi driver or a surgeon). Regarding the latter, one of the many 'work activities' included in the O*NET database (explained further below) is 'communicating with persons outside the organisation'. That sounds promising – until you realise that such communication can be 'in person, in writing, or by telephone or email', and that O*NET rates this work activity as an important component of such highly-offshorable jobs as editor and telemarketer. A human being, of course, understands that communications with an editor are most likely to be via email and communications with a telemarketer are certainly telephonic. A computer does not.

For these reasons and others, I decided that there was no reasonable alternative to a subjective, judgemental ranking of 'offshorability'. However, the section below entitled 'Three cross-checks' nonetheless reports on the attempt (just mentioned) to construct a purely objective ranking. In addition, it also describes both a second, independent subjective ranking, done by an experienced human resources professional, and a large replication study by a team at the Harvard Business School. While none of these matches my own ranking, the latter two come much closer.

---

[11] In my subjective 0–100 ranking of offshorability, computer programmers and data entry keyers are the two most offshorable occupations (rating = 100). Lawyers, judges, farmers and postmasters/postmistresses are all rated completely non-offshorable (rating 25 or below).

[12] On my subjective scale, telephone operators are given a 95 and billing clerks a 90.

Using the O*NET data to create an index[13]

The O*NET, an online service developed for (but not by) the US Department of Labor,[14] is the successor to the better-known *Dictionary of Occupational Titles*, which was last revised in 1991. In the version I used (release 10.0, June 2006), O*NET contains at least partial information on more than 950 US occupations, most of which correspond closely to the Labor Department's Standard Occupational Classification (SOC). Data were missing for two of the 801 SOC codes and, for reasons to be explained shortly, I added 18 synthetic occupations by subdividing some of the codes. Thus my database consisted of 817 detailed occupations. The six-digit occupational breakdown is quite detailed in some areas. For example, 'Education Administrators' (SOC 11-903) are subdivided into 'preschool and child care center/program', 'elementary and secondary school', 'postsecondary' and 'all other'. Secretaries (SOC 43-601) are broken down into 'executive secretaries and administrative assistants', 'legal secretaries', 'medical secretaries' and 'secretaries except legal, medical, and executive'.

For each occupation, O*NET offers a short verbal description, a (sometimes lengthy) list of common job titles associated with that occupation, the median hourly wage rate, employment in 2004, the educational attainment of people in that occupation and, most important for my purposes, a wealth of detailed descriptive information on the nature of the job, including:

- *tasks* typically performed by people in that occupation – a variable number of open-ended categories, specific to each occupation
- *knowledge* required by the occupation – in 33 fixed categories; examples – clerical, mathematics
- *skills* required by the occupation – in 35 fixed categories; examples – time management, persuasion
- *abilities* needed to do the job – in 52 fixed categories; examples – oral expression, stamina

---

[13] Readers uninterested in the details and wanting to get to the results more quickly can skip this section. But I do not encourage this because, as they say, 'the devil is in the detail'.

[14] Found at http://online.onetcenter.org.

- *work activities* that typify the job – in 41 fixed categories; examples – getting information, assisting and caring for others
- *work context* in which the job normally is performed – in 57 fixed categories; examples – face-to-face discussions, spend time standing
- *interests* of people on that job – in six fixed categories; examples – social, artistic
- *work styles* that are typical on that job – in 16 fixed categories; examples – persistence, integrity
- *work values* in the occupation – in six fixed categories; examples – relationships, independence
- *work needs* for the job – in 21 fixed categories; examples – variety, authority.

To illustrate how this mass of data was used to assign an index number of offshorability to each occupation, I will use one occupation from each end of the offshorability scale – data entry keyers (index = 100) and child care workers (index = 0) – as examples. Remember that the central question is whether the service is amenable to electronic delivery and, if so, whether its quality is seriously degraded when so delivered. So, for example, it is literally impossible to deliver child care (which requires close physical contact) or farm labour (which is tied to a particular geography) over long distance. As mentioned earlier, college teaching probably can be so delivered, but we believe (or is it that *we hope*?) that electronic delivery is vastly inferior to face-to-face delivery. So all of these jobs are classified as highly non-offshorable – that is, assigned indexes near zero. At the other end of the spectrum, keyboard data entry, writing computer code and answering queries in a call centre are naturally and easily delivered electronically with little or no loss of quality. So these jobs are classified as highly offshorable – that is, given indexes at or near 100.

The top-line written descriptions of the two occupations in O*NET tell us, for example, that the job of a data entry keyer is to 'operate data entry device, such as keyboard or photo composing perforator. Duties may include verifying data and preparing materials for printing.'[15] These activities are so clearly offshorable that we need hardly inspect the copious detail that follows. Similarly, the job of a child care worker is described

[15] All such quotations come from pages of the O*NET website.

as to 'attend to children at schools, businesses, private households, and child care institutions. Perform a variety of tasks such as dressing, feeding, bathing, and overseeing play.' These activities clearly cannot be provided electronically over a long distance.

But most occupations are less easily classified, requiring us to peer more deeply into the O*NET database. (Think, for example, of clerks, customer service representatives or scientists.) After spending some time studying the various types of data available in O*NET, we concluded that most of the relevant information is to be found under 'tasks' and 'work activities'.[16] For example, what O*NET classifies as 'knowledge' (e.g. knowledge of chemistry), 'skills' (e.g. writing), and 'abilities' (e.g. inductive reasoning) are all quite important to knowing how well qualified any given person is for a specific occupation. But they are pretty much irrelevant to whether the job can be performed offshore. For example, are jobs requiring good deductive reasoning skills harder or easier to offshore?[17]

Although 'tasks' and 'work activities' sound similar in English, they are quite different in O*NET terminology. Under 'tasks', O*NET describes, in free-form prose, the main things that a person in that occupation does on the job. So, for example, the two top tasks for child care workers are to:

1. 'Support children's emotional and social development, encouraging understanding of others and positive self-concepts'
2. 'Care for children in institutional setting, such as group homes, nursery schools, private businesses, or schools for the handicapped'

whereas the two top tasks for data entry keyers are to:

1. 'Compare data with source documents, or re-enter data in verification format to detect errors'
2. 'Compile, sort and verify the accuracy of data before it is entered.'

In the O*NET, tasks like these are specific to each occupation, rather than standardised. Thus, the list of 20 tasks performed by child care workers

[16] This is not a 'royal we'. My research assistant, Yanliang Miao, and I spent many hours developing and discussing the classifications. His assistance was invaluable.

[17] On the criteria employed by Autor *et al.* (2003), such jobs would presumably be rated as harder to routinise and computerise. This illustrates one respect in which their criteria and mine are different. For example, the job of a scientist working for a pharmaceutical company is offshorable but probably not routinisable.

and the list of nine tasks performed by data entry keyers have no elements in common. O*NET 'tasks' provide a great deal of useful texture about what actually goes on in each occupation. But because they are not standardised, they do not provide comparable data across occupations.

By contrast, the 41 'work activities' do comprise a standardised list, identical for every occupation, but with dramatically different relative importances (which O*NET ranks on a 0–100 scale) across occupations.[18] So, for example, 'assisting and caring for others' has an importance of 84 for a child care worker, but only 4 for a data entry keyer. On the other hand, 'interacting with computers' has an importance of 75 for a data entry keyer, but just 15 for a child care worker. Several of these work activities – whose importances are rated for almost every occupation – carry useful hints about whether the job can or cannot be performed offshore. Some examples of work activities that clearly identify personal, and hence non-offshorable, services are (with the importances of each activity for child care workers versus data entry keyers, respectively, indicated in parentheses): 'assisting and caring for others' (84 vs 4), 'establishing and maintaining interpersonal relationships' (68 vs 25), 'coaching and developing others' (49 vs 0) and 'communicating with persons outside the organisation' (41 vs 8).[19] We leaned heavily on these and a few other work activities to rank the offshorability of occupations. The principle was always the same: the more personal a service is, or the more closely tied to a specific geographical location in the US, the harder it is to offshore.

Finally, there is some information to be gleaned from O*NET's 'work contexts', though not as much as one might think from the English-language word phrase. For example, three of the work contexts are: 'contact with others', 'face-to-face discussions' and 'deal with external customers'. All three sound highly germane to the distinction between personal and impersonal services – until you realise that both 'contact with others' and 'dealing with external customers' can be telephonic, and that 'face-to-face discussions' can be with fellow workers rather than with customers. This illustrates once again why it is so hazardous to construct a purely mechanical index of offshorability.

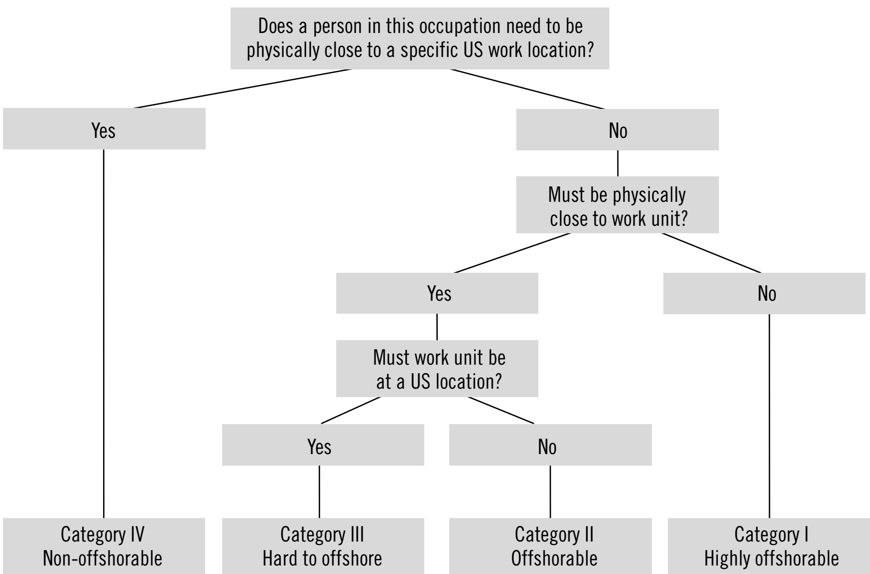
[18] O*NET also reports the level of the activity needed for each job – for example, both editors and order clerks must be able to write, but editors must be able to write at a much higher level. More on this later.
[19] Note, however, that much of the communication might be electronic.

So, instead, we eyeballed the O*NET data on each occupation, paying particular attention to the job description, tasks and work activities, to assign an admittedly subjective two-digit index number of offshorability to each occupation. We did this in two stages.

The first stage is illustrated by the flow diagram in Figure 1. We first asked whether the worker is required to be at a specific work location in the US in order to perform the job – as is the case, for example, for a child care worker, a farmer, an attendant at an amusement park or a dentist. If the answer was 'yes', we classified that job as 'non-offshorable', or in Category IV, and assigned it an offshorability rank between 0 and 25. In everything that follows, all the Category IV jobs, and there are a lot of them,[20] are treated as impossible to offshore. Doctors, nurses, taxi drivers and college professors were all placed in Category IV.

If the answer to the first question was 'no', we next asked whether the worker had to be physically close to his or her work unit. For example, a factory worker must be in the factory, whether that factory is in the US or abroad, but a proofreader or editor can work virtually anywhere;

Figure 1: The four broad occupational categories



[20] Specifically, 533 occupations out of the total of 817.

in particular, he or she need not be at the publisher's offices or printing plant. If the answer to this second question was 'no', we classified the job as 'highly offshorable', or in Category I, and assigned it an offshorability index between 76 and 100. So, for example, data entry keyers, computer programmers, reservation agents, actuaries and mathematicians all fall in Category I.

Those were the easy cases. If the job makes it important that workers be physically present with their work units (e.g. a factory worker must be in the factory), we next asked whether the entire work unit needed to be in the US. If the answer was 'yes', we classified that job as 'hard to offshore', or in Category III, and assigned it an offshorability rank between 26 and 50. So, for example, shipping clerks, radio and TV announcers, and oil field workers all fell into Category III. But if the answer was 'no', meaning that the whole work unit could be moved abroad, we classified the job as 'offshorable', or in Category II, and assigned a rank between 75 and 51. Prominently, almost all factory jobs fall into Category II, as do physicists, artists, medical technologists and credit analysts.

Table 1 summarises the four broad offshoring categories, indicating the number of SOC occupations and the number of workers (in 2004) in each. Notice that a majority of both US occupations and US workers fall into Category IV, and thus, for the purposes of this paper, are classified as totally immune to offshoring.[21] Similarly, only a small minority of jobs and employment fall into Category I, the easiest-to-offshore category. The interesting

Table 1: The four main occupational categories

Category	Description	Number of occupations	Number of workers (millions)	Offshorability index
I	Highly offshorable	59	8.2	100–76
II	Offshorable	151	20.7	75–51
III	Hard to offshore	74	8.8	50–26
IV	Non-offshorable	533	92.6	25–0
All		817	130.3	100–0

[21] Recall that I rule out breakthrough technologies that might make, for example, college teaching offshorable. Also note that, in calling these occupations 'totally immune' to offshoring, I am considering only direct effects. No occupation is immune to indirect effects that work through, for example changes in relative wages and employment patterns.

cases come in Categories II and III – which, in total, comprise 22.6% of the US workforce. That is where the dividing line must be drawn.

The next step was to assign a specific two-digit number to each occupation in Categories I, II and III.[22] As suggested already, we based these rankings on our own knowledge of what makes a service personal, and on information relevant to that point found in the O*NET database. In particular, several of the O*NET work activities mentioned earlier suggest a strong need for face-to-face contact with end users. O*NET also rates the importance of these activities (and others) to the occupation. When O*NET assigned high importance to work activities that define personally delivered services, we gave that occupation a low ranking on the 0-to-100 offshorability scale. To illustrate our procedures, consider two occupations with which most readers will have at least some acquaintance: financial analysts and sales managers.

O*NET lists the following as the three most important tasks that financial analysts perform on the job (I abbreviate slightly):

1. 'Assemble spreadsheets and draw charts and graphs, using computer'
2. 'Analyse financial information to produce forecasts for use in making decisions'
3. 'Maintain knowledge and stay abreast of developments'.

These and other items that rank high on O*NET's list do not suggest much need for physical presence. But, as mentioned earlier, work activities are more useful because they are directly comparable from one occupation to another.

According to O*NET, the five most important work activities for financial analysts (with importances in parentheses) are: analysing data or information (96), getting information (94), interacting with computers (92), processing information (92), and communicating with supervisors, peers or subordinates (87). None of these is a hallmark of personal service. And the work activities that point most strongly towards face-to-face interactions – such as establishing and maintaining interpersonal relationships (84), coordinating the work of others (62), selling, or influencing others (62), assisting and caring for others (40), and performing for or working

[22] We did not bother to assign numbers to the occupations classified in Category IV because these inherently domestic jobs would be deemed non-offshorable under any definition.

directly with the public (28) – are assigned less importance. On this basis, we assigned an offshorability index of 76 to financial analysts, placing this occupation right at the borderline of Categories I and II. In consequence, financial analyst jobs will be rated as potentially offshorable under any reasonable definition.

Now, turning to sales managers, the three top O*NET tasks are:

1. 'Resolve customer complaints'
2. 'Monitor customer preferences to determine focus of sales efforts'
3. 'Direct and coordinate activities involving sales'

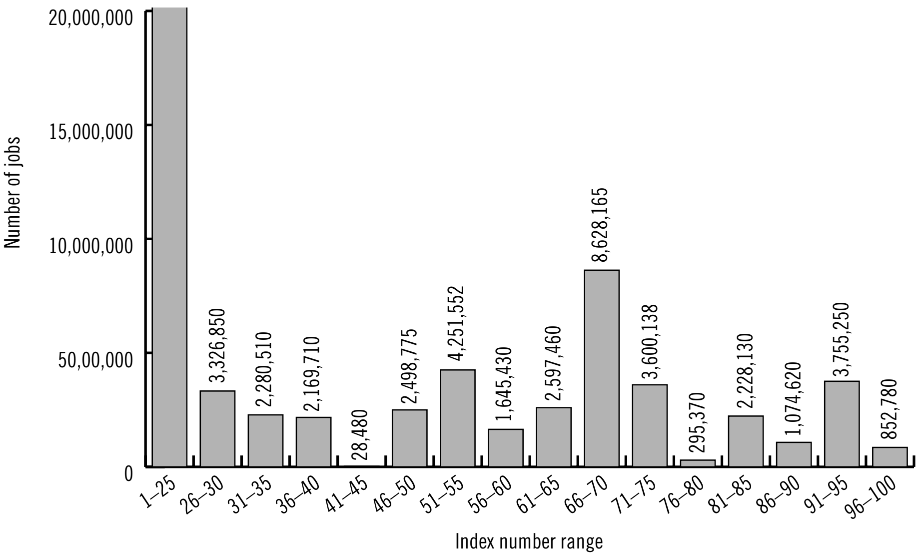
which do suggest some advantage to face-to-face contact. And the top five work activities are: communicating with persons outside the organisation (86), organising and prioritising work (86), communicating with supervisors, peers or subordinates (85), interacting with computers (85), and making decisions and solving problems (85). This list does not give us clear guidance. But some of the most clearly personal work activities – such as establishing and maintaining interpersonal relationships (84), selling, or influencing others (78), guiding, directing and motivating subordinates (74), and performing for or working directly with the public (74) – are ranked as important for sales managers by O*NET. On this basis, we assigned sales managers an offshorability index of 26, which put them right at the borderline of Categories III and IV. Only an extremely aggressive definition of offshorability will deem this occupation to be offshorable.

Just a few more explanatory remarks are in order before I display the results. First, to create a kind of benchmark, we ranked a 'standard manufacturing job' as 68. The consequence of this arbitrary decision is that there is a notable spike in the frequency distribution of the index in the 66–70 range, as is apparent in Figure 2.

Second, rather than assign a single rank to every job in some of the big and diverse occupations, I divided several of them up. Customer Service Representatives (SOC code 43-4051; 2004 employment = 516,925) constitute a good example.[23] Some customer reps do their work over the telephone

[23] The other occupations that were subdivided are: Office clerks, general; Office and administrative support specialists, all other; Computer support specialists; Secretaries, except legal, medical and executive; Interpreters and translators; Financial managers; Receptionists and information clerks; Accountants and auditors; Lawyers; and Legal support workers, all other.

Figure 2: Distribution of employment by offshorability index



or computer, while others are required to travel extensively for frequent face-to-face meetings with customers. Rather than treat this heterogeneous group as a single occupation with a single ranking, we divided it into four equal parts, assigning one part to Category I, one part to Category II, and so on. Thus, the Appendix actually lists 'Customer Service Representatives' three times, placing 129,231 jobs into each category. This augmentation of the database added 18 synthetic occupations, ten of which do not show up in the Appendix because they fall into Category IV.[24]

Third, in several instances there are natural hierarchies of related occupations. For example, we rated managers as less offshorable than the people they manage. Similarly, lawyers were deemed to be less offshorable than paralegals, who in turn were less offshorable than other legal support workers. In these cases, offshorability declines as skill level rises. But, in the sciences and engineering, we made just the opposite judgement – for example, computer scientists were assumed to be more offshorable than computer engineers, who were in turn considered more offshorable than computer operators.

[24] This is why Table 1 includes 817 occupations when there are actually only 799.

With all this as background, the long table in the Appendix displays the two-digit codes that we assigned to all 284 occupations in Categories I, II and III, plus seven 'close calls' (index = 25) that we decided to place in Category IV. (The other 526 occupations in Category IV will not be considered further.) Remember, these rankings are ordinal, not cardinal. But to help readers get a 'feel' for the nature of the scale, and to make it easy to second-guess my choices, Table 2 displays the offshorability index for

Table 2: Major occupations ranked by offshorability[a]

Occupation	SOC code	Category	Index number	Number of workers
Computer programmers	15-1021	I	100	389,090
Telemarketers	41-9041	I	95	400,860
Computer systems analysts	15-1051	I	93	492,120
Billing and posting clerks and machine operators	43-3021	I	90	513,020
Bookkeeping, accounting and auditing clerks	43-3031	I	84	1,815,340
Computer support specialists	15-1041	I and II	92/68	499,860
Computer software engineers, applications	15-1031	II	74	455,980
Computer software engineers, systems software	15-1032	II	74	320,720
Accountants[b]	13-2011	II	72	591,311
Welders, cutters, solderers, and brazers	51-4121	II	70	358,050
Helpers – production workers	51-9198	II	70	528,610
First-line supervisors/managers of production and operating workers	51-1011	II	68	679,930
Packaging and filling machine operators and tenders	51-9111	II	68	396,270
Team assemblers	51-2092	II	65	1,242,370
Bill and account collectors	43-3011	II	65	431,280
Machinists	51-4041	II	61	368,380
Inspectors, testers, sorters, samplers, and weighers	51-9061	II	60	506,160
General and operations managers	11-1021	III	55	1,663,810
Stock clerks and order fillers	43-5081	III	34	1,625,430
Shipping, receiving and traffic clerks	43-5071	III	29	759,910
Sales managers	11-2022	III	26	317,970
Business operations specialists, all other	13-1199	IV	25	916,290

[a] There are a few other occupations in the BLS database with employment over 300,000; but for reasons explained in the text, I distributed these across categories.
[b] SOC code 13-2011 is actually 'Accountants and auditors'. I assumed that accountants comprise three-quarters of the occupation and that auditors are Category IV jobs.
Source: US Bureau of Labor Statistics and author's judgements

the 22 largest occupations, which are those with at least 300,000 workers in 2004.

Counting the potentially offshorable jobs

With the rank ordering of all occupations in the Appendix in hand, assessing the number of jobs that are potentially vulnerable to offshoring is a simple matter of counting – once a dividing line between jobs that are offshorable and jobs that are not has been selected. Of course, no one knows precisely where to draw that line. And, as already mentioned, the line is sure to move down (on my 0–100 scale) over time. So I offer three choices here, corresponding to 'conservative', 'moderate' and 'aggressive' definitions of which jobs are potentially offshorable and which are not. More importantly, every reader can use Figure 2, or the data in the Appendix, to draw the line wherever he or she pleases.

My most conservative estimate includes only the occupations in Categories I and II, a group that comprises offshorability index numbers from 100 down to 51. It thus (see the table in the Appendix) draws the dividing line between such occupations as paralegals and legal assistants,[25] and office machine operators (except computer), which are classified as just barely offshorable, and travel agents and file clerks, which are classified as not quite offshorable. By this definition, which strikes me as clearly too restrictive, some 210 occupations comprising 22.2% of US employment in 2004 (about 28.9 million jobs) are potentially offshorable. Note that even this extremely conservative estimate is roughly double McKinsey's (2005) number (11%).

However, we really do not believe that, for example travel agents and file clerks are immune to offshoring. So my moderate estimate pushes the dividing line down into Category III, classifying all jobs with ranks 37 and higher as potentially offshorable. By this definition, aerospace engineers and a fraction of secretaries, except legal, medical and executive barely qualify as offshorable, while oil field workers (comprising several different occupations), broadcast technicians, and media and communication equipment workers (all other) just miss. Drawing the line here classifies

[25] Lawyer is one of the occupations that we subdivided, placing half of lawyers at the bottom of Category II (index = 51) and the rest in Category IV.

240 occupations, comprising 25.6% of the workforce (or 33.4 millions jobs in 2004), as offshorable.

Finally, my most aggressive definition counts all the Category III jobs as potentially offshorable, thereby drawing the dividing line between rank 26 (such occupations as watch repairers; mail clerks and mail machine operators, except postal service; and sales managers) and rank 25 (which includes photographers; architects, except landscape and naval; and advertising sales agents). This division of the workforce, which strikes me as possibly too aggressive but not wildly so, classifies 284 occupations, comprising 29.0% of all jobs (or a total of 37.8 million) as potentially offshorable. I include it here as a possible representation of a reasonable outer limit, after a decade or two of 'normal' technical progress has occurred. And, remember, I am trying to estimate offshorability, not to forecast actual offshoring. Just as the US still has textile workers and steel workers today (although many fewer than it once had), only a fraction of the offshorable jobs will actually be moved offshore.

Thus, I have offered three possible dividing lines. My own best guess is that something like 26–29% of America's 2004 jobs are, or eventually will be, potentially offshorable. This figure is just below the lower end of my 'guesstimate' in Blinder (2006). Perhaps more importantly, by using the job titles and numbers in the Appendix, each reader can make his or her own judgement about where to draw the line.

Finally, although I do not attempt to forecast future changes of the US occupational distribution, it may be worth reporting that the rank correlation between my offshorability index and the BLS's projected job growth from 2004 to 2014 is almost exactly zero.[26] To me, this surprising result suggests caution in using the BLS projections. Occupations that are highly offshorable may grow more slowly than the BLS currently anticipates.[27]

Three cross-checks

I have already explained why I favour the use of subjective over objective rankings of offshorability. But, as mentioned earlier, some readers may feel uneasy about relying on personal, subjective judgements – and for good

[26] This correlation is computed using BLS employment projections for 2004–2014 released on 7 December 2005; they are available at www.bls.gov/news.release/ecopro.nr0.htm.

[27] However, in making these projections, the BLS does try to take account of offshoring (see BLS 2006).

reason. As an initial cross-check, therefore, I first present in this section an alternative ranking, derived in an entirely mechanical way from numbers in the O*NET database – which makes it, among other things, perfectly replicable.

To create this objective index, I began by selecting five O*NET attributes which indicate that the occupation is likely to require face-to-face interaction with customers and/or is difficult to deliver remotely. These are:

1. establishing and maintaining personal relationships
2. assisting and caring for others
3. performing for or working directly with the public
4. selling, or influencing others
5. social perceptiveness.

Each of these five attributes, which I index by $i = 1, \ldots, 5$, are clearly negative indicators of offshorability.

For each job, O*NET rates both the 'importance' and the 'level' required of each such attribute,[28] which I henceforth denote as I_i and L_i respectively. Take 'assisting and caring for others' (item 2 on the preceding list) as an example; child care workers have $I_2 = 84$ and $L_2 = 65$, while data entry keyers have $I_2 = 4$ and $L_2 = 9$. Arbitrarily assigning a Cobb-Douglas weight of two-thirds to importance and one-third to level, I define each occupation's composite score for non-offshorability, S, as the sum of five components:

$$S_j = \sum_{i=1}^{5} (I_{ij}^{2/3} L_{ij}^{1/3})$$

Since lower values of S_j indicate that occupation j is easier to offshore, it is straightforward to transform the S_j scores into an objective ranking of every occupation by its offshorability. Once this is done, the question is: How well do these purely objective rankings correlate with my original subjective rankings?

The answer is, not very well. Specifically, computed over the 259 occupations that can be ranked objectively given the availability of O*NET

[28] Because complete data are available for only 259 of the 291 occupations listed in the Appendix, my objective ranking is limited to these 259 occupations.

data, the rank correlation is only +0.16. While that number is positive, it is not very high. Such a low correlation is, of course, open to at least two very different interpretations. My preferred interpretation is that it illustrates how unreliable any mechanical ranking of offshorability is. But a sceptic might use the same fact to cast doubt on my subjective ranking.

So which interpretation is more reasonable? Table 3 offers some suggestive evidence by displaying the nine occupations (out of the total of 259) for which the subjective and objective rankings differ by at least 200 ranks. That is a colossal difference – larger, I believe, than you would ever get from any two sensible human beings. And, in every case, my subjective ranking seems far more plausible than the mechanically derived objective ranking.[29]

Table 3: Largest discrepancies between subjective and objective rankings

Occupation	Subjective ranking	Objective ranking
Network systems and data communications analysts	24	225
Film and video editors	8	215
Travel guides	34	246
Telemarketers	8	208
Reservation and transportation ticket agents and travel clerks	14	256
Proofreaders and copy markers	8	234
Furniture finishers	207	7
Gas plant operators	242	41
Photographic process workers	229	11

Note: A low number connotes high offshorability. For example, according to the subjective ranking, telemarketers are (tied for) the eighth most offshorable occupation.

As a second cross-check, I hired a human resources professional with more than 12 years of field experience in personnel matters to create her own offshorability index for each of the same 799 occupations.[30] To ensure that the two rankings would be as independent as possible, I did *not* instruct her to approach the task in the same way as we did – as

[29] Travel guides (SOC 39-6022) may appear to be an exception to this rule. But according to the O*NET, the job of travel guides is to 'plan, organize, and conduct long distance cruises, tours, and expeditions for individuals and groups'. This is quite different from another closely related occupation, namely tour guides and escorts (SOC39-6021), which requires more close personal contact, and hence is classified as not offshorable.

[30] Recall that I had 817 occupations because I decided to subdivide several of the SOC codes. She did not. So the comparisons that follow are all based on 799 occupations.

illustrated, for example, by the flow diagram in Figure 1. However, I did tell her that:

- the key attributes that determine whether or not an occupation is offshorable are (a) whether it is tied to a specific US geographical location, and (b) whether face-to-face, personal contact with the end-user is important
- it was not necessary to assign scores to occupations that she deemed impossible to move offshore (corresponding roughly to my Category IV).

The first item, of course, merely defines the task; I wanted her to use essentially the same criteria for offshorability as I did. The second item is strictly a time saver, and she in fact took this option for 58.6% of the occupations. (I took it for 64.4%.) Other than that, she was instructed to use her own judgement, based on her own knowledge and experience – and, of course, she had access to the same O*NET data that we did. So, for example, the human resources professional did not see our rankings, she was not told the process by which we arrived at them, and we did not discuss her rankings with her as she was developing them. I was even careful not to offer any examples that might influence her views – except for some obvious cases (such as keyboard data entry and child care) that I used to illustrate the principles involved. Thus I view the two subjective rankings as about as independent as can be.

Because there are so many ‘zeroes’ in each ranking, there is no single statistic by which the ‘correlation’ between the two rankings can be assessed. So I offer instead a variety of comparisons.

I begin by simply coding all the rankings into either ‘no’ for totally non-offshorable jobs (my Category IV) or ‘yes’ for potentially offshorable jobs – that is, for the occupations that are assigned a numerical ranking (my Categories I–III). To derive the simplest, non-parametric measure of association, I then use this ‘yes, no’ classification to create a two-by-two contingency table (Table 4). The χ_1^2 test statistic for the null hypothesis of independence between the two rankings in this contingency table is over 158, which rejects the null hypothesis at any imaginable

Table 4: Two-by-two contingency table

	No (514)	Yes (285)
No (468)	385	83
Yes (331)	129	202

level. But how well correlated are they? Maxwell (1970, p. 652) suggests using the kappa coefficient, 'which may be interpreted in the same way as a correlation coefficient'.[31] For the data in Table 4, $\kappa = 0.79$. So, based only on this crude binary treatment of the data, the two rankings are highly correlated.

Turning to some of the details, among the 468 occupations that she judged to be virtually impossible to offshore ('no' in the top row of the contingency table above), I concurred in 385 cases, or 82.2%. Across the 83 cases of disagreement (17.7%), my average offshorability index (on the 26–100 scale that I used) was 55.5, which is sizeable, so some of these discrepancies do represent substantial differences of opinion.[32] Among the 514 occupations that I placed in Category IV ('no' in the left-hand column of Table 4), she rated 385 (74.9%) as totally non-offshorable, too. Across the 129 cases of disagreement (25.1%), her average offshorability score (on the 1–100 scale that she used) was just 29.3, which is low.[33]

There are 202 cases in which both of us judged the occupation to be at least conceivably offshorable ('yes, yes' in the contingency table above), and therefore both assigned a numerical rating. Within that subset, the rank correlation between our two subjective rankings was +0.38. Finally, whereas Table 3 displays nine cases in which my subjective ranking differed from the objective ranking by at least 200 ranks, there are no discrepancies that large between my rankings and those of the human resources professional.[34]

So was this a successful replication? I leave that to the reader to judge. On the one hand, the human resource professional's subjective rankings are far closer to mine than are the mechanically derived objective rankings (rank correlation 0.38 versus 0.16), and the two of us agreed on the 'yes, no' classification in roughly 80% of the cases. On the other hand, a rank

---

31 Denote the four elements of the contingency table as:

a	b
c	d

Then kappa is defined as $\kappa = [(a + d)/N - \Delta)]/[1 - \Delta]$, where N is the number of observations (so that $a + b + c + d = N$), and $\Delta = (a + c)(a + b)/N^2 + (d + c)(d + b)/N^2$. It is clear from this formula that $\kappa = 1$ when all data are on the diagonal ($a + d = N$, $c = b = 0$), and that $\kappa = 0$ when the data are equally distributed in the table ($a = b = c = d = N/4$).

32 As a point of reference, I assigned a score of 55 to medical scientists, except epidemiologists and to logisticians.

33 As a point of reference, she assigned a score of 30 to radio and TV announcers and to a number of types of post-secondary teachers.

34 There are, however, 27 cases in which our respective rankings differ by at least 100 ranks.

correlation of 0.38 is pretty far from perfect agreement. In the end, these truly are subjective judgements. That said, I am confident that more effort to specify in detail, and therefore to homogenise, the criteria used to assess offshorability would have produced substantially greater agreement.

After an earlier draft of this paper had been completed and circulated, a group of Harvard Business School faculty, as a class exercise, had 901 MBA students replicate my rankings (see Smith & Rivkin 2008).[35] Since the task of ranking 800 occupations is huge, the students were divided into 152 teams, and each team rated the offshorability of just 20 occupations. However, the 901 students as a whole rated every occupation multiple times; indeed, the average occupation was rated more than 20 times. Surveying all these replications, the Harvard researchers concluded that, 'Overall the MBA students' assessments of offshorability matched Blinder's well' (Smith & Rivkin 2008). Across occupations, the correlation between my ranking and the students' was 0.60. The students concluded that between 21% and 42% of US jobs are offshorable (compared to my 22–29%). But the most stunning similarity was that their density function for the offshorability index was almost identical to mine (see Figure 2) once you pass an offshorability rank of about 46.[36]

Perfect replicability of a subjective ranking should never be expected. But looking at all this evidence leads me to two tentative conclusions. First, humans can perform this task far better than computers. Second, the degree of cross-person disagreement is small enough to be tolerable.

Skills and offshorability

One major point of Blinder (2006) was that offshorable jobs are to be found all along the skill spectrum. It is not obvious, I argued, that there is much correlation between the skill or education level that typifies a job and its vulnerability to offshoring. It is possible to use the (subjective) index of offshorability created in this paper to test this 'no-correlation hypothesis' because BLS data also provide for each occupation the two measures that economists normally use to rate labour market skill: wage rates and educational attainment.

[35] I should state that I had nothing to do with initiating, designing or carrying out this work.
[36] Below index number 46, the Harvard students were substantially more sanguine than I about the possibility of offshoring various occupations.

Regarding wages, the median wage in 2004 is available for each of the 291 occupations that are ranked by my offshorability index. Regarding educational attainment, O*NET also reports BLS data on the fractions of holders of each job (between the ages of 25 and 44) in 2004 whose education fell into each of the following three ranges:

1. E1 = the fraction with 'high school or less' education
2. E2 = the fraction with 'some college' education
3. E3 = the fraction with a 'bachelor's degree or higher'.

There are clearly only two independent variables here, and I turned them into two different scalar measures of educational attainment, as follows:

1. E4 = E3 – E1
2. E5 = 10E1 + 14E2 + 18E3

Measure E4 shows the balance (positive or negative) between college graduates (or more) and high school graduates (or less). In principle, this measure runs from +1.0 to –1.0 across occupations; in practice, the actual data come close to filling that entire span – ranging from a high of +0.97 to a low of –0.88. The measure E5 is an approximation to average years of education created by treating 'high school or less' as ten years, 'some college' as 14 years, and 'bachelor's degree or higher' as 18 years. E4 and E5 are conceptually different, and are measured in very different units. But when I transform each set of cardinal numbers into ordinal rankings, the rank correlation between the two is nearly perfect – greater than 0.999. So it does not matter which measure is used.

What, then, is the rank correlation between an occupation's offshorability (according to our subjective ranking) and its educational attainment, as measured by either its E4 or E5 ranking? The answer is just +0.08. There are two messages here. First, this rank correlation is very small, indicating that the 'no correlation hypothesis' of Blinder (2006) comes pretty close to the truth. Second, however, it is positive, not negative. A common presumption has been that jobs requiring low levels of education are more vulnerable to offshoring than jobs requiring high levels. But the estimated rank correlation points, albeit very weakly, in the opposite direction, indicating that occupations with higher educational attainment are (slightly) more offshorable.

The other way to measure skill is by wages. To assess the correlation between skill and offshorability in this alternative way, I calculated the rank correlation between offshorability and wages. It is essentially zero (actually 0.01), this time literally suggesting no correlation.

Leamer's (2007) notion of the contestability of jobs raises another natural question: Are workers in highly offshorable occupations already paying a wage penalty because of potential competition from abroad? Notice that the issue here is one of contestability rather than competition. By 2004, only a very small number of service jobs had actually been offshored. So, in estimating the effect of offshorability on wages, I am looking mostly for the impact of potential offshorability rather than of actual offshoring.

This line of thought suggests that we should expect to find such an effect only on the wages of workers in the most offshorable occupations. However, in looking for such an effect, we should at least control for educational attainment. So I ran the following log-wage equation across the 291 ranked occupations:

$$\ln(w_i) = \alpha + \beta(\mathrm{E5}_i) + \mathbf{OD}_i + \varepsilon_i$$

where **OD** is a vector of offshorability dummies. Specifically, I created a set of eight dummy variables indicating offshorability indexes ranging from 0 to 25 (group one), from 26 to 35 (group two), and so on, up to the top group, which comprised ranks 86 and higher. Choosing group two as the omitted category, and hence as the reference group, the regression shows statistically insignificant estimated coefficients for all the offshorability dummies except the highest (pertaining to ranks 86–100, and comprising 5.7 million workers), which gets a highly significant coefficient of –0.138 (with a *t*-ratio of 2.10 and a *p*-value of 0.04).[37] Thus, controlling for education,[38] only the 5.7 million most offshorable jobs seem to be paying a wage penalty – estimated to be about 14% – at present.

[37] The estimated coefficient for the group seven dummy (ranks 76–85) was –0.118 with a *t*-ratio of 1.42 (implying a *p*-value of 0.16). The other coefficients were all smaller than this, with *t*-ratios below 1.

[38] The estimated coefficient on E5 ('years of education') was 0.152, with a *t*-ratio of 19.1.

Conclusions

Based on detailed, though subjective, analysis of the characteristics of jobs, I have derived and presented here a new index of the 'offshorability' of 291 US occupations. Using this index, I estimate that the outer limit of potential offshorability encompasses between 22% and 29% of all the jobs in the 2004 US workforce, with the upper half of that range perhaps more likely than the lower half. Contrary to conventional wisdom, the more offshorable occupations are not low-end jobs, whether measured by wages or by education. The correlation between skill and offshorability is almost zero. And there is some suggestive evidence that, controlling for education, holders of the most highly offshorable jobs were already paying a notable wage penalty in 2004.

My hope is that the index provided here will prove useful to researchers interested in many of the issues raised by offshoring, and that it will not only be used, but also improved upon, by others.

Appendix: Ranking of 291 occupations by offshorability

Occupation (SOC code)	Rank	Offshorability index	Employment	Cumulative sum
Computer programmers (151021)	1	100	389,090	389,090
Data entry keyers (439021)	1	100	296,700	685,790
Electrical and electronics drafters (173012)	3	98	30,270	716,060
Mechanical drafters (173013)	3	98	74,650	790,710
Computer and information scientists, research (151011)	5	96	25,890	816,600
Actuaries (152011)	5	96	15,770	832,370
Mathematicians (152021)	5	96	2,930	835,300
Statisticians (152041)	5	96	17,480	852,780
Mathematical science occupations, all other (152099)	9	95	7,320	860,100
Film and video editors (274032)	9	95	15,200	875,300
Medical transcriptionists (319094)	9	95	90,380	965,680
Telemarketers (419041)	9	95	400,860	1,366,540
Telephone operators (432021)	9	95	29,290	1,395,830
Proofreaders and copy markers (439081)	9	95	18,070	1,413,900
Numerical tool and process control programmers (514012)	9	95	17,860	1,431,760
Customer service representatives A (434051)*	16	94	516,925	1,948,685
Reservation and transportation ticket agents and travel clerks (434181)	16	94	160,120	2,108,805

(continued)

Occupation (SOC code)	Rank	Offshorability index	Employment	Cumulative sum
Word processors and typists (439022)	16	94	153,580	2,262,385
Office clerks, general A (439061)*	16	94	749,343	3,011,727.5
Office and administrative support workers, all other A (439199)*	16	94	71,818	3,083,545
Computer systems analysts (151051)	21	93	492,120	3,575,665
Editors (273041)	21	93	96,270	3,671,935
Technical writers (273042)	21	93	46,250	3,718,185
Interpreters and translators (273091)****	21	93	21,930	3,740,115
Desktop publishers (439031)	21	93	29,910	3,770,025
Insurance claims and policy processing clerks (439041)	21	93	239,120	4,009,145
Computer support specialists A (151041)**	27	92	124,965	4,134,110
Network systems and data communications analysts (151081)	27	92	185,190	4,319,300
Information and record clerks, all other (434199)	27	92	288,730	4,608,030
Computer specialists, all other (151099)	30	90	116,760	4,724,790
Architectural and civil drafters (173011)	30	90	101,040	4,825,830
Drafters, all other (173019)	30	90	20,870	4,846,700
Survey researchers (193022)	30	90	21,650	4,868,350
Writers and authors (273043)	30	90	43,020	4,911,370
Billing and posting clerks and machine operators (433021)	30	90	513,020	5,424,390
Statistical assistants (439111)	30	90	18,700	5,443,090
Economists (193011)	37	89	12,470	5,455,560
Fine artists, including painters, sculptors, and illustrators (271013)	37	89	10,390	5,465,950
Multimedia artists and animators (271014)	39	87	23,790	5,489,740
Cartographers and photogrammetrists (171021)	40	86	11,260	5,501,000
Graphic designers (271024)	40	86	178,530	5,679,530
Travel guides (396022)	40	86	3,120	5,682,650
Insurance underwriters (132053)	43	85	98,970	5,781,620
Animal scientists (191011)	43	85	3,000	5,784,620
Commercial and industrial designers (271021)	43	85	31,650	5,816,270
Bookkeeping, accounting, and auditing clerks (433031)	46	84	1,815,340	7,631,610
Biochemists and biophysicists (191021)	47	83	17,690	7,649,300
Microbiologists (191022)	47	83	15,250	7,664,550
Biological scientists, all other (191029)	47	83	26,200	7,690,750
Medical records and health information technicians (292071)	47	83	160,450	7,851,200
Operations research analysts (152031)	51	82	52,530	7,903,730
Atmospheric and space scientists (192021)	52	81	7,050	7,910,780
Credit authorisers, checkers, and clerks (434041)	53	80	65,410	7,976,190
Fabric and apparel patternmakers (516092)	53	80	9,650	7,985,840
Food scientists and technologists (191012)	55	79	7,570	7,993,410
Mathematical technicians (152091)	56	78	1,430	7,994,840
Designers, all other (271029)	57	77	12,410	8,007,250
Correspondence clerks (434021)	57	77	17,990	8,025,240
Financial analysts (132051)	59	76	180,910	8,206,150

(continued)

Occupation (SOC code)	Rank	Offshorability index	Employment	Cumulative sum
Financial managers (113031)**	60	75	353,963	8,560,113
Database administrators (151061)	60	75	99,380	8,659,493
Receptionists and information clerks (434171)**	60	75	362,800	9,022,293
Computer operators (439011)	60	75	129,160	9,151,453
Pressers, textile, garment, and related materials (516021)	60	75	78,620	9,230,073
Sewing machine operators (516031)	60	75	233,130	9,463,203
Shoe and leather workers and repairers (516041)	60	75	7,680	9,470,883
Shoe machine operators and tenders (516042)	60	75	3,850	9,474,733
Sewers, hand (516051)	60	75	11,090	9,485,823
Textile bleaching and dyeing machine operators and tenders (516061)	60	75	21,660	9,507,483
Textile cutting machine setters, operators and tenders (516062)	60	75	21,420	9,528,903
Textile knitting and weaving machine setters, operators and tenders (516063)	60	75	42,760	9,571,663
Textile winding, twisting, and drawing out machine setters, operators and tenders (516064)	60	75	47,670	9,619,333
Textile, apparel, and furnishings workers, all other (516099)	60	75	24,740	9,644,073
Computer software engineers, applications (151031)	74	74	455,980	10,100,053
Computer software engineers, systems software (151032)	74	74	320,720	10,420,773
Computer hardware engineers (172061)	76	73	78,580	10,499,353
Fashion designers (271022)	76	73	12,980	10,512,333
Accountants and auditors (132011)**	78	72	788,415	11,300,748
Chemical engineers (172041)	78	72	27,550	11,328,298
Engineers, all other (172199)	78	72	152,940	11,481,238
Industrial engineering technicians (173026)	78	72	73,310	11,554,548
Mechanical engineering technicians (173027)	78	72	46,580	11,601,128
Dispatchers, except police, fire, and ambulance (435032)	78	72	172,550	11,773,678
Biomedical engineers (172031)	84	71	11,660	11,785,338
Materials engineers (172131)	84	71	20,950	11,806,288
Electronics engineers, except computer (172072)	86	70	130,050	11,936,338
Industrial engineers (172112)	86	70	191,640	12,127,978
Mechanical engineers (172141)	86	70	220,750	12,348,728
Customer service representatives B (434051)*	86	70	516,925	12,865,653
Office clerks, general B (439061)*	86	70	749,343	13,614,995
Office and administrative support workers, all other B (439199)*	86	70	71,818	13,686,813
Tool and die makers (514111)	86	70	99,680	13,786,493
Welders, cutters, solderers, and brazers (514121)	86	70	358,050	14,144,543
Heat treating equipment setters, operators, and tenders, metal and plastic (514191)	86	70	26,310	14,170,853
Lay-out workers, metal and plastic (514192)	86	70	10,970	14,181,823
Plating and coating machine setters, operators, and tenders, metal and plastic (514193)	86	70	40,550	14,222,373
Metal workers and plastic workers, all other (514199)	86	70	49,650	14,272,023

(continued)

Occupation (SOC code)	Rank	Offshorability index	Employment	Cumulative sum
Semiconductor processors (519141)	86	70	44,720	14,316,743
Helpers – production workers (519198)	86	70	528,610	14,845,353
Marine engineers and naval architects (172121)	100	69	6,550	14,851,903
Secretaries, except legal, medical, and executive A (436014)***	100	69	436,095	15,287,998
Cutters and trimmers, hand (519031)	100	69	28,360	15,316,358
Moulders, shapers, and casters, except metal and plastic (519195)	100	69	41,250	15,357,608
Tyre builders (519197)	100	69	19,860	15,377,468
Tax preparers (132082)	105	68	58,850	15,436,318
Computer support specialists B (151041)**	105	68	374,895	15,811,213
First-line supervisors/managers of production and operating workers (511011)	105	68	679,930	16,491,143
Coil winders, tapers, and finishers (512021)	105	68	23,190	16,514,333
Structural metal fabricators and fitters (512041)	105	68	93,490	16,607,823
Fibreglass laminators and fabricators (512091)	105	68	30,560	16,638,383
Computer-controlled machine tool operators, metal and plastic (514011)	105	68	136,490	16,774,873
Extruding and drawing machine setters, operators, and tenders, metal and plastic (514021)	105	68	87,290	16,862,163
Forging machine setters, operators, and tenders, metal and plastic (514022)	105	68	33,850	16,896,013
Rolling machine setters, operators, and tenders, metal and plastic (514023)	105	68	37,500	16,933,513
Cutting, punching, and press machine setters, operators, and tenders, metal and plastic (514031)	105	68	265,480	17,198,993
Drilling and boring machine tool setters, operators, and tenders, metal and plastic (514032)	105	68	43,180	17,242,173
Grinding, lapping, polishing, and buffing machine tool setters, operators, and tenders, metal and plastic (514033)	105	68	101,530	17,343,703
Lathe and turning machine tool setters, operators, and tenders, metal and plastic (514034)	105	68	71,410	17,415,113
Milling and planing machine setters, operators, and tenders, metal and plastic (514035)	105	68	29,140	17,444,253
Metal-refining furnace operators and tenders (514051)	105	68	17,960	17,462,213
Pourers and casters, metal (514052)	105	68	14,340	17,476,553
Moulding, coremaking, and casting machine setters, operators, and tenders, metal and plastic (514072)	105	68	157,080	17,633,633
Multiple machine tool setters, operators, and tenders, metal and plastic (514081)	105	68	98,120	17,731,753
Welding, soldering, and brazing machine setters, operators, and tenders (514122)	105	68	45,220	17,776,973
Tool grinders, filers, and sharpeners (514194)	105	68	18,180	17,795,153
Extruding and forming machine setters, operators, and tenders, synthetic and glass fibres (516091)	105	68	23,040	17,818,193
Chemical plant and system operators (518091)	105	68	58,640	17,876,833

(continued)

Occupation (SOC code)	Rank	Offshorability index	Employment	Cumulative sum
Chemical equipment operators and tenders (519011)	105	68	50,610	17,927,443
Separating, filtering, clarifying, precipitating, and still machine setters, operators, and tenders (519012)	105	68	41,250	17,968,693
Crushing, grinding, and polishing machine setters, operators and tenders (519021)	105	68	41,480	18,010,173
Grinding and polishing workers, hand (519022)	105	68	44,890	18,055,063
Mixing and blending machine setters, operators and tenders (519023)	105	68	129,440	18,184,503
Cutting and slicing machine setters, operators and tenders (519032)	105	68	78,030	18,262,533
Extruding, forming, pressing, and compacting machine setters, operators and tenders (519041)	105	68	80,420	18,342,953
Packaging and filling machine operators and tenders (519111)	105	68	396,270	18,739,223
Coating, painting, and spraying machine setters, operators and tenders (519121)	105	68	100,830	18,840,053
Painters, transportation equipment (519122)	105	68	52,650	18,892,703
Painting, coating, and decorating workers (519123)	105	68	27,830	18,920,533
Cementing and gluing machine operators and tenders (519191)	105	68	25,650	18,946,183
Cleaning, washing, and metal pickling equipment operators and tenders (519192)	105	68	15,250	18,961,433
Cooling and freezing equipment operators and tenders (519193)	105	68	9,640	18,971,073
Etchers and engravers (519194)	105	68	10,050	18,981,123
Paper goods machine setters, operators, and tenders (519196)	105	68	107,560	19,088,683
Production workers, all other (519199)	105	68	296,340	19,385,023
Physicists (192012)	145	67	15,160	19,400,183
Artists and related workers, all other (271019)	145	67	5,290	19,405,473
Payroll and timekeeping clerks (433051)	145	67	205,600	19,611,073
Procurement clerks (433061)	145	67	71,390	19,682,463
Brokerage clerks (434011)	145	67	70,110	19,752,573
Order clerks (434151)	145	67	259,760	20,012,333
Chemists (192031)	151	66	76,540	20,088,873
Materials scientists (192032)	151	66	7,880	20,096,753
Physical scientists, all other (192099)	151	66	23,800	20,120,553
Electrical and electronic equipment assemblers (512022)	151	66	207,270	20,327,823
Electromechanical equipment assemblers (512023)	151	66	57,200	20,385,023
Engine and other machine assemblers (512031)	151	66	49,430	20,434,453
Bill and account collectors (433011)	157	65	431,280	20,865,733
Team assemblers (512092)	157	65	1,242,370	22,108,103
Model makers, metal and plastic (514061)	157	65	8,120	22,116,223
Patternmakers, metal and plastic (514062)	157	65	6,850	22,123,073
Foundry mould and coremakers (514071)	157	65	15,890	22,138,963
Credit analysts (132041)	162	64	61,500	22,200,463
Electrical engineers (172071)	162	64	144,920	22,345,383

(continued)

Occupation (SOC code)	Rank	Offshorability index	Employment	Cumulative sum
Art directors (271011)	162	64	29,350	22,374,733
Assemblers and fabricators, all other (512099)	162	64	258,240	22,632,973
Jewellers and precious stone and metal workers (519071)	162	64	28,100	22,661,073
Timing device assemblers, adjusters, and calibrators (512093)	167	62	2,460	22,663,533
Machinists (514041)	168	61	368,380	23,031,913
Budget analysts (132031)	169	60	53,510	23,085,423
Model makers, wood (517031)	169	60	2,280	23,087,703
Patternmakers, wood (517032)	169	60	2,000	23,089,703
Inspectors, testers, sorters, samplers, and weighers (519061)	169	60	506,160	23,595,863
Medical and clinical laboratory technicians (292012)	173	59	142,330	23,738,193
Bindery workers (515011)	173	59	64,330	23,802,523
Bookbinders (515012)	173	59	7,660	23,810,183
Prepress technicians and workers (515022)	173	59	72,050	23,882,233
Furnace, kiln, oven, drier, and kettle operators and tenders (519051)	173	59	28,140	23,910,373
Medical and clinical laboratory technologists (292011)	178	58	155,250	24,065,623
Job printers (515021)	178	58	50,580	24,116,203
Printing machine operators (515023)	180	57	192,520	24,308,723
Upholsterers (516093)	180	57	41,040	24,349,763
Cabinetmakers and bench carpenters (517011)	180	57	121,660	24,471,423
Sawing machine setters, operators, and tenders, wood (517041)	180	57	60,280	24,531,703
Woodworking machine setters, operators, and tenders, except sawing (517042)	180	57	94,690	24,626,393
Woodworkers, all other (517099)	180	57	10,550	24,636,943
Natural sciences managers (119121)	186	56	40,400	24,677,343
General and operations managers (111021)	187	55	1,663,810	26,341,153
Computer and information systems managers (113021)	187	55	259,330	26,600,483
Industrial production managers (113051)	187	55	153,950	26,754,433
Wholesale and retail buyers, except farm products (131022)	187	55	132,900	26,887,333
Purchasing agents, except wholesale, retail, and farm products (131023)	187	55	267,410	27,154,743
Logisticians (131081)	187	55	52,220	27,206,963
Medical scientists, except epidemiologists (191042)	187	55	73,670	27,280,633
Life scientists, all other (191099)	187	55	12,790	27,293,423
Agricultural and food science technicians (194011)	187	55	19,340	27,312,763
Biological technicians (194021)	187	55	67,080	27,379,843
Chemical technicians (194031)	187	55	59,790	27,439,633
Media and communication workers, all other (273099)	187	55	25,660	27,465,293
Aircraft structure, surfaces, rigging, and systems assemblers (512011)	187	55	22,820	27,488,113
Stationary engineers and boiler operators (518021)	187	55	43,110	27,531,223
Engineering managers (119041)	201	54	187,410	27,718,633
Production, planning, and expediting clerks (435061)	201	54	287,980	28,006,613
Advertising and promotions managers (112011)	203	53	41,710	28,048,323

(continued)

Occupation (SOC code)	Rank	Offshorability index	Employment	Cumulative sum
Marketing managers (112021)	203	53	166,470	28,214,793
Legal support workers, all other (232099)*****	205	52	28,424	28,243,217
Lawyers (231011)*****	206	51	105,838	28,349,055
Paralegals and legal assistants (232011)	206	51	217,700	28,566,755
Camera operators, television, video, and motion picture (274031)	206	51	22,530	28,589,285
Securities, commodities, and financial services sales agents (413031)	206	51	251,710	28,840,995
Office machine operators, except computer (439071)	206	51	87,900	28,928,895
Cost estimators (131051)	211	50	204,330	29,133,225
Financial specialists, all other (132099)	211	50	122,320	29,255,545
Network and computer systems administrators (151071)	211	50	270,330	29,525,875
Travel agents (413041)	211	50	88,590	29,614,465
Switchboard operators, including answering service (432011)	211	50	194,980	29,809,445
File clerks (434071)	211	50	229,830	30,039,275
Human resources assistants, except payroll and timekeeping (434161)	211	50	161,870	30,201,145
Administrative services managers (113011)	218	49	239,410	30,440,555
Training and development managers (113042)	218	49	28,720	30,469,275
Human resources managers, all other (113049)	218	49	57,830	30,527,105
Purchasing managers (113061)	218	49	69,300	30,596,405
Transportation, storage, and distribution managers (113071)	218	49	84,870	30,681,275
Producers and directors (272012)	218	49	59,070	30,740,345
Actors (272011)	224	48	59,590	30,799,935
Interviewers A, except eligibility and loan (434111)	224	48	100,895	30,900,830
Photographic processing machine operators (519132)	224	48	53,970	30,954,800
Electrical and electronic engineering technicians (173023)	227	47	165,850	31,120,650
Electro-mechanical technicians (173024)	227	47	15,130	31,135,780
Engineering technicians, except drafters, all other (173029)	227	47	78,300	31,214,080
Compensation, benefits, and job analysis specialists (131072)	230	46	97,740	31,311,820
Loan interviewers and clerks A (434131)	230	46	115,850	31,427,670
Furniture finishers (517021)	232	43	24,610	31,452,280
Communications equipment operators, all other (432099)	233	41	3,870	31,456,150
Broadcast news analysts (273021)	234	40	6,680	31,462,830
Life, physical, and social science technicians, all other (194099)	235	39	63,810	31,526,640
Customer service representatives C (434051)*	236	38	516,925	32,043,565
Secretaries, except legal, medical, and executive B (436014)***	236	38	436,095	32,479,660
Office clerks, general C (439061)*	236	38	749,343	33,229,002
Office and administrative support workers, all other C (439199)*	236	38	71,818	33,300,820
Aerospace engineers (172011)	240	37	81,100	33,381,920
Audio and video equipment technicians (274011)	241	36	40,390	33,422,310
Broadcast technicians (274012)	241	36	30,730	33,453,040
Radio operators (274013)	241	36	1,190	33,454,230
Sound engineering technicians (274014)	241	36	12,680	33,466,910

(continued)

Occupation (SOC code)	Rank	Offshorability index	Employment	Cumulative sum
Media and communication equipment workers, all other (274099)	241	36	17,200	33,484,110
Derrick operators, oil and gas (475011)	241	36	13,270	33,497,380
Rotary drill operators, oil and gas (475012)	241	36	15,500	33,512,880
Service unit operators, oil, gas, and mining (475013)	241	36	19,530	33,532,410
Continuous mining machine operators (475041)	241	36	9,000	33,541,410
Mine cutting and channelling machine operators (475042)	241	36	6,080	33,547,490
Mining machine operators, all other (475049)	241	36	2,450	33,549,940
Rock splitters, quarry (475051)	241	36	3,600	33,553,540
Roof bolters, mining (475061)	241	36	4,140	33,557,680
Roustabouts, oil and gas (475071)	241	36	33,570	33,591,250
Helpers – extraction workers (475081)	241	36	25,550	33,616,800
Extraction workers, all other (475099)	241	36	9,060	33,625,860
Geological and petroleum technicians (194041)	257	35	11,130	33,636,990
Earth drillers, except oil and gas (475021)	257	35	18,800	33,655,790
Explosives workers, ordnance handling experts and blasters (475031)	257	35	4,800	33,660,590
Nuclear technicians (194051)	260	34	6,050	33,666,640
Stock clerks and order fillers (435081)	260	34	1,625,430	35,292,070
Medical appliance technicians (519082)	260	34	10,810	35,302,880
Ophthalmic laboratory technicians (519083)	260	34	26,740	35,329,620
Photographic process workers (519131)	260	34	28,000	35,357,620
Sailors and marine oilers (535011)	260	34	31,090	35,388,710
Ship engineers (535031)	260	34	13,240	35,401,950
Environmental science and protection technicians, including health (194091)	267	33	32,460	35,434,410
Library technicians (254031)	267	33	115,770	35,550,180
Pharmacy technicians (292052)	269	32	266,790	35,816,970
Food batchmakers (513092)	270	31	89,400	35,906,370
Astronomers (192011)	271	30	970	35,907,340
Radio and television announcers (273011)	271	30	41,090	35,948,430
Shipping, receiving, and traffic clerks (435071)	273	29	759,910	36,708,340
Gas plant operators (518092)	273	29	10,530	36,718,870
Petroleum pump system operators, refinery operators and gaugers (518093)	273	29	40,470	36,759,340
Plant and system operators, all other (518099)	273	29	13,920	36,773,260
First-line supervisors/managers of helpers, labourers and material movers, hand (531021)	277	28	176,030	36,949,290
First-line supervisors/managers of transportation and material-moving machine and vehicle operators (531031)	277	28	221,520	37,170,810
Weighers, measurers, checkers, and samplers, recordkeeping (435111)	279	27	79,050	37,249,860
Food cooking machine operators and tenders (513093)	279	27	43,100	37,292,960
Sales managers (112022)	281	26	317,970	37,610,930
Mail clerks and mail machine operators, except postal service (439051)	281	26	148,330	37,759,260

(continued)

Occupation (SOC code)	Rank	Offshorability index	Employment	Cumulative sum
Camera and photographic equipment repairers (499061)	281	26	3,160	37,762,420
Watch repairers (499064)	281	26	3,080	37,765,500
Business operations specialists, all other (131199)	285	25	916,290	38,681,790
Architects, except landscape and naval (171011)	285	25	96,740	38,778,530
Health and safety engineers, except mining safety engineers and inspectors (172111)	285	25	25,330	38,803,860
Music directors and composers (272041)	285	25	8,610	38,812,470
Photographers (274021)	285	25	58,260	38,870,730
Advertising sales agents (413011)	285	25	153,890	39,024,620
Postal service mail sorters, processors, and processing machine operators (435053)	285	25	208,600	39,233,220

Notes:
*This occupation consists of jobs spanning virtually every industry in an economy and defies easy classification. We assigned one quarter of the jobs in this occupation to each of our four offshorability categories.
**These occupations consist of jobs spanning different industries and different levels of skill and offshorability. We divided each such occupation between Category I and Category IV jobs.
***These occupations were divided into Category II, III and IV jobs.
****These occupations were divided between Categories I and Category IV.
*****A small proportion of legal positions are offshorable. In recognition of this, we divided these two occupations between Category II and Category IV.

References

Autor, D., Levy, F. & Murnane, R. (2003) The skill content of recent technological change: an empirical exploration. *Quarterly Journal of Economics*, **118**, 4 (November), pp. 1279–1333.

Bardhan, A.D. & Kroll, C. (2003) *The New Wave of Outsourcing*. Fisher Center Research Report No. 1103, November. Berkeley, CA: University of California.

Blinder, A.S. (2006) Offshoring: the next industrial revolution? *Foreign Affairs*, March/April, pp. 113–128. (A longer version with footnotes and references appeared as: Fear of offshoring. CEPS Working Paper No. 119, December 2005.)

Blinder, A.S., Levy, F. & Murnane, R. (2006) What sorts of rich-country jobs (and how many) are at risk to globalization? Pro and contra. *CESifo Forum*, **7**, 2 (Summer), pp. 38–40.

Jensen, J.B. & Kletzer, L.G. (2006) Tradable services: understanding the scope and impact of services offshoring. In: Collins, S.M. & Brainard, L. (eds) *Brookings Trade Forum 2005, Offshoring White-Collar Work*. Washington, DC: Brookings Institution Press.

Kletzer, L.G. (2006) The scope of tradable services and the task content of offshorable services jobs. Unpublished paper, University of California, Santa Cruz, April.

Leamer, E.E. (2007) A flat world, a level playing field, a small world after all, or none of the above? A review of Thomas L. Friedman's *The World is Flat*. *Journal of Economic Literature*, **45**, 1 (March), pp. 83–126.

Levy, F. & Yu, K.-H. (2006) Offshoring of professional services: radiology services from India. Unpublished paper, Massachusetts Institute of Technology, March.

Mankiw, N.G. & Swagel, P. (2006) The politics and economics of offshore outsourcing. *Journal of Monetary Economics*, **53**, 5 (July), pp. 1027–1056.

Maxwell, A.E. (1970) Comparing the classification of subjects by two independent judges. *British Journal of Psychiatry*, **116**, June, pp. 651–655.

McCarthy, J. (2004) *Near-Term Growth of Offshoring Accelerating*. Cambridge, MA: Forrester Research.

McKinsey Global Institute (2005) *The Emerging Global Labor Market*. June. New York: McKinsey & Company.

National Academy of Public Administration (2006) *Offshoring: An Elusive Phenomenon*. January. Washington, DC: National Academy of Public Administration.

Smith, T. & Rivkin, J.W. (2008) A replication study of Alan Blinder's 'How many US jobs might be offshorable?' Unpublished paper, Harvard Business School, June.

Sturgeon, T.J., Levy, F., Brown, C., Jensen, J.B. & Weil, D. (2006) *Services Offshoring Working Group Final Report*. Industrial Performance Center, Massachusetts Institute of Technology, 10 September. Retrieved from http://web.mit.edu/ipc/publications/pdf/IPC_Offshoring_Report.pdf. Accessed 12 June 2009.

US Bureau of Labor Statistics (BLS) (2006) *Occupational Projections and Training Data*, 2006–07 edition, February, Chapter II, pp. 12–15. (Available online at www.bls.gov/emp/optd.)

Van Welsum, D. & Vickery, G. (2005) *Potential Offshoring of ICT-Intensive Using Occupations*. Digital Economy Papers, No. 91. Paris: Organisation for Economic Co-operation and Development (OECD).