Freie Universität Berlin

Graduate School of North American Studies

Inaugural-Dissertation zur Erlangung des akademischen Grades eines Doktors der Wirtschaftswissenschaft des Fachbereichs Wirtschaftswissenschaft der Freien Universität Berlin

A Task-Based Approach to U.S. Service Offshoring

vorgelegt von

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Berlin,

Januar 2013

Datum der Disputation: 14.05.2013

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Acknowledgements

I am sincerely grateful to my advisor, Irwin Collier for supervising my thesis, for the support that he showed me while writing my dissertation and for offering me the room to work in my own way. I also owe sincere and earnest thanks to Ronnie Schöb for agreeing to evaluate this thesis. I am truly indebted to my dear colleague and good friend Alessandro Maravalle, who constantly encouraged me - during countless discussions about this topic and many others - and without whom I would not have had the strength to write this dissertation. During my doctoral studies, I spent a year at the Graduate School of Economics at Princeton University, NJ. This stay significantly improved the quality of this dissertation and I am particularly grateful to Stephen J. Redding, who provided numerous inspiring insights. I am also obliged to Gustav Schepker and the team at the Auslandsamt of the Freie Universität Berlin for their support and joint effort that enabled my stay at Princeton University. I also thank my colleague, Martin Knoll, who helped me to get to know STATA. Above all, I am incredibly grateful for the unconditional love, patience, and constant encouragement of my family, friends, and partner, Boris Vormann. I deeply appreciate your belief in me.

Julia Püschel

Berlin, January 2013

Contents

1 Introduction

Scholarly research in international trade faces a new challenge to disentangle the economic puzzle posed by globalization. The period between 1850 and the First World War can be described as a "first wave of globalization" (Baldwin and Martin 1999). Economic integration has now reached a similarly high level of interconnectedness, which has been fueled, in particular, by significant decreases in transportation and communication costs since the 1980s. Furthermore, many large emerging market economies, for example China and India, have been integrated into the world economy and the productivity-adjusted wage differentials between advanced and economically less-developed countries have widened significantly as compared to the 1980s (OECD 2007a, p. 144; Krugman 2008). These cost reductions and increases in potential benefits enabled a new phenomenon, i.e., the international fragmentation of the production process, hereafter referred to as offshoring.[1] During the 1980s most firms engaged in the offshoring of goods-producing tasks. Beginning in the 1990s, offshoring started to include service-oriented tasks so that the "unbundling spread from factories to offices" (Baldwin 2006, p. 7).[2] Since then, service offshoring has realized the most dynamic growth rates among all aspects of international trade and the share of intermediate services trade in overall services trade has steadily increased (OECD 2007a, pp. 111-112).[3]

This new trade phenomenon has attracted significant attention in the political and public realms of the United States and prompted heated discussions among trade economists.[4] One reason for this lively interest is the fact that service offshoring potentially exposes service workers to international competition, a group of workers that was previously assumed to be shielded from international pressures. Fears related to service offshoring are aggravated by the fact that even within manufacturing industries many workers are employed in service occupations (e.g., Lejour and Smith 2008) and that workers in services tend to have, on average, higher skills than manufacturing workers (e.g., Jensen and

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[1] Economists have used a plethora of different terms to describe the phenomenon of offshoring: disintegration (Grossman and Rossi-Hansberg 2006), fragmentation (Jones and Kierzkowski 1990), international sourcing (van Welsum and Vickery 2005), international outsourcing (Geishecker and Goerg 2005), outsourcing (Feenstra and Hanson 1996), production sharing (Feenstra and Hanson 2001), slicing the value chain (Krugman 1995), spatial unbundling (Baldwin 2006), and vertical specialization (Hummels et al. 2001).

[2] First sporadic instances occurred earlier, of course. Examples of material offshoring include the 1964 Maquiladora Program between Mexico and the United States and the 1965 North American Auto Pact between Canada and the United States. For further details, see the case studies in Hummels et al. (1998). An early instance of service offshoring is the offshoring of design tasks to Germany by the British motor industry in 1979 (see Amiti and Wei 2004).

[3] In 2006, 73 percent of all services trade consisted of trade in intermediates (Molnar et al. 2009). Estimates by the Organisation for Economic Co-operation and Development (OECD) suggest that, in contrast to service offshoring, the growth rate of material offshoring started to slow down in the second half of the 1990s (OECD 2007a, pp. 11-112).

[4] For an overview of the public and political debates - and also the discussions among economists, see Mankiw and Swagel (2006).

Kletzer 2008).[5]

In the early 2000s, a new strand of research, the "trade-in-tasks" (Grossman and Rossi-Hansberg 2008) literature, has emerged which seeks to account for the characteristic features of service offshoring. The analytical origins of the trade-in-tasks literature can be traced back to the works of labor economists. In their influential analysis, Autor et al. (2003) challenge the notion of skill-biased technological change. They argue that the answer to the question of whether machines can replace human beings in a certain job depends on the character of the tasks that are performed in this occupation, rather than on the educational attainment of the workers performing these tasks. In particular, they presume that technological change is biased against certain tasks - i.e., routine tasks - and introduce the notion of task-biased technological change. Autor et al. (2003) support their argument by showing that the employment share in routine occupations has declined since the 1970s in the United States and that this shift away from routine tasks has taken place within all educational levels.[6]

The task-based approach by Autor et al. (2003) in combination with the advent of service offshoring in the mid-1990s elicited the trade-in-tasks literature. This body of research builds on the insight that the task content of occupations offers relevant information for a systematic analysis of service offshoring that is not covered by dimensions traditionally considered in trade theories such as the skill level of different workers. The central insight of this research is that the task content of occupations affects the costs of offshoring independently of the traditional comparative advantage based on the factor performing the task.

Already before the trade-in-tasks literature, early theoretical Heckscher-Ohlin trade models had shifted the object of analysis away from the trading sector and towards the task that is traded by incorporating trade in intermediate goods (e.g., Batra and Casas 1973). Feenstra and Hanson (1996), for instance, have very prominently emphasized that in the context of offshoring, countries enjoy comparative advantages at the level of different stages of the production process (tasks), rather than in final products. However, these previous analyses have largely assumed that only material products are tradable and

[5] Several vaguely defined terms are used in the context of material and service offshoring. One example is an estimate conducted by McCarthy (2002) for Forrester Research. The results predict that 3.3 million U.S. service-industry occupations will be offshored by 2015. However, in the further details it becomes clear that service occupations in both manufacturing industries and service industries have been considered. In this dissertation the notion of *service occupations* will be used for service-providing occupations, regardless of the industry with which they are affiliated.

[6] Subsequent works by labor economists primarily focus on the explanatory power of such a task-based approach for the wage and employment polarization that has occurred in the United States (e.g., Autor et al. 2006; Autor 2010; Acemoglu and Autor 2011; Oldenski 2012b) and in several European countries (Goos et al. 2009; Dustmann et al. 2009; Kampelmann and Rycx 2011) since the 1990s. Before the task-based approach empirical contributions have already employed information about job tasks. However, this information has largely been an alternative way to measure skills, rather than a complementary information. For more information on the measurement of skills in economic analyses, see, e.g., Borghans et al. (2001) and Stasz (2001).

that changes in trade costs have essentially similar effects across these tradable goods.[7] The advent of service offshoring meant that this traditional assumption about the structure of trade costs had to be refined to account for this new aspect of international trade. In particular, the fact that certain services are offshored from high-skilled abundant countries even though service workers have, on average, higher skills than manufacturing workers cannot be accounted for by factor proportions arguments.

Several researchers have tried to identify the determinants of offshorability. Rather than only focusing on the educational attainment of the workers, they argue that the occupational task content determines whether an occupation can be performed abroad (Bardhan and Kroll 2003; Garner 2004; van Welsum and Vickery 2005; Blinder 2006; Jensen and Kletzer 2008; Moncarz et al. 2008). For instance, Blinder (2006) emphasizes that many low-skilled service occupations, such as nannies, are shielded from international competition, whereas several medium-skilled and high-skilled service occupations, such as accountants and computer programmers, are increasingly offshored. In this body of research it became clear that it was not only the group of tradable products that had been extended by decreases in transportation and communication costs but that, within the group of tradable products, there is also significant heterogeneity in offshorability. In other words, some tradable services are more easily offshorable than others. Or, as an article in the Economist puts it, the offshorability of services is often "a matter of degree, not kind" (Economist 2007). So far, however, we know very little about the ways in which the task content and decreases in communication and transportation costs interact. The skill-based distinction between winners and losers from globalization may no longer hold and the labor market effects of service offshoring are harder to predict (see also Baldwin 2006).[8]

First theoretical contributions that incorporate the importance of the task content have recently started to emerge. The main reference is Grossman and Rossi-Hansberg (2006), who have incorporated heterogeneous offshoring costs across tasks into a general equilibrium model of offshoring.[9] Such an additional

[7] More precisely, trade costs have traditionally been modeled as iceberg costs (Samuelson 1952) that allow for a certain type of variation. Iceberg trade costs are equivalent to an ad valorem tax, so that more expensive goods tend to face higher trade costs.

[8] Traditionally the standard framework to assess the distributional effects of trade on income has been the Heckscher-Ohlin (HO) model. According to the HO trade model a country will specialize in the export of that good which uses the country's abundant factor relatively intensively in its production. The Stolper-Samuelson theorem states that this specialization increases the real return to the factor that is relatively abundant and decreases the return to the relatively scarce factor. The reason for the prevalence of the HO model has been that the "two major waves of innovation in international trade theory" (Krugman 2008, p. 112), the New Trade Theory (Krugman 1979, 1980, 1991) and the heterogeneous firms and monopolistic competition trade model (Melitz 2003), do not address the distributional effects of trade within countries. This has begun to change since the early 2000s. For a review of new approaches to trade and inequality, see Harrison et al. (2011).

[9] In a subsequent contribution, Grossman and Rossi-Hansberg (2010) develop a corresponding framework for offshoring between similar countries. Rather than factor price differences due to different factor endowments or differences in productivity, increasing returns to scale at the task level give rise to offshoring.

layer of heterogeneity can refine existing theoretical frameworks in such a way that we obtain significantly different results. For instance, theoretical contributions based solely on factor proportions arguments predict that relatively high-skill abundant economies specialize in high-skill intensive activities (Feenstra and Hanson 1999; Bhagwati et al. 2004; Markusen and Strand 2007). In the Grossman and Rossi-Hansberg (2006, 2008) framework, by contrast, the resulting pattern of offshoring under this different set of assumptions is determined by factor cost differences across countries and by offshoring cost differences across tasks. Feenstra sees this "as an important step beyond the Heckscher-Ohlin model [and] a robust way to model [...] service offshoring" (Feenstra 2010, p. 42).[10]

Several streams of empirical research have followed Grossman and Rossi-Hansberg's (2008) seminal contribution. It needs to be stressed that, even though the trade-in-tasks approach is particularly relevant for service offshoring, most of these empirical works have focused on material offshoring due to data constraints.[11] A first branch of the literature investigates whether offshoring gives rise to productivity gains, which Grossman and Rossi-Hansberg emphasize. The empirical works so far do not provide clear evidence.[12] Importantly for the present work, the insight that offshoring can act like labor-augmenting technological progress has been stressed before (Jones and Kierzkowski 1990 is the classical reference) and this point does not depend on the assumption of task-specific offshoring costs.[13]

Another branch of the literature analyzes the labor market effects of service offshoring. Amiti and Wei (2005) find modest negative effects on total employment for the United States. Several other works have distinguished between the labor market effects of offshoring for low-skilled and high-skilled workers based on factor proportions arguments. Feenstra and Hanson (1996) have conducted one of the first empirical studies on the effect of material offshoring on the skill wage premium. They find a strong positive effect of material offshoring on the relative wage of skilled workers in the United States over the period 1972 to 1992.[14]

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[10] Feenstra also states that Hanson's and his approach (Feenstra and Hanson 1996) to offshoring, which assumes uniform offshoring costs across tasks, is most appropriate to model material offshoring (Feenstra 2010, pp. 101-102). Other scholars similarly argue that the task-specificity of offshoring costs is primarily an issue for services (e.g., Baldwin 2006). Baldwin and Robert-Nicoud (2010) develop an integrating framework which incorporates goods trade and offshoring.

[11] In general, services trade data is provided at a more aggregate level than data on goods trade. Jensen (2011), the U.S. Government Accountability Office (2004), and the National Academy of Public Administration (2006b, pp. 43-56) provide in-depth analyses of this issue.

[12] Amiti and Wei (2006, 2009) and Winkler (2009) find productivity-enhancing effects of service offshoring, whereas, Daveri and Jona-Lasinio (2008) only find such effects for material offshoring but not for service offshoring.

[13] This result rather depends on the assumption that a reduction in offshoring costs not only extends the set of tasks that are offshored but also reduces the costs for those tasks that are already offshored. For a discussion about this "inframarginal" assumption, see Grossman and Rossi-Hansberg (2008) and Taylor (2006).

[14] Offshoring models that are based only on factor proportions arguments (e.g., Feenstra and Hanson 1996) predict that in relatively high-skilled labor abundant economies, like the

A more recent strand of empirical research enriches the analyses of the labor market effects of offshoring with the insights on task-based determinants of offshoring costs. Overall, the evidence suggests that it is important to control for the task content of occupations in addition to the traditional proxy measures for skill levels, i.e., the educational attainment of the workers performing the tasks.[15] For instance, Crinò (2010) estimates the impact of service offshoring on employment in the United States over the period from 1997 to 2002. His results indicate that service offshoring positively impacted high-skilled workers' employment, whereas employment of low- and medium-skilled workers was negatively affected. Furthermore, employment in tradable occupations was negatively affected by service offshoring, whereas employment in occupations classified as non-tradable increased across all skill levels.

As this short survey illustrates, and mostly due to the novelty of these empirical and theoretical insights, the respective research on the "task-based" approach to offshoring is strongly fragmented and has still left several avenues of research unexplored. In the present dissertation, I combine and build upon several of these prior strands of research to improve our understanding of the particularities of service offshoring. I address the issue of a lack of sufficiently detailed data by employing information from a comprehensive set of datasources for the United States. The United States is a particularly relevant case to provide new evidence on this more nuanced, task-based view of international trade. Among the developed economies, intermediate services have a particularly important role in the U.S. economy.[16] Taking into consideration a rich, task-based specification of offshoring costs allows me to analyze different aspects of U.S. service offshoring: How do task characteristics affect service offshoring flows from United States? How do they interact with country-level characteristics? To which extent does service offshoring affect wages in the United States?

1.1 Structure of the dissertation

This dissertation consists of three essays that empirically analyze different aspects of a task-based approach to U.S. service offshoring. The first two essays seek to broaden our understanding of the structure of offshoring costs. The first essay focuses on the measurement of task-based offshoring susceptibility. The second essay extends the empirical exploration to the interplay of the task content and country-level trade determinants in shaping offshoring patterns. The

United States, increased offshoring with developing and low-skilled labor-abundant countries would result in shifting the relative labor demand in favor of skilled workers by expanding the labor demand of relatively skill-intensive activities. In contrast to the predictions of the HO model, this demand shift would occur within, rather than between, industries and even firms.

15 Examples include Hummels et al. (2011) for Denmark; Becker et al. (2009), Baumgarten et al. (2010), and Kampelmann and Ryxc (2011) for Germany; and Goos and Manning (2007) for the United Kingdom.

16 In 2007, 25 percent of overall employment in the United States occurred in the business service sector (Jensen 2011, pp. 3-4). Furthermore, U.S. imports and exports of computer and information services, as well as other business services, have more than tripled in real terms from 1995 to 2009 (see the OECD Statistics on International Trade in Services).

third essay analyzes the wage effects of service offshoring by accounting for such a richer structure of offshoring costs.

The first challenge in providing new evidence on service offshoring from a trade-in-tasks perspective stems from the lack of consensus on how to construct a task-based offshoring susceptibility measure. The first essay (chapter 2) fills this gap by employing techniques of factor and regression analyses to assess and compare three different approaches that have been proposed in previous works. I consider these indices because they establish continuous rankings of occupations and are based on a composite of different task characteristics rather than exclusively considering the routine content of an occupation. I start by surveying the conceptual ideas behind the different approaches and the construction of each index. I then establish an offshoring susceptibility ranking of service occupations for each index and find that the three indices lead to significantly different representations of reality. Such a sharp disagreement between the measures significantly limits the comparability of empirical studies and suggests that different measures reflect different phenomena. I propose and perform an empirical test to provide an objective standard to select the most valid index, i.e., I compare the indices' external validity. I also elucidate which task characteristics are most relevant in determining an occupation's susceptibility to offshoring.

In the second essay (chapter 3), I consider another gap in the literature and analyze the way in which the task content of services interacts with traditional country-level determinants of services trade in shaping offshoring costs. This interaction has so far been treated as a black box. The task content influences the costs that arise from the fragmentation of the production process, regardless of whether this fragmentation takes place within or across country borders. In the context of offshoring, this fragmentation can incur extra costs because it occurs across international borders. I build on previous empirical works and consider a broad set of country characteristics that have been found to affect bilateral services trade flows. Unlike these previous analyses, I focus on whether the effects of these country-level variables differ systematically with the task content of the respective service industry. By connecting the task-based approach to the literature on the generalization of the sources of comparative advantage, the second essay offers new insights into the mechanisms through which country characteristics affect offshoring patterns.

In the third essay (chapter 4), I estimate the impact of service offshoring on the real wages of workers in the United States by controlling for workers' skill levels and the offshoring susceptibility of different occupations. Traditionally, international trade economists have seen the fortunes of workers as tied to their skill levels. The findings of first task-based analyses indicate that these predictions need to be refined and that, next to the workers' skill levels, the task content of occupations shapes the labor market effects of offshoring. If we consider recent evidence that certain occupations (tasks) are more susceptible to offshoring and that, especially in the short run, it is likely that there are frictions to switching between occupations, we would expect the wage effects of service offshoring to depend not only on the respective skill level but also on the character of the tasks performed. My study differs from existing works in significant ways. First, in contrast to most studies, I focus on service offshoring rather than material offshoring. Second, I use wage data at the individual rather than at the firm or industry level. Third, I focus on the interplay between traditional proxy measures of skills and the occupational task content in determining wages. Fourth, I estimate the impact of offshoring across industries. In doing so, I take the effects of labor mobility across industries into account and analyze a situation that is more in concordance with a general-equilibrium setting.

Chapter 5 concludes this dissertation by summarizing and discussing the main findings of the three essays. Furthermore, I outline promising avenues for future research, which include cross-country analyses that adopt a similar methodology, further studies investigating the interaction between labor market institutions and service offshoring, and the exploration of task complementarities.

2 Measuring task content and offshorability

Abstract

Task characteristics have been identified as crucial determinants of an occupation's susceptibility to offshoring in the recent trade literature. However, no consensus has been established on the most valid task-based measure of offshorability. This study opens the black box of offshoring susceptibility and assesses three continuous indices based on a composite of different task characteristics that have been proposed in the literature. It finds that the three indices lead to significantly different rankings of occupations in terms of their offshoring susceptibility, bearing the risk of using the same label to describe different phenomena. To avoid such risk, I propose and perform a test providing an objective standard to select the most valid index. Furthermore, to analyze the importance of three task characteristics that have frequently been assumed to affect an occupation's offshorability in the previous literature, I construct three proxy measures for these task characteristics and employ the same test to assess their explanatory power.

Keywords: *Task content, offshoring, services*

JEL classification: *C83, B4, F16*

2.1 Introduction

Service offshoring is one of the most dynamic phenomena in international trade.[17] With the advent of this new aspect of international trade in the mid-1990s and building upon the seminal works of the labor economists Autor et al. (2003),

[17] Even if the level of service offshoring is currently still low, this aspect of international trade has realized the highest growth rates among trade phenomena (Amiti and Wei 2009). Offshoring refers to the location of certain stages of the production process, regardless of the control structure of the firm. As a consequence, offshoring comprises both international outsourcing and foreign direct investments. Most economists have services trade via mode 1 according to the General Agreement on Trade in Services in mind when they discuss the economic effects of service offshoring. Mode 1 (i.e., cross-border trade) involves transactions in which the consumer of the service is located in one country and the provider in another (Bhagwati et al. 2004).

trade economists have realized that the susceptibility of a service occupation to offshoring crucially depends on its task content rather than its educational requirements.[18] Tasks are characteristics of the occupation, whereas the traditional proxy measure for skills, i.e., educational attainment, is a characteristic of the worker.[19] Because first evidence suggests that there is no clear relationship between skills and tasks, information on the tasks actually performed in occupations is necessary for a systematic understanding of service offshoring and, in particular, its effects on labor markets.

Due to the novelty of this insight, no consensus has been established on the most appropriate task-based measure of offshorability. Several contributions have proposed different task characteristics as potential determinants of an occupation's offshoring susceptibility.[20] Even if researchers consider the same set of task characteristics, they often obtain different occupational rankings because of a lack of official data. Consequently, the comparability between different studies is limited, and there is a risk of using the same term, "offshorability," to describe different phenomena.

In this paper I offer an assessment of different measures of the task content. In particular, I focus on replicable, continuous indices that are based on a composite of different task characteristics and that aim to measure the susceptibility to offshoring for occupations in the United States, that is, the indices by Blinder (2007), Moncarz et al. (2008), and Crinò (2010). I start with a survey of the conceptual ideas behind the different approaches by reviewing the set of task characteristics that researchers assume to be related to offshorability and how they obtain occupational rankings based on these characteristics.

After this survey, I compare the occupational rankings that result from the adaption of the three indices. In this comparison I find that each measure leads to a different representation of the susceptibility to offshoring across occupations. Such a sharp disagreement between the measures significantly limits the comparability of empirical studies and suggests that the different measures reflect different phenomena. This confusion is clearly reflected in the recent literature that analyzes the labor market effects of service offshoring. For instance, Blinder (2007) and Crinò (2010) have both found that U.S. service offshoring has been associated with decreases in employment for the "most offshorable" occupations. It might appear as though both contributions have obtained similar results, even though their findings apply to two different sets of occupations

[18] An occupation's offshoring susceptibility is hereafter synonymously referred to as "offshorability."

[19] "A task is a unit of work activity that produces output. In contrast, a skill is a worker's endowment of capabilities for performing various tasks" (Acemoglu and Autor 2011, p. 1044).

[20] Next to empirical contributions analyzing the labor market effects of offshoring, other fields have also increasingly started to construct and employ measures of the task content. For instance, Bombardini et al. (2012) estimate whether countries with greater skill dispersion specialize in sectors that are characterized by higher skill substitutability. They build on the theoretical contribution of Grossman and Maggi (2000), which shows in a two-country, two-sector framework that the second-order moments of the skill distribution matter for the patterns of comparative advantage. Bombardini et al. (2012) find empirical support for this prediction.

because they employ different offshorability measures.

To avoid such confusion, we need to determine objective criteria to assess the indices. I propose an empirical criterion to compare the indices' external validity, i.e., how well they represent the phenomenon that they aim to measure. In particular, I assess how well the different measures perform in capturing the variation in actual offshoring flows across occupations. The results of an ordinary least squares (OLS) regression and a Poisson pseudo-maximum likelihood (PPML) regression indicate that the index by Moncarz et al. (2008) performs best in this respect. I proceed similarly to also elucidate which of the three task characteristics that are frequently assumed in the literature to affect offshorability (routine content, face-to-face contact, and dependence on information and communication technologies [ICTs]) are most relevant for an occupation's susceptibility to offshoring. I construct proxy measures for the three different task characteristics by means of principal component analysis (PCA) and test how well these measures explain actual offshoring flows. The results of both the OLS and the PPML regression suggest that among the different task characteristics the dependence of occupations on ICTs is the task characteristic that best captures actual offshoring flows.

The remainder of this chapter is structured as follows. Section 2.2 offers a survey of the methodological approaches that have been developed to rank service occupations according to their offshoring susceptibility. In section 2.3, I first draw attention to the fact that the occupational rankings that result from adopting the indices differ sharply in their representation of reality. Then, I use techniques of factor and regression analyses to compare the explanatory power of the three different indices and of the three separate task dimensions. Section 2.4 summarizes and discusses the findings.

2.2 Review of methodological approaches

There is a plethora of contributions that aim to identify those task characteristics that affect a service occupation's offshorability. I focus on three replicable works that have developed continuous indices based on a composite of different task characteristics and that aim to measure the susceptibility to offshoring for occupations in the United States: The indices by Blinder (2007), Moncarz et al. (2008), and Crinò (2010). Before describing the construction of these three indices in more detail, I will explain the motivation behind this index selection.

First, I focus on continuous indices because working with a discrete binary classification of offshorable and non-offshorable services oversimplifies reality and offshorability often is "a matter of degree, not kind" (Economist 2007).[21]

[21] Hence, this work does not consider contributions, which focus on identifying characteristics that distinguish between offshorable and non-offshorable services (Bardhan and Kroll 2003; Garner 2004; van Welsum and Vickery 2005; Blinder 2006; Liu and Trefler 2008). Such binary classifications are typically used to obtain estimates of the number of jobs that are potentially offshorable. Jensen and Kletzer (2005) derive an offshorability ranking based on information about the geographical concentration of production. Unfortunately, they divide their continuous ranking into three groups. As a result, their ranking cannot be compared with the continuous rankings analyzed in the present work.

As Blinder and Krueger illustrate:

> In some cases, offshorability is clear and unambiguous as in the examples of call-center operators (offshorable) and taxi drivers (not). But in other cases, the degree of offshorability is not so clear. Think, for example, about accounting, filing documents, watch repair, and paralegal work. (Blinder and Krueger 2009, p. 4)

Indices that consider this heterogeneity are important because a recent branch of empirical contributions shows that accounting for varying degrees of offshorability within the group of tradable products has important implications for the distributional effects of offshoring. First evidence suggests that the employment and wage effects of offshoring differ according to the occupation's offshoring susceptibility (Baumgarten et al. 2010; Crinò 2010; Ebenstein et al. 2011).

Second, I focus on indices that are based on a composite of different tasks. Many (early) contributions on the task determinants of offshorability argue that the routine content of an occupation is the crucial task characteristic that determines an occupation's offshoring susceptibility (e.g., Levy and Murnane 2006; Ebenstein et al. 2011). This focus stems from the origins of the task-based approach, which lie in the works of labor economists. In their seminal contribution, Autor et al. (2003) argue that rather than being skill-biased, technological change is biased against certain tasks.[22] In this context, Autor et al. (2003) highlight that computers can only replace tasks that are sufficiently well-understood and that follow precise, rule-based procedures, i.e., routine tasks. Similarly, Levy and Murnane (2006) argue that routine occupations are typically the easiest ones to offshore, because they are easy to explain and easy to monitor. However, even though a considerable overlap between tasks that can be easily automated and offshored certainly exists, Autor stresses the point that

> [...] there are many examples of tasks that can currently be offshored but not automated ([...] staffing call centers or reading x-rays) and [...] tasks that can currently be automated but not offshored, [...] vacuuming floors or picking stock items from warehouse shelves. (Autor 2010 p. 13)

Consequently, other task characteristics also seem relevant in determining an occupation's offshorability. Next to the routine content of an occupation, two other task characteristics are frequently assumed in previous works to affect an occupation's offshorability, i.e., the degree of face-to-face contact required with the customer (e.g. Bardhan and Kroll 2003; van Welsum and Vickery 2005; Blinder 2006; Jensen and Kletzer 2008), and the degree to which inputs and outputs can be conveyed electronically without a reduction in quality (Bardhan and Kroll 2003; Garner 2004; van Welsum and Vickery 2005; Blinder 2006; Jensen and Kletzer 2008; Moncarz et al. 2008). Consequently, the present work only analyzes indices that go beyond the simple routine/non-routine dichotomy and consider a more comprehensive set of task characteristics.

The composites of task characteristics in the three indices that I have selected are only partially overlapping because, so far, no consensus has been established

[22] In the course of early 19th century industrialization, technological change has substituted for skilled labor rather than complemented it (Goldin and Katz 2008).

on the set of relevant task characteristics. Crinò (2010) classifies occupations according to three task characteristics: To which degree occupations involve routine decisions, require face-to-face contact, and depend on ICTs. He constructs proxy measures for these task characteristics by employing information from the Occupational Information Network (O*Net) database. In the O*Net each occupation is described in terms of several standardized activities that are performed to different degrees in each occupation. Official coders assign points to each activity according to its importance within a certain occupation (see the box on page 14).[23] However, it is not clear which of these standardized O*Net activities best reflect the task characteristics of interest, so that the mapping from the O*Net activities to the abstract tasks is necessarily subjective (see also Blinder and Krueger 2009; Collins 2008). Table 2.1 illustrates which O*Net activities Crinò (2010) assumes to reflect the three task characteristics that he aims to measure.

Blinder (2007) uses information on those O*Net activities that he assumes to indicate the degree to which the performance of an occupation requires face-to-face contact (see table 2.1). He supplements these data with a ranking of occupations based on his judgement of how easily a job can be performed at a distance from the United States.[24]

Moncarz et al.'s (2008) index is based on the most comprehensive set of tasks and considers four characteristics. Two of theses task characteristics are assumed to be positively associated with offshorability: The routine task content of an occupation and the degree to which inputs and outputs can be conveyed at a distance. The other two task characteristics are considered to be negatively related to offshorability: The required interaction with other workers and the required "local knowledge" (Moncarz et al. 2008, p. 75). Specialists from the Bureau of Labor Statistics' (BLS) Employment Projections Program have assessed compliance with these four criteria for each different service occupation.

In short, the two indices by Crinò (2010) and Blinder (2007) differ in the degree to which they employ the importance scores that are available in the O*Net, with the ranking of Crinò relying entirely on such precoded information. The ranking by Moncarz et al. (2008) does not employ rankings based on the importance of O*Net activities altogether.

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23 One limitation of the O*Net is that occupational titles are not consistently coded over time and that updating frequencies differ across occupations. As a consequence, it is difficult to identify changes in the task content within occupations over time. Employing information from the Qualification and Career Survey, Spitz-Oener (2006) was able to track changes within occupations over time for West Germany, and her results indicate that occupations became more complex between 1979 and 1998/99. These results were also found within occupation-education and occupation-age groups (Spitz-Oener, 2006).

24 More information on the underlying decision process can be found in appendix A.

The O*Net

Next to reported job titles, median hourly wages, and employment and educational attainments, the O*Net database by the U.S. Department of Labor offers detailed information on the task content of 840 occupations classified according to the Standard Occupational Classification (SOC) system.[a]

The detailed task information (hereafter referred to as "activities") is grouped into several broader categories, such as, for instance, "tasks," "work activities," and "work context." Unfortunately, some of these categories, such as "tasks," offer descriptions that are specific to every occupation and that are therefore not directly comparable across occupations. Other categories, such as "work activities," "work context," and "abilities," consist of a standardized list of activities. Official coders assign points to each activity according to its importance within a certain occupation. For instance, the activity "establishing and maintaining interpersonal relationships" offers information on how important it is in a particular job to "develop [...] constructive and cooperative working relationships with others, and maintaining them over time" (U.S. Department of Labor 2012). For example, coders from the U.S. Department of Labor have assigned 94 points for sales managers and only 29 points for mathematical technicians. Researchers, such as Blinder (2007) and Crinò (2010), have employed variation in the scores for this activity as a proxy measure for variation in the task characteristic "face-to-face contact" (see table 2.1).

[a] An occupation in the SOC system "is a group of jobs in which workers perform similar tasks, duties, or activities" (Bureau of Labor Statistics 2001, p. 102). Detailed occupations are grouped together in 461 broad occupations, 97 minor groups, and 23 major groups. For further information, see the website of the BLS.

2.3 Comparison among indices

The existence of different offshorability measures is only problematic if they lead to substantially different descriptions of reality while using identical terminology. To compare the occupational rankings resulting from the three indices, I normalize all indices to a zero to one scale, with one indicating the highest susceptibility to offshoring. I then employ these normalized indices to produce three offshorability rankings of yearly individual-level data from the Current Population Survey (CPS) Outgoing Rotation Groups (ORGs) for the years 2006 to 2009.[25]

The Spearman rank correlation coefficients in table 2.2 show that there are significant differences across the three indices in the ranking of occupations according to their offshoring susceptibility. The maximum degree of correlation is only 0.54 (significant at the one-percent level), i.e., the correlation between the ranking based on Moncarz et al. (2008) and the ranking based on Blinder (2007). The other correlations are even lower, and the lowest one is found between the

[25] Note that the indices have an ordinal rather than a cardinal scale. Further details on the construction of the different rankings can be found in appendix A. The CPS ORGs offer information about workers' skills and workers' occupational affiliation.

Table 2.1: O*Net activities

Activity	Name	Employed by	As a measure of
1	Importance of repeating the same tasks	Crinò (2010)	routine content
2	Visual color discrimination	Crinò (2010)	routine content
3	Documenting/recording information	Crinò (2010)	routine content
4	Getting information	Crinò (2010)	routine content
5	Inspecting equipment, structures, materials	Crinò (2010)	routine content
6	Face-to-face discussions	Crinò (2010)	face-to-face
7	Performing for or working directly with the public	Blinder (2007) Crinò (2010)	face-to-face
8	Deal with external customers	Crinò (2010)	face-to-face
9	Establishing and maintaining interpersonal relationships	Blinder (2007) Crinò (2010)	face-to-face
10	Assisting and caring for others	Blinder (2007)	face-to-face
11	Coaching and Developing Others	Blinder (2007)	face-to-face
12	Coordinating the work and activities of others	Blinder (2007)	face-to-face
13	Guiding, directing, and motivating subordinates	Blinder (2007)	face-to-face
14	Communicating with persons outside organization	Blinder (2007)	face-to-face
15	Selling or Influencing Others	Blinder (2007)	face-to-face
16	Interacting with computers	Crinò (2010)	ICT content

Table 2.2: Correlation coefficients of overall indices

	Blinder (2007)	Moncarz et al. (2008)	Crinò (2010)
Moncarz et al. (2008)	0.5457	1	
Crinò (2010)	0.2984	0.1645	1

ranking based on Moncarz et al. and the one based on Crinò (0.1645, significant at the one-percent level).

Table 2.3 illustrates these disagreements across the rankings for the ten most and the ten least offshorable occupations according to each index. One obvious difference between the ranking based on Crinò (2010) and the ones based on Blinder (2007) and Moncarz et al. (2008) is that Crinò's ranking includes many engineering occupations among the most offshorable service occupations.[26] Despite the differences, computer programmers are listed as a top ten offshorable occupation in all three rankings. Furthermore, the rankings based on Blinder (2007) and Moncarz et al. (2008) both list data entry keyers and telemarketers among the ten most offshorable occupations.

Different rankings of occupations according to their offshoring susceptibility also lead to different offshorability distributions across certain worker characteristics. For instance, depending on which index we employ, we obtain significantly different distributions of offshorability across workers' skill levels.[27] This is particularly problematic because, so far, we know very little about the relationship between skills and tasks. Improving our understanding of this relationship is important because recent empirical evidence suggests that the interplay of skills and tasks shapes the labor market effects of offshoring (e.g., Crinò 2010; Ebenstein et al. 2011). As illustrated in table 2.4, the offshorability mean across educational groups, according to Moncarz et al.'s index, increases with the educational attainment of the workers. High-skilled workers are, on average, employed in occupations which are classified as more offshorable than those of low- or medium-skilled workers. Based on Blinder's and Crinò's rankings, however, medium-skilled workers are, on average, employed in occupations that are classified as more offshorable than those of low- or high-skilled workers.

[26] The SOC codes of engineering occupations start with "17-."

[27] I define skill groups according to the International Standard Classification of Education of the UNESCO (2011). With low-skilled workers having lower secondary education or less, medium-skilled workers having between upper secondary education and first-stage tertiary education, and high-skilled workers possessing at least second-stage tertiary education.

Table 2.3: List of the ten most and the ten least offshoring susceptible occupations

Index	Occupation					
	Most susceptible			Least susceptible		
	Occupation title	*Occupation code*	*Value*	*Occupation title*	*Occupation code*	*Value*
Blinder (2007)	Data entry keyers	43-9021	1	Nursing, psychiatric, and home health aides	31-1010	0
	Computer programmers	15-1021	1	Computer software engineers	15-1030	0
	Actuaries	15-2011	0.96	Managers, all other	11-9199	0
	Mathematicians	15-2021	0.96	Maids and housekeeping cleaners	37-2012	0
	Statisticians	15-2041	0.96	Locksmiths and safe repairers	49-9094	0
	Telemarketers	41-9041	0.95	Cooks	35-2010	0
	Proofreaders and copy markers	43-9081	0.95	Engineering technicians	17-3020	0
	Railroad brake, signal, and switch operators	53-4021	0.95	Social workers	21-1020	0
	Word processors and typists	43-9022	0.94			
	Reservation and transportation ticket agents and travel clerks	43-4181	0.94			
						0
Moncarz et al. (2008)	Parts salespersons	41-2022	1	Hairdressers, Hairstylists, and Cosmetologists	39-5012	0
	Billing and posting clerks	43-3021	1	Special Education Teachers	25-2040	0
	Computer operators	43-9011	1	Grounds Maintenance Workers	37-3010	0
	Data entry keyers	43-9021	1	Registered Nurses	29-1111	0
	Computer programmers	15-1021	1	Automotive Body and Related Repairers	49-3021	0
	Word processors and typists	43-9022	1	Nursing, Psychiatric, and Home Health Aides	31-1010	0
	Payroll and timekeeping clerks	43-3051	0.9375	Construction Managers	11-9021	0
	Telemarketers	41-9041	0.9375	Retail Salespersons	41-2031	0
	Proofreaders and copy markers	43-9081	0.9375	Secondary School Teachers	25-2030	0
	Tax preparers	13-2082	0.9375	Managers, All Other	11-9199	0
Crinò (2010)	Database administrators	15-1061	1	Retail salespersons	41-2031	0
	Architectural and civil drafters	17-3010	0.9751381	Advertising sales agents	41-3011	0.0911602
	Computer support specialists	15-1041	0.9475138	Switchboard operators, including answering service	43-2011	0.1491713
	Materials engineers	17-2131	0.9392266	Parts salespersons	41-2022	0.1546961
	Petroleum engineers	17-2171	0.9281768	Sales representatives, wholesale and manufacturing	41-4010	0.1657458
	Statistical assistants	43-9111	0.9005525	Property, real estate, and community association managers	11-9141	0.2872928
	Computer programmers	15-1021	0.8950276	Cost estimators	13-1051	0.3066298
	Mining and geological engineers	17-2151	0.8922652	Administrative services managers	11-3011	0.3259668
	Industrial engineers	17-2110	0.8839779	Construction managers	11-9021	0.4005525
	Mechanical engineers	17-2141	0.801105	Telemarketers	41-9041	0.4005525

Table 2.4: Comparison of offshorability distributions across skill groups

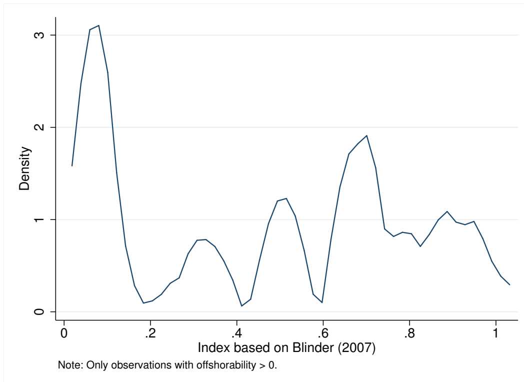
	All	Low-skilled	Medium-skilled	High-skilled
Blinder (2007)				
Mean	0.102	0.031	0.105	0.103
Median	0	0	0	0
Standard deviation	0.246	0.136	0.252	0.244
Wilcoxon rank-sum test	$H_0 : \mu_{low-skilled} = \mu_{medium-skilled}$ $z = -31.227$ $p = 0.000$		$H_0 : \mu_{medium-skilled} = \mu_{high-skilled}$ $z = -32.415$ $p = 0.001$	
Moncarz et al. (2008)				
Mean	0.156	0.027	0.121	0.206
Median	0	0	0	0
Standard deviation	0.272	0.135	0.261	0.282
Wilcoxon rank-sum test	$H_0 : \mu_{low-skilled} = \mu_{medium-skilled}$ $z = -36.772$ $p = 0.000$		$H_0 : \mu_{medium-skilled} = \mu_{high-skilled}$ $z = -103.762$ $p = 0.000$	
Crinò (2010)				
Mean	0.434	0.367	0.459	0.409
Median	0.644	0.491	0.655	0.641
Standard deviation	0.387	0.345	0.377	0.398
Wilcoxon rank-sum test	$H_0 : \mu_{low-skilled} = \mu_{medium-skilled}$ $z = -31.270$ $p = 0.000$		$H_0 : \mu_{medium-skilled} = \mu_{high-skilled}$ $z = 39.199$ $p = 0.000$	
Observations	311,033	8,903	163,360	138,770

However, such averages hide significant variation within each skill group and figures 2.1, 2.2, and 2.3 illustrate that, according to each ranking, high-, medium-, and low-skilled workers perform occupations that are among the most offshorable ones as well as among the least offshorable ones.[28] This finding offers empirical support for the justification of the task-based approach by indicating that within each skill group, occupations differ according to their task content.

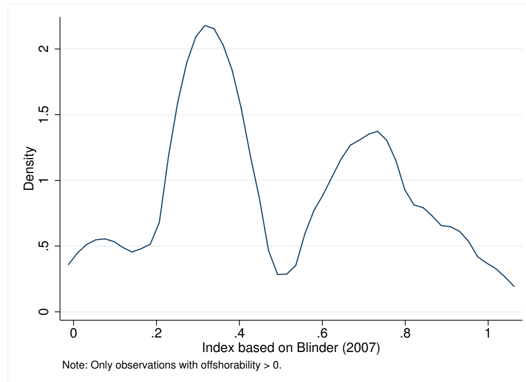
[28] Note that for illustrative purposes the graphical representations in figures 2.1. to 2.3 are only considering observations with an offshoring susceptibility score greater than zero. Based on Crinò's index, 43.91 percent of all observations have a zero-value score; based on Blinder's index, this share increases to 79.12 percent; and according to Moncarz et al.'s index 72.26 percent of all observations have an offshoring susceptibility score of zero.

Figure 2.1: Blinder (2007)

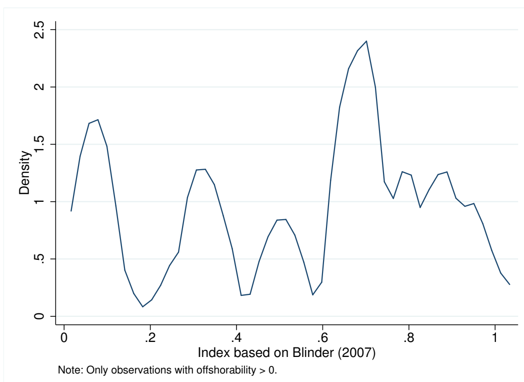
(a) All workers



(b) Low-skilled workers



(c) Medium-skilled workers



(d) High-skilled workers

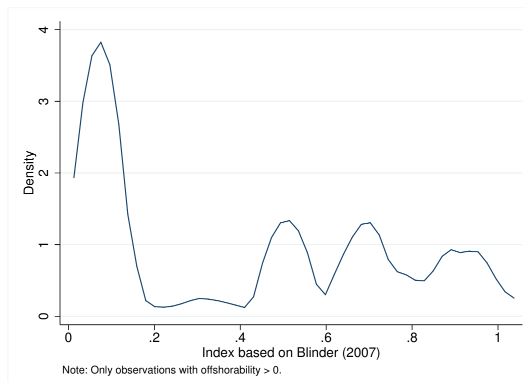
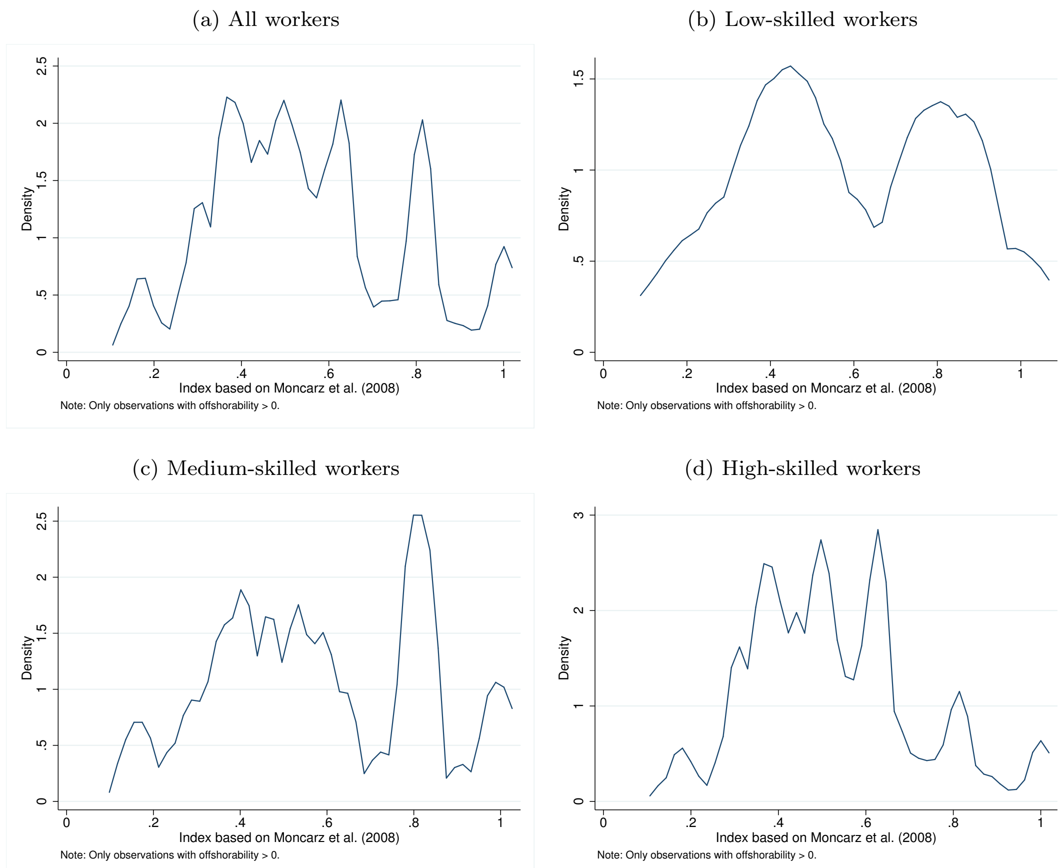


Figure 2.2: Moncarz et al. (2008)



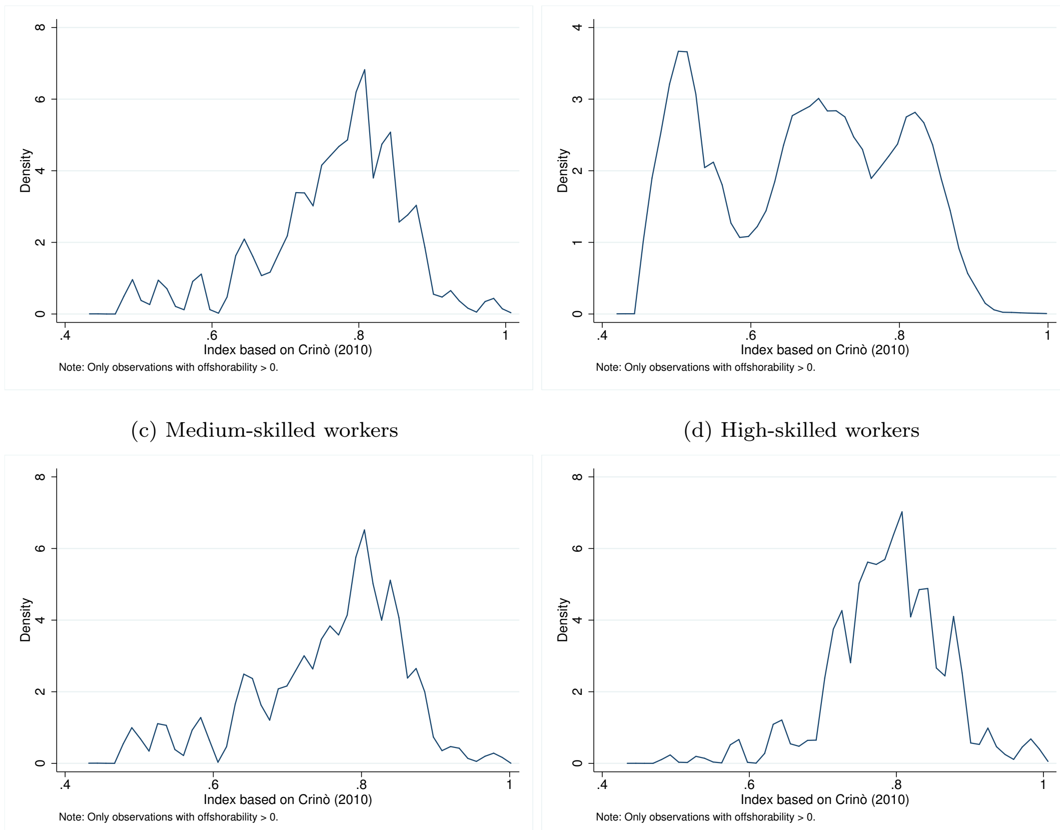
(a) All workers

(b) Low-skilled workers

(c) Medium-skilled workers

(d) High-skilled workers

Figure 2.3: Crinò (2010)



(a) All workers (b) Low-skilled workers

(c) Medium-skilled workers (d) High-skilled workers

Such disagreement between the measures bears important implications since it significantly limits the comparability across empirical studies, especially for analyses of the labor market effects of service offshoring. To avoid such confusion, we need to determine selection criteria for such offshorability indices. There are no theoretical grounds to prefer one of the measures over another and, as table 2.2 illustrates, all three rankings generally seem plausible. Consequently, I propose an empirical criterion to compare the indices' external validity, i.e., how well they represent the phenomenon that they aim to measure. More specifically, I assess how well the different measures perform in capturing the variation in actual offshoring flows across occupations. Therefore, I compare their explanatory power in a simple regression with actual offshoring flows as the dependent variable:

$$OFF_{ot} = \exp\left(c + \beta X_o + d_t + \varepsilon_{ot}\right). \tag{1}$$

$o = 1, \ldots, O$ *Occupation*
$t = 1, \ldots, T$ *Time*

OFF_{ot} indicates the U.S. service offshoring intensity in service occupation o in year t over the period 2006 to 2009, and d_t is a time fixed effect. One issue that arises when performing such a test is that rather than at the occupational level, trade data are collected at the industry or firm level. I address this problem by matching trade data at the industry level with industry-specific occupational employment estimates. Details on the construction of this variable can be found in appendix B. X_o is a set of proxy measures for offshorability, which includes the three overall indices described above. As mentioned earlier, no consensus has yet been established on which task characteristics are most relevant in determining offshorability and previous works have frequently assumed three different task characteristics as relevant in this regard. These three tasks include the required face-to-face contact (Bardhan and Kroll 2003; van Welsum and Vickery 2005; Blinder 2006; Jensen and Kletzer 2008), the routine content of occupations (Levy and Murnane 2006; Ebenstein et al. 2011), and the ICT dependence of an occupation (Bardhan and Kroll 2003; Garner 2004; van Welsum and Vickery 2005; Blinder 2006; Jensen and Kletzer 2008; Moncarz et al. 2008). To elucidate how relevant each of the three task characteristics is for an occupation's susceptibility to offshoring, I construct three proxy measures for these task characteristics and estimate three additional specifications of equation (1), in which I replace X_o with these proxy variables.

Similarly to Crinò (2010), I construct proxy measures for these task characteristics by employing information from the O*Net. I consider those O*Net activities that have been stressed by Blinder (2007) and Crinò (2010) as proxy measures for these task characteristics (table 2.1).[29] If Blinder and Crinò have assumed several O*Net activities to reflect a certain task characteristic, I construct a weighted average by retaining the first component from a principal component analysis (PCA) of the relevant O*Net activities across 370 cross-sectional units (six-digit SOC service occupations).[30]

Table 2.5 illustrates the results of an ordinary least squares regression (OLS). The coefficients on each offshorability proxy measure are statistically significant at the one percent level. However, the amount of variation that is explained by each offshorability measure differs significantly and ranges from 0.2 percent to 30 percent. The specification in column (2) that includes the index by Moncarz et al. shows the highest adjusted R-squared (30 percent). The ICT index explains the second highest amount of variance in actual offshoring flows (19.1 percent; see column (6)), followed by Blinder's index with an R-squared of 16.4 percent (column (1)). Column (3) suggests that the index by Crinò explains the lowest

[29] Further details on these O*Net activities can be found in table A.1.

[30] For further details on the PCAs, see appendix A. I normalize all three proxy measures so that they lie between zero and one, with one indicating the highest manifestation of the respective task characteristic.

amount of variance in actual offshoring flows among the three indices, i.e., only 2.4 percent. These results suggest that among the different task characteristics that have been put forward as determinants of offshorability (see section 2.2), the one that best captures actual offshoring flows is the ICT dependence of different occupations. This result is consistent with the argument that the developments in ICTs in the 1980s and 1990s have been a necessary precondition for service offshoring (U.S. Government Accountability Office 2004, p. 10; World Trade Organization 2006, p. 2; Lejour and Smith, 2008 pp. 175-176). Furthermore, the low adjusted R-squared of the proxy measure for the routine content of an occupation (0.2 percent; see column (4)) is in agreement with the anecdotal evidence by Autor (2010, p. 13) and casts the assumption into doubt that the routine content of an occupation is the sole determinant of an occupation's offshoring susceptibility (see also page 12 of this dissertation).[31]

The specification that includes the index by Moncarz et al. (2008) shows the highest adjusted R-squared (30 percent). There could be several reasons for this result, which future studies could seek to disentangle in more detail. First, the index by Moncarz et al. contains information that is not contained in the other indices because the BLS' economists base their ranking on the most comprehensive set of tasks. Second, compliance with those task characteristics has been assessed entirely based on judgment of the BLS' economists. In other words, Moncarz et al. do not rely on rankings based on the importance of O*Net activities. The low amount of variance in actual offshoring flows that is explained by Crinò's index in comparison to the ones by Blinder and Moncarz et al. shows that caution is indicated when using survey responses that have been codified for different purposes such as the O*Net.[32]

As a robustness check, I perform an alternative estimation technique that has recently been proposed by Santos Silva and Tenreyro (2006) and that also considers zero-value observations in actual offshoring flows.[33] Following Santos

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[31] Note that the coefficient on the proxy measure for routine content is statistically significant and negative. It should, hence, be interpreted with caution.

[32] However, this does not imply that additional survey questions have to be developed to accurately measure offshorability, only that the respective responses have to be judged with the objective of determining an occupation's offshorability. In this regard, the Princeton Data Improvement Initiative (PDII) offers a promising pilot study for future work. First results suggest that professional coders can classify occupations according to their offshorability based on information provided in existing labor force surveys. I am grateful to Alan S. Blinder for providing me with the access to the data. I have also compared the occupational ranking resulting from information in the PDII with the other three continuous indices. However, the PDII data currently only offer information about 212 occupations. The Spearman rank correlation between the PDII ranking and the one provided in Moncarz et al. (2008) is fairly high (0.65, significant at the one-percent level). Similarly, the offshorability distribution across the educational attainments of workers and the performance in explaining actual offshoring flows are very similar across these two indices. Results are available upon request.

[33] Santos Silva and Tenreyro (2006) have most prominently criticized the approach to take the logarithm to transform multiplicative models, such as the gravity equation, into an additive form before employing an OLS estimator. Most relevant for the present work is the problem that such an approach cannot handle data that are rich in zero-value observations because the logarithm is not defined for non-positive values. In the present analysis, 1.9 percent of all offshoring intensity observations are zero-value observations.

Table 2.5: Explanatory power of the indices (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:						
Log offshoring intensity						
X_0*: Indices*						
Blinder	2.497***					
	(0.00901)					
Moncarz et al.		3.286***				
		(0.0106)				
Crinò			2.014***			
			(0.0152)			
X_0*: Task proxy measures*						
routine				-0.0727***		
				(0.0152)		
face-to-face					0.238***	
					(0.0155)	
ICT						2.810***
						(0.0147)
Fixed effects	Year	Year	Year	Year	Year	Year
Observations	180,204	180,204	180,204	180,204	180,204	180,204
adj. R-squared	0.164	0.300	0.024	0.002	0.003	0.191

Silva and Tenreyro, I directly estimate the multiplicative form of equation (1) with a Poisson pseudo-maximum likelihood (PPML) estimator.[34] Again, the coefficients on each index are positive and statistically significant at the one percent level. The ranking in terms of the variance explained is in line with the one obtained by OLS (see table 2.7). Furthermore, there is strong evidence in favor of the index developed by Moncarz et al. (2008) (see column (2)) in comparison with the other indices according to the Bayesian information criterion (BIC).[35]

2.4 Conclusion

This work opens the black box of offshoring susceptibility and is of special interest to empirical researchers in the field of international economics. Even if a lot of the recent research in international economics - and in labor economics - has been emphasizing "the" task content of occupations, there has not been a systematic analysis of the different proxy measures. This study offers an assessment of three different approaches that have been proposed in previous works and that aim to measure the susceptibility of occupations to offshoring in the United States, i.e., the indices by Blinder (2007), Moncarz et al. (2008), and Crinò (2010). I consider these indices to be the most relevant for the literature on the distributional effects of service offshoring because they establish continuous rankings of occupations and are based on a composite of different task characteristics rather than only considering the routine content of an occupation.

In the review in section 2.2, I stress that there is no consensus in the quickly growing trade-in-tasks literature on how to construct an index of an occupation's offshorability. The existence of conceptually different measures is problematic because these indices measure different aspects of reality while employing an identical term. Indeed, an analysis of the resulting offshorability rankings across the three continuous indices reveals significant variation. Moreover, different offshorability rankings of occupations also lead to different offshorability distributions across certain worker characteristics. This highlights the risk of providing sharply different representations of the impact of service offshoring on the labor market. For instance, depending on which index we employ, we obtain significantly different distributions of offshorability across workers' skill levels: Blinder's and Crinò's indices classify medium-skilled workers, on average, as employed in the most offshorable occupations, whereas Moncarz et al. classify high-skilled workers, on average, as employed in the most offshorable occupations.

To compare the indices' external validity and to select among them, I propose an objective criterion, which assesses how well the different measures perform

[34] Maximum likelihood theory has shown that for the Poisson estimator to be consistent, the dependent variable needs to show a distribution that belongs to the linear exponential family, $E[y_i \,|x\,] = \exp(x_i\beta)$ (Gourieroux et al. 1984). Consequently, the dependent variable does not need to be Poisson distributed and not even to be a count variable.

[35] For further details, see appendix C.

Table 2.7: Explanatory power of the indices (PPML)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Offshoring intensity						
X_0: Indices						
Blinder	1.025***					
	(0.00996)					
Moncarz et al.		1.866***				
		(0.00778)				
Crinò			1.973***			
			(0.0141)			
X_0: Task proxy measures						
routine				-0.0266***		
				(0.00154)		
face-to-face					0.404***	
					(0.0134)	
ICT						0.0207***
						(0.000165)
Fixed effects	Year	Year	Year	Year	Year	Year
Observations	183,702	183,702	183,702	183,702	183,702	183,702
Log pseudo likelihood	-3644.1476	-3544.8995	-3666.046	-3680.964	-3679.024	-3606.0116
AIC	7298.295	7099.799	7342.092	7371.928	7368.048	7222.023
BIC	7348.901	7150.404	7392.697	7422.533	7418.653	7272.629
Pseudo R^2	.0632123	.17908227	0.0214414	.00502822	.00814442	.12729005

in capturing the variation in actual offshoring flows across occupations. The results suggest that the index by Moncarz et al. performs best in this regard, whereas the composite indices by Blinder (2007) and Crinò (2010) do not add meaningfully to the explanatory power of the separate O*Net activity "interacting with computers." Moreover, the low amount of variance in actual offshoring flows that is explained by Crinò's index in comparison to the ones by Blinder and Moncarz et al. shows that caution is indicated when using survey responses that have been codified for different purposes. The present analysis suggests that offshorability is a multidimensional phenomenon that cannot be successfully measured by adding up information on univariate task characteristics that has not been collected to measure an occupation's offshorability. The findings imply that the trade-in-tasks literature needs to use its research terminology more consistently and would benefit greatly from more customized datasets.

Appendix A: Offshoring susceptibility scores

Information on the overall indices comes from Moncarz et al. (2008), Blinder (2007), and Crinò (2010) respectively.[36] The indices by Moncarz et al. (2008) and by Crinò (2010) are restricted to service occupations. These include the following SOC major groups: 11, 13, 15 to 29, 31 to 39, 41, 43, 49, and 53. Blinder (2007) includes two additional goods-providing groups in his analysis, i.e., construction and extraction occupations (SOC 47-0000) and production occupations (SOC 51-0000). To ensure comparability, I have not considered the information on manufacturing occupations in the present analysis.

Blinder (2007) and Moncarz et al. (2008) construct their rankings in two steps. In the first step of constructing his ranking, Blinder classifies all occupations into one of four offshorability groups. He proceeds as follows: First, he decides whether "a person in this occupation need[s] to be physically close to a specific U.S. work location" (Blinder 2007, p. 20). If this is the case, he assigns this occupation to Group IV (highly non-offshorable). If this is not necessary, he decides whether the person needs to "be physically close to the work unit" (Blinder 2007, p. 20). If this is not the case, the occupation falls into Group I (highly offshorable). If physical proximity to the work unit is required, Blinder asks whether this work unit must be at a U.S. location. If the answer to this question is yes, the occupation is assigned to Group III (non-offshorable), and if the answer is no, then the occupation is classified into Group II (offshorable). In the second step, he assigns an offshorability score to all occupations classified as Groups I to III.

The BLS' economists classify 355 of the 515 service-providing occupations in the SOC system as entirely non-tradable. Entirely non-tradable occupations consist of those services that require performance in a certain geographical location, such as e.g. security guards, or that need face-to-face contact with customers, such as e.g. hairdressers. Then, the BLS' economists assign an offshoring susceptibility score to the remaining occupations (Moncarz et al. 2008).

Appendix B: Offshoring intensity measures

There is no direct measure of offshoring flows available in official datasources. As has been proposed by Feenstra and Hanson (1996), offshoring is likely to lead to imports of intermediate products that can be used as a proxy measure for offshoring. To obtain an estimate of intermediate service imports, I employ information from U.S. input-output tables, which is provided by the Bureau of Economic Analysis (BEA).

The share of offshoring in gross production in service industry s at time t is calculated based on the following equation (see also Amiti and Wei 2009):

[36] Information on Crinò's tradability index can be obtained from his web appendix.

$$OFF_{st} = \left[\frac{SP_{st}}{TSO_{st} + SI_{st} - SE_{st}}\right] \frac{SI_{st}}{TSO_{st}}. \tag{2}$$

$TSO \ldots$ Total service output
$SI \ldots$ Service imports
$SE \ldots$ Service exports
$SP \ldots$ Service purchases
$s = 1, \ldots, S$ Service industry
$t = 1, \ldots, T$ Time
$c = 1, \ldots, C$ Country

In a second step, I adapt the approach by Ebenstein et al. (2011) and reweight this offshoring intensity proxy measure at the industry level to obtain an occupational-level offshoring proxy measure:

$$OFF_{ot} = OFF_{st} \times \sum_{s=1}^{S} \frac{N_{os}}{N_o}. \tag{3}$$

$o = 1, \ldots, O$ Occupation
$N \ldots$ Number of workers

Importantly, Ebenstein et al. (2011) have not employed an industry-level offshoring intensity proxy measure similar to the one obtained by equation (2). Instead, they have employed information solely on affiliated trade, i.e., foreign direct investments. In such trade data, there is only one industry classification because, unlike in input-output tables, no distinction is made between those industries that produce and those that purchase the intermediates. In the present analysis, we have to decide whether to construct the weights based on employment information about sector of supply p or the sector of use u. Remember that the objective of computing an offshoring proxy measure at the occupational level is to obtain "a measure of the effective exposure of an occupation to offshoring" (Ebenstein et al. 2009, p. 29). I argue that considering the occupational distribution within the industries producing the intermediates ($p = 1, ..., P$) offers information about which types of occupations are "embodied" in the offshored products and decide to construct the weights based on employment information from the producing industry p. This information is publicly accessible in the industry-specific occupational employment and wage estimates at the Bureau of Labor Statistics' website.

To merge data from input-output tables with the industry-specific occupational employment and wage estimates of the BLS, the information provided in both datasources has to be converted to a common industry classification. The BLS classifies data according to the North American Industry Classification System (NAICS) and in input-output tables service industries are classified according to input-output codes. These input-output codes can be converted to categories of the North American Industry Classification System (NAICS) according to the list provided in the BEA input-output tables. The results are displayed in table A.2.

Table A.1: Concordance between input-output codes and NAICS codes

Input-output codes	**2002 NAICS codes**
521C1, 523, 525	522000, 523000, 525000
524	524000
513	517000
5415, 514	541500
55	551100
5411	541100
5412OP	541900

Appendix C: Task proxy measures

The construction of the three task proxy measures employs information from O*Net activities that have been proposed by Blinder (2007) and Crinò (2010). Table A.1 offers details on these sixteen separate O*Net activities. The first column shows the number of each activity that is used as an abbreviation throughout this chapter. The second column lists the name of each activity and the third column offers a detailed description of each activity that is taken from the O*NET. The fourth column names the informational category under which the respective activity can be found in the O*Net database. The fifth column lists the respective researchers who have employed information on the importance of this activity for the construction of a proxy measure for certain tasks. The last column names the task, such as routine content, that the researchers assume to be reflected by the respective O*Net activity. For instance, activity 1 is called “importance of repeating the same task” in the O*Net database. This information can be found in the category “work context,” and variation in the importance scores for this activity across occupations has been employed by Crinò (2010) as a proxy measure for the routine content of an occupation.

Table A.2: Description of separate O*Net activities

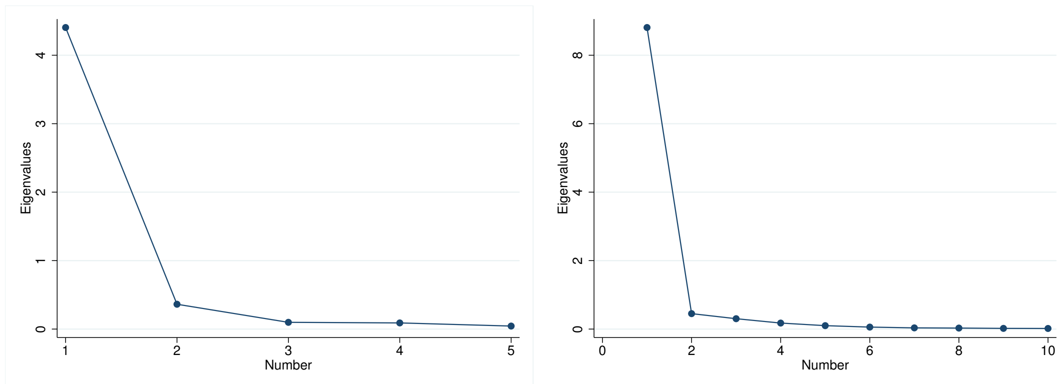
Activity	Name	Description	O*Net data category	Used by	Used to measure
1	Importance of repeating the same tasks	How important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job?	Work context	Crinò (2010)	routine content
2	Visual color discrimination	The ability to match or detect differences between colors, including shades of color and brightness	Abilities	Crinò (2010)	routine content
3	Documenting/recording information	Entering, transcribing, recording, storing, or maintaining information in either written form or by electronic/magnetic recording	Work activities	Crinò (2010)	routine content
4	Getting information	Observing, receiving, and otherwise obtaining information from all relevant sources	Work activities	Crinò (2010)	routine content
5	Inspecting equipment, structures, materials	Inspecting or diagnosing equipment, structures, or materials to identify the causes of errors or other problems or defects	Work activities	Crinò (2010)	routine content
6	Face-to-face discussions	How often do you have to have face-to-face discussions with individuals or teams in this job?	Work context	Crinò (2010)	face-to-face
7	Performing for or working directly with the public	Performing for people or dealing directly with the public. This includes serving customers in restaurants and stores, and receiving clients or guests	Work activities	Blinder (2007) Crinò (2010)	face-to-face
8	Deal with external customers	How important is it to work with external customers or the public in this job?	Work context	Crinò (2010)	face-to-face

Table A.1: continued

Activity	Name	Description	O*Net data category	Used by	Used to measure
9	Establishing and maintaining interpersonal relationships	Developing constructive and cooperative working relationships with others, and maintaining them over time.	Work activities	Blinder (2007) Crinò (2010)	face-to-face
10	Assisting and caring for others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients	Work activities	Blinder (2007)	face-to-face
11	Coaching and developing Others	Identifying the developmental needs of others and coaching, mentoring, or otherwise helping others to improve their knowledge or skills	Work activities	Blinder (2007)	face-to-face
12	Coordinating the work and activities of others	Getting members of a group to work together to accomplish task	Work activities	Blinder (2007)	face-to-face
13	Guiding, directing, and motivating subordinates	Providing guidance and direction to subordinates, including setting performance standards and monitoring performance	Work activities	Blinder (2007)	face-to-face
14	Communicating with persons outside organization	Communicating with people outside the organization, representing the organization to customers, the public, government, and other external sources. This information can be exchanged in person, in writing, or by telephone or e-mail.	Work activities	Blinder (2007)	face-to-face
15	Selling or Influencing Others	Convincing others to buy merchandise/goods or to otherwise change their minds or actions.	Work activities	Blinder (2007)	face-to-face
16	Interacting with computers	Controlling computer functions by using programs, setting up functions, writing software, or otherwise communicating with computer systems	Work activities	Crinò (2010)	ICT content

Figure A.1: Scree plots

(a) Routine content (b) Face-to-face contact



Blinder (2007) and Crinò (2010) have assumed several O*Net activities to reflect the routine content and the required face-to-face contact of an occupation (see table A.1). To obtain a proxy measure for these two task characteristics, I construct a weighted average across the respective activities by relying on statistical considerations. In particular, I perform a principal component analysis of the relevant O*Net activities across 370 six-digit SOC service occupations.[37]

There are different criteria on how to determine the number of components to retain. One rule builds on Kaiser (1974), who recommends keeping only components with an eigenvalue equal to/or greater than one. Another rule is based on the graphical representation of the eigenvalue graphs and recommends retaining those components prior to the breaking point, at which the eigenvalue graph flattens out (Costello and Osborne 2005). In the present analysis, both criteria lead to the same number of components to retain; that is, always the first component (see the eigenvalues in table A.2 and the scree plots in figure A.1). The composition of the eigenvectors of each first and second component are shown in table A.3. Table A.4 shows the summary statistics for the three proxy measures, and table A.5 illustrates the bivariate correlation coefficients between these measures.

[37] The present study employs information from the most recent version of the O*Net (15.1).

Table A.2: Principal component analyses

Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	4.40488	4.04213	0.8810	0.8810
Component 2	0.362755	0.264225	0.0726	0.9535
Component 3	0.0985298	0.00864981	0.0197	0.9732
Component 4	0.08988	0.0459281	0.0180	0.9912
Component 5	0.0439519		0.0088	1.0000

(a) Routine content

Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	8.80998	8.35907	0.8810	0.8810
Component 2	0.450904	0.148001	0.0451	0.9261
Component 3	0.302902	0.127129	0.0303	0.9564
Component 4	0.175774	0.0756544	0.0176	0.9740
Component 5	0.100119	0.0423119	0.0100	0.9840
Component 6	0.0578075	0.0225475	0.0058	0.9897
Component 7	0.03526	0.00579686	0.0035	0.9933
Component 8	0.0294631	0.00948722	0.0029	0.9962
Component 9	0.0199759	0.00215884	0.0020	0.9982
Component 10	0.0178171	.	0.0018	1.0000

(b) Face-to-face contact

Table A.3: Eigenvectors

(a) Routine content

	Component 1	Component 2	Component 3	Component 4	Component 5	Unexplained
Importance of repeating the same tasks	0.4458	-0.4208	0.7782	-0.0271	0.1337	0
Visual color discrimination	0.4546	0.3038	-0.1895	-0.7113	0.3989	0
Documenting/recording information	0.4520	-0.3525	-0.5023	0.5016	0.4092	0
Getting information	0.4630	-0.2245	-0.2557	-0.1796	-0.7985	0
Inspecting equipment, structures, materials	0.4194	0.7457	0.2019	0.4576	-0.1340	0

(b) Face-to-face contact

	Component 1	Component 2	Component 3	Component 4	Component 5	Unexplained
Face-to-face discussions	0.3278	0.0303	-0.1512	-0.3302	-0.0593	0
Performing for or working directly with the public	0.3004	0.5819	0.1898	0.2250	-0.4771	0
Deal with external customers	0.3245	0.2715	0.1276	-0.1336	-0.2789	0
Establishing and maintaining interpersonal relationships	0.3285	-0.0657	-0.108	-0.3856	-0.0164	0
Assisting and caring for others	0.2978	0.4351	-0.5481	0.2376	0.5466	0
Coaching and developing others	0.3213	-0.3047	-0.1735	0.3593	0.0145	0
Coordinating the work and activities of others	0.3218	-0.3471	-0.1592	0.0747	-0.0701	0
Guiding, directing, and motivating subordinates	0.3161	-0.4057	-0.0162	0.3543	-0.3027	0
Communicating with persons outside organization	0.3211	-0.1231	0.1261	-0.5551	0.1674	0
Selling or influencing others	0.3011	-0.0114	0.7356	0.2215	0.5170	0
	Component 6	Component 7	Component 8	Component 9	Component 10	Unexplained
Face-to-face discussions	-0.5651	0.0863	-0.0193	0.3146	0.5745	0
Performing for or working directly with the public	0.2739	0.3541	0.1351	-0.0655	0.1845	0
Deal with external customers	-0.2736	-0.5925	-0.3436	-0.2038	-0.3515	0
Establishing and maintaining interpersonal relationships	-0.0945	0.4248	0.3152	0.1248	-0.6502	0
Assisting and caring for others	0.1495	-0.1456	-0.0124	0.1412	-0.0528	0
Coaching and developing others	-0.2806	0.0355	0.3134	-0.6763	0.0946	0
Coordinating the work and activities of others	0.2305	0.3431	-0.7535	-0.0385	-0.0005	0
Guiding, directing, and motivating subordinates	0.1923	-0.3567	0.2577	0.5352	-0.0325	0
Communicating with persons outside organization	0.5554	-0.2415	0.1687	-0.2420	0.2754	0
Selling or influencing others	-0.1490	0.0993	-0.0545	0.1258	-0.0292	0

Table A.4: Summary statistics

Variable	Observations	Mean	Standard Deviation	Min	Max
routine	311033	.402422	.3596835	0	1
face-to-face	311033	.3861941	.3518427	0	1
ICT	311033	.3543168	.3581955	0	1

Table A.5: Correlation coefficients

	routine	face-to-face	ICT
face-to-face	0.9551	1	
ICT	0.8832	0.8705	1

Appendix D: Poisson pseudo-maximum likelihood regression

Martin and Pham (2008) have argued that the efficiency of the PPML estimator depends on the frequency of zero-value observations. If the data shows overdispersion (i.e., the mean is smaller than the variance), the negative binomial model would be more appropriate for the data. In this model, the variance also depends on a dispersion parameter (Cameron and Trivedi 2010, pp. 577-582). However, the likelihood ratio test for overdispersion shows no statistically significant evidence of overdispersion (G^2= 0.000, p = 1.000).[38] Consequently, the Poisson regression model is a better fit for the data.

I also test for the existence of "excess" zeroes. If there were more zero-value observations than predicted by a Poisson model, a zero-inflated Poisson model (ZIP) would be preferred over a standard Poisson regression model. The Vuong test compares both regression models and indicates that the standard Poisson regression is a better fit for the data than the zero-inflated Poisson model (z-value of -127.20).[39]

Table A.6 shows the results of the PPML regression. The pseudo R-squared, the Akaike (AIC) and the Bayesian information criteria (BIC) help to compare the efficiency of predicting actual offshoring flows across different non-linear specifications. Stata calculates the reported pseudo R-squared for maximum-likelihood estimators as follows:

[38] The likelihood ratio test statistic is chibar-0-1 distributed. For more details, see Cameron and Trivedi (2010, pp. 414-416). No consensus has been established as to whether the efficiency of the PPML estimator depends on the frequency of zero-value observations. Santos Silva and Tenreyro (2011) have argued that the evidence provided by Martin and Pham (2008) is not applicable to constant-elasticity models.

[39] The test statistic is standard normally distributed. Large positive values indicate that the zero-inflated version is more appropriate, whereas large negative values favor the standard model (Long and Freese 2006, pp. 408-409).

$$\widetilde{R}^2 = 1 - {}^{\ln L_{fit}}/_{\ln L_0},$$

where $\ln L_{fit}$ is the log likelihood of the fitted model, and $\ln L_0$ is the log likelihood of the constant-only model (see Cameron and Trivedi 2010, p. 359).[40]

The AIC and the BIC can also be used to select among several models. Both criteria are based on the log likelihood of the model and introduce penalties for adding parameters to the model which can increase the log likelihood. Stata calculates them as follows:

$$AIC = -2 \ln L + 2P_k,$$

$$BIC = -2 \ln L + P_k \ln N,$$

where $\ln L$ is the log likelihood of the model and $2P_k$ and $P_k \ln N$ are the penalties for the model size. Because a larger log likelihood is preferred, the model with a smaller AIC and BIC is favored, in particular, the second model is favored when $BIC_1 - BIC_2 > 0$ (Long and Freese 2006, pp. 112-113; Cameron and Trivedi, 2010, pp. 359-360). Raftery (1996) suggests the guidelines shown in table A.6 for assessing the difference in the BICs from different models.

Table A.6: BIC, Strength of evidence

Difference	Evidence
0-2	Weak
2-6	Positive
6-10	Strong
>10	Very strong

Source: Long and Freese (2006, p.113)

[40] Note that for continuous data, it is possible that $\widetilde{R^2} > 1$, $\widetilde{R}^2 < 0$ and that the pseudo R-squared does not increase when parameters are added (Cameron and Trivedi 2010, pp. 357-358).

3 Task dependence of U.S. service offshoring patterns

Abstract

This chapter offers new insights into the determinants of U.S. service offshoring across countries and across service industries. Combining different data sources over the 2006-2009 period, I find that certain country characteristics affect offshoring costs identically for all services, while the effects of other characteristics depend on the task content of the respective service industry. The results from a zero-inflated Poisson pseudo-maximum likelihood estimation indicate that the effects of a membership in NAFTA and of colonial ties on service offshoring patterns depend on the task content of the services. The quality of legal institutions, a common legal origin, geographic distance, and time zone differences influence offshoring patterns identically across all service industries.

Keywords: *Offshoring, services, tasks, Poisson pseudo-maximum likelihood*

JEL classification: *F14, F23, F20*

3.1 Introduction

The considerable decline in communication costs resulting from several technological improvements in the 1980s and 1990s has initiated a change in the way countries trade and has caused many service activities that were traditionally seen as non-tradable to become tradable. In the United States imports of computer and information services as well as other business services, which are mainly used as intermediate services by firms (e.g., Amiti and Wei 2005), more than tripled in real terms from 1995 to 2009.[41] However, because of data constraints, little empirical evidence has been provided to improve our understanding of service offshoring. In this chapter, I combine two prior strands of

[41] Because OECD data for these two service categories have only been collected since 2005, I employ data for the largest importer of these service categories, the United States, to illustrate the growth of imports since 1995. The United States is also the world's largest exporter of these services, and U.S. exports have likewise almost tripled in real terms from 1995 to 2009. All data are taken from the OECD Statistics on International Trade in Services.

research to offer new insights on the determinants of U.S. service offshoring patterns.

Recent trade models that build on the concept of supermodularity offer theoretical guidance on how country and industry characteristics jointly influence the pattern of trade (Costinot 2009b). Thus far, the empirical analyses related to this body of literature have largely focused on the interplay between institutional quality and industry-level institutional dependence. However, service industries do not only differ in their reliance on institutional quality. With the advent of service offshoring, scholars have argued that different types of services face a different susceptibility to offshoring according to their task content (Garner 2004; Blinder 2006, 2007; Jensen and Kletzer 2005; Moncarz et al. 2008). For instance, many service occupations, such as those of general operations managers, still require "proximity" to other activities performed in the production process and are consequently more difficult to offshore. I propose to obtain a proxy measure for these differences in offshoring susceptibility by building on previous works that have emphasized the influence of different characteristics at the task level on an occupation's offshoring costs and to aggregate this information up to the industry level. Moreover, this work also extends previous empirical works on the country-level determinants of services trade, which find, for instance, that colonial ties (Kandilov and Grennes 2007; Miroudot et al. 2009; Head et al. 2009) and mutual membership in free trade agreements (Kandilov and Grennes 2007) positively affect bilateral services trade flows.

The present analysis estimates whether and to what extent country characteristics and the task content of services jointly explain the U.S. service offshoring pattern. The intuitive interplay of the task content and country-level determinants in determining offshoring costs is new to the empirical literature and suggests a more nuanced story regarding the determinants of service offshoring patterns. The United States offers an especially interesting case for combining these two strands of research - i.e., the research on country characteristics and on task content - because it is the top service-offshoring country in dollar amount and because the service sector is particularly important in the U.S. economy.[42]

Methodologically, I build on the works of Romalis (2004) and Nunn (2007) and estimate a gravity-like equation with interaction terms.[43] Scholars have recently criticized the traditional approach of employing an ordinary least squares (OLS) estimator in the context of the standard gravity model. Santos Silva and Tenreyro (2006) as well as Westerlund and Wilhelmsson (2006) have argued that estimates will be biased and inconsistent because of the presence of zero-values and heteroscedasticity. After performing a number of tests to determine the

[42] For instance, 25 percent of all U.S. employment occurred in the business service sector in 2007 (Jensen 2011, pp. 3-4)

[43] Interaction terms were first included into a gravity equation by Rajan and Zingales (1998) in their analysis of the joint impact of financial development and financial requirements on industry growth. More recently, e.g., Levchenko (2007) and Chor (2010) have developed similar functional forms to estimate how the interplay between country and industry characteristics shapes the pattern of trade. The works by Romalis (2004) and Nunn (2007) are among the most influential works that have employed such an empirical specification.

correct estimation technique, I estimate the gravity equation via a zero-inflated Poisson pseudo-maximum likelihood (PPML) estimator.

The results indicate that services that have a relatively low susceptibility to offshoring are offshored relatively more to countries that are North American Free Trade Agreement (NAFTA) members and that have colonial ties with the United States. The quality of legal institutions, a common legal origin, geographic distance, and time zone differences influence offshoring patterns identically across all service industries, regardless of their task content.

This chapter is structured as follows. In section 3.2, I review the relevant literature on how the interplay between country and industry characteristics can shape patterns of comparative advantage and extend this approach to task-specific offshoring costs. Section 3.3 presents the data and the calculation of actual offshoring flows and offshoring susceptibility proxies. In section 3.4, I address econometric issues regarding the estimation techniques and present the estimation results. Section 3.5 summarizes and discusses the findings.

3.2 Theory and prior empirical research

Which theoretical trade models can guide the empirical analysis of trade patterns across countries and industries? Sharp predictions about trade patterns in neoclassical trade models, such as the Ricardian model and the Heckscher–Ohlin model, were traditionally derived in environments restricted to a small number of countries, goods, and factors. Unfortunately, these sharp results could not be preserved in settings with higher dimensionality, i.e., many goods and many countries. As a result, these standard models were difficult to apply to the data.[44]

The theoretical basis of the present empirical analysis relies on the generalization and extension of the sources of comparative advantage developed by Costinot (2009b). He develops an assignment model of the sources of comparative advantage that can be applied to differences in technology and likewise to differences in factor endowments. The key concept in his model is log supermodularity, i.e., a mathematical notion of complementarity that captures the idea that the relative return to one variable is increasing in another variable. He shows that if factor productivity across different industries is log supermodular with respect to certain country characteristics γ, e.g., the quality of a country's financial system, and to certain industry characteristics σ, e.g., financial requirements, then aggregate output is also log supermodular. In other words, the productivity of sectors that have higher financial requirements is relatively more enhanced by a better financial system than the productivity of sectors

[44] During the last ten years, the Ricardian trade model has experienced a revival because of Eaton and Kortum's (2002) stochastic version of the model. These researchers have developed a tractable general equilibrium model of international trade with multiple countries and goods that - unlike most traditional formal trade models - incorporates a role for geography. However, the Eaton and Kortum framework analyzes aggregate trade volumes rather than industry-level trade flows. Hence, their contribution offers only limited guidance for the present analysis, which also seeks to account for the cross-industry variation in offshoring patterns.

that are less dependent on the quality of the financial system (log supermodularity of factor productivity). As a result, high-γ countries have a comparative advantage in high-σ industries.[45]

An emergent literature has provided microfoundations for the concept of log supermodularity by focusing largely on institutions.[46] For instance, Costinot (2009a) assumes that complex products are produced by combining a large number of tasks and that production consequently requires many contracts with the workers performing the tasks. If the degree to which these contracts are enforced differs across countries, the products that have high "contractual input intensities" (Helpman 2006, p. 23) will be relatively more exported from those countries in which contracts are strictly enforced by the legal system. Nicolini's (2007) empirical results support this hypothesis for the cross-country patterns of U.S. foreign direct investments (FDIs).[47]

However, in the context of service offshoring, industries do not only differ in their reliance on institutional quality. The emergent literature on trade in tasks has stressed that different types of services face different offshoring costs according to their task content (see 3.3.2). These offshoring costs stem from "exchanging information necessary to coordinate various tasks into a single production process," (Baldwin and Robert-Nicoud 2010, p. 9) i.e., transaction costs and transportation costs. I argue that the notion of "costs" has to be used more carefully, and that the task content influences the preconditions required for offshoring and - in line with Costinot's (2009b) work - the interplay between these requirements and country endowments determines actual offshoring costs.

Because I do not focus on the degree to which industries differ in their institutional dependence but rather on the degree to which services differ in their offshoring requirements, the set of country characteristics that could influence the pattern of offshoring shifts accordingly. In addition to the institutional quality of a country, several other determinants could affect transaction and transportation costs between two countries. I build on previous empirical works

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45 More formally, this case represents a Ricardian economy, in which factor productivity satisfies $q(\omega, \sigma, \gamma) = h(\omega)\, a(\sigma, \gamma)$. Where ω are characteristics of multiple factors of production, which are similarly productive across industries. Now assume that $a(\sigma, \gamma)$ is log supermodular. Thus, if $\gamma^{c1} \geq \gamma^{c2}$ and $\sigma^{s1} \geq \sigma^{s2}$ for any pair of countries c_1 and c_2 and for any pair of industries s_1 and s_2 and $a\left(\sigma^{s1}, \gamma^{c2}\right) \neq 0$ and $a\left(\sigma^{s2}, \gamma^{c2}\right) \neq 0$, then

$$\frac{a\left(\sigma^{s1}, \gamma^{c1}\right)}{a\left(\sigma^{s1}, \gamma^{c2}\right)} \geq \frac{a\left(\sigma^{s2}, \gamma^{c1}\right)}{a\left(\sigma^{s2}, \gamma^{c2}\right)}.$$

In other words, factors in high-γ countries are relatively more productive in high-σ industries.

46 One exception is Romalis (2004), who analyzes how the interplay between skill endowments and skill intensities shapes the pattern of goods trade.

47 Other empirical papers underpin the importance of "institutional dependence" and "institutional quality" (Costinot 2009b, p. 1166) for the pattern of comparative advantage in the Ricardian sense, e.g., Nunn (2007) and Levchenko (2007). Manova (2006) focuses on credit market imperfections and Cuñat and Melitz (2007) on labor market rigidities. See also Acemoglu et al. (2007) for a theoretical contribution analyzing how incomplete contracts and institutional cross-country variation can act as a source of comparative advantage. For a recent literature review on the incomplete contracts literature, see Helpman (2006).

and consider a broad set of country characteristics that have been found to affect bilateral services trade flows (see 3.3.3). Unlike these previous analyses, I focus on whether the effects of these country-level variables differ systematically with the task content of the respective service industry.[48] Hence, I analyze whether the pattern of bilateral service offshoring depends on the interplay between country characteristics and the services' offshoring susceptibility.

3.3 The Data

To test the hypothesis that U.S. service offshoring patterns depend on the interaction between offshoring requirements and country characteristics, I need to construct several measures that are not directly available in the data. Section 3.3.1 provides details on the construction of the service offshoring intensity measure and presents the first evidence on U.S. service offshoring patterns across countries and industries. Section 3.3.2 determines the relative offshoring requirements across different service industries and presents the resulting industry ranking. Section 3.3.3 describes the country-level characteristics that are considered as potential determinants of offshoring costs.

3.3.1 Offshoring intensity measure

Offshoring refers to the location rather than to the control over the production process. As illustrated in figure 3.1, offshoring can take place via FDIs and via international outsourcing (van Welsum and Vickery 2005; Feenstra 2010, pp. 5-6).[49]

One challenge in analyzing offshoring stems from the fact that no official data directly measure the volume of offshoring. However, offshoring can be measured indirectly. Because the intermediate products produced in a foreign country are likely to be imported back to the home country to be further integrated into the production process of the final good or service, offshoring can be expected to result in imports of intermediate inputs.[50]

[48] Other empirical contributions on services trade have already shown that the effects of country-level characteristics, such as time zone differences, differ across service categories (e.g., Head et al. 2009). However, I am not aware of any other analysis that has tied these differences to the task content of the respective service categories. Oldenski (2012a) estimates the interaction effects between task content and country characteristics to examine the decision between exports and horizontal FDIs. The present study differs from hers by focusing on the locational decision, rather than on the modes of serving foreign markets, and by analyzing a composite of task characteristics as influencing offshoring requirements instead of focusing on one separate dimensions, i.e., complexity.

[49] Much of the recent trade literature analyzes the organizational choices of a global firm with regard to its boundaries. For a review, see Helpman (2006). In this chapter, I will not address a firm's decision whether to keep activities in-house or to outsource them. Rather, I will focus on its decision in which country to locate the activities. This limitation follows not only from the research focus of this chapter, but also from the data availability. See footnote 53 for further information.

[50] Feenstra and Hanson (1996) were the first to proxy material offshoring by trade in intermediate inputs. An intermediate (input) is "[a]n input to production that has itself been produced and that, unlike capital, is used up in production. As an input, it is in contrast to

Figure 3.1: Organization of the production process

	Location of production stages	
Control of production stages	Foreign country	Home country
In-house	**Foreign direct investment (FDI)**	Integration
Arms-length	**International outsourcing**	Domestic outsourcing

Source: Author's illustration adapted from van Welsum and Vickery (2005, p. 5) and Feenstra (2010, p. 5)

By adapting this approach and by combining two data sources, i.e., input-output tables with bilateral cross-border services trade data, I can calculate an offshoring proxy measure for the United States for different offshored services and distinguish among different destination countries.

In a first step, I have to estimate imported service intermediates because no official trade data separate trade in intermediate inputs from trade in final services for the United States.[51] Building on Amiti and Wei (2005, 2006), the National Academy of Public Administration (2006b, pp. 57-68), and the OECD (2007b, pp. 51-52), I estimate the imported intermediates of a particular service industry s by multiplying the value of the intermediate purchases of that service by the ratio of total imports to the total domestic supply of that service (see equation (8) in appendix A for further details):[52]

$$impint_{st} = \left[\frac{SI_{st}}{TSO_{st} + SI_{st} - SE_{st}} \right] SP_{st}. \tag{4}$$

$TSO \ldots$ Total Service Output
$SI \ldots$ Service Imports
$SE \ldots$ Service Exports
$SP \ldots$ Service Purchases
$s = 1, \ldots, S$ Service
$t = 1, \ldots, T$ Time
$c = 1, \ldots, C$ Country

a primary input, and as an output, it is in contrast to a final [product]“ (Deardorff 2006, p. 144). This approach has been applied to service offshoring by Amiti and Wei (2005, 2006) and Crinò (2010).

51 For more detailed analyses of the lack of detail available in services trade statistics, see Jensen (2011) and the reports by the U.S. Government Accountability Office (2004) and by the National Academy of Public Administration (2006b, pp. 43-56).

52 I assume that the import ratio of a certain service is the same irrespective of its use. In other words, if 10 percent of all financial services are imported, it will be assumed that 10 percent of all intermediate financial services are imported. An OECD report has calculated the aggregation bias associated with this assumption and the results suggest that the extent of imported intermediates tends to be biased downwards (Hatzichronoglou 2005, p. 13).

In a second step, I distinguish among different destination countries. I follow Egger and Egger (2003) as well as Miroudot et al. (2009) and weight the imported intermediate services obtained by (4) with the share of service imports from a certain country c in the worldwide imports of that respective service (see also equation (9) in appendix A). After canceling, this value yields the volume of service offshoring across seven service industries, 183 countries, and four years:

$$off_{sct} = \left[\frac{SP_{st}}{TSO_{st} + SI_{st} - SE_{st}}\right] SI_{sct}. \tag{5}$$

An explanation of the sample size in terms of industry and year coverage is indicated. The Bureau of Economic Analysis (BEA) disaggregates bilateral trade data on total private services for the United States into *travel, passenger fares, other transportation, royalties and license fees* and *other private services.* I focus on the category of *other private services*, which excludes services such as tourism that are not subject to the offshoring debate and includes services such as management and legal services. Appendix A provides further descriptions of these subcategories and additional details on the data sources. From the year 2006 onwards, the BEA started to publish information for affiliated *and* unaffiliated trade in the constituting subcategories of the *other private services* category.[53] These data offer an important improvement over earlier data collections because before 2006 statistics at this detailed level of service categories were only available for unaffiliated trade, which ignored an important aspect of service offshoring.[54]

With respect to the service industry coverage, the level of analysis is determined by the least disaggregated data. Unfortunately, input-output tables provide certain information only at a more aggregate industry level than bilateral trade data. As a consequence, I can only calculate an offshoring proxy measure for the following seven subcategories of the *other private services* category: financial services, insurance services, telecommunications, computer and information services, legal services, management, consulting and public relations, and other business, professional, and technical services.

Figure 3.2 illustrates the results and shows the variation in offshoring volumes by service industry. We can see that, in nominal dollar values, insurance services constituted the top offshored service industry from 2006 to 2009.

[53] However, information at the industry level is not provided separately for affiliated and unaffiliated trade. As a result, it is not possible to examine different impacts across the two rows of the column “Foreign country” in figure 3.1.

[54] With U.S. $74.125 millions in 2008, the services supplied within the boundaries of multinational companies accounted for almost one-third of the overall imports in other private services to the United States (in comparison, imports of unaffiliated services accounted for U.S. $157.894 millions). This information is taken from the BEA’s "Detailed statistics for cross-border trade."

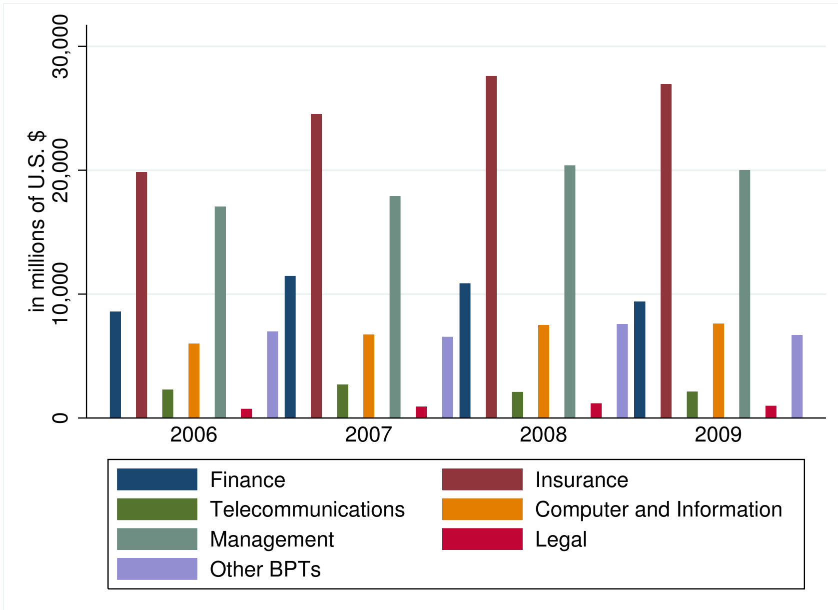

Figure 3.2: U.S. service offshoring by service industry

Figure 3.3 shows that this picture changes if I control for the respective industry size by normalizing the volume of offshoring with the gross production of each service industry, i.e., $OFF_{sct} = \frac{off_{sct}}{TSO_{st}}$.[55] After normalizing, we see that management, consulting and public relations become the service industry for which the biggest share of gross production, i.e., roughly five percent, has been offshored over all four years. Although five percent might still seem low, Amiti and Wei (2005) have shown that service offshoring grew rapidly at an average annual rate of 6.3 percent from 1992 to 2000.[56] Service offshoring has become increasingly important in accounting for overall services trade, i.e., services trade in final and intermediate services, and trade in intermediate services has accounted for roughly 73 percent of overall trade in services in 2006 (see Miroudot et al. 2009). As figure 3.4 shows, the averages over all destination countries hide significant variation across countries within each service industry.[57] For instance, computer and information services are mainly offshored to India, whereas legal services are mainly offshored to Great Britain and Canada. These heterogeneous cross-country patterns across service categories are neces-

[55] This normalization also considers the concern that during the sample period gross production of financial services could have been distorted due to the financial crisis.

[56] Before the mid-1990s offshoring primarily concerned manufacturing activities and the scale of service offshoring was close to zero (e.g., Crinò 2009). Estimates by the OECD (2007a, pp. 111-112.) suggest that, in contrast to service offshoring, the growth rate of material offshoring started to slow down in the second half of the 1990s.

[57] Note that the countries are only an exemplary selection of the complete set of U.S. service offshoring destinations. See table A.2 for a complete list of these countries.

sary to test the hypothesis of the present study.

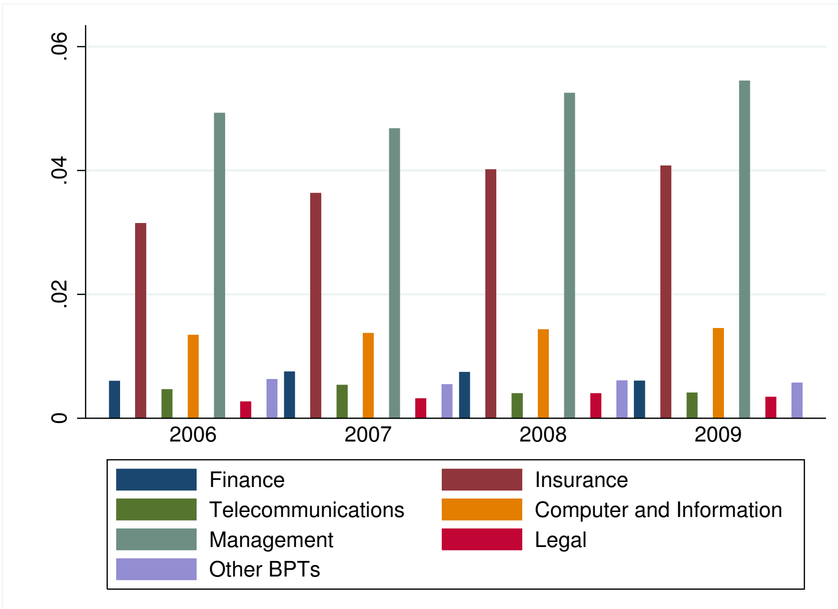

Figure 3.3: U.S. service offshoring as a share in gross production per service

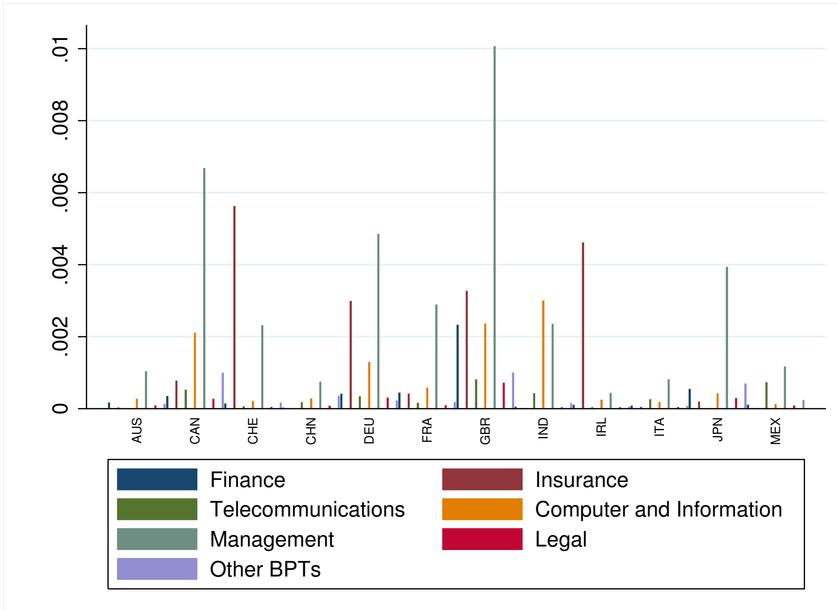

Figure 3.4: U.S. service offshoring as a share of gross production per service across countries and services in 2006

3.3.2 Offshoring requirements

Another difficulty in testing the joint impact of offshoring requirements and country-level characteristics stems from the fact that offshoring requirements at the industry level are not observable in the data. Therefore, I construct a proxy measure for a service industry's offshoring requirements by employing the classification provided in Moncarz et al. (2008). They report the results of a classification scheme developed by more than 20 economists from the Bureau of Labor Statistics' (BLS) Employment Projections Program. I have decided to employ the ranking developed by Moncarz et al. (2008) for two reasons.[58] First, instead of emphasizing one particular task characteristic, their ranking is very comprehensive. It is based on a set of occupational task characteristics that were emphasized to different degrees by several other contributions as influencing the costs of offshoring (Bardhan and Kroll 2003; Garner 2004; Jensen and Kletzer 2005; van Welsum and Vickery 2005; Blinder 2006). Second, unlike most of the other contributions, Moncarz et al. have established a continuous ranking of an occupation's offshorability. A dichotomy that instead classifies occupations as either offshorable or non-offshorable would not be useful in the present analysis because I am interested in the differences in offshoring requirements within the group of offshorable tasks.

[58] Furthermore, this index performs best in terms of explained variance of actual offshoring flows. For more details, see chapter 2 of this dissertation.

The economists of the BLS' Employment Projections Program identified 160 service occupations according to the Standard Occupational Classification System (SOC) as potentially offshorable and assigned all of these occupations an "offshoring susceptibility" score.[59] This score depends on the degree to which the occupations comply with different criteria. Based on teh compliance with these criteria, The BLS' economists ranked the service occupations according to their relative offshoring requirements.

Some tasks inherently require more coordination than other tasks. For instance, managers have to stay in contact with many different departments of a firm, whereas computer programmers only interact with parts of the firm. Levy and Murnane (2006) argue that routine occupations are typically the easiest ones to offshore because they are easy to explain and easy to monitor.[60] In the context of the literature on institutions and trade, this finding has been interpreted as indicating the degree to which tasks rely on successful contract enforcement. However, "easy" also means that fewer prerequisites are necessary for a successful exchange of information. Leamer and Storper (2001) argue that once people have acquired the underlying symbol systems (e.g., language and mathematical skills), these symbols can be used to communicate the required information and instructions as well as to monitor the results of routine tasks and tasks that are based on codifiable information. As a result, these tasks can be easily conveyed at a distance. On the contrary, complex, tacit information cannot be transmitted solely through the acquisition of the respective symbol system. Successful performance requires mutual understanding and trust because this information is context-dependent. For instance, many marketing occupations may not be performed very successfully without familiarity with the target market.[61]

By using the information provided in the industry-specific occupational employment estimates of the BLS, I can aggregate the occupation-level information provided in Moncarz et al. (2008) up to the service-industry level. This aggregation is necessary because the offshoring proxy measure is calculated at the service-industry level (see equation (5)). More specifically, I calculate a weighted average for each of the seven service industries by weighting the offshoring susceptibility score for each service occupation o with the share of occupational employment in total employment across all occupations within a given service

[59] For further details on the SOC, see appendix B.

[60] Moncarz et al. (2008) address this issue with the following two questions: "To what degree do the duties of this occupation require interaction with other types of workers?" and "To what degree can the work of the occupation be routinized or handled by following a script?" (Moncarz et al. 2008, p. 75)

[61] Moncarz et al. (2008) consider two different criteria. "To what degree can the inputs and outputs of the occupation be transmitted electronically, or otherwise be easily and cheaply transported?" and "To what degree is knowledge of social and cultural idiosyncrasies, or other local knowledge, of the target market needed to carry out the tasks of this occupation?" (Moncarz et al. 2008, p. 75)

industry s in 2003:[62]

$$OFFscore_s = \sum_{o=1}^{O} \frac{offscore_o \times totemp_{os}}{totemp_s}. \qquad (6)$$

I normalize this industry-level score in such a way that it lies between zero and one, with one indicating the lowest susceptibility to offshoring and zero indicating the highest offshoring susceptibility. Figure 3.6 shows the resulting classification across the seven service industries.[63] Insurance services are classified as the most prone to offshoring, whereas management, consulting, and public relations are the least susceptible to offshoring.

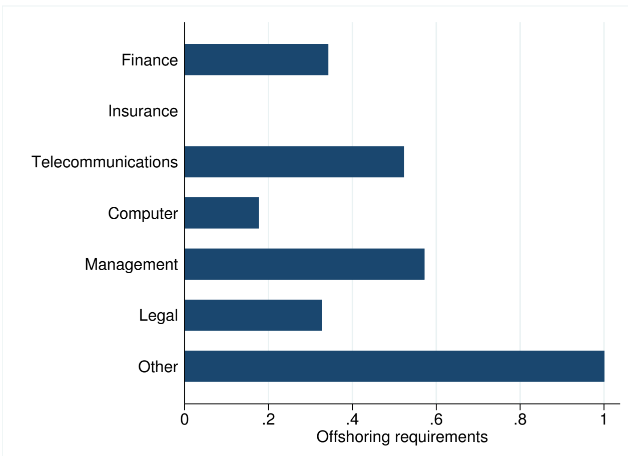

Figure 3.5: Offshoring requirements per service industry

3.3.3 Country-level determinants

By requiring more prerequisites, the task content described on pages 48-49 influences the costs that arise from the fragmentation of the production process, regardless of whether this fragmentation takes place within or across country borders. In the context of offshoring, this fragmentation can incur extra costs

62 These data are publicly accessible at the BLS' website. I employ information from the year 2003, which is the first year for which information on occupational employment is based on the 2002 North American Industry Classification System (NAICS) coding structure. This feature renders the data compatible with the classification utilized in the trade data and in the input-output data. However, using older data would have been preferable in this context because even if offshoring does not necessarily imply layoffs of workers in the home country, it can still change relative employment and hence the occupational composition within industries. Derimoglu gives an example that helps to illustrate this point: "[C]onsider a firm that expands its back office jobs by hiring abroad rather than in the United States — that expansion would not displace U.S. workers, but it would be a case of offshoring, as the firm substitutes production abroad for its production in the United States" (Derimoglu 2006, p. 5).

63 Note that the resulting proxy measure has an ordinal rather than a cardinal scale.

because it occurs across international borders. Several country-level variables have been found to influence the bilateral volume of services trade and I focus on those characteristics that could influence the offshoring costs between the home and destination countries.[64] Following previous empirical works, I concentrate on the following set of country-level determinants: common language, cultural similarity, mutual membership in a free trade agreement (FTA), geographic distance, internet penetration, common legal origins, quality of legal institutions, and differences in time zones. In the following, I explain in more detail how each of these characteristics could influence offshoring costs. Table 3.1 summarizes the expected signs of the effect of each country-level variable according to previous findings.[65]

Table 3.1: Effect of country-level characteristics on offshoring costs

Variables	Expected Sign
D: Common language	-
D: Colonial ties	-
D: NAFTA	-
Geographic distance	+
ICT penetration	-
Quality of legal institutions	-
D: Common legal origins	-
Time zone difference	+ / -

Crémer et al. (2007) have argued that communication and thus coordination are easier within firms because they have developed a common "language" and share common norms and values. Accordingly, coordination failures can be expected to be less frequent if people speak the same language and fewer misunderstandings occur as a result. Head et al.'s (2009) results suggest that countries sharing a common language tend to have higher bilateral services trade flows.

Even if the populations of the two countries do not speak the same language, citizens can be familiar with the cultural idiosyncrasies of the other country. Familiarity can be expected to go hand in hand with higher levels of trust and understanding, which, in turn, facilitate coordination. Several variables could affect such cultural familiarity among countries. With respect to the impact of colonial ties as a proxy measure for cultural similarity, the results for services trade have not yet provided clear evidence (e.g., Kandilov and Grennes 2007; Head et al. 2009).

I also include a dummy variable for the North American Free Trade Agreement (NAFTA). Even if free trade agreements are designed to enhance goods

64 Production costs are affected, for instance, by the productivity-adjusted wage differentials between the source and the destination country.

65 For details on the data sources and the construction of these country-level variables, see appendix C.

trade, the resulting intensified trade relationships could also lead to a greater familiarity with local conditions. In line with this argument, Kandilov and Grennes (2007) as well as Manning et al. (2009) have provided evidence that mutual membership in a free trade agreement positively impacts the volume of services trade between two countries.

Many scholars argue that geographic distance should not have a significant impact on service offshoring. Because services are transported electronically, these scholars argue, the transport costs for services – unlike those for goods – do not depend on the geographic distance over which the service is transmitted. For instance, Kandilov and Grennes (2007) find that geographic distance has no explanatory power for services trade after controlling for the effect of networks, such as internet penetration among trading partners. However, there is evidence that distance does affect services trade and that it needs to be taken into account as a country-level determinant of offshoring costs (Head et al. 2009). The reason for this is that travel costs tend to be higher over long distances, people tend to have fewer travel experiences, and geographic distance can, hence, proxy for unfamiliarity (e.g., Grossman 1996). In line with this argument, the first instances of service offshoring occurred among trading partners that were geographically relatively close to each other (see also Baldwin 2006).[66]

Developments in Information and Communication Technologies (ICTs), such as the emergence and the spread of the Internet and the World Wide Web during the 1980s and 1990s, have significantly reduced the costs of the almost real-time transmission of instructions and information.[67] These cost reductions are seen as an important prerequisite in enabling the tradability of services. Accordingly, Freund and Weinhold (2002) found internet penetration to exhibit a strong positive effect on trade in services (see also Kandilov and Grennes 2007).

The findings of the incomplete contracts literature mentioned above indicate that the quality of the legal system enhances the security of contract enforcement, property rights etc. (Anderson and Marcouiller 2002). Furthermore, a similar legal system reduces the cost of gathering information about the relevant rules in the partner country. Both characteristics could enhance formal trust (Anderson 2000; Huang 2007) and thereby facilitate coordination that is required when tasks are offshored.

Time zone differences, on the one hand, can lead to offshoring benefits because they offer the possibility of providing certain services, such as call centers, around the clock ("continuity effect"). On the other hand, time zone differences complicate real-time communication during business hours ("synchronization effect," see Head et al. 2009, p. 435) and could thus hamper coordination. Hence, the overall effect is ambivalent, and previous works have not yet found

[66] An early instance of service offshoring was the offshoring of design tasks to Germany by the British motor industry in 1979 (Amiti and Wei 2004).

[67] The significant growth of the global telecommunications infrastructure in 1990 was facilitated by the immense investments in fiberoptic cables during the dot-com boom. In particular, the bust in 2001 has enabled many – also developing – countries to use these networks almost for free and thus gave another boost to offshoring (e.g., U.S. Government Accountability Office 2004, p. 10; Derimoglu 2006).

clear evidence on this matter (e.g., Head et al. 2009).

3.4 Econometric analysis

I estimate variants of the following equation to examine the joint impact of country-level characteristics and offshoring requirements on U.S. service offshoring patterns:

$$OFF_{sct} = \exp\left(c + \beta X_s * Z_c + \gamma Z_c + \delta X_s + d_t + \varepsilon_{sct}\right). \tag{7}$$

$s = 1, \ldots, S$ *Service*
$t = 1, \ldots, T$ *Time*
$c = 1, \ldots, C$ *Country*

OFF_{sct} is the U.S. service offshoring intensity in service industry s to country c in year t. X_s is the proxy measure for the offshoring requirements of service industry s, Z_c is a vector of country characteristics, $X_s * Z_c$ is a set of interactions between different country characteristics and the offshoring requirement proxy measure, X_s, and d_t is a set of time fixed effects.[68]

Equation (7) resembles a gravity equation. Usually, scholars employ gravity equations to estimate the effects of different country characteristics on bilateral trade flows.[69] In the present analysis it is the differential impact of country characteristics across service industries that is of interest, i.e., the coefficient β on the interactions. An example will help to illustrate this idea. The country-level variables that are assumed to affect offshoring costs include colonial ties. If the origin and destination countries share certain norms and values, these shared attributes will facilitate communication and thus coordination between the countries. As a consequence, I expect colonial ties to have a positive effect on the expected volume of service offshoring. This positive impact across all services is captured by the coefficient γ. In addition, I can test whether the impact of colonial ties differs with the task content and the offshoring requirements of the services. A statistically significant coefficient β on the interaction term would support this idea.

[68] Because the proxy measure of offshoring requirements is collinear with service industry fixed effects, these effects are excluded.

[69] Gravity models predict that the volumes of bilateral trade flows depend upon "centrifugal" and "centripetal forces" (Baldwin and Venables 2010, p. 3) that differ across trading partners. For a recent survey of the theoretical foundations and empirical specifications, see Baldwin and Taglioni (2006).

3.4.1 Discussion of estimation methods

In the following paragraphs, I examine the appropriateness of different estimators that have been discussed in debates about the econometric estimation of the gravity model.[70]

Traditionally, scholars have estimated multiplicative models, such as the gravity equation, by taking the logarithm to transform these models into an additive form before employing an ordinary least squares (OLS) estimator. However, this estimation approach suffers from two flaws. First, it cannot handle data that are rich in zero-value observations because the logarithm is not defined for non-positive values. As a consequence, many previous empirical studies have dropped the zero-value observations (e.g., Levchenko 2007; Chor 2010). However, these zero-value observations also depend on the regressors because they are more likely to occur, for instance, for distant and small countries.[71] Thus, dropping the zero-value observations implies a selection bias because the sample is no longer random (Westerlund and Wilhelmsson 2006).[72]

Santos Silva and Tenreyro (2006) emphasize a second problem. Even under the assumption that the dependent variable only takes on positive values, an OLS estimation of the logarithmic transformation has to address the problem of inherent heteroscedasticity, which can lead to inconsistent estimates. Even if the mean of the error term in the original model is independent of the regressors, if heteroscedasticity is present, the expected value of the logarithm of the error term is a function of the covariates because the expected value of the logarithm of a random variable also depends on its higher-order moments, such as the variance (see also Winkelmann 2008, pp. 97-98).[73]

As a solution to both problems, Santos Silva and Tenreyro (2006) propose to directly estimate the multiplicative form of the model with a Poisson pseudo-maximum likelihood (PPML) estimator. The basic Poisson regression model assumes a conditional Poisson distribution for the dependent variable. In other words, the density of the dependent variable is determined entirely by the conditional mean because the conditional variance and mean are assumed to be equal, $E(y|x) = V(y|x)$. However, the Poisson estimators are consistent even

[70] The focus on econometric issues was initiated by Anderson and van Wincoop's (2003) contribution showing that the traditional gravity equation has been misspecified because it only considers absolute measures as regressors and does not control for relative ones. They suggest augmenting it by introducing multilateral resistance terms, which are often proxied by remoteness indices. As has been shown by Feenstra (2004, pp. 161-163), an alternative approach that also leads to consistent estimates is to introduce exporter and importer fixed effects. See Burger et al. (2009) for a recent overview of possible estimation techniques in the context of the gravity equation.

[71] Trade values will also be registered as zero-value observations if they do not reach a certain minimum value, which is U.S. $500,000 for the United States.

[72] According to the Monte Carlo simulations conducted by Santos Silva and Tenreyro (2006), other procedures will also lead to inconsistent and biased estimators to different degrees. These approaches include the use of a Tobit estimator and the replacement of $Y_{sct} = 0$ with $Y_{sct} + 1$, which is followed by the estimation with OLS.

[73] Santos Silva's and Tenreyro's (2006) illustration focuses on the gravity model but their criticism applies to constant-elasticity models and the OLS estimation of their non-linear transformations in general.

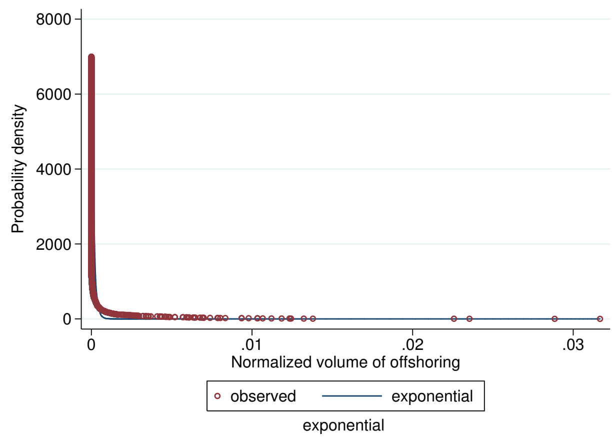

Figure 3.6: Density probability plot exponential

if the dependent variable is not a count variable and the underlying distribution is not Poisson. According to maximum likelihood theory, for the estimator to be consistent, the conditional mean of the dependent variable needs to be correctly specified by a distribution belonging to the linear exponential family, i.e., $E\left[y_i \left| x_i \right.\right] = \exp\left(x_i \beta\right)$ (Gourieroux et al. 1984). Plotting the empirical and theoretical density probabilities in figure 3.6, I find that the exponential distribution seems to describe the data well. Another advantage offered by the exponential distribution is that it accounts for the fact that offshoring flows can be zero but not negative.[74]

A potential problem is that the data exhibit overdispersion (i.e., the mean is smaller than the variance). Hence, the assumption that the conditional variance is proportional to the conditional mean is violated. As a result, the standard errors will be downward biased and p-values misleadingly small (see Long and Freese 2006, p. 376). Overdispersion may be addressed through the application of a negative binomial (NB) model. In this case, the variance depends not only on the conditional mean, but also on a dispersion parameter. Whether the Poisson or the negative binomial regression model is a better fit to the data can be tested by applying a likelihood ratio test for overdispersion. If the dispersion parameter alpha is zero, the NB model reduces to the Poisson model (see Cameron and Trivedi 2010, pp. 577-581). This case applies to the present analysis, and there is no significant evidence of overdispersion (G^2= 3.3e - 05,

[74] Another possibility to correct for the selection bias introduced by non-random zero-value observations is the two-step Heckman (1979) sample selection model or its extension by Helpman et al. (2008), which additionally controls for the bias resulting from unobserved firm heterogeneity. However, unlike the Poisson-family models, these methods rely on stringent distributional assumptions, in particular with respect to the homoscedasticity of the error term (see Santos Silva and Tenreyro 2009). Furthermore, a practical drawback compared to the PPML technique is the necessity to find an exclusion restriction to facilitate identification of the second stage.

p = 0.498).[75]

Another problem I could encounter are "excess" zeroes (i.e., there would be more zero-value observations than predicted by a Poisson model). This problem can be addressed by applying zero-inflated models, such as the zero-inflated Poisson (ZIP) model. Zero-inflated models are based on the assumption that zero-value observations can result from two different data generating processes.[76] In the inflated part of the regression model the effects on the probability of observing zero-value offshoring volumes are estimated by a logit model, $P(y = 0 \mid x)$. This probability may depend, for example on geographic distance but also on other factors, such as trade embargoes, that do not influence the volume of offshoring. Then, in a second step, the impact of the regressors on the volume of offshoring (which can also be zero) is estimated by a Poisson model for all observations that have a non-zero probability of offshoring (see Cameron and Trivedi 2010, pp. 599-605). In other words, also countries that are not receiving any offshored services in a certain year or a certain service industry would be included in this sample because they could potentially have obtained offshored services. As a result, the effects of the regressors are allowed to differ for offshoring flows that have a zero probability and for those that have a non-zero probability of offshoring. To compare the standard Poisson model and the zero-inflated regression model, I employ the Vuong test. Under the null hypothesis that the probability of being in the "always zero" group is zero, the test statistic has an asymptotic standard normal distribution. Large positive values indicate that the zero-inflated version is more appropriate, whereas large negative values favor the standard model (Long and Freese 2006, pp. 408-409). The Vuong test shows that the zero-inflated Poisson regression is a better fit for the data than the standard Poisson model (z-value of 34.29). As a result of the different tests performed, I estimate equation (7) via a zero-inflated Poisson (ZIP) regression model.[77]

3.4.2 Estimation results

This section examines the estimation results of the ZIP regression. Table 3.2 reports the estimates of equation (7), with column (1) presenting the baseline

[75] The likelihood ratio test statistic is based on the difference between the two log-likelihood values; the distribution is a mixture of a chi-squared distribution with no degrees of freedom and a chi-squared distribution with one degree of freedom (see Winkelmann 2008, pp. 113-114).

[76] According to Greene (1994) excess zeroes can "masquerade" as overdispersion and it is important to disentangle both problems because we need to employ different methods to address them. In other words, even if the negative binomial model can deal with the problem of overdispersion due to unobserved heterogeneity, unlike zero-inflated models, it assumes an identical data generating process for all zero-value observations. More precisely, zero-inflated models allow for two types of zeroes (unlike hurdle models, which allow for only one type of zero). See Winkelmann (2008, pp. 188-189).

[77] No consensus has yet been achieved as to whether the efficiency of the PPML estimator depends on the proportion of zero-value observations (see, e.g., Martin and Pham 2008 as compared to Santos Silva and Tenreyro 2011). I have also estimated equation (7) via PPML, and the results on the interaction terms are robust across these different estimation techniques. Results are available upon request.

results. The results in column (2) are based on clustered standard errors at the country level, and column (3) presents the preferred specification.[78]

One obvious concern is that the estimates of equation (7) could be biased because of omitted variables. Hence, in addition to the variables of interest, I include several control variables for alternative determinants of service offshoring patterns that could be correlated with (parts of) the interaction terms. In particular, I include a proxy measure for skill intensity at the industry level, a proxy measure for skill endowments at the country level, their interaction term, and a wage proxy measure, i.e., gross domestic product (GDP) per capita.[79]

The result in column (1) of table 3.2 implies that an increase in the offshoring requirement proxy variable decreases the expected share of offshoring. In line with the construction of this proxy variable (see pp. 48-50), this finding suggests that an increase in this score indicates an increase in offshoring costs. This result is also economically significant in magnitude and indicates, ceteris paribus, that for a one standard deviation increase in the offshoring requirement score, roughly 0.29, the expected share of offshoring decreases by roughly 99 percent.

In line with previous results, I find that the higher the quality of a country's legal environment, as measured by the Kaufman et al.'s (2009) rule of law index, the higher is the expected share of offshored services that a country attracts. This result is significant at the 1 percent level. With respect to the magnitude of this effect, the ZIP specification in column (1) suggests that a one standard deviation increase in the rule of law index, roughly 0.21, increases the expected share of offshoring by a factor of 4.46.

Similar to the quality of legal institutions, a common legal origin (i.e., UK legal origins), colonial ties, and time zone differences positively affect the expected service offshoring flows that a country attracts from the United States, whereas geographic distance and being a member of NAFTA decrease the expected offshoring flows. The coefficients on the common language dummy and on the measure of internet penetration are not statistically significant at any of the conventional levels.

Let us now focus on the discussion of the results regarding the interaction effects. The coefficients on the respective interaction terms with the offshoring requirement measure are not statistically significant at any of the conventional levels for the following country-level variables: the quality of legal institutions, a common legal origin, a common language, internet penetration, and time zone differences. These findings do not imply that these variables do not affect off-

[78] The regression results for the inflated part of the ZIP regression are suppressed because none of the regressors is statistically significant at any of the conventional levels. These results are available upon request.

[79] Skill endowments are measured by the average years of tertiary schooling in a country and skill intensity is measured by the share of college graduates in the overall employment of an industry. See appendix C for details on the data sources.

Table 3.2: Zero-inflated Poisson regression (ZIP)

	(1)	(2)	(3)
Dependent variable: *Offshoring intensity*			
Offshorability score	-25.88***	-25.88	-33.06*
	(7.732)	(16.91)	(15.96)
Skill intensity	1.234	1.234	1.047
	(0.750)	(1.348)	(1.309)
Skill endowment	0.0596	0.0596	-0.0873
	(0.527)	(1.087)	(1.100)
interacted with			
*skill intensity	-1.063	-1.063	-0.784
	(0.828)	(1.599)	(1.425)
Rule of law	7.125***	7.125	6.317
	(1.364)	(3.870)	(3.935)
interacted with			
*offshorability score	-2.149	-2.149	
	(1.751)	(2.321)	
D: Common legal origin	0.788**	0.788	0.588
	(0.264)	(0.614)	(0.415)
interacted with			
*offshorability score	-0.431	-0.431	
	(0.521)	(0.797)	
D: Common language	0.307	0.307	0.462
	(0.252)	(0.562)	(0.599)
interacted with			
*offshorability score	-0.911	-0.911	-1.370
	(0.571)	(0.899)	(1.085)
D: Colonial ties	0.939**	0.939	0.896
	(0.331)	(0.572)	(0.593)
interacted with			
*offshorability score	2.043**	2.043*	2.343*
	(0.710)	(0.975)	(0.959)
. . .			

Table 3.2: ZIP; continued

	(1)	(2)	(3)
Dependent variable:			
Offshoring intensity			
D: NAFTA	-3.463*	-3.463	-3.682
	(1.700)	(4.118)	(3.891)
interacted with			
*offshorability score	9.796***	9.796*	11.06**
	(2.130)	(4.482)	(4.240)
Time zone differences	0.276**	0.276	0.294
	(0.0855)	(0.248)	(0.235)
interacted with			
*offshorability score	-0.0521	-0.0521	-0.0910
	(0.131)	(0.309)	(0.290)
log(Geographic distance)	-2.334**	-2.334	-2.489
	(0.711)	(1.913)	(1.812)
interacted with			
*offshorability score	3.090**	3.090	3.703
	(0.942)	(2.113)	(1.986)
Internet penetration	0.000607	0.000607	0.000596
	(0.000509)	(0.000932)	(0.000765)
interacted with			
*offshorability score	-0.000185	-0.000185	
	(0.00114)	(0.00136)	
log(GDP per capita)	-0.153	-0.153	-0.160
	(0.219)	(0.619)	(0.606)
Fixed effects	Year	Year	Year
Observations	3,724	3,724	3,724
Log pseudolikelihood	-4.6577169	-4.657717	-4.661246

Column (1): Robust standard errors in parentheses;

columns (2) and (3): Clustered standard errors at the country level in parentheses;

* significant at 10%; ** significant at 5%; *** significant at 1%

shoring; they only suggest that the variables do not significantly affect relative offshoring shares of services depending on their task content. Put differently, regardless of the task content of the respective service, these country-level characteristics affect the expected share of offshoring identically.

The coefficients on the interaction terms with the NAFTA dummy, the colonial ties dummy and geographic distance are all positive and statistically significant at least at the five percent level. Unfortunately, the zero-inflated Poisson regression cannot yet be extended to a fixed-effect estimator (see Winkelmann 2008, p. 227). However, the standard Poisson pseudo-maximum likelihood estimator can be extended to a fixed-effect Poisson pseudo-maximum likelihood estimator (see Westerlund and Wilhelmson 2006). To check the robustness of the interaction effects with regard to potential unobserved country heterogeneity, I also performed a fixed-effect Poisson quasi-maximum likelihood regression. Problematically, not only are time-invariant regressors wiped out, but also those observations for which the volume of offshoring does not change over time.[80] Because the panel is relatively short, this is highly likely to occur. When employing a fixed-effect Poisson pseudo-maximum likelihood estimator, the number of observations drops from 4,585 to 917. Many zero-value observations are eliminated and, as argued on page 54, because the zeros in the sample are not random this not only implies a loss of information but also a sample selection bias.[81] As an alternative robustness check for unobserved country-level heterogeneity, I base inference in the ZIP regression on clustered standard errors at the country level. Column (2) in table 3.2 shows the results. The results regarding the interaction effects of NAFTA and colonial ties are robust to this additional control, whereas the interaction effect with geographic distance loses statistical significance. Second, I estimate a ZIP regression with clustered standard errors without those interaction effects that were not significantly different from zero at the 10 percent significance level. Column (3) presents the results and shows that the interaction effects with the NAFTA dummy and the colonial ties dummy are, again, robust to this alternative estimation.[82]

The following economic interpretation of the interaction effects focuses on the results in column (3). Colonial ties increase the expected share of offshoring (see column (1)). The positive and significant interaction term suggests that this effect is even stronger for those services with relatively high offshoring requirements. As colonial ties proxy for cultural similarity, this result is consistent

[80] As a result, the effects of time-invariant country-level regressors cannot be estimated because they are wiped out by the fixed effects. In the case of the present sample, one can neither estimate the effects of bilateral variables - because there is only one source country, i.e. the United States. This is not an insurmountable problem because I can nonetheless focus on the interaction effects of industry-level and country-level characteristics.

[81] To check the robustness of the interaction effects with regard to potential unobserved country heterogeneity, I nonetheless performed a fixed-effect Poisson quasi-maximum likelihood regression. The interaction effects are, again, statistically significant and have the same signs. The economic magnitude is similar, but slightly smaller. Results are available upon request from the author.

[82] Table A.10 in appendix D shows the results of the stepwise deletion of insignificant variables. Note that the interaction terms with NAFTA and colonial ties are statistically significant in each of these steps.

with expectations. A higher cultural familiarity enhances trust and understanding and is especially important for exchanges of information that rely primarily on mutual understanding. With respect to the economic magnitude of this effect, let us focus on two services, i.e., management and consulting services as well as financial services, and on two countries, i.e., the United Kingdom and Poland. These two industries and countries offer cases for which the calculation of the economic magnitude is easily illustrated. The reason for this is that the colonial ties dummy is one for the United Kingdom and zero for Poland, and, similarly, the offshoring susceptibility proxy measure is zero for financial services as compared to one for management/consulting services. The coefficient on the interaction term in column (3) implies that, ceteris paribus, the offshoring flows of management and consulting services (relative to financial services) are higher in the United Kingdom than in Poland by a factor of 10.41.[83]

The NAFTA dummy has a differential impact depending on the service industry's task content. For those services that have the lowest offshoring requirements, the expected share of offshoring is lower for Canada and Mexico (see column (1)). In contrast, for those services that require more prerequisites for offshoring, the expected share of offshoring increases for NAFTA countries. One economic interpretation is that for highly complex, context-dependent services, offshoring costs also depend on smooth communication and understanding, and the respective coordination is easier with those countries either because of the experiences already gained in previous trade relations or because these countries have a common border with the United States.[84] The result in column (3) implies that, ceteris paribus, for a one standard deviation increase in the offshorability score, service offshoring flows are higher in Canada than in Germany by a factor of 24.71.[85]

3.5 Conclusion

Service offshoring is currently one of the most heatedly debated aspects of international trade, in academic and political debates alike. However, because of data limitations, little empirical evidence has been provided to broaden our understanding of this new trade phenomenon. This chapter offers new evidence on the determinants of U.S. service offshoring by matching data on the task content of service industries with bilateral services trade data and input-output data from the Bureau of Economic Analysis.

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83 See Winkelmann (2008, pp. 71-72) for the proof that

$$E\left[\frac{Z_c=1, X_s=1}{Z_c=1, X_s=0} \Big/ \frac{Z_c=0, X_s=1}{Z_c=0, X_s=0}\right] = \exp(\beta).$$

84 Because I only consider the United States as the offshoring country, the NAFTA dummy and the common border dummy are perfectly collinear, so that I cannot disentangle these two variables.

85 Nunn (2007) emphasizes that there could be reverse causal influence. In other words, the pattern of specialization influences institutional features, such as the quality of legal institutions. However, in the present analysis, the country characteristics in the relevant interaction terms are such, that they are unlikely to be affected by the pattern of offshoring.

Much of the recent literature in international trade and in labor economics has argued that offshoring costs differ across services according to their task content. I connect this task-based approach to the literature on the generalization of sources of comparative advantage to offer new insights into the mechanisms through which country characteristics affect offshoring patterns. More specifically, I have tested whether the interplay of the task content and country endowments determines actual offshoring costs.

The present results suggest that the interaction between task characteristics and country characteristics is important for the effects of colonial ties and of a membership in NAFTA. A better quality of legal institutions, a common legal origin, geographic distance, and time zone differences influence offshoring patterns identically across all service industries, regardless of their offshoring requirements. This evidence extends previous empirical works on the country-level determinants of service offshoring and presents a more fine-grained picture.

Many scholars have argued that services will become increasingly tradable because of technological progress. These scholars argue that technological change enables the cheaper transmission of ever more data (Blinder 2007). In contrast, some evidence suggests that the task content of service occupations has become more complex over time (Spitz-Oener 2006). The present analysis suggests that such complex services rely particularly on understanding and trust, which for the United States are enhanced by its colonial ties and a membership in NAFTA. These findings shed doubt on the prediction that the spread of ICTs is automatically leading to an increasingly flat world for trade flows of services.

Acknowledgements I would like to thank Eduardo Morales, Andreas Moxnes, and Petra Zloczysti for helpful comments on earlier versions of this article.

Appendix A: Offshoring proxy measure

Following the National Academy of Public Administration (2006b, p. 62), I calculate the ratio of intermediate uses to total domestic supply per service industry as follows. First, to calculate the total domestic supply per service industry, I add Service Imports (SI) to Total Service Output (TSO) because they enhance the domestic availability of a certain service. Second, domestic availability decreases if the service is exported such that Service Exports (SE) have to be subtracted:

$$\frac{SP_{st}}{TSO_{st} + SI_{st} - SE_{st}}. \tag{8}$$

The information needed to estimate equations (4) and (8) comes from BEA input-output tables.

The volume of U.S. service offshoring for different destination countries is calculated based on the following equation:

$$off_{sct} = impint_{st} \times \frac{SI_{sct}}{\sum_{c=1}^{C} SI_{sct}}, \tag{9}$$

which after canceling leads to equation (5).

The information on bilateral U.S. services imports comes from the BEA bilateral trade data. Figure 3.7 illustrates the structure of the service industry classification in official U.S. statistics.

Figure 3.7: Structure of the service industry classification in U.S. statistics

- Government services
- Private services
    - Travel Passenger fares
    - Other transportation
    - Royalties and license fees
    - Other private services
        - Education
        - **Financial services**
        - **Insurance services**
        - **Telecommunications**
        - Business, professional, and technical services (BPTs)
            - **Computer and information services**
            - **Management and consulting services**
            - Research and development and testing services
            - **Legal services**
            - **Other (BPT) services**
        - Other (private) services

Within the category of other private services, I disregard information on two subcategories, i.e., education and other (private) services. Education includes the payments of U.S. students studying abroad and excludes payments for distance learning. Other (private) services consist mainly of copyright payments for foreign motion pictures and television programs (see Koncz and Flatness 2008, p. 20).

Business, professional, and technical services can be classified into nine different subcategories. Unfortunately, the input-output tables provide information for these subcategories only at a more aggregate level than bilateral trade data. The activities within two subcategories (i.e., construction, architectural, and engineering services and installation, maintenance, and repair of equipment) need to be performed in a fixed location. Consequently, I classify them as entirely non-tradable and exclude them from the analysis. The remaining subcategories include computer and information services, legal services, management, consulting, public relations, and other business, professional, and technical services. The latter category includes among other things accounting, auditing, bookkeeping, and training services. In table 5 of the Detailed statistics for cross-border trade, the BEA provides information on *telecommunications, financial services,* and *insurance services.* In table 7, the BEA offers information classified by trading partner at the level of *legal services, computer and information services, management, consulting, public relations*, and *other business, professional, and technical services.*

The traded services in bilateral trade data are classified according to a commodity basis, with commodity groups approximating the categories of the North American Industry Classification System (NAICS). In the input-output tables, commodities are classified according to so-called input-output codes. The BEA offers a concordance list between these codes and the industry classifications according to the three- and four-digit 2002 NAICS. As a result, information from both data sources can be converted to the common classification of three- or four-digit 2002 NAICS.

Concordance has been established between the commodity group titles and three- or four-digit 2002 NAICS codes by using information provided in table 7 of the BEA's "Detailed statistics for cross-border trade" as well as information on the content of industries according to the NAICS classification. The list provided in the BEA's input-output tables has served to create concordance between the input-output codes and the NAICS codes. The results are displayed in table A.1 and table A.2 lists the destination countries of U.S. service offshoring between 2006 and 2009.

Table A.1: Concordance between BEA commodity codes, input-output codes and NAICS codes

Commodity industry	**Input-output codes**	**2002 NAICS codes**
Financial services	521C1, 523, 525	522000, 523000, 525000
Insurance services	524	524000
Telecommunications	513	517000
Computer and information services	5415, 514	541500
Management, consulting and public relations	55	551100
Legal services	5411	541100
Other (business, professional and technical) services	5412OP	541900

Table A.2: U.S. service offshoring destinations

Argentina	Germany	Malaysia	Spain
Australia	Hong Kong SAR, China	Mexico	Sweden
Belgium	India	Netherlands	Switzerland
Bermuda	Indonesia	New Zealand	Thailand
Brazil	Ireland	Norway	United Kingdom
Canada	Israel	Philippines	Venezuela, RB
Chile	Italy	Saudi Arabia	
China	Japan	Singapore	
France	Korea, Rep.	South Africa	

Appendix B: Offshoring susceptibility index

The 2000 SOC system distinguishes between 840 detailed occupations according to their occupational definitions. To facilitate classification, the system groups detailed occupations with similar job duties in 461 broad occupations, 97 minor groups, and 23 major groups. Service occupations include the major groups 11, 13, 15 to 29, 31 to 39, 41, 43, 49, and 53. For further information, see the Bureau of Labor Statistics webpage. Of all service occupations, Moncarz et al. (2008) classify the following major groups as entirely non-tradable: community and social service occupations (SOC 21-0000); food preparation and serving-related occupations (SOC 35-000); building and grounds cleaning and maintenance occupations (SOC 37-0000); personal care and service occupations (SOC 39-0000); and transportation and material moving occupations (SOC 53-0000).

Table A.3 exemplarily illustrates the information on the occupational-level offshoring susceptibility measure provided in Moncarz et al. (2008) for the major group management occupations (SOC 11-0000).

Table A.3: Offshoring susceptibility score

SOC code	Occupation title	Offshoring susceptibility score Moncarz et al. (2008)
11-3041	Compensation and benefits managers	9
11-3031	Financial managers	7
11-3042	Training and development managers	7
11-1011	Chief executives	6
10-1021	General and operations managers	6
11-3011	Administrative services managers	6
11-3021	Computer and information systems	6
11-2011	Advertising and promotions managers	5
11-2021	Marketing managers	5
11-2022	Sales managers	5
11-2031	Public relations managers	5
11-9041	Engineering managers	5
11-9121	Natural science managers	5

Source: Moncarz et al. (2008)

Appendix C: Country-level variables

Information about GDP (in current U.S. dollars) and population for all countries is provided by the World Development Indicators database. Average years of tertiary schooling are provided by the Barro-Lee database on educational attainment. To construct a proxy measure for skill intensity at the industry level, information about educational attainment at the occupational level is obtained from Moncarz et al. (2008) and then aggregated up to the industry level in the way described in equation (6) for the offshoring susceptibility proxy measure. I follow the traditional approach in the gravity equation literature and measure the so-called great circle distance. This variable measures the geographic distance between the economic centers of countries, with the centers assumed to be the capitals. This distance measure is provided by the CEPII database. Information on time zone differences was obtained from Wikipedia and from the World clock. I followed Head et al. (2009) and calculated time zone differences by employing $\min\{|h_{US} - h_c|, 24 - |h_{US} - h_c|\}$. Based on information provided by the ethnologue-based version of common language, I created a dummy variable that takes the value of one if at least nine percent of the population in the destination country speak English. A dummy which indicates whether English is an official language in the destination countries might not provide a very good proxy measure for the existence of English skills in the relevant business circles because English is a common second language in many countries, particularly in business environments. For instance, English is the standard in the provision of technology related services (Rishi and Saxena 2005, p. 8).[86] The dummy for a common legal system takes the value of one if the destination country is – like the United States - classified as having UK legal origins. Information on this is taken from Andrei Shleifer's database. Moreover, I control for the quality of legal institutions in the destination country by employing information on the rule of law from Kaufmann et al. (2009). I transform the original variable so that it only takes on non-negative values. NAFTA membership is indicated by a dummy variable taking the value of one if the country is a member, i.e., for Canada and Mexico. I follow Kandilov and Grennes (2007) and Head et al. (2009) and employ information on colonial ties as a proxy measure for cultural similarity. This information is again obtained from the CEPII bilateral database. Internet penetration is measured as secure servers per 10,000 people. This information is provided by the World Development Indicators database.

Table A.5 shows the summary statistics for these country-level variables and confirms that all variables have the expected range. Table A.6 shows the correlation coefficients between the different country-level variables.

Table A.4: Country-level characteristics, summary statistics

Variable	Observations	Mean	Standard Deviation	Min	Max
D: Colonial ties	5124	0.0327869	0.1780957	0	1
D: Common language	5124	0.420765	0.4937301	0	1
log(Distance)	5124	8.934286	0.5365834	6.306995	9.691551
log(GDP per capita)	4928	8.278473	1.596703	4.794486	11.67806
Internet penetration	4795	147.8556	329.373	.0127152	3229.814
D: Legal origin UK	5124	0.3224044	0.4674424	0	1
D: NAFTA	5124	0.010929	0.103979	0	1
Rule of law	5096	0.5637054	0.2120641	1337076	.9999999
Time zone difference	5124	5.68306	3.282677	0	12
Skill endowment	3892	0.3780683	0.3182467	.0064	1.5562

[86] The interaction effects are robust to the alternative common language measure that indicates whether English is an official language in the destination country. The results are available upon request from the author.

Table A.5: Correlation coefficients between country-level characteristics

	D: Colonial ties	D: Common language	log(Dist-ance)	log(GDP per capita)	Internet penetration	D: Legal origin UK	D: NAFTA	Rule of law	Skill endowment
D: Common language	0.1135	1							
log(Dist-ance)	-0.0244	-0.2061	1						
log(GDP per capita)	0.1317	-0.0896	-0.2432	1					
Internet penetration	0.0609	-0.0255	-0.2222	0.6139	1				
D: Legal origin UK	-0.0437	0.3774	0.2178	-0.1058	0.0215	1			
D: NAFTA	-0.0210	0.1495	-0.4295	0.1101	0.1317	0.0478	1		
Rule of law	0.1462	-0.0416	-0.1053	0.8138	0.7175	0.0577	0.0735	1	
Skill endowment	0.2048	-0.0280	-0.2239	0.6455	0.5235	-0.1265	0.1969	0.5458	1
Time zone difference	0.0820	-0.3771	0.7233	-0.0325	0.0157	0.1069	-0.2084	0.1035	0.0856

Appendix D: Additional regression results

Table A.8 presents additional results of the zero-inflated Poisson regressions. Column (1) is the specification shown in column (2) of table 3.2. Column (4) is identical to the preferred specification shown in column (3) of table 3.2.

To decide which variables to include in the model, I perform the Wald test. The Wald test shows that I cannot reject $H_0 : \beta = 0$ for internet penetration, time zone differences, common legal origin, rule of law, and common language; both separately and interacted with the offshoring requirement measure, because $p > 0.05$.

Kandilov and Grennes (2007) have shown that distance is a proxy measure for time zone differences and linguistic differences. Consistent with their findings, the measures for time zone differences and geographic distance are highly correlated (0.7233; see table A.6 in appendix C). Consequently, I keep the interaction terms that include time zone differences and the common language dummy to control for these variables.

The Akaike information criterion (AIC) and the Bayesian information criterion (BIC) can be used to select among several (nested and non-nested) models. Both criteria are based on the log likelihood of the model and introduce penalties for adding parameters to the model which can increase the log likelihood. Stata calculates them as follows:

$$AIC = -2 \ln L + 2P_k,$$

$$BIC = -2 \ln L + P_k \ln N,$$

where $\ln L$ is the log likelihood of the model and $2P_k$ and $P_k \ln N$ are the penalties for the model size. Note that the BIC penalizes increases in model size more strongly. Because a larger log likelihood is preferred, the model with a smaller AIC and BIC is favored. In particular the second model is favored when $BIC_1 - BIC_2 > 0$ (see Long and Freese, 2006, pp. 112-113; Cameron and Trivedi, 2010, pp. 359-360). Raftery (1996) suggests the guidelines shown in table A.7 for assessing the difference in the BICs from different models. In the present analysis, there is at least strong evidence in favor of the last specification (column (4)) in comparison with every other specification in table A.8.

Table A.6: BIC, Strength of evidence

Difference	Evidence
0-2	Weak
2-6	Positive
6-10	Strong
$>$10	Very strong

Source: Long and Freese (2006, p. 113)

Table A.7: Zero-inflated Poisson regression (ZIP)

	(1)	(2)	(3)	(4)
Dependent variable:				
Offshoring intensity				
Offshorability score	-25.88	-25.86	-25.64	-33.06*
	(16.91)	(16.86)	(15.90)	(15.96)
Interaction between				
Internet penetration	-0.000185			
& offshorability score	(0.00136)			
D: Common legal origin	-0.431	-0.434		
& offshorability score	(0.797)	(0.788)		
Rule of law	-2.149	-2.393	-2.587	
& offshorability score	(2.321)	(1.888)	(1.772)	
Time zone differences	-0.0521	-0.0482	-0.0528	-0.0910
& offshorability score	(0.309)	(0.306)	(0.297)	(0.290)
D: Common language	-0.911	-0.922	-1.203	-1.370
& offshorability score	(0.899)	(0.874)	(1.120)	(1.085)
D: Colonial ties	2.043*	2.072*	2.169*	2.343*
& offshorability score	(0.975)	(0.906)	(0.928)	(0.959)
D: NAFTA	9.796*	9.825*	9.731*	11.06**
& offshorability score	(4.482)	(4.419)	(4.201)	(4.240)
log(Geographic distance)	3.090	3.098	3.085	3.703
& offshorability score	(2.113)	(2.105)	(1.998)	(1.986)
Skill intensity	1.234	1.216	1.255	1.047
	(1.348)	(1.295)	(1.324)	(1.309)

...

Table A.7: ZIP; continued

	(1)	(2)	(3)	(4)
Dependent variable:				
Offshoring intensity				
Skill endowment	0.0596	0.0409	0.0766	-0.0873
	(1.087)	(1.070)	(1.116)	(1.100)
interacted with				
*skill intensity	-1.063	-1.037	-1.087	-0.784
	(1.599)	(1.517)	(1.554)	(1.425)
log(GDP per capita)	-0.153	-0.152	-0.141	-0.160
	(0.619)	(0.618)	(0.609)	(0.606)
Fixed effects	Year	Year	Year	Year
Observations	3,724	3,724	3,724	3,724
Log pseudolikelihood	-4.657717	-4.657764	-4.658309	-4.661246
AIC	109.3	105.3	107.3	103.3
BIC	420.4	404.0	412.2	395.8

Columns (1) to (4): clustered standard errors at the country level in parentheses;

* significant at 10%; ** significant at 5%; *** significant at 1%

4 Wage effects of U.S. service offshoring by skills and tasks

Abstract

In this chapter, I estimate the impact of service offshoring on the real wages of U.S. workers by controlling for workers' skill levels and the offshoring susceptibility of occupations. Matching individual-level wage data with input-output tables over the period from 2006 to 2009, I am further able to account for unobservable individual-level heterogeneity. The results from a Mincerian wage regression indicate that within skill groups, the impact of service offshoring on real wages depends on the task content of the respective occupation. The real wages of medium- and high-skilled workers employed in the least offshorable occupations were positively affected by service offshoring. However, within the groups of medium- and high-skilled workers, service offshoring negatively affected the real wage of the most tradable occupations.

Keywords: *Offshoring, services, tasks, wages*

JEL classification: *F14, F16, J31, F20*

4.1 Introduction

Before the mid-1990s, the supply of intermediate inputs from abroad primarily concerned the trade in goods. However, during that same time period, service-providing tasks started to become increasingly offshored. The offshoring of service occupations, that were previously considered as non-tradable, has led researchers to question whether service offshoring affects labor markets in a qualitatively and quantitatively different manner from the offshoring of manufacturing activities (e.g., National Academy of Public Administration 2006a; Molnar et al. 2007; Bhagwati and Blinder 2009). Alan S. Blinder (2006) has even predicted that the resulting changes in occupational compositions could turn out to be comparable to the industrial revolution.

Traditionally, the fortunes of workers were seen as tied to their skill levels. According to the Heckscher-Ohlin trade model the interplay of country factor endowments and industry factor intensity shapes the distributional consequences of trade. Recent empirical insights indicate that these predictions need to be refined. With the advent of service offshoring it became clear that there might be no systematic relationship between the offshoring susceptibility of different occupations and the educational attainments of the workers performing the occupations. Moreover, even if two occupations are classified as susceptible to offshoring, several scholars emphasize that the offshoring costs across them may be heterogeneous and may change over time (Blinder 2007; Moncarz et al. 2008). As a consequence, the distributional effects of globalization are more complex and harder to identify than traditionally assumed. As Paul R. Krugman concludes, "[p]utting numbers on these effects [...] will require a much better understanding of the increasingly fine-grained nature of international specialization and trade." (Krugman 2008, p. 135) In other words, one of the main tasks for trade and labor economists is to quantify the impact of service offshoring on the labor market at a finer level of aggregation.

I estimate the effect of service offshoring on the real wages of workers in the United States by controlling for skills and tasks. Skills are measured by the educational attainment of the workers and tasks by the offshoring susceptibility of occupations. The present analysis differs from similar studies for the United States in the following respects: First, in contrast to most studies, I focus on service industries rather than manufacturing industries. Second, I use wage data at the individual level rather than at the firm or industry level. Third, I focus on the interplay between skills and tasks in determining wages. Fourth, I estimate the impact of offshoring across industries. In so doing, I take the effects of labor mobility across industries into account and analyze a situation that is more in concordance with a general-equilibrium setting.

Two similar analyses by Baumgarten et al. (2010) and Ebenstein et al. (2011) confirm that the wage effects of offshoring become significant if one accounts for the cross-industry movements of workers. My work differs from Ebenstein et al. (2011) because it focuses on offshoring rather than total trade or foreign direct investment. Furthermore, I analyze a set of potential offshoring susceptibility determinants different from those analyzed by both Ebenstein et al. (2011) and Baumgarten et al. (2010). Finally, I focus on service industries in the United States rather than on manufacturing industries in Germany, as Baumgarten et al. (2010) do.[87]

Because I examine the period from 2006 to 2009, this analysis also contributes to the literature by using more recent data than most other analyses. As Feenstra (2010, p. 104) has emphasized, although offshoring has further in-

[87] Ebenstein et al. (2011) have also focused on manufacturing industries. Regarding the task content, Ebenstein et al. (2011) have only taken the routine content of an occupation into account, even though many recent contributions suggest that - unlike for a occupation's automatization potential - routineness is only one of many task characteristics that influence an occupation's offshoring susceptibility. See chapter 2 of this dissertation for an analysis that sheds doubt on the assumption that the routine content is the sole determinant of offshorability. Baumgarten et al. (2010) have established two binary classifications. One is based on the routine content of occupations and the other one on the degree to which occupations involve interactive tasks.

creased during the last decade - for example, because of further declines in data transmission costs - trade economists have not empirically assessed the impact of offshoring on U.S. wages during this period.[88]

Methodologically, I longitudinally match the Outgoing Rotation Group (ORG) samples from the Current Population Survey (CPS) to obtain a panel data set for U.S. workers' real wages. Then, I combine these matched CPS ORG data for 2006–2009 with input-output tables from the Bureau of Economic Analysis (BEA).

The results indicate that, depending on the offshoring susceptibility of the respective occupation, service offshoring can influence wages in different directions. The real wages of medium- and high-skilled workers employed in the least offshorable occupations have increased, whereas, within these skill groups, the occupations that are most susceptible to offshoring have experienced real wage declines with increasing service offshoring.

This chapter is subdivided into four sections. Section 4.2 offers a short review of the relevant theoretical and empirical literature. Section 4.3 presents the data (4.3.1) and describes the empirical specification (4.3.2). Section 4.4 presents the results and section 4.5 consists of a summary and discussion of the findings.

4.2 Literature review

Researchers in labor economics and international economics have recently started to devote substantial attention to the so-called task-based approach. The main insight of this approach is that the task content of occupations offers information that is relevant for a systematic analysis of the labor market. In particular, this body of literature distinguishes between the workers' educational attainments and the tasks that they perform in their occupations. This distinction becomes crucial when we acknowledge that workers with a certain educational level can perform a variety of different tasks, such that there is no one-to-one relationship between skills and tasks and that international trade and technological change affect the demand for tasks across skill levels (see, e.g., Autor et al. 2003). Supporting these ideas, Acemoglu and Autor (2011) provide evidence that the worker's occupational affiliation has gained in importance as a determinant of wages in comparison with the educational attainments of the workers or their industry affiliations since the 1990s.

In the context of international trade, winners and losers were traditionally identified by their respective skill categories.[89] The focus on skills was justified

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[88] Ebenstein et al.'s (2011) analysis also suggests that the impact of material offshoring has increased over time. They find the strongest impact of offshoring on wages during the latest sub-period of their sample. However, this period only lasts from 1997 to 2002. Crinò (2010) has analyzed the period from 1997 to 2006, but focuses on the impact of service offshoring on employment in the United States.

[89] The human capital literature provides different views on the appropriate characterization of labor market skills. The international trade literature employs proxy measures for the so-called general human capital and largely distinguishes solely between skilled and unskilled workers by employing information about non-production and production workers (e.g., Feen-

by the assumption that the interplay of factor abundance and factor intensities shapes the pattern and, hence, the wage effects of trade.[90] In the framework of the trade-in-tasks literature, it became clear that the pattern of offshoring is also determined by task-specific offshoring costs. These costs do not show a clear relationship with the educational attainment of the workers performing the tasks and, hence, with its traditional comparative advantage (see, e.g., Garner 2004; Blinder 2006; Jensen and Kletzer 2005, 2008).

Grossman and Rossi-Hansberg (2008) incorporate such heterogeneous trade costs across tasks into a perfect competition trade model. Products are produced using a continuum of tasks, which are either performed by low-skilled workers (L-tasks) or high-skilled workers (H-tasks) and which can be performed either in the home country or abroad. Offshoring may be beneficial because of factor cost differences, but it also entails costs. These costs are assumed to differ across tasks within one group of skills. By introducing such a richer structure of offshoring costs, differences in factor prices across countries and trade cost differences across tasks determine the pattern of trade. Feenstra sees this approach as "clearly a new aspect of trade, or of the costs of doing trade" (Feenstra 2010, pp. 102-103).

Grossman and Rossi-Hansberg (2008) analyze the impact of a decrease in offshoring costs on wages in different specific trading environments and decompose the overall wage effect into three effects: a productivity effect, a labor-supply effect, and a relative-price effect. The productivity effect refers to the fact that offshoring is similar to technological change. This effect leads to a real wage gain for the factor that performs the offshored tasks. In contrast, the labor-supply effect leads to a real wage decline for the factor performing the offshored tasks by increasing the labor supply of this factor. As the price of the final product using the offshored intermediate inputs declines, this relative-price effect leads to negative wage effects for the factor performing the offshored tasks (Stolper-Samuelson effect). Overall, the effect of increased offshoring depends on the relative strength of the negative and positive effects.[91] In the Grossman and Rossi-Hansberg (2008) framework the law of one price holds for each skill group. In other words, workers with the same skill level receive the same wage - notwithstanding the tasks they are performing. If the law of one price was violated, no worker would perform tasks paying lower wages. Consequently, the wage effect of offshoring is the same across all tasks within each skill group.

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stra and Hanson 1996, 1999) or years of schooling (e.g., Liu and Trefler 2008). In particular, it is the development of wage polarization since the mid-1990s that has illustrated the limitations of such binary skill classifications. Only recently, trade economists have also begun to employ skill distinctions that go beyond the skilled/unskilled dichotomy (e.g., Geishecker and Goerg 2008).

[90] This assumptions stems from the prevalence of the Heckscher-Ohlin model in analyzing the distributional impact of trade, see also footnote 8 on page 3.

[91] The Grossman and Rossi-Hansberg (2008) framework does not allow for analytical solutions in the cases of a large economy or an economy that is specialized in producing a single good. Rojas-Romagosa (2011) performs several numerical simulations to investigate the wage effects of the Grossman and Rossi-Hansberg model and his findings suggest that an increase in offshoring leads to an increase in wage inequality except for the special case of a small, Heckscher-Ohlin economy.

Especially in the short run, this assumption of perfect labor mobility across occupations is unlikely to hold. There likely are frictions to switching between occupations and the matching process to reallocate resources is time consuming, due to, for example, necessary retraining. As emphasized by the OECD (2007a, p. 126) the requirements for the lost occupations are not necessarily the same as those for the newly created ones. This idea is supported by recent empirical evidence suggesting that human capital is partly occupation specific (e.g., Kambourov and Manoskii 2009). If we consider the evidence that certain occupations (tasks) are more susceptible to offshoring, and thus more likely to be relocated abroad, offshoring is likely to affect real wages for occupations differently - according to their offshorability. In order to investigate this, I estimate whether - in addition to the respective skill level - the wage effects of service offshoring depend on the character of the tasks performed.

First empirical contributions have been testing a similar hypothesis and thereby went beyond the traditional skill distinction in identifying the distributional impact of trade. Such a task-based approach seems especially appropriate for analyzing service offshoring (see Feenstra 2010, p. 42). However, most of the previous empirical contributions have focused on material offshoring because of data limitations on services trade in general and on "trade in tasks" (Grossman and Rossi-Hansberg 2008) in particular.[92] An exception that focuses on the U.S. labor market effects of service offshoring is the study by Crinò (2010). He estimates the impact of service offshoring on employment in the United States over the period from 1997 to 2002. His results indicate that service offshoring positively impacted high-skilled workers' employment, whereas employment of low- and medium-skilled workers was negatively affected. Furthermore, employment in offshorable occupations was negatively affected by service offshoring, whereas employment in occupations classified as non-offshorable increased. Overall, this evidence indicates that it is important to control for the task content of occupations in addition to the traditional proxy measures for skill levels, i.e., the educational attainment of the workers performing the tasks. In contrast to the present analysis, Crinò employs industry-level employment data. As a result, he cannot control for unobservable individual characteristics of the workers. Furthermore, he calculates an industry-level offshoring proxy measure so that his analysis is based on the assumption of no labor mobility across industries.

Liu and Trefler (2008) perform a study that examines the wage effects of international outsourcing of services by U.S. companies to unaffiliated firms in China and India and of international outsourcing of services to the United States. Similar to Crinò (2010), they link wage data at the occupational-industry level to international outsourcing proxy measures at the industry level from 1996 to 2006.[93] They distinguish between occupations that are exposed

[92] For an analysis of the reasons for the lack of detailed data on services trade, see Jensen (2011).

[93] This approach ignores an important aspect of service offshoring. According to the BEA's "Detailed statistics for cross-border trade," services trade within multinational companies accounted for almost one-third of the overall imports in other private services to the United States in 2008.

to offshoring and those that are not by mapping occupations to actual services trade. Their findings suggest that service outsourcing has only had very small wage effects, which leads them to conclude that the extensive attention that service offshoring has attracted is "much ado about nothing" (Liu and Trefler 2008, p. 35). Arguably, this conclusion is owed to measuring techniques.

As Ebenstein et al. (2009, 2011) have recently suggested, the partial equilibrium nature of previous analyses could explain why the impact of offshoring on wages within an industry was found to be relatively low. Even if theoretical contributions have already emphasized that offshoring takes place at the level of tasks across industries (see, e.g., Feenstra and Hanson 1996), empirical researchers have mostly calculated offshoring proxies at the industry level because trade data is collected at the firm or industry level rather than at the task level. Ebenstein et al. (2009) propose a weighting scheme to circumvent this challenge and to calculate an occupation-specific measure of material offshoring. Their results show that the decision to measure offshoring at the occupational or the industry level leads to significantly different wage effects (more details on these different approaches are discussed on page 82).

In this chapter, I combine these insights gained in previous contributions to improve our understanding of the interplay of tasks and skills in determining the wage effects of service offshoring. I estimate the impact of service offshoring on the real wages of U.S. workers by including information on the educational attainments of workers and the offshoring susceptibility of occupations into a Mincerian wage regression.

4.3 Empirical specification

In this section, I provide details on the empirical specification. Section 4.3.1 describes the data. I start by outlining the longitudinal matching of the Outgoing Rotation Group (ORG) samples of the Current Population Survey (CPS) to obtain a panel data set for yearly data about the real hourly wages of U.S. workers from 2006 to 2009. The two subsequent paragraphs deal with the challenges in constructing measures for two of the main regressors (i.e., the offshoring intensity proxy measure and the offshoring susceptibility measure), before I present the estimation equation (4.3.2).

4.3.1 Data

Individual-level wage data

In line with the seminal work by Feenstra and Hanson (1996), most empirical contributions that explore the impact of offshoring on wages have employed data at the firm or industry level rather than at the individual level.[94] Individual-

[94] Feenstra and Hanson (1996) have provided a theoretical framework that accounts for the increasing importance of material offshoring. They have also provided empirical evidence that the contribution of material offshoring to the increase in U.S. wage inequality during the 1980s was qualitatively and quantitatively akin to skill-biased technological change (Feenstra and Hanson 1996, 1999). See footnote 14 on pages 4-5 for details on their theoretical framework.

level data makes it possible to employ the educational attainment of the workers as a proxy measure for skill levels.[95] In contrast, studies employing firm- or industry-level data only possess information about which skills are, on average, required in a certain occupation. In other words, skill level and occupation are perfectly collinear. By allowing for individual skill level variation within each occupation, I am able to analyze the interplay between skills and tasks in shaping the wage effects of service offshoring. Furthermore, data at the individual level offer the advantage of being able to control not only for observable individual characteristics that could affect wages, such as the educational attainment of workers, but also for unobservable, time-invariant individual characteristics, such as ability.

The CPS offers information about employment and wages at the individual level of U.S. workers. This survey collects information on hours, earnings, employment, unemployment, and union affiliation based on monthly household surveys, which are conducted by the Bureau of the Census for the Bureau of Labor Statistics with approximately 50,000 to 60,000 households (see Feenberg and Roth 2007). Each household is surveyed for four months and, after an interview break of eight months, again surveyed for four months. Information on workers' weekly hours and earnings are only collected at the fourth and eighth interviews. The surveys from these interviews are the so-called *Outgoing Rotation Groups* (ORGs) (see the NBER website).

Even if the CPS has a longitudinal dimension, most studies either use samples from separate months or treat the data as repeated cross-sectional data. In the present analysis, I exploit the information from the longitudinal dimension and build on Madrian and Lefgren (2000), who have developed an algorithm to match two consecutive March surveys of the CPS. I have adapted this matching algorithm to longitudinally match the CPS ORG samples in two steps. In a first step, individuals are matched based on a household identifier, a household number, and an individual line number within a household. If all three variables are identical in two consecutive ORG samples, this mechanism results in a so-called "naïve" match. In a second step, this naïve match is validated if there are no inappropriate changes in an individual's sex, age, and race (see appendix A for further details). As a result, the unbalanced panel covers 95,527 individuals and two years over the period from 2006 to 2009. Due to missing data the total number of observations is 146,359.

Offshoring intensity

This section provides details on the construction of the proxy measure for the service offshoring intensity and presents first evidence on U.S. service offshoring patterns across occupations.

[95] More specifically, I define skill groups according to the International Standard Classification of Education (ISCED) of the UNESCO (2011). Low-skilled workers have a lower secondary education or less, medium-skilled workers have a degree between upper secondary and first-stage tertiary education, and high-skilled workers possess at least second-stage tertiary education.

Because of data limitations, it is not possible to directly measure the volume of offshoring.[96] However, a proxy measure can be calculated to measure offshoring indirectly. Given that offshoring refers to the international "unbundling" (Baldwin 2006) of the production process, intermediate services are likely to be imported back to the home country to be further integrated into the production process of the final good or service. As a result, I follow Feenstra and Hanson (1996) and expect offshoring to lead to imports of intermediate inputs.[97]

Unfortunately, even for trade in intermediates, there are severe data limitations. For the United States, official services trade data only measure overall trade (i.e., trade in intermediate services and trade in final services combined).[98] However, I can employ industry-level information from input-output tables and thereby calculate an offshoring proxy measure for the United States for different offshored service industries.

First, following Amiti and Wei (2005, 2009), the National Academy of Public Administration (2006b pp. 57-68), and the OECD (2007b pp. 51-52), I multiply the value of the intermediate purchases of a service industry s with the ratio of the total imports to the total domestic supply of that service industry to obtain an estimate of the imported intermediates of the respective service industry (see appendix B for further details).[99] Furthermore, to control for the different sizes of the respective service industries, I normalize this value with the value of gross production in each industry. The share of offshoring in gross production in service industry s at time t is calculated based on the following equation:

$$OFF_{st} = \frac{SP_{st}\left[\frac{SI_{st}}{TSO_{st}+SI_{st}-SE_{st}}\right]}{TSO_{st}}. \tag{10}$$

$TSO\ldots$ Total Service Output
$SI\ldots$ Service Imports
$SE\ldots$ Service Exports
$SP\ldots$ Service Purchases
$s = 1,\ldots,S$ Service Industry
$t = 1,\ldots,T$ Time
$c = 1,\ldots,C$ Country

96 Offshoring refers to the act of performing parts of the production process in a foreign country rather than in the home country, such that both foreign direct investments (FDIs) and international outsourcing constitute offshoring (e.g., van Welsum and Vickery 2005; Feenstra 2010, pp. 5-6).

97 Feenstra and Hanson (1996) have proposed to use trade in intermediate inputs as a proxy measure for material offshoring. This approach has been extended to service offshoring by Amiti and Wei (2005, 2009).

98 For detailed reports on the challenge of measuring the phenomenon of offshoring by employing information from official data sets in the United States, see the reports by the U.S. Government Accountability Office (2004) and by the National Academy of Public Administration (2006b, pp. 43-56). Jensen (2011) discusses the reasons for the general lack of detail in services trade statistics.

99 This approach assumes that the import ratio is identical for intermediate and final products. OECD researchers have shown that this assumption leads to a downward aggregation bias (Hatzichronoglou 2005, p. 13).

The standard approach in the literature on offshoring and its labor market effects has been to regress wage and/or employment changes within an industry on changes in such industry-level offshoring intensities, i.e. OFF_{st}. In contrast, Ebenstein et al. (2009) propose to calculate an occupation-specific measure of offshoring across industries. The underlying idea is that offshoring takes place at the level of tasks and across different industries. For instance, computer programmers are employed in several industries, ranging from the mining sector to the accommodation and food service sector.[100] If such programmers are increasingly offshored this is likely to affect workers performing similar tasks across all industries. As a result, offshoring affects labor demand for a certain occupation across all industries rather than changing labor demand for all occupations within an industry. This notion implies worker mobility across industries. In other words, in flexible labor markets, such as the United States, workers may switch industries in response to international competition, whereas switching occupations is likely to be more difficult and may involve higher losses of occupation-specific human capital.[101] Baumgarten et al. (2010) see the strategy of allowing for potential worker mobility across industries as being more in concordance with a general-equilibrium setting than the standard approach. When comparing the estimation results of both strategies, Ebenstein et al. (2011) find no wage effects when employing an industry-level measure of material offshoring but large and significant effects on occupation-specific wages for routine workers.[102] These findings are supported by Baumgarten et al. (2010), who build on Ebenstein et al. (2009) and also employ an occupation-level material offshoring measure in their analysis of offshoring on the wages of German workers. Both works suggest that the partial equilibrium nature of previous analyses is the reason why offshoring was often found to have only a low impact on wages.

I adapt the approach by Ebenstein et al. (2011) to service offshoring and compute a measure of U.S. service offshoring intensity at the occupational level. More specifically, I re-weight the offshoring proxy measure at the industry level (i.e., OFF_{st}) with the number of workers in a certain occupation o within a service industry s relative to the number of workers employed in occupation o across all service industries:[103]

$$OFF_{ot} = OFF_{st} \times \sum_{s=1}^{S} \frac{N_{ost}}{N_{ot}}. \tag{11}$$

$o = 1, \ldots, O$ Occupation
$N \ldots$ Number of workers

[100] See the occupational employment statistics of the Bureau of Labor Statistics' website for further information.

[101] For a recent empirical paper supporting the idea that human capital is occupation-specific, see Kambourov and Manovskii (2009).

[102] Ebenstein et al. (2011) employ an occupation-level measure of foreign affiliate employment and find that for the period from 1997 to 2002 a one-percent increase in affiliate employment in low-income countries decreases U.S. real wages by 0.11 percent.

[103] For more details on this weighting procedure, see appendix B.

Offshoring susceptibility

In order to assess whether the real wage effects of U.S. service offshoring do not only depend on traditional skill proxy measures but also on the offshoring susceptibility of occupations and on the interplay of skills and tasks, I have to obtain a measure of offshoring susceptibility. I employ the classification provided in Moncarz et al. (2008) for the following two reasons.[104] First, the ranking is continuous, whereas most other contributions only establish a dichotomy between offshorable and non-offshorable tasks. Such a dichotomy would not be useful in the present analysis because - in addition to the differences in wage effects across potentially offshorable and entirely non-offshorable occupations - I am also interested in whether wage effects differ within the group of offshorable occupations according to the degree of offshoring susceptibility. Second, among the plethora of different contributions that have tried to identify the characteristics of tasks that influence the susceptibility to offshoring (e.g., Bardhan and Kroll 2003; Garner 2004; Jensen and Kletzer 2005; van Welsum and Vickery 2005; Blinder 2006), the ranking by Moncarz et al. (2008) is, to my knowledge, the most comprehensive ranking.

Moncarz et al. (2008) build their classification on the works of twenty economists from the Bureau of Labor Statistics' (BLS) Employment Projections Program who have ranked all 515 service occupations in the Standard Occupational Classification System (SOC) according to their offshorability.[105] First, they identified 355 service occupations as entirely non-offshorable. Examples of such services include occupations that require face-to-face contact with customers (e.g., barbers) or need to be performed in a fixed location (e.g., security guards). For all other service occupations, the BLS economists evaluated the compliance of the task content of the occupation with the following four criteria and assigned an offshoring susceptibility score between four and sixteen to each of the service occupations.[106]

1. To what degree can the inputs and outputs of the occupation be transmitted electronically, or otherwise be easily and cheaply transported?
2. To what degree do the duties of this occupation require interaction with other types of workers?
3. To what degree is knowledge of social and cultural idiosyncrasies, or other local knowledge, of the target market needed to carry out the tasks of this occupation?
4. To what degree can the work of the occupation be routinized or handled by following a script?

(Moncarz et al., 2008, p. 75)

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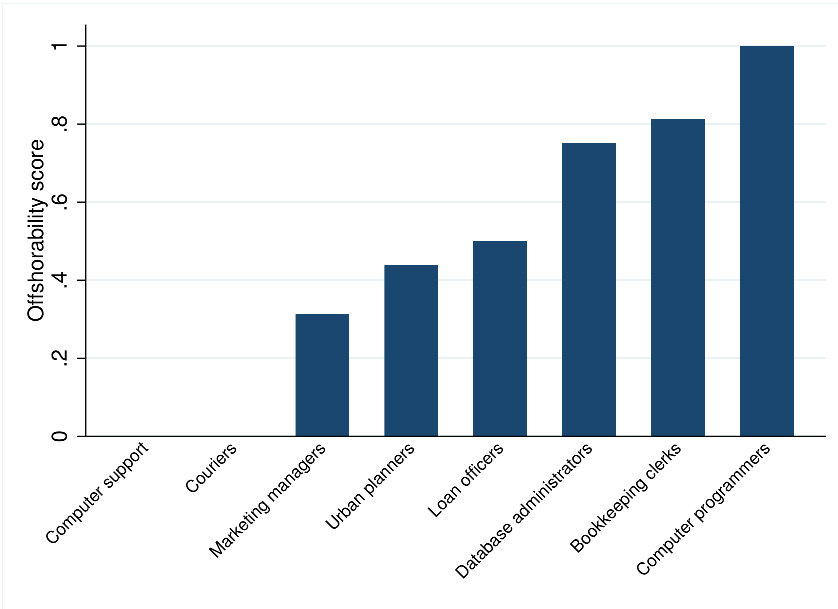
[104] Furthermore, this index performs best in terms of explained variance of actual offshoring flows. For more details, see chapter 2 of this dissertation.

[105] The 2000 SOC system distinguishes between 840 detailed occupations. Service providing occupations comprise the major groups 11, 13, 15 to 29, 31 to 39, 41, 43, 49, and 53. For further information, see the Bureau of Labor Statistics' webpage.

[106] One has to be careful in using the term "offshoring susceptibility." The actual pattern of offshoring depends on potential costs as well as on potential benefits, which are not taken into account in this ranking. Furthermore, as has been shown in chapter 3 of this dissertation, actual offshoring costs also depend on the interactions between the task content and country characteristics. The classification by Moncarz et al. (2008) ranks tasks according to their offshoring requirements.

Figure 4.1: Offshoring susceptibility by 6-digit SOC code



To render the interpretation of the wage effect estimations easier, I normalize this score to lie between zero and one for each of the 515 service-providing occupations. A value of one indicates the highest susceptibility to offshoring, and a zero value indicates that the respective occupation is classified as non-offshorable. Figure 4.1 shows the resulting ordinal classification for eight exemplary service occupations. Among the highest-ranked occupations in terms of offshoring susceptibility are computer programmers (SOC code 15-1021) and bookkeeping, accounting, and auditing clerks (SOC code 43-3031). Database administrators (SOC code 15-1061) and loan officers and counselors (SOC code 13-2070) are among the middle-ranked occupations. Urban and regional planners (SOC code 19-3051) and marketing managers (SOC code 11-2021) are assigned to the lowest offshorability group. Couriers and messengers (SOC code 43-5021) and computer support specialists (SOC code 15-1041) are classified as non-offshorable.

Note that this classification is based on the task content of the respective occupation and that it does not consider the educational attainment of the workers performing the tasks. In the following, I analyze the relationship between the task characteristics of occupations and the skill levels of workers in some more detail to improve our understanding about the relationship between tasks and skills.

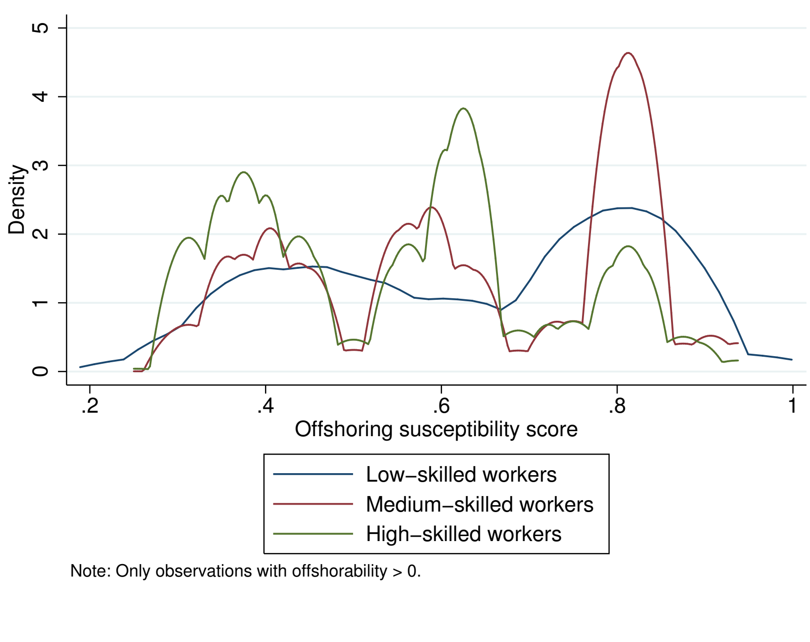
Table 4.1 shows that there are statistically significant differences between the

[107] 39.39 percent of all observations are zero-value observations.

Table 4.1: Comparison of offshoring susceptibility distributions across skill groups

	All	Low-skilled	Medium-skilled	High-skilled
Offshorability				
Mean	0.211	0.037	0.176	0.264
Median [107]	0	0	0	0
Standard deviation	0.318	0.163	0.316	0.317
Wilcoxon rank-sum test		$H_0 : F_{low-skilled} = F_{medium-skilled}$ $z = -27.904$ $p = 0.000$	$H_0 : F_{medium-skilled} = F_{high-skilled}$ $z = -103.661$ $p = 0.000$	
Observations	146,359	3,680	78,267	64,412

Figure 4.2: Distribution of offshoring susceptibility by skill



Note: Only observations with offshorability > 0.

underlying distributions of the offshoring susceptibility score across educational groups. In particular, I can reject the null hypothesis of the Wilcoxon rank-sum test that the offshoring susceptibility distributions across educational groups are equal ($z = -27.904$ and $z = -103.661$, $p = 0.000$). For instance, high-skilled workers, on average, are employed in occupations that are classified as more offshorable than those of low- or medium-skilled workers (i.e., $\mu = 0.264$ as compared to $\mu = 0.037$ or $\mu = 0.176$).[108] However, these averages hide significant heterogeneity within each skill group. Figure 4.2 shows that also low-skilled workers are employed in occupations that are very easy to offshore.[109]

4.3.2 Empirical model

After having constructed these three main variables, I can estimate the effect of U.S. service offshoring on real wages. With respect to the empirical specification, I build on Baumgarten et al. (2010) and estimate the following Mincer log wage equation:

$$
\begin{aligned}
w_{iot} = \alpha + \sum_{e-1} \beta_e EDU_{eit} \\
+ \sum_{e} \gamma_e EDU_{eit} \times TASK_o + \sum_{e} \delta_e EDU_{eit} \times OFF_{ot} \\
+ \sum_{e} \theta_e EDU_{eit} \times TASK_o \times OFF_{ot} \\
+ \kappa_o + \mu_t + \iota_i + \varepsilon_{iot}, \quad (12)
\end{aligned}
$$

$i = 1, \ldots, I \;\; Worker$
$o = 1, \ldots, O \;\; Occupation$
$t = 1, \ldots, T \;\; Time$

where w_{iot} is the log hourly wage of worker i in occupation o at time t. $\sum_{e-1} EDU_{eit}$ denotes a set of educational control variables that contains educational dummies for high and medium educational attainment of workers; low education is the omitted category. I control for the task content by including the measure $TASK_o$, which indicates the normalized offshoring susceptibility score for the respective occupation. By interacting this task content measure with the educational dummies, I allow for heterogeneous wage effects of the task content across different skill groups, $\sum_{e-1} EDU_{eit} \times TASK_o$. OFF_{ot} is a measure that indicates the U.S. service offshoring intensity for occupation o at time t. This proxy measure is interacted with the three educational dummies to account for the differential wage effects of offshoring across skill groups, $\sum_e EDU_{eit} \times OFF_{ot}$. I also include triple interaction terms to account for the

[108] Note that in the present sample there are few service workers with low educational attainment (i.e., only 3,680 observations out of a total of 146,359 observations).
[109] For illustrative purposes, the density distribution plot in figure 4.2 is based only on those observations that have an offshorability score higher than zero (i.e., 88,714 observations).

differential effects of offshoring within each educational group according to the task content, $\sum_e EDU_{eit} \times TASK_o \times OFF_{ot}$.

The error term is decomposed into occupational fixed effects κ_o, time-specific effects μ_t, and individual fixed effects ι_i. Time-specific effects capture general macroeconomic trends and individual fixed effects control for time-invariant observable and unobservable individual characteristics. The remaining error term ε_{iot} is assumed to be normally distributed.[110]

4.4 Estimation results

This section examines the estimation results of the fixed-effects model (FEM) regression of equation (12).[111] Column (1) in table 4.2 presents the baseline results without any interaction terms. Column (2) includes the interaction terms between the offshoring proxy measure and educational groups as well as between the task content and educational groups. This column also includes the triple interaction terms between the offshoring proxy measure, the task content and the education dummies.

The significant coefficients on the medium- and high-skilled dummies in column (1) suggest that, ceteris paribus, - in comparison to low-skilled workers, which constitute the baseline category - real wages are 6.22 percent higher for the group of people who have between six to ten years of education and 14.6 percent higher for those people who have more than ten years of education.[112]

The task content has no statistically significant wage effect at any of the conventional levels across all three skill levels (see column (1)). However, this average hides significant differences across educational groups. The coefficients on the interaction terms in column (2) suggest that within the groups of medium- and high-skilled workers, wages differ according to the offshoring susceptibility of the occupation. Within each of these skill groups, workers who are employed in those occupations that are the most susceptible to offshoring earn more than those workers with a similar skill level who are employed in the least offshoring susceptible occupations.

The positive coefficient on the offshoring proxy measure in column (1) suggests that service offshoring has a statistically significant and positive effect on real wages. However, the coefficients on the interaction terms between the offshoring proxy measure and the educational dummies in column (2) ($\sum_e \delta_e EDU_{eit} \times OFF_{ot}$) indicate that this overall positive effect of offshoring hides significant

[110] Because the task content measure is a time-invariant variable at the occupational level, the occupation dummies and task content measures are perfectly collinear. As a consequence, I omit the occupation dummies in the estimation.

[111] Unobserved individual heterogeneity is likely to be correlated with some of the regressors, such as, for example, educational attainment of the workers. In line with this theoretical argument, the Hausman specification test rejects the null hypothesis of zero correlation between individual effects and the error terms ($\chi^2(14)$,$p = 0.000$). Such zero correlation would be required for the estimates of a random-effects model to provide consistent estimates (see also Cameron and Trivedi 2010, p. 267).

[112] This convexity of wages in educational attainment is in line with other findings in the literature (e.g., Lemieux 2006).

differences across educational groups. More specifically, the interaction effects in column (2) indicate that only medium- and high-skilled workers benefit from service offshoring, whereas the effect for low-skilled workers is not statistically significant at any of the conventional levels.[113]

Thus far, we have only analyzed the effect of an increase in the offshoring intensity for those workers who are employed in the least offshorable occupations ($TASK_0 = 0$). Let us now consider whether the effects of offshoring change for the group of workers employed in the most offshorable occupations ($TASK_0 = 1$). The coefficients on the triple interaction terms ($\sum_e \theta_e EDU_{eit} \times TASK_o \times OFF_{ot}$) provide an answer to this question. The marginal effects of offshoring on wages for each educational group are given by:

$$\frac{\delta w_{iot}}{\delta OFF_{ot}} = \delta_e + \theta_e \times TASK_o. \tag{13}$$

The negative triple interaction terms in column (2) outweigh the positive effect of the skill-interacted offshoring proxy measure ($\sum_e \delta_e EDU_{eit} \times OFF_{ot}$). This finding indicates that for the medium- and high-skilled workers in the most offshorable occupations, an increase in service offshoring leads, ceteris paribus, to a decline in real wages. Figure 4.3 illustrates how the marginal effect of service offshoring on real wages of medium- and high-skilled workers changes over the range of the occupational offshoring susceptibility.[114]

Notwithstanding the statistical significance of the effects, we are mainly interested in economic significance. Therefore, based on the results of the preferred specification in column (2), I calculate the cumulated effect of service offshoring over the period from 2006 to 2009. I do so separately for low-, medium-, and high-skilled workers and further distinguish between workers in the least offshorable occupations ($TASK_o = 0$) and workers in the most offshorable occupations ($TASK_o = 1$). Table 4.3 shows the results. In the following discussion of these results, I focus on those cases in which the two coefficients of interest (δ_e and θ_e) are jointly statistically significant, i.e., for medium- and high-skilled workers.

Medium-skilled workers in the least offshorable occupations experienced a four dollar cents (0.28 percent) increase in real hourly wages because of the cumulated increase in service offshoring over the period from 2006 to 2009, while workers with the same skills who were employed in the most offshorable occupations realized an eight dollar cents (0.51 percent) decline in real wages.

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[113] The fact that I cannot identify any wage effect for low-skilled workers with sufficient precision could be due to the low number of observations within the low-skilled category (see also table 4.1).

[114] I wish to thank Thomas Brambor, William Roberts Clark, and Matt Golder, who provide an excellent documentation on the graphical representation of interaction effects on their website. See also Brambor et al. (2006).

Table 4.2: Panel regression (FEM)

Dependent variable: Log hourly wage	(1)	(2)
D: Medium-skilled	0.0622**	0.0519*
	(0.0198)	(0.0212)
D: High-skilled	0.146***	0.138***
	(0.0220)	(0.0240)
Task content	0.0125	
	(0.0128)	
interacted with		
*D: Low-skilled		-0.0753
		(0.0770)
*D: Medium-skilled		0.0741***
		(0.0125)
*D: High-skilled		0.0524**
		(0.0178)
Offshoring proxy	2.877***	
	(0.588)	
interacted with		
*D: Low-skilled		5.106
		(12.12)
*D: Medium-skilled		12.61***
		(1.734)
*D: High-skilled		11.07***
		(1.848)
Offshoring proxy *Task content		
interacted with		
*D: Low-skilled		-1.784
		(16.73)
*D: Medium-skilled		-17.44***
		(2.474)
*D: High-skilled		-12.68***
		(2.823)
Constant	2.714***	2.706***
	(0.0200)	(0.0214)
Fixed effects	Year, individual	Year, individual
Observations	146,359	143,359
adj. R-squared	0.717	0.717

Columns (1), (2) and (3): Robust standard errors in parentheses;
* significant at 10%; ** significant at 5%; *** significant at 1%

If we assume 2,087 yearly work hours, the gross yearly income (in constant 2009 prices) for medium-skilled workers in the least offshorable occupations increased by 93.81 dollars.[115] For medium-skilled workers in the most offshorable occupations, gross yearly income (in constant 2000 prices) declined by 169.33 dollars.

A similar pattern emerges for the group of high-skilled workers. The hourly wages of high-skilled workers employed in the least offshorable occupations increased by 11 dollar cents (0.4 percent), whereas the hourly wages of workers with the same skill level who were employed in the most offshorable occupations declined by seven dollar cents (0.28 percent). If we again assume 2,087 yearly work hours, this assumption implies that the gross yearly income of high-skilled workers in the least offshorable occupations (in constant 2009 prices) increased by 267.50 dollars. The gross yearly income of high-skilled workers in the most offshorable occupations (in constant 2009 prices) declined by 166.96 dollars.[116]

One implicit assumption in the FEM estimation of equation (12) is that the regressors are exogenous and, hence, $E\left(x_i \varepsilon_i\right) = 0$. If this assumption was violated, the coefficients in table 4.2 would be inconsistent and biased estimates of the true parameter values. The exogeneity assumption could be violated in particular for the case of the offshoring intensity proxy measure, OFF_{ot}, because of reverse causality. In other words, if wages of a certain occupation increase, firms could decide to increasingly offshore those occupations.

Several arguments support the conclusions that I have drawn from the FEM estimation.[117] First, by matching individual-level wage data with offshoring intensity proxy variable at the occupational level I reduce the likelihood of reverse causality in comparison to traditional analyses of the wage effects of offshoring that largely employ information on wages and offshoring intensities at the same level of aggregation. In other words, it is less likely that the variation in individual wages causes changes in the occupation-level offshoring intensity measure.[118] Third, I statistically test the assumption that the offshoring intensity measure is exogenous by estimating equation (12) additionally with an instrumental variable general method of moments (GMM) approach. Based on the results of the C-test, I fail to reject the exogeneity of the offshoring intensity measure within reasonable confidence bounds. These findings indicate that the FEM is a consistent estimator of the true value of the parameter.

---

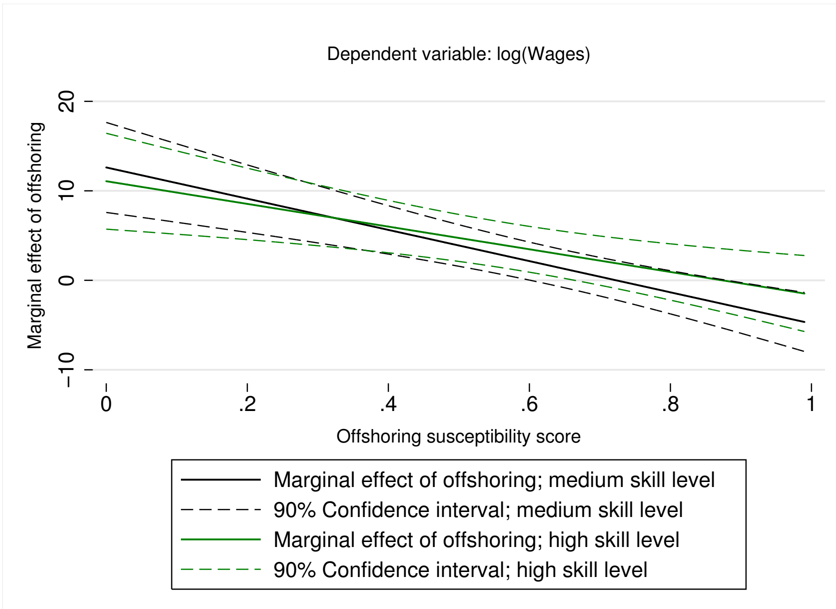
[115] According to the BLS, wage and salary workers worked, on average, 5.27 hours per day in 2011 (see table 5 of the American Time Use Survey).

[116] Baumgarten et al. (2010) find negative effects of material offshoring on the real wages of low- and medium-skilled workers in Germany from 1991 to 2006. Unlike the present analysis, their findings suggest that only the magnitude (and not the sign) of the effects of offshoring depends on the task content of the respective occupation. A possible explanation could be that in a more flexible labor market such as the United States, wages can adjust more easily, whereas in less flexible labor markets (in terms of prices) such as Germany, adjustment takes place primarily via the quantity.

[117] Furthermore, I have estimated equation (12) with a full set of occupation-specific time trends that control for technological change at the occupational level. The coefficients were robust to this additional control, which, however, was not statistically significant at any of the conventional levels.

[118] This argument is elaborated in a more formal manner in appendix C.

Figure 4.3: Marginal effect of service offshoring on real wages across the offshoring susceptibility range



Source: Author's calculation and illustration; based on column (2) of table 4.2

Table 4.3: Economic significance calculations

	Low skilled		Medium skill		High skill	
Average hourly wage 2006 in Dollar	10.54475		15.67739		27.66987	
Joint significance of offshoring	F=0.27 p=0.7649		**F=27.12** **p=0.0000**		**F=19.31** **p=0.0000**	
Cumulated effect of offshoring 2006-2009	*in Dollar*	*in percent*	*in Dollar*	*in percent*	*in Dollar*	*in percent*
$TASK_o = 0$	0.0007	0.007	**0.04495**	**0.287**	**0.1124**	**0.405**
$TASK_o = 1$	-0.0188	-0.178	**-0.081**	**-0.518**	**-0.079**	**-0.2881**

Source: Author's calculation; based on column (2) of table 4.2

4.5 Conclusion

The offshoring of service occupations, which were previously deemed to be shielded from international competition, has spawned controversial debates in academic and political circles. Perhaps the most contested question pertains to the implications of service offshoring for wages. The present analysis highlights features of the data that have traditionally been overlooked because of the aggregate level of analysis. It indicates that the wage effects of service offshoring depend on the interplay of the worker's educational attainment and the occupational task content.

By employing wage information from individual-level data and matching these data with occupation-specific information on offshoring intensities and susceptibilities, I have analyzed how service offshoring affects the real wages of U.S. workers. The results suggest that, in addition to the skill level of workers, task characteristics play an important role in determining the effect of service offshoring on wages. Depending on the offshoring susceptibility of the respective occupation, service offshoring can have qualitatively different impacts on wages. Medium- and high-skilled workers employed in those service occupations that are the least susceptible to offshoring experience real wage increases, whereas medium- and high-skilled workers in those occupations that are the most offshorable experience real wage declines. These interaction effects are robust to the control for unobservable individual heterogeneity. Such new empirical evidence broadens our understanding of the determinants of residual wage inequality within the groups of medium- and high-skilled U.S. workers.

Put differently, occupations which, according to their task content, are the most susceptible to offshoring, also experience real wage declines with increased service offshoring. This finding bears important implications for the future of the labor market. Even if the present level of service offshoring is still low, offshoring, especially of those occupations that - in terms of their task content - are most susceptible to offshoring, can be expected to increase. According to the index by Moncarz et al. (2008), these services are characterized by complexity, personal interaction, and context-dependency. This finding contradicts existing education policies and their insistence on standardized testing, because tasks that will be demanded in the future require an individual's capacity to react promptly and flexibly in complex situations. In a similar vein, Alan S. Blinder criticizes that the U.S. school system "will not build the creative, flexible, people-oriented workforce we will need in the future by drilling kids incessantly with rote preparation for standardized tests in the vain hope that they will perform as well as memory chips" (Blinder 2006, p. 7).

Acknowledgements I would like to thank Avraham Ebenstein and Holger Goerg for their helpful comments.

Appendix A: Individual-level wage data

I use the Center for Economic Policy Research (CEPR) version of the CPS ORG samples for the years 2006 to 2009, which are available at the CEPR website.[119] As a measure of hourly real wages, I employ the wage variable recommended by the CEPR. This variable does not include overtime, tips, and commissions. The top-coded wages are computed by assuming a log-normal distribution for weekly earnings (see Schmitt 2003). The economists at the CEPR have converted the nominal hourly wage calculated by the National Bureau of Economic Analysis (NBER) to a real wage by using the Consumer Price Index for 2009. The sample is restricted to the wages of workers who were at least 16 years old and employed at the time of the survey.

Because workers are surveyed more than once, I can build on Madrian and Lefgren (2000), who have developed an algorithm to match two consecutive March surveys of the CPS. This approach can be adapted to merge the CPS' Outgoing Rotation Group files. After creating two data extracts, one for time t and one for t+1 by renaming certain variables, I use information from three formal identifying variables (i.e., the household identifier [HHID], the household number [HHNUM], and the individual line number [LINENO]) to obtain a "naïve" match of the records. The maximum share of observations that could be matched in the CPS ORG samples is approximately 50 percent (see the potential match rate in table A.1). In the present analysis, the fraction of individuals that are naïvely matched is around 33 percent for each year pair. This actual matching rate is lower than the theoretical one because of non-response, mortality, migration, and recording errors. For the same reasons, however, some false positive matches are also included. Thus, in a second step, I evaluate the validity of these naïve matches by comparing the information on sex, age, and race across the matches and drop those matches that cannot be true based on these three criteria (the so-called S|R|A criterion in Madrian and Lefgren [2000]). Approximately 18 percent of all naïve matches are dropped in this second step such that the final matching rate is around 27 percent for each year pair (see table A.1).

Table A.1: CPS matching rates

Year	Potential Match	Naïve Match	Valid Match	Final Match
2006-2007	49.78	32.73	82.10	26.87
2007-2008	50.10	33.36	82.76	27.61
2008-2009	49.46	33.16	82.89	27.49

Note: "Valid match" indicates the percentage of naïve matches that are valid according to the S|R|A criterion in Madrian and Lefgren (2000).

One issue arises from matching the CPS ORG data with the offshoring susceptibility information from Moncarz et al. (2008). Both occupational classi-

[119] Details on how the CPS raw data from the Census Bureau has been processed by the CEPR can also be found on this website.

fications are based on the 2000 SOC codes. However, some of the occupations in the CPS ORG extracts are coded at a more aggregate level than they are in Moncarz et al. (i.e., at the five-digit rather than the six-digit level). In those cases, I employ information about the six-digit SOC occupations that each of those five-digit SOC occupations consists of (see the BLS' website on the SOC codes). Then, I assign the average offshoring susceptibility score of all six-digit SOC occupations to the respective five-digit occupation.

Appendix B: Offshoring intensity measure

The BEA provides public access to input-output tables (see The Use of Commodities by Industries before Redefinitions (1997 to 2009)), which classify service industries according to input-output codes. The industry-specific occupational employment and wage estimates of the BLS, which provide the necessary information for the weighting procedure according to Ebenstein et al. (2011), are classified according to the North American Industry Classification System (NAICS). Input-output codes can be converted to categories of the North American Industry Classification System (NAICS) according to the list provided in the BEA input-output tables. The results are displayed in table A.2.

Table A.2: Concordance between input-output codes and NAICS codes

Input-output codes	**2002 NAICS codes**
521C1, 523, 525	522000, 523000, 525000
524	524000
513	517000
5415, 514	541500
55	551100
5411	541100
5412OP	541900

Ebenstein et al. (2011) have not computed their offshoring measure as described in equation (9). Instead they have employed foreign affiliate employment as a proxy measure for offshoring. In affiliate trade data there is no distinction between those industries that produce certain products and those that purchase these products - as is the case in input-output data. If we want to compute an offshoring proxy measure at the occupational level based on the information regarding imported intermediate inputs, we must decide whether to weight the industry-level offshoring intensity measure with the respective ratio calculated based on information about employment in the producing industry p or the industry of use u. The idea behind constructing an offshoring proxy measure at the occupational level is to obtain “a measure of the effective exposure of an occupation to offshoring“ (Ebenstein et al. 2009, p. 29). When we take into consideration the occupational distribution within the industries that produce the intermediates ($p = 1, ..., P$), this offers insights about which types of occupations are "embodied" in the offshored products. This is why I have decided to use the employment of a specific occupation o within the producing industry p as a weight.

Table A.3: Correlation coefficients

	log (Real wage)	Education	Offshorability
Education	0.5097	1	
Offshorability	0.2097	0.2043	1
log(Offshoring)	0.4097	0.3208	0.5519

Table A.4: Summary statistics

Variable	Observations	Mean	Standard Deviation	Min	Max
Hourly real wage	250,375	21.22619	15.98083	1.743494	344.4235
D: Low-skilled	8,852	1	0	-	-
D: Medium-skilled	163,184				
D: High-skilled	138,788				
Offshoring susceptibility	310,824	0.1565522	0.2722418	0	1
Offshoring intensity	183610	0.0032616	0.0051085	0	0.0451897

Appendix C: Exogeneity of the offshoring variable

By matching individual-level wage data with offshoring intensity proxy measures at the occupational level I reduce the size of the potential endogeneity bias as compared to analyses that employ information on wages and offshoring intensities at the same level of aggregation. More formally, we can illustrate this argument by analyzing the following equation, which is a simplified version of equation (12) and an adapted version of the example of Baumgarten et al. (2010, pp. 45-46):

$$w_{iot} = \alpha + \mu OFF_{ot} + \varepsilon_{iot}. \tag{14}$$

If, in addition, we have reverse causality and the offshoring intensity depends on the level of wages, this implies that:

$$OFF_{ot} = \sigma + \nu w_{iot} + \varsigma, \tag{15}$$

with $\nu \neq 0$ holds.

This violates the assumption that each regressor is uncorrelated with the error terms and hence the OLS estimator is biased and inconsistent (Wooldridge 2002, pp. 53-58). The potential endogeneity bias of the OLS estimator can then be written as:

$$bias = \frac{Cov\,(OFF, \varepsilon)}{Var\,(OFF)}. \tag{16}$$

Substituting for $Cov\,(OFF, \varepsilon)$ by using the reduced form of equation (15), we obtain:

$$bias = \frac{\nu}{(1 - \nu\mu)} \frac{Var\,(\varepsilon)}{Var\,(OFF)},$$

with $\nu\mu \neq 1$.

Because $\frac{\delta bias}{\delta \nu} > 0$, we can see that, ceteris paribus, the size of the bias increases in ν.

Let us now compare ν for the case that we employ wage and offshoring data at the same level of aggregation and for the case of the combination of individual-level with occupational level data. In the first case, we obtain that:

$$\nu_{same} = \frac{Cov\,(OFF_{ot}, w_{ot})}{Var\,(w_{ot})}.$$

And for the case of the present analysis:

$$\nu_{diff} = \frac{Cov\,(OFF_{ot}, w_{iot})}{Var\,(w_{iot})}.$$

Because $Var\,(w_{iot}) > Var\,(w_{ot})$ and $Cov\,(OFF_{ot}, w_{ot}) = Cov\,(OFF_{ot}, w_{iot})$, we know that $\nu_{same} > \nu_{diff}$.

The GMM estimations and tests are performed by employing the user-written Stata command *xtivreg2* developed by Baum et al. (2007).[120] One challenge in performing such an exogeneity test is the necessity to find valid instruments for offshoring intensity, i.e. variables that are correlated with a firm's decision to offshore but are uncorrelated with changes in wages. I employ lagged values of the offshoring intensity and the offshoring susceptibility measure of an occupation as instrumental variables for the offshoring intensity proxy measure. In a second step, I perform different diagnostic tests to assess the need for performing a GMM estimation rather than a FEM estimation. The results are shown in table A.5 and will be discussed in the following paragraphs.

The results of the first stage regression show that the coefficients on all of the instruments are statistically significant. The first-stage F-test indicates that the instruments are jointly significantly different from zero. In addition to being relevant, which means that the instruments are correlated with the potentially endogenous regressor, instrumental variables must also be valid. In other words, the instruments need to be uncorrelated with the error terms of the second stage estimation. Validity can be tested only if the equation is overidentified, which is the case in the present analysis. Based on the Hansen J statistic, we fail

[120] The GMM allows for efficient estimation even in the presence of arbitrary heteroscedasticity (see Hansen 1982; Wooldridge 2002, pp. 213-216).

Table A.5: Diagnostic tests for GMM estimation

First-stage F-test
F=293.16
p=0.000000
Overidentification test of all instruments: Hansen J statistic (for excluded instruments)
Chi^2=0.769
p=0.6809
Exogeneity test of regressors: C-test
Chi^2=1.188
p=0.2757
Observations: 47,712

to reject orthogonality of the instruments to the error process.[121] This result supports the instruments' validity.

After having tested for the instruments' relevance and validity, I can now test whether the offshoring intensity measure can be treated as exogenous. Based on the results of the C-test, I cannot reject the exogeneity of the offshoring intensity measure within reasonable confidence bounds.[122]

[121] Under the null hypothesis that all instruments are valid, the J statistic has a chi-squared distribution with two degrees of freedom (Wooldridge 2002, pp. 228-229).

[122] Under the null hypothesis that the regressor can be treated as exogenous, the endogeneity test statistic has a chi-squared distribution with one degree of freedom (Hayashi 2000, pp. 233-234).

5 Conclusion

This dissertation provides important new insights for the emergent literature on trade in tasks and improves our understanding of service offshoring. Using a task-based approach is complicated by the fact that the existing literature in this field has not yet reached an agreement about the definition and measurement of its core concepts.

The first essay provides the necessary requirement for a task-based analysis and selects the most valid task-based measure for an occupation's offshorability. The co-existence of conceptually different measures in the current academic debate is problematic because these indices measure different aspects of reality while employing an identical label. The study in chapter 2 assesses the three most relevant approaches for the trade-in-tasks literature that have been proposed in previous works to rank occupations in the United States: The indices by Blinder (2007), Moncarz et al. (2008), and Crinò (2010). An analysis of the resulting offshorability rankings across those three continuous indices of offshoring susceptibility reveals significant variation. Such variation results in different representations of the offshorability distributions across certain worker characteristics. Particularly problematic for analyses of the labor market effects of service offshoring is the variation in the relationship between workers' skill levels and the occupation's offshoring susceptibility. Blinder's and Crinò's indices classify medium-skilled workers, on average, as employed in the most offshorable occupations, whereas Moncarz et al. classify high-skilled workers, on average, as employed in the most offshorable occupations. To select the most valid task-based measure of an occupation's offshoring susceptibility, I propose an objective criterion which assesses how well different measures perform in capturing the variation in actual offshoring flows across occupations. The results of an ordinary least squares regression and a Poisson pseudo-maximum likelihood regression suggest that the index by Moncarz et al. performs best in this regard, whereas the composite indices by Blinder (2007) and Crinò (2010) do not add meaningfully to the explanatory power of the separate O*Net activity "interacting with computers." The two essays that follow build upon these first findings and investigate how such task-based offshoring susceptibility interacts with traditional determinants of trade costs and benefits in shaping the pattern of service offshoring and its distributional consequences.

In chapter 3, I provide new evidence on the structure of offshoring costs by analyzing the interplay of a service's offshoring susceptibility and different country-level determinants. Much of the recent literature in international trade and in labor economics has argued that offshoring costs differ across services according to their task content. I connect this task-based approach to the literature on the generalization of the sources of comparative advantage (Costinot 2009b) to offer new insights into the mechanisms through which country characteristics affect offshoring patterns. This empirical exploration suggests a more nuanced story regarding the determinants of service offshoring patterns across countries and across services industries. Thus far, the empirical analyses related to Costinot's (2009b) work have largely focused on the interplay between institutional quality and industry-level institutional dependence. However, service industries do not only differ in their reliance on institutional quality: With the advent of offshoring scholars have argued, different types of services face different degrees of susceptibility to offshoring according to their task content. I argue that the task content influences the preconditions required for offshoring and - in line with Costinot's (2009b) model - the interplay between these requirements and country endowments determines offshoring costs. Methodologically, I have matched data on the task content of service industries with bilateral services trade data and input-output data from the U.S. Bureau of Economic Analysis. The results of the zero-inflated Poisson pseudo-maximum likelihood estimation suggest that the interaction between task characteristics and country characteristics determines the effects of colonial ties and of a NAFTA membership on offshoring patterns. A better quality of legal institutions, a common legal origin, geographic distance, and time zone differences influence offshoring patterns identically across all service industries, regardless of their offshoring requirements. These findings shed doubt on the prediction that the spread of information and communication technologies is automatically leading to an increasingly flat world for the trade flows of services.

In chapter 4, I estimate the impact of service offshoring on the real wages of U.S. workers by controlling for workers' skill levels and the offshoring susceptibility of different occupations. If we consider the recent evidence that certain occupations (tasks) are more susceptible to offshoring, and thus more likely to be relocated abroad, and if we also take into account that in the short run there are labor market frictions to switching between occupations, we would expect the wage effects of service offshoring to depend on the character of the tasks performed. I test this hypothesis by exploiting the information from the longitudinal dimension of the Current Population Survey. Methodologically, I have adapted the matching algorithm that has been developed by Madrian and Lefgren (2000). This enables me to account for unobservable individual-level heterogeneity in the estimations. I merge these individual-level wage data with occupational-level information on service offshoring. This information results from the combination of input-output tables and industry-specific occupational employment estimates over the period from 2006 to 2009. The results from a fixed-effects Mincerian wage regression indicate that, within skill groups, the impact of service offshoring on real wages depends on the task content of the respective occupation. Medium-skilled and high-skilled workers employed in the least offshorable occupations experience real wage increases, whereas medium-skilled and high-skilled workers in the most offshorable occupations experience real wage declines. These findings raise several questions with respect to the optimal design of education policies.

This dissertation suggests a variety of possible avenues for future research. It would be particularly interesting to investigate whether applying a similar methodology would lead to similar results across other countries. So far, previous works are hardly comparable because they differ in the measurement of core concepts, such as offshoring intensity and offshorability, and the empirical specifications that are estimated. More comparable cross-country evidence could, for instance, provide insights into the importance of labor market institutions in shaping the labor market effects of offshoring. Due to measurement challenges, empirical research on the interplay of labor market institutions and offshoring is still very scarce.[123] The task-based approach could offer new insights on the relationship between international trade and declining unionization rates, because such an approach could circumvent the problem of reverse causality that plagues existing studies. More specifically, the task-based approach would facilitate an analysis of how the offshoring susceptibility of different occupations affects unionization rates. However, a prerequisite for this type of analysis would be time-varying information on the occupational task content, which is not yet available for the United States.

This data constraint also has an impact on another field of research that deserves more attention in future works, that is, the time-variant task content of an occupation. Spitz-Oener's (2006) findings, for instance, suggest that the task content of occupations in Germany has become increasingly complex over time. So far, very little is known about the complementarities of different tasks within an occupation. With the increasing sensitivity for the necessity of task-based data, research on such within-occupation task complementarities will likely become an active area of research.

[123] First empirical works analyze the impact of institutions on the labor market effects of offshoring in cross-country analyses, for example Geishecker et al. (2010) and Milberg and Winkler (2011).

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Berlin, 31. Januar 2013

Erklärung

Hiermit versichere ich, Julia Püschel, dass ich diese Arbeit selbstständig verfasst und alle Quellen ordnungsgemäß gekennzeichnet habe.

Ich versichere, dass die Dissertation nicht bereits in einem früheren Promotionsverfahren angenommen oder als ungenügend beurteilt worden ist.

Julia Püschel

Abstract

This dissertation consists of three essays that empirically analyze different aspects of a task-based approach to U.S. service offshoring. The first two essays seek to broaden our understanding of the structure of offshoring costs. The first essay focuses on the measurement of task-based offshoring susceptibility. The second essay extends the empirical exploration to the interplay of the task content and country-level trade determinants in shaping offshoring patterns. The third essay analyzes the wage effects of service offshoring by accounting for such a richer structure of offshoring costs.

The first challenge in providing new evidence on service offshoring from a trade-in-tasks perspective stems from the lack of consensus on how to construct a task-based offshoring susceptibility measure. The first essay (chapter 2) fills this gap by employing techniques of factor and regression analyses to assess and compare the three most relevant approaches that have been proposed in previous works. I establish an offshoring susceptibility ranking of service occupations for each index and find that the three indices lead to significantly different representations of reality. Such a sharp disagreement between the measures significantly limits the comparability of empirical studies and suggests that different measures reflect different phenomena. To select the most valid task-based measure of an occupation's offshoring susceptibility, I propose an objective criterion which assesses how well different measures perform in capturing the variation in actual offshoring flows across occupations. The two essays that follow build upon these first findings and investigate how such task-based offshoring susceptibility interacts with traditional determinants of trade costs and benefits in shaping the pattern of service offshoring and its distributional consequences.

In the second essay (chapter 3) I consider another gap in the literature and analyze the way in which the task content of services interacts with traditional country-level determinants of services trade in shaping offshoring costs. This interaction has so far been treated as a black box. The task content influences the costs that arise from the fragmentation of the production process, regardless of whether this fragmentation takes place within or across country borders. In the context of offshoring, this fragmentation can incur extra costs because it occurs across international borders. I build on previous empirical works and consider a broad set of country characteristics that have been found to affect bilateral services trade flows. Unlike these previous analyses, I focus on whether the effects of these country-level variables differ systematically with the task content of the respective service industry. The results of the zero-inflated Poisson pseudo-maximum likelihood estimation suggest that the interaction between task characteristics and country characteristics determines the effects of colonial ties and of a NAFTA membership on offshoring patterns. A better quality of legal institutions, a common legal origin, geographic distance, and time zone differences influence offshoring patterns identically across all service industries, regardless of their offshoring requirements. These findings shed doubt on the

prediction that the spread of information and communication technologies is automatically leading to an increasingly flat world for the trade flows of services.

In the third essay (chapter 4), I estimate the impact of service offshoring on the real wages of workers in the United States by controlling for workers' skill levels and the offshoring susceptibility of different occupations. Traditionally, international trade economists have seen the fortunes of workers as tied to their skill levels. The findings of first task-based analyses indicate that these predictions need to be refined and that, next to the workers' skill levels, the task content of occupations shapes the labor market effects of offshoring. If we consider the recent evidence that certain occupations (tasks) are more susceptible to offshoring and that, especially in the short run, it is likely that there are frictions to switching between occupations, we would expect the wage effects of service offshoring to depend not only on the respective skill level but also on the character of the tasks performed. My study differs from existing works in significant ways. Most importantly, I focus on service industries rather than manufacturing industries and I use wage data at the individual rather than at the firm or industry level. The results from a fixed-effects Mincerian wage regression indicate that, within skill groups, the impact of service offshoring on real wages depends on the task content of the respective occupation. Medium-skilled and high-skilled workers employed in the least offshorable occupations experience real wage increases, whereas medium-skilled and high-skilled workers in the most offshorable occupations experience real wage declines. These findings raise several questions with respect to the optimal design of education policies.

Several questions deserve more attention in future works. For instance, so far, very little is known about the complementarities of different tasks within an occupation. With the increasing sensitivity for the necessity of task-based data, research on such within-occupation task complementarities will likely become an active area of research.

Zusammenfassung

Die vorliegende kumulative Dissertationsschrift setzt sich aus drei Einzelbeiträgen zusammen. Der gemeinsame Forschungsschwerpunkt ist die aufgaben-basierte Analyse von Dienstleistungsoffshoring aus den Vereinigten Staaten - der sogenannte “trade-in-tasks” Ansatz. Die USA stellen eine besonders relevante Fallstudie dar, da Dienstleistungen, insbesondere solche, die von Unternehmen nachgefragt werden, eine besonders herausragende Rolle in der US-Wirtschaft einnehmen.

Die vorliegende Arbeit gliedert sich wie folgt. Die Einleitung erläutert den möglichen Erkenntnisgewinn eines aufgaben-basierten Ansatzes (Kapitel 1). Insbesondere die Berücksichtigung von Offshoringkosten, die entsprechend des Aufgabengehalts über verschiedene Dienstleistungen variieren, kann bisherige Handelstheorien beträchtlich differenzieren. Davon ausgehend leitet sich die Notwendigkeit neuer empirischer Überprüfungen ab.

Der erste Beitrag (Kapitel 2) *Measuring task content and offshorability* liefert eine notwendige Voraussetzung für eine solche aufgaben-basierte Analyse. Anhand eines empirischen Kriteriums wird die Gültigkeit verschiedener existierender aufgaben-basierter Maße beurteilt, welche darauf abzielen, Dienstleistungen bezüglich ihrer Eignung ins Ausland verlagert zu werden zu klassifizieren (Verlagerungseignung). Bislang existiert kein Konsens in der trade-in-tasks Literatur, wie solche Maße konstruiert werden sollten und verschiedene Forscher haben unterschiedliche Ansätze verfolgt. Kapitel 2 analysiert die drei relevantesten Ansätze für die trade-in-tasks Literatur in den Vereinigten Staaten (Blinder 2007; Moncarz et al. 2008; Crinò 2010). Ein Vergleich der Klassifikationen macht deutlich, dass die unterschiedlichen Maße zu verschiedenen Ergebnissen führen. Dies ist insbesondere deshalb problematisch, weil die Autoren die selbe Terminologie verwenden. Um die Vergleichbarkeit verschiedener Studien zu gewährleisten, bedarf es eines objektiven Kriteriums, welches die Gültigkeit der verschiedenen Maße beurteilen kann. Hierfür wird im vorliegenden Beitrag der Erklärungsanteil an der Varianz von tatsächlichen Offshoringströmen vorgeschlagen. Die Ergebnisse verschiedener Schätzungen zeigen, dass der Ansatz von Moncarz et al. (2008) die höchste Erklärungskraft aufweist.

Die darauffolgenden zwei Beiträge berücksichtigen diese ersten Ergebnisse und untersuchen wie solch ein aufgaben-basiertes Maß der Verlagerungseignung mit traditionellen Determinanten von Handelskosten und -vorteilen interagiert. Insbesondere wird analysiert, wie dieses Zusammenspiel die Handelsmuster und Verteilungseffekte von Dienstleistungsoffshoring beeinflusst.

Der zweite Beitrag (Kapitel 3) *Task-dependency of U.S. service offshoring patterns* untersucht die Interaktion zwischen dem Aufgabengehalt verschiedener Dienstleistungen und Länderdeterminanten von Handelskosten und liefert damit neue Einsichten in die Struktur von Offshoringkosten. Zahlreiche Arbeitsmarkt- und Handelsökonomen haben argumentiert, dass für Dienstleistungen entsprechend ihres Aufgabengehalts unterschiedliche Offshoringkosten anfallen. Ich kombiniere diesen aufgaben-basierten Ansatz mit der Generalisierung und Erweiterung der Quellen komparativer Kostenvorteile, um neue Erkentnisse über die Determinanten tatsächlicher Offshoringmuster zu gewinnen. Insbesondere teste ich die Hypothese, ob der Aufgabengehalt die notwendigen Anforderungen für eine Verlagerung ins Ausland beeinflusst und ob das Zusammenspiel zwischen diesen Anforderungen und bestimmten Ländercharakteristika Offshoringkosten beeinflusst. Durch die Kombination verschiedener Datenquellen für den Zeitraum 2006 bis 2009 zeigt die Analyse, dass bestimmte Ländercharakteristika Offshoringkosten für alle Dienstleistungen beeinflussen, wohingegen die Effekte anderer Charakteristika von den Offshoringanforderungen der entsprechenden Dienstleistungsindustrien abhängen. Die Effekte einer Mitgliedschaft im Nordamerikanischen Freihandelsabkommen (NAFTA) und gemeinsamer kolonialer Beziehungen auf Offshoringmuster hängen vom Aufgabengehalt der ausgelagerten Dienstleistung ab. Im Gegensatz dazu beeinflussen die Qualität legaler Institutionen, gemeinsame juristische Ursprünge, geographische Distanz und Zeitzonendifferenzen zwischen Ländern Offshoringmuster unabhängig vom Aufgabengehalt identisch.

Der dritte Beitrag (Kapitel 4) *Wage effects of U.S. service offshoring* analysiert den Einfluss von Dienstleistungsoffshoring auf die Reallöhne von Arbeitern in den Vereinigten Staaten. Hierbei wird sowohl für das Bildungsniveau der Arbeiter als auch für die aufgaben-basierte Verlagerungseignung verschiedener Dienstleistungen kontrolliert. Durch dieses Vorgehen teste ich die Hypothese, ob sich die Lohneffekte von Dienstleistungsoffshoring auch entsprechend des Aufgabengehalts der jeweiligen Dienstleistung unterscheiden. Methodisch passe ich einen Algorithmus an, der Individuen in verschiedenen Datenerhebungen des Current Population Surveys identifiziert, so dass die Zeitdimension dieses Datensatzes genutzt werden kann. Dadurch bin ich in der Lage für unbeobachtbare individuelle Heterogenität zu kontrollieren. Die Ergebnisse einer fixed-effects Mincer Lohnregression bestätigen die getestete Hypothese. Reallöhne von mittel- und hoch-ausgebildeten Arbeitern fallen in solchen Dienstleistungen, welche die stärkste Verlagerungseignung aufweisen, wohingegen sie für mittel- und hoch-ausgebildete Arbeiter in den am wenigsten verlagerungsgeeigneten Aufgaben steigen. Diese Ergebnisse bestätigen Dienstleistungsoffshoring als eine Determinante gestiegener residualer Lohnungleichheiten.

Insgesamt vertieft die vorliegende Dissertation das Verständnis einer relativ neuen Tendenz des internationalen Handels, dem Dienstleistungsoffshoring, und liefert neue Einsichten für die trade-in-tasks Literatur. Es bedarf einer zunehmend vereinheitlichten Anwendung der Schlüsselkonzepte der trade-in-tasks Literatur sowie der Erhebung speziell angepasster Datensätze, damit die trade-in-tasks Literatur in der Zukunft ein dynamisches Forschungsfeld bleibt.

CURRICULUM VITAE

For reasons of data protection, the curriculum vitae is not included in the online version.