Offshoring and Relative Labor Demand from a Task Perspective *

Jan Hogrefe
(ZEW Mannheim)

Abstract

Recent trends in trade theory emphasize the role of offshoring and task trade. This paper takes up these theoretical developments and redefines the classical problem of relative labor demand from a task perspective. Labor demand is derived as employment and cost shares of different tasks based on recent offshoring theory and an estimation linking these cost shares to offshoring is carried out in a translog short-run cost function environment via GMM-IV. Empirical results support the theoretical notion that offshoring shifts labor demand towards more complex tasks with higher relocation cost. Importantly, this demand shift is also observed within skill groups and is markedly stronger for offshoring to non-OECD countries.

keywords: offshoring, trade, tasks, labor demand
JEL codes: F16, F23, J23

*This version: August 2011. Author contact details: Jan Hogrefe, Centre for European Economic Research (ZEW), Mannheim. Address: L7,1 68161 Mannheim, Germany. Email: hogrefe[at]zew.de. Phone: +49 (0)621 1235 348

1 Introduction

The relationship between the relocation of parts of the production chain abroad - offshoring - and the relative demand for various types of labor has been analyzed by a large economic literature. Prominent contributions such as Feenstra & Hanson (1996) and Hijzen et al. (2005) argue that in developed countries low-skilled workers or workers engaged in production jobs face growing competition from abroad and therefore shrinking demand for the type of labor they have to offer. Yet, important changes in the pattern of international trade have recently been uncovered. Among others, Grossman & Rossi-Hansberg (2008) argue that a certain part of trade has reached a much finer level of resolution and is now best described by an international allocation of labor inputs at the level of single tasks. This aspect has scarcely received rigorous testing in the empirical literature so far. If the nature of trade is changing, the lines defining heterogeneity in the effect of globalization on individuals might have to be redrawn as well. If task-tradability is the crucial determinant and if this correlates little with the (previously analyzed) educational achievement of workers performing these tasks, a new and more refined pattern in the distribution of globalization's cost and benefits may be emerging.

This paper takes up recent theoretical trends emphasizing the importance of offshoring and redefines its impact on relative labor demand from a task perspective. It does so by drawing on progress in the empirical literature uncovering certain characteristics of tasks which determine their idiosyncratic offshoring costs. Two concepts have received particular attention. On the one hand, based on Autor et al. (2003), tasks are believed to be the more replaceable by computers and therefore more offshorable the more rules-based and routine their execution is. On the other hand, Blinder (2006) has stressed the importance of interactivity in determining task tradability. If the performance of a task involves direct physical presence and interaction, it will be hard, if not impossible, to offshore. Thus, it is the nature of tasks performed by individuals that determines their vulnerability to international relocation via offshoring - not the success of the firm or the viability of the industry they work in. This may well give rise to a very different effect on labor demand than a skill-based analysis as workers with the same educational achievement usually carry out a multitude of job specific tasks. Therefore, the question of whether the task perspective indeed sheds light on a new aspect is answered by estimating relative demand for tasks *within* different skill groups as well.

Besides addressing the policy relevant question of which jobs have a more promising future in the domestic market, this paper's inquiry into task-level labour demand can be seen as a test of the offshoring mechanism detailed in Grossman & Rossi-Hansberg (2008) where an increase in offshoring is intimately related to a reduction in the demand for easy-to-offshore tasks in the home economy. Yet, there is more to the analysis then a mere projection of theoretical considerations into the space of empirics. In fact, the set-up in this paper allows for a discussion of what this demand shift actually means. Is it a simple re-focussing of the tasks performed on the job - as summarized by Harrison et al. (2010) in a recent survey article? Or is the demand shift occurring *between* occupations? That is, employment shares of occupations are driving the economy-wide demand shift while the tasks within each occupation remain mostly unchanged. Compared to simply doing different things within the same job over time, this latter mechanism, for which there is indeed comprehensive evidence emerging throughout the analysis, holds vastly different implications for labor market outcomes - with the potential for frictions in the reallocation process of individuals across occupations probably being the most crucial one.

This paper exploits the availability of uniquely suitable data covering the offshoring cost of tasks at the occupation level, as well as comprehensive information on individual's employment and income. The latter in particular allows for the calculation of cost shares within individual sectors of German manufacturing, an asset permitting the panel set-up in this paper. Moreover, the coverage of a recent time period (1998 - 2007) sets this analysis further apart from the existing literature. This time period is particularly important given the further integration of emerging countries like China and India into the world trading system - with offshoring possibilities reaching new levels.

A few recent empirical papers take note of the importance of tasks in analyzing the impact of offshoring on the labor market. Ebenstein et al. (2009) and Baumgarten et al. (2010) show negative wage effects for individuals performing mostly routine tasks in the US and Germany, respectively. Focusing on employment in the US, Crinò (2010) points out that service offshoring penalizes more tradable occupations within a given skill group and Ottaviano et al. (2010) provide some evidence that manufacturing offshoring tends to shift native workers into communication intensive occupations. Goos et al. (2009) document that more offshorable jobs show relative employment losses thereby contributing to the polarization of the labor market. They do not, however, directly test for the impact of offshoring on labor demand. Hakkala et al. (2008) take the firm-level perspective and find evidence of within-firm task reallocation when Swedish firms are acquired by multinational enterprises. In a similar vein, Becker et al. (2009) produce evidence for German multinationals reducing demand for routine tasks at home when expanding employment in their affiliates abroad. While being driven by a similar idea, this latter study remains limited in that it looks at selective within-firm offshoring only and draws on a very short 4-year sample ending in 2001. A focus on multinational firms possibly misses effects on other firms and therefore higher-level aggregates. It seems likely that such linkages between firms engaged in offshoring and such that source only domestically exist through supplier networks or competition in local labor markets, for example. A comprehensive study analyzing the connection between manufacturing offshoring and relative labor demand from a task perspective at a more aggregate level thus far is missing - in particular for the most recent decade marked by significant international integration. This paper therefore adds to this young and growing literature in an attempt to closing this gap.

Following this introduction, the theoretical considerations underlying the approach will be presented. Section 3 then provides details on the data used and the definitions applied. The econometric strategy is presented in section 4, with comprehensive results and thorough robustness checks following in section 5. A final discussion with summarizing remarks and a reference to promising further research opportunities concludes the paper.

2 Theoretical Considerations

The theoretical underpinnings are derived from Grossman & Rossi-Hansberg (2008). This paper features a straight-forward characterization of the offshoring mechanism. It is assumed that firms produce goods employing a continuum of tasks - part of which are produced at home, part abroad. The cutoff point on the unit interval determining the marginal task I for which the firm is indifferent regarding the location of its performance is implicitly defined by a trade-off between lower labor cost abroad ($w^* < w$) and a task related trade cost, $\beta t(i)$: $w = w^* \beta t(I)$. The cost of trading tasks ($\beta t(i) \geq 1$) are divided into a general economy-wide component which is intuitively linked to technological improvements in communication technology, β, and a task-specific component, $t(i)$. It is this latter component that is approximated by the task content of occupations as detailed below. All tasks i are ordered such that $t'(i) > 0$, i.e. the higher i the more difficult it is to offshore the task, possibly because of its non-routine or interactive nature. It is easily shown that with a decrease in β (e.g. improvement in communication technology) the marginal task shifts up: $\frac{dI}{d\beta} = -\frac{t(I)}{t'(I)\beta} < 0$. This is precisely what the authors refer to as offshoring, the relocation of tasks abroad that were previously too expensive to separate from home production, i.e. tasks that used to have a $t(i) > t(I)$. It is important to note that the upward shift in I is caused by a decrease in β at constant levels of $t(i)$; the idiosyncratic offshoring cost of individual tasks is assumed to be fixed. The focus on technological improvements in the general offshoring technology β furthermore rules out wage movements as the driving force behind production relocation. That is, the extensive offshoring margin in this partial equilibrium setting is entirely determined by the offshoring cost.

A simple and direct implication of this shift in the marginal task is that the tasks that remain onshore are on average more costly to offshore. In other words, and applied to the framework in this paper, the average task at home will be characterized as more non-routine and interactive than before the increase in offshoring (decrease in β). Following Wright (2011), the employment weighted average task-related offshoring cost at home can be written as

$$[A(I)] = \frac{\int_I^1 D(i)\, i\, di}{\int_I^1 D(i)\, di}$$

which is the employment share of non-routine and interactive tasks, a measure of relative labor demand for such tasks. Consequently, $[1 - A(I)] = D_r$ is the demand for routine tasks at home. For the effect of offshoring (via a decrease in β) on relative demand D_r for such tasks it follows that:

$$\frac{dA(I)}{dI} = \frac{D(i)}{\int_I^1 D(i)\, di} \times [A(I) - I] > 0 \quad \Rightarrow \quad \frac{d[1 - A(I)]}{dI} < 0$$

In short, offshoring decreases the relative importance of easy-to-offshore tasks at home as those tasks are moved overseas. It indeed manifests itself as a labor demand shift away from routine and non-interactive tasks. This is the main hypothesis tested in this paper. A second hypothesis - that this task-demand shift is driven by a variation in occupation level employment - is tested within the specific construction of labor demand as detailed below.

3 Data and Construction of Labor Demand Variables

This section details the approach taken towards the definition and calculation of offshoring cost. It furthermore gives an introduction to the income and employment data used in the construction of cost and employment shares. While the basic structure of the data and the idea behind the set-up is explained here, more detailed information is relegated to the appendix. Before leading over to the empirical analysis in the next section, the offshoring intensity as the crucial explanatory variable is introduced as well.

3.1 Task Data

In order to inquire into the structure of offshoring cost and the related demand shifts in the offshoring process, it has to be clear what is understood as a task. In theory, a single task is infinitesimally small and part of a continuum. Empirically, it has often been a challenge to find an adequate approximation. In this paper, the unit of analysis for task-related offshoring cost is the level of a 2-digit occupation of which 74 in the German "KldB" classification will be used. Note that this is not meant to strictly define one occupation as one task. Yet, an occupation is regarded as a unit which can be relocated internationally. From a firm perspective such an occupation seems like a natural unit when restructuring employment. This renders the offshoring cost of an occupation a crucial determinant in the offshoring decision of firms. In this paper, this cost is seen as being determined by the distribution of tasks within individual occupations, or the nature of the tasks bundled into one occupation. That is, the more routine or non-interactive tasks are performed within an occupation, the less costly it is to offshore its performance. This does not mean, that each individual task within one occupation is necessarily routine or non-interactive. It yields the same predictions if one assumes limited separability of tasks within occupations, however.

Given the above considerations, the empirical equivalent to the task continuum in Grossman & Rossi-Hansberg (2008) is a vector of 74 occupations ordered according to their offshoring cost - the latter being based on their share of routine and non-interactive tasks. The task shares within occupations are represented by average task performance over individuals. The best data on this topic comes from the "BIBB/IAB-Survey 1998/99".[1] This database has previously been used by Spitz-Oener (2006) among others and has become one of the standard sources for task related information. The database holds survey-results describing the tasks individual workers perform. For the analysis in this paper, 13 different activities are grouped into either difficult-to-offshore (non-routine and interactive) or easy-to-offshore tasks (routine and non-interactive). Based on the frequency of task performance, individual level task intensities are calculated which are subsequently aggregated to the 2-digit occupational level as simple mean values. The individual level task intensities are derived as:

$$R_k = \frac{\text{number of routine or non-int. tasks performed by individual k}}{\text{number of all tasks performed by individual k}}$$

This calculation of tasks intensities is a variant of a method proposed by Antonczyk et al. (2009) and is distinct from approaches such as Spitz-Oener (2006) or Becker et al. (2009) where the number of type-n tasks (with $n \in routine, non-routine$) an individual performs is related to all possible type-n tasks. The measure applied here therefore does not relate to a category-specific intensity but rather yields an approximation of how an individual splits her job into different tasks. Thus, this paper's measures of task intensities of type-n tasks within all 74 occupations considered add up to one.

[1]The data used is the BIBB/IAB study: "Acquisition and Application of Occupational Qualifications 1998/99", provided to the author by GESIS Cologne, Germany. No. ZA3379. Datafile version 1.0.0, 13.04.2010, doi:10.4232/1.3379.

3.2 Income and Employment Data

The outcome of the above calculations are occupation-level $t(i)$-values, which derive from how intensively an occupation uses a certain type of task on average. In order to construct sector level task cost- and employment shares, these measures are combined with time varying income and employment data from administrative individual employment records ("BA-Employment Panel").[2] These data hold information on the employment of and the total income paid to individuals in a given time period. Crucially, and in contrast to other data sets with smaller dimensions, this data has a sufficient number of observations to provide for representative distributions of occupational employment and income within 2-digit industries. A straight forward calculation of the empirical equivalent of $A(I)$ is then to take the employment shares of each education, multiply them with the task scores and aggregate this to the sector level. Such calculations are done for 19 manufacturing sectors over the time period between 1998 and 2007 at yearly frequency.

Although the theory as in Grossman & Rossi-Hansberg (2008) does not feature task specific wages, the empirical literature usually considers cost shares as measures of relative labor demand. As a complement to the task-employment shares and to better align this paper's analysis with the present empirical literature on (skill-related) relative labor demand, cost shares are calculated as well. This is done using income information provided in the BA data set. Using the occupation-level task intensities, each individual's income is split according to how frequent her occupation uses a certain type of task by multiplying the task intensity (which is between zero and one) with the yearly wage. Aggregated to the sector level this represents, for a given sector and year, a calculation of cost spend on, e.g., routine task labor inputs. Dividing this by total income spent across all tasks (total labor cost) yields the cost share of such tasks.

[2] This study uses the factually anonymous BA-Employment Panel (Years 1998 - 2007). Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

It is crucial to note what the above implies in terms of variation used for estimation in later sections of this paper. Importantly, all of the variation in relative labor demand stems from variations in income and employment shares. One important characteristic of this approach is that the task content of individual occupations is assumed to be constant over time, a characteristic shared with the Grossman & Rossi-Hansberg (2008) model. Although this assumption is frequently taken in empirical work as well (see e.g. Becker et al. (2009) or Crinò (2010)), it may be problematic if some occupations change their task intensities and are relocated abroad not due to a general fall in offshoring cost β but due to themselves becoming idiosyncratically more tradable. Yet, from a similar task-survey for 2005/06, there is evidence to be found that is strengthening the validity of this assumption. On average, there was hardly any movement in within-occupational task intensity over the sample period considered and the average share of routine tasks within an occupation decreased by only -0.78%. The ranking of occupations in terms of their easy-to-offshore-task intensity also remained mostly the same. Estimation of a Spearman's rank coefficient yields a value of $\rho = 0.934$ indicating a very high persistence of the occupational ranking over time.

It thus seems plausible to rely on variation in employment shares and income over time. Assessing the relevance of this channel also allows to address the question of which nature the task-trade effect of Grossman & Rossi-Hansberg (2008) really is. Given a significant connection between shifts in occupation level employment and offshoring, one could conclude that task trade occurs mainly in the form of an international reallocation of jobs rather than simply changing the task content of occupations. This issue will receive additional attention in the estimation below.

3.3 Offshoring Data

The offshoring intensities for each sector and year are calculated using a method similar to Feenstra & Hanson (1996). In particular, the measures are constructed to represent the share of imported intermediate inputs in total industry output - a slight variation of the original measure following Geishecker (2006). The necessary data on input-use as well as output both by industry and year are taken from the import matrices that are part of the Input-Output tables provided by the Statistical Office of Germany. It is important to note that only inputs which originate in the same industry j^* as the the home industry j are included. Thereby it is ruled out that traditionally imported intermediates that do not reflect an offshoring decision are counted in. This makes the offshoring indices constructed here resembling the "narrow" measure of Feenstra & Hanson (1996):

$$OFF_{jt} = \frac{IMP_{j^*t} \times \Omega_{j^*jt}}{Y_{jt}}. \tag{1}$$

Ω represents the share of imported inputs from a specific industry j^* used in the same industry j at home. IMP measures all imports from the respective foreign industry.[3] These imports can be split in order to differentiate among different offshoring destinations.[4] To provide for the closest fit with theory based offshoring considerations, which are rooted in labor cost differentials across countries, a non-OECD country specific offshoring intensity is calculated to complement the worldwide measure. This region specific calculation entails the assumption that Ω does not differ across country groups. This is a strong assumption, yet one that is frequently taken in the empirical offshoring literature (e.g. Geishecker (2006)).

[3] These trade data are taken from the OECD STAN database.

[4] The imports from non-OECD countries are available for 18 out of the 22 2-digit nace industries. Therefore imports from sectors 15-16, 17-19 and from 21-22 had to be taken as aggregates. Note, however, that this limitation does not apply to Ω values and is furthermore weakened by the time-series based identification strategy in the empirical analysis.

Table 1 gives an overview of the constructed variables. Offshoring intensities vary substantially between sectors and over time, with most industries showing an increase over the sample period. Offshoring to non-OECD countries is much less important from a levels perspective, yet, it does show much stronger growth and has increased for all considered industries. It is of no surprise to observe relatively high offshoring intensities in the wearing and apparel and textile industries as well as in basic metals. This holds true for both world-wide and non-OECD offshoring. The highest growth is found in the radio, television and communication industry, however. At the same time the share of routine and non-interactive tasks fell in most sectors.[5] While this points to a possible relationship between the variables, it will be left to the empirical analysis in the following sections to uncover the strength and significance of this link.

Table 1: **Descriptives: Offshoring and Task Intensity**

sector name	offshoring world			offshoring non-OECD			cost share of routine tasks		
	1998	2007	change	1998	2007	change	1998	2007	change
Food Products And Beverages	3.27	4.08	0.81	0.50	0.75	0.26	36.63	37.17	0.54
Textiles	11.19	8.83	-2.36	4.21	4.85	0.63	45.54	43.41	-2.13
Wearing Apparel; Dressing ...	17.99	13.27	-4.72	6.77	7.28	0.51	32.32	26.25	-6.06
Wood Products, Except Furniture	4.80	3.57	-1.23	0.98	1.21	0.23	45.56	45.39	-0.17
Pulp, Paper And Paper Products	9.19	8.55	-0.63	0.45	0.77	0.32	44.57	45.75	1.19
Publishing, Printing ...	0.09	0.88	0.79	0.00	0.08	0.07	33.82	29.61	-4.21
Chemicals And Chemical Products	11.46	14.28	2.82	0.78	1.20	0.42	34.32	33.83	-0.48
Rubber And Plastic Products	0.97	1.70	0.72	0.09	0.25	0.16	47.77	47.20	-0.57
Other Non-metallic Mineral Products	2.26	2.02	-0.24	0.22	0.39	0.17	43.18	41.92	-1.26
Basic Metals	13.24	20.79	7.55	2.17	4.99	2.82	48.44	49.86	1.42
Fabricated Metal Prod., excl. Mach.	1.48	1.75	0.27	0.25	0.43	0.17	46.38	46.76	0.38
Machinery And Equipment NEC	6.10	8.30	2.20	1.05	2.33	1.28	40.37	38.73	-1.64
Office Machinery And Computers	10.75	9.34	-1.41	2.65	4.42	1.77	25.26	22.46	-2.80
Electrical Machinery ...	5.78	6.82	1.04	0.99	1.68	0.69	36.94	35.77	-1.17
Radio, Television, Communication	5.16	13.80	8.64	1.20	5.35	4.15	32.80	28.80	-4.00
Medical, Precision And Optical ...	4.38	5.15	0.78	0.65	0.97	0.32	33.44	32.08	-1.36
Motor Vehicles, Trailers ...	6.90	9.52	2.62	0.20	0.61	0.41	44.24	41.56	-2.68
Other Transport Equipment	8.16	9.98	1.82	0.37	1.05	0.68	36.67	32.93	-3.74
Furniture; Manufacturing NEC	7.23	9.26	2.04	2.12	4.38	2.25	42.18	40.36	-1.82

[5] Yet, it also emerges that the shift in manufacturing wide labor demand is hardly dramatic. Over the sample period the share of the aforementioned tasks decreased from 40.4% to 39.4%.

4 Econometric Specification

After having described the theoretical motivation and structure behind the cost and employment shares of certain tasks in section 2 and 3, these measures are now linked to potential explanatory variables. The derivation of an estimation set-up is based on a model in which firms minimize their short run variable cost functions over the variable inputs - task-employment in this case.[6] They do so by deciding on the occupational distribution of their home country labor force. As in Berman et al. (1994) the cost function is specified in a translog form and allows treating capital and output as fixed in the short run. This cost function can generally be written as $C_{SR} = C_{SR}(w_r, w_{nr}, Y, (K/Y), Z)$ where the subscript r stands for routine and non-interactive tasks and nr identifies non-routine, interactive ones. Z represents a vector of shift factors, such as offshoring or technological change. This specification has the convenient feature that, under the assumption of linear homogeneity and concavity in factor prices, variable factor demands are easily derived from the translog approximation using Shephard's Lemma. That is, a variable factor n's share in total variable cost, S_n, emerges as: $\frac{\delta ln C_{SR}}{\delta ln w_n} = \frac{w_n L_n}{C_{SR}}$. Following this workhorse model of the literature on relative labor demand, the following estimation equation for the cost share of routine and non-interactive (easy-to-offshore) tasks in sector j at time t emerges:

$$S_{r,jt} = \beta_1 OFF_{jt} + \beta_2 ln Y_{jt} + \beta_3 ln(K/Y)_{jt} + \beta_4 ln(w_r/w_{nr})_{jt} + \gamma Z_{jt} + \delta_j + \delta_t + u_{jt}. \quad (2)$$

Note that time and sector fixed effects have been included to control for unobserved heterogeneity in the respective dimension. In such a set up, the effect of offshoring is identified based on variation over time, on different time variation across sectors to be precise. It is investigated whether an increase in offshoring leads to a decrease in relative labor demand for routine and non-interactive tasks. The estimated coefficient $\hat{\beta}_1$ is thus expected to be

[6] For a full exposition of the well-known translog approximation and the derivation of the cost shares see e.g. Hijzen et al. (2005).

negative and statistically different from zero.

5 Does Offshoring Affect Relative Labor Demand for Tasks?

Having derived a suitable framework for estimation, it can be investigated whether and to what extend offshoring shifts the relative labor demand for tasks. Since the pure task-trade effect in Grossman & Rossi-Hansberg (2008) does not include task-level wage changes, this section opens with the presentation of regressions based on employment shares instead of cost shares. That is, the only variation driving shifts in sector level task intensities derives from changes in employment shares of different occupations with heterogeneous task content. In particular, it will be tested whether offshoring leads to a decrease in relative employment of those occupations being particularly intensive in easy-to-offshore tasks. Following an arguably simplifying approach as in Hijzen et al. (2005) and Becker et al. (2009) this baseline estimation does not include the relative wage term at first. In further specifications the term is included, with little effect on $\hat{\beta}_1$, however. Table 2 shows the outcome of performing the baseline employment share regressions. In the first column results are presented from estimating equation (2) with only output and capital intensity included as further determinants of relative labor demand. This baseline specification already reveals the main result, which is changed little in further specifications. Offshoring reduces the relative labor demand for easy-to-offshore task; and it does so by shifting employment away from occupations intensive in those tasks. The results indicate that on average a one percentage point increase in the worldwide offshoring intensity leads to a fall of .05 percentage points in the routine (and non-interactive) task intensity. This finding is derived upon the inclusion of sector and year dummies. Taking a look at the results in column 2, it becomes evident that - as expected - the effect of offshoring to non-OECD countries is higher, with a one percentage point rise in offshoring shrinking the demand for routine and non-interactive tasks by .36 percentage points. The inclusion of further control variables does not alter the results significantly. These extra explanatory variables control for task shifts related to technological change that is not directly related to changes in offshoring cost β and for the role of the institutional set-up which could limit the reallocation of labor. Note, however, that only differential movements in these variables across sectors are picked up here as all economy wide time trends and sector specific time-constant factors are already controlled by the fixed effects. In general, adding the sector level R&D intensity as an, arguably crude, approximation of technological progress or the labor share to account for some institutional factors only provides a slight hint of further explanatory power and barely changes the offshoring coefficients. The same holds true for the inclusion of the relative wage, which is based on task share weighted occupational averages.

Moving away from the purely employment based analysis and taking a look at cost shares of tasks confirms the result of a negative link between offshoring and the relative demand for routine and non-interactive tasks. Table 3 shows the basis for this claim. The offshoring coefficients are very similar to the earlier table's results hinting at most of the effect operating through employment shifts rather than wage effects. The capital intensity has more of an impact and shows a higher level of statistical significance with its negative coefficient. Including the relative wage in the cost share specification is warranted based on the derivation of equation (2) but directly raises doubts due to an endogeneity concern, the reason simply being the use of wages in the construction of the cost shares as the left hand side variable. The relation is thus more based on a definition than on a true economic mechanism - a reason which lead several researchers to omit the term.

Thus far, the innovative nature of a task based approach has simply been postulated. It may well be that the routine and non-interactive characterization of occupations and the corresponding sector level task intensities simply reflect the same fault lines as the high-skilled vs. low-skilled dichotomy always did. Relabeling an old phenomenon would hardly constitute a

contribution to the literature. Therefore, the next step is to test for shifts in relative labor demand within skill groups. Table 4 shows the outcome of this important exercise. Again, offshoring is found to shift relative labor demand in favor of non-routine and interactive tasks. The result furthermore shows a similar robustness as the full sample analysis did. Crucially, the effect is very similar within skill groups, an important finding suggesting that the skill based view on relative labor demand captures hardly any of the task related variation. The low-skill characterization for the potentially adversely affected group of workers does not suffice to unveil the true distribution of hardships. Within education based skill groups the task dimension seems to matter a great deal. This is a result in line with Baumgarten et al. (2010) where task-level (i.e. occupation specific) wage effects are found to be present within skill groups.
The evidence thus far crucially relies on the regressions being unbiased in term of endogeneity and thus on the assumption of offshoring being exogeneous to the employment of certain tasks. That might not hold true in all cases, however. Indeed, testing this assumption by employment of a C-test gives rise to some doubts. While the exogeneity assumption is technically not rejected for worldwide offshoring, the p-value is not convincingly high ($\chi^2 = 1.27$, $p = 0.26$ in a cost share model including all controls but excluding the relative wage). For offshoring to non-OECD countries, the exogeneity assumption is clearly rejected, casting some doubt on previous results ($\chi^2 = 4.74$, $p = 0.03$). The analysis thus proceeds with regressions in which this potential endogeneity is explicitly taken into account and offshoring is instrumented with its first and second lag.

Estimation is then conducted via GMM and results are displayed in table 5. Reassuringly, the negative relationship between offshoring and the demand for easy-to-offshore tasks is still clearly visible. In particular, offshoring to non-OECD countries decreases relative labor demand for those tasks. The coefficient is higher now with a one percentage point higher offshoring reducing routine task demand by .79 percentage points. Translating those numbers into a measure of how important offshoring is for the observed demand shift reveals that about 67% of the observed decrease in routine and non-interactive task demand is attributable to an increase in offshoring to non-OECD countries. Turning to the estimates in table 5 again, it is seen that the within skill group effect remains valid as well. Offshoring is still found to affect relative labor demand on a more detailed level than the simple skill-dichotomy is able to depict. The validity of the chosen instrument structure for the non-OECD offshoring regression is confirmed by the J-statistics shown in table 5.

Further doubts regarding the robustness of the results are dispelled by numerous alterative specifications. Table 6 holds results for a shorter sample span, alternative measures of offshoring regarding the sources (Geishecker (2006)), reduced samples in which the sectors with the largest increase in offshoring (32) and the largest decrease in routine task intensity (18) are dropped, and finally cost shares of tasks constructed with task measures as in Spitz-Oener (2006). None of these alterations change the results in any disturbing way.

Table 2: **Regressions Based on Employment Shares**

all skills	1	2	3	4	5	6
offshoring intensity	-0.0613**		-0.0745**		-0.0764**	
	(0.0233)		(0.0284)		(0.0301)	
offshoring intensity to non-OECD		-0.360***		-0.357***		-0.363***
		(0.0844)		(0.0997)		(0.106)
$ln(Y_{jt})$	0.0120	0.00902	0.0242	0.0176	0.0248	0.0181
	(0.0211)	(0.0145)	(0.0211)	(0.0160)	(0.0207)	(0.0155)
$ln(K_{jt}/Y_{jt})$	-0.0232	-0.0280**	-0.0191	-0.0223	-0.0173	-0.0203
	(0.0195)	(0.0131)	(0.0182)	(0.0129)	(0.0181)	(0.0130)
RnD intensity			0.237*	0.126	0.219	0.105
			(0.121)	(0.153)	(0.128)	(0.161)
ln (labor share)			0.018	0.0121	0.0164	0.0102
			(0.0186)	(0.0162)	(0.0192)	(0.0166)
ln (rel. wage)					0.0212	0.0232
					(0.0257)	(0.0228)
sector fixed-effects	yes	yes	yes	yes	yes	yes
year fixed-effects	yes	yes	yes	yes	yes	yes
Observations	190	190	162	162	162	162
R-squared	0.571	0.633	0.610	0.650	0.614	0.655
Number of sector	19	19	18	18	18	18

Robust standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 3: **Regressions Based on Cost Shares**

all skills	1	2	3	4	5	6
offshoring intensity	-0.0618***		-0.0771***		-0.0815**	
	(0.0209)		(0.0262)		(0.0304)	
offshoring intensity to non-OECD		-0.343***		-0.320***		-0.335***
		(0.0871)		(0.0986)		(0.108)
$ln(Y_{jt})$	0.0126	0.00955	0.0242	0.0173	0.0256	0.0184
	(0.0234)	(0.0177)	(0.0228)	(0.0202)	(0.0221)	(0.0193)
$ln(K_{jt}/Y_{jt})$	-0.0310	-0.0353**	-0.0288*	-0.0311*	-0.0247	-0.0269*
	(0.0187)	(0.0139)	(0.0162)	(0.0151)	(0.0160)	(0.0150)
RnD intensity			0.248*	0.160	0.208	0.115
			(0.143)	(0.164)	(0.153)	(0.177)
ln (labor share)			0.0294	0.0232	0.0259	0.0192
			(0.0235)	(0.0215)	(0.0236)	(0.0212)
ln (rel. wage)					0.0483**	0.0495**
					(0.0207)	(0.0188)
sector fixed-effects	yes	yes	yes	yes	yes	yes
year fixed-effects	yes	yes	yes	yes	yes	yes
Observations	190	190	162	162	162	162
R-squared	0.561	0.602	0.605	0.623	0.622	0.642
Number of sector	19	19	18	18	18	18

Robust standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 4: **Cost Share Regressions by Skill Groups**

	1	2	3	4	5	6	7	8
VARIABLES	low-skilled only				high-skilled only			
offshoring intensity	-0.0498***		-0.0653***		-0.0346		-0.0538**	
	(0.0131)		(0.0166)		(0.0200)		(0.0204)	
offshoring intensity to non-OECD		-0.300***		-0.259***		-0.214**		-0.262**
		(0.0793)		(0.0689)		(0.101)		(0.0969)
$ln(Y_{jt})$	0.0236	0.0212	0.0284	0.0225	0.0376**	0.0360**	0.0539**	0.0491**
	(0.0222)	(0.0176)	(0.0209)	(0.0199)	(0.0169)	(0.0140)	(0.0214)	(0.0177)
$ln(K_{jt}/Y_{jt})$	-0.0191	-0.0231**	-0.0268**	-0.0285***	0.0143	0.0113	0.0203	0.0179
	(0.0164)	(0.0101)	(0.00997)	(0.00921)	(0.0149)	(0.0126)	(0.0188)	(0.0157)
RnD intensity			0.274**	0.206			0.0414	-0.0410
			(0.118)	(0.134)			(0.0741)	(0.0973)
ln (labor share)			0.0348	0.0296			0.0262**	0.0220*
			(0.0250)	(0.0239)			(0.0112)	(0.0105)
sector fixed-effects	yes	yes	yes	yes	yes	yes	yes	yes
year fixed-effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	190	190	162	162	190	190	162	162
R-squared	0.261	0.324	0.368	0.387	0.227	0.265	0.284	0.318
Number of sector	19	19	18	18	19	19	18	18

Robust standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

Notes: high-skilled defined as tertiary education, low-skilled otherwise.

Table 5: **GMM-IV Regressions for Cost Shares by Skill**

	1	2	3	4	5	6
	all skills		low-skilled only		high-skilled only	
offshoring intensity	-0.159		-0.248**		-0.0516	
	(0.117)		(0.114)		(0.111)	
offshoring intensity to non-OECD		-0.790***		-0.594***		-0.688*
		(0.260)		(0.201)		(0.359)
$ln(Y_{jt})$	0.0266	0.0244*	0.0374**	0.0226	0.0605***	0.0634***
	(0.0185)	(0.0132)	(0.0164)	(0.0165)	(0.0208)	(0.0172)
$ln(K_{jt}/Y_{jt})$	-0.0597***	-0.0435***	-0.0653***	-0.0412***	0.00650	0.00754
	(0.0142)	(0.0132)	(0.0189)	(0.0112)	(0.0153)	(0.0169)
RnD intensity	0.125	0.0162	0.226**	0.0799	0.00245	-0.0421
	(0.106)	(0.0813)	(0.112)	(0.0829)	(0.114)	(0.0952)
ln (labor share)	0.0620**	0.0282	0.0788***	0.0357**	0.0418**	0.0326*
	(0.0260)	(0.0173)	(0.0297)	(0.0171)	(0.0186)	(0.0172)
sector dummies	yes	yes	yes	yes	yes	yes
year dummies	yes	yes	yes	yes	yes	yes
Observations	126	126	126	126	126	126
R-squared	0.996	0.996	0.993	0.994	0.958	0.955
Hansen J-Statistic	2.912	0.884	2.888	0.294	2.476	0.008
p-value	0.0879	0.347	0.0893	0.5879	0.1156	0.93

Robust standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

Notes: high-skilled defined as tertiary education, low-skilled otherwise.

Table 6: **Robustness Checks, Cost Share Regressions**

	1	2	3	4	5
VARIABLES	1999-2006	no 32	no 18	Spitz-Oener Tasks	Geishecker Offshoring
offshoring intensity to non-OECD	-1.017***	-1.326***	-0.847*	-0.809**	
	(0.385)	(0.410)	(0.436)	(0.348)	
offshoring intensity to Asia					-1.452***
					(0.337)
$ln(Y_{jt})$	-0.0891***	-0.0694***	-0.0576***	-0.0274*	-0.0436**
	(0.0237)	(0.0238)	(0.0163)	(0.0142)	(0.0188)
$ln(K_{jt}/Y_{jt})$	-0.0140	0.0123	-0.00323	0.0278**	-0.0396*
	(0.0163)	(0.0189)	(0.0187)	(0.0136)	(0.0226)
sector dummies	yes	yes	yes	yes	yes
year dummies	yes	yes	yes	yes	yes
Observations	114	144	144	152	85
R-squared	0.996	0.993	0.994	0.994	0.997
Hansen J-statistic	0.992	0.125	1.022	0.028	1.73
p-value	0.3194	0.7232	0.3121	0.868	0.1884

Robust standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

6 Concluding Remarks

If trade is indeed becoming more of a task related phenomenon due to the increase in offshoring activities by firms, the pattern of effects across workers may be changing as well. In particular, the skill-based characterization of winners and losers would fall short of comprehensively capturing the effects. Task trade occurs based on relocation cost for individual activities which do not necessarily coincide with skill intensities. This paper puts this claim to a test by analyzing relative labor demand from a task perspective. First, sector level task intensities are constructed based on survey data on task performance, secondly these are combined with income and employment data to derive cost and employment shares of tasks. The variation in these shares over time is subsequently linked to offshoring within a GMM-IV framework. A clear and robust result emerges. An increase in offshoring significantly reduces demand for routine and non-interactive tasks - in particular if this offshoring is directed towards non-OECD countries. The insufficiency of skill related measures is demonstrated by the fact that much of this demand shift is occurring within skill groups.

This paper can furthermore be seen as providing support for the mechanism in recent task trade theory where offshoring occurs as a relocation of the easiest-to-offshore tasks. Yet, the analysis adds to this simple claim by discussing the nature of this international relocation process. Estimation reveals that change in occupation-level employment is the main driving force behind the observed demand shift. It seems as if changes in task demand are more than mere reorientations of work contents within a job. And this holds important implications. In particular, if offshoring triggers reallocations between occupations, the flexibility of the labor market becomes a key factor in determining the overall effects on the labor force. Most of the positive wage and employment effects, which are derived in some recent models of offshoring, are only obtainable with a smooth reallocation. Research investigating the task based reallocation mechanism in a suitably modeled labor market after an offshoring shock is scare so far - and so are the corresponding empirical implementations.[7] The implications for individual wages, for inequality and for overall employment emerge as promising opportunities for future investigation.

7 Appendix

7.1 Labor market data from the BA Employment Panel

The BA Employment Panel ("BA-Beschäftigtenpanel") is a 2% random sample derived from official German employment records based on social security data. It holds information on a wide variety of individual worker characteristics. It is quarterly in nature, yet, allows for the calculation of yearly variables. Before calculating cost and employment shares, the sample is restricted to full time regular employees. For the employment share calculations information from the December waves only are used. This is not problematic since the empirical approach taken in the paper relies on variation over time. Yet, using the June waves as a test for robustness reveals the results not to hinge on the choice of sample waves. The income information is retrieved from all quarters since this yields an important advantage; it allows for a more precise calculation of cost spend on employment of different occupations in that it tracks individuals that switch jobs more precisely. Imputed incomes, so-called "Fortschreibefälle", are deleted. One potential issue with administrative data is that income is top-coded at the legal threshold of social security contributions. This issue is likely of less relevance in the manufacturing sector, however, and in particular for the sub-sample of low-skilled individuals. Furthermore, the results in this paper which are based on employment share calculations as measures of labor demand are completely unaffected by this limitation.

[7] A recent exception is the theoretical paper by Kohler & Wrona (2010)

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