

Does fragmentation of production imply fragmentation of jobs?

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Abstract

The possibility of deepening international specialization through trade in tasks has raised concerns about jobs and earnings in occupations hitherto sheltered from international competition. Trade in tasks cannot be measured directly. It is, however possible study how recent developments in international trade patterns are associated with changes in the task content of local production. From a labour market point of view this is the interesting question. The task content of goods and services is estimated by combining information from the O*Net database on the importance of a set of 41 tasks for a large number of occupations and information on employment by occupation and industry. The study shows that tasks that can be digitised and offshored are often complementary to tasks that cannot. We therefore cluster tasks that tend to be performed together across occupations and analyse how changes in the content of these task clusters are associated with international trade. Import penetration in business services is associated with a shift in local task content from information and communication related tasks towards tasks related to handling machinery and equipment, while import penetration of other services has exactly the opposite effect. It appears that offshoring of business services complements manufacturing activities while offshoring of other services complements local information-intensive tasks.

JEL classification: F16

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1. Introduction

Globalisation has led to deepening specialisation through trade in intermediate goods and services as well as different varieties of final products. International fragmentation of the value chain has vastly improved productivity and consumer choice, making even high-technology products such as smart-phones available and affordable almost everywhere. Trade in tasks could represent a new turn in this virtuous cycle of deepening specialisation, expansion of the market and productivity growth.

Trade in tasks has, however, attracted a lot of attention not for its contribution to international division of labour and growth, but for its possible detrimental impact on labour markets, particularly in high-income countries. Recent literature has estimated that between 20 and 30% of all jobs, including medium and high-skilled jobs, in a number of OECD countries can be offshored (Van Welsum and Vickery, 2005; Blinder, 2009 and Jensen and Kletzer, 2010). This estimate is based on information on the importance of tasks that can be codified and provided over the internet in almost all occupations in the economy.

However, as pointed out by Lanz *et al.* (2011), tradability of a task is not only determined by the technical feasibility of its unbundling and digitisation, but also by transaction costs and possible economies of scope that keep tasks together. Multi-tasked workers may be more effective at solving problems at source. Multi-tasked workers may also be better at incremental process and product innovation (Dohse *et al.* 1985). In sectors where product differentiation is important, therefore, there may be a trade-off between gains from specialisation and economies of scope.

Empirical research on the importance of trade in tasks and its labour market effects is in its infancy, and paucity of data necessitates innovative approaches. A theoretical model developed by Grossman and Rossi-Hansberg (2008) shows that the offshoring of tasks produced with a particular factor is equivalent to technological progress that augments the productivity of that factor. As a result, low-skill wages may rise in the event of offshoring of low-skilled tasks in skills abundant countries. However, Rojas-Romagosa (2011) shows that this result is a special case that does not hold under more general assumptions as far as

relative factor endowments, country size and parameter values are concerned. To our knowledge empirical research to shed more light on this is not available.

Another concern is that trade in tasks may contribute to polarisation of the labour force. Since the late 1990s the shares of employment in both high- and low-skill jobs have increased at the expense of medium-skilled jobs in OECD countries on both sides of the Atlantic (Goos and Manning, 2007; Goos *et al.*, 2010; Autor *et al.*, 2010). The shift towards high-skilled jobs observed during the 1980s was largely attributed to skills-biased technological progress.¹ The polarisation observed since the late 1990s, however, did not quite fit into that framework, neither could it be explained by trade-related structural changes, since it is difficult to argue that a country has comparative advantage for both low and high-skills intensive sectors at the same time. The solution to the puzzle emerges when going beyond sectors and comparing the tasks that are performed in the contracting middling jobs versus those performed at the expanding high- and low-skills ends respectively.

Middle-skilled workers tend to do manual or cognitive tasks that lend themselves to automation or codification. Examples are book-keeping, monitoring processes and processing information. Because these tasks can be substituted by machines or offshored, demand for middle-skilled workers declined and the returns to their skills likewise. At the high-skills end, workers tend to perform cognitive non-routine tasks that are complementary to information technology. Therefore, demand for high-skilled workers increases in tandem with investment in information technology. Finally, low-skilled non-routine tasks involve services activities such as operating vehicles and assisting and caring for others. These activities are not directly affected by trade or technology, but employment shifts into these occupations anyway for two reasons. First, as societies grow richer and greyer, demand for personal services grow in step with income. Second, productivity growth in non-routine low-skilled jobs is slow, and employment growth will be

1. An interesting debate in the academic literature addressed to what extent skills-biased technological change or trade was the main explanation for growing income inequalities at the time. Although consensus was not reached, the conclusion seemed to be that the major driving force was technology. See Acemoglu (2002) for a review.

closely related to output growth in these sectors.² Polarisation of the labour market can in other words be explained by proliferation of information technology *and* trade and is best understood at the occupation and task level.

Trade and production data are not recorded at the task level. It is therefore not possible to analyse the labour market implications of trade in tasks directly. It is, however, possible to estimate the task content of local production and analyse empirically the relationships between trade flows in goods and services and changes in the relative importance of tasks performed at home. This paper proposes a novel approach to doing so and makes a first estimate of the relationship between trade and task content of local production. It follows previous studies in using the Occupational Information Network (O*Net) database from the US, a rich and comprehensive database on occupational information sponsored by the US Department of Labour, for studying variation in the task content of occupations. We differ from existing studies in several ways, however. First, we do not make any a priori assumption on which occupations and tasks are tradable, but use the complete set of tasks rather than a subset believed to be tradable in our analysis. Second, we cluster tasks that tend to be performed together across occupations and define production functions of goods and services as the performance of a set of task clusters, where sectors differ in their task intensity. From this production function we derive demand for each task and estimate empirically the demand elasticity for each task with respect to imports of intermediate goods and services. Finally, while existing studies focus on one country, usually the US, we extend the analysis to EU countries and Switzerland.

The rest of the study is organised as follows: Section two briefly reviews related literature. Section three presents the cluster analysis of tasks across occupations and calculates the task content of sectors. Section four presents regression results relating the tasks content of local production to import penetration of intermediate goods and services, while section five concludes.

2. Structural changes in the labour market also have an interesting gender dimension observed in the United States. It appears that for women the decline in middle-skilled employment is mirrored by an increase in high-skilled employment, while men to a larger extent move from middle-skilled to low-skilled jobs, an issue that has created concern about social consequences.

2. A small but rapidly growing literature presents mixed results

Since information on trade in tasks is not readily available, trade policy analysts have looked for indirect ways of measuring such trade. The first studies limited themselves to assessing the tradability of tasks, using detailed information on the task content of occupations from the O*Net database from the US or similar databases for other countries.³ The potential for trade in tasks was estimated by identifying the activities that can be easily codified and provided electronically at a physical distance and next determine the importance of such activities for the conduct of each occupation (Van Welsum and Vickery, 2005; Blinder, 2009; Jensen; Kletzer, 2010). These studies found that between 20 and 29% of all jobs in major economies such as the United States, Canada and Australia could be offshored. Furthermore, these jobs include medium to high-skilled professions that hitherto have been sheltered from international competition. The first papers studying tradability of tasks focused on simple typologies opposing for example routine and non-routine tasks, or cognitive and manual tasks (Autor *et al.*, 2003). Studies based on a larger set of tasks, such as Blinder (2009) or Jensen and Kletzer (2010), also tend to rely on a limited number of tradable tasks.

Crinò (2009) also developed indices of tradability of occupations using the O*Net database. He took the analysis one step further by calculating labour demand elasticities with respect to import penetration of intermediate services as a share of total non-energy intermediate inputs for each occupation. The study explores to what extent labour demand elasticities vary systematically with tradability, using US data for the period 1997-2006. He found that offshoring of services is associated with an expansion of employment in high-skilled occupations, in spite of the fact that computer use and information processing are most important in this skills category. However, among services occupations requiring the same level of skills, the most tradable were found to be the most likely to shed jobs in the event of offshoring.

Before the great recession hit in 2008/09, the unemployment rate was historically low in the United States and a host of other OECD countries. Therefore, concerns about offshoring and jobs were as

3. Becker et al. (2009) use similar but less detailed information from Germany, while Ariu and Mion (2012) use data from Belgium.

much related to developments in relative wages as total employment. The evidence of possible links between offshoring and stagnation of middle-income wages and growing income inequality is mixed. It is clear that skills are less important as a determinant of income than it used to be, as wages vary significantly across occupations for a given level of skills as measured by education and experience (Autor *et al.*, 2010). It has also been found that the return to skills that can be automated or offshored has declined, and thus that declining employment in the middle is accompanied by shrinking relative and even absolute wages in occupations dominated by medium skilled manual or cognitive routine tasks. Finally, it appears that workers who perform tasks that are complementary to offshorable tasks at both ends of the skills spectrum have seen wages rise (Autor *et al.*, 2010; Firpo *et al.*, 2011).

Lanz *et al.* (2011) argued that multi-tasked workers have become the norm in most occupations and that the rationale for this may be economies of scope of keeping tasks together. Based on this hypothesis they performed a cluster analysis of the tasks entailed in the O*Net database across the 855 occupations for which information is available. They identified ten clusters of tasks, most of them a combination of tasks that previous studies have found to be tradable and non-tradable. If indeed tradable and non-tradable tasks are complementary, this needs to be taken into account when analysing tradability of tasks. Conversely, studying the tradability of individual tasks may not result in meaningful predictions of future trade patterns.

This paper is closely related to Lanz *et al.* (2011) and Crinò (2009). It calculates the task content of output using the clusters identified in the former study and estimates the elasticity of local demand for each cluster of tasks with respect to imports of intermediate goods and services. Defining production as a bundle of tasks, it addresses the question of structural changes at the task level directly. Crinò (2009) estimated labour demand by occupation and encountered the problem of a high degree of censoring of the dependent variables because sectors only employ a limited number of occupations. This problem is avoided when defining the production function as a set of tasks, since all the 41 standardised tasks identified in the O*Net database and all the 10 clusters of tasks identified in Lanz *et al.* (2011) are performed to a larger or lesser extent in most occupations and sectors.

3. Up to the task: a calculation of the task content of occupations based on O*Net

We wish to analyse empirically the relationship between offshoring of goods and services and the composition of tasks performed locally. Does offshoring lower the demand for routine, cognitive tasks and information processing tasks as predicted by the early literature? Or do offshored tasks complement medium and high-skilled tasks performed at home, raising demand for instance for information processing tasks at home as suggested by more recent studies? Our paper sheds light on this and contributes to the literature by proposing an in our view more suitable analytical framework and performing the empirical analysis on a panel of countries.

Our empirical analysis starts by calculating the task content of production in manufacturing and services sectors in countries for which sufficiently detailed information on employment by occupation and employment by sector is available. These countries are the United States, 21 EU countries and Switzerland. The starting point is the O*Net content model, which describes the key features of occupations with a variety of attributes and requirements classified in six categories: worker characteristics, worker requirements, experience requirements, occupational requirements, workforce characteristics and occupation-specific information. The category of interest is “occupational requirements” and the sub-category “generalized work activities”, which entails 41 tasks.

Data comparable to the O*Net on the task content of occupations are not available for the other countries in our sample. An open question is to what extent the task content of US occupations can be applied to occupations in the other countries. Does for instance a building engineer, a teacher or a computer software designer perform the same tasks in the US and Germany? This question has been analysed in the personnel psychology literature and Taylor et al. (2007) found that the tasks content of occupations are very similar in the US, Hong Kong, China and New Zealand. We therefore believe that assuming that task content of each occupation is the same across the countries in our sample should not create a serious problem. As a consequence, our analysis will mainly reflect differences in occupations by industry rather than tasks by occupation.

To calculate the proportion of tasks in each occupation, we follow earlier literature (Blinder, 2009; Jensen and Kletzer, 2010; and Firpo *et al.*, 2011) and calculate the task intensity TC_{ths} as a Cobb-Douglas weighted average of the importance of the tasks and the level of the tasks, where the weight of importance is 2/3 and the weight of level 1/3. To calculate the task content of each sector, we follow Lanz *et al.* (2011) as follows: The intensity of task h of sector s at time t TI_{ths} is represented by the matrix multiplication:

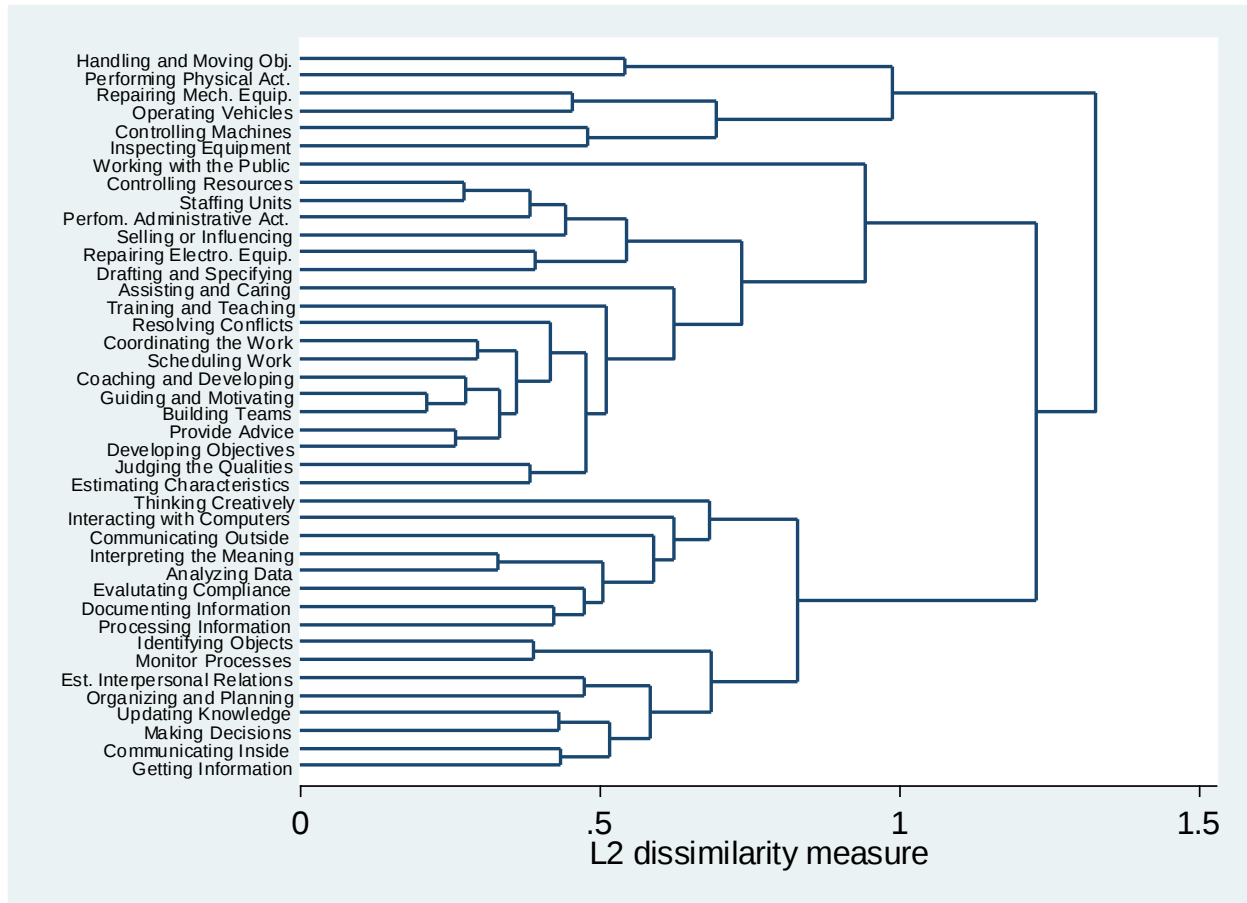
$$TI_{ths} = \begin{bmatrix} TC_{11} & TC_{1j} \\ TC_{h1} & TC_{hj} \end{bmatrix} \times \begin{bmatrix} \lambda_{t11} & \lambda_{t1s} \\ \lambda_{tj1} & \lambda_{tjs} \end{bmatrix} \quad (1)$$

The first matrix is an $h \times j$ matrix where the intensity of task h in occupation j is depicted. The second matrix is a $j \times s$ matrix containing the share of occupation j in total employment in sector s . The occupation shares in the second matrix are calculated on the basis of the Occupational Employment Statistics (OES) in the case of the United States and from the Labour Force Survey (LFS) in the case of the European Union. One issue when comparing the United States and European Union economies is that their employment surveys rely on a different classification of occupations: the Standard Occupation Classification (SOC) system in the case of the United States and the International Standard Classification of Occupations (ISCO) in the case of the European Union and Switzerland. The structure of the two classifications is quite different; this is why we did not try to match the occupation data. We use a common industry classification (ISIC Rev. 3) for which we have a correspondence with NAICS industries (US) and NACE industries (EU) but the calculation of the task intensity of industries relies on SOC for the United States and ISCO for the European Union. We have the data for the period 1999 to 2008.

Multiplying the two matrices yields an employment-weighted average index of the intensity of task h in sector s at time t . TI_{ths} is a $h \times s$ matrix where $\sum_h TI_{ths} = 1$. Given the limited number of observations that we have, 23 countries over 10 years, it may not be feasible to estimate an equation system with 40 equations. Besides, as demonstrated by Lanz *et al.* (2011) tasks tend to be performed

together in clusters, and clusters of tasks may be a more meaningful unit of analysis. We reproduce the cluster analysis using version 15.1 of the O*Net database, which contains 855 occupations. The result is depicted in Figure 1.

Figure 1. Task content of occupations



Note: The dendrogram is obtained by applying hierarchical cluster analysis to the tasks by occupation dataset. Euclidian (L2) distance between clusters is calculated with the complete-linkage method.

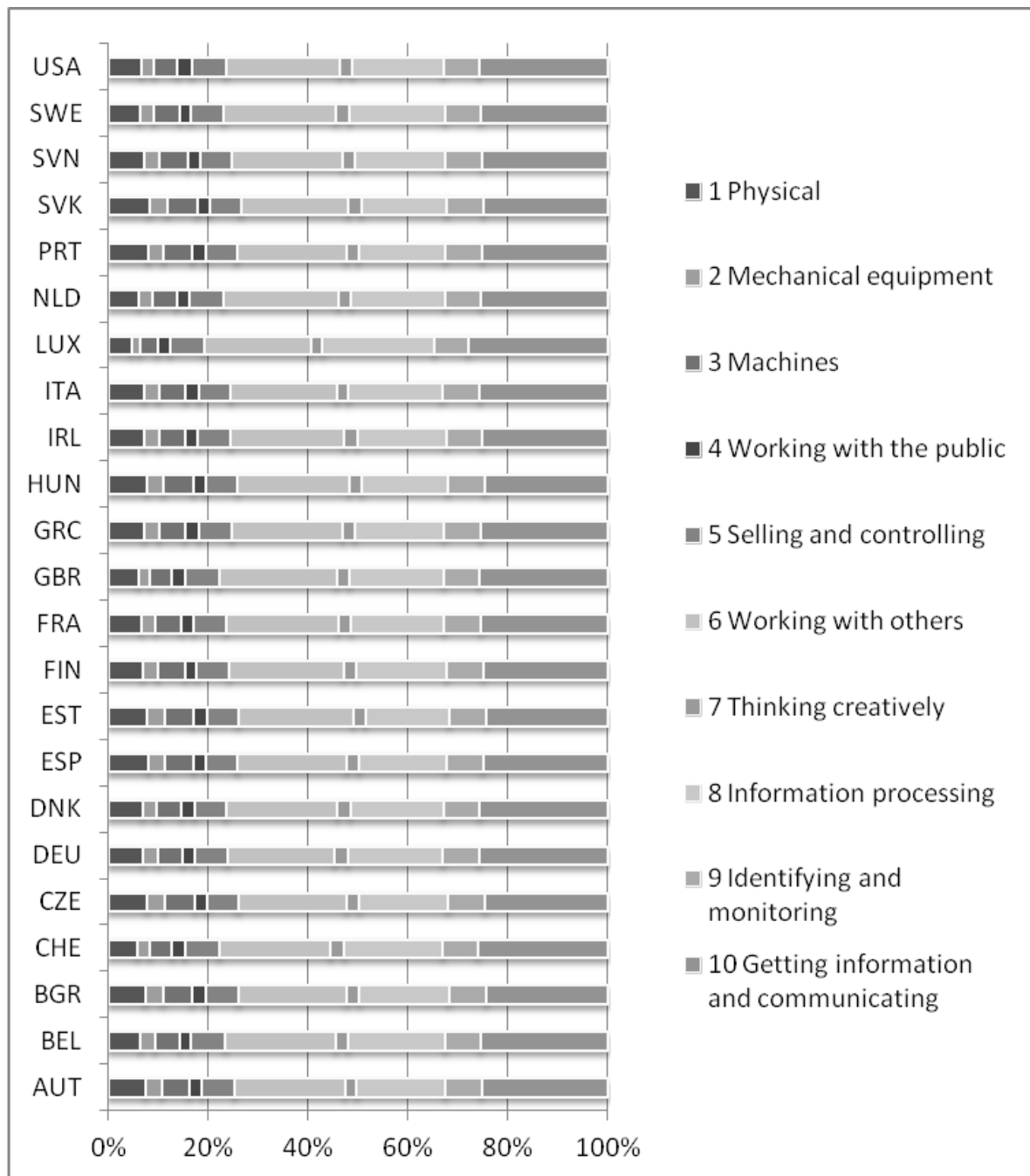
Figure 1 is a “dendrogram”, which is simply a tree showing how tasks are clustered together statistically. The tree shows the hierarchy in the clustering, the higher the value on the horizontal axis the more dissimilar are tasks (in the sense that the same tasks tend not to appear together in occupations). Starting from the right, the two first branches divide the list of tasks (represented on the vertical axis) into two groups. The first group involves tasks related to “handling and moving objects”, “performing general physical activities”, “repairing and maintaining mechanical equipment”, “operating vehicles” and

“controlling machines and processes”. These tasks are rather manual and the cluster makes sense for all occupations involving manual work or mechanical work. All the other tasks are in a second cluster. Following the tree from the right to the left, one can see how these other tasks bundled together are further divided in sub-groups. A cut-off line about 0.5 on the dissimilarity measure yields ten clusters. In the following we will analyse how the relative importance of these ten clusters is associated with international trade in intermediate goods and services. The intensity of each cluster in each sector is derived by summarizing over individual tasks entailed in the cluster. We first calculate the contribution of each of the ten task clusters, h to the total economy for each country c in our sample at time t , T_{th}^c , by multiplying the matrix of task cluster intensity by sector by a vector of sector outputs, Y :

$$T_{cth}^c = \begin{bmatrix} TI_{ct11}^c & TI_{ct1s}^c \\ TI_{cth1}^c & TI_{cths}^c \end{bmatrix} X \begin{bmatrix} Y_{t1}^c \\ Y_{ts}^c \end{bmatrix} \quad (2)$$

The result for 2000 is depicted in Figure 2. Clusters are named after the tasks entailed in them. We see that there is considerable variation in the task composition of output in these countries, but clusters 6 (working with others), 8 (information processing) and 10 (getting information) are the three most important in all our sample countries – we indeed live in the informatin age! It is recalled that cluster 10 contains “getting information”, which other studies have considered one of the most tradable tasks, but also “establishing and maintaining interpersonal relationships” and “making decisions and solving problems”, two tasks that are considered among the least tradable by other studies. Cluster 8 contains a number of information processing and handling tasks considered to be highly tradable by other studies, while cluster 6 contains many of the least tradable tasks.

Figure 2. Task content of output (2000)



5. How are changes in task content of production related to international trade?

As noted, trade in tasks can only be measured indirectly. To assess the relationship between task intensity and exposure to international trade, a system of nine equations is estimated that explains the allocation of country output and industry employment in terms of task clusters. Since task clusters are measured as

intensities, i.e. shares at either the country or industry level, a reduction in the intensity of one task cluster will be reflected in a respective increase in the intensity(-ies) of another task cluster. To account for this interdependence, task clusters are estimated simultaneously instead of using cluster by cluster OLS regressions. To make identification of the system of equations possible, one task cluster is omitted in the system so that equations for nine task clusters are estimated simultaneously at the country level:

$$T_{th}^c = \beta_0 + \beta_1 IPG_t^c + \beta_2 IPS_t^c + \beta_3 output_t^c + \beta_4 output\ p.w._t^c + t + e_{th}^c \quad (3)$$

T_{th}^c indicates the intensity of task cluster h in total output of country c in year t . IPG_t^c and IPS_t^c indicate import penetration of goods and services respectively and are defined as the share of goods or services imports in expenditure of country c . While goods trade data are from the OECD ITCS database and services trade data from the OECD TISP database, expenditure is calculated using output data from the OECD STAN database and trade data, e.g. $IPG_t^c = (\text{goods imports}) / (\text{output} - \text{exports} + \text{imports})$. Import penetration measures at the industry level are calculated analogously, but while services trade data still come from the OECD ITCS database, goods trade data are directly sourced from OECD STAN. Data for output ($output_t^c$), output per worker ($output\ p.w._t^c$) at the sector and country level and labour cost per worker ($labour\ cost\ p.w._t^c$) at the sector level are from OECD STAN and are measured in natural logarithms, while t denotes time dummies and captures year specific shifts in the intensity of task clusters. The residual e_{cth} captures random shocks to task intensities. Table 1 shows the regressions results for the ten clusters. As the sample size is small, results should be interpreted with a large amount of caution.

Import penetration of both goods and services are associated by differences in the composition of tasks performed in the local economy. Furthermore, imports of intermediate goods from the EE5 (Brazil, China, India, Indonesia and South Africa) has a larger effect than imports from other sources. Thus, imports of intermediate inputs from these countries tend to shift resources from manual tasks related to machines and equipment towards tasks that requires face-to-face interaction with people (selling and controlling and working with others). Imports of services other than business services have a similar effect,

but such services also seem to be complementary to information-related tasks. Business services, however, have quite the opposite effect on the composition of locally performed tasks shifting local task away from information processing tasks towards manual tasks related to machinery and equipment.

Interestingly, variation in the share of cluster seven “thinking creatively” across countries appears not to be affected by any of the variables included in the analysis and the explanatory power of the regression is quite low. “Working with others”, which is most important in sectors such as health and education appears to be unaffected by services trade. The shift in the task composition towards cluster eight and ten is not surprising, since other studies have also found that services offshoring has this effect in some of the countries included in our sample. But the contrasting effect of business services and other services are somewhat surprising. It appears that imported business services complements tasks related to operating machinery and equipment, tasks typically found in manufacturing, while other services complement information-intensive tasks typically found in services sectors and services functions in industries. These findings are further explored in the next section which studies how shifts in task intensity in individual sectors are associated to trade in intermediate goods and services.

Table 1. Regression analysis: relationship between the output share of task clusters at the country level and import penetration

	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9	Cluster 10
	Tasks related to mechanical equipment	Tasks related to machines	Working with the public	Selling and controlling	Working with others	Thinking creatively	Information processing	Identifying and monitoring	Getting information and communicating
Import penetr. Goods: OECD	-0.009*	0,001	-0.016***	0.006**	-0.051***	0	0.044***	-0,004	0.028***
	(0.005)	(0.008)	(0.003)	(0.003)	(0.012)	(0.002)	(0.009)	(0.003)	(0.005)
Import penetr. Goods: EE5	-0.116**	-0.295***	0,004	0.142***	0.619***	0,006	0.352***	-0.060*	-0,04
	(0.056)	(0.091)	(0.040)	(0.034)	(0.141)	(0.020)	(0.113)	(0.031)	(0.066)
Import penetr. Goods: ROW	0,025	0,036	0,001	-0,013	-0,049	-0,002	-0,038	0,005	-0,026
	(0.016)	(0.026)	(0.012)	(0.010)	(0.041)	(0.006)	(0.033)	(0.009)	(0.019)
Import penetr.: Business Services	0.184***	0.320***	-0.140***	-0,013	0,069	0,009	-0.332***	0,022	-0.390***
	(0.049)	(0.080)	(0.035)	(0.030)	(0.123)	(0.017)	(0.099)	(0.027)	(0.057)
Import penetr.: Other Services	-0.067***	-0.116***	0.044***	0.017**	0,031	0,001	0.064**	-0.027***	0.107***
	(0.014)	(0.023)	(0.010)	(0.008)	(0.035)	(0.005)	(0.028)	(0.008)	(0.016)
Output	-0.001***	-0.001***	0	0.000**	-0.001**	-0.000*	0.002***	-0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Output per worker	-0.001***	-0.003***	0	0.001***	0.003**	0.000**	0.006***	0	0.002***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Constant	0.084***	0.135***	0.029***	0.037***	0.230***	0.024***	0.045***	0.094***	0.165***
	(0.007)	(0.011)	(0.005)	(0.004)	(0.017)	(0.002)	(0.013)	(0.004)	(0.008)
R-squared	0,595	0,614	0,379	0,574	0,305	0,179	0,644	0,445	0,679
Number of observations	161	161	161	161	161	161	161	161	161

Notes: The dependent variables in the system of 9 equations are the shares of each task cluster in country output. The variables output and output per worker are measured in logs. Year dummies are included. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

We now turn to an empirical analysis of the relations between the task intensity by sector calculated in equation (1), controlling for output and output per worker as above. The systems of equations at the industry level:

$$T_{ths}^c = \alpha_0 + \alpha_1 IPG_{ts}^c + \alpha_2 IPS_{ts}^c + \alpha_3 output_{ts}^c + \alpha_4 output\ p.w._{ts}^c + \alpha_5 labour\ cost\ p.w._{ts}^c + t + e_{ths}^c$$

T_{ths}^c indicates the employment-weighted intensity of task cluster h in sector s in year t . Table 2 shows the regression results of the system of equations explaining the intensities of task clusters in country output. The regressions are run for 22 countries during the period 1999-2008 using time and country fixed effects. The coefficients indicate how the explanatory variables are related to the allocation of tasks in a country, or, in other words, how these variables shift task intensities within a country.

[Analysis to be included]

6. Trade in tasks and structural changes: concluding remarks

This study has emphasized the importance of taking into account both the forces that contribute to unbundling tasks and the forces that keep them together when analysing the potential for trade in tasks. Our cluster analysis suggests that there may be important synergies in keeping tasks together – and transaction and coordination costs in unbundling them. Econometric results suggest that the tasks embodied in business services imports are complementary to tasks related to manufacturing and substitutes for information gathering and processing performed in the home economy, while the tasks embodied in other services complements information gathering and substitutes for manual tasks.

[to be completed]

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