Income and Employment Effects of Trade and Offshoring in Modern Labor Markets

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Jan Hogrefe
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Dekan:	Prof. Dr. rer. soc. Josef Schmid
1. Gutachter:	Prof. Dr. Wilhelm Kohler
2. Gutachterin:	Prof. Dr. Claudia M. Buch

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

The ongoing globalization of goods and factor markets is without a doubt a major influence shaping labor market outcomes in many advanced and developing economies. In parallel to more and more goods and services circulating the globe, economic research on the interactions between trade phenomena and employment and earnings in the labor market has seen an impressive expansion.[1] Yet, many new questions are constantly arising from changes in the structure of trade towards offshoring and more complex international value chains, from more countries joining global markets, and from better data and more sophisticated theories available to researchers. There is still plenty to discover. This dissertation sets out to explore some of the still unanswered questions in an attempt to contribute to a further completion of the picture of how international trade affects labor markets. The text is modular in its composition, with every one of the main chapters providing a conclusive discussion of one specific aspect of the overall theme. All chapters are, however, dealing in some way with effects of increased trade on labor income.

[1]The research in this field has grown to dimensions which are hard to cover in a single survey article. Within a large scale project coordinated by the Organisation for Economic Co-operation and Develpoment (OECD), Newfarmer & Sztajerowska (2012) nevertheless manages to deliver a summary of fairly established facts on how trade, wages and employment are linked.

Following this introduction, chapter 2 takes a look at factor prices from an aggregate perspective. In particular, it studies the evolution of the labor share of income in a set of OECD countries and the driving forces behind the decline observed in recent years. Such a decline is important since it is an indication for rising inequality, both at the macroeconomic and microeconomic level. Macroeconomic inequality is understood as the relative factor earnings of labor and capital, which is just what the labor share of income measures. Importantly, it has implications for interpersonal inequality (microeconomic inequality) as well. Since richer individuals are generally more likely to receive capital income, a falling labor income is compensated by increased returns to capital only for some. Thus, studying what is behind the decline in the labor share commands a multi-level importance. Naturally, the acceleration of the growth of international trade makes globalization a prime candidate for a force behind the downward pressure on the labor share. The main contribution of this chapter is to take a long term perspective and employ a sound econometric strategy to test for the relevance of variables identified in standard theoretical models. Using – for the first time in this context – dynamic panel estimators, which are able to deal with potential heterogeneity in estimated slope coefficients, we identify factor-biased technological change and increased trade openness as the main driving forces behind changes in labor shares across OECD countries. Interestingly, the trade effect only materializes for the period since the 1980s.

A common feature of modern research in international economics is its increased ability to answer very detailed questions. On the one hand, this is due to theories becoming more "micro-founded". On the other hand, this deeper focus is an outcome of the fascinating possibilities of using newly available and very detailed data sets and tackling the econometric challenges with high levels of computing power. While chapter 2 clearly takes a macroeconomic multi-country perspective, chapters 3, 4, and 5 answer more detailed questions. This finer resolution comes from a focus on offshoring as one particular phenomenon of globalization.

There are many definitions of the term “offshoring”, but there seems to be some convergence towards interpreting it as the relocation of activities of firms outside the border of the firm’s home country. Furthermore, offshoring refers to production or service activities moving outside the firm’s home country, irrespective of whether the activities stay within the legal boundaries of the firm or are conducted at arm’s length in the foreign market. Another defining feature is often indirectly introduced through the way offshoring is measured. Offshoring is seen as a trade phenomenon and its extent is inferred from the amount of intermediate inputs imported from abroad. In this case, offshoring thus refers to production relocation, the output of which is traded back to the home country. As such, it has much in common with the idea of vertical FDI, except that it does not assume anything about the specific ownership structure of firms in the value chain.

The analyses in this dissertation follow the above definitions and furthermore restrict the attention to offshoring observed in manufacturing industries. Although service offshoring has received a considerable amount of attention as well, manufacturing offshoring still dwarfs service offshoring in terms of magnitude and its share in international trade. For example, in 2007 the value of imported intermediates used in any German manufacturing or business services industry was more than 5 times larger for manufacturing intermediates than for services.[2] In addition, manufacturing offshoring growth, in particular to emerging and developing nations, is certainly impressive, with aggregate manufacturing offshoring to these countries

[2]This relation is derived from the 2007 import table of the German Input-Output tables provided by the national statistical office (`www.destatis.de`) within the national accounts data. Business services are industries 64-67 and 71-74.

rising by 109% between 1998 and 2007.[3] Furthermore, manufacturing offshoring is profoundly affected by recent ICT innovations and improvements. Computer based management of global production chains crucially relies on these technologies. Better ways of setting up and running these production networks related to ICT are certainly one major factor behind the increase in offshoring. On the one hand, improvements in ICT allow cost savings from running already fragmented parts of the production process more efficiently in foreign countries like, for instance, China. On the other hand, these improvements matter for expanding the range of activities that can efficiently be done abroad due to better ways of communicating around the globe.

Finally chapters 3, 4, and 5 all use data covering aspects of the labor market in Germany. Nevertheless, the methods used, and much of the evidence found, should apply to research focusing on other advanced economies as well. In the following paragraphs, each chapter on offshoring is introduced in more detail and its main contributions and results are summarized.

Chapter 3 presents a first-time study looking at the variability of income. This complements the existing literature, which mostly studies the effect of offshoring on income levels.[4] The chapter delivers a scientific discussion of the much-voiced perception that offshoring is leading to a more volatile labor market. The analysis thus centers on measuring variability of income and linking it to offshoring. Importantly, income risk – which is the unexpected variation in income – is split into a transitory and permanent component, using recent econometric techniques. This distinction is important since only looking at the permanent component, which is

[3]Following the measure used in most the analyses in this dissertation, this number refers to all intermediate goods imported by one industry that stem from the same industry abroad divided by total industry output. It is for offshoring with non-OECD countries only. Worldwide offshoring growth has been around 47%.

[4]For a summary of level effects on various labor market measures, see Crinò (2008).

generally uninsurable, allows for considerations on how welfare is affected. When linking offshoring and the permanent component of income risk at the industry level in German manufacturing over time, an important and perhaps unexpected result emerges. An increase in offshoring is significantly related to a decrease in the permanent component of income risk. This finding could potentially be explained by the special characteristic of offshoring as describing international production relocation. If volatility is relatively more costly in a highly regulated labor market compared to markets abroad, firms might offshore the most volatile parts of the production chain. As a result, aggregate industry level income risk falls.

Chapter 4 more directly deals with the question of what type of labor is relocated abroad - yet it does so from a different perspective: The main focus is on how offshoring shifts the relative labor demand for *tasks*. Tasks describe the work content of occupations in a way characterizing their potential for being offshored. That is, an occupation with a high share of routine and non-interactive tasks could potentially more easily be done at a distance and thus be offshored. Interestingly, there is recent evidence that the nature of tasks – in terms of routine and non-interactive job content – is only weakly correlated with the worker's skill level measured through education (Blinder 2006). It is conceivable, for instance, that computer-aided design of production parts or internal accounting activities are sufficiently described by rules, or their output is electronically transmittable, such that there is scope for offshoring them. This chapter thus redefines the classical topic of offshoring and relative labor demand from a task perspective. This redefinition entails a reformulation of the theoretical underpinnings, in which individuals are treated as providing a bundle of tasks to the market. The model presented in this chapter differs from the standard high-skilled versus low-skilled case, known from Feenstra & Hanson (1996), in that there are no longer two independently supplied and freely mobile labor input factors.

Yet, it is shown that a sorting model of the labor market can provide the necessary fix and still lead to the prediction of falling relative labor demand for routine and non-interactive tasks in the face of increased offshoring. This result is confirmed at the industry level for German manufacturing for a recent time period from 1998 - 2007. The econometric analysis builds on the cumbersome but fruitful combination of different sources of individual level data and their aggregation to the industry level, where a fixed effect panel analysis is conducted. Furthermore, the chapter provides some novel evidence on heterogeneity in the effect and demonstrates that offshoring relations with non-OECD countries have a particularly strong effect – an effect, which on the other hand is more important for female individuals and younger people. Crucially, all main results also hold when controlling for the industries' skill composition. The task perspective is thus able to shed light on labor market effects beyond what the skill-based perspective is able to offer.

The preceding chapter 4 emphasizes the reallocation processes that offshoring can trigger in the labor market. Chapter 5 takes these adjustments to the level of the worker and links offshoring to individual skill upgrading through on-the-job training. The idea is that workers potentially react to changing rewards for different types of supplied labor. The analysis thus starts with the contribution of introducing a worker level adjustment margin into an offshoring model in the spirit of Grossman & Rossi-Hansberg (2008). Individuals can invest in costly skill upgrading to eventually perform the higher-paying task set. However, they are only willing to do so if the wage differential is sufficiently large and exceeding the training cost. This is where offshoring comes into play; it increases the wage differential and thus triggers a training reaction by some part of the workforce. Following the theoretical exposition, this increase in participation in on-the-job training is empirically related to offshoring growth. Using uniquely suited data on training in Germany, that at the same time holds detailed workplace level controls for technological change, the analysis in this paper for the first time links industry level offshoring growth to individual level training participation in a Probit model. Using industry level variation in offshoring has the advantage that the estimates are likely unbiased in the sense that individual training is unlikely to directly feed back into industry level trade developments. The findings confirm the theoretical prediction: In industries with a higher growth in offshoring, there is a significantly increased likelihood across individuals to observe training participation. Taking this result to a more general level, the newly found link between offshoring and skill upgrading in this chapter offers a novel perspective on how offshoring shapes modern knowledge-based economies by emphasizing endogeneous worker level adjustment.

Following chapter 5, a concluding chapter 6 sorts and summarizes the main findings put forth in this dissertation and gives an outlook to promising further research questions arising from them.

Chapter 2

The Labor Share of Income: Heterogeneous Causes for Parallel Movements?[1]

2.1 Introduction

The share accruing to labor in the division of national income is one of the classical topics of macroeconomics. However, it lay dormant for decades – assumed away in standard macroeconomic treatments as constant and straightforwardly derived from a Cobb-Douglas production function. This constancy of the labor share has recently been challenged and with it one of the stylized facts in macroeconomics. Declining labor shares in a large number of countries, particularly in continental Europe, have brought the topic back onto the political agenda – often accompanied by passionate discussions about implied inequality concerns. To put it shortly: It seems as if the

[1]This chapter is based on an article jointly written with Marcus Kappler, which is available online in the *Journal of Economic Inequality* (doi: 10.1007/s10888-012-9221-8), see Hogrefe & Kappler (2012). The concept for this paper was developed jointly. The empirical analysis and the writing of the published version were shared equally, with Marcus Kappler predominantly contributing to the technical description of the estimators, while the author of this thesis wrote most of the remainder of the text.

labor share is making an impressive comeback.[2]

The labor share of income is the macroeconomic counterpart to the personal income distribution; it is concerned with how different production factors – capital and labor – are rewarded. Yet, the renewed interest in the development and the driving forces of labor shares stems from more than just the desire to re-assess a dusty textbook concept. Given that falling income shares are an expression of how the owners of production factors are rewarded relative to each other, there are important implications for the interpersonal income distribution as well. The link is simple. Capital income in addition to labor income is spread unequally across workers with a clear bias towards higher income groups. Since falling labor shares are expressing that participation in overall income growth is reduced for labor, and if a balancing share of individual capital income is only available for some, measures of personal income inequality increase as well. In this paper we thus take a fresh look at the problem of falling labor shares seeking to enlighten both the functional income distribution and – rather indirectly – the personal income distribution, the latter through a channel that is unrelated to standard explanations such as rising skill premia for tertiary education.

Focusing on the development of labor shares over time, figure 2.1 clearly shows the source of concern: For a sample of OECD countries, the output-weighted average labor share has declined by roughly six percentage points since 1960 and by about 9 percentage points since its peak in the mid 1970s. For individual countries the picture is similar. The vast majority of countries in the sample individually reports a decline over the full period and they all share the downward trend since the 1980s.[3]

[2]See Atkinson (2009) and the references therein for a re-appraisal.

[3]See section 2.4 for descriptive statistics, details on the sample, and the computation of variables.

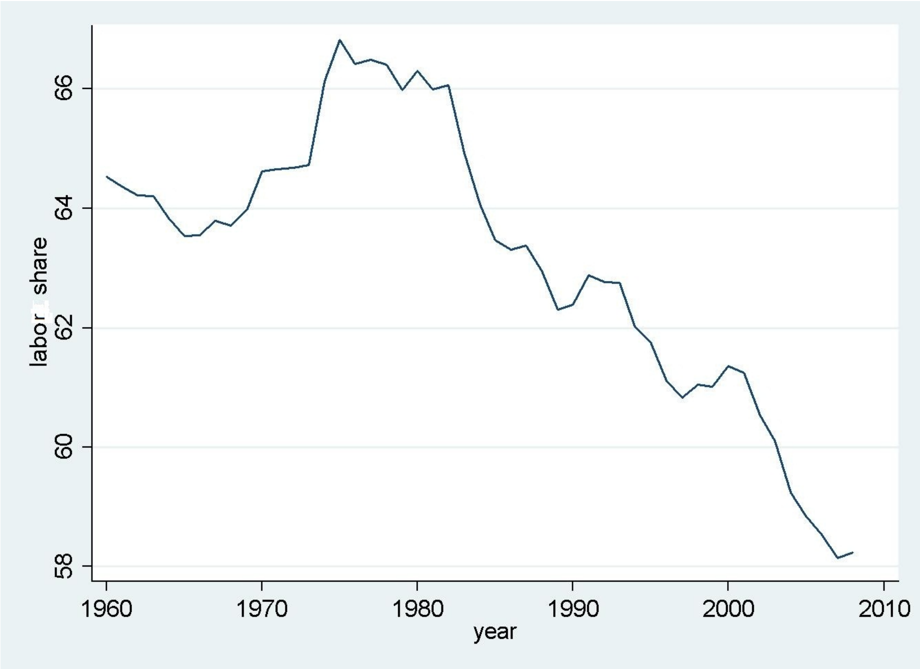


Figure 2.1: Average labor share in a sample of OECD countries

In the face of labor shares declining almost in parallel across a vast majority of developed countries, some recent studies try uncovering the underlying forces and possible implications. The strands of arguments may roughly be grouped into the following segments: effects of structural and technological change, influences of globalization and increased product market integration, and the importance of institutional settings, often with a focus on wage bargaining structures.

The effects of changes in relative factor inputs in production and technological change are most prominently discussed in Bentolila & Saint-Paul (2003). These authors show that the impact of changes in relative factor inputs and factor prices can be comprehensively modeled via the capital output ratio. The direction of the impact on the labor share then depends on the elasticity of substitution between labor and capital. With the two factors being substitutes, the labor share declines with an increase in the capital output ratio. As far as technological change is concerned, they show that only capital augmenting technological change has the potential to shift the capital output schedule and create long-term downward pressure on the labor share. A recent contribution by Arpaia et al. (2009) extends this model to incorporate different skill categories of labor to highlight the important issue of capital-skill complementarity.

In recent work, globalization took center stage as the most likely candidate among many explanatory factors in the analysis of declining labor shares all over continental Europe and beyond. In general, it is argued that greater trade openness exerts downward pressure on the labor share either through Stolper-Samuelson-type relative factor price effects or via power shifts in the wage bargaining process. In the latter case it is assumed that in more open economies the firm's outside option improves relative to that of employees if costs of relocating production or sourcing goods from abroad are falling. Furthermore, stiffer international competition can decrease mark-ups of firms, raising labor shares. An early study by Harrison (2002) shows negative effects of increasing trade openness and occurrences of exchange rate crises for a large sample of developing and developed countries. Jaumotte & Tytell (2007) add further measures of globalization, including immigration, and also establish a negative link. However, the effect of increased trade openness cannot be regarded as conclusively established. Across studies, there are important differences with respect to the time period considered, the region analyzed or the particular variable constructed.

Besides globalization, labor market institutions are frequently brought up as explanatory factors in the quest for uncovering the mechanisms of factor share dynamics. Checchi & Garcia-Peñalosa (2008) point to potentially heterogeneous effects of institutions on the labor share and stress the importance of empirically determining the direction of the overall effect. Blanchard & Giavazzi (2003) emphasize the intertemporal aspect of such institutions. They propose that in the short-run institutions which increase the bargaining power of workers could lift the labor share, while the same institutions could set the labor share off on a declining track when employers substitute capital for relatively more expensive labor in the long-run. Most studies with a focus on globalization also integrate into the analysis aspects of labor market institutions. Unfortunately, besides the ambiguity of the expected direction of the effect on the labor share, including institutional characteristics into a panel analysis often suffers from incomplete data, measurement problems across countries, and little time series variations within countries.

We contribute to the inspiring research outlined above by analysing the development of the labor share over a long sample for the years 1960 through 2008 which allows us to address some important issues. First, we assess the role of explanatory variables in different time periods thereby uncovering the sources for some of the inconclusive results in the literature. Second, we stress the role of dynamics in specifying the econometric model, a point that so far has received rudimentary attention at best. Furthermore, we take heterogeneity in estimated slope coefficients across countries into account. In combination, the latter two points are important for assessing the validity of the simple static estimators and the corresponding results in the previous literature. In particular, as Pesaran & Smith (1995) have shown, there is considerable danger in blind trust in pooled dynamic models. In such models, severely biased estimates could be the results of data best described by heterogeneous slope coefficients across sample units, i.e. if the effects of certain variables differ across countries in our case. Therefore, we apply estimators which allow us to directly test the homogeneity assumption of all slope-coefficients inherent in most previous studies. Assessing heterogeneity furthermore enables us to retrieve country specific insights into the driving forces of movements in the labor share – in particular with respect to the search for common drivers behind the parallel downturn over the last three decades. A final contribution of our empirical approach is that we augment the dynamic models by an unobserved common factor component. The common factor allows us to take unobservable influences such as business cycle shocks into account and to accommodate cross-sectional dependencies among countries. In contrast to models with a time dummy approach, we allow these shocks to differently impact on the labor share due to country specific transmission mechanisms. Consequently, we estimate heterogeneous loading factors for the common component in our dynamic models.

The idea of possibly heterogeneous slope coefficients seems valid a-priori; each of the most prominent explanatory variables in studies on the labor share gives at least some reason to question a uniform impact mechanism across countries. As stated above, this also implies worries about potentially biased results in dynamic estimations. The impact of the capital output ratio has been shown by Bentolila & Saint-Paul (2003) to be sector-dependent – crucially influenced by the sector's elasticity of substitution between production factors. This in turn implies that different sectoral compositions of the economies in the sample could potentially introduce heterogeneity across countries as well. However, the distribution of value added and employment across sectors is fairly similar for the countries in our sample. This might limit the scope for heterogeneous coefficients in this case. The impact of total factor productivity (TFP) developments – as a measure for technological advances – across countries may also differ.[4] This variable is mostly included in order to capture the nature of technological change. This makes TFP a more or less suitable variable on a country-by-country basis, given the true nature of technological change may be different across countries. Reason to doubt the cross-country homogeneity

[4]See the data section for a discussion of measurement issues surrounding the use of TFP.

of the influence globalization exerts on the labor share particularly comes from the complex interaction of trade openness and the production and employment structure in the respective countries. In addition, if one assumes that increased openness puts labor at a general disadvantage in the wage bargaining process, the country specific institutional arrangements matter as well. Note that for all these cases, should heterogeneity be indeed important, fixed effect methods provide insufficient controls, since they merely account for the time-constant elements of country specific characteristics and capture heterogeneity through differing intercepts only.

However, it is not clear whether and to what degree this heterogeneity is indeed important. It might not be much of a reason for concern after all. For now, we merely state the possibility and take it seriously in the estimation below. That is, we rely on technical methods to check the validity of the pooling assumption implied in most econometric treatments the literature offers so far.

We test a basic model of the labor share consisting of the main explanatory variables that have surfaced in the literature. Yet, we do not restrict the influence of those factors to be homogeneous across countries and estimate the driving forces of labor share fluctuations in a dynamic heterogeneous panel framework. Particularly, we employ the pooled mean group (PMG) estimator and the mean group (MG) estimator as in Pesaran et al. (1999) and Pesaran & Smith (1995), respectively. The PMG estimator represents a dynamic pooled model with a homogeneity restriction on all long-run coefficients, which are in the focus of our analysis. The MG estimator explicitly allows for slope heterogeneity in those long-run coefficients in contrast to mere intercept or short-run heterogeneity. Furthermore, our estimates allow for a comparison with the results previously brought forward in the literature, since we also employ standard static fixed effects estimators and compare the results to our preferred specifications.

This paper is organized as follows: The section following this introduction briefly outlines the theoretical framework and clarifies the predicted impacts of our explanatory variables. In section 2.3 the theoretical model is transformed into an estimation setup and the empirical strategy is explained. The estimators are introduced and their suitability and particular use are carefully discussed. Section 2.4 reports sources and computations of the data, while section 2.5 presents the results of our econometric exercises. A final section concludes.

2.2 Theoretical background

The goal of this section is to motivate, in a way consistent with theory, the explanatory variables that are assumed to affect the labor share (LS). We mostly build on Bentolila & Saint-Paul (2003). They show that movements in the labor share can in general be explained in terms of three different channels. First, they show the capital output ratio $k = K/Y$ to, under certain assumptions, comprehensively explain movements of the labor share triggered by effects such as changes in wages or factor shares in production. Secondly, they show that certain departures from the original assumptions can shift this relationship. Thirdly, they provide guiding theory for cases in which the economy is put off the schedule defined by the relationship between k and LS. We follow their theoretical insights and briefly introduce each case.

The capital output ratio as a simple but comprehensive determinant of fluctuations of the labor share emerges irrespective of a strict functional form. As long as firms produce under constant returns to scale, labor and capital are the sole inputs, labor markets are perfectly competitive, and technological progress is not capital augmenting, the labor share can be expressed as a function of k, $LS = g(k)$. This encompasses all changes in wages, interest rates, factor inputs or labor augmenting technological change, as long as the above assumptions are maintained. The direction of the effects on the labor share then depends on the elasticity of substitution. It can be shown that a higher k only lowers the labor share if the factors are substitutes, i.e. $\delta LS/\delta k < 0$ only if the elasticity of substitution between capital and labor is greater than one.

If the assumption on the nature of technological progress is lifted and capital augmenting technological change is allowed for, changes in k are no longer a sufficient explanation for labor share movements. Bentolila & Saint-Paul (2003) show that capital augmenting technological change shifts the curve described by $g(k)$ in a multiplicative way. This means that the original relationship is preserved and a change in factor prices or inputs moves the labor share following the same mechanism as above, but it does so at a different level of LS, which is determined by the size of the factor bias inherent in capital augmenting technological change. At this point it is enough to note that now $LS = g(k, A)$, with A representing capital augmenting technological change.

A second possibility for deviations from the original, purely k-based, relationship are non-competitive features in the product or labor market. If factors are not paid their marginal product, the economy moves off the schedule derived under the strict set of assumptions above. Consider for example a situation in which bargaining takes place over wages and assume that the process can be modeled in an efficient bargaining context. Then, the labor share is affected by the relative bargaining power of employers and employees. Following the literature, we consider trade openness an important indicator of relative bargaining power. If trade openness is a valid approximation for an economy's integration into world markets and its cost of access to the latter, the value of the outside option of firms in the bargaining process increases with openness. Thus, the labor share is negatively affected. It is interesting to note that trade openness can affect the labor share in numerous ways. If trade triggers Stolper-Samuelson-type effects, those should be captured by the $g(k)$ schedule, since they imply simple changes in factor inputs and prices. Trade openness could also act as competition enhancing, driving down mark-ups of firms via reducing their market power. For now, we consider the impact and sign of the coefficient of trade openness an empirical issue and postpone further details to later sections. At this point we simply state a general relationship for the labor share as $LS = g(k, A)h(X)$, with X standing for all possible "shift factors" driving a wedge between the marginal product of labor and the real wage. We assume $h(\cdot)$ to have an exponential form.

In the estimations detailed in section 2.5, we allow for all the above cases by including the variables most commonly used in the literature. We directly control for the capital output ratio and allow for the possibility of capital augmenting technological change by including an index of total factor productivity. An important test will be to compare the signs of the estimated coefficients on k and TFP. Only with the coefficients for k and TFP being equally signed one can infer that technological change is indeed capital augmenting. Figure 2.2 summarizes this section in a graphical framework based on Bentolila & Saint-Paul (2003).

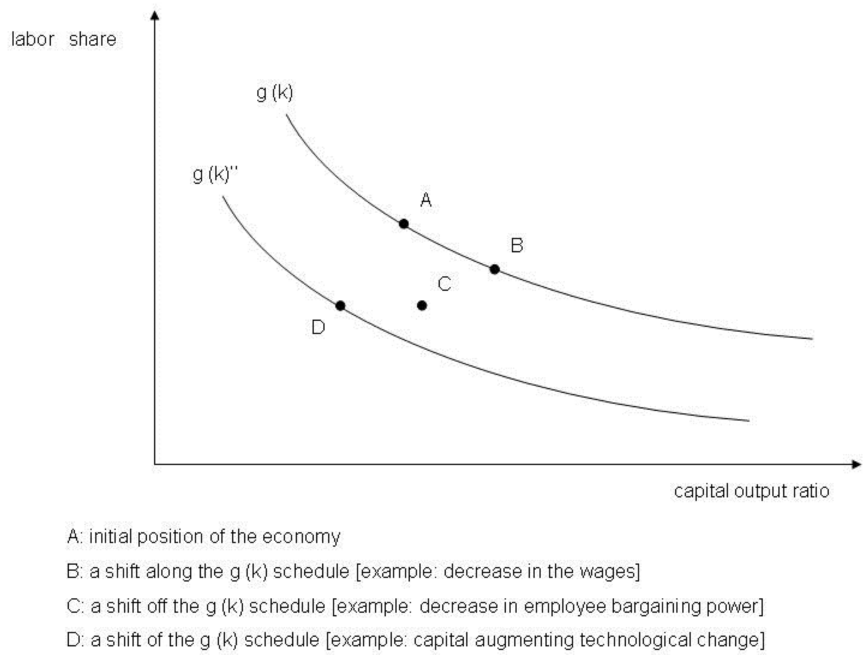


Figure 2.2: Theoretical influences on the labor share

2.3 Empirical framework

The aim of the remaining sections is to test the explanatory power of the outlined theory. To this end, we have to chose suitable estimators among the many that panel econometrics, in particular for macro panel data, offer. Two principles guide us through this selection process. The first principle is that we take serious account of cross-sectional heterogeneity in the data, i.e. we carefully deal with the question whether to employ pooled or country specific estimators in order to receive reliable empirical results. The second principle is the preference of estimators based on dynamic rather than static models since our objective is not only to explain cross-country differences in the labor shares but also to gauge the persistence in the evolution over time.

Obeying to the second principle is straightforward by considering an autoregressive distributed lag (ARDL)-Model as in Pesaran et al. (1999)

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{it-j} + \sum_{j=0}^{q} \delta'_{ij} \mathbf{x_{it-j}} + \mu_i + \epsilon_{it} \tag{2.1}$$

in which y_{it} represents country i's observation of the log-labor share in period t and $\mathbf{x_{it-j}}$ is the vector of the explanatory variables. Slope coefficients to be estimated are given by λ_{ij} and δ'_{ij}, while μ_i is a time-invariant fixed effect. The indices run from $t = 1, \ldots T$ and $i = 1, \ldots N$.

By reparameterization the following error-correction representation of (2.1) emerges

$$\Delta y_{it} = -\phi_i y_{it-1} - \beta'_i \mathbf{x}_{it} + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta y_{it-j} + \sum_{j=0}^{q-1} \delta^{*'}_{ij} \Delta x_{it-j} + \mu_i + \epsilon_{it} \tag{2.2}$$

where $\phi_i = (1 - \sum_{j=1}^{p} \lambda_{ij})$, $\beta_i = \sum_{j=0}^{q} \delta_{ij}$, $\lambda^*_{ij} = -\sum_{m=j+1}^{p} \lambda_{im}, j = 1, \ldots, p-1$ and $\delta^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im}$, $j = 1, \ldots, q-1$.

These two equations suffice for organizing ideas and for demonstrating the parameter restrictions inherent to the estimators we look at.

2.3.1 Consistency versus efficiency

To begin with, we consider the static fixed effects (FE) estimator, which is still the model of choice in many empirical studies, in particular the ones that seek to estimate the determinants of the labor share. In terms of our model, the FE estimator imposes the following parameter restrictions

$$\lambda_{ij} = 0 \quad \forall i, j \tag{2.3}$$

$$\delta'_{ij} = 0 \quad \forall j > 1 \quad \text{and} \quad \forall i \tag{2.4}$$

$$\delta_{i1} = \delta_1 \quad \forall i \tag{2.5}$$

and it is evident that such a model may easily be rejected by the data: It implies no delayed effects from the endogenous and explanatory variables and the only source of cross-country heterogeneity is attributed to the country fixed effect μ_i. The FE estimator, however, is adequate if the long-run response of the labor share is indeed best captured by the cross-country variation in the data and if dynamic effects are negligible.

Contrary to this, if heterogeneity between countries dominates then the data is more appropriately explained by a set of country-by-country regressions. In this case, the overall effect in the panel may be summarized by computing the Mean Group (MG) estimator of Pesaran & Smith (1995). The MG estimator is the simple average of the country specific slope estimates and proven to be a consistent parameter estimator if slope coefficients are heterogeneous and N and T are sufficiently large. Since the interest is in the long-run effects, the MG estimator computes $\theta^{MG} = \frac{1}{N}\sum_{i=1}^{N} \frac{-\hat{\beta}_i}{\hat{\phi}_i}$, where we obtain $\hat{\beta}_i$ and $\hat{\phi}_i$ from N individual unrestricted regressions of equation (2.2).

An alternative procedure that brings a balance between the strongly restricted FE estimator and the fully heterogeneous MG estimator is given by the Pooled Mean Group (PMG) framework of Pesaran et al. (1999). Taking equation (2.2) as reference, the PMG estimator imposes the following homogeneity restrictions

$$\beta_i = \beta \quad \forall i. \tag{2.6}$$

The PMG estimator restricts the long-run parameters to be the same across countries but leaves the parameters concerning the error correction coefficients ϕ_i and the coefficients of the short-run dynamics unrestricted. The set of long-run parameters that maximizes the concentrated likelihood function belonging to the panel data model gives the PMG estimator β^{PMG}.

If homogeneity of the β-parameters holds, then the PMG estimator is consistent and efficient, whereas the MG estimator is only consistent. Likewise, if the model is homogeneous and dynamic responses are absent, then the FE estimator is preferable in terms of efficiency. Principally, in choosing among the FE, MG and PMG estimators we face a trade-off between consistency and efficiency. From the outset it is not clear which estimator accurately measures the relationships between the labor share and its determinants. Theory suggests that there might be both heterogenous and homogeneous causes for the parallel movement in the labor shares, but in order to clarify which explanatory variable exerts what effect, we employ Hausman specification tests to check whether homogeneous or heterogeneous parameter estimates are consistent with the observed data.

2.3.2 Cross-sectional dependence

We have not yet discussed in detail the assumptions about the error terms ϵ_{it} in equation (2.1) and (2.2) and the consequences arising for estimation.[5] The standard FE, MG and PMG estimation framework assumes that the disturbances ϵ_{it} are independently distributed across i and t. Given there are likely important international linkages and common macroeconomic shocks, a more reasonable assumption is that

[5]This subsection builds on Kappler (2007), where a more detailed discussion can be found.

countries are cross-correlated. Not accounting for such dependencies leads to inefficient parameter estimates and is likely to lead to size distortions of conventional tests of significance. We can model such dependencies by a factor error structure, which is a convenient way to incorporate cross-sectional dependence in our framework. With such an assumption imposed, the errors of equation (2.2) are given by

$$\epsilon_{it} = \gamma_i f_t + e_{it} \tag{2.7}$$

in which f_t is an unobserved common effect and e_{it} are independently distributed country specific errors. γ_i are country specific factor loadings. We believe such a model is better able to capture the influence of variables like technological change on the labor share since these variables are likely to be characterized by a common component across countries.

One possible option is to directly augment the panel model with cross-sectional averages of all variables, which would capture the correlated error component as shown in Pesaran (2006). Yet, in our case, which features a large time-series dimension, we prefer to follow Binder & Bröck (2011) in using a more parsimonious two-step procedure in the estimation of equation (2.8).

According to the discussion of the common correlated effects estimator in Pesaran (2006), an approximation to the unobserved common factor can be retrieved as

$$\hat{f}_t = \Delta\overline{y}_t + \widehat{\overline{\phi}}\overline{y}_t - \widehat{\overline{\beta}'}\overline{\mathbf{x}}_t - \sum_{j=1}^{p-1} \widehat{\overline{\lambda_j^* \Delta y}}_{t-j} - \sum_{j=1}^{q-1} \widehat{\overline{\delta_{\mathbf{j}}^{*}}}' \overline{\mathbf{\Delta x}}_{t-j} \tag{2.8}$$

where variables topped with a bar denote cross-sectional averages la $\overline{\bullet}_t = \sum_{i=1}^{N} \bullet_{it}$ and hatted coefficients stem from a first step estimation of

$$\Delta\overline{y}_t = -\overline{\phi}\overline{y}_t - \overline{\beta}'\overline{\mathbf{x}}_t + \sum_{j=1}^{p-1}\overline{\lambda_j^*\Delta y}_{t-j} + \sum_{j=1}^{q-1}\overline{\delta_{\mathbf{j}}^*}'\overline{\mathbf{\Delta x}}_{t-j} + \varepsilon_t \tag{2.9}$$

The second step entails replacing f_t from (2.7) with $\hat{f}_t$ from (2.8) and estimating the error correction model as in equation (2.2) by employing this factor estimate.

2.4 Data

This section describes the data and provides details on the calculations of all variables used in the next section's estimations. The labor share of income is one of the most classical measures in macroeconomics, yet, it is not uniquely defined. In order to avoid the confusion of different concepts underlying the measurement of our variables, we use data provided by the European Commission in the AMECO database for all variables.

The labor share is defined as the share of compensation of employees in total gross domestic product, both at market prices. Labor compensation includes salaries and wages as well as the social security contributions paid by the employer. It is important to note that labor compensation contains an imputed labor income of the self-employed, thereby providing a better cross-country comparability as stressed by Gollin (2002). Thus, structural differences with respect to the share of self-employed in an economy and its evolution over time are taken into account. The capital output ratio is measured as the net capital stock per unit of gross output at constant market prices.[6] Trade openness is the ratio of imports plus exports of goods and services over GDP. The European Commission computes total factor productivity as

[6]Note that the calculation of capital output ratios for Germany prior to unification is very difficult, in particular if the sample dates back to 1960. In the regressions we therefore drop Germany. Also note that this is not crucial for the second half of our sample, however. With values imputed based on West German growth rates, in the 1980 - 2008 sample keeping Germany hardly changes the results.

the residual from a standard growth accounting approach, which uses time-varying factor shares for the weighting of the labor and capital contribution to production (GDP at 2000 levels in national currency). Importantly, this measure is not based on the assumption of constant labor shares – an assumption frequently connected to the use of a Cobb-Douglas-type production function in older treatments.

All data are at yearly frequency. Table 2.1 shows summary statistics for our resulting balanced sample of 19 OECD countries over a maximum of 49 years (1960 - 2008). The descriptive statistics again clarify the downward movement of labor shares across almost every country in the sample. All countries except Denmark and Belgium show a lower labor share in 2008 compared to 1965.[7] Furthermore, the table replicates the evidence of a hump-shaped pattern already evident in figure 2.1, with rising labor shares in the first half of the sample followed by a (unanimous) decrease in the second half. At the same time, countries have become more open and experienced substantial increases in total factor productivity. The assessment is less clear with regard to the capital output ratio, which has increased for some and decreased for others. While the descriptive statistics point to some interesting relationships between variables, it remains for the next section to establish significant links between the labor share and its driving forces.

[7]We show values for 1965 instead of 1960 since the calculations of the capital output ratio are based on methods relying on the same initial values. Showing these initial values did not seem a particularly interesting set of numbers to us.

Table 2.1: Summary statistics

Country	Labor share			Capital output ratio			TFP, 2000=100			Trade openness		
	1965	1980	2008	1965	1980	2008	1965	1980	2008	1965	1980	2008
Australia	58.73	63.86	54.89	2.77	2.66	2.99	70.65	84.23	99.53	27.00	31.18	45.02
Austria	70.01	70.10	57.25	2.93	2.95	3.24	56.36	80.66	106.86	47.04	68.92	112.61
Belgium	56.33	66.99	60.96	2.75	2.63	2.63	57.87	81.24	103.61	79.96	112.43	170.53
Canada	62.21	59.98	56.80	2.63	2.49	2.66	72.99	84.82	99.00	37.31	54.31	68.68
Denmark	59.31	62.31	60.24	2.62	2.63	2.35	60.82	74.82	100.33	61.44	68.04	107.01
Finland	69.75	63.68	55.93	3.01	2.96	2.35	47.30	68.12	112.56	40.32	63.74	89.91
France	63.59	66.34	56.70	2.77	2.91	3.13	57.89	80.41	101.95	25.61	44.04	55.59
Germany	61.64	65.33	55.36	.	3.14	3.06	60.42	79.23	106.53	30.40	44.88	88.52
Greece	69.76	59.23	53.33	2.75	3.22	3.41	63.61	97.01	116.74	28.77	51.91	60.04
Ireland	67.80	70.94	53.05	3.14	3.57	2.72	41.35	57.04	105.09	73.01	104.37	157.82
Italy	67.16	66.36	54.81	2.96	2.73	3.10	54.89	81.89	97.15	26.42	44.76	58.32
Japan	70.88	73.94	59.23	2.47	2.73	3.24	46.85	78.28	109.14	19.36	27.94	34.89
Netherlands	62.52	68.08	57.27	2.91	3.06	2.74	60.83	79.39	107.13	86.08	104.73	144.96
Norway	58.72	55.20	45.28	3.00	3.13	2.67	56.46	72.09	102.69	71.74	80.39	78.14
Portugal	67.35	69.73	61.53	2.31	2.09	2.86	43.97	73.10	99.29	41.74	56.62	74.98
Spain	64.41	66.76	56.27	2.36	2.67	3.22	59.19	85.87	99.12	21.47	31.95	58.69
Sweden	64.36	67.11	57.68	2.85	3.23	2.95	67.72	76.75	110.68	43.86	60.68	99.66
UK	65.26	66.12	61.72	2.90	2.98	2.52	58.84	71.33	106.92	37.68	51.82	61.12
US	62.84	65.08	60.08	2.69	2.55	2.42	68.77	78.39	105.82	9.69	20.76	30.76

2.5 Results

With the empirical strategy in place, we can proceed to describing the results and their interpretation. Table 2.2 shows alternative estimates of the ARDL model of the labor share. The short-run dynamics of the PMG and MG models have been specified with the aid of the Akaike information criterium, where we allowed for a maximum lag of order one.

Table 2.2: Estimates based on full sample, 1960-2008

	FE	PMG	MG	Hausman test
$\ln(k)$	-0.055	-0.564***	-0.624***	0.13
	(0.090)	(0.059)	(0.176)	(0.72)
$\ln(TFP)$	-0.180***	-0.366***	-0.323***	2.28
	(0.044)	(0.035)	(0.045)	(0.13)
Trade openness	-0.089	-0.075	-0.021	0.45
	(0.091)	(0.045)	(0.092)	(0.50)
Joint H-test				37.67
				(0.00)

Notes: ***/**/* denotes significance at the 1%/5%/10% level, respectively, according to the two-sided critical values of the Student's t distribution. Figures in brackets are the standard errors, which are corrected for possible heteroscedasticity in the case of the FE estimates. The figures in brackets for the Hausman tests report p-values according to the critical values from the $\chi^2(1)$ and the $\chi^2(3)$ distribution.

For the log of the capital output ratio $\ln(k) = \ln(K/Y)$ the coefficient is negative for all three estimated models – FE, PMG and MG. However, a large (heteroscedasticity-corrected) standard error renders the FE estimator insignificant. It seems as if there is a strong dynamic element in the data that the static FE estimator – by construction – is unable to pick up. According to theory, the negative coefficient sign hints to an average economy-wide elasticity of substitution larger than one, pointing to labor and capital being substitutes. The PMG and MG estimates with values of -0.56 and -0.62 are in line with other estimates in the literature as, for example, in Hutchinson & Persyn (2012) or Bentolila & Saint-Paul (2003). More importantly, the MG estimate seems broadly in line with its pooled counterpart, suggesting the validity of the pooling assumption in this case - a point emphasized by a Hausman test, which takes the value of 0.13 and therefore does not reject the homogeneity of the $\ln(k)$ coefficient according to the critical value of the $\chi^2(1)$ distribution. A similar picture emerges with regard to total factor productivity. Estimated coefficients are negative and significant. The PMG and MG estimates turn out to be quite similar in magnitude and the Hausman test does not reject the poolability hypothesis. The FE estimate deviates considerably from the MG estimate, which is the only consistent estimate to summarize the overall effect in the panel if slope coefficients are heterogenous. We take these first two results as a first indication of the weakness of the static fixed effects estimator. Theory tells us that equally signed coefficients for $\ln(k)$ and $\ln(TFP)$ reveal technological progress to be capital augmenting, to which our results thus lend support (Bentolila & Saint-Paul 2003). The slope estimates of the trade openness variable are negative but insignificant. Thus, the idea that greater openness lowers the labor share, due to relative factor price effects or through power-shifts in the wage bargaining process to the disadvantage of labor, is not supported by the data if we estimate over the whole period from 1960 to 2008. We furthermore note that a dynamic specification is preferable over a static one given that for all country specific models at least two of the variables are significant in contemporaneous values as well as when included with one lag. There is not a single country for which the labor share is best described by a static model.

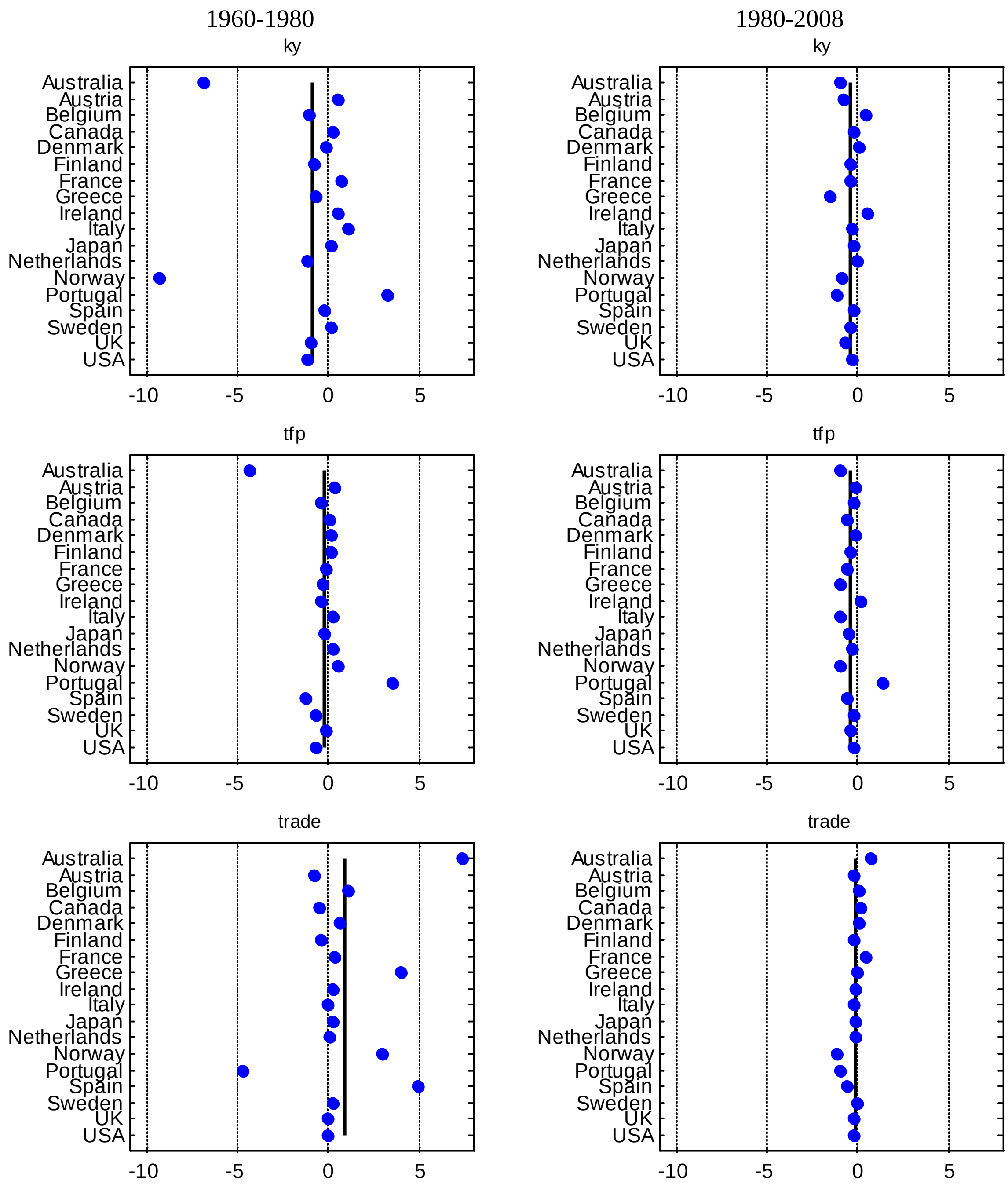
In order to check the stability of our results, as well as to gain insights into changing impacts on the labor share over time, we split our sample in two subperiods. Table 2.3 reports results of the same estimators as before which are applied for the periods from 1960 to 1980 and from 1980 to 2008. Figure 2.3 shows country specific slope estimates and their deviations from the MG estimates for the two subperiods. Tables in the appendix provide more detailed results of country specific OLS estimates.

Table 2.3: Estimates based on sample split

	1960-1980				1980-2008			
	FE	PMG	MG	H-test	FE	PMG	MG	H-test
$\ln(k)$	-0.035	-0.375***	-0.887	0.59	-0.082	-0.475***	-0.432***	0.14
	0.179	0.126	0.677	(0.44)	0.100	0.045	0.125	(0.71)
$\ln(TFP)$	0.024	-0.450***	-0.195	0.61	-0.370***	-0.324***	-0.380***	0.20
	0.116	0.077	0.336	(0.44)	0.077	0.027	0.130	(0.66)
Trade op.	0.044	1.095***	0.864	0.15	-0.103**	-0.143***	-0.171	0.08
	0.154	0.143	0.614	(0.70)	0.045	0.023	0.101	(0.78)
Joint H-test				2.47				0.65
				(0.48)				(0.88)

Notes: See notes to table 2.2.

As shown in the left part of table 2.3, both the FE estimates and the MG estimates turn out to be insignificant for the earlier period. The MG estimate for the slope coefficient of the capital output ratio differs quite substantially from the PMG estimate. This difference traces back to the cross-country heterogeneity of the slope estimates, which are illustrated in the upper left part of figure 2.3. The variation of slope estimates across countries is striking. However, only for three economies (France, Italy and the Netherlands), these slope estimates are significant (see table 2.4 in the appendix for details). Table 2.4 provides additional insights into the stability of the estimated relationships. The last column shows estimates of ϕ, which is the loading coefficient of the underlying error correction representation of the ARDL model. Only if these coefficient estimates are negative and significant, the model succeeds to estimate a stable long-run relationship. This is the case for 7 out of 18 country specific models which implies that for 11 models the hypothesis of a long-run connection between the labor share and its determinants gets rejected by the data for the subperiod between 1960 and 1980. In contrast, if we look at the country specific OLS estimates over the estimation period from 1980 to 2008,



Notes: Dots show the individual estimates of the long-run coefficients. The solid line indicates the MG estimate.

Figure 2.3: Individual vs. MG estimates

we see that for all countries except Portugal the loading parameter estimates are significant and negative (table 2.5). There are also more significant slope estimates for $\ln(k)$, $\ln(TFP)$ and trade openness and less "outliers" than in the earlier sample. Generally, a first main result emerges in that the period between 1980 and 2008 is better explained by the empirical model than the period between 1960 and 1980 for which we find less convincing results.

The coefficients in table 2.3 show some support to the standard model put forward in Bentolila & Saint-Paul (2003). Increases in capital intensity and total factor productivity tend to depress labor shares. Yet, the impact of trade – as a prominent shift factor in much of the literature – differs substantially across sample periods. Indeed, it shows the opposite impact between periods. Higher openness to trade seems like a strong driver of rising labor shares in the 1960s and 70s. Afterwards, however, it played an important role in depressing it. This pattern is all the more interesting as trade openness increased almost equally strong in both sample periods. In the two decades preceding 1980, average trade openness across the countries in our sample increased by roughly 17 percentage points. From 1980 to 2008, the numbers show a very similar trend – an increase by around 16 percentage points.

It should be noted, however, that the estimated coefficients for the first sample period also differ substantially between models. The FE estimate is rather close to zero and not significantly different from it. The MG estimate is very high but, again, not significant. Only the PMG model yields a positive and significant coefficient. Taking a look at the country specific estimates in figure 2.3 casts some doubts on this estimate, however. There is clear heterogeneity in the individual coefficients and visual inspection already suggests the PMG and MG estimates to be driven by outliers. From whichever angle one takes a look at those numbers, it does remain clear, however, that trade had a significant and negative influence on the labor share after 1980. Taking the increase in trade openness in combination with the coefficient from table 2.3, around a third of the fall in the labor share since 1980 can be explained by rising trade openness.

Returning to the numbers showing trade openness to rise similarly in both periods, simple claims, such as trade having been simply not as important and that therefore predictions derived from traditional trade models would not hold for earlier periods, do not seem justified. Rather the nature of trade must have changed. There is indeed ample evidence that this is the case. Prominent contributions such as Hummels et al. (2001) and Yi (2003) show that vertical specialization contributed strongly to the growth of world trade since the 1980s. It seems plausible that this led to a higher degree of specialization in advanced countries towards capital intensive production. Also, many developing and emerging countries became more integrated in world markets throughout the 1980s and 1990s when global trade barriers were brought down. In fact, most of the measured growth in trade openness over the last two or three decades directly stems from increased trade with non-OECD countries. This led to further possibilities of production sharing across countries. It also increased the pressure labor is facing in the wage bargaining process, where workers are now often confronted with the threat of plant closure at home and relocation abroad. Additionally, unions lost support continuously over time thereby being less able to counterbalance the competition from low-cost labor abroad. It remains to be seen, what exactly is the main driving force underlying the impact of trade openness on labor shares. Our general measure of trade openness likely captures all the above aspects to a certain extent. At the same time, it stands for an impact that has become much more homogeneous across countries over time.[8] Disentangling the

[8]The increased similarity in the effect across countries is confirmed by the Hausman test comparing PMG and MG estimates. This test in unable to reject the hypothesis of equal coefficients across models.

effects underlying this convergence in trade's impact on the labor share emerges as an interesting topic for further research.

2.6 Conclusion

This paper's motivation is to shed some light on the key driving forces underlying the downward movement in labor shares across a variety of countries. More precisely, it is about assessing whether the explanatory variables exert the same influences in all countries. Given that estimates can be flawed in the presence of heterogeneous dynamics in the data, we test the pooling assumption of slope homogeneity implied by almost all existing studies on the topic. For this purpose, we estimate the determinants of labor share movements with standard fixed effects models as well as in a dynamic heterogeneous panel framework. The latter allows us to employ estimators which differ in their assumptions on slope homogeneity and to subsequently compare the results. Furthermore, we investigate the driving forces of labor shares over time. We assess the model fit for two different time periods, 1960-1980 and 1980-2008. Our findings lend some support to the basic theory on movements in the labor share; we find the capital intensity of an economy to exert a negative influence on the labor share. Increases in TFP also decrease it. However, these effects are better estimated in dynamic models. The static fixed effects set-up is unable to significantly identify the effect and is rejected based on dynamic model specification tests. For trade openness in particular, we find important differences across sample periods. The impact can only be identified as decreasing the labor share for the later sample starting in 1980. The effects are also shown to become much more similar across countries over time.

In general, the empirical models – and thus the theory they are founded in – fit the data much better for this later period. We thus conclude that it is best to assess the development of labor shares in more recent samples using dynamic estimators, which can cope with heterogeneous dynamics across countries.

2.7 Appendix to chapter 2

Table 2.4: Country specific OLS estimates: 1960-1980

Country	ln K/Y	ln TFP	Trade openness	ϕ
Australia	-6.95	-4.37	7.37	-0.11
Austria	0.52	0.31	-0.81	-0.33
Belgium	-1.07	-0.44	1.08	-0.15
Canada	0.21	0.10	-0.47**	-0.62**
Denmark	-0.13	0.10	0.63**	-0.77***
Finland	-0.79	0.10	-0.40	-0.41
France	0.71**	-0.12	0.31	-0.41**
Greece	-0.67	-0.35	3.99	-0.08
Ireland	0.53	-0.42**	0.22	-0.69***
Italy	1.05***	0.20***	-0.02	-0.99***
Japan	0.11	-0.19	0.22	-0.28*
Netherlands	-1.16*	0.24***	0.07	-0.48***
Norway	-9.35	0.57	3.01	-0.09
Portugal	3.24	3.53	-4.71	0.13
Spain	-0.22	-1.26	4.95	-0.10
Sweden	0.14	-0.67	0.23	-0.22
UK	-1.01	-0.10	-0.05	-0.29
USA	-1.13	-0.75	-0.07	-0.19

Notes: ***/**/* denotes significance at the 1%/5%/10% level, respectively.

Table 2.5: Country specific OLS estimates: 1980-2008

	ln K/Y	ln TFP	Trade openness	ϕ
Australia	-1.02**	-0.95***	0.67	-0.33***
Austria	-0.84**	-0.13	-0.19***	-0.41**
Belgium	0.46	-0.18*	0.01	-0.38**
Canada	-0.26	-0.60**	0.13	-0.30*
Denmark	0.06	-0.15	0.07	-0.42***
Finland	-0.40*	-0.43***	-0.26*	-0.34***
France	-0.45	-0.64***	0.40***	-0.36***
Greece	-1.58***	-0.98***	-0.00	-0.61***
Ireland	0.50	0.11	-0.17	-0.28***
Italy	-0.29	-0.94***	-0.18*	-0.59***
Japan	-0.24	-0.47***	-0.12	-0.26*
Netherlands	-0.09	-0.29**	-0.15***	-0.65***
Norway	-0.85*	-1.02***	-1.19***	-0.57***
Portugal	-1.20	1.38	-0.96	-0.11
Spain	-0.21	-0.62*	-0.62**	-0.16**
Sweden	-0.40*	-0.25	-0.03	-0.40***
UK	-0.67	-0.43	-0.25	-0.39***
USA	-0.30*	-0.22**	-0.23	-0.50***

Notes: ***/**/* denotes significance at the 1%/5%/10% level, respectively.

Chapter 3

Offshoring and Labor Income Risk[1]

3.1 Introduction

Globalization is often perceived as creating a more volatile working environment on the labor market. In particular, trends such as the relocation of parts of production abroad (offshoring) induce fears of job loss and higher fluctuations in individual income. While the long-run *level* effects of different types of offshoring on income and employment have been documented by a large literature, see e.g. Feenstra (2010), a lot less academic attention has been paid to the analysis of effects on the *variability* of incomes. Our paper further completes the picture of how offshoring has an impact on characteristics of labor income by estimating its relationship to income risk with data from German manufacturing. To the best of our knowledge, our paper is the first to put the link between offshoring and income risk at the heart

[1] This chapter is based on joint work with Yao Yao. It is a slightly revised version of the ZEW Discussion Paper 12-025, available as Hogrefe & Yao (2012). Another working paper version is the SOEP Discussion Paper 515-2012. The concept for this paper was developed mainly by the author of this thesis. Yao Yao contributed codes and expertise with regard to the estimation of labor income risk. The empirical analyses involving the connection between offshoring and labor income risk were conducted by the author of this thesis. All parts were mutually discussed and improved, however, such that they should be regarded as joint work. The writing of the text, with the exception of the technical description of the estimation of labor income risk, was done primarily by the author of this thesis.

of an empirical analysis.

Income risk is defined as the variance of changes in the unexplained component of individual income. As such, it describes changes in income that are not a result of observable and predictable characteristics like age or education. Crucially, and in line with the literature, we econometrically distinguish between transitory and permanent risks to income. Transitory shocks to income are more likely to be smoothed out by self-insurance mechanisms such as saving and borrowing. However, this does not hold for permanent shocks, i.e. shocks that permanently shift an individual's income trajectory. Following the literature, we assume permanent income risk to be uninsurable from an individual perspective. Then, unexpected permanent variation in income affects the present value of lifetime earnings, which impacts on individual welfare (Aiyagari 1994). It is thus the permanent component of income shocks we are interested in. Linking offshoring to changes in the variance of permanent income shocks yields evidence on the effect of offshoring on labor income which allows for considerations on welfare consequences.

Our analysis proceeds in several steps. First, we derive and estimate measures of income risk, which we subsequently link to offshoring. We provide two variants of the analysis. We begin our effort by taking a long-run perspective and estimate the permanent component of income risk from the German Socio-Economic Panel (SOEP). Here, income risk is estimated at the industry level from individual income data as the average variance of changes in the unexplained component of individual income. The latter is retrieved from standard Mincerian wage regressions. Based on this data, we uncover average income risk over five-year intervals, which we link to average offshoring intensities at the industry level in a panel setting. We therefore aim at answering whether a structural change in the economy, with ever more production stages being performed abroad, leads to domestically higher or lower income risk. Subsequently, we turn to a yearly analysis. At this stage we use individual level data from official German social security records to estimate industry level income risk, allowing us to link offshoring and income risk at a higher frequency. Both approaches rely on panel methods, helping us to answer the question of whether an increase in offshoring over time is correlated with a decrease in income risk. The offshoring measures are calculated at the industry level in a way similar to Feenstra & Hanson (1999). We use detailed yearly import matrices from input-output tables in combination with output and trade data.

From the outset, it is not clear whether offshoring increases or decreases income risk – especially with respect to the permanent component. On the one hand, there is empirical evidence at the industry level that offshoring tends to raise labor demand elasticities, which could lead to higher income risk, e.g. (Senses 2010). On the other hand, this evidence is in part contradicted at finer levels of aggregation. Becker & Muendler (2008) find offshoring to actually lower separation rates in employment at the firm level and Buch & Lipponer (2010) directly cast doubt on the claim that offshoring is responsible for changes in labor demand elasticities within multinational firms. It is important to note, however, that most studies within the rather inconclusive empirical literature are only indirectly related to the concept of income risk, and its permanent component in particular. As mentioned above, our analysis specifically tries to address a measure of "insecurity" that has clear and well-documented welfare implications – a characteristic generally attributed to the permanent component of income risk.

In addition to the mixed empirical results, theory recently suggested offshoring to be much less of a specter to workers than what is reflected in public anxiety and job loss fears. For example, Bergin et al. (2009) show that offshoring has the potential to exert a dampening effect on economic volatility in the offshoring country if demand shocks are buffered by excess production activity in offshore plants. In other words, fluctuations are "exported" and firms face a less volatile domestic economic environment; and potentially their workers do as well.[2] It is also possible that offshoring induces what may be called a "composition effect". If offshoring is understood as trade in tasks, as in Grossman & Rossi-Hansberg (2008), and the tasks as such differ in their specific income volatilities, the relocation of certain tasks abroad might lead to aggregate changes in industry level income risk. If the offshored tasks are at the same time more volatile with respect to income, the average income risk of the tasks remaining onshore falls. One could think of this effect as arising from firms effectively insuring themselves against fluctuations in economic activity. If institutional rigidities in the home market make adjustment costly, firms would be expected to relocate the activities most affected in places where adjustment is less costly. Such considerations seem particularly plausible in light of the European Union's enlargement to the East and Germany's location close to the new EU member states.[3]

The particular focus on offshoring also sets this paper apart from the recent literature studying effects on income risk arising from other forms of globalization such as import competition and tariff reductions. Krebs et al. (2010) analyse how tariff reductions and the ensuing integration of the Mexican economy into the world market (in particular the North American part of it) affected income risk. They show income risk to increase as a response to trade liberalization, inducing the emergence of negative welfare effects. Yet, the Mexican economy may be considered a rather

[2]Yet, the opposite holds true for the receiving country. Volatility abroad (e.g. in Mexico for the case of US offshoring) is amplified.

[3]Note that this does not necessarily lead to an aggregate employment loss with less volatile, yet lower, overall employment at home since offshoring also triggers productivity effects possibly leading to net job creation (Kohler & Wrona 2011).

special case, in particular with regard to its proximity to the US and the existence of the "maquiladora" sector near the northern border.[4] Krishna & Senses (2009) set out to find the roots of income risk in the US labor market. Their prime candidate is import competition, which they show to raise the permanent component of income risk.[5] We focus on offshoring to explicitly contrast the concerns about increased risks often raised in the public debate with the potentially risk smoothing effects of a more efficient international allocation of production tasks.

Our findings contradict the general impression of offshoring as a major factor in raising long-run income volatility. They suggest an increase in offshoring is significantly correlated with a *decrease* in the permanent component of income risk at the industry level. For instance, using the yearly data, the observed rise in the overall offshoring intensity implies, on average, a 12% fall in permanent income risk compared to its mean value. For offshoring to non-OECD countries, the corresponding numbers for the observed increase reach up to around 30%. Looking at offshoring as a particular type of international trade, we thus find the *opposite* effect in comparison with other studies relating more general measures of globalization to permanent income risk.

The paper is structured as follows. The next section details the approach for estimating income risk, presents the data we use, and gives further insight into measuring the offshoring intensity at the industry level. In sections 3.3 and 3.4, we describe in detail the econometric specification and provide results on how income risk is affected

[4]In fact, this "maquiladora" sector has been shown in Bergin et al. (2009) to have a particularly high volatility due to its role in the production sharing with the US economy.

[5]As a robustness check, which consists of including a host of further variables, these authors also employ an offshoring variable which shows a negative coefficient in their estimations. However, this variable differs in its construction from the ones used here and its impact is not further discussed by the authors.

by offshoring, respectively. A concluding section features some important considerations on welfare effects.

3.2 Estimation and calculation of variables

3.2.1 Estimating labor income risk

The approach taken in this paper involves a three-stage procedure to first estimate the permanent component of individual income risk (stage one and two), and then relating these to carefully constructed offshoring indices at the industry level (stage three). The goal of this section is to motivate our measure of income risk and to derive the corresponding estimation procedure. We follow the bulk of the literature and define income risk as the unpredictability of individual income, while referring to this variability from an ex-ante perspective (Carroll & Samwick 1997, Meghir & Pistaferri 2004). As such, income risk accompanies people whenever their future income is stochastic. In this sense, income risk is conceptualized as a deviation of the future income stream from its expectation, and is estimated as the variance of changes in the unexpected component of individual income.

In our paper, as in most of the related literature, the estimated income risk has two components: transitory income risk and permanent income risk. This distinction is important since the two components have vastly different welfare effects. Transitory risk refers to the variance of stochastic income changes without persistence. Therefore, it could be effectively "self-insured" by individuals through saving and borrowing. Such unexpected transitory variation could be introduced by windfall labor income or changes in hours worked, which do not persist until the end of an individual's working life. Thus, following common theoretical considerations, there are no reasons for individuals to change their consumption and savings pattern, and therefore there are hardly any welfare effects (Levine & Zame 2002). For the permanent component of income shocks, however, a different picture emerges. Permanent income risk has profound effects on the consumption and savings decision of individuals in environments with imperfect insurance possibilities. Permanent income shocks reflect the stochastic trend of income. These shocks have persistent power over the remaining working period of individuals. This affects the present value of lifetime earnings and thus individuals "consume" out a certain amount of permanent shocks. Therefore, and in contrast to transitory risk, permanent income risk has a direct effect on individual welfare (Constantinides & Duffie 1996, Krebs 2003). Permanent shocks are observed as permanent events during workers' employment – for example, promotion beyond expectation or changes in employment resulting in a different matching quality of an individual's abilities and the job's requirements. Given its welfare relevance, we thus focus our analysis on the connection between offshoring and permanent labor income risk. Following related studies, we disregard the transitory component.[6]

The procedure for estimating the components of income risk starts with the identification of the unexplained component of individual income. This component is retrieved as the residual from standard Mincerian wage regressions of the following form:

$$y_{it} = \alpha_{jt} + \beta_t X_{ijt} + u_{ijt} \tag{3.1}$$

Note that the regressions are run year-by-year and include fixed effects for industries j. The control vector X_{ijt} includes the commonly used wage determinants such as age, education, marital status, nationality and firm-size.[7] Notice that the estimation

[6] Another reason for ignoring transitory income risk is that this measure will pick up all measurement error in the estimation procedure outlined below (Krebs et al. 2010).

[7] In the SOEP data, due to the lower number of observations at our disposal, we include both male and female individuals and add a corresponding dummy variable to the control vector. In the

allows for changes in the returns to observable characteristics over time. An increase in the skill premium, for instance, is not regarded as contributing to income risk. The regressions are run on a restricted sample, which includes individuals fully employed in manufacturing industries in West Germany. y_{it} is the natural logarithm of our income variable for individual i in year t, specified in more detail in the database descriptions below. The assumptions underlying the above model imply that individuals develop expectations about their future income from a projection based upon individually observable and predictable characteristics. Thus, u_{ijt} is the unexpected and stochastic component of individual earnings, which is idiosyncratic and unpredictable to them. We show exemplary results from this first stage regression in the appendix.

For the estimation of income risk and its components, we make the following assumptions. Suppose u_{ijt} has two components: a permanent one ω_{ijt} and a transitory one ϵ_{ijt}. Furthermore, assume ω_{it} to follow a random walk process.[8]

$$u_{ijt} = \omega_{ijt} + \epsilon_{ijt} \tag{3.2}$$

$$\omega_{ijt} = \omega_{ijt-1} + \eta_{ijt} \tag{3.3}$$

In equation (3.2), ϵ_{ijt} is white noise, which has only a temporary effect on labor income and would vanish in the next time period. η_{ijt}, however, has persistence because ω_{ijt} follows a random walk process.

BA data, we focus on male individuals since they are usually assumed to be the household head with their income being less affected by intra-household labor substitution.

[8]The random walk assumption is not the only possible structure underlying the income process. For instance, other papers have suggested including a third, MA(1), component. Yet, it has been shown that the permanent component of income risk is hardly affected by different assumptions on the income process. We therefore stick to the random walk assumption.

Based on this assumed structure of the unexplained part of income, we can single out the permanent component of income risk. Recall that we are interested in the variance of the changes in this unexplained part of income. There are two different strategies usually employed in the literature. They differ in their assumptions on whether income risk can be assumed to be time-independent. As can be seen from the following subsections, assuming time-independence (at least within sub-periods) substantially simplifies the estimation. We will nevertheless calculate both time-invariant and year-specific income risk. However, we will have to use different data sources in the two cases.

Time-invariant income risks

In this subsection, we assume that shocks are time-invariant, that is, ϵ_{it} and η_{it} in each period are white noise and i.i.d distributed.[9]

$$\epsilon_{it} \sim N(0, \sigma_\epsilon^2) \tag{3.4}$$

$$\eta_{it} \sim N(0, \sigma_\eta^2) \tag{3.5}$$

ϵ_{it} and η_{it} are independent for all leads and lags, that is, $cov(\epsilon_{it}, \epsilon_{is}) = 0, \forall t \neq s, cov(\eta_{it}, \eta_{is}) = 0, \forall t \neq s, cov(\epsilon_{it}, \eta_{is}) = 0, \forall t, s$. For the changes in the unexplained income over time, we can generally write the n-year difference of u_{it} as

$$\triangle_n u_{it} = u_{it+n} - u_{it} = \eta_{it+1} + ... + \eta_{it+n} + \epsilon_{it+n} - \epsilon_{it} \tag{3.6}$$

Hence, assuming $\eta_i = \eta_{it}$ the variance of $\triangle_n u_{it}$ is simply given by:

$$V[\triangle_n u_i] = n\sigma_\eta^2 + 2\sigma_\epsilon^2 \tag{3.7}$$

[9]In this section we drop the subscript j to improve on the exposition. Naturally, all income risk measures estimated and used in the analysis in further sections are to be understood as industry level variables.

where σ_ϵ^2 and σ_η^2 are the variances of the transitory and permanent shocks to income, respectively. Note that $2\sigma_\epsilon^2$ is a constant. Thus, the simplifying assumption of time-invariant income risk allows us to retrieve $\hat{\sigma}_\eta^2$ from a simple linear regression.[10] This is the approach taken by the vast majority of the literature on the estimation of income risk (see Gottschalk & Moffitt 1994, Carroll & Samwick 1997, Krishna & Senses 2009). Note that with a sufficiently large T, it is possible to still retrieve quasi time-varying coefficients for income risk if time-independence is assumed to hold within but not between subperiods m. This is the approach we follow for part of the analysis in this paper, where we assume income risk to be constant within 5 year sub-periods.

Time-specific income risks

The above assumption of time-independence may seem to be a strong one, and the quick-fix solution of looking at changes in permanent income risk between subperiods somewhat arbitrarily rests on the choice of the length of m. Shocks to permanent labor income in reality could differ across time periods due to, e.g. macroeconomic factors such as business cycle movements or trade related influences.[11] In fact, this is exactly what our paper is aiming to identify: How *changes* in permanent income risk can be explained. We therefore briefly describe the adjustments needed for estimation of yearly values of permanent income risk.

Dropping the assumption of time-constancy of income risk, ϵ_{it} and η_{it} are no more i.i.d normally distributed in each period. They now depend on time, that is,

$$\epsilon_{it} \sim N(0, \sigma_{\epsilon t}^2) \tag{3.8}$$

$$\eta_{it} \sim N(0, \sigma_{\eta t}^2) \tag{3.9}$$

[10]In more detail, we minimize $\sum_t \sum_1^{T-t} [V[\triangle_n u_{it}] - (n\sigma_\eta^2 + 2\sigma_\epsilon^2)]^2$ by using OLS methods.

[11]Storesletten et al. (2004) argue that the conditional variance of these permanent income shocks is counter-cyclical, increasing during contractions and decreasing during expansions. Krebs et al. (2010) find that trade policy has a significant effect on income risk.

Still, ϵ_{it} and η_{it} are independent with each other at all leads and lags. $cov(\epsilon_{it}, \epsilon_{is}) = 0, \forall t \neq s, cov(\eta_{it}, \eta_{is}) = 0, \forall t \neq s, cov(\eta_{it}, \epsilon_{is}) = 0, \forall t, s.$

In contrast to (3.7) above, the variance of changes in the unexplained component of individual income between period t and $t + n$ now is given by:

$$V[\triangle_n u_{it+n}] = \sigma^2_{\eta,t+1} + ... + \sigma^2_{\eta,t+n} + \sigma^2_{\epsilon,t} + \sigma^2_{\epsilon,t+n}. \tag{3.10}$$

The estimation furthermore relies on additional moment conditions for the transitory component. In particular, it is assumed that this component of income risk is identical for the first and last two periods. Naturally, this also restricts the permanent component to being the same for those periods. According to Krebs et al. (2010), the permanent component of income risk can be estimated from (3.10) using GMM methods. In particular, given the relatively small sample size of our available data, we use the equally weighted minimum distance (EWMD) estimator as this is superior to a two-step GMM approach using the optimal weighting matrix once small sample bias is taken into account (Altonji & Segal 1996).

3.2.2 Data and implementation

In order to implement the above estimation strategy, our data has to meet certain requirements. On the one hand, we need a sufficient amount of variation within each industry for each year. On the other hand, it is desirable to have a long time dimension in order to track the relationship of offshoring and income risk for several years. We have two different data sets at our disposal, each of which has its particular advantages. The first data set is a long-run survey, the so-called German Socio-Economic Panel (SOEP).[12] The second is a sample from official social

[12] The SOEP data are provided by the DIW Institute in Berlin. Information on variables and data access can be found in Wagner et al. (2007) and at `http://www.diw.de/en/diw_02.c.222724.en/soepinfo.html`

security records from the German Employment Agency ("BA-Employment panel").[13]

In both cases we use information on income for individuals that stay within the same 2-digit industry over time.[14] We thus predominantly observe income variation for people who remain employed, yet face income changes due to wage changes and changes in other payments such as bonuses. Yet, we do not exclude individuals that lose their job once or several times as long as they are re-employed in the same industry at some point in our sample, irrespective of how long the unemployment spell is. In fact, temporary job loss is likely an important source of variation in income as job transition is often accompanied by a loss of occupation or employer-specific human capital leading to persistent changes in income. If an individual is employed in several industries over the sample period, we treat it as if it were two different individuals. That is, we use variation occurring during employment within an industry, but not between industries. We thus do not include variation based on individuals switching between industries or out of manufacturing in general. We admit that switching industries can be a source of income risk, yet one that is difficult to assign to any industry's aggregate income risk. This also makes it impossible to link it to industry level offshoring in our framework.[15] Even within these limits, we will show that there is considerable variation in individual income and that a substantial part of this is reflected in permanent income risk.

[13] 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). For detailed information on the database, see Schmucker & Seth (2009).

[14] About 87% of observed individuals stay within the same 2-digit industry.

[15] Krishna & Senses (2009) estimate income risk to be higher for individuals experiencing a transition from one industry to another when compared to individuals staying in one industry. We thus regard our estimations of income risk as representing a lower bound. On the difficulty of including this variation in a study exploring the causes for changes in income risk, also see Krebs et al. (2010).

While the SOEP data covers individuals since the mid-1980s and therefore allows for a longer-run view on income risk, it has insufficient observations by year and industry to fully estimate time-varying income risk. We therefore divide this data into 5-year sub-periods and estimate the permanent component of income risk based on (3.7) within each one of them. Thus, we assume that the transitory and permanent components can change between periods, but are constant within each 5-year period m. That is, $\epsilon_{it} \sim N(0, \sigma^2_{\epsilon,m})$, $\eta_{it} \sim N(0, \sigma^2_{\eta,m})$. The wage regressions are run on a sample restricted to west German residents aged 18 to 65 that are fully employed in one of the 22 two-digit NACE 1.1 manufacturing industries. The income variable in this case is the log-hourly wage rate, for which we set a threshold at the minimum social security transfer payment in order to exclude individuals who report implausibly low labor income. We also adjust for oversampling of high income individuals.

In contrast to the SOEP, the BA-Panel is rather short with its 10 year time period. Yet, it has significantly more observations per industry and year. Thus, it allows us to estimate yearly income risk. It represents a 2 percent random sample drawn from official German employment records based on social security contributions for the years from 1998 to 2007. Income information in this case is log-monthly income and includes non-wage payments such as bonuses to the employees. Again, we restrict the panel to full-time employed, working age, West German residents. This still leaves us with a total of more than 770,000 individual observations. We then proceed by applying the estimation approach for time-varying income risk. Note that our focus on permanent income implies that we only obtain estimates for the years up to 2005, since persistence of shocks is hard to observe when approaching the last years of the sample. Furthermore our estimation approach technically relies on the additional assumption that in the first two periods, income risk values are identical. This leaves us with observations for the years 1999 to 2005.

A common concern about such official German employment records is that the accompanying income information is censored at the legal threshold for social security contributions. This is the case in the present data as well. It is of potential concern that some income variation might be precluded from the analysis. Note that even an approach as ours, which relies on variation over time between industries when linking offshoring and income risk, is affected since the share of individuals at the income threshold is non-constant. On the other hand, the problem is less severe in manufacturing and particularly among low-skilled workers. These individuals simply rarely reach the threshold income. Yet, we tackle the problem, as most studies in the literature by imputing the censored part of the wage distribution (Dustmann et al. 2009). We follow Gartner (2005) and use an approach based on truncated regressions and draws from a log-normal distribution.[16]

Finally, the BA-panel data is quarterly in its original style. Yet, most of the income information is based on one entry per year only (so called "Jahresmeldung"). Thus, only yearly information can be calculated. We do so by using time-weighted averages over all reported monthly income data points as long as the individual does not change the industry of employment within the year.[17][18]

[16]Note that censoring of the wage variable plays no role in the SOEP as this is survey data.

[17]We also provide estimates based on just using information from a single wave per year; the June wave in our case. This more restrictive alternative yields estimates that are qualitatively very similar to results detailed below, interestingly for 2-year lags, and are shown in the appendix.

[18]Assumed imputed incomes, which are reported in the absence of a report by the employer, so-called "Forschreibefälle" are deleted as well.

3.2.3 Income risk: results

Table 3.1 shows estimates of the permanent component of income risk based on the SOEP data.[19] It can be seen that the estimates vary quite a bit across industries, both with respect to levels and the change from the first to the last period.[20] The estimates imply an employment weighted average standard deviation of 0.077. That implies an average (permanent) yearly change of around 8% of the residual hourly wage rate.

In table 3.2, we present results derived from the more detailed BA-panel. Again, we see some heterogeneity across industries. The estimates are similar, yet a bit lower than the ones in table 3.1. The employment weighted average risk to residual monthly wages stands at around 6 %. The differences in the estimated values for permanent income risk stem mainly from the use of different data. In particular, income risk estimates are usually sensitive to sample length. More importantly, we do not rely on level values in our estimations below. Instead, we estimate the effect using fixed effect methods in a panel setting.

The above estimates are somewhat lower than those found in other studies, e.g. in Krebs et al. (2010). Note, however, that this latter study, as well as others, overestimates permanent income risk since it assumes all remaining income variation after 4 quarters to be permanent, whereas we treat changes from one year to the next as transitory still. Furthermore, some studies rely on total household income which inherently has higher risk since it includes the outcomes of labor-leisure choice and

[19]Since our offshoring data is for the years after 1991 only, we do not show income risk estimates prior to 1991.

[20]Note that for industry 36, the estimate is negative which is unrealistic since a variance is by definition a positive value. This estimate, as well a few others, is not statistically significant, however. We show in the appendix that exclusion of the few insignificant income risk estimates does not alter much our estimates of the influence of offshoring on income risk.

substitution effects between household members. Additionally, it is plausible that by international standards the German labor market features lower income risk due to stronger institutions such as employment protection and wage bargaining coordination.

Table 3.1: Descriptives: income risk, SOEP

Industry	Code	$\hat{\sigma}^2_{\eta,j}$	$\hat{\sigma}_{\eta,j}$	Change($\hat{\sigma}^2_{\eta,j}$)
Food Products and Beverages	15	0.0080	0.0896	0.0103
Tobacco Products	16	0.0301	0.1736	-0.0022
Textiles	17	0.0044	0.0661	0.0027
Wearing Apparel; Dressing and Dyeing	18	0.0074	0.0859	-0.0048
Tanning,Dressing Of Leather; luggage	19	0.0376	0.1940	0.0210
Wood Products, Except Furniture	20	0.0012	0.0347	-0.0010
Pulp, Paper and Paper Products	21	0.0081	0.0901	0.0116
Publishing, Printing and Reproduction	22	0.0072	0.0850	-0.0074
Coke, Refined Petroleum Prod.	23	0.0126	0.1121	0.0067
Chemicals and Chemical Products	24	0.0067	0.0816	0.0124
Rubber and Plastic Products	25	0.0111	0.1055	0.0084
Other Non-metallic Mineral Products	26	0.0018	0.0425	-0.0006
Basic Metals	27	0.0085	0.0921	0.0263
Fabricated Metal Prod., Ex. Machinery	28	0.0043	0.0657	0.0165
Machinery and Equipment NEC	29	0.0054	0.0732	0.0021
Office Machinery and Computers	30	0.0278	0.1667	-0.0036
Electrical Machinery and Apparatus	31	0.0048	0.0690	-0.0020
Radio, Television and Communication	32	0.0029	0.0538	0.0028
Medical, Precision and Optical Instr.	33	0.0056	0.0751	0.0089
Motor Vehicles, Trailers	34	0.0071	0.0842	0.0003
Other Transport Equipment	35	0.0099	0.0994	-0.0051
Furniture; Manufacturing NEC	36	-0.0006		-0.0032

Notes: Values for income risk are averages over time. Changes are first-to-last period differences of absolute values. The employment weighted industry average (excl. Tobacco) is 7,7 % ($\bar{\hat{\sigma}}_{\eta,j} = 0.077$). Industry names may be incomplete.

3.2.4 Measuring the offshoring intensity

Offshoring is measured using input-output tables and trade data following a method introduced by Feenstra & Hanson (1999) and extended by Geishecker (2006). The offshoring intensities are calculated to represent the amount of an industry's inter-

Table 3.2: Descriptives: income risk, BA-panel

Industry	Code	$\hat{\sigma}^2_{\eta,j}$	$\hat{\sigma}_{\eta,j}$	Change ($\hat{\sigma}^2_{\eta,j}$)
Food Products and Beverages	15	0.0045	0.0673	0.0002
Textiles	17	0.0046	0.0680	-0.0011
Wearing Apparel; Dressing and Dyeing	18	0.0067	0.0820	0.0072
Wood Products, Except Furniture	20	0.0036	0.0602	0.0046
Pulp, Paper and Paper Products	21	0.0025	0.0502	-0.0021
Publishing, Printing and Reproduction	22	0.0050	0.0704	-0.0019
Chemicals and Chemical Products	24	0.0024	0.0488	0.0034
Rubber and Plastic Products	25	0.0043	0.0654	-0.0013
Other Non-metallic Mineral Products	26	0.0035	0.0594	0.0034
Basic Metals	27	0.0033	0.0578	-0.0022
Fabricated Metal Prod., Ex. Machinery	28	0.0049	0.0700	-0.0032
Machinery and Equipment NEC	29	0.0041	0.0637	-0.0016
Office Machinery and Computers	30	0.0062	0.079	-0.0110
Electrical Machinery and Apparatus	31	0.0035	0.0592	-0.0021
Radio, Television and Communication	32	0.0050	0.0708	0.0016
Medical, Precision and Optical Instr.	33	0.0043	0.0652	0.0024
Motor Vehicles, Trailers	34	0.0027	0.0519	0.0006
Other Transport Equipment	35	0.0034	0.0582	0.0014
Furniture; Manufacturing NEC	36	0.0049	0.0699	-0.0015

Notes: Values for income risk are averages over time. Changes are first-to-last period differences of absolute values. The employment weighted industry average is 6.2 % ($\bar{\hat{\sigma}}_{\eta,j} = 0.0619$). Industry names may be incomplete.

mediate inputs purchased from the same industry abroad in total industry output. This emphasizes the fact that the product could have likely been produced at home as well, and precludes situations in which traditionally imported goods count as offshoring. The offshoring intensity therefore is assumed to describe the outcome of multiple firm's make-or-buy decisions aggregated to the industry level. Note that it captures offshoring that occurs within as well as outside of a firm. In terms of the original notation introduced by Feenstra & Hanson (1999) our measure is the offshoring intensity in a "narrow" sense. Technically it looks as follows:

$$OFF_{jt} = \frac{IMP_{j^*t} \times \Omega_{j^*jt}}{Y_{jt}}. \tag{3.11}$$

Y_{jt} is output of j at time t. Ω_{j^*jt} describes the share of all imports from a specific 2-digit NACE 1.1 industry (j^*) abroad, used in the respective industry (j) at home. These shares are derived from yearly import matrices that are part of the input-output tables provided by the Statistical Office in Germany.[21] IMP_{j^*t} are all imports from the foreign industry j^*, taken from the OECD STAN database, just as the output values. The data on imports and industry output are deflated using an aggregate manufacturing import price deflator and industry specific producer price indices, respectively.[22] This deflation strategy may be problematic, however, if industry level import prices deviate strongly from the average. Consider, for example, a situation in which the import price falls strongly for a certain industry. This fall will not be adequately captured by the average import price index which will be "too high". Yet, to the extent that the same price trends are also present in the producer prices, where they are adequately represented due to the more disaggregated indices, there will be an "asymmetric" deflation that by itself raises the offshoring intensity. In the subsequent estimations we therefore also check whether deflating all variables with aggregate indices affects the results.

We furthermore differentiate between worldwide offshoring and offshoring to non-OECD countries. Here we again draw on the OECD STAN database and multiply the imports in (3.11) by the share of imports coming from non-OECD countries.[23] Note that this region-specific calculation of offshoring entails the common assumption of identical Ω_{j^*jt} for the two groups of countries, since the input-output tables do not

[21]For the years prior to 1995 those tables are not comparable to the more recent ones due to data revisions. For those years we keep Ω_{j^*jt} constant at its 1995 value - a strategy commonly employed in the literature whenever yearly I-O tables are not available, see e.g. Hijzen & Swaim (2010).

[22]The import price index is taken from Destatis and the industry specific indices for producer prices come from the EU KLEMS (March 2008) release.

[23]When calculating import shares for non-OECD countries, we had to rely on aggregates for industries 15-16; 17-19 and 21-22 and thus use the same non-OECD share for each industry within the respective group. Note, however, that this only applies to the non-OECD trade share and neither to total imports IMP_{j^*t} nor Ω_{j^*jt}.

hold any region specific information. The special distinction of non-OECD offshoring is meant to reflect the cost savings motive inherent in offshoring – a concept at the core of most theoretical approaches as well as the common public worries.

Table 3.3 shows offshoring intensities for the different manufacturing industries. Overall, worldwide offshoring has reached significantly higher levels than offshoring to low-income countries. Yet, starting from low values, growth is much stronger for offshoring to non-OECD countries, where intensities have more than doubled in 9 industries. Additionally, we observe positive growth in all industries but tobacco as well as coke and refined petroleum for non-OECD offshoring, while only about two thirds of the industries had a higher worldwide offshoring intensity in 2005 compared to 1991. Interestingly, for both measures the industries show quite some heterogeneity with respect to variations over time. This variation will be important in identifying the effect of offshoring on income risk later on.

3.3 Econometric specification

We now turn to developing a suitable estimation strategy for an evaluation of the impact of offshoring on income risk. The data at hand permits a panel approach controlling for unobserved heterogeneity in two dimensions: industry and time. Industry-specific effects may well matter for the relationship between offshoring and income risk. Some industries are probably more inherently risky than others. This may be due to different demand elasticities for their products or unique employment structures in terms of jobs and tasks that can differ in their idiosyncratic risk. As long as these characteristics are specific to an industry and do not vary over time, a fixed effects setup will capture this type of unobserved heterogeneity.[24] For time-

[24]The same logic holds true for using an approach based on first-differencing (FD) the data. In our case, employing FD estimation yields qualitatively and quantitatively very similar results.

Table 3.3: Offshoring - descriptives

Industry	Code	worldwide 1991	worldwide 2005	worldwide change	non-OECD 1991	non-OECD 2005	non-OECD change
Food Products and Beverages	15	3.85	3.97	0.12	0.61	0.63	0.02
Tobacco	16	1.00	0.88	-0.13	0.16	0.14	-0.02
Textiles	17	10.70	8.79	-1.91	3.95	4.42	0.47
Wearing Apparel; Dressing	18	12.13	12.94	0.81	4.48	6.51	2.03
Tanning and Dressing of Leather,	19	19.30	18.19	-1.11	7.13	9.15	2.02
Wood Products, Except Furniture	20	4.73	3.49	-1.24	1.06	1.11	0.06
Pulp, Paper and Paper Products	21	9.87	8.87	-1.01	0.40	0.54	0.15
Publishing, Printing	22	0.47	0.92	0.45	0.02	0.06	0.04
Coke, Refined petroleum products	23	3.12	3.33	0.21	0.56	0.45	-0.10
Chemicals and Chemical Products	24	11.77	13.73	1.96	0.81	0.98	0.18
Rubber and Plastic Products	25	1.05	1.48	0.43	0.08	0.19	0.12
Other Non-metallic Mineral Products	26	2.36	2.08	-0.28	0.27	0.34	0.07
Basic Metals	27	12.65	16.35	3.70	2.19	3.36	1.17
Fabricated Metal Prod., excl. Mach.	28	1.15	1.81	0.66	0.23	0.37	0.15
Machinery and Equipment NEC	29	4.48	7.35	2.86	0.54	1.94	1.40
Office Machinery and Computers	30	16.60	13.85	-2.75	2.51	6.06	3.56
Electrical Machinery	31	2.84	6.57	3.73	0.39	1.52	1.13
Radio, Television, Communication	32	17.67	19.75	2.07	3.33	6.99	3.66
Medical, Precision and Optical	33	2.52	4.52	2.01	0.25	0.71	0.46
Motor Vehicles, Trailers	34	12.71	10.21	-2.49	0.39	0.55	0.16
Other Transport Equipment	35	10.12	13.03	2.91	0.37	1.18	0.81
Furniture; Manufacturing NEC	36	2.21	9.42	7.20	0.61	3.81	3.20

Notes: Values are calculated according to $OFF_{jt} = \frac{IMP_{j^*t} \times \Omega_{j^*jt}}{Y_{jt}}$ (see text) and represent percentage values. Changes are absolute changes.

varying coefficients that are unobservable to us, such as business cycle effects at the country or world level, we can employ time fixed effects, which capture this variation as long as it is uniform across industries. All remaining variation will have to be picked up by the variables included in the model. These will naturally be measures for offshoring along with controls for technological change, and other time-varying industry specific variables. We will specify the exact nature of the control vector further below. At this point it is sufficient to state that identification of the effect of offshoring on income risk will be based on differential movements in industry level offshoring over time. A further point deserves attention. Given the structure of our data set, we have to be careful when calculating standard errors (Krebs et al.

2010). Our dependent variable $\hat{\sigma}^2_{\eta jt}$ is by itself the outcome of an estimation at the industry level. With different standard errors across industries from the first-stage estimations, we are facing heteroscedasticity. Furthermore, there is the possibility of serial dependence of error terms within industries. We therefore follow the literature in reporting robust standard errors.[25]

With the above considerations in mind, we arrive at the following empirical models, where the first one is applied to the long-run data set based on m 5-year average values and the second model is used in the analysis of the yearly data. Importantly, this latter model also allows for the inclusion of lagged effects of offshoring on income risk if we chose $N > 0$:

$$\sigma^2_{\eta jm} = \beta_1 OFF_{jm} + \gamma X_{jm} + \phi_j + \varphi_m + \nu_{jm} \tag{3.12}$$

$$\sigma^2_{\eta jt} = \Sigma^N_{i=0} \beta_i OFF_{jt-i} + \gamma X_{jt} + \phi_j + \varphi_t + \nu_{jt} \tag{3.13}$$

In these models, the control vector X_{jt} holds a variable approximating technological progress using the share of R&D expenditure in industry value-added. Country-wide trends in technology upgrading, that are unrelated to offshoring but impact on income risk, are picked up by the year effects. Furthermore, it includes measures for the export share in production (capturing another dimension of dependency on international output fluctuations), the import penetration ratio (to provide for a comparison with the literature – Krishna & Senses (2009), in particular), and the industry level labor share of income (meant to broadly capture the influence of labor market institutions on income risk).[26] In addition we use different measures for the offshoring intensity based on an alternative deflation strategy (using aggregate price

[25]Krebs et al. (2010) state that the dependent variable being the outcome of an estimation does not introduce a bias in the coefficient estimates while standard errors have to be adjusted.

[26]All these data are retrieved from the OECD STAN database.

indices for both imports and output) and differentiate between worldwide offshoring and offshoring to non-OECD countries, the latter again based on the standard deflation procedure. In both cases, ϕ_j represents the industry fixed effects. φ_m and φ_t are binary variables for 5-year periods (m) and years (t), respectively. ν_{jm} and ν_{jt} represent the two model's error terms.

3.4 Results: offshoring and income risk

In this subsection we present the results based on the above models. We begin with a discussion of model (3.12)'s results and subsequently turn to estimating equation (3.13).

Table 3.4 has a clear message: an increase in offshoring correlates with lower permanent income risk. We find negative coefficients on the different offshoring variables throughout columns (1) to (6) in table 3.4. The results are always statistically significant at conventional levels. The coefficient value in column (1) implies that, on average, an increase in the offshoring intensity by one percentage point decreases the permanent component of income risk by -0.00131. Compared to its (employment weighted) mean across industries and over time of 0.0060, this represents a decrease of more than 20% for every percentage point increase in the overall offshoring intensity. The effect is stronger for offshoring to non-OECD countries. The results in column (3) show the effect to be roughly three times the size of the corresponding value for worldwide offshoring. This type of offshoring, however, shows a smaller absolute increase over time: roughly half a percentage point.

Including a number of industry level control variables leaves the main message untouched. Offshoring is still a negative and significant influence on permanent income risk. Yet, the coefficients of the control variables hold a small bit of additional information. The import penetration ratio is found to increase income risk. A finding which weakly confirms the result found in Krishna & Senses (2009) for the US also for Germany. The labor share on the other hand correlates negatively with permanent income risk. This potentially expresses the influence labor market institutions and union presence have in smoothing the long-run income path. The R&D share does not have any significant effects. It seems as if this variable is unable to approximate technological change above and beyond common aggregate-level trends captured by the time effects. Overall, the above results suggest that offshoring-induced structural change within manufacturing – with an ever higher share of tasks located abroad – is associated with a decrease in income risk.

In table 3.5, we turn to the results based on model (3.13) using yearly data. Again, we find average permanent income risk to be reduced by an increase in offshoring. We present results for one-year lagged values of offshoring as explanatory variables, because we do not find any significant contemporaneous correlation. This points to the impact offshoring has on income risk as the outcome of a change in how employment and production are organized internationally. Recall that income risk measures shocks from an ex-ante perspective, i.e. it describes how shocks at a given time play out over future periods. We can therefore state that, on average, workers in an industry that shifts more tasks abroad will subsequently face less severe shocks to permanent income.[27]

The coefficient values are somewhat smaller now, implying a decrease in income risk of only about 8.8% compared to the mean value following an increase in the overall

[27] This does not say anything about the possible effects of displacements at the margin of offshoring. Yet, according to some recent studies, offshoring does not seem to be a major cause of overall job-loss at the industry level (OECD 2007, Harrison & McMillan 2011).

Table 3.4: Results based on 5-year averages, 1991-2005

income risk (permanent component)	1	2	3	4	5	6
offshoring intensity (world)	-0.131**			-0.179**		
	(0.0586)			(0.0659)		
offshoring intensity (world; alt. defl.)		-0.105*			-0.139**	
		(0.0585)			(0.0653)	
offshoring intensity (non-OECD)			-0.350**			-0.379*
			(0.165)			(0.213)
export-share in production				-0.0667	-0.0253	-0.0514
				(0.0417)	(0.0402)	(0.0348)
import penetration				0.0705	0.0350	0.0674*
				(0.0432)	(0.0385)	(0.0375)
R&D share in value added				0,0070	0.0117	-0,0020
				(0.0346)	(0.0332)	(0.0399)
labor share				-0.0293*	-0.0276	-0.0290*
				(0.0162)	(0.0180)	(0.0165)
time-period fixed effects	yes	yes	yes	yes	yes	yes
industry fixed effects	yes	yes	yes	yes	yes	yes
Observations	66	66	66	63	63	63
R-squared	0.186	0.200	0.181	0.288	0.232	0.287
Number of industries	22	22	22	21	21	21

Notes: Estimation is by fixed effects. The coefficient values on the offshoring measures are to be understood as follows: a one unit change in offshoring (= percentage point change) corresponds to a $\hat{\beta}/100$ change in the variance of persistent changes in the unexplained component of income (= permanent income risk). Industry 36 has incomplete data coverage which leads to a slightly reduced number of observations in some cases. Cluster-robust standard errors are shown in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

offshoring intensity by one percentage point. The results are not strictly comparable to the ones of model (3.12), however, because they are based on different data sets and a different estimation of income risk itself.[28] Turning back to the estimates, the coefficient for non-OECD offshoring implies roughly a forty percent decrease in permanent income risk for every percentage point increase in offshoring (compared to the mean value of income risk). Note, however, that average offshoring to non-OECD countries grew from 0.8% to 1.4% - a change of a little more than half a percentage point. With respect to the control variables, not much seems to be gained from their

[28]Furthermore, the BA-panel data do not allow us to estimate income risk for manufacturing industries 19 and 23, which turn out to be marked by particularly high levels of income risk. Excluding those industries in the estimation of model (3.12) lowers the coefficient on the offshoring variable and brings it closer to the values obtained from model 2.

inclusion. None of them have a significant impact, although the coefficients show the same sign as in table 3.4. In summary, our results from both models show a negative and significant effect of offshoring on the permanent component of income risk. Offshoring to non-OECD countries has a particularly strong effect.

Table 3.5: Results based on yearly data, 1999-2005

income risk (permanent component)	1	2	3	4	5	6
1-year lagged offshoring intensity (world)	-0.0390*			-0.0370*		
	(0.0210)			(0.0205)		
1-year lagged offshoring intensity (world; alt. defl.)		-0.0435*			-0.0373*	
		(0.0241)			(0.0202)	
1-year lagged offshoring intensity (non-OECD)			-0.183*			-0.160*
			(0.0908)			(0.0778)
export-share in production				-0.0289	-0.0257	-0.0237
				(0.0217)	(0.0203)	(0.0216)
import penetration				0.0183	0.0178	0.0171
				(0.0236)	(0.0225)	(0.0241)
R&D share in value added				0.0036	-0.0041	-0.0120
				(0.0179)	(0.0142)	(0.0122)
labor share				0.0045	0.00608	0.0069
				(0.0085)	(0.0078)	(0.0069)
year fixed effects	yes	yes	yes	yes	yes	yes
industry fixed effects	yes	yes	yes	yes	yes	yes
Observations	114	114	114	108	108	108
R-squared	0.245	0.320	0.380	0.393	0.417	0.460
Number of sector	19	19	19	18	18	18

Notes: Estimation is by fixed effects. The coefficient values on the offshoring measures are to be understood as follows: a one unit change in offshoring (= percentage point change) corresponds to a $\hat{\beta}/100$ change in the variance of persistent changes in the unexplained component of income (= permanent income risk). Industry 36 has incomplete data coverage which leads to a slightly reduced number of observations in some cases. Cluster-robust standard errors are shown in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

3.5 Conclusion

The analysis in this paper presents offshoring as a source of changes in permanent income risk. Income risk is an important factor in determining the consumption, savings and thus welfare patterns in an economy. We single out offshoring as a potential influence, given the anxiety it regularly stirs up in the public debate as well as its large role in international trade transactions. Within the limits of our available data, we seeks to answer whether the fears regarding income insecurity often associated with it are justified. We find that they are not. On the contrary, within manufacturing industries, increased offshoring is associated with a *decrease* in the permanent component of income risk.

In our empirical analysis, we first estimate industry level income risk from individual level data, isolating the welfare-relevant permanent component for two different data sets. We then link it to offshoring at the industry level in a panel framework. We find offshoring to have a negative and statistically significant effect on income risk for employees within industries in manufacturing. Furthermore, there is strong evidence for a differentiated impact across destination regions, with a stronger than average effect for offshoring to non-OECD countries. This is expected as offshoring in this case is closer to a process of wage related labor substitution in an ongoing reallocation of different tasks around the globe.

However, with respect to welfare implications the results are less straight forward. Clearly, taken by itself, a reduction in income risk brought about by a higher offshoring intensity would imply a positive welfare effect. Yet, this effect might not be the only welfare-affecting change. Two points deserve particular attention. First, the wage level still matters as well. Individuals may have a smaller benefit if risk decreases but this comes as a trade-off with lower average wages. Yet, on an aggregate level, this is not necessarily to be expected. Grossman & Rossi-Hansberg (2008) theoretically show that the wage effects of offshoring are ambiguous, and empirical evidence often documents relative wages for different skill groups to change while *overall* wages are hardly affected. Leaving considerations with respect to a skill-specific effect to further research, we are therefore leaning towards the conclusion that lower income risk does not come at the cost of lower average wages in manufacturing.

The second possible concern is related to employment levels. A shift of more volatile occupations (or tasks) abroad may change average income risk in the home country at the expense of lower overall employment levels. The volatile jobs would move offshore and – as a consequence – the remaining ones show a lower average income risk. Yet, it is hard to argue that this situation is desirable from an aggregate perspective if overall employment falls. Ideally, if composition effects are at work, one would want the home employment to stay constant or to grow due to productivity effects from offshoring and the workers whose tasks are moved offshore would find re-employment in less volatile jobs. There are some hints that offshoring is not responsible for falling employment levels in manufacturing. For instance, the OECD states that "*(...) the industrial sectors that have most downsized their workforce are not the ones that have most engaged in offshoring. Offshoring does not therefore emerge as a major cause of job losses.*" (OECD 2007). This finding has recently been confirmed by Harrison & McMillan (2011) for the United States, who find most of the manufacturing employment decline to be a result of capital-labor substitution rather than international labor reallocation. We therefore conclude on a slightly optimistic tone. If offshoring lowers the permanent component of income risk, while average wages do not fall and overall employment stays widely unaffected, there may be positive effects on welfare.

3.6 Appendix to chapter 3

This first additional table (3.6) shows results from the first stage regression generating the income residuals. Coefficients on industry fixed effects are not shown. The results are based on BA data with imputed wages from the cross section for the year 2005. Results for any other year virtually look the same. All coefficients have the expected sign and significance. That is, income grows with age, skill, firm size, etc.

Table 3.6: First stage wage regression for 2005

ln wage	1
Age	0.0089***
	(0.0001)
Foreign nationality	-0.0992***
	(0.0034)
Firm size	0.0532***
	(0.0006)
Medium-skilled	0.2170***
	(0.0052)
High-skilled	0.4825***
	(0.0032)
Constant	7.1712***
	(0.0066)
Industry fixed effects	yes
Observations	72,723
R-squared	0.4621

The following table 3.7 provides results from using BA data from the June waves only. As in all previous tables, offshoring is associated with a decrease in permanent income risk, albeit with a two-year lag.

In table 3.8 we address the concern of some income risk estimates being individually insignificant when using SOEP data. (With the BA data we do not face this problem to any comparable extent.) We simply drop these observations and re-run the regressions. We still find increased offshoring to be associated with a decrease in permanent income risk.

Table 3.7: Results based on yearly data, 1999-2005, June waves only

income risk (permanent component)	1	2	3
2-year lagged offshoring intensity (world)	-0.0443*		
	(0.0233)		
2-year lagged offshoring intensity (world; alt. defl.)		-0.0470*	
		(0.0253)	
2-year lagged offshoring intensity (non-OECD)			-0.218**
			(0.0811)
export-share in production	-0.0457**	-0.0396*	-0.0267
	(0.0214)	(0.0188)	(0.0160)
import penetration	0.0417	0.0371	0.0233
	(0.0268)	(0.0248)	(0.0195)
R&D share in value added	-0.0358*	-0.0467*	-0.0464**
	(0.0179)	(0.0240)	(0.0208)
labor share	0.00396	0.00419	0.000334
	(0.00498)	(0.00499)	(0.00640)
year fixed effects	yes	yes	yes
industry fixed effects	yes	yes	yes
Observations	90	90	90
R-squared	0.514	0.520	0.589
Number of sector	18	18	18

Notes: Estimation is by fixed effects. The coefficient values on the offshoring measures are to be understood as follows: a one unit change in offshoring (= percentage point change) corresponds to a $\hat{\beta}/100$ change in the variance of persistent changes in the unexplained component of income (= permanent income risk). Industry 36 has incomplete data coverage which leads to a slightly reduced number of observations in some cases. Cluster-robust standard errors are shown in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3.8: Results, 5-year averages, 1991-2005, indiv. significant risk estimates only

income risk (permanent component)	1	2	3
offshoring intensity (world)	-0.235***		
	(0.0531)		
offshoring intensity (world; alt. defl.)		-0.241***	
		(0.0554)	
offshoring intensity (non-OECD)			-0.508**
			(0.217)
export-share in production	0.00805	0.00430	0.0658
	(0.0581)	(0.0585)	(0.0545)
import penetration	0.00191	0.00820	-0.0600
	(0.107)	(0.107)	(0.0960)
R&D share in value added	-0.00194**	-0.00208**	-0.000936
	(0.000896)	(0.000901)	(0.000966)
labor share	-0.0621	-0.0617	-0.0596
	(0.0602)	(0.0597)	(0.0682)
time-period fixed effects	yes	yes	yes
industry fixed effects	yes	yes	yes
Observations	27	27	27
R-squared	0.611	0.615	0.525
Number of industries	15	15	15

Notes: Estimation is by fixed effects. The coefficient values on the offshoring measures are to be understood as follows: a one unit change in offshoring (= percentage point change) corresponds to a $\hat{\beta}/100$ change in the variance of persistent changes in the unexplained component of income (= permanent income risk). Industry 36 has incomplete data coverage which leads to a slightly reduced number of observations in some cases. Cluster-robust standard errors are shown in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Chapter 4

Offshoring and Relative Labor Demand from a Task Perspective

4.1 Introduction

The link 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. Similar concerns are frequently echoed in the public debate on globalization. Yet, important changes in the pattern of international trade have recently been uncovered. Building on Grossman & Rossi-Hansberg (2008), some important recent contributions argue that a certain part of trade has reached a much finer level of resolution and is now best conceptualized as being determined by the tasks defining an occupation, rather than overall skills in an economy (Crinò 2010, Becker et al. 2013). The implications of such an approach are crucial. Since the nature of trade is changing, the lines defining heterogeneity in the effect of globalization on individuals might have to be redrawn as well. With task-tradability as the crucial determinant rather than the (previously analyzed) educational achievement of workers performing these tasks, a new and more refined pattern in the distribution of globalization's costs and benefits might emerge. This paper presents novel empirical evidence on how offshoring shifts relative labor demand for different types of tasks and thus goes beyond the classical skill-based distinction in the effects of trade on workers. In particular, it is found that increased offshoring is linked to a reduction in the industry level cost share of routine and non-interactive tasks – an effect which is relatively stronger for offshoring to non-OECD economies. Additionally, novel evidence is presented that this effect is primarily driven by occupation level reallocation of women and younger individuals.

In order to consistently estimate such an effect, some changes to the classic theory of relative labor demand, as in Feenstra & Hanson (1996), are necessary. While high-skilled and low-skilled labor are supplied to the market by different individuals, tasks, in contrast, are usually bundled within occupations. This means that the same individual engaged in production is performing some routine and some non-routine tasks, yet in different proportions across occupations. Importantly, such a fixed bundling contrasts with the assumption of free movement of factors across industries and thus labor cannot be split into two independent and freely mobile factors anymore. Deriving predictions on relative cost shares of tasks in such a context presents a challenge. Yet, a sorting model of the labor market can provide a solution. In such a setting, individuals are endowed with different abilities across tasks. Based on these abilities, and occupation specific wages, they sort into occupations, which are in turn characterized by fixed requirements of tasks. The abilities each individual possesses determines in which occupation a unit of output can be produced with the least amount of effort. Individuals maximize the wage per unit of effort. With individuals sorted into jobs, firms face the decision whether to offshore any given occupation. The costs of offshoring are conceptualized following Grossman & Rossi-Hansberg (2008). They include a general component, which is equal for all occupations, and an idiosyncratic one, that is directly related to the occupation level task intensity. Since occupations are fixed bundles of tasks and non-routine and interactive tasks are seen as having higher offshoring costs, the more intensively an occupation uses these tasks the more costly it will be to offshore it. Importantly, the idea here follows Feenstra & Hanson (1996) again in that entire occupations are reallocated internationally.[1] This assumption is linked to the fixed and indivisible bundling of tasks in occupations. This bundling could be due to binding work contracts which specify job contents, for instance, and is commonly assumed in recent contributions such as Autor & Handel (2013) or Firpo et al. (2011). Offshoring is introduced from a partial equilibrium perspective in terms of adjustment happening at fixed occupational wages. It is being triggered by a downward shift in the general cost component of offshoring costs, possibly due to trade liberalization or technological innovations. Given such a cost reduction, the offshore production of some occupations might become profitable and the corresponding occupations will go abroad. Individuals previously employed in these jobs will re-sort into the now optimal occupation, given the reduced range over which optimization takes place. As a result, the new equilibrium will have individuals being employed in occupations, which are on average more intensive in non-routine and interactive tasks. Since individuals furthermore derive a larger share of income

[1] Regarding occupational task composition as fixed is also consistent with estimating task employment and wage responses with time-invariant data on which tasks make up an occupation. This data structure is common to almost any data on tasks used in academic research. Examples for data sets on task content without a (short-run) time variation are the German BIBB data set used here and in Becker et al. (2013), or the O*NET data base for the US (see Crinò 2010, Costinot et al. 2011), which are widely used in the literature – also on a number of topics beyond international economics. Using such data demands an approach such as the one presented here, which is consistent with this data structure.

from these tasks in the new equilibrium, the cost share of routine and non-interactive tasks will fall with offshoring. This paper thus contributes a theoretical approach, linking offshoring and relative labor demand for tasks, that is consistent with using data that treats occupations as bundles of tasks.

In a second step, the prediction regarding relative labor demand for tasks is tested in a panel set-up at the industry level for the years 1998 - 2007, using data from the German manufacturing sector. The data set used for estimation combines information on offshoring, derived from yearly input-output tables and industry level trade data, with industry level cost shares of different tasks, which in turn are calculated from information on individual level earnings and employment. Heterogeneity in tasks is conceptualized by drawing on recent progress in the empirical literature, which uncovers certain characteristics of tasks to determine their idiosyncratic offshoring costs. Two concepts have received particular attention. On the one hand, based on Autor et al. (2003) and Levy & Murnane (2004), tasks are believed to be the more replaceable by computers or foreign workers 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 difficult, 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 necessarily only their university degree, the success of their employer, or the viability of the industry they work in. Since the focus of this paper is not on the work content as such, but on its implications for the offshoring costs of occupations, non-routine and interactive tasks will be grouped together as difficult to offshore and are denoted as N-tasks. Analogously, routine and non-interactive tasks will be summarized as R-tasks.

This paper's results uncover a more nuanced effect on labor demand than a skill-based analysis since workers with the same educational achievement usually carry out a multitude of job specific tasks. Consequently, the question of whether the task perspective indeed sheds light on a new aspect is answered by estimating relative demand for tasks conditional on the skill-composition of an industry. The results indeed point to important effects operating within industries and within skill groups. Offshoring is shown to significantly reduce relative labor demand for routine and non-interactive tasks when explicitly controlling for the share of high-skilled or medium-skilled individuals in the labor force, particularly if production offshoring occurs in non-OECD countries. This link is shown to be robust across various measures of task-based labor demand and multiple estimation methods, including instrumental variables models.

While a sizeable literature studies the effects of trade and offshoring on workers with different educational qualifications or following the traditional blue collar/white collar distinction, a few recent empirical papers take note of the importance of tasks in analyzing trade and labor market interactions. Among these papers are several key contributions, changing the way the literature approaches heterogeneity in the labor market effects of globalization. Taking a long-term perspective, Kemeny & Rigby (2012) show that imports from developing countries are linked to the decline of routine task intensive jobs in US manufacturing since the 1970s. With an emphasis on individual worker's earnings, Ebenstein et al. (2013) and Baumgarten et al. (2010) show negative wage effects for individuals performing mostly routine tasks in the US and Germany, respectively. Importantly, these effects can work in opposite directions compared to skill-premia based on education. In an influential study, Crinò (2010) focuses on the US labor market and points out that service offshoring penalizes more tradable occupations within a given skill group. Ottaviano et al. (2013) provide some evidence that manufacturing offshoring tends to shift native workers into communication intensive occupations. Goos et al. (2009) and Oldenski (2012) document that more offshorable jobs show relative employment losses, contributing to the polarization of the labor markets in Europe and the US, respectively. Hakkala et al. (2008) investigate the link at the firm level and find evidence of within-firm task reallocation when Swedish firms are acquired by multinational enterprises. In what is probably the highest-impact firm level study, Becker et al. (2013) produce evidence that German multinationals reduce relative labor demand for routine tasks at home when expanding employment in their affiliates abroad.

The present paper tackles the issue at the industry level. It aims at delivering a more general analysis in that the industry perspective captures effects on labor demand arising from linkages between offshoring firms and others, such as supplier networks or competition in local labor markets. Additionally, labor demand by multinational firms may not be representative of sector or country level trends if individuals, set free by such firms, are re-employed and perform similar tasks in non-multinational firms. In this case, the firm level effect measured by the previous literature would uncover differences in labor demand across heterogeneous firms, rather than aggregate trends in employment structures. A comprehensive study analyzing the connection between manufacturing offshoring and relative labor demand from a task perspective at such a more aggregate level thus far is missing. Moreover, a contribution lies in the coverage of a recent time period (1998 - 2007), which is particularly important given the further integration of emerging countries like China and India into the world trading system. This latter aspect is emphasized by devoting special attention to offshoring to non-OECD economies. A further novel result put forth in this paper is first time evidence on demographic heterogeneity in the effect. In particular, it is found that adjustment to offshoring is strongest among women and younger workers, which is in line with more volatile employment patterns generally attributed to these groups.

Following this introduction, a new partial equilibrium model of how offshoring affects relative labor demand for tasks with an explicit role for task bundling is developed, serving as the underpinnings of the empirical approach. Section 4.3 then provides details on the data used and the definitions applied. The estimation framework and comprehensive results follow in section 4.4. Robustness checks are presented in section 4.5. A final discussion with summarizing remarks and a reference to promising further research opportunities concludes the paper.

4.2 Theoretical considerations

The classic theoretical background for much recent work on offshoring and relative labor demand is Feenstra & Hanson (1996). This skill-based model is not easily transferable to an analysis of the link between offshoring and relative labor demand for tasks, however. Feenstra & Hanson (1996) features a continuum of production stages, which each require the input of high-skilled and low-skilled labor, which is contracted on labor markets. These stages of production are subject to the offshoring decision and the skill shares determine how attractive such a move would be. In Feenstra & Hanson (1996) there is no role for tasks. In contrast to this model, modern theory introduces the notion of tasks, which are differently tradable, depending on how routine or interactive they are. These characteristics do not have to coincide with education-based categories of skills, however. In the model by Grossman & Rossi-Hansberg (2008), tasks are built-in as an additional layer within high-skilled and low-skilled labor. A single task is always connected to either high-skilled or low-skilled labor and labor types are both mobile across industries.

The model presented here, differs in its conceptualization of tasks. On the labor market, different and fixed *bundles* of tasks are contracted. These bundles are called occupations and are made up of two fundamental types of tasks: R-tasks, which are routine and non-interactive, and N-tasks, which are non-routine and interactive. These categories are chosen to directly reflect tradability characteristics. Consequently, the offshoring cost of an occupation is determined by the proportion of R-tasks and N-tasks. In both the domestic and foreign market, different occupations pay different wages but individuals within each occupation earn the same wage. Individuals, in turn, are heterogeneous and endowed with varying amounts of talent for the performance of R-tasks and N-tasks, respectively. Based on these talents, which determine the amount of effort needed to produce one effective unit of labor in a given occupation, an individual self-selects into one specific occupation, depending on the unit wage offered for the respective bundle of tasks in different occupations. The crucial difference to both the Feenstra & Hanson (1996) and the Grossman & Rossi-Hansberg (2008)-type models is the bundling of tasks. The consequence is that tasks cannot be treated as separate factors being supplied to the market independently.[2] In the following, the task-based characterization of the labor market will be developed, building on insights recently put forth in Liu & Trefler (2011) and Autor & Handel (2013), that in turn represent modern interpretations of Roy (1951)-type models.[3] Subsequently, it will be described in more detail how an exogenous change in the costs of offshoring leads to changes in the relative demand for tasks – changes

[2]This equally applies to many empirical approaches using the more general "translog" production function as a starting point for deriving a reduced form empirical relationship. Such an approach also necessarily requires the different tasks to be independently supplied to the market.

[3]While the set up of the labor market is similar in these papers, there are distinct differences in terms of how offshoring is conceptualized. In Autor & Handel (2013) there is no direct link to offshoring or trade. In Liu & Trefler (2011) offshoring occurs as a shift of tasks out of an occupation. In contrast, the mechanism here follows the idea, put forth in Feenstra & Hanson (1996), of entire occupations being shifted abroad.

which are tightly linked to shifts in the occupational employment structure towards more non-routine and interactive jobs.

There is one final good Y being produced from a range of intermediate activities k, with $[k = 1, \ldots, K]$. These intermediate activities are different occupations, which use labor $L = \{N, R\}$ and capital B to produce output.[4] Each occupation requires the performance of a different mix of tasks. That is, some occupations more intensively use non-routine and interactive N-tasks, while in others most of the tasks are routine or non-interactive (R). The amount of these tasks required within each occupation is fixed. Hence the production structure of an occupation k is described by $\phi_k = \{N_k, R_k, B_k\}$. The occupations are furthermore ordered such that a higher ϕ_k means a higher relative intensity of N-tasks.

Individuals are heterogeneous. Each individual i is characterized by specific abilities in the performance of tasks, which are denoted by A_{iN} and A_{iR} for N-tasks and R-tasks, respectively. These abilities can be seen as individual talents – whether innate or acquired through education and training. Importantly, they are regarded as exogenously given and fixed. When supplied to the labor market, they will determine the amount of effort needed to deliver an efficiency unit of labor input of occupation k in a way that a higher A_{iN} is connected to less effort needed in occupations intensive in N-tasks. Framing the sorting mechanism in terms of effort is a crucial difference to recent contributions like Ohnsorge & Trefler (2007) and Liu & Trefler (2011), where individual abilities determine individual earnings in an occupation. In contrast, the mechanism introduced here will not generate different earnings across individuals within each occupation but instead will preserve a common occupation

[4]Capital in this case is assumed to be freely mobile across occupations as well as internationally and thus has one single equilibrium price b. Furthermore, it is assumed to be a fixed input in the short-run, which takes it out of the decision regarding a firm's optimal choice of production location.

specific wage. Sorting works through the mechanism that differently endowed individuals will need different amounts of effort for attaining that wage, which generates disutility and thus leads to a trade-off between higher wages and higher disutility from effort. That is, the individuals select themselves into a certain occupation so as to maximize the wage received per unit of effort. A single occupation specific wage is an important feature as this wage is the basis firms will decide on when considering shifting certain occupations offshore. Using this effort based individual sorting, a more formal characterization of occupations from an individual's perspective is given by:

$$F_{ki}(A_{iN}, A_{iR}) = A_{iN}^{\phi_k} A_{iR}^{1-\phi_k} \tag{4.1}$$

where $1/F_{ki}$ is the amount of individual effort needed to generate a unit of effective occupation k-type labor with individual abilities A_{iN} and A_{iR}. Following Liu & Trefler (2011), in order to derive the individual sorting rule, it is useful to define $r = \ln A_{iR}$ and $n = \ln A_{iN}$ and to write $f_{ik}(n, r)$ as the function implicitly defined by $F_{ki}(A_{iN}, A_{iR}) = f_{ik}(n, r)$. Taking logs, a transformed expression for the relation between individual abilities and the effort needed to perform a given occupation derives as:

$$\ln f_{ik}(n, r) = \phi_k n + (1 - \phi_k) r = \phi_k (n - r) + r, \tag{4.2}$$

which is the same expression as in Liu & Trefler (2011), yet with a different interpretation that replaces extra earnings with task specific abilities and thus (inverse) effort. Sorting of individuals into occupations takes this effort function into account and combines it with an occupation specific wage w_k. In choosing an occupation, individuals are maximizing the wage per unit of effort:

$$\max_k (W_{i1}, \ldots, W_{iK}) = w_k f_{ik}(n, r). \tag{4.3}$$

To see how each individual finds an optimal occupation, equation (4.3) can be expressed in log terms as

$$\ln W_{ik} = \ln w_k + \phi_k(n - r) + r. \tag{4.4}$$

Since ϕ_k is increasing in k – that is, the slope of any line with $\phi_k > \phi_k'$ is relatively steeper – there is exactly one occupation not being strictly dominated by another for every individual. With the sorting mechanism as described above, given a certain vector of wages $(w_1, \ldots, w_K)$, individual sorting based on equation (4.4) leads to occupation specific labor supply determined by the joint distribution $g(n, r)$ over individual abilities in the population:

$$L_k^s = L_k(w_1, \ldots, w_K) \quad [k = 1, \ldots, K]. \tag{4.5}$$

So far little has been said about the occupation specific wages w_k. Intuitively, such a uniform wage within each occupation could be the result of union agreements on wages – a situation still prevalent in many industries in countries like Germany. In terms of the model, these occupation specific wages will complete the description of the sorting of workers into occupations. In order to determine these equilibrium wage rates $(w_k, \ldots, w_K)$, consider the production of the final good Y again. This is produced in Cobb-Douglas fashion with share parameters θ_k determining the "overall importance" of each occupation k. Equilibrium then requires:

$$\frac{w_k L_k(w_1, \ldots, w_K)}{Y} = \theta_k \quad [k = 1, \ldots, K] \tag{4.6}$$

According to equation (4.6), wages could freely differ across occupations based on different labor supply and variation in the importance of any given occupation for final goods production, for instance. However, as will shortly be seen, for a cut-off occupation – separating home production from offshored activities – in terms of N-task intensity to emerge there has to be some monotonic ordering of wages in terms of ϕ_k. That is, wages either have to monotonically increase or decrease (or be the same) for all ϕ_k. Intuitively, occupations with a relatively high non-routine task intensity should pay higher wages. This could arise in this framework as well. The wage pattern across occupations is determined by demand and supply, and a relatively routine intensive occupation will pay a relatively low wage, if it commands low prominence in technology and if individual talent distributions are such that a large mass of individuals will select themselves into this occupation. Empirical evidence also seems to point in the same direction. While it is difficult to establish monotonicity, a regression of the average occupation level log wage ($\ln w_k$) on the average non-routine intensity, ϕ_k, in the data set used for the analyses below yields a highly significant positive relationship, with a one standard deviation higher ϕ_k increasing wages by around 12%.

To generate such a relationship from the equilibrium in equation (4.6), it is assumed that the θ_k's are also increasing in ϕ_k. This seems plausible. Consider the value an additional engineer designing a new production robot brings to the production of Y against the additional effect of employing another worker on the factory floor. The increase in output is likely larger in the first case, which would be reflected in a higher θ_k for the engineering occupation. With the assumption of θ_k increasing in ϕ_k, the equilibrium in equation (4.6) can be obtained either through wages or labor supply increasing with the non-routine intensity of an occupation, or a mixture of both. More formally, it holds that if $\theta_k/\theta_{k'} > L_k/L_{k'}$ then $w_k > w_{k'}$. As argued above, it seems reasonable to assume that $\theta_k/\theta_{k'} > 1$ for $\phi_k > \phi_{k'}$. A further assumption is to take $L_k/L_{k'}$ to be smaller than one. If one is willing to assume that the amount of people with the right amount of "talent" in non-routine tasks is decreasing in this amount, one gets a decreasing labor supply into higher ϕ_k occupation at given wages. Now, if wages are higher in higher ϕ_k jobs, this might make up for the extra effort an individual will need when working in that occupation. At this point the increasing wage schedule arises with one additional assumption: if the difference in wages paid by occupation k and k' is less than the decline between k and k' in population mass selecting themselves into these occupations, the equilibrium in equation (4.6) is consistent with wages increasing in ϕ_k. Then, $L_k/L_{k'} < 1$ and $\theta_k/\theta_{k'} > L_k/L_{k'}$ holds.

All of the above considerations hold without any role for offshoring. To see how offshoring alters the equilibrium sorting, and thus the relative shares of R and N-tasks in the economy, consider that offshoring costs are also related to occupational characteristics. In particular, the N-intensity of an occupation, ϕ_k, determines the costs of potentially offshoring the occupation to another country, which is denoted by $\beta t(k)$. The structure of these offshoring costs follows Grossman & Rossi-Hansberg (2008). On the one hand, it has a general component, β, describing a common cost factor linked to the technological possibilities of conducting certain operations abroad. On the other hand, offshoring costs for each occupation are characterized by the idiosyncratic component, $t(k)$, which is assumed to be increasing in k. Hence, the more non-routine and interactive an occupation is, the more costly its offshore performance will be. This is intuitive as the tasks related to intense communication needs, or tasks which are particularly prone to generating problems that need to be solved in a non-routine manner, are naturally difficult to perform at a distance. In their offshoring decision, firms compare the costs of occupational production across locations Home and Foreign. Due to overall technological disadvantages, wages are assumed to be lower in Foreign. Yet, the relative ordering is preserved. The same holds true for occupational task requirements.

The result is that wages w_k^* in Foreign strictly lie below the ones at Home for all occupations. In their decision to offshore firms have to weigh this lower wage against the occupation specific offshoring costs $t(k)$. An occupation is thus offshored only if:

$$w_k > w_k^* \beta t(k). \tag{4.7}$$

The parallel increasing ordering of occupations, in terms of both wages and offshoring costs, yields one cut-off occupation, $\tilde{k}$, which is the lowest ϕ_k occupation at home. Observing a cut-off occupation means that $L_k(w_1, \ldots, K) = 0$ for all k where $w_k > w_k^* \beta t(k)$. This also implies that workers only sort into the occupations with $k \geq \tilde{k}$ since these are the only ones being demanded at home.

Now, consider an exogenous change in offshoring. The source for an increase in offshoring studied here is the same as in most of the literature and follows Grossman & Rossi-Hansberg (2008). The idea rests on overall technological progress in terms of information and communication technologies (ICT) reducing the general and common component of offshoring costs, β, equally for all occupations. Such a fall in β makes offshoring less costly for all occupations. Importantly, it could be that it alters the position of the cut-off occupation and thus the range of occupations active in onshore production.[5] If the fall in β is large enough to trigger such an adjustment, the range of occupations performed at home will shrink from $\{\tilde{k}, \ldots, K\}$ to $\{\tilde{k}', \ldots, K\}$, with $\tilde{k}' > \tilde{k}$. This leads to a reallocation of individuals previously employed in occupations $\tilde{k} \leq k < \tilde{k}'$ since they are set free, with their optimally chosen occupation no longer in demand at home. Given the sorting rule described by equation (4.4), these workers

[5] Note that with a finite number of occupations it might still be that a small downward shift of β does not trigger an expansion of offshoring. Only if the shift is large enough to tip the scale in the trade-off between k and $k+1$ there will be an effect on the range of offshored occupations.

will now sort into "the next best" occupation, which is the lowest ϕ_k one still left at home. From a partial equilibrium perspective, at given wages, this will increase the share of non-routine and interactive tasks performed in the home economy relative to routine and non-interactive ones.[6] This upward shift in employment shares will also impact on the cost share of tasks. Strictly speaking there is no income paid separately for the two types of tasks, only income paid for separate occupations. Yet, since the non-routine intensity of occupations is increasing in k, the share of income paid for non-routine tasks is increasing. Under the assumption that an occupation's income can be split up into task specific payments by multiplying it with ϕ_k, the cost share of N-tasks is the following:

$$S_N^C = \frac{\sum_k w_k L_k \phi_k}{\sum_k w_k L_k} \quad [k = \tilde{k}, \ldots, K] \tag{4.8}$$

With $0 \leq \phi_k \leq 1$, the share of R-tasks is just $S_R^C = 1 - S_N^C$. Hence, the cost share of R-tasks in overall labor income will fall with an increase in offshoring. This is the main hypothesis being put to the test in the subsequent empirical section of this paper.

[6]The model used here to inform the estimation in later sections is a partial equilibrium model in the sense that is looks at re-sorting at given wages. In general equilibrium, worker sorting into new occupations is going to affect the wages in these occupations, which will in turn affect the optimal sorting again. An increase in labor supply could lead to a fall in the wage rate leading to more workers switching "up". This inflow of workers into the next higher ϕ_k occupation again lowers wages there, leading to some individuals switching up out of this job as well. As a results, there could be a general movement of workers up the "occupational latter" leading to more people being employed in higher ϕ_k occupations. Additionally, increases in output Y, due to the cost savings from offshoring, would disproportionately accrue to the higher ϕ_k jobs as well (through higher θ_k's). Without fully working out the details, these general equilibrium effects would likely reinforce the partial equilibrium effects.

4.3 Data and construction of labor demand variables

This section details the approach taken towards the definition and calculation of measures of relative labor demand for tasks. To this end, the translation of the theoretical concept of occupation level offshoring costs into an empirical measure is presented at first. Subsequently, these measures are connected to wage and employment shares of certain tasks at the industry level. This yields the dependent variables for the estimations to follow: cost and employment shares of routine and non-interactive tasks. 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 constructed and its benefits are discussed.

4.3.1 Task data

In order to assess the structure of offshoring costs and the related demand shifts in the offshoring process, it has to be clear how tasks are assumed to be bundled into occupations. In the theory outlined in the previous section, there is a number of intermediate inputs, each produced by one occupation through the performance of a specific bundle of tasks. Empirically, it is a challenge to find an adequate approximation in available data. In this paper, the unit of analysis for task-related offshoring costs is the level of a 2-digit occupation, of which 74 in the German "KldB 88" classification will be used.[7] Note again that this is not meant to strictly define one occupation as one task but rather as a bundle of them. Moreover, the tasks to be performed within an occupation are usually fixed by a specific work contract which

[7] These 74 occupations exclude agricultural and military occupations.

is assumed to be binding at least in the short-run.[8] Thus, from a firm perspective such an occupation seems like a natural unit when restructuring employment. This renders the offshoring costs of an occupation a crucial determinant in the offshoring decision of firms - just as described in the model above. In this paper, these costs are seen as being determined by the distribution of differently costly tasks within individual occupations. That is, the more routine or non-interactive tasks are performed within an occupation, the less costly it is to offshore. These lower costs can, for instance, be related to routine tasks being easier to supervise from a distance or the fact that they are less likely to produce complicated problems which need direct and costly intervention. Highly interactive tasks, beyond those requiring physical presence, are also more costly to do at a distance. While internet based communication has constantly reduced the costs of international communication, there are still many situations in which communication across time zones about complex problems remains costly.

Given the above considerations, the empirical equivalent to the range of jobs from the model in the previous section is a vector of 74 occupations ordered according to their offshoring costs - the latter being based on their share of R-tasks in total tasks. The task shares within occupations are represented by an average of task intensities at the individual level. For Germany, the best data on this topic comes from the "BIBB/IAB-Employment Survey 1998/99".[9] This database has previously been used by Spitz-Oener (2006) and Becker et al. (2013), among many others, and has proven to be the source of choice for task related information. The database holds survey-

[8]In the long run, the task composition of occupations is likely changing. Examples are found in Spitz-Oener (2006) where evidence for long run trends over several decades is presented. An update of the analysis of long run task changes can be found in Antonczyk et al. (2009). These long-run changes relate to the work content as such, however. They are not directly related to offshoring costs.

[9]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.

results describing the tasks individual workers perform. It is thus a direct account of observed work contents. This sets the data used here apart from classifications based on external expert assessments of an occupation's typical work content such as the O*NET data base developed for the United States. For the analysis in this paper, 13 different activities are grouped into either N-tasks (non-routine and interactive) or R-tasks (routine and non-interactive).[10] Individual-level task intensities are calculated and subsequently aggregated to the 2-digit occupational level as simple mean values. The individual level task intensities are derived as:

$$\lambda^i(k) = \frac{\text{number } N\text{-tasks performed by individual } i \text{ in occupation } k}{\text{number of all tasks performed by individual } i \text{ in } k} \tag{4.9}$$

These individual specific task intensities are averaged within each occupation as $\lambda(k) = \sum \lambda^i(k)/L(k)$.[11]

This calculation of tasks intensities is a variant of a method proposed by Antonczyk et al. (2009). The measure yields an approximation of how an individual splits her job into different tasks. Thus, the measures of task intensities within all 74 occupations considered add up to one.[12] Naturally, $(1 - \lambda(k))$ describes the share of R-tasks in total tasks. It is similar to, yet distinct from approaches using category specific intensities such as Spitz-Oener (2006) or Becker et al. (2013), where the number of type-τ tasks (with $\tau \in routine,\ non-routine$) an individual performs is related to all possible type-τ tasks.

[10]The grouping is a further aggregation of the five categories in Spitz-Oener (2006), with non-routine analytical, non-routine interactive, and non-routine manual being summarized in the N-group with higher costs of offshoring. Routine manual and routine cognitive tasks form the lower cost R-group. The individual tasks grouped into these categories are very similar to the ones used in Spitz-Oener (2006). The individual tasks are also listed in the appendix.

[11]The task intensity $\lambda(k)$ is directly and positively related to the theoretical expression ϕ_k. Yet, since this empirical measure holds no capital, it is denoted differently.

[12]Further details on the data used and the calculation of the task intensities can be found in the appendix.

4.3.2 Income and employment data

The outcome of the above calculations are occupation level values for offshoring costs, $\lambda(k)$, which derive from how intensively an occupation uses a certain type of task on average. In order to construct industry 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") at the occupation level.[13] 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, the data set has a sufficient number of observations to provide for representative distributions of occupational employment and income within 19 out of the 22 2-digit manufacturing industries. This is a crucial element, enabling the use of panel methods to infer the effect of offshoring on relative labor demand for tasks from different within industry movements over time.

A straight forward calculation of the employment share of routine and non-interactive tasks for industry j, $S^E_{R,jt}$, is to calculate the employment share of each occupation k in industry j and year t, π^{kjt}, multiply them with the task scores, $\lambda(k)$ and aggregate this to the industry level. Such calculations are done for 19 manufacturing industries over the time period between 1998 and 2007 at yearly frequency. They look as follows in more formal terms:

$$S^E_{R,jt} = \sum_k [1 - \lambda(k)] \times \pi^{kjt} \tag{4.10}$$

In addition to the straight forward employment shares, cost shares of R-tasks are calculated as well. These will differ from employment shares if wages are systemati-

[13]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).For detailed information on the database, see Schmucker & Seth (2009).

cally higher in relatively N-intensive occupations, which is one of the features of the model in section 4.2.[14] Calculations of cost shares are done using income information provided in the BA data set. The occupation level task intensities are now multiplied with income of occupations. That is, total occupational income, $\widetilde{w}_{kjt}$, is split according to relative task intensities within the respective occupation.[15] Aggregated to the industry level this represents, for a given industry and year, a calculation of cost spent on, e.g., routine and non-interactive task labor. Dividing this by total income spent across all tasks (total labor cost) yields the cost share of such tasks:

$$S^{C}_{R,jt} = \frac{\sum_k \widetilde{w}_{kjt} \times [1 - \lambda(k)]}{\sum_k \widetilde{w}_{kjt}} \tag{4.11}$$

It is crucial to note what the above implies in terms of variation used for estimation in this paper. Importantly, all of the variation in relative labor demand measures stems from variations in occupation-industry employment shares or differential wage movements across occupations. This is in line with nearly all of the related literature, which also uses the between occupation variation when looking at aggregate (either industry of firm level) task changes (see Becker et al. 2013, Crinò 2010, Costinot et al. 2011). Note that not only is the variation used here based on the preferred approach in the literature, it is also consistent with the theory as described in section

[14]Furthermore, changes in cost shares could arise from general equilibrium effects after offshoring changes that benefit relatively N-intensive occupations wages relatively more.

[15]Again, this expression is the empirical version of a theoretical item. In this case, the wage-sum paid to all labor represents the $\sum_k w_k L_k$ from the cost share in equation (4.8) from the theory.

4.2, which explicitly considers occupations as fixed bundles of tasks.[16]

4.3.3 Offshoring data

The offshoring intensities for each industry and year are calculated using a method similar to Feenstra & Hanson (1999). 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 by both 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 foreign industry j^* as 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 (1999)[17]:

$$OFF_{jt} = \frac{IMP_{jt} \times \Omega_{j^*jt}}{Y_{jt}}. \tag{4.12}$$

Ω_{j^*jt} represents the share of imports from a specific industry j^* used in the same industry j at home. IMP_j measures all imports of industry j.[18] These imports can be split in order to differentiate among different offshoring destinations. To

[16] It may be problematic to assume fixed task compositions of occupations if some occupations change their task intensities and are relocated abroad not due to a general fall in offshoring costs β, but due to themselves becoming idiosyncratically more tradable. Besides the argument that short-run compositional changes are inhibited by binding contracts, there is also little evidence of such change. From a similar task-survey for 2005/06, there is evidence to be found that is strengthening the validity of the assumption taken here. On average, there was hardly any movement in within-occupational R-task intensity over the sample period considered and the average share of routine and non-interactive tasks within an occupation decreased by only -1.91%. The ranking of occupations in terms of their R-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.

[17] An alternative specification would be to use the share of intermediate inputs from all foreign industries. This variant is called "wide" in Feenstra & Hanson (1999).

[18] These trade data are taken from the OECD STAN database. See the appendix for details.

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.[19] This region specific calculation entails the assumption that Ω_{j^*jt} does not differ across country groups, an assumption which is frequently taken in the empirical offshoring literature (see Geishecker 2006). Y_{jt} is the industry j's output in year t as supplied by the OECD in the STAN data base. Output and import values are deflated using industry specific producer price indices, from the EU Klems data base, and an aggregate import price index supplied by the German Statistical Office, respectively.[20][21]

Table 4.1 gives an overview of the constructed variables. Offshoring intensities vary substantially between industries 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 worldwide and non-OECD offshoring. The highest growth is found in the radio, television and communication industry. At the same time, the cost share of routine and non-interactive tasks fell in most industries. Employment shares also fell, but are excluded from this table due to expositional reasons. Employment shares of routine and non-interactive tasks are slightly higher. This is intuitive since using employment shares is equivalent to assuming equal wages across occupations. With R-task intensive occupations being rewarded at a lower wage, the industry level wage cost share of these tasks is lower compared to their

[19]See the appendix for details regarding the data sources and the methods used.

[20]For additional details, see the appendix.

[21]Using output, which is equivalent to value added plus inputs, has the advantage of better accounting for domestic outsourcing. If firms outsource inputs domestically, the input measure will rise but this increase will be counterbalanced by a decrease in value added.

employment share. While falling relative labor demand in the face of increased offshoring intensities point 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 4.1: Descriptives: offshoring and task intensity

industry name	offshoring world			offshoring non-OECD			cost share of R-tasks		
	1998	2007	change	1998	2007	change	1998	2007	change
Food Products And Beverages	3.27	4.64	1.37	0.50	0.86	0.36	36.63	37.17	0.54
Textiles	11.19	9.26	-1.93	4.21	5.08	0.87	45.54	43.41	-2.13
Wearing Apparel; Dressing	17.99	13.74	-4.25	6.77	7.54	0.77	32.32	26.25	-6.06
Wood Products, Except Furniture	4.80	3.54	-1.26	0.98	1.20	0.22	45.56	45.39	-0.17
Pulp, Paper and Paper Products	9.19	14.07	4.88	0.45	1.26	0.82	44.57	45.75	1.19
Publishing, Printing	0.09	0.88	0.80	0.00	0.08	0.08	33.82	29.61	-4.21
Chemicals and Chemical Products	11.46	14.57	3.11	0.78	1.23	0.44	34.32	33.83	-0.48
Rubber and Plastic Products	0.97	1.61	0.63	0.09	0.23	0.14	47.77	47.20	-0.57
Other Non-metallic Mineral Products	2.26	2.09	-0.17	0.22	0.40	0.18	43.18	41.92	-1.26
Basic Metals	13.24	23.52	10.27	2.17	5.64	3.48	48.44	49.86	1.42
Fabricated Metal Prod., excl. Mach.	1.48	1.89	0.40	0.25	0.46	0.21	46.38	46.76	0.38
Machinery and Equipment NEC	6.10	8.33	2.24	1.05	2.34	1.29	40.37	38.73	-1.64
Office Machinery and Computers	10.75	10.86	0.11	2.65	5.14	2.49	25.26	22.46	-2.80
Electrical Machinery	5.78	6.16	0.38	0.99	1.52	0.53	36.94	35.77	-1.17
Radio, Television, Communication	5.16	16.90	11.75	1.20	6.55	5.35	32.80	28.80	-4.00
Medical, Precision and Optical	4.38	5.30	0.92	0.65	0.99	0.34	33.44	32.08	-1.36
Motor Vehicles, Trailers	6.90	9.71	2.80	0.20	0.62	0.42	44.24	41.56	-2.68
Other Transport Equipment	8.16	11.71	3.55	0.37	1.23	0.86	36.67	32.93	-3.74
Furniture; Manufacturing NEC	7.23	8.82	1.60	2.12	4.17	2.05	42.18	40.36	-1.82

Notes: The table shows the offshoring intensities for all industries included in the sample - both for worldwide offshoring and non-OECD country offshoring. Offshoring is the share of intermediate inputs (originating from the same industry abroad) in industry output. It also shows the cost shares which are calculated as total wage bill of routine and non-interactive tasks (occupation wage-sum multiplied by tasks intensity) over total wages. All values are expressed in %. Changes are simple differences. Some industry names are abbreviated.

4.4 Does offshoring affect relative labor demand for tasks?

4.4.1 Estimation set-up

The estimation set up seeks to test the main hypothesis from the theory in section 4.2: It should uncover how offshoring is linked to changes in the task composition across industries. The empirical analysis takes the main insights from the model to build a reduced-form relationship between these key variables. It is reduced-from in that it treats output and capital as fixed in the short-run and thus abstracts from some potential general equilibrium effects offshoring might have on these variables. This seems valid in the sense that the period under study comprises ten years only. Given the short-run perspective, the estimation resembles those in Feenstra & Hanson (1996), Berman et al. (1994), and Becker et al. (2013).[22] The cost share (or employment share in some variations) of routine and non-interactive tasks as dependent variable is regressed on the logarithm of the industry's capital intensity, $\ln(K/Y)_{jt}$ and the logarithm of its output $\ln(Y)_{jt}$, capturing that the effect of offshoring is conditional on output and capital – a direct implication of the short-run perspective.[23] Offshoring is included not in log-form but as the share of imported intermediates as defined in equation (4.12). Just as in Feenstra & Hanson (1996) offshoring acts as a shift variable of relative labor demand. In a slight deviation from the theory, further shift variables, such as research and development spending and import penetration ratios, are admitted to affect the cost share in the preferred specification. They are collected in the vector $\mathbf{Z}_{jt}$. Including the research and development variable, as an approximation to technological advances, might also help to rule out biased coefficient

[22]What is missing from the model is the relative wage term between factors since tasks are explicitly not treated as separate factors independently supplied to production due to the bundling assumption.

[23]These control variables enter in nominal terms, which is equivalent to deflating with an aggregate manufacturing price index since the estimations always include year fixed effects.

due to the correlation of technology and relative labor demand for tasks. In particular, Liu & Trefler (2011) stress that it should be included as a separate regressor in any model linking offshoring and the labor market. The unobserved variation in the estimation equation is assumed to be captured by the composite term $\nu_{jt} = \delta_t + \mu_j + u_{jt}$. Part of this unobserved variation can be controlled for using fixed effects for year (δ_t) and industry (μ_j), which control for economy wide trends and industry specific time-invariant characteristics, respectively.[24] The remaining part of unobserved variation (u_{jt}) is assumed to be uncorrelated with any included variable and thus the standard independent error term in the equation. Standard errors are clustered at the industry level.[25] Taken together, the following estimation equation for the cost share of routine and non-interactive tasks in industry j at time t is used:

$$S^C_{r,jt} = \gamma_1 OFF_{jt} + \gamma_2 \ln Y_{jt} + \gamma_3 \ln(K/Y)_{jt} + \gamma \mathbf{Z}_{jt} + \mu_j + \delta_t + u_{jt}. \tag{4.13}$$

With a suitable framework for estimation at hand, it can be investigated whether and to what extend offshoring shifts the relative labor demand for tasks. The next subsection opens with the presentation of regressions based on cost and employment shares of R-tasks in total tasks. Subsequently, the effect of offshoring on relative task demand will be estimated controlling for the industry level skill composition – thus answering whether there are indeed additional insights to be gained from using a task-based approach. A further subsection within the empirical analysis is devoted to a look at demographic heterogeneity in the effect, which is a first in this context. A discussion of the robustness of the results to possible endogeneity issues, to adjustment

[24] An alternative approach do dealing with constant and industry specific components of the composite error term would be to first-difference the data. However, given that the main variables in the model are calculated from a variety of sources, there is some scope for measurement error on a year-to-year basis. According to Griliches & Hausman (1986), the fixed effects estimator is better able to deal with measurement error and is thus the preferred model in nearly the entire related literature and in this study.

[25] See section 4.5 for a discussion of the appropriate handling of inference with few clusters.

of standard errors and inference with few clusters, and to data alterations completes the empirical analysis.

4.4.2 Estimation results

Table 4.2 shows the outcome of estimating model (4.13) for both cost and employment shares of routine and non-interactive tasks, $S^C_{R,jt}$ and $S^E_{R,jt}$, respectively. In the first column, results are presented from estimating equation (4.13) for cost shares with only output and capital intensity included as further determinants of relative labor demand. This baseline specification already reveals the main result, which is hardly changed in further specifications: An increase in offshoring reduces the relative labor demand for routine and non-interactive tasks. The results indicate that, on average, a one percentage point increase in the offshoring intensity (worldwide) leads to a fall of 0.075 percentage points in the R-task intensity. This finding is derived upon the inclusion of industry and year fixed effects controlling for common trends across all industries as well as time-invariant heterogeneity between them. The effect is statistically significant at the 1% level. Taking a look at the results in column 2, it becomes evident that – as expected due to the cost savings motive in, and thus a closer resemblance to, common offshoring models – 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 0.439 percentage points.[26] The inclusion of further control variables does not alter the main message of the results so far, albeit the coefficient on non-OECD offshoring is lowered by about one quarter. These extra explanatory variables control for task shifts related to technological change, that is not directly related to changes in offshoring costs, β, and for further

[26]Note that the effect for worldwide offshoring is not driven by non-OECD offshoring alone. Running the regression (as in column 3 of table 4.2) with OECD-only offshoring, instead of worldwide offshoring, yields a nearly unchanged coefficient ($\hat{\gamma}_1 = 0.0666$), with a slightly higher standard error (0.0326) that preserves significance at the 10% level. For reasons of comparison with the literature and in order to provide general results, coefficients for worldwide offshoring will be presented along with the ones for non-OECD offshoring in the following.

competitive pressures coming from increased import penetration at the industry level. Note, however, that only differential movements in these variables across industries are picked up here, as all economy wide time trends and industry specific time-constant factors are already controlled for in the estimation. In general, adding the industry level R&D intensity, as an approximation of technological progress, or the industry's import penetration ratio provides a bit of further explanatory power, yet hardly changes the offshoring coefficients, other than reducing the coefficient on non-OECD offshoring. The coefficient on the R&D intensity is positive and significant. At first sight this may seem surprising since studies looking at relative labor demand in terms of skill categories usually find negative coefficients with mixed significance. Note, however, that the task categories here do not necessarily lead to expect the same result. While most R&D tasks are performed by high-skilled employees, these tasks could also be characterized by low interactivity and some routine steps – characteristics that enable offshoring. Import penetration is shown to reduce the relative labor demand for R-tasks, with high standard errors in columns 4 casting some doubt on the statistical significance, however. In columns 5 and 6, results arising from using employment shares are shown. Interestingly, these are very similar to the cost share results hinting at most of the effect working through shifts in occupational employment - shifts away from occupations relatively intensive in routine and non-interactive tasks.

The coefficients from the preceding estimations permit a first look at the economic relevance of the results. Using the estimates from column 3 in table 4.2, it emerges that a one percentage point increase in worldwide offshoring decreases the relative labor demand for tasks by 0.0672 percentage points. The total output weighted average decline in the cost share of routine and non-interactive tasks was about one percentage point over the sample period. Worldwide offshoring increased by around

Table 4.2: Baseline regressions for cost and employment shares

	1	2	3	4	5	6
	cost share of R-tasks				emp. share of R-tasks	
offshoring intensity	-0.0752***		-0.0672**		-0.0582**	
	(0.0220)		(0.0268)		(0.0260)	
offshoring intensity to non-OECD		-0.4389***		-0.3294***		-0.3065***
		(0.1014)		(0.1048)		(0.1000)
$ln(Y_{jt})$	0.0231	0.0192	0.0256	0.0211	0.0195	0.0159
	(0.0275)	(0.0201)	(0.0242)	(0.0226)	(0.0210)	(0.0191)
$ln(K_{jt}/Y_{jt})$	-0.0265	-0.0332*	-0.0290	-0.0323*	-0.0235	-0.0267*
	(0.0244)	(0.0172)	(0.0178)	(0.0181)	(0.0140)	(0.0139)
R&D intensity			0.1234***	0.0894**	0.1126***	0.0813***
			(0.0295)	(0.0313)	(0.0260)	(0.0267)
import penetration			-0.0283**	-0.0202	-0.0245*	-0.0165
			(0.0130)	(0.0127)	(0.0117)	(0.0118)
Observations	190	190	190	190	190	190
R-squared	0.5241	0.5917	0.6042	0.6275	0.5303	0.5634
Number of sector	19	19	19	19	19	19

Notes: The dependent variable is the industry level cost or employment share of R-tasks. Cluster-robust standard errors are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. All regressions control for industry and year fixed effects. The sample consists of 19 industries over 10 years (1998-2007).

2.8 percentage points, or 47% of its initial value. Thus, worldwide offshoring accounts for about 20 percent of this total decline in the cost share of R-tasks. Offshoring to non-OECD destinations shows an increase by 0.89 percentage points, a little more than a doubling over the sample period. Using the above estimate of $\hat{\gamma}_1 = -0.329$ from column 4 of table 4.2, the equivalent number of the share of explained variation in relative labor demand for routine and non-interactive tasks stands at a remarkable 30,61%. Offshoring is thus able to explain a considerable part – one fifth to one third – of the observed shift in relative labor demand for tasks.

4.4.3 Estimations controlling for skill composition

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 industry 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 while explicitly controlling for the industry level skill composition following an idea put forth in Becker et al. (2013). Table 4.3 shows the outcome of this important exercise. The first two columns show the familiar results without skill share controls for comparison. The further columns include control for shifts in the share of highly skilled individuals and medium-skilled individuals, respectively. While the high-skill versus low-skill distinction has a long history in the literature, recent papers have stressed that individuals in the middle of the skill distribution are mostly engaged in routine and non-interactive tasks (see Acemoglu & Autor 2011). It thus seems necessary to check what the inclusion of these skill shares does to the effect of offshoring on relative labor demand for tasks. The result is reassuring. 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 baseline analysis did. Crucially, the estimated coefficient on the offshoring variable is still negative and statistically significant in all variations and only slightly reduced in magnitude. Taking a look at offshoring induced shifts in relative labor demand from a task perspective thus adds information beyond what the skill-based view is able to explain. Within education-based skill groups, the task dimension seems to be a relevant source of heterogeneity. This is a result in line with Baumgarten et al. (2010), where occupation specific wage effects are found to be present within skill groups, or Crinò (2010), where labor demand elasticities are heterogeneous across occupations within skill groups, according to how intensive they are in tasks showing relatively more tradable characteristics.

Table 4.3: Cost share regression with skill share controls

cost share of R-tasks	1	2	3	4	5	6
offshoring intensity	-0.0672**		-0.0640***		-0.0696***	
	(0.0268)		(0.0166)		(0.0142)	
offshoring intensity to non-OECD		-0.3294***		-0.2549***		-0.3036***
		(0.1048)		(0.0625)		(0.0574)
$ln(Y_{jt})$	0.0256	0.0211	0.0485**	0.0427**	0.0291	0.0238
	(0.0242)	(0.0226)	(0.0183)	(0.0171)	(0.0210)	(0.0196)
$ln(K_{jt}/Y_{jt})$	-0.0290	-0.0323*	0.0027	-0.0006	-0.0261	-0.0291*
	(0.0178)	(0.0181)	(0.0097)	(0.0094)	(0.0156)	(0.0144)
R&D intensity	0.1234***	0.0894**	0.0230	-0.0012	0.0823***	0.0521*
	(0.0295)	(0.0313)	(0.0186)	(0.0198)	(0.0258)	(0.0267)
import penetration	-0.0283**	-0.0202	-0.0169*	-0.0122	-0.0051	0.0006
	(0.0130)	(0.0127)	(0.0087)	(0.0089)	(0.0159)	(0.0146)
share of high-skilled			-1.0065***	-0.9754***		
			(0.1022)	(0.1005)		
share of medium-skilled					0.2987***	0.2859***
					(0.0642)	(0.0636)
Observations	190	190	190	190	190	190
R-squared	0.6042	0.6275	0.8364	0.8433	0.7036	0.7183
Number of sector	19	19	19	19	19	19

Notes: The dependent variable is the industry level cost share of R-tasks. Cluster-robust standard errors are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. All regressions control for industry and year fixed effects. The sample consists of 19 industries over 10 years (1998-2007). High-skilled is defined as having tertiary education; low-skilled otherwise. Medium-skilled is defined as having a vocational training education versus either a tertiary degree or no vocational training.

4.4.4 Demographic heterogeneity

The above analyses document that a large part of the shift in relative labor demand away from routine tasks is driven by changes in employment. Switching occupations is thus a likely driving force behind this effect. It is equally likely that the individuals affected differ in their individual switching costs. It could be that women have both different exposure and different labor supply responses to shocks than men, for instance. These differences might be rooted in heterogeneity in job contents (and thus different exposure to offshoring), or might be due to different retraining behavior and other outside options given household level income substitution possibilities. A second dimension of heterogeneity, that intuitively comes to mind, is age. As Autor & Dorn (2009) argue, age is directly linked to the process of job reallocation triggered by technological change or offshoring. Their argument builds on job specific human capital. If there is a lot of job specific human capital, older workers are more likely to be retained by the employer and less likely to voluntary switch out of their current job. It may also be that older workers in general hold more complex jobs that require a certain experience and are at the same time less offshorable. Taken together, there is enough reason to look for demographic heterogeneity in the effect of offshoring on relative labor demand for tasks.

Since the underlying reasoning is related to employment switching, and wages across demographic groups might be affected for reasons unrelated to task related offshoring, the estimations are run using employment shares of R-tasks rather than cost shares. These employment shares are calculated using data for the respective groups only. Table 4.4 shows the results. The first column restates the results from the baseline regressions for comparison. The further columns of the table show the change in the employment share of routine and non-interactive tasks within age and gender specific subgroups. The upper panel documents the findings for worldwide offshoring, the lower one does the same for offshoring to non-OECD countries. The results are remarkable; they show a distinct pattern of demographic differences in the effect. With respect to age, it looks as if the effect is driven by younger and middle aged workers. The coefficient for workers over the age of 50 years, on the other hand, is insignificant and almost decreases to zero. This finding is thus consistent with the reasoning in the recent work of Autor & Dorn (2009). The results for gender differences are even more striking; nearly the entire effect is due to variation stemming from female individuals. The coefficient for worldwide offshoring remains outside the conventional significance levels for the male sub sample, while non-OECD offshoring shows significance at the 10% level. There is thus some evidence that it is predominantly women who switch out of the most routine jobs and into more interactive or non-routine jobs.[27] Both patters, for age and gender, are clearly visible for each of the two measures of offshoring.

Table 4.4: Demographic heterogeneity in the effect of offshoring on tasks

worldwide offshoring						
employment share of R-tasks	1a	2a	3a	4a	5a	6a
	all	age 16-29	age 30-49	age 50 and up	male	female
offshoring intensity	-0.0582**	-0.1179***	-0.0550**	-0.0039	-0.0292	-0.1334***
	(0.0260)	(0.0408)	(0.0261)	(0.0327)	(0.0247)	(0.0275)
Observations	190	190	190	190	190	190
R-squared	0.5303	0.6701	0.4705	0.3528	0.3487	0.6248
Number of industries	19	19	19	19	19	19

offshoring to non-OECD countries						
employment share of R-tasks	1b	2b	3b	4b	5b	6b
	all	age 16-29	age 30-49	age 50 and up	male	female
offshoring intensity to non-OECD	-0.3065***	-0.3404**	-0.3324***	-0.1555	-0.1878*	-0.5498***
	(0.1000)	(0.1442)	(0.1130)	(0.0921)	(0.1006)	(0.0844)
Observations	190	190	190	190	190	190
R-squared	0.5634	0.6633	0.5038	0.3657	0.3738	0.6423
Number of industries	19	19	19	19	19	19

Notes: The dependent variable is the industry level employment share of R-tasks. Cluster-robust standard errors are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. All regressions control for industry and year fixed effects. All regressions furthermore include $\ln Y_{jt}$, $\ln(K_{jt}/Y_{jt})$, R&D intensity, and import penetration as additional control variables (coefficients not shown). The sample consists of 19 industries over 10 years (1998-2007).

4.5 Robustness of the results

4.5.1 Discussion of possible endogeneity

The above results represent correlations between within industry offshoring fluctuations and relative labor demand for tasks. They represent a confirmation of

[27]It is also possible that women and younger individuals more frequently switch out of manufacturing or leave the labor force. In this case the shift in relative labor demand would go hand in hand with a downward shift in absolute employment in manufacturing.

the predictions arising from the theory presented in section 4.2. There is no claim that the results are necessarily to be interpreted in a causal way. Nevertheless, this section carefully discusses the underlying assumption of exogeneity of the offshoring measures and possible estimation strategies relying on instrumental variables.

The assumption of exogeneity of the offshoring variables may be called into question if one thinks about industry level technology shocks that could affect both, relative labor demand and offshoring. However, the results presented so far already account for some of these potential influences. By controlling for industry fixed effects, general technological differences between industries that do not vary over time are no longer an issue. Neither are technological developments that affect all industries in the same way since these common trends are captured by the year fixed effects. Some time varying industry specific influences are measured through the R&D expenditure shares and the capital output ratios. Together, the above should control for a lot of variation possibly induced by technology shocks. The scope for bias thus seems limited, yet, it is not completely impossible that some disturbance remains. In addition to the argument around industry specific technology shocks, Wright (2012) has recently discussed the possibility of reverse causality in the offshoring context. The idea behind this source of bias is that changes in labor market variables could trigger lobbying activities from groups most severely affected. These protectionist measures could in turn impact on the trade-based offshoring measures. In the present context this issue appears less problematic since labor interests are generally not organized along task lines – in particular since the task dimension cuts right through the skill dimension in many cases. While ameliorating some concerns, neither of the above arguments are able to completely rule out endogeneity of the offshoring measures, however. In the following, two possible instrumental variable strategies are thus discussed.

The first strategy uses lagged offshoring values and has some tradition in the literature (Geishecker & Görg 2008, Becker et al. 2013). Using lags as instruments rests on the assumption that past offshoring does influence current offshoring but is at the same time unrelated to current relative labor demand for tasks. As reallocations of individuals across occupations or wage effect within jobs likely take some time, there may be lagged adjustment to offshoring in the labor market, however. Going further back in time might overcome this problem. Here, the second and third lag will thus be used. Implementing such a strategy, two general points are crucial. First, the instruments have to explain a sizeable portion of the variation in the offshoring measures. Second, the instruments have to be valid in the sense that they are uncorrelated with the error term of the final estimation equation in the second stage. The explanatory power of the second and third lag of offshoring for current values is within the range of what is usually considered necessary, with an F statistic of 19.43 (p-value: 0.000) for worldwide offshoring and 10.33 (p-value: 0.001) for non-OECD offshoring.[28] Looking at the Hansen-J statistic, it is not possible to reject the null hypothesis of zero correlation between the instruments and the error term in the second stage, which gives support to the chosen specification. A final question, however, is whether the instruments are actually needed in this case. This is tested by means of a C-test, which compares estimated coefficients from the regular fixed effects model with the ones from the IV regressions. In the spirit of a Hausman test, it is then tested whether there is a statistically significant difference between the two estimates. In the present case there is not (p-values: 0.8236 (worldwide) and

[28] All regressions are run with STATA 12 using the xtvireg2 command (Schaffer 2012). Since the errors are still clustered at the industry level, this F statistic is the Kleinbergen-Paap rk Wald statistic. While the first stage F-statistic yields values just within what is usually accepted, more detailed tests of underidentification weaken the case for the second and third lag as instruments. Here the p-values for the according Kleinbergen Paap rk LM statistic are 0.1697 (worldwide) and 0.1834 (non-OECD), respectively.

0.4910 (non-OECD)). This means that the coefficients from the two models with and without offshoring being instrumented are essentially, in a statistical sense, the same. Considering the efficiency loss associated with IV estimation, there is thus no strong case to be made for the rejection of the results presented in the previous sections.

A second idea that has recently been introduced to the offshoring literature is to instrument offshoring in one industry with offshoring in that same industry in another country or region (Autor et al. 2013, Geishecker & Görg 2013). The argument for such a strategy is that offshoring trends in different countries are driven by the same global factors – factors closely related to a fall in the general offshoring costs β. If this constitutes a good and valid instrument, the correlation between offshoring in the same industry across countries would be sufficiently high, while offshoring in the other country would not directly impact on relative labor demand for tasks in the country originally under study. However, the assumption of no correlation between offshoring in one country and labor market variables in another also raises doubts. In competitive international markets, spillovers through shifts in markets shares of internationally active firms seem likely, all the more so in a border-less European Union. From a more technical perspective, a second issue arises. The variation that needs to be instrumented is what is left after controlling for industry and year fixed effects. Yet, the argument for using offshoring in another country as instrument rests on the idea of having a common downward trend in offshoring costs affecting industries in both countries. Such a general trend, however, would be picked up by the year fixed effects. What remains is the industry specific offshoring reaction to a common shock. In addition, there are industry fixed effects controlling for the time-invariant component of differences in shock absorption across industries. Thus, there is very little common variation left and this variation may be far from representing a common influence of globally falling β's. These doubts about the validity of using another country's offshoring experience as an instrument in models including industry and year fixed effects in both stages of the estimation are confirmed by looking at some test statistics related to such an approach. Using similarly constructed data from French industries as instruments for German industries' offshoring in a model with fixed year and time effects, together with all control variables previously introduced, shows how little and insufficient correlation is left between the offshoring values across countries.[29] The F-statistics reach levels of 2.02 (worldwide) and 2.11 (non-OECD), which are far from confirming an acceptable amount of explanatory power. It is interesting to note that leaving out both types of fixed effects and the control variables – hence leaving the correlation between French and German offshoring to be unconditional – yields significantly higher F-statistics and other test statistics very much in favor of using the approach. The danger of retrieving otherwise biased results is eminent in such a rudimentary model, however. In any case, the conclusion of statistically insignificant differences between estimators derived from instrumental variable regression and regular fixed effects models remains. Hence, this second approach, again, does not provide a solid basis for choosing instrumental variable methods over the ones underlying the results in previous sections.

4.5.2 Inference with few clusters

Recently, Cameron et al. (2008) have voiced concerns about inference in empirical settings with clustered standard errors when the number of clusters is small. Their suggestion is to use a cluster wild bootstrap-t procedure that provides an asymptotic refinement. This research has made an impact on some empirical studies in the last years. However, the study by Cameron et al. (2008) is careful enough to point

[29] The data for France are constructed using the import table of the Input-Output table provided by Eurostat (`http://epp.eurostat.ec.europa.eu/portal/page/portal/esa95_supply_use_input_tables/introduction`) for 2000, which limits the variation in constructed offshoring measures to derive from trade and output data since changes the share of intermediates used in any specific industry over time (Ω) are not included. This is the only difference compared to the German data. Trade and output data are from the OECD STAN data base.

out that their results are derived from simulations conducted in certain settings. It provides a detailed discussion on how well cluster robust standard errors perform relative to different bootstrap-*se* and bootstrap-*t* methods – always in relation to varying numbers of clusters. While they generally favor the wild-bootstrap-*t* procedure in most settings using micro level data, their results do not imply its use is mandatory for all possible settings with few clusters. With respect to the setting in this paper, where the analysis features 19 clusters (industries), one important result stands out. Evidence from simulations conducted by Cameron et al. (2008), with data from Bertrand et al. (2004), which have a similar setting to the one used here, building on industry aggregate measures over time, reveal the performance of cluster robust standard errors not to be significantly outperformed by *any* bootstrap procedure for 20 clusters. Only when reducing the number of clusters below 10, some bootstrap methods outperform the cluster robust standard error based procedures. The procedure used in the preceding estimations presented here – implementing cluster robust standard errors – thus receives support from the study by Cameron et al. (2008). Yet, in order to deliver an alternative to cluster robust inference, the main regressions for the cost share of R-tasks are re-run using a wild bootstrap-*t* procedure. Reassessing the models with all controls as in tables 4.2 and 4.3, statistical significance is always preserved at conventional levels.[30]

4.5.3 Data alterations

Further doubts regarding the robustness of the results are dispelled by numerous alterative specifications. Table 4.5 looks at the offshoring intensity to non-OECD

[30] The implementation was done via the user written STATA ado-command "cgmwildboot" provided by Judson Caskey at `https://webspace.utexas.edu/jc2279/www/data.html`. It was run with 1000 repetitions and a null hypothesis of zero imposed for the offshoring variables. Instead of using industry fixed effects as binary regressors, which is infeasible in this setting, the data are de-meaned using xtdata before running cgmwildboot, which may be suboptimal. Year effects are included as well as all control variables from the previous analyses: $ln(Y_{jt})$, $ln(K_{jt}/Y_{jt})$, R&D intensity, import penetration, and for checking table 4.3, the share of high-skilled or medium-skilled, respectively.

Table 4.5: Robustness, cost share regressions

	1	2	3	4	5
	1999-2006	exclude ind. 32	exclude ind. 18	Spitz-Oener Tasks	Geishecker Offshoring
offshoring intensity to non-OECD	-0.3953***	-0.4781***	-0.2596**	-0.3194***	-0.9329***
	(0.0969)	(0.1292)	(0.0974)	(0.1076)	(0.2048)
$ln(Y_{jt})$	0.0231	0.0096	0.0019	0.0302	-0.0255
	(0.0180)	(0.0226)	(0.0167)	(0.0209)	(0.0158)
$ln(K_{jt}/Y_{jt})$	-0.0290*	-0.0517**	-0.0363*	-0.0141	-0.0239*
	(0.0139)	(0.0236)	(0.0189)	(0.0174)	(0.0130)
R&D intensity	0.0512***	0.1012**	0.0811***	0.0380	0.0116
	(0.0113)	(0.0462)	(0.0274)	(0.0233)	(0.0397)
import penetration	-0.0042	-0.0296**	-0.0226*	-0.0273**	-0.0270
	(0.0116)	(0.0129)	(0.0110)	(0.0122)	(0.0161)
Observations	152	180	180	190	119
R-squared	0.6945	0.6145	0.5945	0.6405	0.6365
Number of sector	19	18	18	19	17

Notes: The dependent variable is the industry level cost share of R-tasks. Cluster-robust standard errors are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. All regressions control for industry and year fixed effects. In the last column offshoring is to Asian countries and not to all non-OECD countries since this distinction was not available in the alternative data provided by Ingo Geishecker (`http://www.uni-goettingen.de/en/99958.html`) available until 2004 and for 17 of the industries used here.

countries, since this is the concept of offshoring most closely related to the theoretical considerations and to improve the exposition.[31] It holds results for a shorter sample span (1999-2006), for reduced samples, in which the industries with the largest increase in offshoring (32) and the largest decrease in routine task intensity (18) are dropped, for cost shares of tasks constructed with task measures as in Spitz-Oener (2006), and finally for alternative measures of offshoring regarding the sources (Geishecker 2006). The main message of this paper remains unaltered: Offshoring remains a significant and strong factor in the decline of relative labor demand for routine and non-interactive tasks.

[31] The results for worldwide offshoring show a similar robustness. The coefficients are very similar in magnitude to the ones from previous sections and are all still statistically significant.

4.6 Conclusion

Since trade is becoming more of a task-related phenomenon due to the increase in offshoring activities by firms, the pattern of effects across workers is changing as well. In particular, the skill-based characterization of differentially affected groups falls short of comprehensively capturing the effects. Offshoring occurs based on relocation cost for single occupations, 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, a model is developed to describe the mechanisms underlying the link between offshoring and shifts in employment and cost shares of tasks. This model explicitly treats occupations as fixed bundles of tasks which are, as a whole, subject to the offshoring decision. This is a crucial difference to skill-based approaches, in which individuals either supply high-skilled or low-skilled labor. Furthermore, the model highlights the between occupation dimension in task share changes in the economy. The model introduces a sorting mechanism of individuals across occupations, which relies on a trade off between occupation specific wages and individual abilities in terms of effort needed for the execution of certain tasks. In such a setting, a general fall in offshoring costs can shift the cut-off occupation, which separates home from foreign production, such that the range of occupations at home shrinks. Crucially, the remaining occupations are characterized by a higher non-routine and interactive task content. Since workers whose jobs have gone offshore re-sort into these occupations, average employment and cost shares of routine and non-interactive tasks fall in the home economy.

Second, the theoretical predictions are tested with industry level data from German manufacturing. A clear and robust result emerges. An increase in offshoring significantly reduces home country relative demand for routine and non-interactive tasks – in particular if this offshoring is directed towards non-OECD countries. The explanatory insufficiency of skill related measures is demonstrated by the fact that this demand shift is occurring when controlling for the skill composition of industries. The results are able to account for about 20% to 31% of observed "task-upgrading" over the period 1998-2007.

An important message of this study – and one that does not directly emerge from models such as Grossman & Rossi-Hansberg (2008) – is that between-occupation re-allocations are a common response to offshoring. This is an important insight for policy makers concerned with providing a policy framework that provides the necessary flexibility in this adjustment process.

4.7 Appendix to chapter 4

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, its income information does not provide this detail since many employers only submit one record a year. For both the cost share calculations and the employment share calculations, yearly information from the December waves only were used. Before calculating cost and employment shares, the sample is restricted to full-time regular employees. Assumed imputed incomes, so-called "Fortschreibefälle", are deleted. Income below 400 Euro and above 10,000 Euro per month is regarded as measurement error and is 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 industry, however. Additionally, the recommended imputation procedure in Gartner (2005) ascribes wages on the basis of individual characteristics by "filling in" the tail of a normal distribution. Wages by occupation are thus only affected to the degree that individual characteristics are correlated with occupational choice. Furthermore, those results in this paper which are based on employment share calculations as measures of labor demand are completely unaffected by this limitation. From a theory perspective, the main effect is operative at the bottom of the wage distribution – where offshoring induced re-sorting occurs – and thus does not rely on variation at the top of the distribution. Nevertheless, all main results from tables 4.2 and 4.3 were tested with cost shares based on imputed incomes following Gartner (2005). There was hardly any effect on the coefficients, which were all similar in magnitude and all significant at conventional levels.

Data and method used for calculation of task intensities

The data holding information on task performance stem from the BIBB/IAB study: "Acquisition and Application of Occupational Qualifications 1998/99". This survey contains about 34,000 individual observations. Among other things, individuals are asked if and how often they perform certain tasks. Table 4.6 lists these tasks. In order for a task performance to be counted, the individual has to indicate "often" from a scale with further options "sometimes" and "never". The number of tasks of a certain category are then divided by the total number of tasks an individual reports to perform often. The individual values are aggregated to the occupational level. It is assumed that the average task content of any given occupation does neither differ across industries nor across individual characteristics (age, gender, ...) nor working arrangements (full-time versus part-time). No sampling weights were applied to individual observations in the calculation of task measures. Using such weights does not affect the results neither qualitatively nor quantitatively, however. This was confirmed when running the regression for all specifications in table 4.2 and 4.3 with task shares based on previously sample weighted data. Examples of the most R-intensive occupations are (code and routine task-score given in parenthesis): metal-worker (32; 0.81), metal caster (20; 0.81), glass-maker(13; 0.79). Examples of highly non-routine or interactive occupations are: legal advisor(81; 0.03), translator(82; 0.05), office worker(78; 0.05).

Further data sources

The data for the construction of the offshoring values stem from two sources. The share of imported intermediates used in the same industry as the origin industry, Ω, is calculated from the import tables of the yearly input-output tables published by the German Statistical Office. The import price index stems from the same source. Nominal industry output values are from the OECD STAN database. The price

Table 4.6: Classification of tasks

Classification used here	Spitz-Oener classification	Tasks
difficult-to-offshore	non-routine analytic	Researching, analyzing, evaluating and planning, making plans/contructions, designing, sketching, working out rules/ prescriptions, and using and interpreting rules
$= N$	non-rountine interactive	Negotiating, lobbying, coordinating, organizing, teaching or training, selling, buying, advising customers, advertising, entertaining or presenting, and employing or managing personnel
	non-routine manual	Repairing or renovating houses/ apartments/ machines/ vehicles, restoring art/ monuments, and serving or accommodating
easy-to-offshore	routine cognitive	Calculating, bookkeeping, correcting texts/ data, and measuring length/ weight/ temperature
$= R$	routine manual	operating or controlling machines and equipping machines

index for industry output, used in the calculation of offshoring intensities, is from the EU Klems data base, March 2008 release (`www.euklems.net`). For 2006, 2007 the values are interpolated using the growth rates of the slightly more aggregated sectors from the Klems 2009 release. The robustness to this is confirmed by dropping the years 2006 and 2007, which leaves all main results valid and similar in magnitude and significance. Trade data by world region are calculated using shares derived from the OECD STAN bilateral trade database. The imports from non-OECD countries are available for 17 out of the 19 2-digit NACE 1.1 industries used here. Therefore non-OECD shares for industries 15-16, 17-19 and from 21-22 had to be taken as the supplied aggregates, and were set equal for each element of the 3 industry pairs or groups. The results are robust to the exclusion of these sectors. Industry level R&D

intensity is based on the share of R&D expenditure in industry production value and is taken from the STAN indicators, as is the import penetration ratio - defined as total imports of an industry divided by domestic absorption. The capital stock data used for the construction of the capital output ratios are the gross capital stocks as supplied by the OECD.

Chapter 5

Trade, Tasks, and Training: The Effect of Offshoring on Individual Skill Upgrading[1]

5.1 Introduction

It is a common feature of advanced economies that their workforces are increasingly engaged in the performance of more complex production and service tasks. Along with this changing structure of skill requirements, individuals constantly retrain and update their capabilities. According to Eurofound's European Working Conditions Survey 2010, industry on-the-job training rates in Germany have increased from on average 28.4% in 2005 to about 40% in 2010.[2] At the same, time more and more firms find it optimal to restructure their production process by relocating the

[1]This chapter is based on joint work with Jens Wrona. The concept for the paper was developed jointly. The theoretical model was primarily developed by Jens Wrona, while the empirical analysis was primarily conducted by the author of this thesis. Both parts were mutually discussed and improved, however, such that they should be regarded as joint work. The writing of the text was shared equally.

[2]The survey results are available at `http://www.eurofound.europa.eu/surveys/smt/ewcs/results.htm`

performance of offshorable tasks to low-wage countries abroad. Data from the OECD STAN bilateral trade data base show that the output share of intermediate imports from non-OECD countries in German manufacturing has increased by a remarkable 62% over the same time span. In this paper, we argue that both phenomena are linked. We offer a theory to explain the mechanism behind this link and an empirical analysis to show its significance and magnitude.

In general a positive link between offshoring and training should not come as a surprise as offshoring, which – in particular in the public opinion – is associated with the relocation of tasks to low-wage countries abroad, in the end (at least temporary) displaces some workers from their jobs. As shown by Hummels et al. (2012), workers who are displaced because of offshoring have a particularly high probability to acquire vocational training during the subsequent period of transitional unemployment. We add to this literature, focusing instead on the impact offshoring has on *currently employed individuals* and not only on those who directly loose their job through offshoring. This new focus has two reasons: On the one hand, the number of workers displaced by offshoring is dwarfed by the mass of individuals staying with their job.[3] On the other hand, we know from the theoretical trade literature that offshoring not only leads to direct job losses for workers whose tasks are shifted abroad, but also has a (positive) *productivity effect*, which benefits *all* workers through higher wages (Grossman & Rossi-Hansberg 2008). It is exactly this productivity effect, which in our theoretical model creates incentives for on-the-job training by increasing the associated wage gain of workers beyond the cost of skill upgrading.

[3] For example, in the sample of Hummels et al. (2011), only 9% of all workers observed from 1998 to 2006 loose their job through mass-layoff events. Out of those layoffs, again only 10% can be associated with increased offshoring by the respective employers.

To structure our idea, we set up a small-open-economy model of offshoring in the spirit of Grossman & Rossi-Hansberg (2008), featuring two offshorable sets of tasks, which differ in their skill requirements. Unlike in standard trade models (where endowments are fixed), workers in our model may react to a given offshoring shock by selecting into costly on-the-job training, thereby gaining abilities that are needed to perform the skill-intensive high-wage tasks. Since the productivity effect of offshoring (cf. Grossman & Rossi-Hansberg 2008) proportionally scales up wages for both task sets, the gap between these wages increases as well, letting on-the-job training appear more attractive from the workers' perspective. As a consequence, workers select into skill upgrading as long as the (offshoring induced) gap in wages is larger than the associated fixed cost of skill upgrading.

We translate our theoretical model into an empirically testable specification by focusing on the training indifference condition, which links the fixed training cost to the expected wage gain from skill upgrading. Given this condition, we expect that offshoring leads to more observed on-the-job training at the individual level – a relationship that we can estimate using a standard Probit model. Our offshoring variable is based on the import of intermediate products, measuring the share of intermediates imported from the same industry in non-OECD countries in the industry level output of 22 manufacturing industries in Germany (Feenstra & Hanson 1999). The identification in our empirical model comes from varying offshoring growth rates across industries. Using industry level variation has the advantage that offshoring growth can be seen as exogeneous to single workers, whose individual training decisions should not feed back into industry level offshoring growth. This approach embeds our analysis into a recent and growing literature, which uses industry level variation in globalization measures to identify effects that arise at the individual level (Ebenstein et al. 2013, Geishecker & Görg 2008). Data on individual skill upgrading come from the "BIBB/BAuA Employment Survey 2005/06", which holds detailed information on participation in on-the-job training. Crucially, the unique detail of the data allows us to observe the introduction of technological innovations directly at the workplace, giving us the opportunity to separate the effect of offshoring from the one working through technological change. Our findings offer clear support for the theoretical mechanism laid out in our theoretical model. Offshoring growth has a positive and significant impact on the individual propensity to engage in on-the-job training. This link holds for a number of specifications and is robust to the inclusion of various controls at the individual, firm, and industry level. After taking account of technological change, business cycle effects, and demographic differences, a one standard deviation higher offshoring growth at the industry level over the period 2004 to 2006 is related to an increase in the propensity to observe individual on-the-job training by between 3 to 6 percentage points.

The paper is structured as follows. In the next section, we develop our theoretical model and derive as main prediction that offshoring growth leads to more individual skill upgrading. Subsequently, we look for the proposed link in the data and present an empirical analysis, which includes a description of the econometric set-up, the data used, the results obtained and a discussion on the timing and the robustness of the link between offshoring and on-the-job training. A final section concludes the paper.

5.2 A simple model of offshoring and on-the-job training

The goal of this section is to describe an intuitive mechanism, which links offshoring and on-the-job training. To this end, we employ a simplified version of the Grossman & Rossi-Hansberg (2008) model of trade in tasks, focusing on a single industry, which produces a homogeneous, constant returns to scale output Y at a given world market price normalised to $p \overset{!}{=} 1$.[4] The production of final output requires the performance of two task sets, $\widetilde{S}$ and $\widetilde{N}$, such that $Y = F(\widetilde{S}, \widetilde{N})$. While the $\widetilde{S}$-set requires workers to have task specific skills, no such skills are needed to perform tasks from the $\widetilde{N}$-set. For simplicity, it is assumed that both tasks sets consist of only two tasks: a non-offshorable task, S or N, and an offshorable task, S^* or N^*. These tasks are combined according to technologies, $\widetilde{S} = \widetilde{S}\,(S, S^*)$ and $\widetilde{N} = \widetilde{N}\,(N, N^*)$. The offshorable task will be performed abroad, if the cost of doing so are sufficiently low, i.e. if $w_S \geq \tau_S w_S^*$ and $w_N \geq \tau_N w_N^*$, with $\tau_S, \tau_N \geq 1$ denoting the usual iceberg-type offshoring cost and w_S^* and w_N^* being the (constant) unit cost of performing the tasks S^* and N^* at a low-cost location abroad. The unit-costs for the task sets, $\widetilde{S}$ and $\widetilde{N}$, may then be written as $\omega_S\,(w_S, \tau_S w_S^*) = \Omega_S w_S$ and $\omega_N\,(w_N, \tau_N w_N^*) = \Omega_N w_N$, where $\Omega_S \equiv \omega_S\,(w_S, \tau_S w_S^*)\,/w_S \leq 1$ and $\Omega_N \equiv \omega_N\,(w_N, \tau_N w_N^*)\,/w_N \leq 1$ denote the cost savings factors from offshoring tasks S^* and N^* (see Grossman & Rossi-Hansberg 2008). Analogously, the unit-cost for the final output Y may be expressed as $c\,(\Omega_S w_S, \Omega_N w_N) = \gamma c\,(w_S, w_N)$, with $\gamma \equiv c\,(\Omega_S w_S, \Omega_N w_N)\,/c\,(w_S, w_N) \leq 1$ denoting the total cost savings factor from (partly) offshoring both inputs used in $Y = F(\widetilde{S}, \widetilde{N})$. To start with, we assume a homogeneous workforce of size, $\bar{L} > 0$. Workers can either perform tasks from the $\widetilde{S}$- or the $\widetilde{N}$-set. In order to perform tasks from the $\widetilde{S}$-set task specific skills are required. No such requirement exists for tasks from the $\widetilde{N}$-set. Hence, to perform tasks from the $\widetilde{S}$-set, workers have to invest into (costly) on-the-job training. The training cost are assumed to be constant and equal $\kappa > 0$ (paid in units of the *numraire*). Workers will then invest into on-the-job training as long as the wage gain $w_S - w_N$ associated with it exceeds the corresponding cost κ. Accordingly,

[4] Note that our framework naturally extends to a richer setting with multiple industries $j = 1, ..., J$ that feature sector specific inputs, which, in the short-run, are assumed to be fixed in supply.

we may write the net gain from on-the-job training as

$$u \equiv w_S - w_N - \kappa \geq 0, \tag{5.1}$$

keeping in mind that in equilibrium $u = 0$ must hold, leaving workers indifferent between both alternatives. Equilibrium wages under autarky (denoted by superscript a) and with offshoring (denoted by superscript o) can be found in the intersection point of the training indifference condition (5.1) and the zero profit condition $\gamma c\left(w_N, w_S\right) = 1$ (see Figure 5.1 below). As outlined above $\gamma \leq 1$ represents the total cost savings factor from offshoring, being one under autarky and smaller than one in an equilibrium with offshoring.

In order to derive testable predictions on how offshoring alters wages and thus the training decision in Eq. (5.1), we have to specify our model in more detail. We assume production of Y to be derived from a Cobb Douglas technology, such that $F(\widetilde{S}, \widetilde{N}) = \widetilde{S}^{\alpha}\widetilde{N}^{1-\alpha}$ with $\alpha \in (0,1)$. It then follows immediately that the total cost savings from offshoring, $\gamma = \Omega_S^{\alpha}\Omega_N^{1-\alpha} \leq 1$ are a weighted geometric mean of the cost savings at the task level, $\Omega_S \leq 1$ and $\Omega_N \leq 1$, respectively. The technology, at which tasks within each set are bundled together, is the same as in Antras & Helpman (2004) and Acemoglu & Autor (2011). Having $\widetilde{S}\left(S, S^*\right) = BS^{\theta}\left(S^*\right)^{1-\theta}$ as well as $\widetilde{N}\left(N, N^*\right) = BN^{\theta}\left(N^*\right)^{1-\theta}$, with $\theta \in (0,1)$ measuring the cost share of non-offshorable tasks and $B \equiv 1/[\theta^{\theta}\left(1-\theta\right)^{1-\theta}] > 0$ being a positive constant, it is easy to infer that the cost savings from offshoring at the task-level are given by $\Omega_S = \left(\tau_S w_S^*/w_S\right)^{1-\theta} \leq 1$ and $\Omega_N = \left(\tau_N w_N^*/w_N\right)^{1-\theta} \leq 1$, respectively. Turing to the profit maximization problem of firms we have

$$\pi = \max_{\widetilde{S},\widetilde{N}} \; F(\widetilde{S}, \widetilde{N}) - \Omega_S w_S \widetilde{S} - \Omega_N w_N \widetilde{N}, \tag{5.2}$$

from which the corresponding first order conditions can be derived as

$$w_S(\tilde{s}) = f'(\tilde{s})/\Omega_S, \tag{5.3}$$

$$w_N(\tilde{s}) = [f(\tilde{s}) - \tilde{s}f'(\tilde{s})]/\Omega_N, \tag{5.4}$$

with $f(\tilde{s}) \equiv F(\widetilde{S}, \widetilde{N})/\widetilde{N} = \tilde{s}^{\alpha}$ referring to our production function in intensive form notation and $\tilde{s} \equiv \widetilde{S}/\widetilde{N}$ denoting the skill intensity in the whole production process.

From Eqs. (5.3) and (5.4), two channels through which offshoring impacts domestic wages can be identified. As in Grossman & Rossi-Hansberg (2008), the *productivity effect* scales up wages by factors, $1/\Omega_S \geq 1$ and $1/\Omega_N \geq 1$, respectively. On the contrary, the *labor supply effect* of offshoring drives a wedge between the skill intensity $\tilde{s}$, that applies for the entire international production process, and the skill intensity $s \equiv S/N$, that reflects the composition of the domestic workforce. Intuitively, the labor supply effect of offshoring thereby favors the factor that is offshored less intensively. To illustrate the labor supply effect, Shephard's Lemma can be applied to $\omega_S(w_S, \tau_S w_S^*)$ and $\omega_N(w_N, \tau_N w_N^*)$, resulting in

$$\frac{\partial \omega_S(w_S, \tau_S w_S^*)}{\partial w_S} \equiv \frac{S}{\widetilde{S}} = \theta\Omega_S \quad \text{and} \quad \frac{\partial \omega_N(w_N, \tau_N w_N^*)}{\partial w_N} \equiv \frac{N}{\widetilde{N}} = \theta\Omega_N. \tag{5.5}$$

Dividing both expressions in (5.5) by each other reveals how the domestic skill intensity, $s \equiv S/N$, is altered by the labor supply effect of offshoring, such that

$$\tilde{s} = \frac{\Omega_N}{\Omega_S} s, \tag{5.6}$$

emerges as the skill intensity that applies in the (international) production process. Intuitively, in the autarky equilibrium (with $\Omega_S = \Omega_N = 1$) the skill intensity in production is pinned down by the composition of the domestic workforce, implying $\tilde{s} = s$.

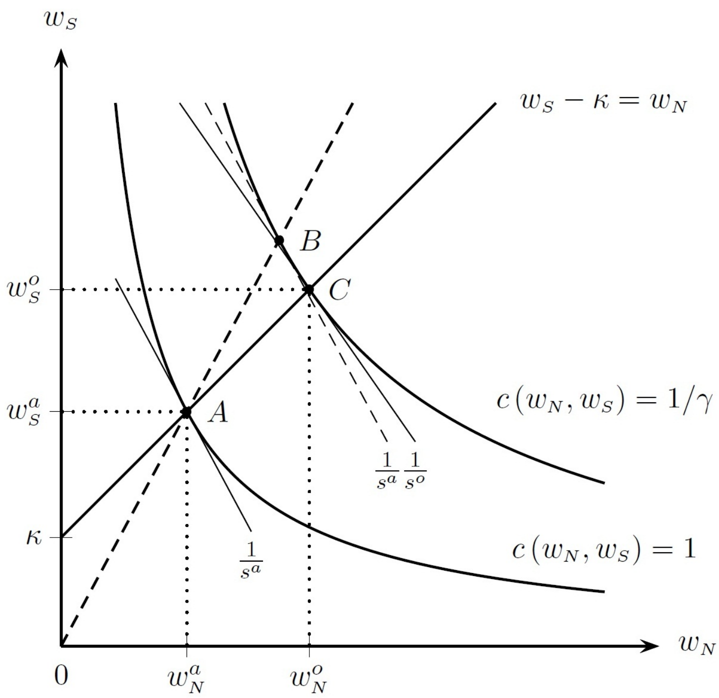


Figure 5.1: Equilibrium skill upgrading with and without offshoring

With offshoring, the skill intensity in production additionally depends on which factor is offshored more intensively, such that $\tilde{s} \gtrless s$ if $N/\widetilde{N} \gtrless S/\widetilde{S}$. Replacing $\tilde{s}$ in (5.3) and (5.4) by (5.6), we find that offshoring increases *both* wages, $w_S^o(\tilde{s}) = w_S^a(s)/\gamma$ and $w_N^o(\tilde{s}) = w_N^a(s)/\gamma$, by the same factor $1/\gamma \geq 1$ for a notionally unchanged domestic factor intensity s. To see the impact on the training decision, we can substitute both wage rates into the training indifference condition (5.1),

$$u = w_S - w_S - \kappa = \frac{\alpha s^{\alpha-1} - (1-\alpha)s^{\alpha}}{\gamma} - \kappa, \tag{5.1$'$}$$

where $\gamma = \Omega_S^{\alpha}\Omega_N^{1-\alpha} < 1$ implies $s^o > s^a$. Intuitively, if both wages are scaled up by an identical factor $1/\gamma > 1$ the same holds true for the gap between these wages. Since then $u > 0$, domestic workers increasingly select into on-the-job training causing a rise in the domestic skill intensity from s^a to s^o.

Figure 5.1 illustrates the effect of offshoring on on-the-job training. Starting out from the autarky equilibrium in A and holding the domestic skill intensity notionally fixed at $s = s^a$, offshoring causes a radial outward expansions of the unit-cost curve by factor $1/\gamma < 1$, which results in the hypothetical equilibrium B.[5] However, in point B we have $u > 0$, giving domestic workers an incentive to select into on-the-job training. As more and more workers decide in favor of on the job training, the domestic skill intensity increases from s^a to s^o until the new (offshoring) equilibrium C is reached. This result is at the heart of our analysis and we frame it in the following Proposition.

Proposition 1 *A decline in the cost of offshoring increases the share of tasks performed abroad, thereby leading to individuals upgrading their skills through on-the-job training.*

Proof Analysis in the text and formal discussion in Appendix 5.5.

Summing up, offshoring positively impacts the individual decision for on-the-job training captured in Eq. (5.1). Interestingly, the training decision does not depend on the task content of offshoring. Even if only one task type is relocated abroad, $\Omega_S < 1$ or $\Omega_N < 1$ will be sufficient to induce $\gamma = \Omega_S^{\alpha}\Omega_N^{1-\alpha} < 1$ and, thus, more on-the-job training. Building upon this insight we put Proposition 1 to the test by estimating the impact of increased offshoring on the training decision displayed in Eq. (5.1).

[5] Fixing the domestic skill intensity at $s = s^a$ means that domestic workers are not allowed to switch tasks between the $\widetilde{N}$- and the $\widetilde{S}$-set. Of course this does not imply that workers are constrained in switching from offshorable N^*- or S^*-tasks to non-offshorable N- or S-tasks within the respective $\widetilde{N}$- or $\widetilde{S}$-set. Intuitively, the latter kind of task-arbitrage is a natural adjustment strategy to increased offshoring and a necessary condition for full-employment in our model.

5.3 The impact of offshoring on on-the-job training

The empirical part of our paper is structured as follows: We lay out our empirical strategy in subsection 5.3.1. Subsection 5.3.2 describes the data we use. The results of our empirical analysis then follow in subsection 5.3.3. Finally, subsections 5.3.4 and 5.3.5 offer some additional discussion on the timing and robustness of the effect.

5.3.1 Empirical strategy

As a natural starting point to test Proposition 1, recall training indifference condition (5.1), which for individual $i = 1, ..., I$ employed in industry $j = 1, ..., J$ can be rewritten as

$$u_{ij} = w_{Sij} - w_{Nij} - \kappa_{ij}.$$

We know from Proposition 1 that any increase in offshoring (triggered by a decline in the offshoring costs τ_S or τ_N) widens the gap between w_{Sij} and w_{Nij}, thereby making on-the-job training more attractive for the individual worker. What we seek to identify in our empirical analysis is the realized on-the-job training in response to a given offshoring shock. We thus identify the adjustment mechanism described in our model above, according to which individuals engage in on-the-job training after an offshoring shock until a new equilibrium with $u_{ij} = 0$ and $s^o > s^a$ is reached. Unfortunately, individual's net gain u_{ij} from on-the-job training is unobservable to us. Yet, we know that individual i selects into on-the-job training (indexed by $U_{ij} = 1$) if $u_{ij} > 0$ and does not do so (indexed by $U_{ij} = 0$) if $u_{ij} \leq 0$. We are thus able to portray the probability of on-the-job training as the outcome of an underlying latent variable model

$$Pr(U_{ij} = 1 \,|\, \cdot) = Pr(u_{ij} > 0 \,|\, \cdot), \tag{5.7}$$

conditioning on a vector $(\cdot)$ of observable covariates. Our main variable of interest is the growth rate of offshoring, $\widehat{O}_j$, in industry j, which, according to Proposition 1, should have a positive impact on the probability of on-the-job training in (5.7). We furthermore allow the individual training decision to depend on individual- and industry-specific characteristics, which we collect in vectors $\mathbf{Y}_i$ and $\mathbf{X}_j$, respectively.[6] While the vectors $\mathbf{Y}_i$ and $\mathbf{X}_j$ will be specified in more detail below, we may for now interpret them as additional controls capturing such things as heterogeneity in the training cost κ_{ij}. Taken together, we can reformulate the training decision (5.1) as:

$$u_{ij} = \beta_0 + \beta\widehat{O}_j + \mathbf{X}_j'\boldsymbol{\delta} + \mathbf{Y}_i'\boldsymbol{\eta} + \varepsilon_{ij}, \tag{5.1$''$}$$

with $\varepsilon_{ij} \sim N(0,1)$ following a standard normal distribution with zero mean and variance one. We can then estimate the probability of on-the-job training $Pr(U_{ij} = 1 \,|\, \cdot)$ in Eq. (5.7) by a Probit model based on the following empirical specification:

$$Pr\,(U_{ij} = 1 \,|\, \cdot) = Pr\,(u_{ij} > 0 \,|\, \cdot) = Pr(\beta_0 + \beta\widehat{O}_j + \mathbf{X}_j'\boldsymbol{\delta} + \mathbf{Y}_i'\boldsymbol{\eta} > \varepsilon_{ij} \,|\, \cdot). \tag{5.7$'$}$$

In line with Proposition 1, we expect a positive effect of offshoring growth $\widehat{O}_j$ on the probability of observing individual on-the-job training, i.e. $\beta > 0$. The identification of this relationship in our empirical model (5.7$'$) comes from varying offshoring growth rates across industries in which individuals are employed. This has the clear advantage that offshoring growth, which is measured at the industry level j, can be seen as exogeneous to worker i, whose individual training decision should not feed back into sector level offshoring growth. Consequently, we do not expect reverse causality to play a major role as potential source of endogeneity in our setting. This approach

[6] Our individual level controls will also capture workplace variables containing information on the individual's employer. However, since we retrieve these data from individual survey responses and, hence, are not able to group individuals according to their employing firms, we collect this information under the label of individual characteristics.

embeds our analysis into a recent and growing literature which uses industry level variation in globalization measures to identify individual level effects (Ebenstein et al. 2013, Geishecker & Görg 2008). To limit the problem of omitted variables as another main reason for potentially biased estimates, we rely on a rich set of individual- and industry-specific covariates (summarized in $\mathbf{Y}_i$ and $\mathbf{X}_j$), which we introduce in section 5.3.2 before discussing their role against the background of our empirical results in section 5.3.3.

5.3.2 Data and definition of variables

Information on individual skill upgrading is taken from the "BIBB/BAuA Employment Survey 2005/06", which contains information on a wide set of workplace related variables for a representative sample of 20.000 individuals that participated between October 2005 and March 2006.[7] We use the latest wave of what has become established as a reliable and detailed source for information related to on-the-job training (Acemoglu & Pischke 1998, Dustmann & Schönberg 2012). Our main dependent variable is the training incidence U_{ij}, which we define as follows: If a respondent stated that she participated in on-the-job training once or several times within the last two years or, alternatively, since being on her current job, we count either one as training incidence and set $U_{ij} = 1$. Otherwise we define $U_{ij} = 0$. The "BIBB/BAuA Employment Survey 2005/06" is particularly suited for our analysis since it combines detailed information on training participation with a rich set of individual controls that already have been identified as important determinants for the individual training decision, cf. Bassanini et al. (2007). In particular, we have information on demographic controls (age, gender, education) and workplace

[7] The following version of the data set is used: Hall & Tiemann (2006) BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2006, SUF 1.0; Research Data Center at BIBB (ed.); GESIS Cologne, Germany (data access); Federal Institute of Vocational Education and Training, Bonn doi:10.4232/1.4820. For further details, also see Rohrbach (2009).

characteristics (firm size, tenure, employment contract). In context of the recent offshoring literature, such as Acemoglu et al. (2012), our data has the great advantage that we are able to observe the introduction of new technologies and organizational changes at the workplace. This allows us to discriminate between offshoring and technological change when explaining the variation in individual training decisions. It also eliminates concerns about technological change being the source of an omitted variable bias, which would arise from a non-zero correlation of technological change with both training and offshoring growth. As another advantage of our data we have information on individual job loss fears. Given that offshoring often is associated with job losses for some workers (usually followed by a period of transitory unemployment and/or training) this information allows us to control for a potential postponement of on-the-job training in favor of later out-of-the-job training activity, as for example identified by Hummels et al. (2012). To control for business cycle effects, which have been linked to training by Méndez & Sepúlveda (2012), and also could be jointly correlated with training and offshoring growth, we can rely on workers' assessment of the employing firm's current business success. However, we also compute industry level output growth between 2004 and 2006.[8] As a further control variable at the sector level we use Herfindahl indices of industry concentration from the German Monopoly Commission for 2003,[9] to control for varying product market competition in different industries (Görlitz & Stiebale 2011).[10]

We measure offshoring as a trade related phenomenon using data on imported intermediates.[11] In line with our identification strategy outlined above, we follow

[8]The data on nominal output at the sector level stems from the OECD's STAN database.

[9]The data is published as part of the Monopoly Commission's annual report to the Federal German government and can be accessed at `http://www.monopolkommission.de/haupt.html`.

[10]For a comprehensive description and more detailed summary statistics of the variables in our final sample please refer to appendix 5.6 and in particular to table 5.4, which is included in this appendix.

[11]Proxies for offshoring based on foreign direct investment (FDI) often suffer from the insufficient decomposability of this data with regard to the motive behind outbound foreign direct investments.

the literature and observe offshoring at the industry level (Ebenstein et al. 2013). In particular, we stick to the concept of Geishecker & Görg (2008) and use input output tables provided by the German Statistical Office to compute the share Θ_{jj^*} of intermediate products used in industry j that originate from the same industry j^* abroad.[12] We then multiply Θ_{jj^*} by IMP_j, which is the total value of sector j's imports of goods that originate from non-OECD countries and finally divide by Y_j, which is the value of sector j's output.[13] In the end we obtain

$$O_j = \frac{\Theta_{jj^*} IMP_j}{Y_j}, \tag{5.8}$$

as a measure for the intensity of offshoring in sector j. Note that our offshoring measure only includes intermediates that are imported from the same sector abroad, resembling the "narrow" concept of offshoring put forth in Feenstra & Hanson (1999).[14] Following our theoretical model from section 5.2, we are interested in offshoring that results from a cost savings motive and, hence, focus only on imports of intermediates that originate from non-OECD countries.[15] After all, this gives us a measure of offshoring to non-OECD countries that varies across 22 manufacturing industries (according to the NACE 1.1 classification). We use this information to compute the sectoral growth rate of offshoring $\widehat{O}_j$ over the relevant sample period from 2004 to 2006. Both, levels and relative changes of our offshoring measure are reported in table 5.5 (see appendix 5.6). The levels can be considered as fairly low, which reflects

As an exception in this literature, Davies & Desbordes (2012) are able to distinguish between greenfield FDI as well as mergers and acquisitions (M&A), which allows them to control for FDI motives such as technology acquisition or the elimination of foreign competitors.

[12]The input output tables are part of the national accounts provided by the German Statistical Office at `https://www.destatis.de/EN/Homepage.html`.

[13]Data on industry level trade and output are taken from the OECD STAN data base. For additional details regarding the description of the construction of IMP_j see appendix 5.6.

[14]For a detailed discussion of the differences between the measure used here and the measure used by Feenstra & Hanson (1999) please refer to Geishecker & Görg (2008).

[15]See Grossman & Rossi-Hansberg (2012) a model of trade in tasks between similar countries, in which firms have incentives to cluster the production of the same tasks at the same location in the presence of external scale economics that operate at the country level.

the fact that trade with non-OECD countries only accounts for a small share in German imports. Yet, growth has been impressive. On average offshoring increased by 36% over the period from 2004 through 2006. To obtain our final estimation sample, we match the growth rate of our offshoring variable with the individual information taken from the "BIBB/BAuA Employment Survey 2005/06" and our further controls at the sector level. Focusing only on individuals holding a full time contract in one of the 22 manufacturing industries considered above leaves us with a total of 3.917 observations.

5.3.3 Estimation results

We estimate several variants of the Probit model specified in section 5.3.1. Starting with table 5.1, in which we provide first evidence on the link between offshoring growth and on-the-job training, we gradually add additional individual control variables, which the training literature already has identified as major determinants of individual skill upgrading (see Bassanini et al. 2007). While we see only limited scope for the emergence of an omitted variable bias from a joint correlation of our individual level variables with the growth of offshoring, which is measured at the more aggregate industry level, we cannot completely rule out such a problem in the data. It still might be the case that certain individual characteristics are a representative reflection of industry wide demographic characteristics, which are more likely to be correlated with sectoral offshoring growth. Including a suitable vector of individual controls rules out the otherwise resulting omitted variable bias, if existent in the first place. Additionally, we check whether the coefficients obtained on the set of individual controls are in line with the results in the related literature in order to validate our data sample as such.

Table 5.1: Offshoring and on-the-job training: individual controls

	(1)	(2)	(3)	(4)	(5)	(6)
Average marginal effect of:						
Offshoring growth	0.1673***	0.1594***	0.1518***	0.1538***	0.1523***	0.1509***
	(0.0561)	(0.0537)	(0.0513)	(0.0434)	(0.0426)	(0.0243)
Age 30 - 39		0.0349	0.0332	-0.0160	-0.0085	-0.0127
		(0.0228)	(0.0234)	(0.0254)	(0.0233)	(0.0200)
Age 40 - 49		-0.0148	-0.0136	-0.0857***	-0.0724**	-0.0689***
		(0.0280)	(0.0301)	(0.0289)	(0.0282)	(0.0241)
Age 50 - 64		-0.0975***	-0.0954***	-0.1977***	-0.1816***	-0.1725***
		(0.0333)	(0.0322)	(0.0280)	(0.0279)	(0.0246)
Age 65+		-0.3266***	-0.3271***	-0.4404***	-0.4227***	-0.4182***
		(0.0769)	(0.0785)	(0.0671)	(0.0660)	(0.0554)
Female			-0.0625***	-0.0412**	-0.0387*	-0.0775***
			(0.0232)	(0.0199)	(0.0198)	(0.0175)
Married			-0.0104	-0.0152	-0.0151	-0.0114
			(0.0238)	(0.0236)	(0.0233)	(0.0225)
Tenure				0.0075**	0.0083**	0.0089**
				(0.0038)	(0.0039)	(0.0039)
Tenure squared				-0.0001	-0.0001	-0.0001
				(0.0001)	(0.0001)	(0.0001)
Medium-skill				0.1184***	0.1172***	0.0379
				(0.0372)	(0.0367)	(0.0350)
High-skill				0.2132***	0.2131***	0.0174
				(0.0256)	(0.0260)	(0.0204)
Importance to have a career					0.0631***	0.0653***
					(0.0198)	(0.0199)
KldB88 (2-digit) occupation FE	no	no	no	no	no	yes
Pseudo R-squared	0.0094	0.0195	0.0217	0.0490	0.0507	0.1134
Observations	3,917	3,917	3,917	3,917	3,917	3,888

Notes: The table shows average marginal effects from estimating variants of the Probit model specified in section 5.3.1. The reference category for an individual's age is: age 16 - 29. Standard errors are clustered at the industry level and are shown in parentheses below the coefficients. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

As a point of reference, column (1) in table 5.1 shows the average marginal effect of offshoring growth from 2004 to 2006 on the probability of on-the-job training participation. According to this first estimate offshoring growth has a strong and significant impact on individual skill upgrading: A doubling of the non-OECD offshoring intensity defined in Eq. (5.8) would lead to an increase in the probability of on-the-job training participation by 0.1673. Taking into account that there has been an immense increase in offshoring between 2004 and 2006, with an average growth rate of more than 35% across industries, we find that a sizable shift in training participation for German manufacturing can be attributed to increased offshoring. Gradually adding further individual controls in the columns (2) to (6) downsizes the effect of offshoring growth only marginally. However, in line with Bassanini et al. (2007) and Méndez & Sepúlveda (2012), we find the usual life cycle pattern in the results in column (2), according to which older individuals are less likely to undertake on-the-job training than their younger counterparts. Including a gender indicator in column (3), we find that men are more likely to select into on-the-job training than women, which at a first sight contrasts with the findings of Arulampalam et al. (2004), who show that in the European context women are in general no less likely to participate in training than men. However, as documented in Bassanini et al. (2007), the effect of gender on training participation, crucially depends on the sector of employment, with woman receiving comparatively less on-the-job training in certain medium/low-tech manufacturing industries. Given that our sample only includes workers employed in manufacturing industries with a strong bias towards male employment (on average 75.9%), we would expect the gender coefficient to be negative. Marital status, which we also introduce in column (3), seems to have no significant effect on training participation. In column (4) we additionally control for work experience and education. Tenure has a positive but small effect on the probability of training participation. We treat this result with caution, since tenure is likely to be endogeneous (Bassanini et al. 2007). Turning to the education indicators, we find the usual result, that high-skilled workers are more likely to participate in training than medium-skilled workers, while medium-skilled workers are again more likely to participate in training than low-skilled workers (see Pischke 2001, Bassanini et al. 2007). To proxy for unobservable heterogeneity among workers (e.g. motivation), we exploit the detailed information included in the "BIBB/BAuA Employment Survey 2005/06" and add a binary indicator variable, which takes the value of one if the individual stated that having a career is (very) important and a value of zero otherwise. As we would expect, individuals, which care more about their career, are also more likely to invest in individual skill upgrading.

Adding occupation fixed effects in column (6) to account for occupation-specific variation in the data, we find most of our coefficients to remain almost unchanged.[16] Only the coefficients for education turn insignificant. This is what we would expect, given that in Germany entry into most occupations is tied to strict skill requirements (e.g. holding a certain university degree). Once controlling for the variation of skills between occupations, the remaining skill variation within occupations should be negligible. Besides their relation to skills, occupation fixed effects also control for possible interaction between occupational work content in terms of tasks and offshoring growth. Recently, several researchers have shown that interactivity and complexity in job content pose severe limits to the offshorability of jobs (Blinder 2006, Goos et al. 2009, Ottaviano et al. 2013). At the same time, these activities may require more frequent skill updating, which we would not want to confuse with the skill upgrading mechanism modeled above.

Summing up, we find that the link between offshoring growth and on-the-job training participation is robust against the inclusion of a wide set of individual control variables. This result should not surprise us too much, since although most of the individual characteristics are correlated with the individual training incidence, it seems unlikely that at the same time they are also correlated with offshoring growth, which is measured at the more aggregate industry level.

More likely candidates for an omitted variable bias, i.e. a joint correlation with both the workers' training and the employers' offshoring decision, are characteristics which either describe the individual workplace or directly refer to the industry in which the respective employer operates. We thus gradually add workplace and indus-

[16] Including occupation fixed effects comes at the cost of losing 29 observations for which no occupational classification is coded in the data or there are too few observation for an occupation specific effect to be estimated.

try level control variables in table 5.2, keeping our individual controls from column (6) in table 5.1 throughout the whole analysis.

Table 5.2: Offshoring and on-the-job training: workplace and sectoral controls

	(1)	(2)	(3)	(4)	(5)	(6)
Average marginal effect of:						
Offshoring growth	0.1128***	0.1125***	0.1082***	0.1096***	0.1085***	0.0829***
	(0.0253)	(0.0252)	(0.0251)	(0.0256)	(0.0250)	(0.0267)
Firm size 10 - 49	-0.0037	-0.0007	-0.0149	-0.0192	-0.0182	-0.0191
	(0.0225)	(0.0215)	(0.0215)	(0.0217)	(0.0217)	(0.0217)
Firm size 50 - 249	0.0698***	0.0756***	0.0534***	0.0486***	0.0524***	0.0494***
	(0.0168)	(0.0148)	(0.0161)	(0.0165)	(0.0160)	(0.0167)
Firm size 250 - 499	0.1236***	0.1301***	0.1046***	0.0985***	0.1011***	0.0985***
	(0.0303)	(0.0288)	(0.0278)	(0.0272)	(0.0281)	(0.0277)
Firm size 500+	0.1516***	0.1582***	0.1340***	0.1273***	0.1315***	0.1253***
	(0.0282)	(0.0270)	(0.0264)	(0.0251)	(0.0261)	(0.0254)
Fixed term contract		-0.0903***	-0.0733**	-0.0767**	-0.0695**	-0.0759**
		(0.0324)	(0.0319)	(0.0321)	(0.0319)	(0.0320)
Temporary work		0.0280	0.0566	0.0522	0.0440	0.0357
		(0.0530)	(0.0535)	(0.0530)	(0.0559)	(0.0561)
Job loss fear		-0.0619***	-0.0629***	-0.0470**	-0.0668***	-0.0508**
		(0.0204)	(0.0208)	(0.0207)	(0.0209)	(0.0204)
New technology introduced			0.1676***	0.1657***	0.1672***	0.1665***
			(0.0220)	(0.0219)	(0.0223)	(0.0218)
Current Firm success (very) good				0.0424**		0.0418**
				(0.0201)		(0.0196)
Industry level output growth					0.0640	
					(0.1543)	
Industry level Herfindahl index						0.0005**
						(0.0002)
Individual controls	yes	yes	yes	yes	yes	yes
KldB88 (2-digit) occupation FE	yes	yes	yes	yes	yes	yes
Pseudo R-squared	0.1242	0.1272	0.1361	0.1370	0.1361	0.1380
Observations	3888	3888	3888	3888	3861	3878

Notes: The table shows average marginal effects from estimating variants of the Probit model specified in section 5.3.1. The reference category for firm size is 1 - 9 employees. The industry output growth is computed for 2004 to 2006. The Herfindahl index, which is published bi-annually by the German Monopoly Commission refers to 2003. Individual controls are the same as in column (6) of Table 5.1. Standard errors are clustered at the industry level and shown in parentheses below the coefficients. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

We start with the inclusion of firm size controls in column (1) of table 5.2. In line with Bassanini et al. (2007), we find that workers employed by larger firms are more likely to undertake on-the-job training than workers in small firms. Including firm size is important since it is likely to be correlated with offshoring growth as well. There is convincing evidence that offshoring firms on average are larger and more productive (see Moser et al. 2009, Bernard et al. 2012). At the same time

Yeaple (2009), among others, shows that more productive multinationals are usually active in more markets and are thus able to take advantage of increased offshoring opportunities abroad due to falling trade cost or improvements in information and communication technology. This constitutes a positive link between offshoring growth and firms size, which in turn is correlated with on-the-job training. Controlling for firm size reduces the impact that offshoring growth has on the probability of individual skill upgrading, which seems a reasonable outcome given the above considerations.

In column (2) of table 5.2, we add controls for the type of contract under which workers are employed and control for individual job loss fears. The type of work contract, if representative for industry in which the individual is employed, could be correlated with increased offshoring, as fixed term contracts are likely to ease international restructuring processes. As in Arulampalam et al. (2004) and Bassanini et al. (2007), workers, which are employed under fixed term contract, are less likely to participate in on-the-job training than workers with permanent contracts. Following human capital theory, this finding is what we would expect, given that workers employed under a fixed term contract have a shorter period of time to realize the returns to their training. By the same token, we would expect that workers, which are employed through temporary work agencies also invest less in on-the-job training. However, this does not seem to be the case, which might be explained by the fact that, after all, only 1% of all workers in our sample are temporarily employed through an external supplier. We furthermore take into account recent findings by Geishecker et al. (2012), claiming that offshoring to low-wage countries can explain 28% of the increase in subjective job loss fears of German workers for the time span from 1995 to 2006. We thus add an indicator variable, which takes a value of one, whenever individuals stated that they face the fear of job loss and zero otherwise. We find that workers, reporting subjective job loss fears, are less likely to participate in on-the-job training. Together with the findings of Hummels et al. (2012), who show that workers who lose their job (through offshoring) are likely to retrain their skills during the subsequent period of transitory unemployment, this result may hint at a delay of on-the-job training in favour of later out-of-job training measures, better tailored towards future reemployment possibilities. Including all of these controls does not significantly alter the average marginal effect offshoring growth has on individual skill upgrading.

In the next step (cf. column (3) of table 5.2), we include a dummy variable capturing the introduction of new technologies, machines or organizational features at individual workplaces. While the offshoring literature traditionally faced the challenge of telling apart the impact of increased offshoring from the implications of technological change (cf. Feenstra 2010), there are two specific reasons why we have to control for the introduction of new technologies in our setting: On the one hand, our theoretical model from section 5.2 predicts that not only increased offshoring, but anything scaling up workers' wages (e.g. the introduction of new technologies) has the potential to trigger individual skill upgrading. On the other hand, it is likely that, whenever new technologies are introduced at the workplace this requires the (re)training of involved workers, thereby (mechanically) leading to increased skill upgrading. Given that the adoption of new technologies as well as the growth of offshoring could be subject to a common trend due to overall technological development at large or at the industry level, we have to differentiate between both phenomena to isolate the effect of offshoring growth. Benefiting from the high resolution of our data, we observe the introduction of new machines, technologies, or business processes directly at the workplace. We find that workers who reported the introduction of new technologies at their workplace are more likely to participate in on-the-job training. Crucially, there still is a positive and significant link from offshoring growth to individual skill upgrading, although – as we would expect – with a lower estimate of the average marginal effect of (now) $\hat{\beta}^m = 0.1082$.

A further concern regarding the exogeneity of offshoring growth refers to a possible co-movement with the business cycle. If on-the-job training is pro-cyclical, for which – despite partly confounding results – at least some evidence (cf. Méndez & Sepúlveda 2012) exists, it could be the case that the positive association of individual skill upgrading with increased offshoring is nothing else than the reflection of the German business cycle, which from 2004 to 2006 was at the beginning of a boom period. These concerns are ameliorated by the fact that we are focusing on non-OECD offshoring growth, which we expect to depend less on business cycle movements but rather on falling offshoring cost. Nevertheless, to rule out this possibility, we use column (4) of table 5.2 to include a control variable reflecting workers' evaluation of the employing firms' current business success. In line with Méndez & Sepúlveda (2012), we find that workers employed by (very) successful firms tend to invest more often in on-the-job training. At the same time, the effect of offshoring growth on skill upgrading is almost unchanged. Admittedly, our measure for the business cycle is a simple one, focusing only on the employing firm thereby ignoring possible inter-firm linkages in the respective industry. To come up with more comprehensive measure we add the log-difference of industry output in column (5) of table 5.2.[17] We do not find a significant effect of output growth on training, which is in line with the somewhat inconclusive literature on the cyclical properties of training (see Méndez & Sepúlveda 2012, Bassanini et al. 2007). Not surprisingly, the effect offshoring has

[17] We use nominal output growth; running the same regressions with real output growth yields nearly identical results. Including sectoral output growth might raise concern about possibly high multicollinearity between output growth and offshoring growth. However, this does not seem to be the case, as the coefficient on output growth stays insignificant even if offshoring growth is excluded from the regression.

on skill upgrading is only slightly reduced and stays highly significant.

A further potential source for an omitted variable bias at the industry level is the intensity of competition in a given sector. Given the positive correlation between firm size and offshoring activities, it could be the case that industries dominated by a few large firms have significantly different offshoring growth patterns. At the same time skill upgrading could differ depending on competition. Yet, the existing literature on the link between training and competition is inconclusive: On the one hand increased competition could lead to higher training needs, necessary to secure a well trained workforce in a dynamic environment (Bassanini & Brunello 2011). On the other hand, poaching, i.e. the transfer of general skills to a different employer via job switching, is usually found to be positively correlated with competition, which, hence, would lead to less training (Schmutzler & Gersbach 2012). Controlling for industry level competition, we use the same measure as Görlitz & Stiebale (2011), the Herfindahl index of industry concentration.[18] We find a positive impact of competition on training, which is significant at the 5% level. Importantly, the effect of offshoring growth on individual skill upgrading is still significant, albeit slightly lower in magnitude. Summing up, we find that according to our preferred specification in column (5) of table 5.2 a doubling of the industry level offshoring intensity defined in Eq. (5.8) would increase the probability of on-the-job training participation by roughly 8.3 percentage points.

5.3.4 The timing of offshoring and on-the-job training

Since the "BIBB/BAuA Employment Survey 2005/06" took place from October 2005 and March 2006 and individuals where asked whether they participated in on-the-

[18]The Herfindahl index for industry 23 (coke & refined petroleum) is not available, which causes the loss of 10 observations. The Herfindahl index is published bi-annually by the German Monopoly Commission. We use the values for 2003, however, our results do not change, when using the values for 2005 instead.

job training two years prior to the survey or since having the current job, we hold no precise information concerning the individual training incidence. For our main analysis we hence use a rather wide time frame covering offshoring growth from 2004 to 2006. As a robustness check, we now use shorter and varying time frames, each covering the growth of offshoring over two periods only. Results are summarized in table 5.3. As we would expect, splitting up the time frame from 2004 to 2006 into

Table 5.3: Offshoring and on-the-job training: timing

	(1)	(2)	(3)	(4)	(5)	(6)
Average marginal effect of:						
Offshoring growth 2002 - 2003	0.0178					
	(0.0111)					
Offshoring growth 2003 - 2004		-0.1321*				
		(0.0781)				
Offshoring growth 2004 - 2005			0.2519***			
			(0.0559)			
Offshoring growth 2005 - 2006				0.2263***		
				(0.0791)		
Offshoring growth 2006 - 2007					-0.1324***	
					(0.0471)	
Offshoring growth 2004 - 2006						0.0821***
						(0.0280)
Individual controls	yes	yes	yes	yes	yes	yes
Workplace and sectoral controls	yes	yes	yes	yes	yes	yes
KldB88 (2-digit) occupation FE	yes	yes	yes	yes	yes	yes
Pseudo R-squared	0.1335	0.1346	0.1372	0.1362	0.1354	0.1435
Observations	3,888	3,888	3,888	3,888	3,888	3,605

Notes: The table shows average marginal effect from estimating the variants of the Probit model in section (5.3.1) for different periods of offshoring growth. The dependent variable is a binary measure of observed skill upgrading through training in the two years prior to the survey or since having the current job. The Herfindahl index is not included since we do not have it for all respective time periods. Standard errors are cluster robust and are shown in parentheses below the coefficients. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

two separate windows, covering 2004 to 2005 and 2005 to 2006, does not change our result: Increased offshoring still has a positive and significant impact on individual skill upgrading. Looking at a period (2002 - 2003) that far precedes the time frame potentially covered by the survey we find – as expected – no effect. For the time frame from 2003 to 2004 we find a negative coefficient which is, however, only weakly significant. We interpret this finding as evidence that on-the-job training is a lumpy investment, which individuals only use discontinuously over time with an optimal period of waiting between single training incidences. Thus, if increased offshoring between 2003 and 2004 caused more training in the period from 2003 to 2004 we would indeed expect that in the following period from 2004 to 2006 an immediate retraining becomes less likely for individuals who just completed their last training in the previous period. Interestingly, when focusing on future offshoring growth over the period from 2006 to 2007 we find a negative impact on the current training probability. Several explanations may account for this result. Assuming that individuals discount the costs and benefits of training at different rates, it could be the case that anticipated, future offshoring growth leads to a postponement of contemporaneous training to later period when the benefits from training are even larger. Another explanation for the negative impact of future offshoring growth on contemporaneous training could be the lack of sufficient *long-run* controls capturing individual job loss fears. Given that offshoring tends to increase subjective job loss fears (cf. Geishecker et al. 2012), anticipated, future offshoring growth could be associated with more uncertain long-run employment prospects, causing a reduction or delay of current on-the-job training. Finally, in column (6) of table 5.3 we only use individuals whose last job switch took place two years before the "BIBB/BAuA Employment Survey 2005/06" was conducted. Since, individuals where asked whether they participated in on-the-job training two years prior to the survey or since having the current job, this treatment gives us a precise matching of the potential training period with the time frame for which we observe our offshoring variable. The resulting coefficient for sectoral offshoring growth is very similar to the one obtained from our preferred specification (column (6) of table 5.2) and highly significant.

5.3.5 Further robustness checks

In this subsection, we check additional specifications and whether the link between offshoring growth and skill upgrading is driven by particular characteristics of our data set in terms of measurement or outliers. The corresponding detailed results can be found in the appendix. We begin with a look at worldwide offshoring, instead of non-OECD offshoring, and find a positive and significant coefficient – which, somewhat surprisingly, is even larger than what we estimated before. Secondly, in column (2) we look at non-OECD offshoring again and use sample weights provided in the data and re-run our preferred specification using these weights. Note, however, that the data set is designed by the BIBB to be balanced and adjustments are taken to control for under representation of low-skilled individuals. Thus, it is not surprising to observe very similar coefficients, both in terms of significance and magnitude. Next, we drop in column (3) of table 5.6 four industries (tobacco; leather & luggage; office machinery & computers; coke & refined petroleum) in which results, due to a low number of observations, could easily be affected by outliers. In column (4) we drop the two industries with the largest (other transport equipment) and smallest (coke & refined petroleum) change in non-OECD offshoring, again to rule out dependence on outliers, which could play an important role in our relatively small sample. Similarly, in column (5) we drop the industries with the highest (chemicals) and lowest (textiles) average training participation rates. Reassuringly, all those changes have almost no effect on the coefficient of sectoral offshoring growth, which remains positive and highly significant throughout all specifications. Finally, let us recall our theoretical model from section 5.2, in which training participation is modeled as a worker's decision and it is the worker to whom both, the cost and the benefits associated with individual skill upgrading, accrue. Translating this mechanism one to one into our empirical model would require a distinction between employer-financed and self-financed on-the-job training. Unfortunately, this information is not available to us. However, we know whether a certain training measure can be traced back to the respective worker's own initiative or to some extrinsic motivation. Assuming that training, which workers' started by own initiative is more likely to be also self-financed, we drop all cases in which workers' training participation followed from the order or suggestion of the respective employer. The results are shown in column (6) of table 5.6. Controlling for workers' initiative to start on-the-job training leads to a slight downward correction of the effect that increased offshoring has on individual training participation. Importantly, the coefficient is still significant and of similar size, when compared to the coefficient that results from the estimation of the full sample.

5.4 Conclusion

In this study we have introduced a new link between offshoring and training. In particular, we developed a theory that outlines a mechanism inducing *employed* individuals to select into training – a new aspect in the literature linking offshoring and training, which has so far mostly analysed training responses to worker displacement. Our mechanism operates through wages for different sets of tasks. We assume that a more complex task set pays higher wages, yet can only be completed by workers with the respective skill, which in turn are costly to obtain. Individuals thus face a trade-off between higher wages and fixed training cost. Offshoring comes into play by affecting the wage gap between task sets and thus altering the trade-off in a way that more individuals will opt to upgrade their skills. Introducing such a worker level adjustment margin into an otherwise standard offshoring model allows for an endogeneous reaction of workers to wage conditions changed by offshoring, which is – as we would argue – an important extension to models that treat workers as completely exogeneously affected.

We furthermore provided first evidence on this link between offshoring and on-the-job training in an empirical analysis. Using data from German manufacturing, we found industry level offshoring growth to be significantly related to the individual probability of training. Importantly, we find this effect to be present in settings that explicitly take account of technological change at the workplace, as well as industry level output growth and competition. We take this evidence as providing support for the mechanism we have described in our model.

5.5 Theory appendix to chapter 5

Proof of proposition 1

Note that $\gamma = \Omega_S^{\alpha}\Omega_N^{1-\alpha} < 1$ in equation (5.1′) still endogenously depends on domestic factor prices, w_S and w_N, respectively. In order to obtain a testable prediction on how falling offshoring costs, τ_S and τ_N, relate to the individual skill upgrading decision of domestic workers in (5.1′) we have to replace w_S and w_N in Ω_S and Ω_N. Using the definitions of $\Omega_S = (\tau_S w_S^*/w_S)^{1-\theta} \leq 1$ and $\Omega_N = (\tau_N w_N^*/w_N)^{1-\theta} \leq 1$, we replace w_S and w_N by (5.3) and (5.4). Skill upgrading condition (5.1′) can then be written as

$$u = \frac{\alpha s^{\alpha-1} - (1-\alpha)\, s^{\alpha}}{\left[A\left(\tau_S w_S^*\right)^{\alpha}\left(\tau_N w_N^*\right)^{1-\alpha}\Omega_S^{\alpha}\Omega_N^{1-\alpha}\right]^{(1-\theta)}} - \kappa,$$

in which $A \equiv 1/[\alpha^{\alpha}(1-\alpha)^{1-\alpha}] > 0$ is a positive constant. Unfortunately the above expression still depends on $\gamma = \Omega_S^{\alpha}\Omega_N^{1-\alpha}$. However, replacing again w_S and w_N in Ω_S and Ω_N by (5.3) and (5.4), we find that after K iterations equation (5.1′) can be rewritten as a sequence $Z(K)$ with

$$u \equiv Z(K) = \frac{\alpha s^{\alpha-1} - (1-\alpha)\, s^{\alpha}}{\left[A\left(\tau_S w_S^*\right)^{\alpha}\left(\tau_N w_N^*\right)^{1-\alpha}\right]^{\sum_{k=1}^{K}(1-\theta)^k}\left(\Omega_S^{\alpha}\Omega_N^{1-\alpha}\right)^{(1-\theta)^K}} - \kappa.$$

Letting K go to infinity we find that sequence $Z(K)$ converges to

$$\lim_{K\to\infty} Z(K) = \frac{\alpha s^{\alpha-1} - (1-\alpha)\, s^{\alpha}}{\left[A\left(\tau_S w_S^*\right)^{\alpha}\left(\tau_N w_N^*\right)^{1-\alpha}\right]^{\frac{1-\theta}{\theta}}} - \kappa,$$

as $\lim_{K\to\infty}\sum_{k=1}^{K}(1-\theta)^k = (1-\theta)/\theta$. The above equation no longer depends on w_S and w_N such that it is easy to infer that $\partial s/\partial\tau_S < 0$ and $\partial s/\partial\tau_N < 0$. Thus, a gradual decline in *any* offshoring cost, τ_S or τ_N, leads to more individual skill upgrading. Taking additionally into account that according to (5.5) the share of tasks performed domestically is proportional to the respective cost savings factor from offshoring, $\Omega_S \leq 1$ or $\Omega_N \leq 1$, proposition 1 follows immediately. *QED*

5.6 Empirical appendix to chapter 5

Data description and summary statistics

Table 5.4 summarizes all variables in our final sample of 3,917 individuals which are full-time employed in manufacturing. More than half (59%) of the respondents participated in on-the-job training between October 2003 and March 2006. Of those who participated, 42% did so by own initiative. We can group individuals into five age groups, with the average worker being of age 42 having 14 years of tenure. Unsurprisingly, the majority of workers (76%) in manufacturing are male. We classify workers according to their education as high-skilled (university degree), medium-skilled (degree from a technical school, e.g. the German "Meister") and low-skilled (all residual workers). The majority of workers (68%) are classified as low-skilled, less are high- (21%) or medium-skilled (11%). Of the respondents 17% stated that having a career is important for them. Only, a small fraction of all workers held a fixed term contract (6%) or were just temporary employed (1%). Among all workers 10 % answered that they face the fear of job loss. We classify employers according to the number of employees and distinguish between five groups: firms with 1 - 9, 10 - 49, 50 - 249, 250 - 499 and more than 500 employees. The majority of firms (90%) introduced new technologies during the sample period. Overall the employing firm's success was largely seen as good or very good, 81% of the respondents answered in this way. Industry output growth is the growth of nominal output, calculated as log-difference, with the data retrieved from the OECD STAN data base. The Herfindahl index of industry concentration is the sum of the squared market shares of all market participants in the respective 2-digit NACE 1.1 industry.

Table 5.4: Summary statistics: estimation sample

Variables	share	mean	st. dev.
Individual characteristics			
On-the-job training	0.586	-	-
Thereof by own initiative	0.421	-	-
Age	-	42.06	10.06
16 - 29	0.117	-	-
30 - 39	0.297	-	-
40 - 49	0.345	-	-
50 - 64	0.231	-	-
$\geq$ 65	0.010	-	-
Education			
Low	0.677	-	-
Medium	0.109	-	-
High	0.214	-	-
Further individual characteristics			
Important to have a career	0.173	-	-
Fixed term contract	0.055	-	-
Temporary work	0.011	-	-
Job loss fear	0.103	-	-
Female	0.241	-	-
Tenure		13.66	9.621
Employer size (# of employees)			
1 - 9	0.109	-	-
10 - 49	0.183	-	-
50 - 249	0.246	-	-
250 - 499	0.132	-	-
$\geq$ 500	0.332	-	-
Further employer characteristics			
New technology introduced	0.896	-	-
Current firm success (very) good	0.805	-	-
Industry characteristics			
Offshoring growth 2004 - 2006	-	.360	0.335
Output growth 2004 - 2006	-	0.125	0.053
Herfindahl index (x 1000) 2003	-	23.501	34.355
Number of observations	3,917		

Industry level offshoring is calculated as described in (5.8). For the industries 15-16, 17-19, and 21-22 the OECD STAN bilateral trade data base only holds information on combined non-OECD trade flows. We hence use the same share of non-OECD imports in total imports for the individual industries within each of the three aggregates and multiply them with total imports, for which we have industry

Table 5.5: Summary statistics: offshoring

j	Industry classification	O_j	$\widehat{O}_j$	j	Industry classification	O_j	$\widehat{O}_j$
35	Other transport equipment	0.84	142.52	22	Publishing & printing	0.05	19.79
27	Basic metals	2.41	95.66	15	Food & beverages	0.58	16.09
34	Motor vehicles	0.40	87.25	29	Machinery, equipment	1.83	16.01
33	Medical, optical & precision instr.	0.63	43.76	20	Wood & cork prod.	1.02	13.74
16	Tobacco	0.11	38.02	30	Office & computing mach.	6.18	12.17
28	Fabricated metal products	0.32	37.21	26	Non-metallic mineral prod.	0.31	8.43
24	Chemicals	0.86	30.92	36	Furniture	3.47	6.36
25	Rubber & plastic	0.17	30.29	17	Textiles	4.80	2.19
18	Wearing apparel	5.71	24.28	31	Electrical machinery	1.56	-1.17
19	Leather & luggage	8.09	23.13	32	Radio, television & comm.	8.50	-12.61
21	Paper	0.50	21.31	23	Coke & refined petroleum	0.49	-44.03

Notes: The offshoring intensity O_j (in percent) is calculated for 2004. Offshoring growth $\widehat{O}_j$ (in percent) is calculated over the time span from 2004 to 2006. Industries are ranked in decreasing order according to the magnitude of sectoral offshoring growth.

specific data in all cases. Checking the robustness of this approach, we dropped the respective sectors and still found our results presented in section 5.3.3 to hold. The deflation of the import values is done using an aggregate import price index from the German Statistical Office. Industry output values are from the OECD STAN database. The price indices for industry specific output are from the EU Klems data base, March 2008 release (`www.euklems.net`). For 2006, 2007 the values are interpolated using the growth rates of the slightly more aggregated industries from the Klems 2009 release. Table 5.5 gives an overview of offshoring intensities across industries, both in levels and growth rates.

Table 5.6: Offshoring and on-the-job training: robustness

	(1) worldwide	(2) weighted	(3) no small industries	(4) no 35 and 32	(5) no 24 no 17	(6) own initiative
Average marginal effect of:						
Offshoring growth	0.2368***	0.0746**	0.0830***	0.0953**	0.0748***	0.0815***
	(0.0692)	(0.0342)	(0.0311)	(0.0396)	(0.0272)	(0.0189)
Age 30 - 39	-0.0048	-0.0304	-0.0009	-0.0042	0.0048	0.0173
	(0.0194)	(0.0235)	(0.0200)	(0.0204)	(0.0197)	(0.0285)
Age 40 - 49	-0.0473**	-0.0573*	-0.0453*	-0.0459*	-0.0397*	-0.0069
	(0.0231)	(0.0299)	(0.0241)	(0.0235)	(0.0235)	(0.0311)
Age 50 - 64	-0.1384***	-0.1584***	-0.1361***	-0.1321***	-0.1349***	-0.0869**
	(0.0284)	(0.0335)	(0.0292)	(0.0295)	(0.0299)	(0.0369)
Age 65+	-0.3379***	-0.3731***	-0.3359***	-0.3421***	-0.3254***	-0.1706***
	(0.0569)	(0.0617)	(0.0578)	(0.0618)	(0.0616)	(0.0560)
Female	-0.0658***	-0.1005***	-0.0648***	-0.0669***	-0.0633***	-0.0442**
	(0.0193)	(0.0206)	(0.0191)	(0.0206)	(0.0222)	(0.0196)
Married	-0.0129	-0.0079	-0.0139	-0.0131	-0.0029	-0.0092
	(0.0214)	(0.0243)	(0.0215)	(0.0226)	(0.0241)	(0.0231)
Tenure	0.0029	0.0039	0.0027	0.0029	0.0008	-0.0016
	(0.0039)	(0.0042)	(0.0039)	(0.0042)	(0.0032)	(0.0051)
Tenure squared	-0.0000	-0.0000	-0.0000	-0.0001	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Medium-skill	0.0386	0.0267	0.0345	0.0341	0.0254	0.1143***
	(0.0355)	(0.0341)	(0.0354)	(0.0365)	(0.0360)	(0.0413)
High-skill	0.0049	-0.0249	-0.0002	0.0039	0.0200	0.0267
	(0.0214)	(0.0241)	(0.0215)	(0.0233)	(0.0215)	(0.0240)
Importance to have a career	0.0646***	0.0633***	0.0617***	0.0602***	0.0565***	0.0815***
	(0.0207)	(0.0236)	(0.0206)	(0.0209)	(0.0215)	(0.0202)
Firm size 10 - 49	-0.0178	-0.0033	-0.0248	-0.0151	-0.0198	-0.1270***
	(0.0218)	(0.0244)	(0.0220)	(0.0216)	(0.0220)	(0.0362)
Firm size 50 - 249	0.0514***	0.0681***	0.0476***	0.0546***	0.0393***	-0.0589***
	(0.0171)	(0.0253)	(0.0164)	(0.0160)	(0.0150)	(0.0217)
Firm size 250 - 499	0.1011***	0.0885**	0.0924***	0.1029***	0.0998***	-0.0270
	(0.0281)	(0.0382)	(0.0283)	(0.0283)	(0.0305)	(0.0247)
Firm size 500+	0.1290***	0.1112**	0.1203***	0.1188***	0.1138***	0.0344
	(0.0251)	(0.0478)	(0.0247)	(0.0248)	(0.0275)	(0.0366)
Fixed term contract	-0.0772**	-0.0588	-0.0793**	-0.0757**	-0.0961***	-0.0968***
	(0.0325)	(0.0430)	(0.0320)	(0.0334)	(0.0328)	(0.0328)
Temporary work	0.0338	0.0589	0.0185	0.0636	0.0379	0.0404
	(0.0553)	(0.0961)	(0.0566)	(0.0556)	(0.0569)	(0.0945)
Job loss fear	-0.0503**	-0.0621**	-0.0502**	-0.0565***	-0.0503**	-0.0433
	(0.0205)	(0.0304)	(0.0206)	(0.0202)	(0.0206)	(0.0325)
New technology introduced	0.1669***	0.1502***	0.1652***	0.1714***	0.1697***	0.1330***
	(0.0221)	(0.0275)	(0.0219)	(0.0228)	(0.0224)	(0.0288)
Current firm success (very) good	0.0382*	0.0414*	0.0416**	0.0457**	0.0401*	0.0478**
	(0.0199)	(0.0252)	(0.0199)	(0.0208)	(0.0212)	(0.0192)
Herfindahl index	0.0013***	0.0006**	0.0005*	0.0005	0.0006***	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
KldB88 (2-digit) occupation FE	yes	yes	yes	yes	yes	yes
Pseudo R-squared	0.1393	0.1362	0.1379	0.1379	0.128	0.2200
Observations	3878	3878	3,845	3,675	3,411	2,617

Notes: The table shows average marginal effects from estimating variants of the Probit model specified in section 5.3.1. The reference category for firm size is 1 - 9 employees. The industry output growth is computed for 2004 to 2006. The Herfindahl index, which is published bi-annually by the German Monopoly Commission refers to 2003. Individual controls are the same as in column (6) of table 5.1. Industry level controls are as in table 5.2. Standard errors are clustered at the industry level and shown in parentheses below the coefficients. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Chapter 6

Concluding Remarks

The chapters of this doctoral thesis provide a collection of analyses surrounding the question of how trade and offshoring shape labor market outcomes, in particular with respect to factor prices. These concluding remarks summarize the findings and sketch some ideas for further research.

6.1 Main findings

Openness to trade is negatively linked to the labor share of income.

The research presented in chapter 2 shows that, besides factor biased technological change, international trade is the main driving force behind falling labor shares across many OECD countries. However, this effect only became apparent after 1980. In order to derive this result, the chapter provides some methodological contribution as well. It takes up the main predictions from a baseline theoretical model of the labor share and puts them to the test in a rigorous econometric analysis. It demonstrates that the relation between the labor share and international trade is generally best estimated in a dynamic panel setting that adequately captures potential heterogeneity in the estimated coefficients. The result of a falling labor share in the face of increased openness to trade indirectly contributes to the discussion on how trade and income inequality are interconnected. If compensation from increased relative gains from capital holdings is available to individuals in higher income groups only, then income inequality between individuals increases as well.

Increased offshoring is connected to a decrease in the permanent component of income risk.

While offshoring generally appears as a specter to people, carrying with it notions of increased insecurity of labor income, chapter 3 shows that this is not necessarily true. First, the focus is directed to the permanent component of income risk, which, in contrast to transitory shocks, is uninsurable and thus welfare relevant. This permanent component is then linked to offshoring at the industry level within German manufacturing. Importantly, this link is shown to be negative: An increase in industry level offshoring over time is correlated with a decrease in industry level permanent income risk. A potential explanation could be that firms offshore more volatile parts of the production chain due to labor market rigidities at home and, hence, the remaining activities are on average characterized by lower permanent income risk.

The relative labor demand for routine and non-interactive tasks is decreasing with increases in offshoring.

This finding highlights the importance of looking at more refined categories of heterogeneity in the labor market in detecting the effects of offshoring on workers. While previous research predominantly focussed on education-based skill groups, the study in chapter 4 uses a task-based approach. That is, it looks at the actual work content of jobs in determining their potential for offshoring. This work content can be very similar for individuals with different formal education levels, thus capturing more of the relevant adjustment margin. The chapter also highlights the need for adjustments to theory since workers provide an indivisible bundle of tasks to the market. It is shown that a model of worker sorting can still deliver the prediction that offshoring decreases the relative labor demand for routine and non-interactive tasks. This prediction is robustly confirmed at the industry level using data for German manufacturing.

Workers react to offshoring with increased individual skill upgrading.
Much of the research on offshoring and its impact on the labor market builds on mechanisms of between-worker adjustment of individuals with fixed attributes. Chapter 5 introduces a worker level adjustment margin. In a theoretical contribution, the main model of offshoring as trade in tasks is extended to feature such an adjustment margin. As a result, workers can invest in costly skill upgrading, but only do so if the resulting wage gains are sufficiently high. Since offshoring affects the relative rewards of different sets of tasks, it also impacts on this worker level trade-off and leads to incentives to engage in skill upgrading. This prediction is empirically confirmed using data for German individuals employed in manufacturing in the mid 2000s. Crucially, the impact of offshoring growth is significant even when technological change and business cycle effects are explicitly included in the analysis. The results, for the first time, document effects of offshoring on skill upgrading that are not linked to worker re-training after or during offshoring-induced unemployment. Since the portion of individuals that is set free by offshoring is relatively small, the results in chapter 5 potentially command a much greater relevance for the overall increase in the complexity of work in advanced knowledge economies.

6.2 Future research

No one single research project can possibly paint a complete picture of all interdependencies between international trade and labor markets. Just as this doctoral thesis builds on and complements the work of others, there will be many interesting new questions arising in the future. This might be due to new data becoming available or established theories being revisited. As the nature of international trade keeps changing, so will the challenges faced by researchers in the field. With respect to the studies comprising this dissertation, the following may be particularly interesting.

International micro level data

Today, many of the analyses digging deeper into the mechanism of labor market adjustment to trade and offshoring use detailed data at the level of single firms or workers. There is ongoing work trying to harmonize these data and to enable researchers to use multi-country panel data sets. This would offer exciting possibilities to study aggregate level heterogeneity in the effects. In particular, institutional settings, which generally differ among countries and are among the prime tools of governments to facilitate adjustment, could be studied. The merging of the detailed micro level mechanisms, which theory and empirics are able to uncover, with macroeconomic policy heterogeneity would be of key interest to researchers, policy makers, and the public.

Non-linear effects of offshoring over time

Usually, the time periods of studies linking offshoring and the corresponding labor market responses rarely exceed ten years. Such a sample span might inhibit the detection of long-run effects that may be quite different from short-run adjustments. Theoretical models, for instance, point to inframarginal gains from falling offshoring costs that accrue to activities already offshored. As offshoring costs keep falling over time, these gains will also increase, leading to productivity effects which positively affect wages and employment. Eventually, and depending on the duration and effectiveness of the ensuing adjustment mechanisms, these gains may grow beyond the short-term losses to workers being displaced from offshoring. There are now many theories documenting the possibilities for these gains. Testing for them using longer-run data will be crucial in any evaluation of the costs and benefits of offshoring.

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