DEPARTMENT OF ECONOMICS
UNIVERSITY OF COPENHAGEN

# PhD Thesis

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# Offshoring, innovation and wages in the global economy

## Evidence from Danish linked employer-employee data

**Supervisor:** Jakob Roland Munch

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# Contents

# Acknowledgments

This thesis is the endpoint of a three-year intellectual journey that began when I was enrolled as a PhD student in November 2012. As with so many other things in life, it is not the final product but the process of getting there that has been the most exciting. Along the way, there have been so many people giving me that little insight or that warm encouragement that eventually brought me to where I am now. I owe you all my gratitude.

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Svend Greniman Andersen
Copenhagen, November 2015

# English Summary

## Overview

Globalization is often considered to have significant impact on a small open economy. This PhD thesis consists of three self-contained chapters all centered on investigating the effects of globalization on firm- and worker-level outcomes such as innovation and wages.

In the first chapter, I look at the complementarity between production and research and development (RnD) in Danish manufacturing firms. I find that firms taking increasing advantage of offshoring of production tend to also engage in further RnD domestically. Moreover, they tend to reallocate RnD resources toward product RnD, possibly at the expense of process RnD.

The second chapter shifts focus to the labor market for top managers, or CEOs. We first construct firm complexity measures related to globalization and document novel stylized facts about globalization and CEO compensation. We then investigate whether the rise in CEO compensation can be explained by increasing firm-level globalization and find that changes in the export volume correlates with changes in CEO compensation, while firm complexity measures play a minor role. This pattern persists when conditioning on firm size. Finally, we find suggestive evidence in favor of the hypothesis that externally hired CEOs are less likely to be rewarded for exogenous changes in exports than internally hired CEOs.

The third and final chapter takes a broader view and estimates the effects of offshoring on worker wages. By constructing an occupation-specific offshoring measure using firm-level data, I can allow for occupation-wide general equilibrium effects and achieve a more precise measure of offshoring and a clear identification. I find little or no evidence of offshoring on wages, possibly reflecting relatively low mobility of workers between the manufacturing and service sectors.

All chapters rely on detailed register data on individuals, firms, RnD and trade flows, and instrumental variable strategies are employed to circumvent potential endogeneity issues.

## 1. Offshoring brains? Evidence on the complementarity between manufacturing and research and development in Danish firms

Much concern has been raised recently by politicians and policymakers in advanced economies as to whether domestic manufacturing activity is a prerequisite for research and development (RnD) activities at home. This is seen in light of the rapid rise in offshoring to low-wage countries over the past two decades coupled with a substantial decline in domestic manufacturing jobs. To investigate whether offshoring is complementary to or a substitute for RnD activities, this chapter employs a firm-level linked employer-employee dataset for Danish manufacturing firms including information on RnD expenditures and the number of RnD professionals employed. Offshoring is instrumented with world export supply to circumvent the inherent endogenous nature of the firm offshoring decision. Results suggest that firms with increased offshoring do in fact tend to engage in further RnD activities at home. Moreover, they also tend to reallocate RnD resources toward product RnD, possibly at the expense of process RnD. This suggests that firms with less internal manufacturing activities have less of an incentive to internally perform RnD related to the production process. On the other hand, cheaper imported intermediate inputs now raise the potential profitability of new products, thus inducing firms to shift RnD focus in this direction.

## 2. Globalization and CEO Pay: Estimating the Value of Good Leaders in Complex Firms

*with David Hummels and Jakob Roland Munch*

Much attention has been given to increasing income shares of top income earners in many advanced economies, particularly in the U.S. This increase is partly driven by so-called ‘supermanagers’, the chief executive officers (CEOs) of the largest firms. In this chapter, we identify CEOs from linked employer-employee data for Denmark for the period 1995-2008 and construct firm complexity measures related to globalization. We document novel stylized facts about globalization and CEO compensation. We investigate whether the rise in CEO compensation can be explained by increasing firm-level globalization and find that changes in the export volume correlates with changes in CEO compensation, while firm complexity measures play a minor role. This pattern persists when conditioning on firm size. Firm exports are then instrumented with world import demand in order to identify the causal impact of exports on CEO earnings. Our results indicate that if the median firm doubles its exports for exogenous reasons, then the relative earnings of its CEO increases by 18% from 3.5 to 4.1 times the income of the average worker in the firm. Finally, we find suggestive evidence in favor of the hypothesis that externally hired CEOs are less likely to be rewarded for exogenous changes in exports than internally hired CEOs.

### 3. Keeping workers occupied: In search of occupation-wide effects of offshoring

One notable aspect of globalization is the dramatic increase in the trade in intermediate goods between countries which has coincided with a notable loss of low-skilled jobs and growing wage inequality domestically. This chapter examines potential occupation-wide general equilibrium wage effects of offshoring in a setting different from the U.S. labor market. This is done by using linked employer-employee data at the firm level to construct an occupation-specific offshoring measure and instrumenting this with world export supply in order to achieve a more precise measure of offshoring and a clear identification. I find little or no evidence of offshoring on wages. This is in contrast to the existing literature generally finding negative wage effects. By capturing economy-wide general equilibrium effects, I use a different methodology for measuring offshoring. This approach relies on variation in offshoring and wages within occupations. Lack of such variation may reflect a relatively unionized labor market where the service sector is viewed as less of an outside option for manufacturing workers facing pressures from offshoring.

# Danish Summary

Globaliseringen anses ofte for at have stor betydning for en lille åben økonomi som den danske. Denne ph.d.-afhandling består af tre selvstændige kapitler, der alle er centrerede omkring undersøgelsen af globaliseringens påvirkninger på arbejder- og virksomhedsniveau, eksempelvis innovation og lønninger.

I det første kapitel ser jeg på komplementariteten mellem produktion og forskning og udvikling (FoU) i danske fremstillingsvirksomheder. Jeg finder empirisk belæg for, at virksomheder, der i stigende grad udnytter mulighederne for offshoring (udflytning) af produktionsaktiviteter, også har tendens til at øge deres FoU-aktiviteter indenlandsk. Derudover er disse virksomheder tilbøjelige til at omallokere deres FoU mod produktudvikling, givetvis på bekostning af processudvikling.

Det andet kapitel flytter fokus til arbejdsmarkedet for virksomhedsdirektører. Her konstruerer vi først mål for virksomheders kompleksitet relateret til globalisering og beskriver nye, generelle sammenhænge mellem globalisering og direktørlønninger. Vi undersøger dernæst, om stigningen i aflønningen af virksomhedsledelse kan forklares ved stigende globalisering på virksomhedsplan og finder, at ændringer i ekportvolumen korrelerer med ændringer i aflønningen, mens andre mål for virksomhedens kompleksitet lader til at have en mindre betydning. Dette resultat gør sig også gældende, når der betinges på virksomhedens størrelse. Endelig finder vi delvist belæg for hypotesen om, at eksternt hyrede direktører har mindre tendens til at blive belønnet for eksogene ændringer i virksomhedens eksport end internt forfremmede direktører.

I det tredje og sidste kapitel ses der mere bredt på effekterne af offshoring på lønninger for danske arbejdere. Ved at konstruere et stillings-specifikt offshoringmål ved brug af virksomhedsdata bidrager jeg med et mere præcist mål for offshoring og tager højde for generelle ligevægtseffekter omfattende hele stillingsgrupper. Jeg finder beskedne eller ingen effekter af offshoring på lønninger, hvilket muligvis afspejler en relativt lav bevægelse af arbejdere mellem fremstillings- og servicesektoren i perioden.

Alle kapitler trækker på detaljeret registerdata for individer, virksomheder, FoU samt udenrigshandel, og der anvendes en tilgang med estimation med instrumentvariabel for at adressere potentielle endogenitetsproblematikker.

# Chapter 1

## Offshoring brains? Evidence on the complementarity between manufacturing and research and development in Danish firms

# Offshoring brains? Evidence on the complementarity between manufacturing and research and development in Danish firms

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September 24th, 2015

**Abstract**

Much concern has been raised recently by politicians and policymakers in advanced economies as to whether domestic manufacturing activity is a prerequisite for research and development (RnD) activities at home. This is seen in light of the rapid rise in offshoring to low-wage countries over the past two decades coupled with a substantial decline in domestic manufacturing jobs. To investigate whether offshoring is complementary to or a substitute for RnD activities, this paper employs a firm-level linked employer-employee dataset for Danish manufacturing firms including information on RnD expenditures and the number of RnD professionals employed. Offshoring is instrumented with world export supply to circumvent the inherent endogenous nature of the firm offshoring decision. Results suggest that firms with increased offshoring do in fact tend to engage in further RnD activities at home. Moreover, they also tend to reallocate RnD resources toward product RnD, possibly at the expense of process RnD. This suggests that firms with less internal manufacturing activities have less of an incentive to internally perform RnD related to the production process. On the other hand, cheaper imported intermediate inputs now raise the potential profitability of new products, thus inducing firms to shift RnD focus in this direction.

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# 1 Introduction

> *Over the past few decades it became conventional wisdom that factory jobs could be done cheaply in some far-flung corner of the world but more important innovation work should stay in-house in high-cost countries. Manufacturing was seen as just a cost centre, so it was often offshored. Now many companies reckon that production makes a big contribution to the success of research and development, and that innovation is more likely to happen when R&D and manufacturing are in the same place, so increasingly they want to bring manufacturing back in-house.*
>
> - The Economist (2013)

Much concern has been raised recently by politicians and policymakers in advanced economies as to whether domestic manufacturing activities is a prerequisite for more knowledge-based activities at home[1]. This is seen in light of the rapid rise in offshoring[2] to low-wage countries over the past two decades coupled with a substantial decline in domestic manufacturing jobs. Since knowledge-based activities are often coupled with technological and technical advances, this debate also concerns the determinants of long-run growth in general. When concerned about domestic labor markets and its ability to sustain high-skilled jobs, it therefore becomes of interest to assess whether globally oriented firms take offshoring and high-skilled inputs as substitutes or complements in the production process. In this paper, the focus is on research and development (RnD) activities as an important high-skilled input for domestic firms.

On the one hand, RnD and offshoring may be substitutes if the development of new products and processes is performed with better synergies when production is carried out at home next to the laboratory instead of abroad. On the other hand, relocating production to a foreign country may mean freeing up resources to increase RnD spending at home where the comparative advantage is present, thus rendering RnD and offshoring complements. The literature so far offers no clear, explicit answer to this question.

[1]The above quotes are examples of many related statements. For an example from the business literature, see e.g. Pisano and Shih (2012).

[2]I shall refer to *offshoring* throughout the paper as the relocation of intermediate inputs from domestic to foreign suppliers, those suppliers being either within or outside the boundaries of the firm. In practice, I measure offshoring at the firm level as the total value of imports and do not distinguish between imports from firms within the same business group and other foreign firms.

This paper therefore seeks to fill this gap by asking the question: Is offshoring complementary to or a substitute for RnD at the firm level? By employing a rich firm-level dataset on RnD activities and intermediate imports as well as looking at exogenous offshoring shocks, I am able to focus on the channel running from offshoring to domestic RnD which is of considerable concern to public policy.

Focusing on the relationship between trade and innovation, a number of papers offer useful theoretical frameworks. One example is Bloom *et al.* (2013) where some production factors are assumed to be "trapped" within firms in the shorter run. After a trade shock reduces the price for one of the goods that the firm had been producing, the opportunity cost goes down for inputs that are trapped within the firm. The firm does more innovation, not because of an increase in the value of a newly designed good, but rather because of a fall in the opportunity cost of the inputs used to design and produce new goods.

Naghavi and Ottaviano (2009) suggest an endogenous growth model with offshoring. The model features an RnD sector supplying blueprints for firms producing intermediate inputs, the production of which may be offshored. Transport cost parameters affect the decision to relocate intermediate goods plants but not RnD. Therefore, it is shown that if offshoring is associated with reduced feedback from plants to laboratories, firms may choose to offshore even though it damages the growth rate of the economy. This highlights the importance of clarifying empirically whether plant and laboratory activities are complementary or substitutable.

Another way of approaching the question asked in the paper is to test directly for complementarity or substitutability in a CES production function framework. This is indeed the approach taken in section 3 of this paper and is inspired by the paper by Kmenta (1967) and subsequent work (e.g. Duffy and Papageorgiou (2000)) applying similar methods, although the mentioned papers use aggregate data to answer questions related to economic growth.

The empirical literature concerning the connection between concepts related to RnD and offshoring can be said to be centered around three papers. On the one hand, we have the contributions by Bustos (2011) and Goldberg *et al.* (2010). Although these papers both look at developing countries and not advanced economies, their research questions are related to my work. On the other hand, we have the study by Bøler *et al.* (2012) for an advanced economy, but where the causal relationship in general runs from RnD to offshoring and not the other way round as in the paper at hand. In addition to these papers, there are a number of studies either with a different focus (e.g. the service sector), different data (survey data, binary measures of offshoring and RnD), or without a clear identification strategy. In section 2, I will briefly review the mentioned references and related articles and point out how this paper contributes to the literature. Overall, this paper contributes by being one of the first to investigate the direct connection between offshoring and domestic RnD activities for an advanced economy using rich firm-level data on both intermediate imports and domestic RnD while at the same time employing a clear identification strategy using an instrumental variable approach.

One problem in the existing literature is the lack of clear identification strategies to confront the endogeneity issues inherent in this type of studies. One source of such potential endogeneity issues is the example of a local demand shock making both further offshoring and RnD more profitable without any direct channel linking these two variables. To address these potential problems, I follow Hummels *et al.* (2014) and instrument offshoring using world export supply (WES)[3]. The idea is to find exogenous variation in the global supply of intermediate goods driven by changes in the exporting country's overall trade patterns as determined by comparative advantage or other classical international trade factors. This variation is then related to the input product bundle used by a given firm.

In the analysis, I choose to measure RnD activity at the firm level in two different ways. First, I use the number of RnD professionals employed. RnD professionals are identified using information about educational attainment and occupational codes from the worker-level data. Second, I look at total internal RnD expenditures of the firm. For offshoring, I choose a broad measure defined simply as the total value of imported goods for any given firm in any given year.

Looking first at RnD as measured by the number of RnD workers employed, my findings initially indicate no immediate connection between offshoring and RnD conditional on firm capital, employment and total sales levels. However, this changes once the IV strategy is implemented. Here, a doubling of offshoring activity leads to another 0.68 RnD professionals employed, corresponding to about 30 percent of the sample mean number of RnD professionals. Looking instead at internal RnD expenditures of the firm, the picture emerging is more or less

[3] A similar instrumental variable method is developed in Autor *et al.* (2013) who look at the effects of import competition from China on the US labor market.

the same. While there is no significant effect of in the initial specifications, the coefficient jumps up and becomes significant once the instrument is applied and firm fixed effects are included. With this formulation, a doubling of offshoring tends to be associated with a 50 percent increase in internal RnD spending.

Having established that increasing offshoring opportunities tend to cause firms to increase overall RnD activity, I then try to dig deeper and look at the composition of RnD activities. Specifically, I separate internal RnD spending into process and product RnD as reported by the firms. Once the IV strategy is applied, we see a doubling of offshoring being associated with a 21 percentage point increase in the share of RnD spending going to product innovation. This indicates that firms deciding to offshore an even larger part of their manufacturing activities in response to an exogenous shock to offshoring opportunities not only choose to increase their overall commitment to internal RnD. They also tend to reallocate RnD resources towards product RnD, possibly at the expense of less process RnD. This suggests that firms with less internal manufacturing activities have less of an incentive to internally perform RnD related to the production process. On the other hand, cheaper imported intermediate inputs now raise the potential profitability of new products, thus inducing firms to shift RnD focus in this direction.

The rest of this paper proceeds as follows. Section 2 provides an overview of existing literature related to this paper. Section 3 provides a simple production function framework highlighting the possibility of substitutability or complementarity between offshoring and RnD activities. Section 4 introduces the data and the identification strategy. Section 5 presents the results. Section 6 concludes.

# 2 Existing literature

This section briefly reviews the main contributions to the empirical literature concerning the connection between concepts related to RnD and offshoring as well as a number of related articles and points out how this paper contributes to the literature.

Bustos (2011) studies the impact of a regional free trade agreement on the technology upgrading of Argentinian firms. This is done by introducing technology choice in a model of trade with heterogeneous firms. The finding is that firms in industries facing higher reductions in tariffs in export markets improve their technology faster than firms in other industries. If improvement of technology is associated with RnD activities, tariff reductions and more global activity leads to higher RnD intensity, although these results are not directly related to offshoring.

Somewhat related is the finding in Goldberg *et al.* (2010) where Indian firms relying on imported intermediate inputs can benefit from an increased variety of those inputs when trade increases. As such, the benefits to producers are conceptually much the same as the benefits consumers enjoy from increased product variety (Feenstra, 2010). Findings suggest that access to more varieties of intermediate inputs lead firms to expand their product scope. Since the development of new products is often intimately tied to RnD, this points to a positive association between offshoring and RnD, although the type of intermediate imports studied here are likely to be much different in nature than what is relevant for the research question of this paper.

In Bøler *et al.* (2012), the authors use Norwegian firm-level data which in many respects is similar to the Danish data used in this paper. They document a number of empirical regularities which all suggest a clear positive relationship between RnD and offshoring. They then set up a theoretical model which they structurally estimate to confirm the empirical regularities. Finally, they use a tax break on RnD activities for a subset of firms as a natural experiment and find that lower marginal RnD costs lead to more RnD spending and employment. Also, innovation is accompanied by more outsourcing of foreign inputs. The difference in my paper is that I consider an exogenous shock to the cost of offshoring rather than to the cost of RnD and then look at the impact on RnD. Also, my identification strategy is different since I use an instrumental variable approach.

In addition to these papers, there are a number of studies either with a different focus (e.g. the service sector or import competition), different data (survey data, binary measures of offshoring and RnD), or without a clear identification strategy. In Bloom *et al.* (2011), panel data for European countries for 1996-2007 is used to examine the impact of Chinese import competition on measures of technical change, including RnD. China's entry into the WTO in 2001 is used to correct for endogeneity. Among other things, they find that employment is reallocated towards more technologically advanced firms ("trade is bringing in the robots"). Individual firms facing more import competition see larger increases in innovation as well. Offshoring is also taken into consideration but no strong positive effect on overall innovation is found.

A number of papers more specifically document an overall positive relationship between offshoring and RnD using different approaches. In Ali-Yrrkö and Deschryvere (2008), the authors ask whether the offshoring of RnD activities (not offshoring in general) affects domestic RnD employment at the firm level. Using Finnish data for 2006, they find that manufacturing firms expanding RnD activities within firm affiliates abroad also tend to plan to increase their domestic RnD. They do not have a natural experiment or an instrumental variable strategy for identification. In Dachs *et al.* (2014), data from the European Manufacturing Survey is used to establish that offshoring firms on average employ a higher share of RnD personnel. However, although they use a kernel based matching approach and exploit the temporal structure of their data (they use data on offshoring collected in years prior to the data on RnD), their method appears unable to deal with e.g. firm-specific demand shocks affecting both the contemporaneous offshoring decision and future RnD activities, an issue which is addressed in my paper. In Görg and Hanley (2011), the authors find a positive effect of international outsourcing of services (not goods) on innovative activity at the plant level for Irish manufacturing firms. They also have an instrumental variable analysis (use of internet as IV for offshoring), although they only have data for 2002-2004.

Using data for 28 emerging market economies, Fritsch and Görg (2015) find a positive relationship between outsourcing and RnD at the firm level, and the results are robust to an instrumental variables strategy. In addition to focus on a country with an advanced economy, my paper contributes by using richer, administrative firm-level data rather than survey data and is thus able to answer questions in more detail by e.g. capturing the intensive margin of RnD activities (rather than using a binary RnD decision variable). Furthermore, since the instrumental variables strategy in Fritsch and Görg (2015) is relying on country-industry variation, they are unable to include industry-year dummies in their analyses. As a result, although the authors are capable of avoiding potential bias arising from firm-specific shocks, they are unable to control for industry-wide shocks within years – an issue that can be resolved by constructing instruments at the country-year-product level, as in the paper at hand.

Finally, there are also studies pointing to a negative relationship, for example the paper by Karpaty and Tingvall (2011). Here, using firm-level data for the Swedish manufacturing sector, a negative effect of offshoring on RnD at home is found mostly for small firms. For the multinationals making up the bulk of the RnD investments, the effect is limited and also confined to offshoring to certain regions. The paper also has no clear identification strategy.

Only one paper to the knowledge of the author investigates the relationship between offshoring and RnD using Danish firm-level data, namely the paper by Junge and Sørensen (2011). They find that firms offshoring core activities have a greater likelihood of being engaged in RnD and also have bigger RnD intensities. Although their paper comes close to investigating the same question as the paper at hand, the authors underscore the possibility of endogeneity issues which are not addressed in their particular framework.

Overall, this paper contributes by being one of the first to investigate the direct connection between offshoring and domestic RnD activities where the focus is an advanced economy. Furthermore, by using rich firm-level data on both intermediate imports and domestic RnD while at the same time employing a clear identification strategy using an instrumental variable approach, this paper is able to provide a detailed and clean attempt to shed light on the issue.

# 3 Theoretical framework

Is offshoring complementary to or a substitute for RnD? To formalize this question, consider a firm producing a final good (Y) using capital (K), labor (L), RnD (R), and imported intermediates (M) as inputs with the following production technology[4]:

$$Y = AK^{\alpha}L^{\beta}\left(R^{\rho} + M^{\rho}\right)^{\frac{\kappa}{\rho}} \tag{3.1}$$

where $A > 0$ is total factor productivity, $\alpha, \beta, \kappa \in (0, 1)$, $\rho = \frac{\sigma-1}{\sigma}$, and $\sigma \geq 0$ is the elasticity of substitution[5].

If R and M are complements, the firm will react to a falling cost of offshoring by increasing both its import of intermediates and its RnD activities. This is the

[4]This formulation is inspired by Hummels *et al.* (2014). The nested CES specification is chosen to allow R and K to be either substitutes or complements while keeping a simple and flexible formulation with relatively few parameters and substitution elasticities restricted to be constant. For simplicity, I have only included one type of labor L, but this could be readily augmented with e.g. high and low-skilled labor input, either of which may be modeled as complements or substitutes for RnD.

[5]Note that $\alpha, \beta, \kappa \in (0, 1)$ without further restrictions implies decreasing returns to scale for each input but nothing about the returns to scale about the aggregate production function.

case if $\rho < 0$ (equivalent to $\sigma < 1$), a condition that can then be tested with the available data.

To arrive at an estimating equation, I begin by taking logs on both sides in equation (3.1):

$$lnY = lnA + \alpha lnK + \beta lnL + \kappa ln\left[(R^{\rho} + M^{\rho})^{\frac{1}{\rho}}\right] \tag{3.2}$$

In the spirit of Kmenta (1967)[6] and subsequent work (see e.g. Duffy and Papageorgiou (2000)), this can be rewritten using a first-order Taylor approximation and some algebra into (see Appendix A for derivation):

$$lnY \approx lnA + \alpha lnK + \beta lnL + \kappa c_0 lnM + \kappa(1 - c_0)lnR + \kappa c_1 \tag{3.3}$$

where $c_0$ and $c_1$ are functions of parameters including $\rho$.

Since I have access to exogenous variation in $M$ and since I am interested in the relationship between $R$ and $M$, I rewrite (3.3) to become:

$$\begin{aligned} lnR \approx \tfrac{c_1}{c_0-1} + \tfrac{1}{\kappa(c_0-1)}lnA \quad & + \frac{\alpha}{\kappa\left(c_0-1\right)}lnK + \frac{\beta}{\kappa\left(c_0-1\right)}lnL \\ & + \frac{c_0}{c_0-1}lnM + \frac{1}{\kappa\left(1-c_0\right)}lnY \end{aligned} \tag{3.4}$$

Obtaining data on R, K, L, M and Y, and assuming a constant total factor productivity A, this lends itself to the following statistical model which can then be estimated using linear methods:

$$lnR = \beta_0 + \beta_1 lnK + \beta_2 lnL + \beta_3 lnM + \beta_4 lnY + \varepsilon \tag{3.5}$$

If $\beta_3$ is found to be positive (negative), firms with larger imports of intermediate inputs tend to also engage more (less) heavily in RnD activities. Additionally, it is possible to use the estimates to derive the implied sign of $\sigma$, the elasticity of substitution. In Appendix A, it is shown that $\sigma < 1 \Leftrightarrow \frac{c_0}{c_0-1} > -1$ , equivalent

[6]Kmenta (1967) approximates in the space of parameters rather than the space of variables. He also includes the second order terms but disregard terms of higher orders.

to $\beta_3 > -1$ in the estimation above. In sum, RnD and offshoring activities are complements ($\sigma < 1$) if the coefficient resembling $\frac{c_0}{c_0-1}$ is not too negative ($\beta_3 > -1$).

# 4 Data sources and identification strategy

## 4.1 Data sources[7]

The dataset used is based on registry data from Statistics Denmark and constructed by combining data on individuals, firms, RnD and foreign trade. Unique firm and individual identifies allow the datasets to be merged and workers and firms to be matched in every year. The sample period chosen is 1995-2008, since 1995 is the first year available and the years after 2008 are excluded to avoid the financial crisis years. Only firms classified as manufacturing firms were kept since attention is restricted to firms who could at least potentially engage in both offshoring and RnD activities, and the manufacturing sector has traditionally been the case in point for offshoring. Finally, I choose to limit attention to importing firms, thus excluding firms on the extensive margin of the offshoring decision. Possible problems connected to excluding these firms are addressed below.

*Measuring RnD*

I acquire data on the number of employees, total sales, and the value of the capital stock for all firms in the sample. I choose to measure RnD activity at the firm level in two different ways. First, I use the number of RnD workers employed. RnD workers are identified using information about educational attainment and occupational codes from the worker-level data. Second, I look at the total internal RnD expenditures of the firm. This data comes from the RnD and innovation survey performed by Statistics Denmark (the Danish version of the CIS-4). It is based on a stratified sample among a population of firms believed to potentially being able to undertake RnD. In addition, the largest firms are pre-sampled and included in every year. These few hundred firms account for the bulk of RnD activities. As such, the data in principle captures all RnD activity in the Danish economy.

In addition to the total RnD expenditures, I have information on the share of

[7]For more details on data sources, see Appendix B.

expenditures going to product RnD, process RnD, and general knowledge accumulation. It should also be noted that I keep firms with no RnD activity in order to include firms at the extensive margin of the RnD decision.

*Measuring offshoring*

The foreign trade statistics on imports contains information on all firms engaged in importing activities. However, a number of observations will have missing values for the world export supply instrument (see below) since part of their trade flows cannot be matched to the BACI trade data for technical reasons. I choose to drop these observations.

I define offshoring using a broad measure as the total value of imported goods for any given firm in any given year. The idea is that these imported goods may have displaced economic activity that could at least potentially have taken place inside the importing firm. Since I am interested in the firm offshoring decision and the link between production and RnD activities, it is necessary to consider whether these imports are final goods or intermediate inputs.

Focusing on the manufacturing sector and disregarding the service sector is useful for capturing imports used as inputs in production rather than as final goods for consumption by domestic consumers. This is so since data for service sector firms includes reselling without value-added, and the share of reselling out of total imports is typically much higher for service sector firms than for manufacturing firms.

When using a broad offshoring measure (i.e. including all imported goods as opposed to only a subset of goods), one concern is that these inputs may not substitute for relevant manufacturing production factors within the firm. For example, imported raw materials or certain manufactured inputs may be unlikely to have been produced by the firm in question in the absence of import opportunities. An alternative would be to compute a so-called narrow offshoring measure, counting only imports from within a set of product categories more closely resembling the product categories produced by the firm. The concern here is that the range of products counted may be too narrow, thus underestimating the extent of offshoring. Using a narrow instead of a broad offshoring measure might yield different results although this is not investigated further in this paper.

Another approach in the literature is to use industry level input-output tables to help identify which inputs a firm is importing. This approach is unlikely to give an accurate picture of imports among Danish firms since even firms within the same industry have relatively few inputs and outputs in common. Therefore, any shock to a foreign seller of a particular intermediate input will have very different effects across Danish firms within the same industry. Instead, utilizing firm-level data appears to be a more attractive way of measuring offshoring.

See Hummels *et al.* (2014) for an extensive discussion of these issues as well as more details about the data patterns mentioned and the possible consequences of different approaches to measuring offshoring using data on Danish firms and their imports.

*Some descriptive statistics*

Table 4.1 shows summary statistics for the key variables used in the following analysis. We see a large dispersion in most variables. For the RnD measures, this owes partially to the fact that a large number of firms have no RnD activities reported in one or more years.

Table 4.1: Summary statistics for final sample

| | Mean | Std. Dev. | Observations |
|---|---|---|---|
| RnD expenditures | 3.3 | 49.0 | 30,871 |
| RnD professionals | 2.3 | 33 | 30,871 |
| Total imports | 32.5 | 129.4 | 30,871 |
| Total employees | 107 | 397 | 30,871 |
| Total sales | 127.5 | 835.6 | 30,871 |
| Capital stock | 43 | 306 | 30,871 |

All monetary variables are in local currency (millions DKK). All statistics (except imports) include observations with values of zero. Sample period 1995-2008.

Information on the share split of RnD expenditures on products or processes is only available for a limited set of firms. This is due to the lack of reporting on this variable by a considerable amount of firms. Table 4.2 shows summary statistics for this limited sample and indicates that the firms with available information on the share split of RnD are generally larger firms. This is further illustrated in Table 4.3. For example, we see that the firms in this limited sample account for 73 percent of the RnD expenditures and 40 percent of the total sales of the full sample, even though the limited sample only accounts for 9 percent of the observations of the full sample. So although any analysis using the share split of RnD is to be interpreted with caution due to the limited nature of the sample, the firms considered still account for a substantial part of the total economic activity of the full sample.

Table 4.2: Summary statistics for limited sample

| | Mean | Std. Dev. | Observations |
|---|---|---|---|
| RnD expenditures | 26.6 | 167.1 | 2,790 |
| RnD professionals | 15 | 103 | 2,790 |
| Total imports | 112.1 | 236.8 | 2,790 |
| Total employees | 366 | 891 | 2,790 |
| Total sales | 563.4 | 2,237.7 | 2,790 |
| Capital stock | 203.3 | 832.7 | 2,790 |
| Product RnD (share) | 54 | 42 | 2,790 |
| Process RnD (share) | 11 | 19 | 2,790 |

All monetary variables are in local currency (DKK). Share variables are shares of total internal RnD expenditures multiplied by one hundred. All statistics (except imports) include observations with values of zero. Sample period 1995-2008.

Table 4.3: Limited sample shares of full sample economic activity

| | Share of value | Share of observations |
|---|---|---|
| RnD expenditures | 73% | 9% |
| RnD professionals | 59% | 9% |
| Total imports | 31% | 9% |
| Total employees | 31% | 9% |
| Total sales | 40% | 9% |
| Capital stock | 43% | 9% |

The table shows for each variable used the aggregate value of the limited sample as a share of the aggregate value of the full sample as shown in table 4.1. Sample period 1995-2008.

One concern related to the full sample is that the RnD measures do not capture the fact that firms might rely on externally delivered RnD services instead of producing them within the firm. To investigate this, Table 4.4 examines the decomposition of aggregate RnD spending in the manufacturing sector into internal and external purchases. It further divides external purchases into several categories. We see that about two-thirds is internal spending while one-third is externally purchased, most of which has a foreign origin. This is confirmed in officially available statistics (see e.g. Statistics Denmark (2014), pp 40-41). What can also be seen from the data at hand is that half of external spending is purchased from the firm's own business group abroad while the rest comes from other foreign firms or research institutions. So while RnD expenditures within the firm on domestic soil make up the bulk of RnD activity, it is not a measure without error.

Table 4.4: Aggregate and median RnD expenditures (millions DKK), 2008

| | Aggregate | Median |
|---|---|---|
| Total internal spending | 14,000 | 2.07 |
| Total external spending* | 6,720 | 0.50 |
| Total foreign spending** | 5,583 | 0.34 |
| Purchases from foreign firms | 2,610 | 0.29 |
| Purchases from own business group abroad | 2,930 | 2.06 |
| Purchases from foreign research institutions | 43 | 0.10 |
| Foreign spending, own business group abroad (share) | 0.52 | 0.58 |
| Foreign spending, foreign firms (share) | 0.47 | 0.45 |
| Foreign spending, foreign research institutions (share) | 0.01 | 0.06 |

The table shows for 2008 the aggregate and median RnD expenditures for manufacturing firms decomposed into various categories. Note that there may be double counting between internal and external spending bought in Denmark (cf. Statistics Denmark (2014) p. 40). For discretion reasons, median firm values are calculated as the mean of the five median firm observations for each variable. For the share variables, values of zero and one are excluded in the median calculations.

*Total external spending equals total external spending in Denmark plus total foreign spending.

**Sum of own business group, foreign firms, and foreign research institutions.

Another concern might be that, although the majority of RnD is performed within the boundaries of Danish firms, some manufacturing firms non-intensive in internal RnD might be heavily relying on external firms or institutions to do the job. However, this does not seem to be the case at any rate of importance. In Table 4.5, we see that the total amount of externally purchased RnD for firms having less than the average level of internal RnD is only around 2 percent of total external purchases (irrespective of which internal RnD measure is used). Thus, we can conclude that most external RnD purchases are performed by firms already intensive in internal RnD, while firms non-intensive in internal RnD are simply not using RnD in general.

Table 4.5: External RnD spending by non-RnD-intensive firms, 2008

| RnD measure | Total spending | Share of aggregate |
|---|---|---|
| RnD professionals | 120 | 0.02 |
| Internal RnD expenditures | 164 | 0.02 |

The table shows for 2008 the aggregate external (domestic or foreign) RnD purchases (in millions DKK) by manufacturing firms with less than average internal RnD intensity (among manufacturing firms) as measured by either the number of RnD professionals or total internal RnD expenditures. The share is out of total external spending among all manufacturing firms in the sample (6,720 mill. DKK).

Finally, Table 4.6 addresses the concern that firms at the extensive margin of the offshoring decision excluded from the analysis might play an important role for domestic RnD activities[8]. In the table, I temporarily include firms with no offshoring and divide the sample into four main categories along the intensive and extensive margins of offshoring and RnD: about three quarters of firm-year observations have neither offshoring nor RnD. However, the firms behind these observations account for only 10 percent of all firm sales, whereas 58 percent is accounted for by the firms behind firm-year observations with positive values for both offshoring and RnD and thus being at the intensive margin for both of these activities. A substantial group of firm-year observations are undertaking offshoring but without any RnD activities. Finally, the mass of firms doing RnD without doing offshoring appears negligible. In sum, restriction attention to firms with offshoring seems to provide a reasonable picture of domestic RnD activities.

Table 4.6: Number of firms with RnD and offshoring, 2008

| | RnD professionals > 0 | RnD professionals = 0 |
|---|---|---|
| Offshoring > 0 | 646 | 4,361 |
| | (58%) | (32%) |
| Offshoring = 0 | 104 | 13,272 |
| | (1%) | (9%) |

The table shows the number of firms with or without RnD or offshoring (as measured by firm imports) or any combination of these two activities. The percentages indicate the share of aggregate firm sales represented by that group of firms.

## 4.2 Identification strategy

In section 5, I will regress time varying RnD measures on time varying firm-level offshoring as measured by the value of firm imports. The identification problem facing this approach is that firm-level shocks to firm productivity or the demand for firm products will tend to affect both the offshoring and RnD decisions of the firm. For example, as firm demand goes up, a given cost saving from offshoring as well as developing a new product might both become more profitable. To confront this problem, I construct instruments correlated with firm imports but uncorrelated with firm productivity and demand structure.

To further illustrate the identification challenge, consider that offshoring firms

[8] Note that the sample of offshoring firms considered here is slightly different from the final sample used in section 5 where some observations have to be dropped to perform the analyses.

are expected to be different from non-offshoring firms. To the extent that these differences are time invariant, identifying off changes within firms over time will be robust to this concern. Table 4.7 shows the result of focusing on firms engaged in offshoring and including firm fixed effects in a regression of offshoring on firm outcome variables. We see that rising offshoring is associated with higher sales, more employees and a larger capital stock. This underlines the identification problem. It might well be that access to cheaper inputs through higher offshoring enables firms to expand operations and shift resources from production to RnD. Conversely, it could be that these outcomes are all affected by shocks to the demand for products or the productivity of the firm, thus causing the correlation between RnD and offshoring to be caused by simultaneity bias.

Table 4.7: Firm-level effects of offshoring

| | Log(Offshoring) |
|---|---|
| Log(Sales) | 0.0705*** |
| | (0.00251) |
| Log(Employees) | 0.635*** |
| | (0.0276) |
| Log(Capital) | 0.0830*** |
| | (0.0116) |
| Firm FE | Yes |
| Observations | 30,871 |

Dependent variable: Log(Offshoring). Sample is identical to main estimation sample and includes larger exporting firms in the manufacturing sector for the years 1995-2008. Standard errors in parentheses clustered at the firm level. *p<0.10, **p<0.05, ***p<0.01.

In order to account for such endogeneity issues, I follow Hummels *et al.* (2014) and instrument offshoring using world export supply (WES), constructed using COMTRADE bilateral trade data. The idea is to find exogenous variation in the global supply of intermediate goods driven by changes in the exporting country's overall trade patterns as determined by comparative advantage or other classical international trade factors. This variation is then related to the input product bundle used by a given firm. Formally, world export supply is defined as:

$$WES_{jt} = \sum_{c,k} s_{jck} WES_{ckt} \tag{4.1}$$

Here, $s_{jck}$ is the share of imports of product category $k$ from country $c$ out of total imports for firm $j$ in the base year. The base year is chosen as the first year of the sample period (i.e. 1995) if the firm is observed in that year; otherwise, the first year the firm is observed is chosen as base year. $WES_{ckt}$ is the total exports from country $c$ of product $k$ in year $t$ to the entire world market less Denmark. By fixing import shares $s_{jck}$ in the base year, the instrumental variable will have strength insofar as this fixing of the share weights reflects actual data patterns. This indeed turns out to be overall consistent with the data and may reflect stable business relationships or the fact that inputs from that particular source is a good match for the importer in question.

When discussing possible threats to identification, one can distinguish between problems with the instrument $WES_{ckt}$ itself and the share weights $s_{jck}$. First, consider a rise in world export supply for some country-product combination caused by both increasing supply and demand globally and in Denmark. Then world export supply may be correlated with the profitability of RnD for the Danish firm in question. As an example, suppose a global construction boom both increases the supply of steel and the demand for pumps globally. Then a Danish manufacturer of pumps using Chinese steel as an input might see both decreasing input costs and rising prices for its output, causing RnD to be more profitable. As a response, the firm might increase both its imports of pumps and its RnD spending. However, this concern is at least partially alleviated by including industry-year fixed effects and firm output in the empirical specifications, since this in effect controls for time-varying demand shocks to particular industries and firms in Denmark.

Secondly, one might be concerned with the share-weighting of world export supply in constructing the instrument. If differences in the technology used across firms affects both the firm's decisions to innovate as well as the types of inputs used, this could cause problems. However, since the following regression analysis is using within-firm variation, this effectively circumvents the issue. Moreover, if technology differences change over time, the fixing of import shares prevents differences in technological change from having effects on RnD and offshoring.

# 5 Results

## 5.1 Empirical specification

In order to answer the question of complementarity between offshoring and RnD, I follow the framework suggested in equation (3.5) and consider estimating the following specification:

$$\log\left(RnD_{jt}\right) = \mathbf{x}_{jt}\boldsymbol{\beta} + \gamma\log\left(OFF_{jt}\right) + \varphi_t + \varphi_{IND} + \varphi_j + \varepsilon_{jt} \tag{5.1}$$

where $\mathbf{x}_{jt}$ is a vector of firm controls (log(capital), log(number of employees) and log(total sales)) and where I include year ($\varphi_t$), industry ($\varphi_{IND}$) and firm-specific ($\varphi_j$) effects.

The model is estimated using each of the RnD measures, i.e. *RnD = internal RnD expenditures* or *RnD = professionals employed*, and both with and without firm-specific effects. I estimate both using OLS and then subsequently instrumenting offshoring (OFF) using world export supply (WES) as described above.

## 5.2 Estimation results

I first consider the relevance of the WES variable as instrument for OFF. The results of these first stage IV regressions are shown in Table 5.1. That is, the table basically show the results of regressing the endogenous offshoring measure on the exogenous instrumental variable and including firm scale controls. The difference between columns (1) and (2) is the inclusion of firm fixed effects. In this section of the paper, the results with firm fixed effects are generally the preferred specifications since relying on cross-sectional variation between firms may not be convincing due to the inherent and large natural differences among firms. Furthermore, as discussed in section 4.2, my identification strategy exploits variation within firms across years, and including firm fixed effects helps isolating the desired exogenous shocks to offshoring.

In all specifications, we see a clear rejection of the exclusion restriction for WES with F-statistics well above conventionally required levels. Thus, WES appears to be a valid instrument for OFF. We note that the coefficient on log(WES) is positive and significant, meaning that firms facing exogenously better conditions for importing intermediate inputs do indeed tend to engage more in offshoring. We further note that firms engaged more heavily in offshoring tend to have more employees and higher total sales (although the total capital stock does not appear significant in this respect).

Table 5.1: First-stage IV regressions

| | Log(Offshoring) | |
|---|---|---|
| | (1) | (2) |
| Log(WES) | 0.109*** | 0.110*** |
| | (0.00789) | (0.00910) |
| Log(Capital) | -0.0196 | 0.00310 |
| | (0.0136) | (0.0114) |
| Log(Employees) | -0.353*** | 0.238*** |
| | (0.0340) | (0.0339) |
| Log(Sales) | 1.518*** | 0.710*** |
| | (0.0309) | (0.0393) |
| Year FE | Yes | Yes |
| Industry FE | Yes | Yes |
| Firm FE | No | Yes |
| Observations | 30,871 | 30,871 |
| First stage F-statistic | 192.21 | 146.74 |

Dependent variable: Log(Offshoring). Sample period 1995-2008. Observations with RnD expenditures = 0 or RnD employees = 0 included. Standard errors in parentheses clustered at the firm level. *p<0.10, **p<0.05, ***p<0.01.

With the power of the instrumental variable WES confirmed, I now turn to answer the main question of complementarity or substitutability of offshoring and RnD at the firm level when RnD is measured as the number of RnD professionals employed. In Table 5.2, the first two columns show no connection between offshoring and RnD conditional on firm capital, employment and total sales levels (we note that firms with higher levels of capital, employment and total sales also tend to undertake more RnD). However, this changes once the IV strategy is implemented in columns (3)-(4). In the preferred specification (4) with both year, industry and firm fixed effects, we see a significantly positive effect with a one percent increase in offshoring activity leading to another 0.0068 RnD professional employed. This should be viewed in light of the vast heterogeneity in offshoring among firms in the sample. If one is willing to extrapolate from the regression results, a doubling of offshoring leads to 0.68 more RnD professionals, which corresponds to about 30 percent of the sample mean number of RnD professionals.

Table 5.2: OLS and IV regressions with RnD = professionals employed

| | OLS regressions | | IV regressions | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log(Offshoring) | -0.530 | -0.0433 | 1.598** | 0.680** |
| | (0.378) | (0.0481) | (0.623) | (0.275) |
| Log(Capital) | 0.893** | 0.291*** | 0.938*** | 0.288*** |
| | (0.352) | (0.0684) | (0.358) | (0.0680) |
| Log(Employees) | 1.649*** | 0.826*** | 2.400*** | 0.642*** |
| | (0.555) | (0.168) | (0.670) | (0.167) |
| Log(Sales) | 1.584* | 0.420** | -1.706* | -0.103 |
| | (0.839) | (0.196) | (1.022) | (0.299) |
| Year FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Firm FE | No | Yes | No | Yes |
| Observations | 30,871 | 30,871 | 30,871 | 30,871 |

Dependent variable: RnD professionals. Sample period 1995-2008. Observations with RnD employees = 0 included. Standard errors in parentheses clustered at the firm level. *p<0.10, **p<0.05, ***p<0.01.

Looking instead at internal RnD expenditures of the firm in Table 5.3, the picture emerging is more or less the same. While there is no significant effect of OFF in the OLS specifications, the coefficient jumps up and becomes significant at the 10 percent level once the instrument is applied and firm fixed effects are included. With this formulation, a doubling of offshoring activity leads to a 50 percent increase in internal RnD spending. Also, for both measures of RnD, the coefficient is well above the value of -1 required for offshoring-RnD complementarity as predicted in section 3.

Having established that increasing offshoring opportunities tend to cause firms to increase overall RnD activity, I now dig deeper and look at the composition of RnD activities. Specifically, I separate internal RnD spending into process and product RnD as reported by the firms. It should be noted that the data used for separating RnD spending into these two categories is much sparser and different from the dataset used in the above[9]. Therefore, the following results should be interpreted with caution.

Table 5.4 shows the result of regressing the share of internal RnD spending going to product RnD on offshoring and controlling for capital, employment and sales as before. Once the IV strategy is applied and firm fixed effects included, we

[9]More specifically, the sample is now limited to exporting, capital intensive firms with a larger number of employees in certain industries. The year 1995 is dropped as well.

Table 5.3: OLS and IV regressions with RnD = Log(total expenditures)

| | OLS regressions | | IV regressions | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log(Offshoring) | 0.0110 | 0.0469 | 0.230 | 0.501** |
| | (0.0187) | (0.0331) | (0.153) | (0.246) |
| Log(Capital) | 0.160*** | 0.142*** | 0.165*** | 0.140*** |
| | (0.0327) | (0.0370) | (0.0332) | (0.0371) |
| Log(Employees) | 0.831*** | 0.519*** | 0.909*** | 0.404*** |
| | (0.0658) | (0.0860) | (0.0859) | (0.108) |
| Log(Sales) | 0.349*** | 0.0758 | 0.0107 | -0.252 |
| | (0.0662) | (0.0664) | (0.241) | (0.184) |
| Year FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Firm FE | No | Yes | No | Yes |
| Observations | 30,871 | 30,871 | 30,871 | 30,871 |

Dependent variable: Log(Total internal RnD expenditures + 1). Sample period 1995-2008. Observations with RnD expenditures = 0 included. Standard errors in parentheses clustered at the firm level. *p<0.10, **p<0.05, ***p<0.01.

see a doubling of offshoring being associated with a 21 percentage point increase in the share of RnD spending going to product innovation. This should be seen in the light of a mean share of RnD spending going to product innovation of 54 percent.

These findings indicate that firms deciding to offshore an even larger part of their manufacturing activities in response to an exogenous shock to offshoring opportunities not only choose to increase their overall commitment to internal RnD. They also tend to reallocate RnD resources toward product RnD, possibly at the expense of less process RnD. This suggests that firms with less internal manufacturing activities have less of an incentive to internally perform RnD related to the production process. On the other hand, cheaper imported intermediate inputs now raise the potential profitability of new products, thus inducing firms to shift RnD focus in this direction.

## 5.3 Extensions

In this section, I examine the effects of offshoring on RnD when offshoring is split between different groups of countries. Table 5.5 show the results of this exercise when RnD is measured as the number of RnD professionals employed while Table

Table 5.4: Composition effects: product RnD (share)

| | OLS regressions | | IV regressions | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log(Offshoring) | -0.642 | -0.953 | 3.768 | 20.72* |
| | (0.766) | (1.778) | (3.843) | (11.69) |
| Log(Capital) | 0.540 | 5.048** | 0.672 | 5.781** |
| | (1.073) | (2.079) | (1.083) | (2.399) |
| Log(Employees) | -2.661 | 6.879 | -1.373 | 6.104 |
| | (2.079) | (5.514) | (2.444) | (6.298) |
| Log(Sales) | 7.892*** | -7.079* | 1.863 | -28.08** |
| | (2.071) | (4.092) | (5.683) | (11.34) |
| Year FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Firm FE | No | Yes | No | Yes |
| Observations | 2,790 | 2,790 | 2,790 | 2,790 |

Dependent variable: product innovation as share of all internal RnD. Sample period 1996-2008. Standard errors in parentheses clustered at the firm level. *p<0.10, **p<0.05, ***p<0.01.

5.6 measure RnD as internal expenditures. A full set of year, industry and firm fixed effects are included as in the preferred specifications above. In both tables, I distinguish between imports from China, all low-income countries, high-income countries, EU15 countries and OECD countries[10]. When considering China for example, only the total value of country-product combinations involving China are counted as imports for any firm, and the share weights will therefore also be positive only for these import categories when constructing the world export supply instrument used here.

The results generally show a negative or no effect when looking at offshoring from China or low-income countries. For the groups of high-income, EU15 and OECD countries, we generally see a positive effect from offshoring on domestic RnD activities.

To further shed light on these differences, I again look at the share of internal RnD expenditures going to product RnD (as opposed to process RnD). Table 5.7 indicates that the share going to product RnD tends to decrease when offshoring is going to China or low-income countries, whereas this share is unchanged when more advanced economies are the targets of offshoring[11].

[10] See Appendix B for details about this country split.

[11] The coefficients here are positive but not statistically significant. The data available for each group of countries is naturally more scarce than for the main results.

Table 5.5: Robustness IV analysis with RnD = professionals employed

| | China | All low-income countries | High-income countries | EU15 countries | OECD countries |
|---|---|---|---|---|---|
| Log(Offshoring) | 1.757 | 0.199 | 0.852*** | 1.109** | 0.614** |
| | (1.852) | (0.885) | (0.328) | (0.520) | (0.246) |
| Log(Capital) | 0.497 | 0.378*** | 0.361*** | 0.389*** | 0.328*** |
| | (0.375) | (0.145) | (0.0910) | (0.111) | (0.0799) |
| Log(Employees) | 2.233* | 1.239*** | 0.750*** | 0.708** | 0.731*** |
| | (1.219) | (0.436) | (0.241) | (0.325) | (0.201) |
| Log(Sales) | -0.425 | 0.444 | -0.0390 | 0.0411 | 0.0297 |
| | (0.931) | (0.642) | (0.356) | (0.476) | (0.302) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,294 | 7,683 | 23,308 | 19,547 | 27,230 |
| First stage F-statistic | 18.17 | 55.88 | 115.64 | 100.04 | 177.82 |

Dependent variable: RnD professionals. Log(Offshoring) instrumented using world export supply. Sample period 1995-2008. Observations with zero RnD employees included. Industry dummies are at the 2-digit NACE level. Standard errors in parentheses clustered at the firm level. See Appendix B for country group definitions. *p<0.10, **p<0.05, ***p<0.01.

Table 5.6: Robustness IV analysis with RnD = Log(total expenditures)

| | China | All low-income countries | High-income countries | EU15 countries | OECD countries |
|---|---|---|---|---|---|
| Log(Offshoring) | -0.895* | 0.0336 | 0.402* | 0.233 | 0.328 |
| | (0.494) | (0.397) | (0.241) | (0.315) | (0.215) |
| Log(Capital) | 0.145 | 0.0729 | 0.183*** | 0.149** | 0.155*** |
| | (0.117) | (0.0556) | (0.0491) | (0.0588) | (0.0437) |
| Log(Employees) | 0.874** | 0.265** | 0.490*** | 0.599*** | 0.488*** |
| | (0.363) | (0.130) | (0.141) | (0.164) | (0.125) |
| Log(Sales) | 0.412 | 0.116 | -0.156 | -0.0582 | -0.109 |
| | (0.320) | (0.290) | (0.183) | (0.225) | (0.161) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,294 | 7,683 | 23,308 | 19,547 | 27,230 |
| First stage F-statistic | 18.17 | 55.88 | 115.64 | 100.04 | 177.82 |

Dependent variable: Log(Total internal RnD expenditures + 1). Log(Offshoring) instrumented using world export supply. Sample period 1995-2008. Observations with zero RnD expenditures included. Industry dummies are at the 2-digit NACE level. Standard errors in parentheses clustered at the firm level. See Appendix B for country group definitions. *p<0.10, **p<0.05, ***p<0.01.

Taken together, these results suggest that firms offshoring to China or low-income countries in general may be motivated primarily by cutting costs, while firms offshoring to more advanced countries are more inclined to focus on increasing

Table 5.7: Robustness IV analysis: product RnD (share)

| | China | All low-income countries | High-income countries | EU15 countries | OECD countries |
|---|---|---|---|---|---|
| Log(Offshoring) | -22.25* | -7.130 | 10.53 | 14.45 | 16.13 |
| | (13.48) | (8.718) | (8.212) | (13.32) | (10.63) |
| Log(Capital) | -0.861 | 3.110 | 5.469** | 3.725 | 4.668** |
| | (8.218) | (6.315) | (2.272) | (2.379) | (2.296) |
| Log(Employees) | 21.63 | 14.95 | 8.255 | 7.748 | 6.206 |
| | (22.49) | (11.66) | (6.163) | (7.420) | (6.814) |
| Log(Sales) | -25.02 | -17.51 | -18.48** | -18.50** | -23.18** |
| | (16.15) | (11.49) | (7.195) | (8.778) | (9.268) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 266 | 677 | 2,607 | 2,444 | 2,727 |
| First stage F-statistic | 2.42 | 8.96 | 6.48 | 7.95 | 6.45 |

Dependent variable: Product innovation as share of all internal RnD. Log(Offshoring) instrumented using world export supply. Sample period 1996-2008. Industry dummies are at the 2-digit NACE level. Standard errors in parentheses clustered at the firm level. See Appendix B for country group definitions. *p<0.10, **p<0.05, ***p<0.01.

RnD activities in pursuit of developing new products. As such, this might indicate that firms indeed tend to react with different strategies as the cost of offshoring changes: some firms emphasize competing through cost-cutting by offshoring to low-cost countries. Other firms tend to attempt quality upgrading and developing new products by engaging in imports from more advanced economies.

# 6 Conclusion

Much concern has been raised recently by politicians and policymakers in industrialized countries as to whether domestic manufacturing activities is a prerequisite for more knowledge-based activities at home. Is offshoring complementary to or a substitute for RnD at the firm level? On the one hand, RnD and offshoring may be substitutes if the development of new products and processes is performed with better synergies when production is carried out at home next to the lab instead of abroad. On the other hand, relocating production to a foreign country may mean freeing up resources to increase RnD spending at home where the comparative advantage is present, thus rendering RnD and offshoring complements. The literature so far offers no clear, explicit answer to this empirical question.

This paper contributes by being one of the first to investigate the direct connection between offshoring and domestic RnD activities where the focus is an advanced economy. At the same time, by using rich firm-level data on both intermediate imports and domestic RnD while at the same time employing a clear identification strategy using an instrumental variable approach, this paper is able to provide a detailed and clean attempt to shed light on the issue.

The evidence reported in this paper suggests that firms facing an exogenous increase in offshoring opportunities respond by increasing their internal RnD expenditures and the number of RnD professionals employed. More specifically, a doubling of offshoring activity leads to a 50 percent increase in internal RnD expenditures. Likewise, the number of RnD professionals employed goes up by 0.68 persons every time offshoring is doubled. Furthermore, firms tend to increase the share of RnD expenditures going to product RnD, while the share to process RnD tends to decrease. This indicates that firms with less internal manufacturing activities have less of an incentive to internally perform RnD related to the production process. On the other hand, the greater scope for using imported intermediate inputs now raises the potential profitability of new products, thus inducing firms to shift RnD focus in this direction.

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# Appendix A

## Derivation of equation (3.3)

Rewrite equation (3.2) with $C \equiv (R^\rho + M^\rho)^{\frac{1}{\rho}} = \left(R^{\frac{\sigma-1}{\sigma}} + M^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$ for notational simplicity:

$$lnY = lnA + \alpha lnK + \beta lnL + \kappa lnC \tag{A.1}$$

We now want to show that $lnC \approx c_0 lnM + (1-c_0)\, lnR + c_1$. First, let $y = ln\left(M/R\right)$. Then $C = R\left(1+e^{y\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$ and $lnC = lnR + g(y)$, where $g(y) = \frac{\sigma}{\sigma-1} ln\left(1+e^{y\frac{\sigma-1}{\sigma}}\right)$. The first-order Taylor approximation for $g(y)$ around $y_0 = ln\left(M_0/R_0\right)$ is $g(y) \approx g(y_0) + g'(y_0)(y-y_0)$, where $g'(y_0) = e^{y\frac{\sigma-1}{\sigma}} / \left(1+e^{y\frac{\sigma-1}{\sigma}}\right)$. Replacing $g(y)$ with its first-order Taylor approximation, we get

$$\begin{aligned}
lnC &= lnR + g(y) \Rightarrow \\
lnC &\approx lnR + g(y_0) + g'(y_0)(y-y_0) \\
&= lnR + g(y_0) - g'(y_0)y_0 + g'(y_0)y \\
&= lnR + c_1 + c_0 ln\left(M/R\right) \\
&= (1-c_0)\, lnR + c_0 lnM + c_1
\end{aligned}$$

where $c_0 = g'(y_0)$ and $c_1 = g(y_0) - y_0 g'(y_0)$.

## Deriving the implied sign of $\sigma$

To derive the implied sign of $\sigma$, the elasticity of substitution between intermediate inputs and RnD, we use the fact that:

$$c_0 = g'(y_0) = \frac{e^{y_0\frac{\sigma-1}{\sigma}}}{e^{y_0\frac{\sigma-1}{\sigma}}+1}\ , \text{ with } y_0 = ln\left(\frac{M_0}{R_0}\right) \text{ being the point of linearization.}$$

Given estimates of the quantity $c_0/(c_0-1)$ from equation (3.4) (i.e. $\beta_3$ in equation (3.5)), we can arrive at a value for $\sigma$ using the following rewriting of the expression for ${}^{c_0}/_{(c_0-1)}$, denoted by $\eta$ below for simplicity:

$$\underbrace{\frac{c_0}{c_0-1}}_{\equiv\eta} = \frac{\frac{e^{y_0\frac{\sigma-1}{\sigma}}}{e^{y_0\frac{\sigma-1}{\sigma}}+1}}{\frac{e^{y_0\frac{\sigma-1}{\sigma}}}{e^{y_0\frac{\sigma-1}{\sigma}}+1}-1} = -e^{y_0\frac{\sigma-1}{\sigma}} \iff ln\left(-\eta\right) = y_0\frac{\sigma-1}{\sigma} \iff \sigma = \frac{y_0}{y_0 - ln\left(-\eta\right)} \ , \tag{A.2}$$

noting that, since from the definition of $c_0$ we can establish that $0 < c_0 < 1$, we have $\eta < 0$ so that logarithms can be taken on both sides.

In order to finally pin down the sign of $\sigma$, we need to ensure $\sigma \geq 0$ by assuming $y_0 > ln\left(-\eta\right) \iff {}^{M_0}/_{R_0} > -\eta$ , the plausibility of which is not explored further in this paper.[12] If this assumption holds, it is clear from inspecting the final equality in equation (A.2) that $\sigma < 1 \iff ln\left(-\eta\right) < 0 \iff -\eta < 1 \iff \eta > -1$ (it follows that $\sigma > 1 \iff \eta < -1$ and $\sigma = 1 \iff \eta = -1$).

In sum, RnD and offshoring activities are complements ($\sigma < 1$) if the coefficient resembling $\eta \equiv {}^{c_0}/_{(c_0-1)}$ is not too negative ($\eta > -1$). Importantly, this result is independent of the value of $y_0 = ln\left({}^{M_0}/_{R_0}\right)$(which otherwise might be measured using a set of values for $M_0$ and $R_0$ for the average or median firm, say).

# Appendix B

## Data appendix

*More on data sources*

The dataset employed covers the universe of Danish firms and the entire population of individuals in Denmark. Data is drawn from administrative registers in Statistics Denmark (DST) and combines firm data from the Firm Statistics Register (FirmStat) and worker data from the Integrated Database for Labor Market Research (IDA). Data on import and export flows comes from the Danish Foreign Trade Statistics Register and is at the product and origin or destination level. This data is combined with the COMTRADE database to obtain data used for

[12]If $y_0 < ln\left(-\eta\right)$, then $\sigma < 0$ for all $y_0 > 0$ which must be ruled out. Whether $y_0 \equiv ln\left(\frac{M_0}{R_0}\right) > 0$ holds or not depends on the ratio of imports and RnD inputs. To have greater imports than RnD inputs may be reasonable for many globalized firms.

preparing the instrumental variable. See also the data section of Hummels *et al.* (2014) for further details of the data, including the data used to construct the world export supply instrumental variable.

The datasets are merged using the CVRNR variable. Only observations with non-missing values of CVRNR in the merged dataset were kept. All firm-year duplicate observations were dropped (except for the first instance). Only firms classified as manufacturing firms (i.e. NACE03 in [150000-4000000]) were kept. The nomenclature for the NACE03 industry variable changes and must therefore be linked across time. The variable adheres to the following nomenclatures in the period: 1995: DB93, 1st revision; 1997-2002: DB93, 2nd revision; 2003-2008: DB03; 2009: DB07. I link DB93,1 to DB93,2 via the key provided in Statistics Denmark (1996). I then use keys provided from Statistics Denmark to link DB93,2 and DB07 to DB03 which builds on and corresponds closely to the NACE 2003 nomenclature.

For the analysis of composition effects between product and process RnD (Table 5.4), the sample is further limited to exporting firms with a capital stock greater than the median and a number of employees greater than the 25th percentile. The year 1995 is dropped and firms in the wood, paper, publishing, mineral processing, misc. metal, misc. electronics, transportation equipment, and recycling plants industries (NACE03 codes 20, 21, 22, 23, 28, 31, 35 and 37) are dropped.

*On the definition of RnD workers using occupational codes (*ISCO4d*)*

Following Kaiser *et al.* (2013), I define RnD workers as employees with either a BA, KA or PhD degree in the technical or natural sciences working in an occupation concerned with RnD. Educational levels are measured using the variable HFFSP (highest level of educational attainment). Our occupational variable ISCO4D is based on the DISCO88 nomenclature from DST (documentation here: http://www.dst.dk/da/Statistik/dokumentation/Nomenklaturer/DISCO-88/Stillingsbeskrivelser.aspx). The first digit of the ISCO4D variable classifies occupations according to their knowledge content. Individuals who "increase the existing stock of knowledge, apply scientific or artistic concepts and theories, teach about the foregoing in a systematic manner, or engage in any combination of these three activities" (category 2) are denoted RnD professionals. Workers categorized as technicians and associate professionals (category 3) are more likely to use already existing knowledge and are counted as RnD support workers.

*More on RnD data*[13]

RnD data from 2007 and onwards is collected by Statistics Denmark. First, a target population of around 20,000 firms is chosen (the number of employees in the target population corresponds to about 66% of the total number of private sector full-time employed). Then, a stratified sample based on industry and number of employees is chosen with the addition of pre-sampled firms to ensure that the most important firms are included (with respect to size and RnD activity). In 2010, the total number of firms sampled was 4,797. This is the number of firms in the raw dataset. The RnD data is collected through electronic or paper forms which are mandatory for the firms to fill in (for the years 2007-2010 only.

For the years prior to 2007, the data was collected by "Center for Forskningsanalyse" and answering was voluntary for the firms. In the transition from 2006-2007 with reporting now made mandatory, Statistics Denmark make the following points. First, it is believed that more firms now report even though the do not have RnD which tends to lower average RnD. Second, large firms with a lot of RnD now also report because they have to and they did not do it earlier because finding out the numbers is complex and costly. In general, RnD increased 2006-2007 but not with a statistically significant amount.

There is a considerable amount of missing observations for the RnD expenditure variable (named U_TOTAL) in several years both before and after 2007. However, investigation indicates that this variable is often zero for the same firm in other years which suggests that the missing observation could be regarded instead as a value of zero. I therefore choose to set missing values of the RnD expenditure variable to zero.

*Country groups (used in section 5.3)*

High-income countries are defined as the United States, Japan and EU15 countries. OECD countries include all OECD member countries as per 1995. Following Ashournia *et al.* (2014), I identify low-income countries using the 1989 World Bank definitions and including Central and Eastern European countries (CEEC) according to the following list.

Low-income countries: Afghanistan, Albania, Angola, Armenia, Azerbaijan, Bangladesh, Benin, Bhutan, Bulgaria, Burkina Faso, Burundi, Burma, Cambodia, Central African Republic, Chad, Czech Republic, Comoros, Republic of the Congo, Cyprus,

[13] See also Statistics Denmark (2011).

Equatorial Guinea, Eritrea, Estonia, Ethiopia, The Gambia, Georgia, Ghana, Guinea, Guinea-Bissau, Guyana, Haiti, Hungary, India, Kenya, Laos, Latvia, Lesotho, Lithuania, Madagascar, Maldives, Mali, Malawi, Malta, Mauritania, Moldova, Mozambique, Nepal, Niger, Pakistan, Poland, Romania, Rwanda, Saint Vincent and the Grenadines, Samoa, Sao Tome and Principe, Sierra Leone, Slovakia, Slovenia, Somalia, Sri Lanka, Sudan, Togo, Uganda, Vietnam, Yemen.

# Chapter 2

## Globalization and CEO Pay: Estimating the Value of Good Leaders in Complex Firms

# Globalization and CEO Pay: Estimating the Value of Good Leaders in Complex Firms

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**Abstract**

Much attention has been given to increasing income shares of top income earners in many advanced economies, particularly in the U.S. This increase is partly driven by so-called 'supermanagers', the chief executive officers (CEOs) of the largest firms. In this paper, we identify CEOs from linked employer-employee data for Denmark for the period 1995-2008 and construct firm complexity measures related to globalization. We document novel stylized facts about globalization and CEO compensation. We investigate whether the rise in CEO compensation can be explained by increasing firm-level globalization and find that changes in the export volume correlates with changes in CEO compensation, while firm complexity measures play a minor role. This pattern persists when conditioning on firm size. Firm exports are then instrumented with world import demand in order to identify the causal impact of exports on CEO earnings. Our results indicate that if the median firm doubles its exports for exogenous reasons, then the relative earnings of its CEO increases by 18% from 3.5 to 4.1 times the income of the average worker in the firm. Finally, we find suggestive evidence in favor of the hypothesis that externally hired CEOs are less likely to be rewarded for exogenous changes in exports than internally hired CEOs.

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# 1 Introduction

The effects of globalization on the distribution of income have traditionally been at the core of international trade theory. The literature has usually been concerned with the relative pay to different production factors, skill groups, or other aggregate quantities. Recently however, much attention has been given to the very top of the income distribution. The economic significance of this rather narrow group of individuals (the 'top one percent' being a notable example) should not be understated: In 2012, the share of total market income (including capital gains, excluding government transfers) earned by individuals in the top percentile of the income distribution in the U.S. was around 22.5 percent (Piketty and Saez (2003) and Piketty (2014)). Atkinson and Søgaard (2015) report top 1 percent income shares over time for a number of countries including Denmark and show that all countries have exhibited increasing top income shares since the 1980s albeit not with such a dramatic pace as in the U.S.

A large part of these top income earners have been found to consist of the CEOs of the top firms, or 'supermanagers'. From a market-based perspective, the increase in relative and absolute pay to these individuals must stem from changes in the supply and demand structure in the market for managerial talent. For example Murphy and Zábojník (2004) argue that general managerial skills have become more important relative to firm-specific managerial skills, which is consistent with improving outside options for CEOs and that CEO openings increasingly are filled through external hires rather than through internal promotions. Since these changes have occurred at the same time as what is normally perceived as a vast increase in globalization, it becomes natural to ask what, if any, connection there may be between these two phenomena.

Using matched worker-firm data for Denmark for the period 1995-2008 we identify CEOs and construct firm complexity measures related to globalization. We document novel stylized facts about globalization and CEO compensation. Among other things, newly hired CEOs broaden the export portfolio and increase the occupational complexity of the firm. We then show that changes in the export volume correlates with changes in CEO compensation, while firm complexity measures play a minor role. This pattern persists when conditioning on firm size. Firm exports are instrumented with world import demand in order to identify the causal impact of exports on CEO earnings. Our results indicate that if the median firm doubles its exports for exogenous reasons, then the relative earnings of its CEO increases by 18% from 3.5 to 4.1 times the income of the average worker in the firm. This increase in relative earnings is not followed by increases in the absolute wages of CEOs. One potential reason may be that the scale and composition of workers in the firm change within the CEO job spell as exports rise.

This paper adds to the literature by exploring a rich dataset on firms and employees in the context of top income earners and firm-level globalization. Data on CEOs and top managers in Danish firms have previously been used for other purposes as in Bennedsen *et al.* (2007) and Smith *et al.* (2013), but the link to firm exports and related activities is novel.

Several explanations have been proposed for the rising top income shares with the most prominent being principal-agent mechanisms, rent extraction and market-based explanations. According to the principal-agent view shareholders of a firm delegate control of a firm to a CEO, where the agency problem is resolved through an incentive contract that relates pay to firm performance. Because CEO compensation increasingly has been linked to firm performance one would expect to see a rise in CEO effort and pay to compensate for the increasing risks taken on. This view has been criticized by several authors. For example, Bertrand and Mullainathan (2001) argue that according to the principal-agent theory one should not be able to find a relationship between CEO pay and the components of firm performance that are not related to CEO effort. They document a strong correlation between oil prices and performance of large U.S. oil companies and find that CEO pay is equally sensitive to overall firm performance and the component of firm performance that is purely driven by oil prices. This may be taken as evidence that CEOs are not only paid for effort but also for luck.

The rent extraction view on CEO compensation holds that contracts are not decided by boards or shareholders but instead set by the CEOs themselves to maximize their own rents. Bertrand and Mullainathan (2001) provide some evidence consistent with this view as better governed oil companies pay their CEOs less for luck. On the other hand, the rent extraction view has also been questioned on the grounds that CEOs should have been interested in extracting rents always, so rent extraction is unable to explain the recent surge in CEO compensation (Murphy and Zábojník (2004)).

As mentioned above, Murphy and Zábojník (2004) propose a market-based explanation behind the rising top income share relying on increasing importance of general managerial skills. Gabaix and Landier (2008) analyze a competitive assignment model where CEOs are heterogeneous in their talents. Talent is more valuable in large firms and so the most talented CEOs are assigned to the largest firms. As a result CEO compensation rises with firm size. Gabaix and Landier (2008) show that the increase in CEO pay in the U.S. since 1980 can be fully attributed to the corresponding growth in firm size. However, the Gabaix and Landier (2008) model has also been criticized for not fitting the data well before 1980 and for being sensitive to sample selection and variable definition issues (Bertrand (2009)).

A small number of papers link increased globalization to the market-based explanations behind rising CEO pay. Marin and Verdier (2012) set up a theoretical model to show that increasing international trade leads foreign firms to enter a war for managerial talent, which in turn puts upward pressure on compensation. Cunat and Guadalupe (2009) use data for a panel of U.S. firms and find that import competition increases the sensitivity of pay to performance and that CEOs experience the largest pay increases in the management team. Chakraborty and Raveh (2015) study managerial wages in a developing country, India, and find that input tariff liberalization increases the compensation share of managers via imports-triggered quality upgrading.

Guadalupe and Wulf (2010) consider a sample of 230 large U.S. manufacturing firms and find that trade liberalization and increased import competition induces firms to remove layers between the CEO and division managers, to increase the number of positions that report directly to the CEO, and that the opportunity to sell in more markets may lead to more management layers (although this finding is weaker). Related to this, Caliendo and Rossi-Hansberg (2012) set up a theoretical model assuming that firms are organized in layers and show that trade liberalization leads expanding exporters to add layers if the expansion is large enough. Caliendo *et al.* (2015) use French firm level data which allows them to distinguish three layers of management (supervisors, senior staff and CEOs), clerks and production workers. They then find that expanding firms reorganize by adding layers, pay the new top manager more and reduce wages in existing layers. They also find that firms who start exporting are more likely to reorganize than domestic firms, and new exporters that add layers decrease wages in existing layers. These results are broadly consistent with the view that general managerial skills become more valuable due to increased firm complexity when firms expand.

Finally, Ma (2015) builds a Melitz (2003)-type model with individuals heterogeneous in human capital endowments choosing career paths as either workers or CEOs. The human capital of a CEO translates directly into the productivity of the firm. In equilibrium, the most productive individuals become CEOs of the most productive firms. Since these firms are also top exporters, they make the highest profits and subsequently pay their CEOs relatively more than less exporting or domestic-only firms. He then uses a new dataset on U.S. firms covering around half of firms required to report executive compensation to show that the CEO-to-worker pay ratio within exporters is more than 40% higher than in domestic firms. However, once firm size is controlled for, the difference in CEO-to-worker pay ratio between exporters and non-exporters vanishes. Ma (2015) supplements the analysis with a calibration exercise for the U.S. economy to examine influence of globalization on top income shares with simulations. It is found that globalization can potentially explain around half of the observed surge in top income shares in the U.S. between 1988 and 2008.

The literature is still silent about the exact mechanism behind the relationship between firm-level export activity, firm complexity and CEO compensation as no study uses exogenous variation in the data to pin down possible channels at work. We first provide a set of stylized facts for Danish exporters and compensation of their CEOs. We then move on to identify exogenous shocks that lead to increased exports and examine the implication for CEO pay.

The paper is organized as follows. Section 2 describes the matched worker-firm data, how we identify managers and construct our instrument. Section 3 describes some overall patterns for CEO and firm characteristics. Section 4 presents stylized facts on globalization and CEO compensation. Section 5 examines in more detail the relationship between firm-level globalization, complexity and CEO compensation. Section 6 concludes.

# 2 Data

In this section we explain our data sources, how CEOs are defined and how we construct various firm complexity measures related to globalization. We also define an instrumental variable for firm exports, which we use to estimate the causal impact of exports on CEO compensation.

## 2.1 Data sources

The dataset employed covers the universe of Danish firms and the entire population of individuals in Denmark for the years 1995-2008. Data is drawn from administrative registers in Statistics Denmark and combines firm data from the Firm Statistics Register (FirmStat) and worker data from the Integrated Database for Labor Market Research (IDA). We use the so-called FIDA link to match workers to firms using the workers' main employment relationships. From IDA we obtain information on several individual characteristics such as education, occupation and annual labor market income. From FirmStat we use information about industry codes (NACE six digit), number of full time employees and total sales, and from the Account Statistics Register we read the value of the firms' capital stock.

The data on CEOs in Danish firms (PERSBEST) comes from administrative data collected by the Danish Business Authority (Ervhervs- og Selskabsstyrelsen) and requires all firms to report, among other things, which individuals are members of the board or management of the firm. From this file we select all records where the individual is a member of a firm's management and match them via the person and firm identifier to the matched worker-firm data set. Firms may have several managers, but in our baseline specification we retain only the top manager using the following algorithm: For the first year a firm is observed, we pick the highest earning manager as CEO. The CEO status is retained as long as that individual stays in the firm without breaks, regardless of whether that individual continues to be the top earner or not. If the individual is not observed in a year, the top earner in that year is selected as CEO and retains CEO status in subsequent years unless there is a new break etc. We provide some summary statistics for this in the next section.

As an alternative definition of CEOs we use occupational codes based on the ISCO88 nomenclature. Attention is limited to workers in the occupational category 'management at the highest level' (one-digit category 1). Again there may be more than one person with these occupation codes in a firm. If so, we pick the highest earning manager using the same algorithm as above.

Data on firm-level trade flows broken down by eight-digit product codes (CN8) and origin or destination countries comes from the Danish Foreign Trade Statistics Register. These data allow us to define a number of firm-level globalization variables of interest. First, our main variable of interest is the total value of exports of goods across destinations and product categories for each firm-year combination. As a measure for the complexity of the firm we also define variables measuring the number of export markets served by a firm and the number of unique HS8 products exported in a given firm-year combination. Finally, using the matched worker-firm data, we construct a variable measuring number of unique four-digit ISCO88 codes present in a given firm in a given year.

We restrict the sample to large (in a Danish context) exporting firms in the manufacturing sector for the following reasons: Most of the analysis is concerned with the intensive margin of exporting using within-firm time variation in export volumes and so attention is limited to exporters. To avoid irregularities associated with small firms, we restrict the sample to firms with more than 50 employees. After cleaning the data and imposing these restrictions, we are left with a panel of 8,607 CEO-year observations spanning 1,621 firms and 2,402 different CEOs over the 14-year period 1995 to 2008.

## 2.2 Construction of Instrumental Variable

Examination of the link between firm-level exports and CEO compensation is challenged by the fact that firm-level exports are endogenous. One type of endogeneity relates to the idea that high-ability managers make their firms more productive and raise exports. If high-ability managers also tend to get paid well, this induces a correlation between unobserved manager ability and firm exports. This type of endogeneity is alleviated by including CEO-firm fixed effects in our analysis.

Another type of endogeneity relates to unobserved firm-level shocks more generally affecting both firm exports and CEO pay. Consider for example a shock to prices or technology causing firm costs to go down. This improved competitiveness may cause the firm to expand operations both domestically and abroad, thus raising exports. At the same time, there is now more surplus to bargain over between the firm and the CEO, possibly causing CEO pay to increase as well. To confront such types of endogeneity problems, we pursue an IV identification strategy as in Hummels *et al.* (2014) and use world import demand (WID) as instrument for firm exports.

The instrument is defined in the following way. We use the COMTRADE database to get the import demand of country $c$ of product $k$ at time $t$ from the rest of the world except Denmark, $WID_{ckt}$. We aggregate these product-country specific world import demands to the firm level by weighting with the presample shares of firm $j$'s products in the total exports of the firm. That is, the instrument for firm $j$ at time $t$ is $I_{jt} = \sum_{c,k} s_{jck} WID_{ckt}$, where $s_{jck}$ is the share of product $k$ exported to country $c$ in total exports for firm $j$ in the presample year , 1995.

This instrument exploits heterogeneity across firms in their initial product-level export mix. Hummels *et al.* (2014) show that the initial product-country export mix of a firm is fairly stable over time and that Danish firms have only few product-country exports in common. This means that time changes in world import demand at the product-country level will affect firms differently. For example, exogenous changes in an importing country's production costs or consumer demand will be reflected in changing imports from the world as a whole by that country, and so a Danish firm that exports to this country more than others will benefit disproportionately from these changes.

# 3 CEO and Firm Characteristics

In this section we provide descriptive statistics for the data on CEOs and their firms. As mentioned in the previous section, some firms have several managers, but of all the firm-year observations, 78% are recorded with only one manager. Unsurprisingly, there is a clear positive relationship between the number of managers and the number of employees. For example the average size of firms with only one manager is 185 employees, while the average size of firms with 5 managers is 1364 employees. However, among managers in multi-manager firms the difference in annual income of the top earner (the CEO) and other managers is modest. For the median multi-manager firm the CEO earns 20% more than other managers and this premium is fairly stable over time. In the following we restrict attention to CEOs such that we have one observation per firm-year.

The average earnings of the CEOs in the sample is slightly more than one million DKK in 2000 prices (corresponding to about 165,000 USD), see Table 1. This amounts to 3.5 times the income of the average worker in the firm, which is much lower than what is documented in U.S. data. For the largest firms with at least 500 employees, average CEO earnings almost two million DKK or about 290,000 USD, while this corresponds to 4.8 times the income of the average worker in the firm. Frydman and Saks (2010) report that by 2005 the ratio of top manager pay to that of average worker earnings was as much as 110 times higher, while in the 1970s it was considerably lower at 30 but still much higher than in our data. Several factors may explain these differences. First, low-paid workers earn considerably more in the Danish labor market due to stronger influence by unions in wage formation. As a result, the income of the average worker is higher. Second, components of CEO pay such as stock options and fringe benefits are not captured by our earnings measure.

Two thirds of the CEOs in the sample have a college degree, see Table 1. The average CEO is around 50 years of age with 23 years of labor market experience of which almost 8 years have been spent in the current firm. Restricting attention to job spells as a CEO in a given firm, the duration is shorter. For the 2,656 CEO job spells in the data, 28% last only one year with a median spell duration of three years and an average duration of 3.5 years. Only 1.9% of the CEOs are women, and this rate has been fairly stable over the sample period. This gender composition is roughly in accordance with the female share reported from U.S. firms (Bertrand (2009)).

The occupation is observed for most of the CEOs, and as expected most (78%) are assigned the one-digit ISCO88 classification for managers. One reason why 22% are not managers according to the occupation code could be measurement error. It is well known that occupation codes in administrative data may show persistence in the sense that firms tend to report the same code for each employee even if the employee is assigned new tasks. Related to this, 73% of CEOs are promoted internally. The tendency to hire CEOs from internal candidates is interesting in light of the market-based explanation behind rising CEO compensation mentioned in the introduction. Murphy and Zábojník (2004) report that the 14.9% of newly appointed CEOs of large U.S. firms were recruited from other firms in the 1970, while this rate increased to 17.2% in the 1980s and 26.5% in the 1990s. This can be interpreted as reflecting an increasing importance of general skills versus firm-specific skills. When firm-specific skills decline in importance external candidates increasingly should be considered, and as a result a larger market for CEOs emerge. The number reported from the 1990s in the U.S. data is in line with the 27% of the CEOs being hired from outside in our data. However, there is no clear time trend in the rate of externally hired CEOs from 1995 and onwards in our data.

The firms in the sample are export oriented with 48% of the sales shipped to markets abroad. This rate has increased from 44% in 1995 to 49% in 2008. We are interested in ways to measure firm complexity because more complex firms may be more difficult to manage and require more talented CEOs. To this end, we define two 'international' complexity measures: the diversity of products exported and the number of export destination markets serviced. The number of products is the total number of unique CN8 product categories exported for each firm-year combination. The number of export destinations is the total number of unique export destinations for each firm-year combination. We also employ two 'domestic' complexity measures: the number of four-digit occupations and the share of workers with a college degree employed for a given firm. The international complexity measures show a clear rising trend over the sample period, see Figure 1. By contrast, the number of occupations in the firms shows a somewhat declining trend, which could be a reflection of the finding in Guadalupe and Wulf (2010), where firms are flattening their organizational structure in response to globalization and increasing product market competition.

To examine whether hiring a new CEO is correlated with changed activities in the firm, we run the following regressions: We take either a dummy for increasing the number of exported products, a dummy for increasing the number of destination markets, or a dummy for increasing the number of occupations in the firm between year t-1 and year t, year t and year t+1 or year t+1 and year t+2 and regress on a dummy for hiring a new CEO in year t, see Table 2. In all cases there is a clear negative correlation between hiring a new CEO in year t and adding products, markets or occupations in year 1. However in year t+1 the correlation turns positive and this holds in year t+2 for adding products as well. This indicates that firms are undergoing a transformation and that new CEOs manage to add to the export portfolio and to increase the occupational complexity of the firm.

# 4 Stylized Facts About Globalization and CEO Compensation

In this section we show some partial correlations between CEO earnings and firm exports and firm complexity measures. We separate our results into two categories based on whether the measure of CEO earnings is in absolute or relative terms. If changes within the firm are believed to be tied to changing 'economies of superstars', we would expect to see increases in both absolute and relative CEO pay since the CEO belongs to a particular group of workers. On the other hand, if CEO wages reflect the general wage trend in the firm, we would expect CEO relative to average worker earnings to remain constant while absolute CEO pay is changing. Note that this implicitly assumes a constant number of workers of various wage levels in the firm. If changes in the environment of the firm means that e.g. the lower paid workers are laid off to reduce the total employment in the firm, lower relative CEO earnings may result even with rising absolute CEO wages and constant wages among the remaining employees.

Table 3 displays coefficient estimates from regressions of CEO earnings (the top panel) or CEO earnings relative to the average worker's earnings (the bottom panel) on export and complexity variables. Firms that export more and have more complex exports as measured by the number of exported products and destinations pay their CEOs more as seen from the coefficients in the first column. Likewise, firms with more occupations and a higher share of high skilled workers compensate CEOs better. Some of this may reflect the fact that larger firms pay higher wages. In the second column we control for the number of workers employed by the firm and total firm sales. The correlations are weaker but still significantly positive. In the third column we include CEO-firm fixed effects (but leave out firm size controls) such that only time variation within CEO job spells is used to identify the correlation. In this case, only exports and the number of occupations show a significant positive correlation. In the last column we also include firm size controls and here only exports correlate with relative CEO earnings.

To better understand which export and complexity variables drive CEO compensation, we include in Table 4 all variables in fixed effects regressions. It is evident that the export volume is the more important factor as all the firm size and complexity variables enter with an insignificant effect while the export volume remains significant in three of four specifications. This means that even relying only on time variation within CEO-firm job spells and controlling for firm size and firm complexity there is a positive correlation between exports and CEO compensation measured in levels or relative to average worker earnings.

Note that most of the control variables included in Table 4 capture variation related to both the scale of the firm and the composition of its activities. For example, the number of products sold can be decomposed into total sales and the number of products per dollar sold. To capture which components drive CEO compensation, we group the variables into scale and composition variables and into input and output variables.

In Table 5 we examine variables measuring firm output activities. The first column is a benchmark case, where exports and sales are included. For both earnings measures exports correlate positively but sales enter with opposite signs suggesting that higher sales increases compensation of CEOs but more so for the average worker. In column (2) we enter the number of products instead of sales and in column (3) we decompose the number of products into sales and the number of products per dollar sold. It is clear that sales it the primary driver of CEO compensation when measured against the number of products exported. In columns (4) and (5) we do the same exercise for the number of export destinations with the same result. In columns (6) and (7) we decompose exports into sales and the export intensity. For CEO compensation measured in levels we find that both sales and its composition in domestic vs. foreign sales matter such that more export intensive firms pay higher CEO salaries. For CEO earnings measured relative to the earnings of the average worker the picture is different as sales reduce relative earnings while the export intensity raises relative CEO earnings.

Taken at face value, these results suggest that while CEOs may be hired to manage complex firm output environments and paid accordingly, changes in CEO salary within the current job spell hinges much more on the ability of the CEO to deliver increased firm scale via higher sales, whereas changes in the CEO's 'span of control' through changes in firm scope only does little to affect the payment received within the tenure period.

In Table 6 we examine variables measuring firm input activities. Column (1) has exports and the number of employees in the firm as a benchmark. The top panel shows that exports and the number of employees have a positive correlation with CEO earnings, while the bottom panel shows that only the number of employees boosts earnings of CEOs relative to the average worker. In columns (2) and (3) we first enter the number of high skilled workers and then this variable's two components, the total number workers and the share of high skilled workers. It is clear that the important driver behind CEO compensation here is the total number of employees. Columns (4) and (5) decomposes the number of occupations in the firm (column (4)) into its components, the total number of employees and the number of occupations per worker (column (5)). The same picture emerges as the total number of workers appear to be the main driver behind CEO compensation.

To summarize, this section has documented that changes in the export volume correlates with changes in CEO compensation, while firm complexity measures play a minor role. Total sales and the number of employees also correlate with CEO compensation, but when controlling for firm size there still appears to be an effect of exports on CEO compensation although the correlation is weaker. This raises the question whether one should control for firm size variables in estimations of the causal impact of exports on CEO earnings. The last column of Table 5 suggests that holding sales constant there could still be an effect of a higher export intensity on CEO earnings. On the other hand, an exogenous rise in exports could increase sales (and other firm-level variables) and therefore CEO earnings. In the following we turn to estimation of the causal impact of exports on CEO earnings with and without firm controls.

# 5 Are CEOs rewarded for Luck in Export Markets?

So far we have relied on time variation within job spells to estimate correlations between exports, firm activities and CEO compensation. However, these relationships may suffer from endogeneity bias as for example unobserved productivity or demand shocks to firms may drive both exports and CEO earnings. In this section we rely on exogenous shocks to firm-level exports to estimate the causal effect of exports on CEO compensation. We will employ the world import demand instrument described in Section 2.2 in a first stage regression. In the second stage we follow the literature (e.g. Hummels *et al.* (2014) and Munch and Skaksen (2008)) and estimate individual level Mincer earnings regressions of the form

$$log\,(Y_{ijt}) = \beta_1 log\,(EXP_{jt}) + \beta_2 x_{it} + \beta_3 z_{jt} + \varphi_{IND,t} + \alpha_{ij} + \varepsilon_{ijt}\ , \tag{5.1}$$

where $Y_{ijt}$ is the CEO earnings measure of CEO $i$ in firm $j$ at time $t$. We use either CEO earnings in levels or relative to the average worker in the firm. $EXP_{jt}$ is firm $j$'s total exports at time $t$, $x_{it}$ captures CEO control variables (labor market experience and experience squared), and $z_{jt}$ contains firm-level variables. As mentioned above we will estimate versions of equation (5.1) with and without these firm controls. $\varphi_{IND,t}$ denotes industry-year fixed effects while $\alpha_{ij}$ represents CEO-firm fixed effects. Including CEO-firm fixed effects means that we only rely on time variation within CEO job spells to identify the coefficient of interest,

$\beta_1$.

We report the results from the first stage regressions in Table 7. The first two columns show the specifications fitting exports with and without the firm control variables. As predicted, the world import demand instrument enters in both cases with a positive sign and it explains a sufficiently large portion of the variation in exports as indicated by the F-statistic. In the third column we directly instrument total sales with the world import demand variable. The idea is that exogenous export shocks ultimately may increase sales. Again, the instrument enters with the predicted sign and an F-statistic suggesting it is not a weak instrument.

Table 8 reports the results from the second stage IV regressions using CEO earnings in levels in the first three columns and CEO relative earnings in the last three columns. Instrumented exports and sales enter with positive signs in all specifications, but they are only significant for relative earnings. For example the coefficient estimate of column (4) means that if the median firm doubles its exports for exogenous reasons then the relative earnings of its CEO increases by 18% from 3.5 to 4.1 times the income of the average worker in the firm. It may seem difficult to explain how exports can raise CEO earnings relative to earnings of the average worker, while CEO earnings in levels are unaffected. One potential reason may be that the scale and composition of workers in the firm change within the CEO job spell as exports rise.

As an extension we next investigate if exports affect CEOs differently depending on whether they are internally promoted or hired from the outside. As mentioned previously, the market based explanation behind rising CEO pay suggests a declining role of firm-specific skills such that candidates increasingly should be hired from outside the firm, where wages better reflect ability and talent. In our context this would mean that externally hired CEOs should be less likely to be rewarded for exogenous changes in exports than internally hired CEOs, since exogenous export shocks are unrelated to CEO ability.

We examine this hypothesis in Table 9 by interacting exports or total sales with a dummy variable taking the value one if the CEO is internally promoted. The first four columns show results for the CEO earnings measured in levels, while the last four columns employ the relative CEO earnings measure. We report results from fixed effects regressions using non-instrumented exports or total sales and from fixed effects regressions using instrumented exports or instrumented total sales. Again we do not find any significant effects when CEO earnings are measured in levels. Using the relative CEO earnings measure we find some suggestive evidence in support of the hypothesis as the interaction between (non-instrumented) exports and the promotion dummy enters with a positive sign in column (5). Likewise, the interaction term between sales and the promotion dummy has a positive effect in column (6). However, when we use predicted exporting and sales from the first stage regressions there are no longer any significant effects of increased exports or sales.

As a final exercise we use the alternative definition of CEOs, which is based on the one-digit occupation code classification of managers, see Table 10. We report both FE and FE-IV results for CEO earnings in levels and relative to earnings of the average workers. However, in no cases do exports correlate with CEO earnings or relative CEO earnings. This may indicate that the occupational variable is not precise enough to define who is in charge of the firm.

# 6 Conclusions

Much attention has been given to increasing income shares of top income earners in many advanced economies, particularly in the U.S. This increase is partly driven by so-called ‘supermanagers’, the chief executive officers (CEOs) of the largest firms. In this paper, we identify CEOs from matched worker-firm data for Denmark for the period 1995-2008 and construct firm complexity measures related to globalization. We document some novel stylized facts about globalization and CEO compensation. Among other things, newly hired CEOs generally manage to add to the export portfolio and increase the occupational complexity of the firm.

We then investigate whether the rise in CEO compensation can be explained by increasing firm-level globalization. We find that changes in the export volume correlates with changes in CEO compensation, while firm complexity measures play a minor role. Total sales and the number of employees also correlate with CEO compensation, but when controlling for firm size there still appears to be an effect of exports on CEO compensation although the correlation is weaker.

Firm exports are instrumented with world import demand in order to identify the causal impact of exports on CEO earnings. Our results indicate that if the median firm doubles its exports for exogenous reasons, then the relative earnings of its CEO increases by 18% from 3.5 to 4.1 times the income of the average worker in the firm. This increase in relative earnings is not followed by increases in the absolute wages of CEOs. One potential reason may be that the scale and composition of workers in the firm change within the CEO job spell as exports rise.

Finally, we relate our results to the idea that an increasing role for general managerial skills at the expense of firm-specific skills should increasingly attract candidates for CEO positions from the outside where wages better reflect ability and talent. This implies that externally hired CEOs should be less likely to be rewarded for exogenous changes in exports than internally hired CEOs, since exogenous export shocks are unrelated to CEO ability. We find some suggestive evidence in favor of this hypothesis when again looking at relative earnings.

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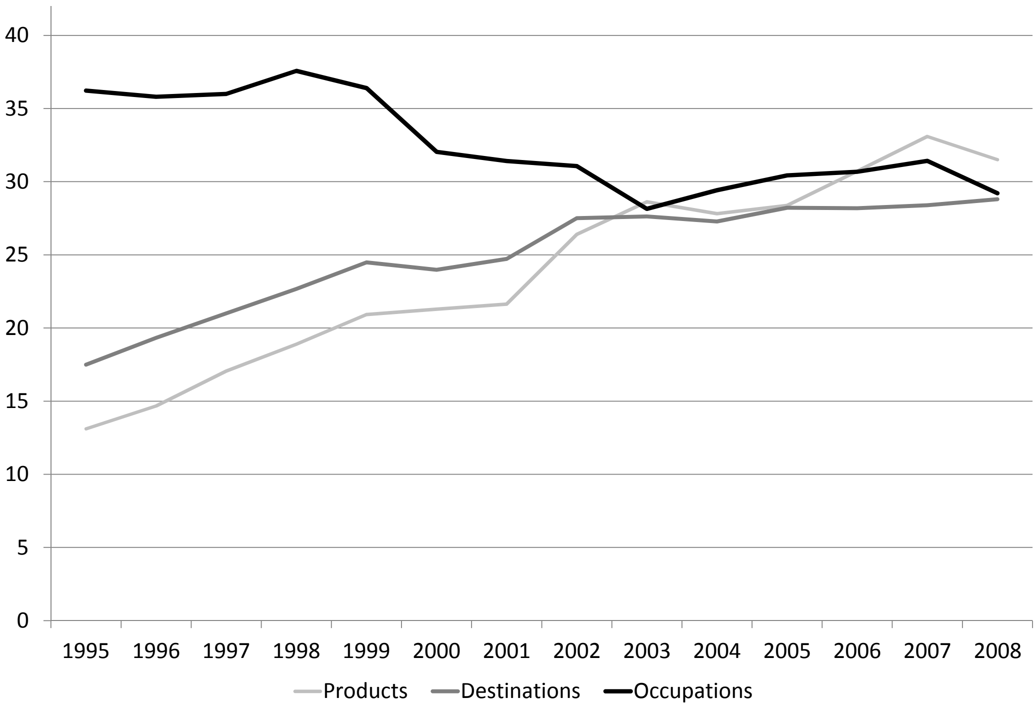
# Appendix: Tables and Figures

Figure 1: Firm complexity measures, 1995-2008




*Notes:* The figure shows the evolution of the yearly average for each of the firm complexity measures included over the sample period 1995-2008. The average is calculated across firms in each year. Products is the total number of CN8 product categories exported for each firm. Destinations is the total number of unique export destinations (countries) for each firm. Occupations is the total number of unique four-digit occupations employed within the firm.

Table 1: Sample Means, 1995-2008

| | No. of obs. | Mean | Std. Dev. |
|---|---|---|---|
| *CEO characteristics:* | | | |
| Age | 8,607 | 49.5 | 8.0 |
| Female | 8,607 | 0.019 | 0.136 |
| Experience | 8,607 | 23.0 | 9.3 |
| Tenure | 8,601 | 7.6 | 6.7 |
| College degree | 8,607 | 0.66 | 0.47 |
| Annual income, 1,000 DKK | 8,607 | 1,044 | 1,047 |
| Internally promoted | 8,089 | 0.73 | 0.44 |
| ISCO one-digit occupations: | | | |
| Legislators, senior officials and managers | 7,594 | 0.78 | 0.42 |
| Professionals | 7,594 | 0.10 | 0.30 |
| Technicians and associate professionals | 7,594 | 0.07 | 0.25 |
| Other occupations | 7,594 | 0.05 | 0.23 |
| | | | |
| *Firm Characteristics:* | | | |
| Employees | 8,607 | 227 | 494 |
| Share with college degree | 8,607 | 0.18 | 0.13 |
| Wage bill, 1.000 DKK | 8,607 | 73,900 | 189,000 |
| Occupations | 8,607 | 32.4 | 19.2 |
| Capital stock, 1.000 DKK | 8,607 | 97,200 | 479,000 |
| Total sales, 1.000 DKK | 8,607 | 320,000 | 904,000 |
| Exports, 1.000 DKK | 8,607 | 164,000 | 543,000 |
| Exports/Total sales | 8,607 | 0.48 | 0.33 |
| Exported products | 8,607 | 24.2 | 32.5 |
| Export destinations | 8,607 | 25.2 | 21.1 |

Notes: Experience is measured as time spent employed since 1980. Tenure is measured as time spent at the current firm. Annual income is labor income including bonuses. Internally promoted is a dummy indicating if the CEO is hired by the firm before the CEO is registered as a CEO. All nominal variables are measured in year 2000 DKK using the GDP deflator.

Table 2: New CEOs and changes in firm complexity

| | | |
|---|---|---|
| Add Products in t | -0.1920*** | -0.1892*** |
| Add Products in t+1 | 0.0709*** | 0.0692*** |
| Add Products in t+2 | 0.0269** | 0.0252* |
| Add Destinations in t | -0.2323*** | -0.2276*** |
| Add Destinations in t+1 | 0.0729*** | 0.0725*** |
| Add Destinations in t+2 | 0.0038 | 0.0026 |
| Add Occupations in t | -0.1917*** | -0.1881*** |
| Add Occupations in t+1 | 0.0409*** | 0.0357*** |
| Add Occupations in t+2 | 0.0031 | 0.0003 |
| Industry and year fixed effects | Yes | Yes |
| Firm size controls | No | Yes |

Notes: Notes: The coefficient estimates are from regressions of dummies for adding products, destinations or occupations in year t, year t+1 or year t+2 on a dummy indicating if it is the CEO's first year in the firm. Firm fixed effects are included in all regressions. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 3: Exports, firm complexity and CEO earnings

| | | | | |
|---|---|---|---|---|
| *Log CEO Earnings:* | | | | |
| Log Exports | 0.1003*** | 0.0109*** | 0.0205*** | 0.0124 |
| Log Products | 0.1494*** | 0.0190*** | 0.0019 | -0.0055 |
| Log Destinations | 0.1755*** | 0.0500*** | 0.0162 | 0.0055 |
| Log Occupations | 0.4581*** | 0.1327*** | 0.0324* | 0.0103 |
| Share of high skilled workers | 1.1182*** | 0.7097*** | 0.0825 | 0.1583 |
| | | | | |
| *Log Relative CEO Earnings:* | | | | |
| Log Exports | 0.0825*** | 0.0165*** | 0.0174** | 0.0195** |
| Log Products | 0.1232*** | 0.0206*** | 0.0044 | -0.0003 |
| Log Destinations | 0.1428*** | 0.0457*** | 0.0264 | 0.0133 |
| Log Occupations | 0.3905*** | 0.0947*** | 0.0395** | -0.0043 |
| Share of high skilled workers | 0.3624*** | 0.1367** | -0.2551 | -0.0315 |
| Industry and year fixed effects | Yes | Yes | Yes | Yes |
| Firm size controls | No | Yes | No | Yes |
| CEO-Firm fixed effects | No | No | Yes | Yes |

Notes: The coefficient estimates are from regressions of CEO earnings or relative CEO earnings on the variables listed in the first column. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 4: CEO earnings, exports and firm complexity

| | Log CEO earnings | | Log CEO rel. earnings | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log Exports | 0.0215*** | 0.0150* | 0.0135 | 0.0210** |
| | (0.0083) | (0.0087) | (0.0089) | (0.0092) |
| Log Products | -0.0068 | -0.0099 | -0.0044 | -0.0068 |
| | (0.0104) | (0.0105) | (0.0112) | (0.0112) |
| Log Destinations | -0.0018 | -0.0023 | 0.0132 | -0.0011 |
| | (0.0175) | (0.0176) | (0.0189) | (0.0188) |
| Log Occupations | 0.0284 | 0.0103 | 0.0325 | -0.0050 |
| | (0.0188) | (0.0200) | (0.0202) | (0.0213) |
| Share of high skilled workers | 0.1291 | 0.1726 | -0.2106 | -0.0193 |
| | (0.1514) | (0.1529) | (0.1629) | (0.1632) |
| Log Sales | | 0.0344 | | -0.2466*** |
| | | (0.0267) | | (0.0285) |
| Log Employees | | 0.0415 | | 0.3457*** |
| | | (0.0335) | | (0.0358) |
| Observations | 8,607 | 8,607 | 8,606 | 8,606 |
| Number of job spells | 2,656 | 2,656 | 2,656 | 2,656 |
| R-squared | 0.015 | 0.016 | 0.022 | 0.039 |

Notes: The coefficient estimates are from regressions of CEO earnings and CEO relative earnings on the variables listed in the first column. Industry, year and job spell fixed effects are included. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 5: CEO earnings and firm output activities

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *Log CEO earnings:* | | | | | | | |
| Log Exports | 0.0131* | 0.0219*** | 0.0149* | 0.0213*** | 0.0140 | 0.0205*** | |
| | (0.0077) | (0.0076) | (0.0080) | (0.0082) | (0.0086) | (0.0073) | |
| Log Sales | 0.0563*** | | 0.0488** | | 0.0522** | | 0.0694*** |
| | (0.0204) | | (0.0220) | | (0.0265) | | (0.0191) |
| Log Products | | -0.0067 | | | | | |
| | | (0.0101) | | | | | |
| Log (Products/Sales) | | | -0.0092 | | | | |
| | | | (0.0101) | | | | |
| Log Destinations | | | | -0.0039 | | | |
| | | | | (0.0170) | | | |
| Log (Destinations/Sales) | | | | | -0.0042 | | |
| | | | | | (0.0170) | | |
| Log (Exports/Sales) | | | | | | | 0.0131* |
| | | | | | | | (0.0077) |
| Observations | 8,607 | 8,607 | 8,607 | 8,607 | 8,607 | 8,607 | 8,607 |
| Number of job spells | 2,656 | 2,656 | 2,656 | 2,656 | 2,656 | 2,656 | 2,656 |
| R-squared | 0.016 | 0.015 | 0.016 | 0.015 | 0.016 | 0.015 | 0.016 |
| *Log CEO relative earinings:* | | | | | | | |
| Log Exports | 0.0256*** | 0.0180** | 0.0256*** | 0.0147* | 0.0228** | 0.0174** | |
| | (0.0083) | (0.0082) | (0.0086) | (0.0088) | (0.0092) | (0.0078) | |
| Log Sales | -0.0623*** | | -0.0623*** | | -0.0496* | | -0.0368* |
| | (0.0219) | | (0.0237) | | (0.0285) | | (0.0206) |
| Log Products | | -0.0027 | | | | | |
| | | (0.0109) | | | | | |
| Log (Products/Sales) | | | -0.0000 | | | | |
| | | | (0.0109) | | | | |
| Log Destinations | | | | 0.0125 | | | |
| | | | | (0.0183) | | | |
| Log (Destinations/Sales) | | | | | 0.0128 | | |
| | | | | | (0.0183) | | |
| Log (Exports/Sales) | | | | | | | 0.0256*** |
| | | | | | | | (0.0083) |
| Observations | 8,606 | 8,606 | 8,606 | 8,606 | 8,606 | 8,606 | 8,606 |
| Number of job spells | 2,656 | 2,656 | 2,656 | 2,656 | 2,656 | 2,656 | 2,656 |
| R-squared | 0.023 | 0.021 | 0.023 | 0.022 | 0.023 | 0.021 | 0.023 |

Notes: The coefficient estimates are from regressions of CEO earnings and CEO relative earnings on the variables listed in the first column. Industry, year and job spell fixed effects are included. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 6: CEO earnings and firm input activities

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *Log CEO earnings:* | | | | | |
| Log Exports | 0.0146* | 0.0165** | 0.0145* | 0.0193*** | 0.0146* |
| | (0.0076) | (0.0074) | (0.0076) | (0.0073) | (0.0076) |
| Log Employees | 0.0658*** | | 0.0691*** | | 0.0715*** |
| | (0.0243) | | (0.0245) | | (0.0266) |
| log High skilled workers | | 0.0466*** | | | |
| | | (0.0174) | | | |
| Log Share of high skilled workers | | | 0.0280 | | |
| | | | (0.0225) | | |
| Log Occupations | | | | 0.0269 | |
| | | | | (0.0187) | |
| Log (Occupations/Employees) | | | | | 0.0105 |
| | | | | | (0.0200) |
| Observations | 8,607 | 8,607 | 8,607 | 8,607 | 8,607 |
| Number of job spells | 2,656 | 2,656 | 2,656 | 2,656 | 2,656 |
| R-squared | 0.016 | 0.016 | 0.016 | 0.015 | 0.016 |
| | | | | | |
| *Log CEO relative earnings:* | | | | | |
| Log Exports | 0.0039 | 0.0115 | 0.0039 | 0.0159** | 0.0040 |
| | (0.0081) | (0.0080) | (0.0081) | (0.0079) | (0.0081) |
| Log Employees | 0.1525*** | | 0.1529*** | | 0.1487*** |
| | (0.0261) | | (0.0263) | | (0.0286) |
| log High skilled workers | | 0.0711*** | | | |
| | | (0.0187) | | | |
| Log Share of high skilled workers | | | 0.0035 | | |
| | | | (0.0241) | | |
| Log Occupations | | | | 0.0350* | |
| | | | | (0.0201) | |
| Log (Occupations/Employees) | | | | | -0.0070 |
| | | | | | (0.0214) |
| Observations | 8,606 | 8,606 | 8,606 | 8,606 | 8,606 |
| Number of job spells | 2,656 | 2,656 | 2,656 | 2,656 | 2,656 |
| R-squared | 0.027 | 0.024 | 0.027 | 0.022 | 0.027 |

Notes: The coefficient estimates are from regressions of CEO earnings and CEO relative earnings on the variables listed in the first column. Industry, year and job spell fixed effects are included. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 7: First-stage FE-IV regressions

| | Log Exports | | Log Sales |
|---|---|---|---|
| | (1) | (2) | (3) |
| Log WID | 0.0445*** | 0.1017*** | 0.0123*** |
| | (0.0066) | (0.0077) | (0.0030) |
| Log Employees | 0.0517 | | |
| | (0.0524) | | |
| Log Sales | 0.6658*** | | |
| | (0.0402) | | |
| Log Capital | -0.0045 | | |
| | (0.0155) | | |
| Log Products | 0.1613*** | | |
| | (0.0159) | | |
| Log Destinations | 0.7366*** | | |
| | (0.0252) | | |
| Log Occupations | 0.0060 | | |
| | (0.0303) | | |
| Share of high skilled workers | -0.5848** | | |
| | (0.2337) | | |
| Experience | 0.0045 | 0.0064 | -0.0078 |
| | (0.0138) | (0.0163) | (0.0063) |
| Experience squared | 0.0284* | 0.0463** | 0.0260*** |
| | (0.0158) | (0.0186) | (0.0072) |
| Observations | 8,607 | 8,607 | 8,607 |
| Number of job spells | 2,656 | 2,656 | 2,656 |
| R-squared | 0.399 | 0.159 | 0.225 |
| F-statistics for instrument | 45.27 | 176.4 | 17.21 |

Notes: The table shows first stage regressions of log exports or log sales using world import demand (WID) as exculded instruments. All specifications include industry-year fixed effects and CEO-firm fixed effects. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 8: CEO earnings regressions

| | Log CEO earnings | | | Log CEO relative earnings | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log Exports | 0.0668 | 0.0416 | | 0.1848* | 0.0963** | |
| | (0.1006) | (0.0431) | | (0.1073) | (0.0464) | |
| Log Sales | | | 0.3447 | | | 0.7980** |
| | | | (0.3574) | | | (0.3841) |
| Log Employees | 0.0234 | | | 0.3476*** | | |
| | (0.0359) | | | (0.0383) | | |
| Log Sales | 0.0132 | | | -0.3417*** | | |
| | (0.0726) | | | (0.0775) | | |
| Log Capital | 0.0055 | | | -0.0204* | | |
| | (0.0105) | | | (0.0112) | | |
| Log Products | -0.0201 | | | -0.0326 | | |
| | (0.0196) | | | (0.0209) | | |
| Log Destinations | -0.0407 | | | -0.1274 | | |
| | (0.0789) | | | (0.0842) | | |
| Log Occupations | 0.0135 | | | 0.0023 | | |
| | (0.0205) | | | (0.0219) | | |
| Share of high skilled workers | 0.0858 | | | -0.0282 | | |
| | (0.1694) | | | (0.1807) | | |
| Experience | 0.0560*** | 0.0547*** | 0.0577*** | 0.0620*** | 0.0556*** | 0.0624*** |
| | (0.0094) | (0.0093) | (0.0097) | (0.0100) | (0.0100) | (0.0104) |
| Experience squared | -0.0774*** | -0.0745*** | -0.0816*** | -0.0897*** | -0.0837*** | -0.1000*** |
| | (0.0110) | (0.0108) | (0.0140) | (0.0117) | (0.0116) | (0.0150) |
| Observations | 8,607 | 8,607 | 8,607 | 8,606 | 8,606 | 8,606 |
| Number of groups | 2,656 | 2,656 | 2,656 | 2,656 | 2,656 | 2,656 |
| R-squared | 0.073 | 0.070 | 0.070 | 0.096 | 0.079 | 0.079 |

Notes: The table shows the results from second-stage CEO-level earnings regressions. All specifications include industry-year fixed effects and CEO-firm fixed effects. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 9: CEO earnings regressions, promotion interactions

| | Log CEO earnings | | | | Log CEO relative earnings | | | |
|---|---|---|---|---|---|---|---|---|
| | FE | | FE-IV | | FE | | FE-IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Log Exports | -0.0124 | | 0.0433 | | -0.0185 | | 0.1018 | |
| | (0.0163) | | (0.1388) | | (0.0173) | | (0.1474) | |
| Log Exports * Promoted | 0.0307 | | -0.0036 | | 0.0412** | | 0.0477 | |
| | (0.0196) | | (0.1496) | | (0.0208) | | (0.1589) | |
| Log Sales | | 0.0257 | | 0.1717 | | -0.1164** | | 0.4934 |
| | | (0.0441) | | (0.3807) | | (0.0469) | | (0.4044) |
| Log Sales * Promoted | | 0.0477 | | 0.2232 | | 0.0962* | | 1.0026 |
| | | (0.0513) | | (0.7019) | | (0.0545) | | (0.7455) |
| Experience | 0.0577*** | 0.0591*** | 0.0579*** | 0.0658*** | 0.0614*** | 0.0609*** | 0.0625*** | |
| | (0.0112) | (0.0112) | (0.0112) | (0.0197) | (0.0119) | (0.0119) | (0.0119) | (0.0210) |
| Experience squared | -0.0573*** | -0.0611*** | -0.0591*** | -0.0808* | -0.0732*** | -0.0703*** | -0.0807*** | -0.1624*** |
| | (0.0151) | (0.0152) | (0.0157) | (0.0478) | (0.0160) | (0.0162) | (0.0167) | (0.0508) |
| Observations | 6,187 | 6,187 | 6,187 | 6,187 | 6,187 | 6,187 | 6,187 | 6,187 |
| Number of job spells | 2,138 | 2,138 | 2,138 | 2,138 | 2,138 | 2,138 | 2,138 | 2,138 |
| R-squared | 0.078 | 0.079 | 0.077 | 0.077 | 0.086 | 0.087 | 0.086 | 0.086 |
| *First stage F-statistics:* | | | | | | | | |
| Log Exports | | | 36.25 | | | | 36.25 | |
| Log Exports * Promoted | | | 45.29 | | | | 45.29 | |
| Log Sales | | | | 9.295 | | | | 9.295 |
| Log Sales * Promoted | | | | 3.684 | | | | 3.684 |

Notes: The table shows the results from CEO-level earnings regressions.. All specifications include industry-year fixed effects and CEO-firm fixed effects. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 10: Robustness: Alternative definition of CEOs

| | Log CEO earnings | | Log CEO relative earnings | |
|---|---|---|---|---|
| | FE | FE-IV | FE | FE-IV |
| | (1) | (2) | (3) | (4) |
| Log Exports | 0.0052 | -0.0067 | 0.0032 | 0.0121 |
| | (0.0060) | (0.0450) | (0.0065) | (0.0485) |
| Experience | 0.0680*** | 0.0680*** | 0.0656*** | 0.0656*** |
| | (0.0062) | (0.0062) | (0.0066) | (0.0066) |
| Experience squared | -0.0979*** | -0.0981*** | -0.0942*** | -0.0941*** |
| | (0.0087) | (0.0087) | (0.0094) | (0.0094) |
| Observations | 11,820 | 11,817 | 11,820 | 11,817 |
| Number of groups | 4,349 | 4,347 | 4,349 | 4,347 |
| R-squared | 0.064 | 0.109 | 0.063 | 0.109 |
| First stage F-statistics | | 131.8 | | 131.8 |

Notes: The table shows the results from CEO-level earnings and relative earnings regressions. CEOs are defined based on the ISCO88 one-digit classification of managers. All specifications include industry-year fixed effects and CEO-firm fixed effects. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

# Chapter 3

## Keeping workers occupied: In search of occupation-wide effects of offshoring

# Keeping workers occupied: In search of occupation-wide effects of offshoring

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**Abstract**

One notable aspect of globalization is the dramatic increase in the trade in intermediate goods between countries which has coincided with a notable loss of low-skilled jobs and growing wage inequality domestically. This paper examines potential occupation-wide general equilibrium wage effects of offshoring in a setting different from the U.S. labor market. This is done by using linked employer-employee data at the firm level to construct an occupation-specific offshoring measure and instrumenting this with world export supply in order to achieve a more precise measure of offshoring and a clear identification. I find little or no evidence of offshoring on wages. This is in contrast to the existing literature generally finding negative wage effects. By capturing economy-wide general equilibrium effects, I use a different methodology for measuring offshoring. This approach relies on variation in offshoring and wages within occupations. Lack of such variation may reflect a relatively unionized labor market where the service sector is viewed as less of an outside option for manufacturing workers facing pressures from offshoring.

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# 1 Introduction

One notable aspect of globalization is the dramatic increase in the trade in intermediate goods between countries. For the case of Denmark over the period 1995-2006, both imports and exports more than doubled with a growing, yet still relatively small, share being attributed to Asian countries (Hummels *et al.*, 2014). This development in world trade has coincided with a notable loss of low-skilled jobs and growing wage inequality domestically. It is therefore natural to ask to which extent this wave of offshoring has affected and is going to affect the future wages of workers of different types. Specifically, it is of interest to understand how trade shocks affect workers both in firms directly influenced by the shock and workers indirectly affected as workers relocate across the economy and switch occupations, possibly changing their productivity. I examine potential general equilibrium wage effects of offshoring in a setting different from the U.S. labor market and contribute by using linked employer-employee data at the firm level to construct an occupation-specific offshoring measure and instrumenting this with world export supply in order to achieve a more precise measure of offshoring and a clear identification.

Among the first to study in depth the consequences of offshoring were Feenstra and Hanson (1997) and Feenstra and Hanson (1999). They used industry-level data combined with input-output tables to document the importance of offshoring to Mexico for the U.S. labor market. Since then, the literature on offshoring and wages has developed both with respect to measurement and identification strategies. Recently, the paper by Hummels *et al.* (2014) use linked employer-employee data from Danish manufacturing firms to estimate the wage effects of offshoring. They use world export supply to instrument offshoring and find that within job spells, increasing offshoring affects the wages of high-skilled workers positively and low-skilled workers negatively[1]. The effects vary substantially within skill types, i.e. across task characteristics and occupations within a skill group.

Another recent paper by Ebenstein *et al.* (2014) emphasizes the importance of taking into account potential general equilibrium effects when workers in certain industries or occupations are affected by offshoring[2]. Offshoring is measured based

[1] A similar instrumental variable method is developed in Autor *et al.* (2013) who look at the effects of import competition from China on the US labor market.

[2] See Ebenstein *et al.* (2015) for another working paper version of the paper using updated data.

on the total employment of foreign affiliates by US multinationals. They first limit attention to the manufacturing sector, construct industry-specific globalization measures (they also look at import competition) and find little effects on wages. They then augment their sample with the service sector and construct occupation-specific measures, weighting each industry by its relative importance for a given occupation. By doing this, they essentially take into account direct effects both on workers displaced from the manufacturing sector finding new jobs in lower-paying service jobs as well as potential indirect effects on workers in occupations on the receiving end of the displaced workers causing downwards pressure on their wages. They show that this approach catch significant negative effects otherwise unaccounted for, although they do not use a major policy change or instrumental variable for identification in their main results.

One potential problem with this approach using industry-level data to construct occupation-specific offshoring measures is that trade shocks are often considered firm-specific, since firm import patterns of intermediate inputs are typically highly idiosyncratic. As an example, imagine a collection of firms in the pharmaceutical sector, all employing a relative similar share of high and low-skilled workers. However, due to the different nature of their production process, some of the firms employ a disproportionate amount of workers in a certain, low-skilled occupation, say office clerks. As some of these particular firms are hit by a trade shock causing increased offshoring opportunities, a disproportionate number of clerks may become laid off, now looking for jobs both in the pharmaceutical sector and among firms in the service sector which most frequently employ clerks. Thus, events having effects on the wages for clerks may not necessarily be comprehended by industry-specific measures of offshoring if important firm-specific shocks are left unaccounted for.

Two contributions to the literature can be found in this paper. First, I examine potential general equilibrium wage effects of offshoring in a setting different from the U.S. labor market. Second, by using linked employer-employee data at the firm level to construct an occupation-specific offshoring measure and instrumenting this with world export supply, I achieve a more precise measure of offshoring and a clear identification.[3]

[3]In the work by Andersen and Malthe-Thagaard (2012), the authors also use Danish data to construct occupation-specific measures and include the service sector to address a related question. However, they use data from input-output tables rather than firm-level data and they do not use an instrumental variables approach or any other identification strategy to deal with the inherent endogeneity issues.

This paper finds little or no evidence of offshoring on wages. The lack of clear effects for the manufacturing sector found elsewhere in the literature may be ascribed to the occupation-specific offshoring measure used, whereas other papers have measured offshoring at the firm level. The advantage of the occupation-specific offshoring measure is that it allows the inclusion of the service sector which has less direct exposure to offshoring.

Including the service sector and allowing for economy-wide, occupation-specific effects of offshoring, clear wage effects still do not materialize. This may have several explanations. First, since the measure of offshoring employed in this paper is based on more precise linked employer-employee data, it is markedly different from that of the existing literature utilizing occupation-specific measures. Second, identifying wage effects using the occupation-specific offshoring measure naturally relies on variation within occupations in wages and offshoring. To the extent that this variation is insufficient to identify effects present in the economy, this analysis is missing important patterns in the data.

One reason for this lack of variation may be insufficient mobility between the manufacturing and service sectors in the Danish labor market, possibly caused by a fairly high degree of unionization. If the wages of the service sector relative to the manufacturing sector are markedly higher in Denmark than in the US, the service sector may appear as less of an outside option for manufacturing workers facing pressures from offshoring. To the extent that switching sectors is associated with a human capital and productivity loss, workers may find it less viable to make this transition and rather accept lower wages in their current positions or simply ending up facing unemployment. This could lead to noticeable employment effects of offshoring.

A number of related papers in the literature on offshoring and labor markets can be mentioned (see Hummels *et al.* (2015) for a recent overview of this literature). In Liu and Trefler (2011), the authors look at service trade and emphasize the importance of workers forced to ’switch down’ in response to a trade shock, meaning that they reallocate to occupations paying less on average than the current occupation. Other papers look at industry-level and local labor-market approaches to estimate direct effects on manufacturing workers and indirect effects in upstream and downstream industries. Among such papers are Autor *et al.* (2013), Autor *et al.* (2014) and Acemoglu *et al.* (2014), although these papers focus on import competition rather than offshoring. Also looking at import competition but using similar data and identification strategies is the paper by Ashournia *et al.* (2014).

Baumgarten *et al.* (2013) use German individual-level panel data and construct offshoring measures at the occupational level and use a similar instrumental variable as used in this paper. They find that when allowing for labor mobility across industries, negative wage effects of offshoring are significant and depend strongly on the occupational characteristics of the worker. However, since their analysis is limited to the manufacturing sector and does not include the service sector, they do not allow for economy-wide general equilibrium effects. They also do not base their measures on firm-level data and so lose some precision in accounting for offshoring.

A similar approach is taken in Kosteas and Park (2015) who use the NLSY79 cohort data for U.S. workers. They point out that downwards wage pressures from worker inflows are generated mostly when workers are received from trade-affected occupations, whereas general cross-occupational movement of workers does not generate this effect. They also do not employ linked employer-employee data and have no clear identification strategy.

The rest of this paper is organized in the following way: Section 2 describes the data sources used as well as the identification strategy. Section 3 presents the results. Section 4 concludes.

# 2 Data sources and identification strategy[4]

## 2.1 Data sources[5]

The dataset employed comes from registry data from Statistics Denmark and is constructed by combining individual, firm and foreign trade data. Unique firm and individual identifies allow the datasets to be merged and workers and firms to be matched in every year. The sample period chosen is 1999-2010 to achieve consistency of variables across time. I drop smaller firms with fewer than 50 employees since they may have imputed balance sheet variables. Only firms classified

[4]The handling of data sources in this paper is closely in line with the methods described in both Andersen and Malthe-Thagaard (2012) and Andersen (2015).

[5]For more details on data sources, see 4.

as manufacturing or service firms were included. In particular, the public sector was excluded in order to focus on the parts of the economy where the forces of supply and demand are more instrumental in determining the going wage.

I focus on full-time workers of age 20-60 years and divide workers into skilled and unskilled. Skilled workers have a tertiary education which corresponds to about levels 5 or 6 in the ISCED nomenclature. Skill groups and occupational codes are fixed at the beginning of job spells to focus on the effects of offshoring and rule out endogenous switches between skill groups and occupations within the same firm[6]. Finally, missing observations on any key variable are dropped[7]. This includes missing observations of the occupation-specific offshoring and world export supply measures (defined below).

Aside from dividing workers by their skill levels, I also construct measures of routine and non-routine for occupations containing particular task characteristics by following Hummels et al. (2014). First, I match my occupational data to the O*NET database of occupations which contains records of detailed questionnaires for each occupation on various activities (e.g. computer use, oral communication, manual dexterity etc.). Second, I pick the O*NET characteristics that most closely match the definitions of routine and non-routine tasks used in Autor *et al.* (2003) and compute the principal component. I then normalize the principal components to achieve measures of the routine and non-routine content of any given occupation with a mean of 0 and a standard deviation of 1 in order to allow for easy comparison.

*Measuring offshoring*[8]

Offshoring is defined with a broad measure as the total value of imported goods for any given firm in any given year. The idea is that these imported goods may have crowded out economic activity that could at least potentially have taken place inside the importing firm. I construct the offshoring variable using imports for manufacturing sector firms only and disregard the service sector in order to capture

[6] About three quarters of the job spells have no occupation switches and about 97 percent have at most two switches over the sample period. For skill groups, only about one percent of job spells include switches between unskilled and skilled.

[7] This amounts to around 1.1 million observations which is about 15 percent of the sample.

[8] I define offshoring to be the case of activity relocated outside the borders of the country, while outsourcing indicates that the task is performed outside the boundaries of the firm but not necessarily outside the country. While the decision concerning whether to perform activities within or outside a given firm on foreign soil is itself an interesting question, this paper limits attention to offshoring in general.

imports used as inputs in production rather than as final goods for consumption by domestic consumers. This is so since data for service sector firms includes reselling without value-added, and the share of reselling out of total imports is typically much higher for service sector firms than for manufacturing firms.

When using a broad offshoring measure (i.e. including all imported goods as opposed to only a subset of goods), one concern is that these inputs may not substitute for relevant production factors within the manufacturing firm. For example, imported raw materials or certain manufactured inputs may be unlikely to have been produced by the firm in question in the absence of import opportunities. An alternative would be to calculate a so-called narrow offshoring measure, counting only imports from within a group of product categories more closely resembling the product categories produced by the given firm. The concern with that methodology would be that the range of products counted may be too narrow, thus underestimating the extent of offshoring. Using a narrow instead of a broad offshoring measure might yield different results although this is not investigated further in this paper[9].

Another approach in the literature is to use industry level input-output tables to help identify which inputs a firm is importing[10]. This approach is unlikely to give an accurate picture of offshoring among Danish firms since even within the same industry, firms are likely to have very different import patterns. Therefore, any shock to a foreign seller of a particular intermediate input will have markedly different effects across Danish firms within the same industry. Instead, utilizing firm-level data appears to be a more attractive way of measuring offshoring.

See also Hummels *et al.* (2014) for an extensive discussion of these issues as well as more details about the data patterns mentioned and the possible consequences of different approaches to measuring offshoring using data on Danish firms and their imports.

*Summary statistics*

The final dataset has 6,227,301 worker-firm observations comprising 6,118 unique firms and 1,221,694 unique individuals distributed among 416 occupational cate-

[9]In their work on offshoring and wages, Hummels *et al.* (2014) use a broad offshoring measure as a robustness exercise to confirm their findings using a narrow measure. The results are similar although the effects are larger when using a broad measure.

[10]As an example of identifying effects of offshoring on wages using input-output tables, see Andersen and Malthe-Thagaard (2012).

gories. Summary statistics are shown in Table 1. The magnitude of the standard deviations compared to the means show that there is considerable heterogeneity among firms as well as workers. Note also that the number of observations for total imports is lower since I choose to only use import data for manufacturing firms when constructing the offshoring measure as discussed above.

The final sample consists of both manufacturing and service sector firms. Since the empirical analysis will consider the effect of occupation-specific offshoring shocks originating in the manufacturing sector on occupation- and economy-wide worker wages, it might be necessary to illustrate potential differences between manufacturing and service firms. Table 2 and Table 3 suggest that the aggregate characteristics of firms and workers in the two sectors are roughly comparable. The main difference remains that workers in the manufacturing firms could be hit directly by trade shocks whereas workers in the service sector are affected indirectly as workers reallocate throughout the economy.

*Occupation-specific globalization measures*

In order to allow for economy-wide effects on wages following occupation-specific trade shocks, I construct an occupation-specific offshoring measure in the following way. First define $OFF_{jt}$ as the total value of imported goods (i.e. offshoring) for firm $j$ in year $t$. Then define $\alpha_{kj99} = {}^{L_{kj99}}/_{L_{k99}}$ as the share of occupation $k$ workers employed in firm $j$ out of total workers in occupation $k$ in 1999 (start of sample period). That is, for any occupation $k$ under consideration, $\alpha_{kj99}$ measures the relative importance of firm $j$ for that occupation in 1999. These shares are fixed in 1999 to isolate changes in the occupation-specific offshoring measure to come from changes in imported goods and not from changes in the composition of occupations within firms. Taken together, this gives the occupation-specific offshoring measure:

$$OFF_{kt} = \sum_j \alpha_{kj99} OFF_{jt}$$

*Occupational characteristics*

In Table 4, I list the ten most frequent occupations among workers in the middle of the sample period (2005). The total number of workers in 2005 is 543,683 and so the top ten occupations account for about 30 percent of workers. One thing worth noting is that while the share of workers working in the manufacturing sector is very different across occupations, the average (across years) share of workers switching from manufacturing to service is quite homogeneous and lowcompared to the average yearly share of manufacturing workers switching from one manufacturing firm to another which I calculated to be 7.2 percent. This may suggest that the service sector is not perceived as an outside option to manufacturing workers facing pressures from globalization.

Since identification in much of the analysis in section 3 below relies on within job-spell variation, it may be of interest to see how the offshoring measure changes over time within occupations. Table 5 lists the ten occupations with the highest growth in occupation-specific offshoring over the sample period as well as additional occupation characteristics. For example, "meat- and fish-processing-machine operators" (occupational code 8271) experienced a 233 percent increase in offshoring for their occupation as a whole. It is worth noting that this particular occupation is indeed among the ten most common occupations with around 13,000 workers in 2005. Thus, there appears to be considerable changes in occupation-specific offshoring within occupations over the sample period for several important occupational groups.

## 2.2 Identification strategy

In section 3, I regress worker-firm-occupation-year level wages on an occupation-year specific measure of offshoring. As described above, the occupation-specific measure of offshoring is based on time varying, firm-level offshoring as measured by the value of firm imports. The identification problem facing this approach is that time-varying, occupation-level shocks to e.g. worker productivity might affect both the offshoring decision and the wage setting of the firms most frequently employing workers from the given occupation. For example, as improved computer software increases the productivity of office clerks, a given cost saving from offshoring might become more profitable for the firm. At the same time, there is now more surplus to bargain over between office clerks and the firm. To confront this problem, I construct instruments correlated with firm imports but uncorrelated with occupation worker productivity and demand conditions.

To further illustrate the identification challenge, consider that offshoring firms are expected to be different from non-offshoring firms. To the extent that these differences are time invariant, identifying off changes within firms over time will be robust to this concern. Table 6 shows the result of focusing on firms engaged in offshoring and including firm fixed effects in a regression of offshoring on firm outcome variables. We see that firm-level offshoring tends to be correlated with sales, employees and the share of workers being high-skilled. This underlines the identification problem. It might well be that access to cheaper inputs through higher offshoring decreases the demand for certain occupations of workers in the firm. Conversely, it could be that these outcomes are all affected by shocks to the productivity of certain occupations of workers, thus causing the correlation between wages and offshoring to be caused by simultaneity bias.

In order to account for such endogeneity issues, I follow Hummels *et al.* (2014) and instrument offshoring using world export supply (WES), constructed using COMTRADE bilateral trade data. The idea is to find exogenous variation in the global supply of intermediate goods driven by changes in the exporting country's overall trade patterns as determined by comparative advantage or other classical international trade factors. This variation is then related to the input product bundle used by a given firm. Formally, world export supply is defined as:

$$WES_{jt} = \sum_{c,p} s_{jcp} WES_{cpt} \tag{2.1}$$

Here, $s_{jcp}$ is the share of imports of product category $p$ from country $c$ out of total imports for firm $j$ in the base year. The base year is chosen as the first year of the sample period (i.e. 1999) if the firm is observed in that year; otherwise, the first year the firm is observed is chosen as base year. $WES_{cpt}$ is the total exports from country $c$ of product $p$ in year $t$ to the entire world market less Denmark. By fixing import shares $s_{jcp}$ in the base year, the instrumental variable will have strength insofar as this fixing of the share weights reflects actual data patterns. This indeed turns out to be overall consistent with the data and may reflect stable business relationships or the fact that inputs from that particular source is a good match for the importer in question.

When instrumenting offshoring with world export supply, I likewise construct an occupation-specific world export supply measure by calculating:

$$WES_{kt} = \sum_{j} \alpha_{kj99} WES_{jt} \quad ,$$

where $\alpha_{kj99}$ measures the relative importance of firm $j$ for occupation $k$ in 1999 as described in section 2.1. By doing so, the firm-specific world export supply variable is aggregated to the occupational level. One advantage of doing so is that potential unobserved shocks at the firm level are less likely to have a major effect at the economy-wide occupation level since the workers of a given occupation are generally spread out over a multitude of different firms. Furthermore, since any firm of importance for a given occupation in terms of the number of workers employed is given a higher weight $\alpha_{kj99}$ when constructing the instrument, this also helps insulating against firm-specific shocks. In this way, some of potential threats to identification related to the world export supply instrument at the *firm* level as discussed in e.g. Hummels *et al.* (2014) are mitigated.

*Threats to identification*

Several challenges confront the identification of the causal effect of occupation-specific offshoring on wages. First, it could be that industries more likely to offshore also tend to have lower wages than other industries. This is accounted for by including industry fixed effects. Likewise, including job-spell fixed effects and fixing occupational codes within job spells effectively limits the analysis to use only variation within occupations over time. This makes sense since wage bargaining in the Danish labor market is often organized at the industry and occupational levels.

Second, it might also be the case that offshoring and wages are simultaneously affected by similar time-varying shocks such as general exchange rate or business-cycle fluctuations. This is countered by including year fixed effects.

Third, one can also discuss possible threats to the identification strategy using the instrumental variable by considering the instrument $WES_{kt}$ itself. Consider an improvement in technology crucial to the production process involving workers of a particular occupation. Again, this could be improved computer software for office clerks. This improved technology may tend to decrease or increase, ceteris paribus, the wages for office clerks, depending on whether the improved technology as a whole tends to substitute for and replace office clerks or complement and enhance the workers. To the extent that this technological development also affects the world export supply of intermediate inputs used heavily in firms employing large numbers of office clerks, endogeneity problems may arise. However, it appears somewhat unlikely that such correlations should systematically occur given the idiosyncratic nature of the Danish industrial structure and labor market institutions.

# 3 Results

## 3.1 Empirical specification

In this section, I first investigate the result of limiting the sample to manufacturing firms and using first a firm-specific and then an occupation-specific offshoring measure. The purpose of this is to contrast the results with existing literature using data from Danish manufacturing firms. I then extend the analysis to include the service sector to compare with the literature stressing the importance of economy-wide general equilibrium effects. In both cases, I consider estimating the following equation:

$$W_{ijkt} = \beta_0 Z_{it} + \beta_1 OFF_{kt} + \beta_2 OFF_{kt} \times Skilled_{it} + \beta_3 X_{jt} + \varphi_{ij} + \varphi_{IND} + \varphi_t + \varepsilon_{ijkt} \ ,$$

where $W_{ijkt}$ is the (log) wage for individual $i$ in firm $j$ and occupation $k$ in year $t$. $Z_{it}$ is a vector of individual-specific controls (experience, experience$^2$, marital status), $OFF_{kt}$ is the occupation-specific offshoring measure, $Skilled_{it}$ is a dummy variable indicating high skilled status, $X_{jt}$ contains firm-specific controls (total sales, employees, capital stock and skilled worker share), and the $\varphi$'s are job-spell, industry and year fixed effects.

I estimate each specification first using OLS and subsequently instrumenting offshoring and its interaction with the high skilled indicator with occupation-specific world export supply $WES_{kt}$ and its respective interaction with the high skilled indicator as discussed in section 2.2.

## 3.2 Estimation results

Before investigating the potential occupation-wide general equilibrium effects of offshoring, I use a firm-specific measure of offshoring for comparison. For the manufacturing sector only, Table 7 shows two things: First, columns (1), (3) and (5) provide no clear correlation between offshoring and wages when firm controls (total sales, capital stock etc.) are included. Second, the specifications in columns (2), (4) and (6) yield positive relationships between wages and offshoring without firm controls. One reason for the lack of connection between wages and offshoring in the first set of specifications may be that the inclusion of firm controls hold fixed the "productivity effect" usually attributed to offshoring[11]: when firms acquire access to cheaper imported inputs, remaining production factors become relatively more productive which is reflected in the adjustments of firm scale and scope. This tends to affect wages positively. Finally, column (6) suggests a stronger negative effect of offshoring for workers with a high routine content of tasks which is consistent with the literature (e.g. Hummels *et al.* (2014)). See section 3.3 for more about taking the routine content of occupations into account.

In order to examine the importance of using an occupation-specific measure of globalization based on firm-level data, I first limit the sample to manufacturing firms only. I then begin by including cross-occupational variation (i.e. I do not include the job-spell fixed effect $\varphi_{ij}$ in the specification listed above) and estimate these specifications by OLS. Columns (3)-(4) of Table 8 show a clear negative effect for unskilled workers and a positive effect for high-skilled workers, and the productivity effect cushions the adverse effects for low-skilled workers (and raises the benefits for high-skilled workers).

To avoid the potential threats to identification discussed in section 2.2, I include job-spell fixed fixed effects and instrument using world export supply. Table 9, columns (3)-(4) show the first stage regressions. We see that offshoring has a positive and significant association with world export supply and the same holds for the interaction with the high skilled indicator. For all specifications, the first stage F-statistic is in the range of values indicating a fairly strong instrumental variable.

Table 10, columns (3)-(4) show the second-stage results. The pattern is similar for both the OLS and IV specifications. In both cases, we see hourly wages moving in the same direction as firm sales and worker labor market experience and marital status. However, we see no clear evidence of an association between wages and offshoring for either low-skilled or high-skilled workers. Excluding firm controls and allowing for the productivity effect as part of the estimated effect of offshoring as discussed above does not change the conclusion (although the point estimates for offshoring do appear more positive).

[11] See e.g. Grossman and Rossi-Hansberg (2008).

These findings are at a first glance at odds with existing evidence for the Danish labor market as in e.g. Hummels *et al.* (2014). Here, offshoring lowers the wages for unskilled workers (elasticity -0.02) while the wages of skilled workers tend to go up (elasticity 0.03). However, it is of crucial importance to remind the difference is the measurement of offshoring. In my analysis, even though the offshoring measure is based on firm-level data, the measure is occupation-specific and so the weighting given to each particular firm is different in nature to that of Hummels *et al.* (2014). This explains the very different set of results obtained here.

In sum, the effects of offshoring when using an occupation-specific measure seem hard to identify for the manufacturing sector alone. As argued, this might mask important economy-wide, occupation-specific effects also prevalent in the service sector. It is exactly this concern which justifies applying an occupation-specific as opposed to a firm-specific measure of offshoring. To shed light on this, columns (1)-(2) and (5)-(6) of Table 10 redo the analysis for all firms and service firms only, respectively. As can be seen, despite taking account of such general equilibrium effects, there are still no clear effects from offshoring on wages.

Several reasons may be given for why these findings differ from the negative effects found by Ebenstein *et al.* (2014) when including the service sector. First, identifying wage effects using the occupation-specific offshoring measure naturally relies on variation within occupations in wages and offshoring. To the extent that this variation is insufficient to identify effects present in the economy, this analysis is missing important patterns in the data. One reason for this lack of variation may be insufficient mobility between the manufacturing and service sectors in the Danish labor market. Using a somewhat similar dataset and sample period, Ashournia (2015) calculates sectoral transition matrices and find an average yearly transition rate from manufacturing into service of 2-5 percent. Although the Danish labor market is generally considered to be relatively flexible in a European context, this may explain some of the lack of variation to the extent that the mobility of workers is lower than for the US labor market.

Second, the measure of offshoring employed in this paper is markedly different. Although occupation-specific, the measure is based on a broad aggregation of the value of firm imports, whereas the measure used by Ebenstein *et al.* (2014) is based on the total employment of foreign affiliates by US multinationals. Redoing my analysis with a more similar measure of offshoring might yield a fruitful comparison.

Another point worth noting in connection to the relatively low mobility between the manufacturing and service sectors is the fairly high unionization rate of the Danish labor market with resulting high equilibrium wages in most sectors of the economy. If the wages of the service sector relative to the manufacturing sector are markedly higher in Denmark than in the US, the service sector may appear as less of an outside option for manufacturing workers facing pressures from offshoring. To the extent that switching sectors is associated with a human capital and productivity loss, workers may find it less viable to make this transition and rather accept lower wages in their current positions or simply ending up facing unemployment.

This line of thought is further corroborated in columns (5)-(6) of Table 8. Here, we see clear positive effects of on wages for workers in the service sector as offshoring increases for their occupational colleagues in the manufacturing sector. This could reflect workers in the service sector enjoying the benefits of offshoring in the manufacturing sector increasing the overall productivity and thus wage level of the economy. Even though displaced manufacturing workers look for jobs in the service sector, they are restricted in their search by the relative low mobility between sectors. This could lead to noticeable employment effects of offshoring.

## 3.3 Extensions

In the literature, it has been common to identify stronger effects of offshoring on wages for workers with particular task characteristics. As described in section 2.1, I compute normalized measures of the routine and non-routine content of any given occupation (the measures are standardized to have mean 0 and a standard deviation of 1).

I then take these measures into account by adding the interaction of offshoring and the routine content of a given occupation to the empirical specification since routine tasks may be easier to codify and hence offshore. Contrary, occupations heavy in non-routine, more cognitively intensive tasks may in fact benefit from offshoring and the rearrangement of production processes. However, Table 12 and Table 13 show that there is little such effect to be found. Again, the explanations are most likely related to the measuring of offshoring and the lack of variation possibly stemming from limited mobility among sectors as well as the nature of the Danish labor market.

In addition to the specifications discussed above, I experiment with adding or removing firm control variables to contrast the case with or without the productivity effect included in the estimates (see Table 14 and Table 15 for these results). I also try to exclude the years in the period 2008-2010 to rule out the possibility that these arguably exceptional years might be driving the results (this is shown in Table 16). In either case, there appears to be limited evidence in favor of occupation-specific effects of offshoring on wages.

# 4 Conclusion

Considerable attention has been given to the possible effects of offshoring on worker wages in the era of globalization. In this paper, I combine two approaches taken in the literature. On the one hand, I employ linked employer-employee data and base my measure of offshoring on firm-level trade data to account for the heterogeneous nature of trade shocks across firms within industries. On the other hand, I construct an occupation-specific offshoring measure to catch effects from offshoring on workers both in firms directly influenced by the shock and workers indirectly affected as workers relocate across the economy and switch occupations, possibly changing their productivity. I instrument offshoring using an occupation-specific world export supply measure.

This paper finds little or no evidence of offshoring on wages. The lack of clear effects for the manufacturing sector found elsewhere in the literature may be ascribed to the occupation-specific offshoring measure used, whereas other papers have measured offshoring at the firm level. The advantage of the occupation-specific offshoring measure is that it allows the inclusion of the service sector which has less direct exposure to offshoring.

Including the service sector and allowing for economy-wide, occupation-specific effects of offshoring, clear wage effects still do not materialize. This may have several explanations. First, identifying wage effects using the occupation-specific offshoring measure naturally relies on variation within occupations in wages and offshoring. To the extent that this variation is insufficient to identify effects present in the economy, this analysis is missing important patterns in the data. One reason for this lack of variation may be insufficient mobility between the manufacturing and service sectors in the Danish labor market. Second, the measure of offshoring employed in this paper is markedly different from that of the existing literature utilizing occupation-specific measures.

Another point worth noting in connection to the relatively low mobility between the manufacturing and service sectors is the fairly high unionization rate of the Danish labor market with resulting high equilibrium wages in most sectors of the economy. If the wages of the service sector relative to the manufacturing sector are markedly higher in Denmark than in the US, the service sector may appear as less of an outside option for manufacturing workers facing pressures from offshoring. To the extent that switching sectors is associated with a human capital and productivity loss, workers may find it less viable to make this transition and rather accept lower wages in their current positions or simply ending up facing unemployment. This would could lead to noticeable employment effects of offshoring.

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# Appendix

## Data appendix

The dataset employed covers the universe of Danish firms and the entire population of individuals in Denmark. Data is drawn from administrative registers in Statistics Denmark (DST) and combines firm data from the Firm Statistics Register (FirmStat) and worker data from the Integrated Database for Labor Market Research (IDA). Data on import and export trade flows comes from the Danish Foreign Trade Statistics Register and is at the product and origin or destination level. This data is combined with the COMTRADE database to obtain data used for preparing the instrumental variable. See also the data section of Hummels *et al.* (2014) for further details of the data, including the data used to construct the world export supply instrumental variable.

The datasets are merged using the CVRNR variable. Only observations with non-missing values of CVRNR in the merged dataset were kept. All firm-year duplicate observations were dropped (except for the first instance). Only firms classified as manufacturing or service firms (i.e. NACE03 in [150000-750000[) were kept. The nomenclature for the NACE03 industry variable changes and must therefore be linked across time. The variable adheres to the following nomenclatures in the period: 1999-2002: DB93, 2nd revision; 2003-2008: DB03; 2009-2010: DB07. I use keys provided from Statistics Denmark to link DB93,2 and DB07 to DB03 which builds on and corresponds closely to the NACE 2003 nomenclature.

The wage variable denotes average (nominal) hourly wage including mandatory pension fund payments for a given year for the individual in question. Provided by Statistics Denmark is a measure of the reliability of the wage data, and only the most reliable wage data is selected for our use (the variable *tlonkval* is required to be at least 50). All instances of negative wage recordings are deleted. We then identify the upper and lower percentiles and delete, from each of these groups, half of the observations. We do this to minimize the risk of outliers and measurement-error based extreme observations significantly affecting our data. We now impute the annual number of hours worked. This is done by dividing the annual wage income reported by employers to the tax system (*lonind* from the 'Idap' registry) with the hourly wage. Once the annual number of worked hours is known, we divide the annual mandatory pension fund payments (variables *arbpen10-16* from the registry 'Indk' which denote various forms of pension payments) with the amount of hours worked to obtain pension contributions per hour worked. This is then added to the hourly wage to obtain a net measure of the gain for the worker of each hour worked which becomes the final wage variable.

For occupational codes, I choose the 4-digit code based on the DISCO88 nomenclature from Statistics Denmark (documentation here: http://www.dst.dk/da/Statistik/dokumentation/Nomenklaturer/DISCO-88/Stillingsbeskrivelser.aspx). This amounts to 423 occupational categories in the final sample over the sample period which appears comparable to e.g. the 476 occupations in the CPS dataset used by Ebenstein *et al.* (2014). Educational levels are measured using the variable HFFSP (highest level of educational attainment) with values of 40000000 or more coded as high skilled.

For both occupational codes and skill groups, I choose to fix these within job spells, i.e. within a worker-firm match. This is done by choosing the most frequent code within a job spell and replacing all other years in this job spell with the given code. The result is 416 occupational categories compared to the 423 categories without the change.

Table 1: Summary statistics for full sample

| | Mean | Std. Dev. | Observations |
|---|---|---|---|
| *Firm-level data* | | | |
| Total imports | 78.3 | 215.8 | 12,920 |
| Total sales | 414.0 | 1,672.9 | 35,869 |
| Capital stock | 102.3 | 792.3 | 35,869 |
| Total employees | 206 | 634 | 35,869 |
| Share, high-skilled workers | .21 | .19 | 35,869 |
| | | | |
| *Worker-firm data* | | | |
| Hourly wage | 223 | 84 | 6,227,301 |
| Experience | 17 | 10 | 6,227,301 |
| High skilled | .21 | .41 | 6,227,301 |
| Married | .53 | .50 | 6,227,301 |

The data used for the panel titled "Worker-firm data" has worker-firm-year observations and the other has firm-year observations. For each variable the mean and standard deviation is reported across all observations. All monetary variables are in local currency (DKK). Imports, sales and capital stock are in millions DKK. Means and standard deviations are calculated including observations with values of zero. Note that information on total imports is included only for some manufacturing firms. Sample period 1999-2010.

Table 2: Summary statistics, manufacturing sector only

| | Mean | Std. Dev. | Observations |
|---|---|---|---|
| *Firm-level data* | | | |
| Total imports | 78.3 | 215.8 | 12,920 |
| Total sales | 385.4 | 1,412.2 | 14,022 |
| Capital stock | 110.0 | 505.7 | 14,022 |
| Total employees | 220 | 541 | 14,022 |
| Share, high-skilled workers | .18 | .13 | 14,022 |
| *Worker-firm data* | | | |
| Hourly wage | 218 | 76 | 2,738,111 |
| Experience | 18 | 9.8 | 2,738,111 |
| High skilled | .20 | .40 | 2,738,111 |
| Married | .56 | .50 | 2,738,111 |

The data used for the panel titled "Worker-firm data" has worker-firm-year observations and the other has firm-year observations. For each variable the mean and standard deviation is reported across all observations. All monetary variables are in local currency (DKK). Imports, sales and capital stock are in millions DKK. Means and standard deviations are calculated including observations with values of zero. Note that information on total imports is included only for some manufacturing firms. Sample period 1999-2010.

Table 3: Summary statistics, service sector only

| | Mean | Std. Dev. | Observations |
|---|---|---|---|
| *Firm-level data* | | | |
| Total sales | 432.4 | 1,820.5 | 21,847 |
| Capital stock | 97.4 | 930.8 | 21,847 |
| Total employees | 198 | 687 | 21,847 |
| Share, high-skilled workers | .23 | .22 | 21,847 |
| *Worker-firm data* | | | |
| Hourly wage | 226 | 89 | 3,489,190 |
| Experience | 17 | 10 | 3,489,190 |
| High skilled | .22 | .41 | 3,489,190 |
| Married | .50 | .50 | 3,489,190 |

The data used for the panel titled "Worker-firm data" has worker-firm-year observations and the other has firm-year observations. For each variable the mean and standard deviation is reported across all observations. All monetary variables are in local currency (DKK). Sales and capital stock are in millions DKK. Means and standard deviations are calculated including observations with values of zero. Sample period 1999-2010.

Table 4: Characteristics of top 10 occupations by number of workers, 2005

| Occupational code | No. workers in occupation | Share of occ. workers in manufacturing | Avg. yearly transition rate | Log(Offshoring) | Routine index (mean zero) |
|---|---|---|---|---|---|
| 5220 | 31,467 | 0.03 | 0.01 | 15.5 | 0.45 |
| 3415 | 22,636 | 0.34 | 0.02 | 17.7 | -1.01 |
| 9330 | 18,082 | 0.24 | 0.04 | 17.7 | 0.27 |
| 4115 | 17,109 | 0.30 | 0.02 | 18.2 | -1.73 |
| 9132 | 16,093 | 0.14 | 0.04 | 17.7 | 0.88 |
| 4142 | 14,932 | 0.02 | 0.01 | 15.5 | 0.61 |
| 9320 | 14,664 | 0.81 | 0.02 | 18.6 | 0.78 |
| 8271 | 13,424 | 0.97 | 0.01 | 18.4 | 0.72 |
| 7233 | 10,780 | 0.79 | 0.02 | 19.2 | 1.55 |
| 4000 | 10,265 | 0.22 | 0.02 | 15.7 | -0.69 |

The table shows the ten occupational codes (at the 4-digit level) with the largest number of workers in 2005. The total number of workers in 2005 is 543,683. The average yearly transition rate is the yearly share of workers within each occupation switching from the manufacturing sector to the service sector, averaged across the sample period 1999-2010. The offshoring measure is occupation-specific. The routine index has mean zero and a standard deviation of one. The occupations represented are: Shop assistants (5220), Salesmen (3415), Transportation workers (9330), Secretaries (4115), Helpers and cleaners (9132), Security workers (4142), Packaging workers (9320), Meat- and fish-processing-machine operators (8271), Agricultural- or industrial-machinery mechanics and fitters (7233), Office clerks (4000).

Table 5: Top 10 occupations by occupation-specific offshoring growth

| Occupational code | Growth in offshoring (percent) | No. workers in occupation | Share of occ. workers in manufacturing | Avg. yearly transition rate | Routine index (mean zero) |
|---|---|---|---|---|---|
| 8271 | 233 | 13,424 | 0.97 | 0.01 | 0.72 |
| 8281 | 170 | 1,603 | 0.94 | 0.01 | 0.98 |
| 2224 | 126 | 1,616 | 0.87 | 0.01 | -1.24 |
| 2419 | 111 | 3,668 | 0.48 | 0.01 | -2.21 |
| 2412 | 108 | 843 | 0.32 | 0.02 | -1.73 |
| 2143 | 104 | 891 | 0.42 | 0.02 | -2.10 |
| 7122 | 96 | 2,582 | 0.06 | 0.01 | 1.05 |
| 3211 | 96 | 3,056 | 0.91 | 0.01 | -0.50 |
| 2145 | 74 | 3,238 | 0.58 | 0.02 | -1.70 |
| 2411 | 72 | 4,681 | 0.12 | 0.01 | -1.98 |

The table shows the ten occupational codes (at the 4-digit level) with the largest growth in occupation-specific offshoring (in percent) during the sample period 1999-2010. The occupations are selected among occupations with at least 500 workers. The remaining variables are for 2005. The total number of workers in 2005 is 543,683. The average yearly transition rate is the yearly share of workers within each occupation switching from the manufacturing sector to the service sector, averaged across the sample period 1999-2010. The routine index has mean zero and a standard deviation of one. The occupations represented are: Meat- and fish-processing-machine operators (8271), Mechanical-machinery assemblers (8281), Pharmacists (2224), Business professionals (2419), Personell professionals (2412), Electrical engineers (2143), Stonemasons (7122), Life science technicians (3211), Mechanical engineers (2145), Accountants (2411) .

Table 6: Firm-level effects of offshoring

| | Log(Offshoring) |
|---|---|
| Log(Sales) | 1.397*** |
| | (0.0406) |
| Log(Employees) | -0.133** |
| | (0.0548) |
| Log(Capital) | -0.00668 |
| | (0.0189) |
| Share, high-skilled workers | 0.618** |
| | (0.259) |
| Firm FE | Yes |
| Observations | 12,920 |

Dependent variable: Log(Offshoring). Sample is identical to the main estimation sample and includes only firms with offshoring for the years 1999-2010. Industry dummies are at the 2-digit NACE level. Standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table 7: OLS regressions using a firm-specific offshoring measure, manufacturing sector only

| | Manufacturing firms only | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(Offshoring) | 0.000467 | 0.00357*** | 0.000181 | 0.00319*** | 0.000485 | 0.00359*** |
| | (0.000558) | (0.000579) | (0.000643) | (0.000669) | (0.000554) | (0.000580) |
| Log(Offshoring) x High-skilled | | | 0.00152 | 0.00197* | | |
| | | | (0.000935) | (0.00101) | | |
| Log(Offshoring) x Routine | | | | | -0.0000854 | -0.000101* |
| | | | | | (0.0000534) | (0.0000577) |
| Log(Sales) | 0.0376*** | | 0.0375*** | | 0.0375*** | |
| | (0.00294) | | (0.00294) | | (0.00293) | |
| Log(Employees) | -0.00241 | | -0.00241 | | -0.00242 | |
| | (0.00486) | | (0.00485) | | (0.00486) | |
| Log(Capital) | 0.00212* | | 0.00212* | | 0.00212* | |
| | (0.00112) | | (0.00112) | | (0.00112) | |
| Share, high-skilled workers | 0.0421* | | 0.0423* | | 0.0419* | |
| | (0.0246) | | (0.0245) | | (0.0245) | |
| Experience | 0.00865*** | 0.00889*** | 0.00865*** | 0.00888*** | 0.00865*** | 0.00889*** |
| | (0.00106) | (0.00104) | (0.00106) | (0.00104) | (0.00106) | (0.00104) |
| Experience$^2$ | -0.000463*** | -0.000470*** | -0.000462*** | -0.000470*** | -0.000463*** | -0.000470*** |
| | (0.0000303) | (0.0000307) | (0.0000303) | (0.0000307) | (0.0000303) | (0.0000307) |
| Married | 0.00295** | 0.00305** | 0.00295** | 0.00304** | 0.00294** | 0.00304** |
| | (0.00122) | (0.00122) | (0.00122) | (0.00121) | (0.00122) | (0.00122) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Job spell FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,648,473 | 2,648,473 | 2,648,473 | 2,648,473 | 2,648,473 | 2,648,473 |
| Number of job-spell fixed effects | 716,865 | 716,865 | 716,865 | 716,865 | 716,865 | 716,865 |

Dependent variable: Log(Hourly Wage). Industry dummies are at the 2-digit NACE level. Sample period 1999-2010. Standard errors in parentheses clustered at the occupation level. *p<0.10, **p<0.05, ***p<0.01.

Table 8: OLS regressions using an occupation-specific offshoring measure and cross-occupational variation

| | All firms | | Manufacturing | | Service | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(Offshoring) | 0.00329 | 0.00488 | -0.0184*** | -0.0168*** | 0.0130*** | 0.0142*** |
| | (0.00444) | (0.00492) | (0.00353) | (0.00373) | (0.00385) | (0.00461) |
| Log(Offshoring) x High-skilled | 0.0139*** | 0.0163*** | 0.0146*** | 0.0156*** | 0.0130*** | 0.0165*** |
| | (0.000722) | (0.00103) | (0.000840) | (0.000932) | (0.00114) | (0.00165) |
| Log(Sales) | 0.0569*** | | 0.0732*** | | 0.0486** | |
| | (0.0166) | | (0.0156) | | (0.0200) | |
| Log(Employees) | -0.0573*** | | -0.0624*** | | -0.0537* | |
| | (0.0208) | | (0.0193) | | (0.0260) | |
| Log(Capital) | 0.00287 | | -0.00240 | | 0.00485 | |
| | (0.00346) | | (0.00677) | | (0.00347) | |
| Share, high-skilled workers | 0.290*** | | 0.193*** | | 0.327*** | |
| | (0.0782) | | (0.0680) | | (0.103) | |
| Experience | 0.0265*** | 0.0267*** | 0.0189*** | 0.0190*** | 0.0311*** | 0.0313*** |
| | (0.00207) | (0.00196) | (0.00139) | (0.00134) | (0.00256) | (0.00225) |
| Experience$^2$ | -0.000490*** | -0.000492*** | -0.000335*** | -0.000336*** | -0.000584*** | -0.000586*** |
| | (0.0000436) | (0.0000425) | (0.0000293) | (0.0000285) | (0.0000553) | (0.0000537) |
| Married | 0.0329*** | 0.0318*** | 0.0225*** | 0.0216*** | 0.0390*** | 0.0377*** |
| | (0.00434) | (0.00432) | (0.00462) | (0.00494) | (0.00626) | (0.00609) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,227,301 | 6,227,301 | 2,738,111 | 2,738,111 | 3,489,190 | 3,489,190 |

Dependent variable: Log(Hourly Wage). Industry dummies are at the 2-digit NACE level. Sample period 1999-2010.
Standard errors in parentheses clustered at the industry level. *p<0.10, **p<0.05, ***p<0.01.

Table 9: First-stage IV regressions

| | All firms | | Manufacturing | | Service | |
|---|---|---|---|---|---|---|
| | Log(Offshoring) | x high skill | Log(Offshoring) | x high skill | Log(Offshoring) | x high skill |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(WES) | 0.546*** | 0.00866** | 0.434*** | 0.00601** | 0.620*** | 0.0108** |
| | (0.0735) | (0.00362) | (0.0465) | (0.00254) | (0.115) | (0.00508) |
| Log(WES) x High-skilled | -0.0781 | 0.430*** | -0.0757 | 0.336*** | -0.110 | 0.463*** |
| | (0.0572) | (0.0489) | (0.0534) | (0.0488) | (0.0810) | (0.0570) |
| Log(Sales) | 0.0147 | 0.00528 | 0.0340* | 0.00865** | 0.00917 | 0.00321 |
| | (0.0111) | (0.00382) | (0.0179) | (0.00348) | (0.0147) | (0.00660) |
| Log(Employees) | -0.00731 | -0.00442 | -0.00849 | -0.00538 | 0.00326 | -0.00438 |
| | (0.0244) | (0.00674) | (0.0322) | (0.00383) | (0.0181) | (0.0115) |
| Log(Capital) | 0.00440 | -0.000109 | 0.0174 | 0.000537 | -0.00771 | -0.00121 |
| | (0.00735) | (0.000952) | (0.0120) | (0.00128) | (0.00492) | (0.00135) |
| Share, high-skilled workers | 0.0708 | -0.00597 | -0.0167 | -0.000123 | 0.124 | -0.00594 |
| | (0.0966) | (0.0234) | (0.217) | (0.0272) | (0.0857) | (0.0266) |
| Experience | 0.00256 | 0.000593 | 0.00468*** | 0.000850 | 0.000563 | 0.000741 |
| | (0.00208) | (0.000719) | (0.00155) | (0.000769) | (0.00340) | (0.00151) |
| Experience$^2$ | -0.0000621 | -0.0000149 | -0.000129* | -0.00000821 | -0.0000318 | -0.0000299 |
| | (0.0000630) | (0.0000179) | (0.0000708) | (0.0000153) | (0.0000894) | (0.0000264) |
| Married | -0.00123 | 0.000204 | -0.00317 | -0.000425 | 0.00139 | 0.000633 |
| | (0.00371) | (0.000661) | (0.00490) | (0.000660) | (0.00371) | (0.00107) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Job spell FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,227,301 | 6,227,301 | 2,738,111 | 2,738,111 | 3,489,190 | 3,489,190 |
| Number of job-spell fixed effects | 1,224,489 | 1,224,489 | 511,141 | 511,141 | 725,162 | 725,162 |
| First stage F-statistic | 40.76 | 40.51 | 49.30 | 23.75 | 26.73 | 41.10 |

The table shows the first stage regressions for log offshoring and its skill interaction using world export supply (WES) and its skill interaction as excluded instruments. Industry dummies are at the 2-digit NACE level. Sample period 1999-2010. Standard errors in parentheses clustered at the occupation level. *p<0.10, **p<0.05, ***p<0.01.

Table 10: OLS and IV regressions with firm controls (OFF*skilled interaction)

| | All firms | | Manufacturing | | Service | |
|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(Offshoring) | -0.00148 | -0.000562 | -0.0000437 | 0.00513 | 0.000759 | 0.00193 |
| | (0.00331) | (0.00609) | (0.00433) | (0.00728) | (0.00367) | (0.00800) |
| Log(Offshoring) x High-skilled | 0.00169 | 0.000419 | -0.000875 | 0.00114 | 0.000550 | 0.00282 |
| | (0.00337) | (0.00711) | (0.00597) | (0.0161) | (0.00334) | (0.00668) |
| Log(Sales) | 0.0188*** | 0.0187*** | 0.0384*** | 0.0379*** | 0.0131*** | 0.0131*** |
| | (0.00175) | (0.00180) | (0.00273) | (0.00276) | (0.00192) | (0.00191) |
| Log(Employees) | 0.0164*** | 0.0164*** | -0.00254 | -0.00235 | 0.0125*** | 0.0125*** |
| | (0.00315) | (0.00321) | (0.00465) | (0.00476) | (0.00258) | (0.00255) |
| Log(Capital) | -0.00112* | -0.00113* | 0.00207* | 0.00199* | -0.000977 | -0.000988 |
| | (0.000601) | (0.000593) | (0.00107) | (0.00109) | (0.000913) | (0.000905) |
| Share, high-skilled workers | 0.0370** | 0.0368** | 0.0354 | 0.0352 | 0.0488*** | 0.0485*** |
| | (0.0147) | (0.0143) | (0.0233) | (0.0235) | (0.0147) | (0.0144) |
| Experience | 0.0153*** | 0.0153*** | 0.00845*** | 0.00842*** | 0.0215*** | 0.0215*** |
| | (0.00147) | (0.00147) | (0.00110) | (0.00109) | (0.00196) | (0.00196) |
| Experience$^2$ | -0.000646*** | -0.000646*** | -0.000466*** | -0.000465*** | -0.000808*** | -0.000808*** |
| | (0.0000443) | (0.0000441) | (0.0000300) | (0.0000295) | (0.0000590) | (0.0000589) |
| Married | 0.00256* | 0.00256* | 0.00283** | 0.00286** | 0.00133 | 0.00133 |
| | (0.00148) | (0.00148) | (0.00126) | (0.00126) | (0.00258) | (0.00258) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Job spell FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,227,301 | 6,227,301 | 2,738,111 | 2,738,111 | 3,489,190 | 3,489,190 |
| Number of job-spell fixed effects | 1,945,067 | 1,224,489 | 742,234 | 511,141 | 1,234,458 | 725,162 |
| First stage F-statistic | | 37.69 | | 44.06 | | 30.84 |

Dependent variable: Log(Hourly Wage). Industry dummies are at the 2-digit NACE level. Sample period 1999-2010. Standard errors in parentheses clustered at the occupation level. *p<0.10, **p<0.05, ***p<0.01.

Table 11: OLS and IV regressions with no firm controls (OFF*skilled interaction)

| | All firms | | Manufacturing | | Service | |
|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(Offshoring) | -0.00116 | -0.000279 | 0.00204 | 0.00928 | 0.000938 | 0.00198 |
| | (0.00354) | (0.00632) | (0.00497) | (0.00761) | (0.00371) | (0.00821) |
| Log(Offshoring) x High-skilled | 0.00143 | -0.000268 | -0.000311 | 0.00207 | 0.0000784 | 0.00166 |
| | (0.00342) | (0.00736) | (0.00666) | (0.0175) | (0.00333) | (0.00666) |
| Experience | 0.0156*** | 0.0156*** | 0.00871*** | 0.00866*** | 0.0217*** | 0.0217*** |
| | (0.00148) | (0.00147) | (0.00108) | (0.00107) | (0.00196) | (0.00196) |
| Experience$^2$ | -0.000655*** | -0.000655*** | -0.000474*** | -0.000472*** | -0.000814*** | -0.000814*** |
| | (0.0000445) | (0.0000443) | (0.0000303) | (0.0000298) | (0.0000591) | (0.0000589) |
| Married | 0.00270* | 0.00270* | 0.00290** | 0.00295** | 0.00141 | 0.00141 |
| | (0.00148) | (0.00148) | (0.00126) | (0.00126) | (0.00258) | (0.00258) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Job spell FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,227,301 | 6,227,301 | 2,738,111 | 2,738,111 | 3,489,190 | 3,489,190 |
| Number of job-spell fixed effects | 1,945,067 | 1,224,489 | 742,234 | 511,141 | 1,234,458 | 725,162 |
| First stage F-statistic | | 37.57 | | 43.25 | | 30.72 |

Dependent variable: Log(Hourly Wage). Industry dummies are at the 2-digit NACE level. Sample period 1999-2010. Standard errors in parentheses clustered at the occupation level. *p<0.10, **p<0.05, ***p<0.01.

Table 12: OLS and IV regressions with firm controls (OFF*routine interaction)

| | All firms | | Manufacturing | | Service | |
|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(Offshoring) | -0.00188 | -0.00130 | 0.00169 | 0.00406 | 0.000108 | 0.00200 |
| | (0.00329) | (0.00635) | (0.00469) | (0.00784) | (0.00346) | (0.00809) |
| Log(Offshoring) x High-skilled | 0.00240 | 0.00229 | -0.00422 | 0.00377 | 0.00178 | 0.00265 |
| | (0.00274) | (0.00616) | (0.00459) | (0.0131) | (0.00272) | (0.00571) |
| Log(Offshoring) x Routine | 0.00110 | 0.00262 | -0.00270 | 0.00197 | 0.00332 | -0.000400 |
| | (0.00330) | (0.00668) | (0.00371) | (0.00743) | (0.00379) | (0.00846) |
| Log(Sales) | 0.0188*** | 0.0187*** | 0.0383*** | 0.0380*** | 0.0131*** | 0.0131*** |
| | (0.00175) | (0.00182) | (0.00271) | (0.00276) | (0.00193) | (0.00198) |
| Log(Employees) | 0.0164*** | 0.0164*** | -0.00247 | -0.00239 | 0.0125*** | 0.0125*** |
| | (0.00317) | (0.00323) | (0.00463) | (0.00475) | (0.00258) | (0.00255) |
| Log(Capital) | -0.00112* | -0.00112* | 0.00207* | 0.00199* | -0.000951 | -0.000991 |
| | (0.000601) | (0.000594) | (0.00107) | (0.00109) | (0.000914) | (0.000907) |
| Share, high-skilled workers | 0.0370** | 0.0367** | 0.0356 | 0.0351 | 0.0485*** | 0.0486*** |
| | (0.0147) | (0.0144) | (0.0232) | (0.0236) | (0.0149) | (0.0148) |
| Experience | 0.0153*** | 0.0153*** | 0.00846*** | 0.00841*** | 0.0215*** | 0.0215*** |
| | (0.00148) | (0.00147) | (0.00110) | (0.00109) | (0.00196) | (0.00196) |
| Experience$^2$ | -0.000646*** | -0.000646*** | -0.000466*** | -0.000465*** | -0.000807*** | -0.000808*** |
| | (0.0000443) | (0.0000443) | (0.0000299) | (0.0000295) | (0.0000593) | (0.0000591) |
| Married | 0.00256* | 0.00257* | 0.00282** | 0.00287** | 0.00134 | 0.00133 |
| | (0.00148) | (0.00148) | (0.00126) | (0.00126) | (0.00259) | (0.00258) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Job spell FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,227,301 | 6,227,301 | 2,738,111 | 2,738,111 | 3,489,190 | 3,489,190 |
| Number of job-spell fixed effects | 1,945,067 | 1,224,489 | 742,234 | 511,141 | 1,234,458 | 725,162 |
| First stage F-statistic | | 53.65 | | 33.51 | | 20.89 |

Dependent variable: Log(Hourly Wage). Industry dummies are at the 2-digit NACE level. Sample period 1999-2010. Standard errors in parentheses clustered at the occupation level. *p<0.10, **p<0.05, ***p<0.01.

Table 13: OLS and IV regressions with firm controls (OFF*non-routine interaction)

| | All firms | | Manufacturing | | Service | |
|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(Offshoring) | -0.00226 | 0.00220 | 0.00345 | 0.00960 | 0.000569 | 0.00310 |
| | (0.00284) | (0.00595) | (0.00288) | (0.00741) | (0.00305) | (0.00764) |
| Log(Offshoring) x High-skilled | 0.00330 | -0.00250 | -0.00562 | -0.000331 | 0.00105 | -0.000420 |
| | (0.00249) | (0.00662) | (0.00553) | (0.0197) | (0.00262) | (0.00632) |
| Log(Offshoring) x Non-Routine | -0.000105 | -0.00138 | 0.00672* | 0.00184 | -0.00313 | -0.000314 |
| | (0.00230) | (0.00415) | (0.00378) | (0.00751) | (0.00217) | (0.00545) |
| Log(Sales) | 0.0172*** | 0.0171*** | 0.0299*** | 0.0293*** | 0.0149*** | 0.0149*** |
| | (0.00155) | (0.00160) | (0.00257) | (0.00265) | (0.00214) | (0.00208) |
| Log(Employees) | 0.0125*** | 0.0127*** | -0.00314 | -0.00293 | 0.0107*** | 0.0107*** |
| | (0.00271) | (0.00279) | (0.00417) | (0.00430) | (0.00277) | (0.00267) |
| Log(Capital) | -0.00100 | -0.00106* | 0.00285** | 0.00269** | -0.00146 | -0.00147 |
| | (0.000639) | (0.000635) | (0.00117) | (0.00120) | (0.00102) | (0.00101) |
| Share, high-skilled workers | 0.0256* | 0.0247* | 0.0161 | 0.0158 | 0.0208 | 0.0201 |
| | (0.0136) | (0.0135) | (0.0181) | (0.0179) | (0.0135) | (0.0137) |
| Experience | 0.0145*** | 0.0144*** | 0.00769*** | 0.00765*** | 0.0207*** | 0.0207*** |
| | (0.00163) | (0.00163) | (0.00140) | (0.00139) | (0.00220) | (0.00220) |
| Experience$^2$ | -0.000702*** | -0.000702*** | -0.000511*** | -0.000510*** | -0.000887*** | -0.000888*** |
| | (0.0000486) | (0.0000488) | (0.0000336) | (0.0000332) | (0.0000659) | (0.0000660) |
| Married | 0.00168 | 0.00171 | 0.00224* | 0.00231* | -0.0000986 | -0.0000868 |
| | (0.00143) | (0.00143) | (0.00124) | (0.00123) | (0.00259) | (0.00259) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Job spell FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,840,496 | 4,840,496 | 2,212,876 | 2,212,876 | 2,627,620 | 2,627,620 |
| Number of job-spell fixed effects | 1,676,706 | 1,007,394 | 667,991 | 442,682 | 1,028,344 | 569,901 |
| First stage F-statistic | | 19.57 | | 3.62 | | 15.63 |

Dependent variable: Log(Hourly Wage). Industry dummies are at the 2-digit NACE level. Sample period 1999-2010. Standard errors in parentheses clustered at the occupation level. *p<0.10, **p<0.05, ***p<0.01.

Table 14: OLS and IV regressions with no firm controls (OFF*routine interaction)

| | All firms | | Manufacturing | | Service | |
|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(Offshoring) | -0.00163 | -0.000980 | 0.00388 | 0.00850 | 0.000249 | 0.00205 |
| | (0.00350) | (0.00661) | (0.00526) | (0.00830) | (0.00350) | (0.00832) |
| Log(Offshoring) x High-skilled | 0.00225 | 0.00149 | -0.00387 | 0.00402 | 0.00138 | 0.00149 |
| | (0.00274) | (0.00642) | (0.00494) | (0.0137) | (0.00277) | (0.00577) |
| Log(Offshoring) x Routine | 0.00128 | 0.00247 | -0.00287 | 0.00146 | 0.00351 | -0.000412 |
| | (0.00336) | (0.00684) | (0.00399) | (0.00806) | (0.00378) | (0.00850) |
| Experience | 0.0156*** | 0.0156*** | 0.00871*** | 0.00865*** | 0.0217*** | 0.0217*** |
| | (0.00148) | (0.00148) | (0.00108) | (0.00107) | (0.00197) | (0.00196) |
| Experience$^2$ | -0.000655*** | -0.000655*** | -0.000474*** | -0.000472*** | -0.000814*** | -0.000814*** |
| | (0.0000446) | (0.0000445) | (0.0000303) | (0.0000298) | (0.0000593) | (0.0000592) |
| Married | 0.00270* | 0.00271* | 0.00289** | 0.00295** | 0.00141 | 0.00141 |
| | (0.00148) | (0.00148) | (0.00126) | (0.00125) | (0.00259) | (0.00258) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Job spell FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,227,301 | 6,227,301 | 2,738,111 | 2,738,111 | 3,489,190 | 3,489,190 |
| Number of job-spell fixed effects | 1,945,067 | 1,224,489 | 742,234 | 511,141 | 1,234,458 | 725,162 |
| First stage F-statistic | | 53.78 | | 33.28 | | 20.88 |

Dependent variable: Log(Hourly Wage). Industry dummies are at the 2-digit NACE level. Sample period 1999-2010. Standard errors in parentheses clustered at the occupation level. *p<0.10, **p<0.05, ***p<0.01.

Table 15: OLS and IV regressions with no firm controls (OFF*non-routine interaction)

| | All firms | | Manufacturing | | Service | |
|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(Offshoring) | -0.00153 | -0.000861 | 0.00379 | 0.00547 | 0.000799 | 0.00191 |
| | (0.00312) | (0.00604) | (0.00312) | (0.00683) | (0.00328) | (0.00793) |
| Log(Offshoring) x High-skilled | 0.00183 | 0.00176 | -0.00962* | -0.0000210 | 0.00150 | 0.00306 |
| | (0.00271) | (0.00643) | (0.00515) | (0.0156) | (0.00263) | (0.00566) |
| Log(Offshoring) x Non-Routine | -0.000216 | -0.00176 | 0.00647 | 0.000840 | -0.00307 | -0.000523 |
| | (0.00260) | (0.00449) | (0.00439) | (0.00587) | (0.00228) | (0.00561) |
| Experience | 0.0153*** | 0.0153*** | 0.00846*** | 0.00842*** | 0.0215*** | 0.0215*** |
| | (0.00147) | (0.00147) | (0.00110) | (0.00109) | (0.00196) | (0.00196) |
| Experience$^2$ | -0.000646*** | -0.000646*** | -0.000466*** | -0.000465*** | -0.000807*** | -0.000808*** |
| | (0.0000443) | (0.0000443) | (0.0000299) | (0.0000295) | (0.0000592) | (0.0000591) |
| Married | 0.00256* | 0.00257* | 0.00281** | 0.00285** | 0.00132 | 0.00133 |
| | (0.00148) | (0.00148) | (0.00126) | (0.00126) | (0.00259) | (0.00258) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Job spell FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,227,301 | 6,227,301 | 2,738,111 | 2,738,111 | 3,489,190 | 3,489,190 |
| Number of job-spell fixed effects | 1,945,067 | 1,224,489 | 742,234 | 511,141 | 1,234,458 | 725,162 |
| First stage F-statistic | | 32.06 | | 9.48 | | 20.35 |

Dependent variable: Log(Hourly Wage). Industry dummies are at the 2-digit NACE level. Sample period 1999-2010. Standard errors in parentheses clustered at the occupation level. *p<0.10, **p<0.05, ***p<0.01.

Table 16: OLS and IV regressions with firm controls, 1999-2007 only (OFF*skilled interaction)

| | All firms | | Manufacturing | | Service | |
|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(Offshoring) | -0.00225 | 0.00221 | -0.000368 | 0.00892 | -0.0000230 | 0.00305 |
| | (0.00290) | (0.00606) | (0.00320) | (0.00814) | (0.00337) | (0.00740) |
| Log(Offshoring) x High-skilled | 0.00326 | -0.00334 | 0.00363 | 0.00239 | 0.000990 | -0.000478 |
| | (0.00299) | (0.00731) | (0.00614) | (0.0181) | (0.00320) | (0.00687) |
| Log(Sales) | 0.0172*** | 0.0171*** | 0.0300*** | 0.0293*** | 0.0149*** | 0.0149*** |
| | (0.00155) | (0.00161) | (0.00255) | (0.00266) | (0.00213) | (0.00211) |
| Log(Employees) | 0.0125*** | 0.0126*** | -0.00316 | -0.00293 | 0.0106*** | 0.0107*** |
| | (0.00273) | (0.00279) | (0.00423) | (0.00432) | (0.00276) | (0.00271) |
| Log(Capital) | -0.00100 | -0.00105* | 0.00280** | 0.00267** | -0.00145 | -0.00147 |
| | (0.000639) | (0.000638) | (0.00117) | (0.00120) | (0.00102) | (0.00101) |
| Share, high-skilled workers | 0.0256* | 0.0248* | 0.0156 | 0.0156 | 0.0210 | 0.0201 |
| | (0.0136) | (0.0135) | (0.0183) | (0.0181) | (0.0135) | (0.0136) |
| Experience | 0.0145*** | 0.0145*** | 0.00769*** | 0.00764*** | 0.0207*** | 0.0207*** |
| | (0.00163) | (0.00163) | (0.00140) | (0.00139) | (0.00219) | (0.00220) |
| Experience$^2$ | -0.000702*** | -0.000702*** | -0.000511*** | -0.000510*** | -0.000888*** | -0.000888*** |
| | (0.0000486) | (0.0000487) | (0.0000337) | (0.0000332) | (0.0000656) | (0.0000657) |
| Married | 0.00168 | 0.00170 | 0.00227* | 0.00232* | -0.000100 | -0.0000869 |
| | (0.00143) | (0.00143) | (0.00124) | (0.00124) | (0.00258) | (0.00259) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Job spell FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,840,496 | 4,840,496 | 2,212,876 | 2,212,876 | 2,627,620 | 2,627,620 |
| Number of job-spell fixed effects | 1,676,706 | 1,007,394 | 667,991 | 442,682 | 1,028,344 | 569,901 |
| First stage F-statistic | | 24.10 | | 21.84 | | 22.52 |

Dependent variable: Log(Hourly Wage). Industry dummies are at the 2-digit NACE level. Sample period 1999-2010. Standard errors in parentheses clustered at the occupation level. *p<0.10, **p<0.05, ***p<0.01.