

# Employers meet Employees

## Essays on Sorting and Globalization

Scheuer, Christian

### *Document Version*

Final published version

### *Publication date:*

2009

### *License*

Unspecified

### *Citation for published version (APA):*

Scheuer, C. (2009). *Employers meet Employees: Essays on Sorting and Globalization*. Copenhagen Business School [Phd]. PhD series No. 24.2009

[Link to publication in CBS Research Portal](#)

### **General rights**

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

### **Take down policy**

If you believe that this document breaches copyright please contact us (research.lib@cbs.dk) providing details, and we will remove access to the work immediately and investigate your claim.

Download date: 04. Jul. 2025

**COPENHAGEN BUSINESS SCHOOL**  
**HANDELSHØJSKOLEN**  
SOLBJERG PLADS 3  
DK-2000 FREDERIKSBERG  
DENMARK

[www.cbs.dk](http://www.cbs.dk)



**Copenhagen  
Business School**  
HANDELSHØJSKOLEN

Employers meet employees

# Employers meet employees

Essays on sorting and globalization

**Christian Scheuer**

ISSN 0906-6934  
ISBN 978-87-593-8405-3

ISBN 978-87-593-8405-3



PhD Series 24.2009

The PhD School of Economics and Management

PhD Series 24.2009

**Employers meet employees**

Christian Scheuer  
*Employers meet employees*  
*Essays on sorting and globalization*

1st edition 2009  
PhD Series 24.2009

© The Author

ISBN: 978-87-593-8405-3  
ISSN: 0906-6934

“The Doctoral School of Economics and Management is an active national and international research environment at CBS for research degree students who deal with economics and management at business, industry and country level in a theoretical and empirical manner”.

All rights reserved.

No parts of this book may be reproduced or transmitted in any form or by any means, electronic or mechanical, including photocopying, recording, or by any information storage or retrieval system, without permission in writing from the publisher.

**Employers meet employees**  
-  
**Essays on sorting and globalization**

**Christian Scheuer**

**PhD Thesis**

**Copenhagen Business School and CEBR**

**June 2009**

# Contents

|  |     |
|--|-----|
| Preface .....  | 3   |
| Introduction .....   | 5   |
| Summery.....   | 6   |
| Summery in Danish .....  | 9   |
| Chapter 1: Determinants of Labor Force Participation for Recipients of Social Assistance: A Panel Data Analysis for Denmark..... | 13  |
| Chapter 2: Job Sampling and Sorting .....  | 43  |
| Chapter 3: Exposure to Low-Wage Country Imports and Skill-Upgrading at the Firm Level.....                                       | 79  |
| Chapter 4: Import Effects on Skill-Upgrading, New Insights from Firm Level Evidence.....   | 105 |

# 1 Preface

This thesis consists of four papers that combined constitute my PhD. In the following I wish to extend my gratitude to all the people who helped me make this thesis possible. First and foremost I would like to thank my Adviser Professor Anders Sørensen who also coauthors chapter 3. This thesis has benefited much from your continued guidance and inspiration. I especially want to thank you for always taking an interest in me, as my friend and mentor, when working together and when discussing subjects outside your own research areas. And referring to the latter, I would also like to thank you for your continued support and encouragement to write about the things I found most interesting, even though they were not all part of my original intends for this PhD

The next group of people that deserves a special appreciation is my fellow students at CBS, CEBR and Princeton. Without you, these years would have been so much less inspiring and enjoyable. A very special thanks goes to Daniel le Maire my coauthor to chapter 1 and 2. I have enjoyed and benefited enormously from working with you, not only in this PhD, but in all the years since we started our studies together at KU in 1998. I cherish your continued friendship, and your dedicated and curious nature has always been an aspiration to me. There are a number of people here in Denmark and in the US that deserves mentioning, but since I am sure you all know how much I have enjoyed my time with you I will confine this thanks to the two people that I spent the most time with in the past three years – Esben and Frederik-Thank you for great discussions and for making CBS such a welcoming place.

I am grateful that I was given the opportunity to write this PhD being part of the faculty at CBS and the research community at CEBR. To all of my colleagues there - thank you for making these years enjoyable and for your engagement and willingness for discussion. Specially, I would like to thank my co-adviser Professor HC Kongsted for many great advices and also thanks to the coauthors to chapter 3 Mikael Andersen and Professor Michael Rosholm. I would also like to extend a special thanks to Professor Peter Mølgaard and Professor Svend-Erik Hougaard for your continued commitment to creating an outstanding working environment and for always taking interest and being helpful.

A very rewarding part of my PhD was the year at Princeton University and I am grateful for this rewarding opportunity. So many people inspired me and helped make my time there utmost enjoyable. Of all things I probably benefitted the most from Professor Orley Ashenfelter and Professor Alan Kruger's labor economics course, and from discussing my work with them. Also, thanks to Professor Bo Honore for welcoming me in Princeton and for all the valuable and much appreciated comments you have given me. Moreover, my Princeton experience would not have been possible without the generous contributions I received from Danmark-Amerika Fondet, Augustinus Fonden, DA's Jubilæums Fond, GTN Fonden, Hedorf Fond, Købmand Svend Hansen og Hustru Ina Hansen Fond, Oticon Fonden, Otto Mønsted's Fond and Rudolph

Als Fondet.

Next I feel very fortunate for the chance of following courses with a number of the world's leading economist made possible by the DGPE program. Especially the people of CAM at Copenhagen University have been very welcoming and I have benefitted much from presenting my research there and from participating in numerous seminars, courses and conferences.

Also thanks to all my former colleagues in the Rockwool Foundation Research Unit and the Danish Welfare commission for their help in shaping me as economist.

Last but certainly not least, I would like to thank my friends and family for their continued support and my girlfriend Nynne for inspiring me to always do my best, for your unconditional support even when worlds apart, and for keeping my head above water whenever times were tough.

Christian Scheuer,

Copenhagen, June 2009



## 2 Introduction

"Leaping into the future of labor economics: the research potential of linking employer and employee data" is the title of a paper by Daniel S Hammermesh published in Labour Economics in 1999. I quote it here, since it captures much of my motivation for the work included in this thesis. Considering applied micro econometrics and labor economics my main fields of interest, the development of linked employer-employee data that took place in Denmark around the time of the new millennium, marked new and exciting possibilities.

For some years Danish researchers have had access to very detailed information on all people living in Denmark, but at the beginning of this century also data on all companies linked to these persons was being made available for research. Combined with modern computer technology this meant access to a linked database following all employers and all employees in Denmark over time.

I had no doubt that this should be the centerpiece of my Ph.D. The result has been two lines of research, one studying the effect of globalization on labor demand in Denmark, and one studying sorting, that is, how and why employers meet employees in the labor market. In the summary I treat each line of research independently although I would like to emphasize, that studying a labor market where firms and workers reacts to one another is the corner stone in both.

### 3 Summary

Chapter 2, 3 and 4 are the main chapters of this thesis, while chapter 1 on the determinants of labor force participation for recipients of social assistance (coauthored by Daniel le Maire) is included and important as well. This first chapter is the earliest of the 4 papers included and was conducted for the Danish Welfare Commission, and as such it is not closely related to the rest of the thesis. The main objective of this first paper is to quantify the importance of economic incentives for persons receiving social assistance in Denmark. The paper includes two empirical strategies for determining to what degree economic incentives are important for persons receiving social assistance. Firstly, we use within-individual variation in the recipients spouse income, and secondly we compute and use own potential net gain of working compared to receiving social assistance. From the recipients spouse income we find no employment effects, a result consistent with workers receiving social assistance benefits being marginalized in the labor market. This finding is supported by the group's compressed wage distribution and the strong state dependence in their labor market status. Using own potential net gain of working compared to receiving social assistance we find participation elasticities in the range of 0.28-0.44 for men and 0.62-0.68 for women. However, in the paper we argue that unobserved heterogeneity likely implies these estimates to be upward biased.

Chapter 2 (coauthored with Daniel le Maire) is about positive assortative matching in the labor market, or more specifically we seek to address the questions if and how above average productive workers ends up in above average productive firms. The paper includes both a theoretical and empirical part and is probably the most comprehensive of the four chapters in this thesis. This paper was impelled by what we considered to be an empirical puzzle. While we find it intuitively that high productive workers should choose to work in high productive firms, the existing empirical evidence found no such evidence, in fact, several papers claim evidence for the opposite result.

In order to analyze this counter-intuitive result, the first part of the paper sets up a theoretical search model with two important capabilities. Firstly, the model predicts positive assortative matching and secondly, the model implies a log wage equation that is additive-separable in worker and firm productivity. Thus, the model deals with the problem that the canonical search model needs log-supermodularity of the production function for assortative matching to arise, which implies that the wage equation is not additive separable. The reason we want an additive separable wage equation is, that this is a key assumption in the existing empirical models used to analyze assortative matching, and hence, with this capability our model can be directly tested against existing estimation procedures. What we do is to allow workers to determine how many jobs they apply for, which we then prove to imply that a supermodular production function, which delivers the wage equation needed, implies positive assortative matching. Furthermore, our model encompasses continuous heterogeneity on both

the worker and firm side, and we add a match productivity effect. We show that with such a match effect present and with positive assortative matching taking place in the model, the existing empirical procedure applied to our simulated data estimates negative correlation between the worker and firm effects. Also we compute several empirical estimates on Danish matched employer-employee data and estimate that a match effect in the wages accounts for 15 per cent of overall log wage variation. All combined we conclude, that the evidence suggests that positive assortative matching is taking place in the Danish labor market.

Chapter 3 and 4 investigate the implications of international trade for skill-upgrading in Danish manufacturing firms, i.e., increasing demand for skilled labor. The demand for skilled and educated labor has increased continuously in relation to unskilled labor in all developed countries at least over the past two decades. Economic theory suggests two important explanations for this development, technological changes especially within information technology and globalization, in the form of increasing international trade.

A number of industries have faced increased competition due to increased product import. Theoretically this has at least two consequences for a country like Denmark. Firstly, a number of firms will have to close and others will emerge. Secondly, existing firms will have to concentrate on more skill intensive products, where the industrialized countries have the largest comparative advantages compared to low wage countries. Empirically however, the latter mechanism has been challenged as several papers have presented evidence that increased demand for educated labor in developed countries has taken place in all industries and not especially in the industries exposed to the highest degree of international competition.

The vast majority of existing studies of changes in firms' labor demand are conducted on industry level data. The employer-employee data base that we gained access to, offered new and exciting possibilities and a chance to readdress some of the questions raised previously in the literature.

In chapter 3 (coauthored by Mikael Andersen, Michael Rosholm and Anders Sørensen) two distinct mechanisms through which internationalization potentially influences firms' demand for skilled and unskilled labor are analyzed.

The first mechanism is an internal firm effect investigating whether there is a significant correlation between skill-upgrading and firm imports. What we have in mind is the standard story of decreases costs of purchasing inputs from abroad leading firms either to produce fewer inputs themselves or to buy fewer inputs from domestic producers. Since production of the relevant inputs is intensive in unskilled labor this leads to lower shares of unskilled workers in production.

The second mechanism is an external product effect investigating whether skill-upgrading is caused by aggregate imports of a particular product type. The mechanism that we have in mind here, is that firms as a consequence of increasing import competition gradually move

into more skill-intensive production to avoid increasing foreign competition from low-wage countries. Import competition in domestic product markets is a measure of aggregate imports of the product types that the firm produces.

According to our knowledge, this is the first paper that studies both of these aspects simultaneously. We have information on origin, value and type of good for nearly all imports in all Danish manufacturing firms. We use this information to split imports according to country of origin in two groups; Imports from low- and middle-income countries and imports from high-income countries. We find that it is of crucial importance to distinguish imports - both in the form of firm import and import competition - by country-of-origin. Furthermore, we conclude that increasing import competition from low-wage countries leads to within-firm skill-upgrading. This finding is robust to different definitions of import competition relevant for the single firm and with respect to the details of the applied product classifications (3 to 5 digit SITC codes). Moreover, the internal firm effect, i.e., firm imports from low-wage countries, is found to be positively and significantly correlated with skill-upgrading within firms but only when restricting the focus to larger firms.

Chapter 4 contributes by showing that rethinking how to use the information on the internal firm effect can reintroduce this effect as an important determinant for skill-upgrading in Denmark. Also, this chapter contains a thorough examination of the potential pitfalls posed by using input-output tables to analyze skill-upgrading. Using information from the UN on their Broad Economic Categories imports is further decomposed according to whether the goods are intermediate inputs or final goods. The ability to decomposed firm level imports both according to country of origin and level of processing leads to three main conclusions. Firstly, using figures from input-output tables and thus disregarding import of final products will significantly bias the results and lead to an under-evaluation of import's role for skill-upgrading. Secondly, distinguishing imports according to country of origin and level of processing is of vital importance. Thirdly, the explanatory power of import of final goods for skill-upgrading is rapidly increasing with firm size. The paper argues that the last fact can be interpreted as supporting the hypothesis either that larger firms have advantage in utilizing the import of final good production from low- and middle-income countries due to scale (e.g. by setting up own production) or that smaller firms to a larger degree utilize third party trading companies, whereby, their "imports" simply do not show up in import data statistics.

## 4 Summary in Danish

Kapitlerne 2, 3 og 4 er de vigtigste i denne afhandling, men kapitel 1 "the determinants of labor force participation for recipients of social assistance" (med Daniel le Maire som medforfatter) er også vigtig og derfor inkluderet. Dette første kapitel er det tidligste af de 4 papirer, som er medtaget her. Papiret blevet skrevet som arbejde for Velfærdskommission, og er som sådan ikke nært beslægtet med resten af afhandlingen. Hovedformålet er at kvantificere betydningen af økonomiske incitamenter for personer, der modtager kontanthjælp i Danmark. I papiret følges to forskellige empiriske strategier for at bestemme i hvor høj grad økonomiske incitamenter er vigtige for personer, der modtager kontanthjælp. Første anvendes variationen i ægtefællers indkomst, og derefter beregnes og anvendes egen potentiell nettogevinst ved at arbejde i forhold til at modtager kontanthjælp. Vi finder at ægtefællers indkomst er uden betydning for kontanthjælpsmodtageres deltagelsesbeslutning, et resultat, som er konsistent med, at denne gruppe er marginaliseret på arbejdsmarkedet. Et faktum, der understøttes af denne gruppes sammenpressede lønstruktur og den høje grad af observeret persistens i gruppens arbejdsmarkeds status. Anvendes egen potentielle nettogevinst ved at arbejde i forhold til at modtager kontanthjælp finder vi deltagelseselasticiteter i størrelsesordenen 0,28-0,44 for mænd og 0,62-0,68 for kvinder. Imidlertid argumenteres der i papirer for, at uobserverbar heterogenitet sandsynligvis indebærer, at disse skøn er overvurderet.

Kapitel 2 (med Daniel le Maire som medforfatter) handler om positive assortativ matchning på arbejdsmarkedet, eller mere specifikt forsøger vi at adressere spørgsmålene om hvorvidt og hvordan arbejdere, som er mere produktive end gennemsnittet, ender i virksomheder, som ligeledes er mere produktive end gennemsnittet. Papir indeholder både en teoretisk og en empirisk del og er nok det mest omfattende af de fire kapitler i denne afhandling. Papiret blev fremprovokeret af, hvad vi mente, var et kontraintuitivt resultat i eksisterende empiriske metoder. Mens vi fandt det intuitivt at højproduktive arbejdere burde vælge at arbejde i højproduktive virksomheder, så kunne de eksisterende empiriske metoder ikke underbygge dette. Faktisk påstod flere papirer at have fundet beviser for det modsatte resultat.

For nærmere at analysere dette kontraintuitive resultat opstilles der i første del af papirer en teoretisk søgemodel med to vigtige egenskaber. Dels giver modellen anledning til positive assortativ matchning, dels medfører modellen en log lønligning, der er additiv separabel imellem arbejder- og virksomhedsproduktivitet. Dermed løser modellen det problem, at den kanoniske søgemodel kræver en log-supermodulær produktionsfunktion før end assortativ matchning kan opstå, hvilket så igen indebærer, at lønligningen ikke er additiv separabel. Årsagen til, at vi ønsker en additiv separabel lønligning, er, at dette er en vigtig forudsætning for de eksisterende empiriske modeller, der anvendes til at analysere assortativ matchning, og dermed en egenskab, der medfører, at vores model kan anvendes til direkte at teste eksisterende empiriske estimators. For at opnå de ønskede egenskaber tillader vi arbejderne at vælge antallet af jobs de ansøger,

hvilket vi så beviser, medfører, at en supermodular produktionsfunktion, som giver den ønskede lønligning, leder til positive assortativ matchning. Desuden indbefatter vores model kontinuert heterogenitet på både arbejder- og virksomhedssiden, og vi tilføjer desuden en matchspecifik produktivitets effekt. Vi viser, at når vi inkluderer en matchspecifik produktivitets effekt, så medfører det, at selvom modellen indbefatter positiv assortativ matchning, så estimerer de eksisterende empiriske procedurer anvendt på simulerede data fra modellen negativ korrelation imellem arbejder- og virksomhedsproduktivitet. Desuden udføres en række empiriske estimater på danske arbejder/virksomheds data, og vi estimerer, at den match specifikke produktivitets effekt udgør 15 procent af den samlede variation i (log)lønningerne. Alt i alt konkluderer vi, at de foreliggende resultater peger på, at positive assortativ matchning finder sted på det danske arbejdsmarked.

Kapitel 3 og 4 beskæftigede sig med konsekvenserne af international handel for den stigende efterspørgsel efter uddannet arbejdskraft i danske virksomheder. Efterspørgslen efter uddannet i forhold til ufaglært arbejdskraft er steget gradvist i alle udviklede lande igennem de seneste årtier. Økonomisk teori peger på to vigtige forklaringer for denne udvikling, teknologiske ændringer især inden for it, og globalisering i form af stigende international handel.

En række industrier har oplevet øget konkurrence som følge af øget produkt import. Teoretisk har dette mindst to konsekvenser for et land som Danmark. For det første vil en række virksomheder lukke, mens andre nye vil opstå. For det andet vil eksisterende virksomheder koncentrere sig om mere uddannelsesintensive produkter, hvor de industrialiserede lande har størst konkurrencefordele i forhold til lavtlønslande.

Sidstnævnte mekanisme er imidlertid blevet udfordret empirisk af flere papirer, som har fremlagt beviser for, at en øget efterspørgsel efter uddannet arbejdskraft har fundet sted i alle brancher og ikke specielt i de brancher, som udsat for den højeste grad af international konkurrence.

Langt størstedelen af de eksisterende studier af ændringer i virksomhedernes arbejdskraftsefterspørgsel gennemføres på industri data. Den arbejder og virksomheds database, som vi har opnået adgang til her, åbner imidlertid for nye og spændende muligheder og en chance for at revurdere nogle af de spørgsmåls, som tidligere er blevet opstillet i litteraturen.

I kapitel 3 (med Mikael Andersen, Michael Rosholm og Anders Sørensen som medforfattere) analyseres to forskellige mekanismer, gennem hvilke internationalisering potentielt påvirker virksomhedernes efterspørgsel efter uddannet og ufaglært arbejdskraft.

Den første mekanisme, en intern firma effekt, undersøger om der er signifikant sammenhæng imellem den stigende efterspørgsel efter uddannet arbejdskraft og virksomheds import. Det, vi har i tankerne, er den gængse historie om, at lavere omkostninger ved køb af input fra andre lande vil medføre at virksomheder enten producerer færre varer selv eller køber færre input fra andre indenlandske producenter. Da produktionen af de importerede varer er intensiv i ufaglært

arbejdskraft vil dette medføre en lavere andele af ufaglærte arbejdere i fremstillingserhvervene.

Den anden mekanisme, en ekstern produkt effekt, undersøger hvorvidt den stigende efterspørgsel efter uddannet arbejdskraft skyldes den samlede import af bestemte varetyper. Den mekanisme, som vi har i tankerne her, er, at virksomheder som følge af stigende importkonkurrence gradvis bevæger sig imod mere uddannelsesintensiv produktion for at undgå stigende konkurrence fra lavtlønslande. Importkonkurrence er den samlede import af de varetyper, som en given virksomhed producerer.

Så vidt vi ved, er dette det første papir, der undersøger begge disse aspekter samtidig. Vi har oplysninger om oprindelse, værdi og type af produkt for næsten al import i alle danske fremstillingsvirksomheder. Vi bruger disse oplysninger til at opdele import efter oprindelsesland i to grupper; import fra lav- og mellemindkomstlande, og import fra højindkomstlande. Vi finder, at det er af afgørende betydning at skelne import efter oprindelsesland, både når det gælder virksomhedens import og import konkurrence. Endvidere konkluderer vi, at øget importkonkurrence fra lavtlønslande medfører, at virksomheder øger deres efterspørgsel efter uddannet arbejdskraft. Resultat er robust overfor forskellige relevante definitioner af importkonkurrence for den enkelte virksomhed og med hensyn til aggregeringsniveauet af de anvendte produkt klassifikationer (3 til 5 cifret SITC-koder). Desuden finder vi, at den interne virksomhedseffekt, dvs. virksomhedens egen import fra lavtlønslande, er positivt signifikant korreleret med øget efterspørgsel efter uddannet arbejdskraft, men kun når fokus begrænses til større virksomheder.

Kapitel 4's bidrag er at vise, at ved at revidere hvordan man bruger oplysninger om den interne virksomhed effekt, kan man reintrodere denne effekt som en vigtig faktor for den øgede efterspørgsel efter uddannet arbejdskraft i Danmark. Kapitlet indeholder endvidere en grundig analyse af de potentielle faldgruber ved at anvende input-output tabeller til at analysere efterspørgsel efter uddannet arbejdskraft. Ved at anvende FN's "Broad Economic Categories" opdeles importen yderligere efter, om varerne er til forbrug i produktionen eller til endelig anvendelse. Evnen til at opdele import på virksomhedsniveau både efter oprindelsesland og forarbejdningsgrad fører til tre vigtigste konklusioner. For det første vil anvendelse af data, som man kender det fra input-output tabeller hvor importen af færdigvarer ignoreres, i høj grad fører til, at effekten af import på den øgede efterspørgsel efter uddannet arbejdskraft undervurderes. For det andet vises det, at en opdeling af import efter oprindelsesland og forarbejdningsgrad er af afgørende betydning for resultaterne. For det tredje vises det, at effekten af import af varer til endelig anvendelse for den øgede efterspørgsel efter uddannet arbejdskraft er kraftig stigende med virksomhedernes størrelse. Papiret argumenterer for, at dette sidste forhold kan fortolkes som støtte til en hypotese om, at større virksomheder har en fordel ved at importere produkter til endelig anvendelse fra lav- og mellemindkomstlande på grund af stordriftsfordele (fx ved at etablere egen produktion i lavtlønslande) eller, at mindre virksomheder i højere grad udnytter danske handelsselskaber, hvorefter deres "import" ganske enkelt ikke medtages i importdata

statistikker.



# Determinants of Labor Force Participation for Recipients of Social Assistance: A Panel Data Analysis for Denmark\*

Daniel le Maire

Christian Scheuer

University of Copenhagen and CAM

Copenhagen Business School and CEBR

June, 2009

## Abstract

In this paper we seek to examine the effects of economic incentives for recipients of social assistance. The workers receiving social assistance benefits are found to be marginalized and we find strong state dependence in their labor market status. We find no employment effects from the within-individual variation in the recipients' spouse incomes, and in contrast to Hyslop (1999) and Croda and Kyriazidou (2002) we argue that for the case of Denmark the spouse income is endogenous, so that we cannot use the between variation of spouse income to obtain meaningful estimates. Therefore, we also compute the net potential gain of working over receiving social assistance. Using this measure we find participation elasticities of 0.28-0.44 for men and in the range of 0.62-0.68 for women. Transforming the elasticities according to definition in the CGE-model DREAM, that is the percentage change in the number of recipients from a percentage change in the income, these amount to 0.09-0.17 and 0.13-0.20 for respectively men and women. However, we argue that it is likely that unobserved heterogeneity implies that both sets of estimated elasticities are upward biased.

**Keywords:** Labor force participation, incentives, nonemployment, state dependence, heterogeneity.

**JEL Classification:** C23, C25, J21, J24.

---

\*We gratefully acknowledge the comments we have received from Karsten Albæk, Martin Browning, Mette Ejrnæs, Jan Vognsen Hansen, Martin Ulrik Jensen, Henrik Jacobsen Kleven, Hans Christian Kongsted, Claus Thustrup Kreiner, Tove Birgitte Pedersen, Søren Leth-Petersen, Bertel Schjerning, Esben Anton Schultz, Anders Sørensen and seminar participants in the DGPE 2005 workshop. Finally, we thank Mikael Kirk for research assistance. All remaining errors are ours.

# 1 Introduction

In this paper we consider intertemporal labor supply and examine the effects of economic incentives on the labor market participation for recipients of social assistance.

The labor supply decision is usually decomposed into the intensive margin, that is the choice of hours, and the extensive margin, that is the participation decision. Even though it is generally believed (see e.g. Heckman (1993)) that the largest effects are to be found on the extensive margin, most empirical studies have focused on the intensive margin. Empirical studies for Denmark have typically found numerical small elasticities from wages on the amount of labor supplied; see e.g. Frederiksen et al. (2001). In fact, the studies that have found largest elasticities have used a Tobit framework and, hence, it seems as if the small elasticities at the intensive margin have been polluted by the jointly modeling of the participation decision.

In Denmark several types of benefits exist. Each of them is more or less directed to a distinct group of people. With respect to participation, recipients of sickness benefits and disablement benefits are for obvious reasons less interesting. Therefore, we restrict our attention to the recipients of social assistance – that is persons that are not eligible to unemployment benefits either because they are not members of an unemployment insurance fund or since they have not been in work recently.

We have access to a rich panel dataset, and we present results from employing different panel data estimators. The first set of estimations follow Hyslop (1999) and Croda and Kyriazidou (2003) closely in the sense that we estimate the effect on the participation decision using spouse disposable income separated into permanent and temporary income.

Focusing solely on married women Hyslop (1999) and Croda and Kyriazidou (2003) argue that spouse income is exogenous due to differences in the participation pattern between men and women. Hyslop (1999) finds elasticities of respectively permanent and transitory spouse income of -0.2 and -0.04 for the US, while Croda and Kyriazidou (2003) for Germany find only very small effects from both permanent and transitory spouse income on the participation decision. However, in the case of Denmark the difference in participation between men and women is less pronounced (see e.g. Dex et al. (1995) for a cross-national comparison) and we should expect a similar picture to emerge for men and women among recipients of social assistance. Consequently, we also perform the estimations for men.

Instead of solely restricting our attention to the effect of spouse income on participation, we also estimate a set of models where we analyze the effect of the worker's own disposable income gap from working on the participation decision. To compute these income gaps we make panel data selectivity predictions of the own wage income for each person. From this we can calculate the disposable income from working full-time and compare this to the disposable income when receiving social assistance.

The paper is organized as follows. In section 2, we present a theoretical labor market

search model. Section 3 outlines the data used in the analysis, and section 4 the econometric methodology. In section 5 and 6, we examine the results when using respectively disposable spouse income and own predicted disposable income gaps. Section 7 concludes.

## 2 Theoretical Background

An important aspect of intertemporal labor supply is the persistence of labor market status. In this section we will briefly consider a stylized labor market search model, which can generate such pattern.

We extend a standard partial equilibrium search model with a stigmatizing effect of becoming nonemployed and by assuming an instant utility function, which is non-linear in income. The first assumption will similarly to Garibaldi and Wasmer (2004) imply state dependence, whereas the latter assumption will allow us to focus on the effect of the spouse's income, which we take to be exogenous to the worker in consideration.

Consider an indefinitely living worker, who is married and whose spouse's labor market status is exogenous. We assume a joint instant utility function  $u(\cdot)$ , where the worker's own labor income  $w$  and her spouse labor income  $s$  are perfect substitutes. Being employed or nonemployed, wage offers are distributed according to  $F(w)$  and arrive with the exogenous Poisson rate  $\lambda$ . Workers who decline the new wage offer become non-employed.

When an employed worker becomes nonemployed the worker experiences a one-time stigmatization effect  $\gamma$ . When  $h_{t-1} = \{0, 1\}$  denotes the labor market state of the previous period the value of being nonemployed  $U(h_{t-1})$  is given by

$$rU(h_{t-1}) = u(s + b - \gamma h_{t-1}) + \lambda \left[ \int_{-\infty}^{\infty} \max(W(x), U(0)) dF(x) - U(h_{t-1}) \right] \quad (1)$$

where  $r$  is the discount rate and  $W(w)$  is the value of being employed at wage  $w$ . The Bellman equation for an employed worker is

$$rW(w) = u(s + w) + \lambda \left[ \int_{-\infty}^{\infty} \max(W(x), U(1)) dF(x) - W(w) \right] \quad (2)$$

The reservation wage for an nonemployed  $R^U$  is the wage where the worker is indifferent between being unemployed and working, that is  $U(0) = W(R^U)$

$$u(s + b) - u(s + R^U) = \lambda \int_{-\infty}^{\infty} \max(W(x), U(1)) dF(x) - \lambda \int_{-\infty}^{\infty} \max(W(x), U(0)) dF(x) \quad (3)$$

Similarly, the reservation wage for an employed  $R^W$  is when  $U(1) = W(R^W)$

$$u(s + b - \gamma) - u(s + R^W) = \lambda \int_{-\infty}^{\infty} \max(W(x), U(1)) dF(x) - \lambda \int_{-\infty}^{\infty} \max(W(x), U(0)) dF(x) \quad (4)$$

Equating equations (3) and (4) gives us

$$u(s + R^U) - u(s + R^W) = u(s + b) - u(s + b - \gamma)$$

and performing a first-order Taylor series approximation in respectively  $s + R^U$  and  $s + b$  gives us

$$\begin{aligned} u'(s + R^U)(R^W - R^U) &= -u'(s + b)\gamma \Leftrightarrow \\ R^W &= R^U - \frac{u'(s + b)}{u'(s + R^U)}\gamma \end{aligned} \quad (5)$$

where it is obvious that  $R^W < R^U$  which implies that employed persons have a higher probability of being employed in the subsequent time period.

Re-arranging equation (4) and integrating by parts gives us

$$u(s + b - \gamma) - u(s + R^W) = -\frac{\lambda}{r + \lambda} \int_{R^W}^{R^U} u'(s + x) F(x) dx$$

and by use of a Taylor series expansion in the point  $s + R^W$  the reservation wage for a nonemployed is

$$R^W = b - \gamma + \frac{\lambda}{r + \lambda} \int_{R^W}^{R^U} \frac{u'(s + x)}{u'(s + R^W)} F(x) dx \quad (6)$$

With a strictly concave utility function the fraction inside the integral is always less than 1, but will be increasing towards 1 as the spouse's income increases and, hence, imply a higher reservation wage  $R^W$ . Moreover, since  $R^U > b$  the difference between the two reservation wages  $R^U$  and  $R^W$  is declining in the spouse income.

In the present model state dependence is a result of the stigmatization effect, but also loss of skill by becoming non-employed can imply state dependence. Furthermore, in Garibaldi and Wasmer (2004) state dependence arises when search costs are higher for nonemployed workers and the value of home market production is stochastic. In addition to this, state dependence can arise if employers use nonemployment as a signal of low productivity. Finally, Hyslop (1999) argues that state dependence also can arise if the marginal utility of consumption is greater when working.

### 3 Data

We have access to an unbalanced panel dataset for 1998-2003.<sup>1</sup> The dataset is a representative 10 per cent sample of the Danish population. The variables originate from five databases. The first four databases, the Income Registry, the IDA database, the Housing Registry and the Health Insurance Registry are all maintained by Statistics Denmark. The fifth database is the

---

<sup>1</sup>In fact, we also have information for 1997, but these are only used to construct the lagged dependent variable used when estimating dynamic discrete choice models.

DREAM database of the Danish Ministry of Employment.

Our interest lies in the group of people in contact with the social assistance system. Social assistance benefits are lower than unemployment benefits and the recipients are persons that are not eligible to unemployment benefits either since they are not insured in an unemployment insurance fund or since they had not recently been in work for a sufficient long period of time. Hence, for most workers in the Danish labor market the relevant alternative to not work is unemployment benefits. Therefore, the characteristics of recipients of social assistance differ remarkably from workers in the labor force, and in this paper we only include persons that in at least one of the years covered, 1998-2003, have primarily been receiving social assistance. We define a recipient of social assistance as a person who has received social assistance benefits in the majority of the year, that is, at least 27 weeks in a given calendar year according to the DREAM Registry, which contains information on all transfers of public benefits on a weekly basis. For these persons we include information for all years available where the individual was either primarily receiving social assistance or primarily was in the labor force. In other words, persons who have been employed in all years are not included in our sample.

Since we are going to model the Danish tax system and compute the taxes paid in various scenarios, we further exclude self-employed, assisting wives, and people not fully taxable in Denmark in a given year from the sample. In addition to this, we have chosen not to include persons observed only once, since they cannot be used in the majority of our estimation procedures.

In Table 1 and 2 we present some characteristics of our sample divided by gender. Hourly gross wage and the partner's disposable income are in constant (1997) Danish kroner. Each table consists of six columns. The first column contains mean values for our full sample, while the next four columns have information on different sub-samples according to the individuals' transition pattern between social assistance and work. The sixth and final column is included to facilitate the understanding of how the characteristics of our sample differ from the labor force. Here, we show mean values for a 33 per cent sample of all Danes who have been in the labor force for at least one year in the period of 1998-2003.

Table 1: Mean values for males

|                                | Full<br>sam-<br>ple | Social<br>assis-<br>tance all<br>years | Single<br>transition<br>from<br>social<br>assistance | Single<br>transition<br>from work | Multiple<br>Transi-<br>tions | Population<br>Mean |
|--------------------------------|---------------------|--|--|-----------------------------------|------------------------------|--------------------|
| Experience                     | 4.91<br>(5.95)      | 3.13<br>(4.78)                         | 4.88<br>(5.89)                                       | 8.12<br>(6.86)                    | 6.58<br>(6.05)               | 17.27<br>(9.87)    |
| Age                            | 35.89<br>(9.73)     | 36.65<br>(10.02)                       | 35.42<br>(9.71)                                      | 35.89<br>(9.37)                   | 34.16<br>(9.01)              | 40.64<br>(10.72)   |
| Neuro medicine(*)              | 0.02<br>(0.24)      | 0.02<br>(0.27)                         | 0.01<br>(0.17)                                       | 0.02<br>(0.28)                    | 0.01<br>(0.17)               | 0.01<br>(0.39)     |
| Psychiatry(*)                  | 0.15<br>(1.38)      | 0.22<br>(1.70)                         | 0.07<br>(0.90)                                       | 0.15<br>(1.32)                    | 0.05<br>(0.69)               | 0.03<br>(0.64)     |
| General medical treatment(*)   | 8.73<br>(17.80)     | 10.04<br>(20.10)                       | 6.76<br>(13.13)                                      | 8.98<br>(18.69)                   | 7.03<br>(13.75)              | 4.91<br>(9.86)     |
| Unskilled                      | 0.70<br>(0.46)      | 0.73<br>(0.44)                         | 0.67<br>(0.47)                                       | 0.66<br>(0.48)                    | 0.69<br>(0.46)               | 0.29<br>(0.45)     |
| Vocational training            | 0.23<br>(0.42)      | 0.19<br>(0.39)                         | 0.24<br>(0.43)                                       | 0.29<br>(0.45)                    | 0.26<br>(0.44)               | 0.46<br>(0.50)     |
| Short-cycle higher education   | 0.02<br>(0.15)      | 0.03<br>(0.16)                         | 0.02<br>(0.15)                                       | 0.02<br>(0.13)                    | 0.02<br>(0.14)               | 0.06<br>(0.23)     |
| Medium-cycle higher education  | 0.03<br>(0.17)      | 0.03<br>(0.17)                         | 0.04<br>(0.20)                                       | 0.02<br>(0.14)                    | 0.02<br>(0.14)               | 0.11<br>(0.31)     |
| Long-cycle higher education    | 0.02<br>(0.15)      | 0.03<br>(0.16)                         | 0.02<br>(0.15)                                       | 0.02<br>(0.13)                    | 0.01<br>(0.12)               | 0.08<br>(0.28)     |
| Immigrant                      | 0.28<br>(0.45)      | 0.35<br>(0.48)                         | 0.35<br>(0.48)                                       | 0.14<br>(0.34)                    | 0.14<br>(0.35)               | 0.04<br>(0.20)     |
| Second generation immigrant    | 0.01<br>(0.09)      | 0.01<br>(0.09)                         | 0.01<br>(0.08)                                       | 0.01<br>(0.08)                    | 0.01<br>(0.10)               | 0.00<br>(0.06)     |
| Married                        | 0.25<br>(0.44)      | 0.29<br>(0.45)                         | 0.32<br>(0.47)                                       | 0.16<br>(0.37)                    | 0.17<br>(0.37)               | 0.56<br>(0.50)     |
| Copenhagen                     | 0.22<br>(0.41)      | 0.23<br>(0.42)                         | 0.22<br>(0.41)                                       | 0.18<br>(0.39)                    | 0.19<br>(0.39)               | 0.10<br>(0.30)     |
| Large city                     | 0.19<br>(0.39)      | 0.22<br>(0.42)                         | 0.18<br>(0.39)                                       | 0.16<br>(0.37)                    | 0.15<br>(0.35)               | 0.14<br>(0.35)     |
| Rural area                     | 0.48<br>(0.50)      | 0.45<br>(0.50)                         | 0.48<br>(0.50)                                       | 0.54<br>(0.50)                    | 0.53<br>(0.50)               | 0.64<br>(0.48)     |
| Children aged 0-6 years        | 0.28<br>(0.67)      | 0.31<br>(0.74)                         | 0.32<br>(0.68)                                       | 0.21<br>(0.56)                    | 0.23<br>(0.57)               | 0.30<br>(0.63)     |
| Children aged 7-17 years       | 0.29<br>(0.75)      | 0.33<br>(0.84)                         | 0.33<br>(0.76)                                       | 0.19<br>(0.58)                    | 0.24<br>(0.64)               | 0.42<br>(0.76)     |
| Owner                          | 0.42<br>(0.49)      | 0.39<br>(0.49)                         | 0.44<br>(0.50)                                       | 0.45<br>(0.50)                    | 0.45<br>(0.50)               | 0.68<br>(0.47)     |
| Hourly gross wage              | 112.11<br>(47.47)   | -                                      | 113.35<br>(45.68)                                    | 110.50<br>(49.95)                 | 112.07<br>(47.19)            | 154.09<br>(71.83)  |
| Partner's disposable income    | 97968<br>(32749)    | 96101<br>(29083)                       | 100072<br>(35136)                                    | 98251<br>(36272)                  | 99981<br>(35258)             | 133770<br>(60918)  |
| No. Years in sample            | 4.67<br>(1.44)      | 4.29<br>(1.63)                         | 4.98<br>(1.23)                                       | 4.78<br>(1.23)                    | 5.33<br>(0.87)               | -                  |
| No. Years of Social Assistance |                     |  |  |                                   |                              |                    |
| 1                              | 25.32               | 7.48                                   | 48.52  | 37.18                             | 35.21                        |                    |
| 2                              | 18.05               | 10.55                                  | 22.62  | 26.39                             | 25.09                        |                    |
| 3                              | 14.69               | 13.03                                  | 14.85  | 17.16                             | 16.65                        |                    |
| 4                              | 13.92               | 16.27                                  | 9.54   | 12.12                             | 14.65                        |                    |
| 5                              | 12.81               | 20.05                                  | 4.46   | 7.15                              | 8.40                         |                    |
| 6                              | 15.21               | 32.61                                  | 0.00   | 0.00                              | 0.00                         |                    |
| Sample Size                    | 41,390              | 19,298                                 | 8,341  | 7,469                             | 6,282                        | 573,498            |

Standard deviations are in parentheses.

(\*) These variables originate from the Health Insurance Registry and are computed as the yearly number of treatments with support from the Danish health system within the given area.

Table 1 shows that the full sample of men consists of 41,390 observations. Looking at the number of years the individuals received social assistance; about 25 per cent received social assistance in just one year during 1998-2003 while about 15 per cent received social assistance

in the full period.

From the sample means a few things are worth noticing. Firstly, even though the mean age is approximately 36 years the mean value of experience (in years) is only approximately 5 years. Secondly, 70 per cent are unskilled compared to 29 per cent in the active population. The combination of lower experience and lower levels of education suggest a high degree of persistence in the labor market status, since males receiving social assistance are clearly less likely to become employed compared to the average male in the active population.

Furthermore, as the average experience indicates our sample is quite different from the average population suggesting that the group under consideration is marginalized in the labor market. The most prominent differences are that 28 per cent of the sample of men are immigrants compared to 4 per cent in the active Danish population. In addition to this, the average wage is 112 DKK per hour while the mean wage for private employed males was 154 DKK. Finally, only 42 per cent are homeowners (68 per cent is the active population)

We proceed by splitting the full sample into 4 subgroups; those receiving social assistance all years (19,298 persons), those who have a single transition from social assistance to work (8,341 persons), those having a single transition from work to social assistance (7,469 persons) and those who have more than one transition between work and social assistance (6,282 persons).

When breaking the sample down by transition patterns we notice that even though the labor market experience is quite different between the three groups of people who at some point have been on the labor market (4.9-8.1 years) the average wage for the people working is much alike (111-113 DKK) suggesting that the minimum wage restriction is binding for the majority of persons belonging to the group. Further, immigrants are much overrepresented among those receiving social assistance in all years and among those having only one single transition from social assistance (35 per cent compared to 14 per cent). This may explain why a larger fraction of these groups is married and why the groups on average have more children.

There is also a striking difference between the spouse's average disposable income as it is much higher for the active population. In particular, the partner income is lowest for those who are receiving social assistance in all years.

Table 2: Mean values for females

|                                | Full<br>sam-<br>ple | Social<br>assis-<br>tance all<br>years | Single<br>transition<br>from<br>social<br>assistance | Single<br>transition<br>from work | Multiple<br>Transi-<br>tions | Population<br>Mean |
|--------------------------------|---------------------|--|--|-----------------------------------|------------------------------|--------------------|
| Experience                     | 2.93<br>(4.60)      | 1.82<br>(3.68)                         | 3.34<br>(4.57)                                       | 6.28<br>(5.80)                    | 5.05<br>(5.39)               | 15.13<br>(8.73)    |
| Age                            | 34.36<br>(9.42)     | 34.62<br>(9.69)                        | 33.90<br>(9.02)                                      | 34.48<br>(9.12)                   | 33.58<br>(8.75)              | 41.26<br>(10.39)   |
| Neuro medicine(*)              | 0.04<br>(0.37)      | 0.04<br>(0.39)                         | 0.02<br>(0.32)                                       | 0.03<br>(0.33)                    | 0.03<br>(0.40)               | 0.02<br>(0.26)     |
| Psychiatry(*)                  | 0.22<br>(1.86)      | 0.26<br>(2.04)                         | 0.13<br>(1.24)                                       | 0.29<br>(2.28)                    | 0.09<br>(0.96)               | 0.07<br>(1.21)     |
| General medical treatment(*)   | 17.65<br>(31.19)    | 19.49<br>(34.27)                       | 13.66<br>(16.08)                                     | 17.32<br>(37.43)                  | 15.11<br>(26.12)             | 9.38<br>(11.37)    |
| Unskilled                      | 0.78<br>(0.42)      | 0.83<br>(0.38)                         | 0.72<br>(0.45)                                       | 0.68<br>(0.47)                    | 0.71<br>(0.45)               | 0.29<br>(0.45)     |
| Vocational training            | 0.16<br>(0.37)      | 0.11<br>(0.32)                         | 0.22<br>(0.41)                                       | 0.27<br>(0.44)                    | 0.24<br>(0.42)               | 0.39<br>(0.49)     |
| Short-cycle higher education   | 0.02<br>(0.13)      | 0.02<br>(0.13)                         | 0.02<br>(0.15)                                       | 0.01<br>(0.10)                    | 0.01<br>(0.08)               | 0.05<br>(0.22)     |
| Medium-cycle higher education  | 0.03<br>(0.17)      | 0.03<br>(0.17)                         | 0.03<br>(0.18)                                       | 0.03<br>(0.18)                    | 0.03<br>(0.16)               | 0.20<br>(0.40)     |
| Long-cycle higher education    | 0.01<br>(0.10)      | 0.01<br>(0.10)                         | 0.01<br>(0.10)                                       | 0.01<br>(0.11)                    | 0.02<br>(0.14)               | 0.06<br>(0.24)     |
| Immigrant                      | 0.32<br>(0.47)      | 0.40<br>(0.49)                         | 0.30<br>(0.46)                                       | 0.11<br>(0.32)                    | 0.12<br>(0.33)               | 0.03<br>(0.18)     |
| Second generation immigrant    | 0.01<br>(0.08)      | 0.01<br>(0.08)                         | 0.01<br>(0.10)                                       | 0.01<br>(0.10)                    | 0.00<br>(0.05)               | 0.00<br>(0.05)     |
| Married                        | 0.32<br>(0.47)      | 0.37<br>(0.48)                         | 0.33<br>(0.47)                                       | 0.19<br>(0.39)                    | 0.18<br>(0.39)               | 0.62<br>(0.49)     |
| Copenhagen                     | 0.18<br>(0.38)      | 0.18<br>(0.39)                         | 0.15<br>(0.36)                                       | 0.18<br>(0.38)                    | 0.18<br>(0.38)               | 0.10<br>(0.31)     |
| Large city                     | 0.18<br>(0.39)      | 0.21<br>(0.41)                         | 0.16<br>(0.37)                                       | 0.13<br>(0.33)                    | 0.13<br>(0.33)               | 0.14<br>(0.35)     |
| Rural area                     | 0.53<br>(0.50)      | 0.51<br>(0.50)                         | 0.55<br>(0.50)                                       | 0.58<br>(0.49)                    | 0.56<br>(0.50)               | 0.63<br>(0.48)     |
| Children aged 0-6 years        | 0.63<br>(0.86)      | 0.72<br>(0.93)                         | 0.53<br>(0.74)                                       | 0.44<br>(0.69)                    | 0.49<br>(0.74)               | 0.30<br>(0.61)     |
| Children aged 7-17 years       | 0.69<br>(1.02)      | 0.73<br>(1.09)                         | 0.69<br>(0.94)                                       | 0.51<br>(0.83)                    | 0.61<br>(0.87)               | 0.50<br>(0.80)     |
| Owner                          | 0.28<br>(0.45)      | 0.23<br>(0.42)                         | 0.34<br>(0.47)                                       | 0.38<br>(0.48)                    | 0.36<br>(0.48)               | 0.71<br>(0.45)     |
| Hourly gross wage              | 100.99<br>(41.81)   | -                                      | 100.59<br>(36.82)                                    | 100.60<br>(44.72)                 | 102.53<br>(49.80)            | 122.83<br>(47.46)  |
| Partner's disposable income    | 108228<br>(43080)   | 99405<br>(38738)                       | 123651<br>(44089)                                    | 116514<br>(49192)                 | 121150<br>(45992)            | 173982<br>(121702) |
| No. Years in sample            | 4.62<br>(1.46)      | 4.45<br>(1.60)                         | 4.87<br>(1.25)                                       | 4.57<br>(1.27)                    | 5.19<br>(0.91)               | -                  |
| No. Years of Social Assistance |                     |  |  |                                   |                              |                    |
| 1                              | 19.91               | 6.44                                   | 42.41  | 37.41                             | 34.08                        |                    |
| 2                              | 14.78               | 9.19                                   | 22.57  | 25.14                             | 20.17                        |                    |
| 3                              | 14.19               | 11.37                                  | 18.69  | 16.13                             | 20.11                        |                    |
| 4                              | 14.49               | 15.88                                  | 10.79  | 14.28                             | 14.30                        |                    |
| 5                              | 14.57               | 19.73                                  | 5.54   | 7.04                              | 11.33                        |                    |
| 6                              | 22.06               | 37.40                                  | 0.00   | 0.00                              | 0.00                         |                    |
| Sample Size                    | 40,170              | 23,698                                 | 8,450  | 4,686                             | 3,336                        | 532,727            |

Standard deviations are in parentheses.

(\*) These variables originate from the Health Insurance Registry and are computed as the yearly number of treatments with support from the Danish health system within the given area.

The corresponding mean values for women are shown in Table 2. The pattern of Table 2 does to a large extent replicate the pattern in Table 1. Therefore, the most important information we retrieve is that also female recipients of social assistance seem to be marginalized in the labor



market. The mean age is 34 years and the mean experience is only 2.9 years, 32 per cent are immigrants and 78 per cent unskilled. Again breaking down on different transition patterns we see that differences in experience are not reflected in the wage rate of those employed from the different groups, again suggesting the minimum wage restriction to be binding. Furthermore, the partner income is now somewhat lower for the group receiving social assistance all years. This may suggest that to some extent persons cohabiting are likely to have a similar attitude towards participating in the labor market, and that this effect might dominate the positive income effect exerted by partner earnings as modeled section 2.

## 4 The Econometric Framework

The estimations dealt with in this paper are reduced-form participation equations. There are different possible sources of the persistence in the individual labor market participation. Here, we study the importance of unobserved heterogeneity and state dependence in generating this persistence. We do not consider serial correlation in the time-varying error component, which similar to state dependence implies that transitory changes in the explanatory variable may have permanent effects on the dependent variable. However, in a similar analysis for Germany Croda and Kyriazidou (2003) find that serial correlation in the time-varying error component does not seem to matter. Hence, we disregarded such error components.

We estimate a number of binary response models. In the following we only shortly consider the econometric specifications, and refer to references mentioned below as well as textbooks such as Greene (2003) and Wooldridge (2002) for a more detailed treatment.

The first estimation considered is the pooled probit model

$$\Pr(y_{it} = 1|X_{it}) = 1(X_{it}\beta + \varepsilon_{it} \geq 0) = \Phi(X_{it}\beta) \quad (7)$$

where  $y_{it}$  is the binary variable for the participation decision of individual  $i$  at time  $t$ ,  $X_{it}$  contains the explanatory variables, and the error term  $\varepsilon_{it}$  is assumed to be independent of the explanatory variables and distributed  $iN(0, 1)$ .

The pooled probit estimator does not exploit the fact that we observe the persons again and again, and since it is very likely that the errors are correlated because the same persons are observed several times, we also estimate a random effects probit

$$\Pr(y_{it} = 1|X_i, \alpha_i) = 1(X_{it}\beta + \alpha_i + \varepsilon_{it} \geq 0) = \Phi(X_{it}\beta + \alpha_i) \quad (8)$$

where the compound error-term  $\alpha_i + \varepsilon_{it}$  is assumed to be independent of the explanatory variables and both terms are assumed to be normally distributed.

Absent state dependence transitory changes in  $X$  can only cause transitory changes in the

dependent variable  $y$ . Allowing for state dependence is equivalent to allowing transitory changes in  $X$  to have permanent effect on  $y$  through the effects of the lagged dependent variable. In the absence of serial correlation this is the only way in which transitory changes in  $X$  can have permanent effects on  $y$ . Failing to allow for state dependence will bias the parameter estimates in presence of (true) state dependence. In addition, it is of interest whether employment is truly state-dependent, since this implies that becoming a recipient of social assistance deteriorates an individual's future labor market prospects. In order to address this issue, we estimate a dynamic random effects probit

$$\Pr(y_{it} = 1 | X_i, \alpha_i, y_{it-1}) = 1(\gamma y_{it-1} + X_{it}\beta + \alpha_i + \varepsilon_{it} \geq 0) = \Phi(\gamma y_{it-1} + X_{it}\beta + \alpha_i) \quad (9)$$

Estimating a dynamic probit raises the question of how to treat the initial observations of the dependent variable  $y_{i0}$ . Heckman (1981) suggests approximating the conditional density of the initial dependent variable by estimating a probit using observations from the first year only and simultaneously specifying the unobserved heterogeneity conditional on the explanatory variables. We use the simpler estimation procedure for the dynamic correlated random effects probit outlined in Wooldridge (2005) where the approximation of the density of the initial dependent variable is left out. Instead the unobserved heterogeneity is allowed to be arbitrarily correlated with the initial dependent variable by inclusion of the initial observation  $y_{i0}$ . Furthermore, we model the unobservable individual component with the means of the time-varying explanatory variables as in Mundlak (1978) in order to be able to better interpret the effects of the time-varying variables. This implies that we assume that

$$\alpha_i = y_{i0}\rho + \bar{X}_i\lambda + \xi_i$$

where  $\xi \sim N(0, \sigma_\xi^2)$ .

We apply these estimators in two scenarios: First, we estimate the effect of changes in partner income and then we estimate the effect from changes in the worker's own potential disposable income gap from working. Besides these income variables  $X_{it}$  includes a quadratic term in age and experience, dummy indicators for level of education, living area, ethnic origin, variables for the number of children, variables for medical treatments as well as variables capturing the regional demand and supply conditions.

Hyslop argues that the spouse's income may have three different effects on the labor market participation, a) a direct effect as in the theoretical search model in section 2, b) an expectation effect as future spouse income increases or decreases may be anticipated, and c) a taste effect from the spouses having the same taste for work by assortative matching in the marriage market. In the presence of state dependence, the expectations of future outcomes of explanatory

variables may affect the current labor market status. This we avoid by assuming that the partner income follows a stationary process. As in Hyslop (1999) stationarity is achieved by dividing spouse income into a permanent and a transitory component. The permanent income is just the average of the spouse's income in the period under consideration, while the transitory income is the yearly deviation from this mean. The taste for work effect can be expected to be in the individual unobservable component and to be correlated with the permanent spouse income, which makes the latter endogenous.

For transitory income on the other hand it is probably reasonable to assume no correlation with taste for work. If this assumption holds there will only be a direct income effect from transitory income. However, in a life-cycle model transitory income shocks should not have an effect on labor supply, since agents can smooth out consumption. Only when there exist credit market constraints transitory spouse income shocks will play a role for the labor supply.

We can take account of possible correlation between  $\alpha_i$  and the time-varying explanatory variables by estimating correlated random effects and fixed effects estimators. Here we apply two fixed effects estimators which both use the logit specification and, hence, instead of assuming that the error-term  $\varepsilon_{it}$  is normally distributed we assume that it is logistically distributed. We need to observe a person in two periods when estimating the conditional maximum likelihood fixed effects logit. The idea is that only a person that changes state, that is for a two-period setting  $y_{i1} + y_{i2} = 1$ , contributes to the likelihood function. Therefore neither persons employed in all years or persons receiving social assistance in all years affect the likelihood function in the fixed effects logit. For  $y_{i1} + y_{i2} = 1$  we have

$$\Pr(y_{i1} = 1 | X_i, \alpha_i, y_{i1} + y_{i2} = 1) = \frac{\exp((X_{i2} - X_{i1})\beta)}{1 + \exp((X_{i2} - X_{i1})\beta)} \quad (10)$$

As with the random effects probit model, naturally, we want to allow for state dependence. Chamberlain (1993) has shown that if individuals are only observed in three periods, the parameters of the dynamic fixed effects logit model are not identified. Subject to some regularity conditions Honoré and Kyriazidou (2000) have shown that the parameters are identified when we have four or more consecutive observations per individual. The basic idea follows that of the conditional likelihood approach. Consider the following events  $A = \{y_{i0}, y_{i1} = 0, y_{i2} = 1, y_{i3}\}$  and  $B = \{y_{i0}, y_{i1} = 1, y_{i2} = 0, y_{i3}\}$  where  $y_{i0}$  and  $y_{i3}$  are either 0 or 1. In this case we have

$$\begin{aligned} \Pr(A | X_i, \alpha_i) &= p_0(X_i, \alpha_i)^{y_{i0}} (1 - p_0(X_i, \alpha_i))^{1-y_{i0}} \times \frac{1}{1 + \exp(X_{i1}\beta + \gamma y_{i0} + \alpha_i)} \\ &\times \frac{\exp(X_{i2}\beta + \alpha_i)}{1 + \exp(X_{i2}\beta + \alpha_i)} \times \frac{\exp(y_{i3}X_{i3}\beta + y_{i3}\gamma + y_{i3}\alpha_i)}{1 + \exp(X_{i3}\beta + \gamma + \alpha_i)} \end{aligned} \quad (11)$$

while

$$\begin{aligned} \Pr(B|X_i, \alpha_i) &= p_0(X_i, \alpha_i)^{y_{i0}} (1 - p_0(X_i, \alpha_i))^{1-y_{i0}} \times \frac{\exp(X_{i1}\beta + \gamma y_{i0} + \alpha_i)}{1 + \exp(X_{i1}\beta + \gamma y_{i0} + \alpha_i)} \\ &\quad \times \frac{1}{1 + \exp(X_{i2}\beta + \gamma + \alpha_i)} \times \frac{\exp(y_{i3}X_{i3}\beta + y_{i3}\alpha_i)}{1 + \exp(X_{i3}\beta + \alpha_i)} \end{aligned} \quad (12)$$

Noticing that if  $X_{i2} = X_{i3}$  we can get rid of the  $\alpha_i$ 's so that we end up with

$$\begin{aligned} \Pr(A|X_i, \alpha_i, A \cup B, X_{i2} = X_{i3}) &= \frac{\Pr(A|X_i, \alpha_i, X_{i2} = X_{i3})}{\Pr(A|X_i, \alpha_i, X_{i2} = X_{i3}) + \Pr(B|X_i, \alpha_i, X_{i2} = X_{i3})} \\ &= \frac{1}{1 + \exp((X_{i1} - X_{i2})\beta + \gamma(y_{i0} - y_{i3}))} \end{aligned} \quad (13)$$

Identification naturally extends to the case with more than 4 observations for each individual, see Honoré and Kyriazidou (2000). Identification in this case comes from all individuals changing state between two of the middle periods (that is any period but the first and last). Honoré and Kyriazidou (2000) propose to estimate  $\beta$  and  $\gamma$  by maximizing

$$\sum_{i=1}^n \sum_{1 \leq t < s \leq T-1} \left[ \ln \left( \frac{1 \{y_{it} + y_{is} = 1\} K\left(\frac{X_{it+1} - X_{is+1}}{h_n}\right)}{1 + \exp((X_{it} - X_{is})b + g(y_{it-1} - y_{is+1}) + g(y_{it+1} - y_{is-1})1\{s-t>1\})^{y_{it}})} \right) \right] \quad (14)$$

over some compact set and where  $K(\cdot)$  denotes a kernel density function which assigns a large probability for values where  $X_{it+1}$  and  $X_{is+1}$  are close. The advantage of this estimator is that it is completely agnostic about the nature of individual heterogeneity.

In the second part of the paper we examine the effect of the worker's own disposable income gain between receiving social assistance benefits and becoming employed. Since we do not observe the wage rate of recipients of social assistance we need to make a selectivity-corrected wage. We do this by estimating the Vella and Verbeek (1998, 1999) sample selection model, where both the equation of interest and the selection equation include random effects and error terms that are allowed to be correlated. We have

$$\begin{aligned} \ln w_{it} &= X_{it}\beta_1 + \mu_i + \eta_{it} \\ y_{it} &= 1(\gamma y_{it-1} + X_{it}\beta_2 + \alpha_i + \varepsilon_{it} \geq 0) = \Phi(\gamma y_{it-1} + X_{it}\beta_2 + \alpha_i) \end{aligned}$$

where  $\ln w_{it}$  is the log of the wage rate,  $\mu_i \sim iN(0, \sigma_\mu^2)$ ,  $\eta_{it} \sim iN(0, \sigma_\eta^2)$ ,  $\alpha_i \sim iN(0, \sigma_\alpha^2)$ , and  $\varepsilon_{it} \sim iN(0, \sigma_\varepsilon^2)$ . Denote the composite error  $v_{it} = \mu_i + \eta_{it}$ . Then, the conditional mean of the log of the wage rate is given by

$$E[\ln w_{it}|X_i, y_{i0}, y_i] = X_{it}\beta + \tau_1 v_{it} + \tau_2 \bar{v}_i \quad (15)$$

where the two last terms are the selection bias we correct for, and where  $\tau_1 = \sigma_{\varepsilon\eta} / \sigma_\varepsilon^2$  and  $\tau_2 = T(\sigma_{\alpha\mu} - \sigma_{\varepsilon\eta}\sigma_\mu^2 / \sigma_\varepsilon^2) / (\sigma_\eta^2 + T\sigma_\mu^2)$  are constants to be estimated.

Similar to Vella and Verbeek (1998) we use the labor market state in the previous year as exclusion restriction and exploit that the earnings equation is static while the participation equation is dynamic. This aligns with the theoretical search model in section 2. For example, consider a negative health shock in the current period. The health shock implies a lower wage and through the reservation wage a lower probability of participating in the current period and, thereby, also in the subsequent period. Our identifying assumption is that in the subsequent period the past period's health shock does not affect the wage, since it is static. Using the lagged dependent variable as exclusion restriction is not necessary innocuous. For example, if state dependence arises because employers use unemployment as a signal of low productivity, it is obviously not reasonable to assume that the wage is not affected by the previous labor market state.

We compute the worker's own disposable income gap on a yearly basis by computing the disposable income from working full time and subtracting the potential disposable income from receiving only social assistance.

In order to compute the disposable income when working we begin by estimating the Vella-Verbeek sample selection model. The resulting wage prediction is used to compute the annual full-time wage income. Next, we use a detailed modeling of the Danish tax system, which takes the joint taxation of the spouses into account, in order to calculate the tax payments and finally we compute the disposable income.

For each person we also make a detailed computation of the social assistance benefits they would be entitled to on a yearly basis. Again, we subtract the appropriate tax payments and calculate the resulting disposable income.

Furthermore, in both scenarios we take full account of housing benefits for renters received from the government, which depend both on the tenant's family income and on the rent.<sup>2</sup>

With this information we compute the gap between the disposable income when working full-time and the disposable income of receiving social assistance. We do not take account of transportation costs and child care costs when we compute the income gaps.

## 5 Does Partner Income Create Work (dis-)Incentives?

In this section we investigate the importance of the spouse's disposable income for the participation decision by including permanent and transitory spouse income among the explanatory

---

<sup>2</sup>The dataset contains information for the yearly rent in 1999. Unfortunately, for only approximately 40 per cent of dwellings for rent we observe the yearly rent. Following Munch and Svarer (2002) we use Heckman's (1979) two-step procedure to predict the yearly rent. As exclusion restriction we use the number of apartments in the building, which has positive effect on the probability of observing a rent.

variables.

Table 3 gives the results for the estimations on the sample of male workers who at some point during the sample window primarily received social assistance. As expected, we find a significant hump-shaped effect from higher experience. More experience raises the probability of participation, but the effect declines with total years of experience. Controlling for this effect, age actually works in the opposite direction, so that older people *ceteris paribus* have lower participation probabilities. Having people with a vocational education as our reference category, we see that more education increases the probability of working.

We find that everything else being equal, immigrants have a higher probability of working. We think this is an effect of immigrants within the social assistance system being a more heterogeneous group than the rest of the recipients. Newly arrived immigrants do not have access to unemployment benefits and this group is likely to contain both marginalized and high productive individuals.

We have included the local gender specific unemployment rate and the number of regional vacancies normalized by the labor force to capture demand and supply effects in the regional labor market. Both variables are significant with expected signs, that is a positive effect of more vacancies and a negative effect of a higher unemployment rate.

Having children - and especially young children - lowers the probability of being employed. Finally, we have included three variables for the health status of the worker. These variables are defined as the yearly number of treatments with financial support from the Danish public health system within the given area. We find that the more neuro medicine treatments, or the more consultations with psychiatrists or doctors the lower the probability of being employed.

The first two specifications the pooled probit model and random effects probit model deliver similar results. Although the pooled probit model correctly predicts 71 per cent of the outcomes, the confusion matrices in Table 10 appendix A reveal that the pooled probit model only does a good job in fitting the  $y = 0$  outcome, while the dynamic correlated random effects model in the third column performs much better in fitting also the  $y = 1$  outcome. In the dynamic correlated random effects specification we approximate the unobserved individual part by the means of age, region dummies, children and health variables besides the random normal term. Besides the improved overall fit the picture does not change much. However, the coefficient to age becomes positive when the individual mean of age is part of the unobservable part. Similarly, the children variables become insignificant. The set of parameter estimates obtained from the fixed effects logit are similar to the various probit estimates, while we only can use the estimation results from the dynamic fixed effects to verify the presence of (true) state dependence.

The final column in Table 3 shows that using an alternative cut-off level of 42 weeks for the definition of being a recipient of social assistance compared to the 27 weeks used in all other

estimations does not matter for the results.

Table 3: Participation probability, partner income, males

|  | Pooled<br>probit    | Random<br>effects<br>probit | Dynamic<br>corre-<br>lated<br>random<br>effects<br>probit | Fixed<br>effects<br>logit | Dynamic<br>fixed<br>effects<br>logit | Dynamic<br>corre-<br>lated<br>random<br>effects<br>probit, 42<br>weeks |
|--|---------------------|-----------------------------|---|---------------------------|--------------------------------------|--|
| Spouse' temporary income               | -0.008<br>(0.007)   | -0.009<br>(0.009)           | -0.007<br>(0.008)   | -0.032<br>(0.016)*        | -0.017<br>(0.052)                    | -0.013<br>(0.009)  |
| Spouse's permanent income              | 0.030<br>(0.004)**  | 0.044<br>(0.007)**          | 0.027<br>(0.005)**  | -<br>-                    | -<br>-                               | 0.024<br>(0.006)**   |
| Age                                    | -0.071<br>(0.011)** | -0.108<br>(0.019)**         | 0.084<br>(0.021)**  | -<br>-                    | -<br>-                               | 0.071<br>(0.025)**   |
| Age squared/100                        | 0.041<br>(0.014)**  | 0.068<br>(0.025)**          | 0.006<br>(0.017)  | -<br>-                    | -<br>-                               | 0.000<br>(0.000)   |
| Experience                             | 0.202<br>(0.006)**  | 0.313<br>(0.012)**          | 0.118<br>(0.009)**  | 0.785<br>(0.070)**        | 0.018<br>(0.117)                     | 0.101<br>(0.010)**   |
| Experience squared/100                 | -0.587<br>(0.025)** | -0.952<br>(0.050)**         | -0.343<br>(0.033)**                                       | -2.938<br>(0.247)**       | -<br>-                               | -0.003<br>(0.000)**  |
| Unskilled                              | -0.117<br>(0.027)** | -0.139<br>(0.053)**         | -0.091<br>(0.034)**                                       | -<br>-                    | -<br>-                               | -0.090<br>(0.039)*   |
| Short-cycle higher education           | 0.097<br>(0.068)    | 0.261<br>(0.132)*           | 0.148<br>(0.085)  | -<br>-                    | -<br>-                               | 0.116<br>(0.094)   |
| Medium-cycle higher education          | 0.161<br>(0.059)**  | 0.208<br>(0.119)            | 0.174<br>(0.076)*   | -<br>-                    | -<br>-                               | 0.169<br>(0.082)*  |
| Long-cycle higher education            | 0.182<br>(0.069)**  | 0.302<br>(0.138)*           | 0.115<br>(0.089)  | -<br>-                    | -<br>-                               | 0.185<br>(0.093)*  |
| Immigrant                              | 0.336<br>(0.032)**  | 0.406<br>(0.062)**          | 0.235<br>(0.041)**  | -<br>-                    | -<br>-                               | 0.151<br>(0.046)**   |
| Second generation immigrant            | -0.039<br>(0.156)   | 0.072<br>(0.262)            | 0.023<br>(0.182)  | -<br>-                    | -<br>-                               | 0.088<br>(0.222)   |
| Copenhagen                             | -0.046<br>(0.046)   | -0.012<br>(0.085)           | 0.101<br>(0.221)  | 0.660<br>(0.396)          | -<br>-                               | 0.084<br>(0.263)   |
| Large city                             | -0.101<br>(0.046)*  | -0.186<br>(0.087)*          | -0.247<br>(0.279)   | -0.144<br>(0.502)         | -<br>-                               | -0.453<br>(0.317)  |
| Rural area                             | -0.070<br>(0.038)   | -0.125<br>(0.072)           | -0.158<br>(0.234)   | 0.141<br>(0.424)          | -<br>-                               | -0.131<br>(0.274)  |
| Children aged 0-6 years                | -0.128<br>(0.014)** | -0.167<br>(0.025)**         | -0.054<br>(0.040)   | -0.207<br>(0.072)**       | -0.746<br>(0.223)**                  | -0.056<br>(0.046)  |
| Children aged 7-17 years               | -0.034<br>(0.013)** | -0.050<br>(0.023)*          | 0.012<br>(0.042)  | -0.054<br>(0.078)         | -<br>-                               | -0.004<br>(0.048)  |
| Unemp. on municipality and gender      | -0.062<br>(0.008)** | -0.077<br>(0.014)**         | -0.052<br>(0.010)**                                       | -0.148<br>(0.040)**       | -<br>-                               | -0.047<br>(0.011)**  |
| Regional vacancies                     | 2.603<br>(0.788)**  | 2.876<br>(1.404)*           | 1.908<br>(0.976)  | 3.574<br>(5.154)          | -<br>-                               | 0.845<br>(1.129)   |
| Neuro medicine                         | -0.187<br>(0.060)** | -0.246<br>(0.084)**         | -0.183<br>(0.085)*  | -0.370<br>(0.191)         | -<br>-                               | -0.150<br>(0.081)  |
| Psychiatry                             | -0.036<br>(0.011)** | -0.028<br>(0.015)           | 0.001<br>(0.019)  | 0.010<br>(0.035)          | -<br>-                               | 0.023<br>(0.021)   |
| General medical treatment              | -0.005<br>(0.001)** | -0.004<br>(0.001)**         | -0.003<br>(0.001)*  | -0.004<br>(0.002)         | -<br>-                               | -0.004<br>(0.002)  |
| y <sub>0</sub> (initial participation) | -<br>-              | -<br>-                      | 0.014<br>(0.037)  | -<br>-                    | -<br>-                               | -0.041<br>(0.044)  |
| Lagged participation                   | -<br>-              | -<br>-                      | 1.312<br>(0.034)**  | -<br>-                    | 2.648<br>(0.215)**                   | 1.292<br>(0.040)**   |
| Observations                           | 15,383              | 15,383                      | 15,383  | 6,761                     | 3,652                                | 11,827   |
| Number of persons                      | 5,212               | 5,212                       | 5,212   | 1,626                     | 694                                  | 4,067  |

Standard errors in parentheses. All equations include time-dummies.

The correlated random effects contain the means of age, region dummies, children and health variables.

\* significant at 5 per cent; \*\* significant at 1 per cent

The spouse's temporary income is insignificant in all estimations, but the fixed effects logit, where the coefficient is significantly negative. In the absence of major tax or benefit reforms

the within change in the spouse's income – the transitory part – is limited. If it takes a certain amount of change in partner income to affect the labor market status, we could fear that we actually observe too little variation in our data to obtain significant estimates. In absence of credit constraints the insignificant parameter estimates suggest that individuals smooth out consumption.

The permanent income only varies between individuals and, hence, the coefficient cannot be identified in the fixed effects specifications. In the rest of the estimations the spouse permanent income is significantly positive. Hence, it seems to be the case that the spouses have the same taste for work by assortative matching in the marriage market. In other words, the positive sign implies that Hyslop's taste effect dominates and, therefore, that the permanent spouse income is endogenous to the employment decision.



Table 4: Participation probability, partner income, females

|  | Pooled<br>probit    | Random<br>effects<br>probit | Dynamic<br>corre-<br>lated<br>random<br>effects<br>probit | Fixed<br>effects<br>logit | Dynamic<br>fixed<br>effects<br>logit | Dynamic<br>corre-<br>lated<br>random<br>effects<br>probit, 42<br>weeks |
|--|---------------------|-----------------------------|---|---------------------------|--------------------------------------|--|
| Spouse' temporary income               | 0.033<br>(0.005)**  | 0.041<br>(0.006)**          | 0.036<br>(0.006)**  | 0.056<br>(0.012)**        | -0.003<br>(0.063)                    | 0.031<br>(0.006)**   |
| Spouse's permanent income              | 0.060<br>(0.003)**  | 0.076<br>(0.005)**          | 0.054<br>(0.003)**  | -                         | -                                    | 0.053<br>(0.004)**   |
| Age                                    | -0.012<br>(0.010)   | 0.006<br>(0.019)            | 0.179<br>(0.021)**  | -                         | -                                    | 0.177<br>(0.023)**   |
| Age squared/100                        | -0.033<br>(0.014)*  | -0.080<br>(0.026)**         | -0.060<br>(0.018)**                                       | -                         | -                                    | -0.001<br>(0.000)**  |
| Experience                             | 0.252<br>(0.007)**  | 0.389<br>(0.015)**          | 0.144<br>(0.011)**  | 0.708<br>(0.079)**        | 0.095<br>(0.221)                     | 0.135<br>(0.013)**   |
| Experience squared/100                 | -0.940<br>(0.035)** | -1.517<br>(0.067)**         | -0.539<br>(0.050)**                                       | -3.570<br>(0.365)**       | -                                    | -0.005<br>(0.001)**  |
| Unskilled                              | -0.348<br>(0.028)** | -0.610<br>(0.055)**         | -0.371<br>(0.037)**                                       | -                         | -                                    | -0.345<br>(0.042)**  |
| Short-cycle higher education           | 0.090<br>(0.081)    | 0.059<br>(-0.168)           | 0.063<br>(-0.106)   | -                         | -                                    | 0.052<br>(0.119)   |
| Medium-cycle higher education          | -0.107<br>(0.066)   | -0.151<br>(-0.131)          | -0.084<br>(-0.086)  | -                         | -                                    | -0.159<br>(0.101)  |
| Long-cycle higher education            | -0.245<br>(0.121)*  | -0.401<br>(0.226)           | -0.327<br>(0.152)*  | -                         | -                                    | -0.370<br>(0.177)*   |
| Immigrant                              | 0.208<br>(0.030)**  | 0.178<br>(0.058)**          | 0.085<br>(0.039)*   | -                         | -                                    | 0.027<br>(0.043)   |
| Second generation immigrant            | 0.316<br>(0.141)*   | 0.479<br>(0.261)            | 0.224<br>(0.180)  | -                         | -                                    | 0.617<br>(0.197)**   |
| Copenhagen                             | -0.031<br>(0.044)   | -0.043<br>(0.084)           | -0.156<br>(0.242)   | -0.203<br>(0.439)         | -                                    | 0.014<br>(0.282)   |
| Large city                             | -0.075<br>(0.045)   | -0.134<br>(0.086)           | -0.586<br>(0.273)*  | -0.731<br>(0.483)         | -                                    | -0.708<br>(0.317)*   |
| Rural area                             | 0.050<br>(0.038)    | 0.025<br>(0.072)            | -0.098<br>(0.220)   | -0.198<br>(0.374)         | -                                    | -0.140<br>(0.258)  |
| Children aged 0-6 years                | -0.278<br>(0.015)** | -0.369<br>(0.025)**         | -0.196<br>(0.041)**                                       | -0.570<br>(0.082)**       | 0.113<br>(0.305)                     | -0.247<br>(0.0460)**   |
| Children aged 7-17 years               | -0.059<br>(0.012)** | -0.096<br>(0.022)**         | -0.107<br>(0.042)*  | -0.339<br>(0.085)**       | -                                    | -0.127<br>(0.045)**  |
| Unemp. on municipality and gender      | -0.037<br>(0.007)** | -0.052<br>(0.013)**         | -0.037<br>(0.009)**                                       | -0.096<br>(0.042)*        | -                                    | -0.044<br>(0.010)**  |
| Regional vacancies                     | 2.468<br>(0.741)**  | 2.598<br>(1.341)            | 2.276<br>(0.944)*   | -5.571<br>(4.882)         | -                                    | 1.622<br>(1.073)   |
| Neuro medicine                         | -0.086<br>(0.033)** | -0.108<br>(0.046)*          | -0.079<br>(0.049)   | -0.117<br>(0.095)         | -                                    | -0.089<br>(0.048)  |
| Psychiatry                             | -0.056<br>(0.010)** | -0.057<br>(0.014)**         | -0.021<br>(0.016)   | -0.043<br>(0.033)         | -                                    | -0.015<br>(0.018)  |
| General medical treatment              | -0.006<br>(0.001)** | -0.005<br>(0.001)**         | -0.001<br>(0.001)   | 0.001<br>(0.002)          | -                                    | -0.003<br>(0.001)*   |
| y <sub>0</sub> (initial participation) | -                   | -                           | -0.202<br>(0.039)**                                       | -                         | -                                    | -0.144<br>(0.044)**  |
| Lagged participation                   | -                   | -                           | 1.537<br>(0.035)**  | -                         | 3.752<br>(0.294)**                   | 1.461<br>(0.039)**   |
| Observations                           | 21,149              | 21,149                      | 21,149  | 7,048                     | 3,335                                | 17,284   |
| Number of persons                      | 6,985               | 6,986                       | 6,986   | 1,736                     | 638                                  | 5,808  |

Standard deviations are in parentheses. All equations include time-dummies.

The correlated random effects contain the means of age, region dummies, children and health variables.

\* significant at 5 per cent; \*\* significant at 1 per cent

The results for women are shown in Table 4. There are some noticeable differences in the parameter estimates compared to men. First, whereas men with higher education have a higher probability of being employed, the comparable effect for women is insignificant or even negative.

Second, there is no significant difference in the employment probability between living in the capital of Copenhagen and in rural areas. For women we find significantly positive effects of both temporary and permanent income, which again reflect the taste effect endogeneity.

Table 5 presents elasticities for the previous estimations. From the dynamic random effects probit model it can be seen that participation in itself increases the probability of also being in the labor market next year by about 40 per cent. In a recent paper Ahmad (2007) also estimates reduced-form participation equations for immigrants receiving social assistance benefits and argues that there is a large degree of state dependence among immigrants in Denmark.

Table 5: Elasticities, partner income

|                           | Pooled<br>probit | Random<br>effects<br>probit | Dynamic<br>random<br>effects<br>probit | Dynamic<br>random<br>effects<br>probit,<br>42<br>weeks |
|---------------------------|------------------|-----------------------------|--|--|
| <b>Males</b>              |                  |                             |  |  |
| Lagged dependent variable | -                | -                           | 0.405                                  | 0.398  |
|                           | -                | -                           | (0.020)**                              | (0.023)**  |
| Spouse's temporary income | -0.002           | -0.002                      | -0.002                                 | -0.004   |
|                           | (0.014)          | (0.013)                     | (0.016)                                | (0.019)  |
| Spouse's permanent income | 0.339            | 0.358                       | 0.303                                  | 0.276  |
|                           | (0.052)**        | (0.068)**                   | (0.067)**                              | (0.081)**  |
| <b>Females</b>            |                  |                             |  |  |
| Lagged dependent variable | -                | -                           | 0.408                                  | 0.379  |
|                           | -                | -                           | (0.022)**                              | (0.024)**  |
| Spouse's temporary income | 0.007            | 0.006                       | 0.007                                  | 0.006  |
|                           | (0.042)          | (0.032)                     | (0.045)                                | (0.051)  |
| Spouse's permanent income | 0.918            | 0.791                       | 0.805                                  | 0.798  |
|                           | (0.054)**        | (0.067)**                   | (0.068)**                              | (0.075)**  |

Standard deviations are in parentheses.

\* significant at 5 per cent; \*\* significant at 1 per cent

Unlike both Hyslop's (1999) and Croda and Kyriazidou's (2003) results for married women we find that the permanent part of the spouse income is endogenous for both men and women and, therefore, that it is not useful for examining the effects of financial incentives for the participation decision. The reason seems to be that the difference in the participation rate between the genders is smaller in Denmark than in Germany and the US. Additionally, the share of women in part-time work is much higher in Germany. With respect to the transitory part of the spouse's income we similar to Hyslop (1999) and Croda and Kyriazidou (2003) find very small and insignificant effects, which suggest that workers are not credit constrained and can smooth out consumption.

## 6 Does Own Income Create Work Incentives?

The results from the previous section show the weakness of using spouse's income as predictor for participation, namely that it may be endogenous. Furthermore, depending on how income is used in a family, it may be the case that the response is larger for the own disposable income gain from working. Hence, the results from the previous section do not necessarily imply that there are low participation elasticities for recipients of social assistance. Instead in this section we use predicted own disposable income gaps to investigate the importance of financial incentives for the participation decision.

Table 6 shows the second step of the Vella-Verbeek sample selection model. It is striking that most of the variables are insignificant. For example for women there is no significant wage difference between being unskilled and having a university degree. This seems to suggest that for the sample of social assistance recipients the human capital model works poorly. This is also reflected in the low  $R^2$  of 7 – 9 per cent. Using Danish register data it is far from unusual to obtain an explanatory power of more than 30 per cent. As a matter of fact, by considering all the persons for whom we observe a wage rate we obtain an  $R^2$  of about 20 per cent using only experience and its square as well as schooling to explain the variation of the log wages.<sup>3</sup> In order to understand the results in Table 6 one might again refer to Table 1 and 2 to see that the level of the mean wage implies, that the minimum wage constraint is binding for a large part of the recipients of social assistance, perhaps suggesting that these people are unable to receive a wage matching their marginal productivity measured by the usual Mincer explanatory variables. Hence, recipients of social assistance seem to be marginalized in the labor market.

For men the selection into the sub-sample of persons for whom we observe the wage is positive with respect to the time-invariant unobservables. This is as expected because this suggests, that people with higher ability earn more and have a higher probability of finding employment. For women we find no significant selection in terms of time-invariant unobservables.

---

<sup>3</sup>These results are not shown.

Table 6: Wage equation, random effects

|                                       | Male                | Female              |
|---------------------------------------|---------------------|---------------------|
| Age                                   | 0.017<br>(0.003)**  | 0.005<br>(0.004)    |
| Age squared/100                       | -0.022<br>(0.004)** | -0.005<br>(0.005)   |
| Experience                            | 0.010<br>(0.003)**  | 0.006<br>(0.003)    |
| Experience squared/100                | -0.023<br>(0.009)*  | -0.012<br>(0.013)   |
| Unskilled                             | -0.021<br>(0.009)*  | 0.002<br>(0.010)    |
| Short-cycle higher education          | 0.027<br>(0.028)    | 0.024<br>(0.036)    |
| Medium-cycle higher education         | 0.110<br>(0.025)**  | 0.114<br>(0.024)**  |
| Long-cycle higher education           | 0.171<br>(0.030)**  | 0.072<br>(0.042)    |
| Immigrant                             | -0.004<br>(0.012)   | -0.002<br>(0.013)   |
| Second generation immigrant           | -0.016<br>(0.042)   | 0.024<br>(0.044)    |
| Copenhagen                            | 0.023<br>(0.014)    | 0.042<br>(0.015)**  |
| Large city                            | -0.017<br>(0.015)   | 0.003<br>(0.017)    |
| Rural area                            | -0.021<br>(0.011)   | -0.011<br>(0.013)   |
| Children aged 0-6 years               | 0.012<br>(0.006)*   | -0.010<br>(0.006)   |
| Children aged 7-17 years              | -0.003<br>(0.005)   | -0.006<br>(0.005)   |
| Unemp. on municipality and gender     | -0.004<br>(0.002)   | -0.006<br>(0.003)*  |
| Regional vacancies                    | -0.558<br>(0.245)*  | 0.020<br>(0.282)    |
| Neuro medicine                        | 0.026<br>(-0.014)   | -0.004<br>(0.009)   |
| Psychiatry                            | 0.008<br>(0.003)**  | -0.002<br>(0.003)   |
| General medical treatment             | 0.000<br>(0.000)    | 0.000<br>(0.000)    |
| Mean (generalized residual)           | 0.028<br>(0.004)**  | 0.003<br>(0.005)    |
| Generalized residual                  | -0.035<br>(0.007)** | -0.032<br>(0.007)** |
| Variance of individual specific error | 0.213               | 0.201               |
| Variance of time-varying error        | 0.224               | 0.219               |
| R-squared                             | 0.087               | 0.075               |
| Observations                          | 11,124              | 7,823               |
| Persons                               | 4,569               | 3,485               |

Note: Standard deviations are in parentheses.

Both equations include time-dummies.

\*significant at 5 per cent; \*\*significant at 1 per cent

Table 7: Participation probability, own income, males

|                                   | Pooled<br>probit    | Random<br>effects<br>probit | Dynamic<br>random<br>effects<br>probit |
|-----------------------------------|---------------------|-----------------------------|--|
| Own income gap/10000              | 0.031<br>(0.003)**  | 0.044<br>(0.005)**          | 0.045<br>(0.004)**                     |
| Age                               | -0.067<br>(0.006)** | -0.082<br>(0.010)**         | 0.040<br>(0.013)**                     |
| Age squared/100                   | 0.037<br>(0.008)**  | 0.041<br>(0.013)**          | 0.007<br>(0.009)                       |
| Experience                        | 0.185<br>(0.004)**  | 0.263<br>(0.007)**          | 0.097<br>(0.005)**                     |
| Experience squared/100            | -0.526<br>(0.016)** | -0.780<br>(0.030)**         | -0.285<br>(0.020)**                    |
| Unskilled                         | -0.127<br>(0.017)** | -0.178<br>(0.032)**         | -0.088<br>(0.020)**                    |
| Short-cycle higher education      | 0.028<br>(0.048)    | 0.076<br>(0.088)            | -0.007<br>(0.057)                      |
| Medium-cycle higher education     | 0.166<br>(0.043)**  | 0.222<br>(0.080)**          | 0.110<br>(0.051)*                      |
| Long-cycle higher education       | 0.258<br>(0.050)**  | 0.299<br>(0.093)**          | 0.077<br>(0.060)                       |
| Immigrant                         | 0.285<br>(0.020)**  | 0.338<br>(0.037)**          | 0.219<br>(0.025)**                     |
| Second generation immigrant       | -0.009<br>(0.076)   | 0.039<br>(0.135)            | 0.001<br>(0.089)                       |
| Copenhagen                        | 0.011<br>(0.027)    | 0.037<br>(0.046)            | 0.025<br>(0.085)                       |
| Large city                        | -0.089<br>(0.028)** | -0.118<br>(0.049)*          | -0.105<br>(0.111)                      |
| Rural area                        | -0.030<br>-(0.022)  | -0.041<br>-(0.040)          | 0.024<br>-(0.089)                      |
| Children aged 0-6 years           | 0.003<br>-(0.012)   | 0.002<br>-(0.019)           | 0.025<br>-(0.026)                      |
| Children aged 7-17 years          | 0.076<br>(0.010)**  | 0.106<br>(0.017)**          | 0.122<br>(0.028)**                     |
| Unemp. on municipality and gender | 0.049<br>(0.005)**  | 0.064<br>(0.008)**          | 0.042<br>(0.006)**                     |
| Regional vacancies                | 2.127<br>(0.483)**  | 1.965<br>(0.814)*           | 1.632<br>(0.571)**                     |
| Neuro medicine                    | 0.077<br>(0.032)*   | 0.084<br>(0.041)*           | -0.068<br>(0.043)                      |
| Psychiatry                        | 0.032<br>(0.006)**  | 0.032<br>(0.008)**          | -0.016<br>(0.010)                      |
| General medical treatment         | 0.006<br>(0.000)**  | 0.005<br>(0.001)**          | -0.002<br>(0.001)**                    |
| $y_0$ (initial participation)     | 0.000<br>(0.000)    | 0.000<br>(0.000)            | 0.079<br>(0.022)**                     |
| Lagged participation              | 0.000<br>(0.000)    | 0.000<br>(0.000)            | 1.325<br>(0.021)**                     |
| Observations                      | -                   | -                           | 41,390                                 |
| Number of persons                 | -                   | -                           | 10,689                                 |

Standard deviations are in parentheses. All equations include time-dummies.

The correlated random effects contain the means of age, region dummies, children and health variables.

\* significant at 5 per cent; \*\* significant at 1 per cent

Table 8: Participation probability, own income, females

|                                   | Pooled<br>probit    | Random<br>effects<br>probit | Dynamic<br>random<br>effects<br>probit |
|-----------------------------------|---------------------|-----------------------------|--|
| Own income gap/10000              | 0.045<br>(0.002)**  | 0.059<br>(0.003)**          | 0.049<br>(0.003)**                     |
| Age                               | -0.014<br>(0.007)*  | 0.001<br>(0.013)            | 0.173<br>(0.016)**                     |
| Age squared/100                   | -0.030<br>(0.009)** | -0.071<br>(0.017)**         | -0.047<br>(0.012)**                    |
| Experience                        | 0.216<br>(0.005)**  | 0.320<br>(0.010)**          | 0.111<br>(0.007)**                     |
| Experience squared/100            | -0.772<br>(0.023)** | -1.188<br>(0.047)**         | -0.412<br>(0.031)**                    |
| Unskilled                         | -0.337<br>(0.020)** | -0.617<br>(0.039)**         | -0.345<br>(0.026)**                    |
| Short-cycle higher education      | -0.039<br>(0.062)   | -0.134<br>(0.125)           | -0.070<br>(0.081)                      |
| Medium-cycle higher education     | -0.195<br>(0.046)** | -0.247<br>(0.089)**         | -0.202<br>(0.058)**                    |
| Long-cycle higher education       | 0.079<br>(0.073)    | -0.133<br>(0.144)           | -0.159<br>(0.094)                      |
| Immigrant                         | 0.041<br>(0.021)    | 0.003<br>(0.042)            | -0.031<br>(0.028)                      |
| Second generation immigrant       | 0.033<br>(0.086)    | 0.083<br>(0.164)            | -0.007<br>(0.108)                      |
| Copenhagen                        | -0.091<br>(0.029)** | -0.131<br>(0.054)*          | -0.109<br>(0.115)                      |
| Large city                        | -0.090<br>(0.031)** | -0.145<br>(0.059)*          | -0.356<br>(0.144)*                     |
| Rural area                        | 0.028<br>(0.026)    | 0.014<br>(0.049)            | -0.082<br>(0.114)                      |
| Children aged 0-6 years           | -0.153<br>(0.011)** | -0.206<br>(0.019)**         | -0.128<br>(0.028)**                    |
| Children aged 7-17 years          | 0.019<br>(0.009)*   | 0.006<br>(0.017)            | -0.032<br>(0.028)                      |
| Unemp. on municipality and gender | -0.026<br>(0.005)** | -0.039<br>(0.009)**         | -0.024<br>(0.006)**                    |
| Regional vacancies                | 1.009<br>(0.540)    | 1.120<br>(0.960)            | 0.387<br>(0.684)                       |
| Neuro medicine                    | -0.073<br>(0.023)** | -0.081<br>(0.031)**         | -0.065<br>(0.032)*                     |
| Psychiatry                        | -0.045<br>(0.006)** | -0.051<br>(0.009)**         | -0.037<br>(0.010)**                    |
| General medical treatment         | -0.003<br>(0.000)** | -0.002<br>(0.000)**         | 0.000<br>(0.001)                       |
| $y_0$ (initial participation)     | 0.000<br>(0.000)    | 0.000<br>(0.000)            | -0.075<br>(0.027)**                    |
| Lagged participation              | -<br>-              | -<br>-                      | 1.503<br>(0.025)**                     |
| Observations                      | 40,170              | 40,170                      | 40,170                                 |
| Number of persons                 | 10,586              | 10,586                      | 10,586                                 |

Standard errors in parentheses. All equations include time-dummies.

The correlated random effects contain the means of age, region dummies, children and health variables.

\* significant at 5 per cent; \*\* significant at 1 per cent

The results from the participation equation where we include the worker's own disposable income gain from working is presented in Table 7 and 8. Overall, the picture is similar compared to Table 3 and 4 although there are some changes due to the fact that Table 7 and 8 also include singles. When we estimate on both couples and singles we find that only children aged 0-6 years have a negative influence on the employment probability and for men we even find significant positive coefficients to the number of children aged 7-17 years.

For women there are two more changes. First, the coefficient to medium-cycle higher education becomes significantly negative, although this does not change the conclusion that there is an insignificant or negative effect on the participation probability of having a longer education. Thus, for workers with a weak attachment to the labor market and low experience, vocational education, which is the reference category, might be the most favourable education. Furthermore, the signaling effect of a social assistance spell to the employer might be more severe for educations with an overall very low unemployment rate.

Second, immigrants are no longer more likely to become employed than natives. This suggests that single female immigrants do not participate to the same degree as married female immigrants. However, the reason might be that single mothers to a larger extent are paid additional benefits in an ad-hoc way, which depends on the local government which, therefore, are impossible to model. This implies that the calculated income gap for single female immigrants is overvalued, which in turn may imply that they seem to be less likely to participate.

Own disposable income gap is significantly positive in both estimation frameworks and for both genders, and thus, having a higher income gap raises the probability of participation.

Table 9: Elasticities, own income gap

|                                     | Pooled<br>probit | Random<br>effects<br>probit | Dynamic<br>random<br>effects<br>probit |
|-------------------------------------|------------------|-----------------------------|--|
| <hr/> Males <hr/>                   |                  |                             |  |
| Lagged dependent variable           | -                | -                           | 0.422                                  |
|                                     | -                | -                           | (0.012)                                |
| Own income gap                      | 0.276            | 0.305                       | 0.422                                  |
|                                     | (0.034)          | (0.037)                     | (0.044)                                |
| Change in own income gap, 5,000 DKK | 0.018            | 0.020                       | 0.028                                  |
| <hr/> Females <hr/>                 |                  |                             |  |
| Lagged dependent variable           | -                | -                           | 0.414                                  |
|                                     | -                | -                           | (0.015)                                |
| Own income gap                      | 0.655            | 0.618                       | 0.678                                  |
|                                     | (0.033)          | (0.037)                     | (0.044)                                |
| Change in own income gap, 5,000 DKK | 0.052            | 0.049                       | 0.054                                  |

Standard deviations are in parentheses.

\* significant at 5 per cent; \*\* significant at 1 per cent

Table 9 presents the elasticities from changing own disposable income gap on the participa-

tion probability. The elasticities for men are in the range of  $0.28 - 0.44$ , while the elasticities for women are roughly double the size. The estimated elasticities imply that increasing the disposable income with 5,000 DKK delivers an increase in the participation probability of 0.025 for men and 0.05 for women. Another way of measuring the participation elasticities, which for example is used in the CGE model DREAM, is the percentage change in the number of recipients of social assistance from a percentage change in the income gap. In Appendix B we show how to convert the elasticities and for men the elasticity is  $0.09 - 0.17$ , while we for women obtain  $0.13 - 0.20$ .

In the absence of major benefit and tax policy changes in the considered period we do not want to identify the effect of the disposable income gap solely from within-individual variation. Therefore, we do not include the mean of disposable income in the linear approximation for the unobservable individual effect. However, this implies that we cannot appropriately control for unobserved heterogeneity, which may bias the results. If receiving social assistance is voluntary, but joy of working is positively correlated with productivity, the elasticity will be upward biased.

It is obviously pointless to consider the effects of economic incentives if receiving benefits is completely involuntary. Even though this extreme is not the case, it is likely that some recipients of social assistance would prefer to be employed, but have a low probability of getting a job due to very low productivities. In this case our estimated model confuses low incentives with low participation probability and the estimated elasticity will also tend to be upward biased. In other words, the effects from an actual tax or benefit reform will be smaller than our income elasticity estimates.

There exist a few other Danish studies also estimating participation income elasticities. Graversen (1996) estimates participation elasticities for workers in the labor force from a natural experiment study of the 1987 tax reform. He finds participation elasticities in the range of  $0.2 - 0.7$  for single women and  $0.05$  for married women. Pedersen and Smith (2002) also computes disposable income gaps from working, but do as Graversen focus on unemployed workers in the labor force. They use survey information on the unemployed worker's expected wage and use information on employed workers' transportation costs and child care costs. For 1996 they find an income elasticity of  $0.3$  for men and  $0.7$  for women. Pedersen and Smith do not solve the potential endogeneity problem of the worker's disposable income. The elasticities are strikingly similar in our study and in Pedersen and Smith, which should imply that the effect of financial incentives are similar among the unemployed workers in the labor force and among recipients of social assistance. However, since the share of very low productivity workers is larger among the recipients of social assistance than the recipients of unemployment benefits, the share who is involuntary out of employment is probably largest among the recipients of social assistance. Hence, it is probably the case that our estimates for the recipients of social assistance have the largest bias.



In contrast to the two mentioned studies, Toomet (2005) focus on social assistance and exploits the fact that the social assistance benefits is increased by 70 per cent when recipients without children turns 25 years, while the benefit level remains constant at the age of 25 years for recipients with children. Hence, Toomet uses the latter group as control group. From a difference-in-difference estimation a participation elasticity of income of 0.4 is found for women while the income effect for men is found to be insignificant.

In a recent survey-based study, Graversen and Tinggaard (2005) examine the effects of the implementation of the social assistance ceiling in 2004.<sup>4</sup> Approximately 1,000 social assistance recipients were interviewed just before the implementation and again nine months after the implementation of the social assistance benefit ceiling. Although the ceiling has reduced the amount of social assistance received and, hence, was expected to provide larger incentives, Graversen and Tinggaard conclude that there seems to be no effect on participation and on whether the recipient search or not. Moreover, Graversen and Tinggaard only find very modest effects on the search intensity.

Finally, in a recent study Graversen (2006) uses the variation in social assistance benefits from the implementation of the social assistance ceiling. A pooled probit model for participation is estimated for each month for 18 months. Graversen compute the income gap from working similar to here although he uses a median wage for all persons rather than a predicted wage. This way Graversen avoids the potential endogeneity of the wages, but the framework only allows Graversen to determine effects from differences in benefits in the short term. No significant employment effects are found from this analysis.

## 7 Conclusion

In this paper we have examined the effects of economic incentives on the labor market participation for recipients of social assistance. A simple examination of the characteristics of recipients of social assistance reveals the group to be marginalized in the labor market. This conclusion is further strengthened by the poor performance of the human capital model and the large degree of state dependence in the employment status. Hence, to some extent we would believe that this group of people is involuntary nonemployed and that only small effects from economic incentives are to be expected. We find no employment effects of incentives from the within variation in the spouse's income. Recently, Graversen and Tinggaard (2005) and Graversen (2006) have evaluated the short-term effect of the social assistance ceiling. They find no or very small effects.

However, from estimations where we use predicted disposable income gain from working

---

<sup>4</sup>The social assistance ceiling aimed at providing economic incentives for married social assistance recipients, by setting a reduced maximum of social assistance benefits that a household can receive. It came into effect January 1, 2004.

we obtain elasticities in the range of  $0.28 - 0.44$  for men and in the range of  $0.62 - 0.68$  for women. These elasticities are of similar magnitude as those Pedersen and Smith (2002) find for workers in the labor force. However, neither we, nor Pedersen and Smith are able to sufficiently control for unobserved heterogeneity of the disposable income gap. Therefore, we believe that the estimates are likely to be upward biased. When converting the elasticities to percentage change in the number of recipients of social assistance from a percentage change in the income gap as used in the CGE model DREAM the estimated elasticities correspond to  $0.09 - 0.17$  for men and  $0.13 - 0.20$  for women.

## References

- [1] Ahmad, N. (2007): Dynamic Labour Market Behaviour of Immigrants in Denmark, working paper, University of Aarhus.
- [2] Chamberlain, G. (1993): Feedback in Panel Data Models, unpublished manuscript, Department of Economics, Harvard University.
- [3] Croda, E. and E. Kyriazidou (2003): Intertemporal Labor Force Participation of Married Women in Germany: A Panel Data Analysis, Working Paper.
- [4] Danish Economic Council (2004): Dansk økonomi efterår 2004, Copenhagen.
- [5] Danish Welfare Commission (2005): Fremtidens velfærd – vores valg, Copenhagen .
- [6] Dex, S., S. Gustafsson, N. Smith and T. Callan (1995): Cross-National Comparisons of the Labour Force Participation of Women Married to Unemployed Men, *Oxford Economic Papers* **47**, pp. 611-635.
- [7] Frederiksen, A., E.K. Graversen and N. Smith (2001): Overtime Work, Dual Job Holding and Taxation, IZA discussion paper 323, Bonn.
- [8] Garibaldi, P. and with E. Wasmer (2004): Raising Female Employment: Reflections and Policy Tools, *Journal of the European Economic Association* **2**, pp. 320-330.
- [9] Graversen, B.K. (2006): Making Work Pay: Is There an Employment Effect for Disadvantaged families, working paper, The Danish National Institute of Social Research.
- [10] Graversen, E.K. (1996): Measuring Labour Supply Responses to Tax Changes by Use of Exogenous Tax Reforms, CLS working paper 96-17, University of Aarhus and Aarhus Business School.

- [11] Graversen, B.K. and K. Tinggaard (2005): Loft over ydelser – Evaluering af loftet over ydelser til Kontanthjælpsmodtagere, working paper, The Danish National Institute of Social Research.
- [12] Greene, W.H. (2003): *Econometric Analysis*, Prentice Hall.
- [13] Heckman, J.J. (1979): Sample Selection Bias as a Specification Error, *Econometrica* **46**, pp. 931-959.
- [14] Heckman, J.J. (1981), The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process, in C. F. Manski and D. McFadden (eds.): *Structural Analysis of Discrete Data with Econometric Applications*, pp. 179–195, MIT Press.
- [15] Heckman, J.J. (1993): What Have Been Learned about Labor Supply in the Past Twenty Years, *American Economic Review* **47**, pp. 116-121.
- [16] Honoré, B. E., and E. Kyriazidou (2000), Panel Data Discrete Choice Models with Lagged Dependent Variables, *Econometrica* **68**, 839–874.
- [17] Hyslop, D. (1999): State Dependence, Serial Correlation and Heterogeneity in Intertemporal Labor Force Participation of Married Women, *Econometrica* **67**, 1255-1294.
- [18] Mundlak, Y. (1978): On the Pooling of Time Series and Cross Section Data, *Econometrica* **46**, pp. 69–85.
- [19] Munch, J.R. and M. Svarer (2002): Rent Control and Tenancy Duration, *Journal of Urban Economics* **52**, pp. 542-560.
- [20] Pedersen, P. J. and N. Smith (2002): Unemployment traps and financial disincentives to work, *European Sociological Review* **18**, pp. 271-288.
- [21] Toomet, O. (2005): Does an Increase in Unemployment Income Lead to Longer Unemployment Spells? Evidence Using Danish Unemployment Assistance Data, working paper, University of Aarhus.
- [22] Vella, F. and M. Verbeek (1998): Whose Wages do Unions Raise? A Dynamic Model of Unionism and Wage Rate Determination for Young Men, *Journal of Applied Econometrics* **13**, pp. 163-183.
- [23] Vella, F. and M. Verbeek (1999): Two-Step Estimation of Panel Data Models with Censored Endogenous Variable and Selection Bias, *Journal of Econometrics* **90**, pp. 239-263.

- [24] Wooldridge, J.M. (2002): *Econometric Analysis of Cross-Section and Panel Data*, MIT Press.
- [25] Wooldridge, J.M. (2005): Simple Solutions to the Initial Conditions Problem in Dynamic, Nonlinear Panel Data Models with Unobserved Effects, *Journal of Applied Econometrics* **20-1**, pp. 39-54.

# Appendix

## Appendix A: Goodness of Fit

Table 10: Confusion matrices, spouse income, males

| Pooled probit |        |       |        | Dynamic random effects probit |        |       |        |
|---------------|--------|-------|--------|-------------------------------|--------|-------|--------|
|               | Actual |       |        |                               | Actual |       |        |
| Predicted     | 0      | 1     | Total  | Predicted                     | 0      | 1     | Total  |
| 0             | 9,234  | 3,248 | 12,482 | 0                             | 9,192  | 1,704 | 10,896 |
| 1             | 1,250  | 1,651 | 2,901  | 1                             | 1,292  | 3,195 | 4,487  |
| Total         | 10,484 | 4,899 | 15,383 | Total                         | 10,484 | 4,899 | 15,383 |

Table 11: Confusion matrices, spouse income, females

| Pooled probit |        |       |        | Dynamic random effects probit |        |       |        |
|---------------|--------|-------|--------|-------------------------------|--------|-------|--------|
|               | Actual |       |        |                               | Actual |       |        |
| Predicted     | 0      | 1     | Total  | Predicted                     | 0      | 1     | Total  |
| 0             | 15,593 | 3,380 | 18,973 | 0                             | 15,609 | 1,942 | 17,551 |
| 1             | 959    | 1,217 | 2,176  | 1                             | 943    | 2,655 | 3,598  |
| Total         | 16,552 | 4,597 | 21,149 | Total                         | 16,552 | 4,597 | 21,149 |

Table 12: Confusion matrices, own income gap, males

| Pooled probit |        |        |        | Dynamic random effects probit |        |        |        |
|---------------|--------|--------|--------|-------------------------------|--------|--------|--------|
|               | Actual |        |        |                               | Actual |        |        |
| Predicted     | 0      | 1      | Total  | Predicted                     | 0      | 1      | Total  |
| 0             | 26,877 | 9,640  | 36,517 | 0                             | 25,068 | 4,276  | 29,344 |
| 1             | 2,172  | 2,701  | 4,873  | 1                             | 3,981  | 8,065  | 12,046 |
| Total         | 29,049 | 12,341 | 41,390 | Total                         | 29,049 | 12,341 | 41,390 |

Table 13: Confusion matrices, own income gap, females

| Pooled probit |        |       |        | Dynamic random effects probit |        |       |        |
|---------------|--------|-------|--------|-------------------------------|--------|-------|--------|
|               | Actual |       |        |                               | Actual |       |        |
| Predicted     | 0      | 1     | Total  | Predicted                     | 0      | 1     | Total  |
| 0             | 29,905 | 7,181 | 37,086 | 0                             | 29,254 | 3,821 | 33,075 |
| 1             | 1,487  | 1,597 | 3,084  | 1                             | 2,138  | 4,957 | 7,095  |
| Total         | 31,392 | 8,778 | 40,170 | Total                         | 31,392 | 8,778 | 40,170 |

## Appendix B: Elasticities Measured as Population Changes

Elasticities are most often defined as the percentage change in participation probability for a percentage change in income gap. Hence, we can define

$$\varepsilon_p = \frac{\partial p}{\partial y} \frac{y}{p} \quad (16)$$

where  $y$  is the disposable income gap and  $p$  is the participation probability. Another way of thinking about participation elasticities is the percentage change in the number of recipients of social assistance from a percentage change in the income gap. We can express this alternative elasticity as

$$\varepsilon_U = -\frac{\partial U}{\partial y} \frac{y}{U} \quad (17)$$

where  $U$  is the number of persons receiving social assistance. Letting  $N$  denote the total population, which is constant, and noticing that  $U = N(1 - p)$  we have that

$$\varepsilon_U = -\frac{-\partial p \cdot N}{\partial y} \frac{y}{N(1 - p)} = \frac{p}{(1 - p)} \varepsilon_p \quad (18)$$

Since  $\varepsilon_U$  is the definition used in two recent tax reform simulations on the CGE model DREAM (cf. Danish Economic Council (2004) and Danish Welfare Commission (2005)) we compute these elasticities from our estimations using the predicted participation probability  $\hat{p}$ , for each individual in our samples.

From (18), we see that only for a participation rate of exactly 50 per cent, the two elasticities are equal. For our sample we have participation rates somewhat below 50 percent, since our samples consist of only people who have been in contact with the social assistance system.

# Job Sampling and Sorting\*

Daniel le Maire

Christian Scheuer

University of Copenhagen and CAM

Copenhagen Business School and CEBR

June, 2009

## Abstract

We propose an equilibrium search model with on-the-job search, where a continuum of heterogenous workers and continuum of heterogenous firms match. Workers are allowed to select a sample size of vacancies to apply to, and more productive workers sample more firms. The possibility of sampling job offers imply that we only need the production function to be strictly supermodular for assortative matching to arise. The model delivers a log-linear wage equation with additively separable worker and firm effects. Therefore, we can simulate the theoretical model and estimate the two-way fixed-effects model as Abowd, Kramarz and Margolis (1999). By adding a match-effect we obtain an estimated negative correlation between the worker and firm effects even though there is assortative matching (positive correlation) in the theoretical model.

**Keywords:** Assortative matching, labor market search, linked employer-employee data, person and firm effects.

**JEL Classification:** C23, C78, J31, J62, J64.

---

\*We are very grateful for helpful comments from Dale Mortensen. Furthermore, we also thank Karsten Albæk, Martin Browning, Fane Groes, Bo Honore, Peter Sørensen and Chris Taber for valuable comments. All remaining errors are ours.

# 1 Introduction

In this paper we propose a labor market search model with two new features. First, the model has three types of continuous heterogeneity, which are worker productivity, firm productivity, and a random match effect. Each of these three productivity terms enters the production function. Second, assortative matching arises even though we only use a strictly supermodular production function.

We solve our search model and simulate data from the model. Using the two-way-fixed effect estimator invented by Abowd, Kramarz and Margolis (1999) (henceforth, AKM) on this simulated data, we show that the presence of a match effect can imply an estimated negative correlation between the worker and firm effects even if there is true positive assortative matching in the model economy. Therefore, this paper aims at explaining the puzzling negative correlation between worker and firm effects found empirically.<sup>1</sup>

Existing models of assignment along the lines of Becker's (1973) marriage model imply positive assortative matching. In fact, the ranking is such that a more productive worker always will have a better job than a less productive one. This result holds in a frictionless economy as long as the production function is strictly supermodular implying that the worker's human capital and firm's capital are complements in production. However, Shimer and Smith (2000) show that for assortative matching to arise in a search model setting it is no longer sufficient that the production function is strictly supermodular. Instead, Shimer and Smith find that a sufficient condition is that the production function is strictly log supermodular. As noted by Atakan (2006) the problem is that the higher gains to more search for more productive workers are offset by higher costs of rejecting an offer. Using this, Atakan shows that if unmatched agents have constant flow costs independent of their type and if the discount rate is zero, the production function only needs to be strictly supermodular in order to imply assortative matching.

We obtain assortative matching with the strictly supermodular Cobb-Douglas production function by letting workers choose how many job offers they wish to sample as in the seminal contribution by Stigler (1961). Assortative matching arises since more productive workers sample more jobs and, hence, they will, on average, end up in better jobs. In order to isolate the effect of the workers' job sampling we - similarly to Acemoglu and Shimer (2000) - assume that each firm that receives more than one application randomly chooses one of its applicants above a reservation threshold.

Previous studies on assortative models have examined the sets of matches that are acceptable

---

<sup>1</sup>See Abowd, Creedy and Kramarz (2002) and Abowd, Kramarz, Lengermann and Perez-Durante (2004) for results for both the US and France, Gruetter and Lalive (2004) for results for Austria, Piekola (2005) for Finland, Andrews, Gill, Schank and Upward (2007) for results for Germany, and Barth and Dale-Olsen (2003) for results for Norway.



by both workers and firms. Most of the studies (e.g. Atakan (2006), Becker (1973), Burdett and Coles (1999), Chade (2001) and Smith (2006)) have found perfect segregation, which implies that the labor market is segmented into multiple non-overlapping markets. Such an approach to study assortative matching is not useful with on-the-job search where the same search technology is available as unemployed and employed, since workers accept any offer greater or equal to the benefit level and subsequently climb the wage ladder by searching on-the-job. Instead of the matching sets approach, we compare the worker distribution over different firm and match productivities conditional on worker type. The latter approach is also used in Lentz (2008), where assortative matching also arises with a strictly supermodular production function since workers are allowed to choose their own search intensity.

When heterogeneous workers and firms match, it seems obvious that both worker and firm productivity should affect the wage paid. However, there are no a priori reasons to believe that these two effects should capture all variation in wages. It is very likely that complementarities between specific workers and firms could exist, or that human capital is accumulated according to the quality of the match between the worker and the firm involved. Both suggest a role for a heterogeneous match specific component. Moreover, several contributions have argued that the quality of the match between workers and firms in itself influences the earnings variation. A prominent example is the search model in Jovanovic (1979), where the flow production is a match quality plus a stochastic term. However, in principle there need not to be a match productivity in order to have a match component of the wage. The match effect could be due to differences in bargaining strength, for instance, as a consequence of the labor market tightness at the time of contract negotiation.

In the proposed model framework we let the match effect be a random productivity component, which enters the production function together with the worker and firm productivity. To our knowledge the model we propose is the first to offer a theoretical framework encompassing the idea of heterogeneity in both firm, worker and match effects.

A useful feature of our theoretical model is that it also implies a log linear wage equation with additively separable worker, firm and match heterogeneity. This is only possible because we can relax the requirement for assortative matching to be strictly supermodularity of the production function. The log linear wage equation with additively separable effects enables us to link the theoretical model directly to the AKM model as also done by Abowd, Kramarz, Lengermann and Perez-Duarte (2004). However, since the log linear wage equation is built into an equilibrium search model with assortative matching it gives us the opportunity to simulate our theoretical model and perform the AKM estimation on this data. When we simulate our model without the match effect and perform the AKM estimation and apply the bias correction in Andrews, Gill, Schank and Upward (2007) the estimated correlation equals the true correlation. In contrast, simulating our model with the match effect and again estimating

the AKM model and bias-correcting we obtain the very interesting result, that even though data is generated from a model with positive assortative matching the estimated correlation is negative.

The intuition behind our results is as follows. The firm effects are identified by workers making job-to-job transitions, and those with relative low realizations of the match effect will *ceteris paribus* be more likely to change jobs. However, since the econometrician does not estimate the match effect, the firm effect will be under-valued, which in turn will imply an over-valued worker effect, and the spurious negative correlation is established.

These results are in line with Woodcock (2007) who suggests an estimation procedure for an empirical model with person, firm and match effects. Using this estimation procedure he finds that the estimated negative correlation of the AKM model on US-data, in fact, is positive when taking the match heterogeneity into account. We apply his estimator both to our simulated and empirical data. From the simulations we learn, that the model performs very well in attributing the different parts of variation in the dependent variable to the firm, person and match effects, but also this estimator consequently underestimates the true correlation between workers and firms.

We apply both set of estimators to a panel of Danish employer-employee data. We estimate that the match effect indeed has empirical relevance since it accounts for 15 per cent of the variation in log wages. Furthermore, we estimate (what consequently is a downward biased) a correlation of worker and firm effects of 12 per cent, which suggests that the Danish labor market is characterized by positive assortative matching.

The paper is organized as follows. In section 2, we present our search model where more productive workers sort themselves into more productive matches. In section 3 we briefly consider the AKM model and the recent alternative estimation procedure outlined in Woodcock (2007). In section 4, we simulate our theoretical model and estimate both the AKM and Woodcock models on this model-generated data, whereas we in section 5 perform estimations on Danish register data. In section 6, we conclude.

## 2 Theoretical Model

Consider an economy with a continuum of firms and a continuum of workers that participate in the labor market. Both the measure of workers and firms are fixed and normalized to 1. All agents are rational, forward-looking, risk-neutral and infinitely lived. Workers have the opportunity of searching both while they are unemployed and employed.

Heterogeneity exists on both sides of the market as well as in the match between a worker and a firm. Workers differ in respect to their productivity such that more productive workers in all types of jobs are more productive. Denote the worker productivity by  $p_w$ , the firm

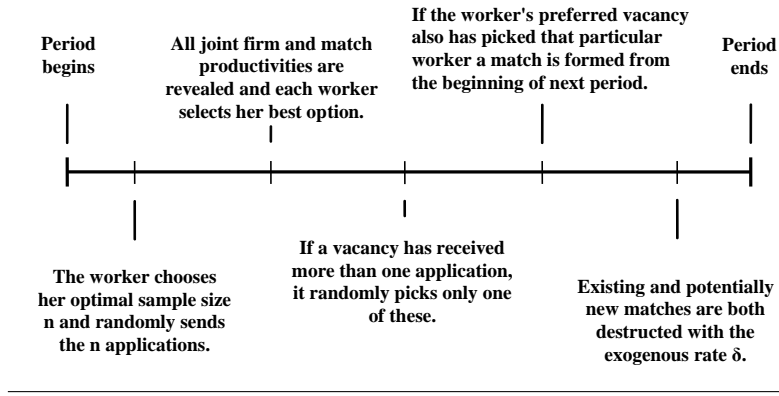
productivity by  $p_f$  and the match effect by  $p_m$ . Both the worker and the firm know their own productivity term as well as the decomposition in a given match and, hence, we rule out uncertainty and learning about any of the productivity terms.

We assume that we have a Cobb-Douglas production function  $f(p_w, p_f, p_m) = p_w^{\alpha_1} p_f^{\alpha_2} p_m^{\alpha_3}$ . The worker searches for the highest possible combination of firm and match productivity. Therefore, it is useful for us to work with the joint firm and match productivity  $p_{fm} = p_f^{\frac{\alpha_2}{\alpha_2+\alpha_3}} p_m^{\frac{\alpha_3}{\alpha_2+\alpha_3}}$ , allowing us to express the production function as  $f(p_w, p_f, p_m) = f(p_w, p_{fm}) = p_w^{\alpha_1} p_{fm}^{\alpha_2+\alpha_3}$ . The Cobb-Douglas function has two important properties. First, it is strictly supermodular, that is,  $\frac{\partial^2 f(p_w, p_{fm})}{\partial p_w \partial p_{fm}} > 0$  for  $\alpha_1 > 0$  and  $\alpha_2 + \alpha_3 > 0$ . Second, it is multiplicatively separable. We need not to assume the Cobb-Douglas form, and all implications of the model are true for all functions admitting strictly supermodularity and multiplicative separability. We use the assumption of multiplicative separability to ease the derivation of the worker's reservation productivity below, but note also that this assumption rules out comparative advantages, since the ratio of output of two firms is independent of the worker's productivity, cf. Sattinger (1975).

The distribution of worker productivity  $p_w$  is given by the cumulative distribution function  $H(p_w) = \int_{p_w}^{p_w} h(p'_w) dp'_w$ . The distribution of the firm and match productivity  $p_{fm}$  is given by  $\Gamma(p_{fm}) = \int_{p_{fm}}^{p_{fm}} \gamma(p'_{fm}) dp'_{fm}$ .

The search environment is closest to Acemoglu and Shimer (2000) although we allow for on-the-job search, but do not consider the firm's investment decision. The model is set in discrete time and the timing of events is illustrated in Figure 1.

FIGURE 1: ONE PERIOD SEQUENCE OF EVENTS



The job searcher, whether unemployed or employed, is given the opportunity to apply for  $n$  different jobs in each time period. Searching is costly and the more jobs applied to, the larger costs. We assume that this flow cost function is strictly convex in the number of jobs applied to,  $c'(n) > 0$  and  $c''(n) > 0$  and that  $c(0) = c'(0) = 0$ . The more jobs applied to, the

more likely the worker is to draw a high joint firm and match productivity. In order for the worker to realize the joint firm and match productivity, the worker needs to apply for a job in the particular firm. Hence, the worker applies to all jobs sampled, although he/ she is only willing to match with the job which turns out to be most productive (if above a reservation productivity level).

Depending on the number of job applications and vacancies, it is likely that a vacancy gets more than one application in each discrete time interval. Each vacancy can only employ one worker and among the applicants with productivity above a reservation value, one application is chosen randomly. One could think of the firms' random choice of worker as a framework, where the firm is only able to use sequential search in continuous time, and where it is random, whose application is the first to arrive.<sup>2</sup>

The implication of this search environment is that the expected number of job applications received is the same for all vacancies and that the acceptance rate workers face is independent of the worker's productivity. If both the worker and firm choose each other a match will be formed from the beginning of next period. Finally, in the end of each period a fraction  $\delta$  of existing and newly formed matches are exogenously destructed.

There is no traditional job arrival rate in this search context, but by abusing the traditional notation the worker's chance of getting his/ her chosen vacancy is denoted  $\lambda$ . That is

$$\lambda = (1 - \delta) \frac{\# \text{vacancies}}{\# \text{job applications}}$$

where the term  $(1 - \delta)$  takes account of that  $\delta$  of the new matches are destroyed before they come to existence.

## 2.1 The Worker Side

As unemployed, the worker receives benefits which depend on her own productivity  $bp_w^{\alpha_1}$ . This takes account of the fact that benefits typically are dependent on previous income as employed. Furthermore, the exact specification used here will simplify the analysis.<sup>3</sup> With the usual notation we denote the value of unemployment  $U(\cdot)$  and the value of employment  $W(\cdot, \cdot)$ . Letting  $r$  denote the discount factor the Bellman equation for an unemployed worker is

$$(1 + r)U(p_w) = bp_w^{\alpha_1} - c(n) + \lambda \int_{p_{fm}}^{\bar{p}_{fm}} \max \{W(p_w, p'_{fm}), U(p_w)\} dQ(p'_{fm}|n) + (1 - \lambda)U(p_w) \quad (1)$$

---

<sup>2</sup>Restricting the firms to consider one worker at a time, makes the model tractable. If also allowing firms to sample workers it is no longer necessarily the case that all workers will prefer the highest joint firm and match productivity. Rather, less productive workers may have a higher chance of becoming employed in less productive firms and, thereby, prefer to join these. Hence, allowing for endogenous sampling on both sides of the market complicates the math, but will only tend to increase the degree of assortative matching.

<sup>3</sup>A similar assumption is used in Postel-Vinay and Robin (2002).

where  $\bar{p}_{fm}$  and  $\underline{p}_{fm}$  denote respectively the upper and lower points of the joint firm and match productivity distribution  $p_{fm}$ , and  $Q(p_{fm}|n) = \Gamma(p_{fm})^n$  denote the distribution conditional on the number of sampled jobs  $n$ . Letting  $p_{fm}^r$  be the worker's reservation productivity and using integration by parts we can express this Bellman equation as

$$rU(p_w) = bp_w^{\alpha_1} - c(n) + \lambda \int_{p_{fm}^r}^{\bar{p}_{fm}} W'_{p_{fm}}(p_w, p'_{fm}) (1 - \Gamma(p'_{fm})^n) dp'_{fm} \quad (2)$$

As employed the worker earns the wage  $w(p_w, p_{fm})$ , and as wage setting rule we employ the simplest: linear output sharing or piece-rate contract as in for example Bagger, Fontaine, Postel-Vinay and Robin (2007):  $w(p_w, p_{fm}) = \beta p_w^{\alpha_1} p_{fm}^{\alpha_2 + \alpha_3}$  where  $\beta$  is the worker's share of the flow production. With probability  $\delta$  the job is destructed and the worker returns to unemployment. The Bellman equation for an employed worker is

$$(r + \delta)W(p_w, p_{fm}) = \beta p_w^{\alpha_1} p_{fm}^{\alpha_2 + \alpha_3} - c(n) + \lambda \int_{p_{fm}^r}^{\bar{p}_{fm}} W'_{p_{fm}}(p_w, p'_{fm}) (1 - \Gamma(p'_{fm})^n) dp'_{fm} + \delta U(p_w) \quad (3)$$

Both workers and firms have minimum values of productivities that they are willing to match with. On the worker side this reservation value is the firm and match productivity for which the worker is indifferent between being employed compared to staying unemployed. This can be derived as

$$\begin{aligned} & \beta p_w^{\alpha_1} (p_{fm}^r)^{\alpha_2 + \alpha_3} - c(n) + \lambda \int_{p_{fm}^r}^{\bar{p}_{fm}} W'_{p_{fm}}(p_w, p'_{fm}) (1 - \Gamma(p'_{fm})^n) dp'_{fm} \\ &= bp_w^{\alpha_1} - c(n) + \lambda \int_{p_{fm}^r}^{\bar{p}_{fm}} W'_{p_{fm}}(p_w, p'_{fm}) (1 - \Gamma(p'_{fm})^n) dp'_{fm} \\ &\Leftrightarrow \\ & p_{fm}^r = \left( \frac{b}{\beta} \right)^{\frac{1}{\alpha_2 + \alpha_3}} \end{aligned} \quad (4)$$

Thus, the firm reservation productivity  $p_{fm}^r$  is identical for all workers. This would not have been the case if all workers received the same amount of unemployment benefits. In that case more productive workers would have a lower joint firm and match reservation productivity than less productive workers, since more productive workers have higher opportunity costs of staying unemployed and, therefore, would be more eager to get a job.<sup>4</sup> With identical  $p_{fm}^r$  across worker type, the reservation wage is increasing in the worker productivity  $p_w$ .

Differentiating the Bellman equation for an unemployed worker (2) and substituting out  $W'_{p_f}(p_w, p_f)$  from (3) gives us the first-order condition for the sample size  $n$  for an unemployed worker

---

<sup>4</sup>A similar result appears in the general model of Burdett and Coles (1999).

$$c'(n) = \lambda \int_{\left(\frac{b}{\beta}\right)^{\frac{1}{\alpha_2 + \alpha_3}}}^{\bar{p}_{fm}} \frac{\beta(\alpha_2 + \alpha_3) p_w^{\alpha_1} (p'_{fm})^{\alpha_2 + \alpha_3 - 1} \left[ -\Gamma(p'_{fm})^n \ln(\Gamma(p'_{fm})) \right]}{r + \delta + \lambda \left( 1 - \Gamma(p'_{fm})^n \right)} dp'_{fm} \quad (5)$$

Since  $[-\Gamma(p_{fm})^n \ln(\Gamma(p_{fm}))] \geq 0$  for all  $p_{fm}$ , the right hand side is increasing in  $p_w$  for  $\alpha_1, (\alpha_2 + \alpha_3) > 0$ . Since  $c''(n) > 0$  and the r.h.s. is decreasing in  $n$  for  $\Gamma(p_{fm}) \in ]0, 1[$ , more productive workers sample more jobs, that is  $n'_{p_w}(p_w, p_{fm}) > 0$ . The restriction that  $\alpha_1, (\alpha_2 + \alpha_3) > 0$  corresponds to the production function having a positive cross derivative,  $f''_{p_w, p_{fm}}(p_w, p_{fm}) > 0$ , which again exactly is the requirement of complementarity (or supermodularity) in the production function for Becker's (1973) model implying assortative matching.

$n$  only take on integer values and the  $n$  maximizing (5) is most likely not an integer. However, since the l.h.s. is increasing in  $n$ , while r.h.s. is decreasing in  $n$ , the optimal integer value of  $n$  is one of the two integers adjacent to  $n$  unless the optimal value of (5) itself is an integer.

Employed workers maximize the right hand side of equation (3) with respect to  $n$

$$c'(n) = \lambda \int_{p_{fm}}^{\bar{p}_{fm}} \frac{\beta(\alpha_2 + \alpha_3) p_w^{\alpha_1} (p'_{fm})^{\alpha_2 + \alpha_3 - 1} \left[ -\Gamma(p'_{fm})^n \ln(\Gamma(p'_{fm})) \right]}{r + \delta + \lambda \left( 1 - \Gamma(p'_{fm})^n \right)} dp'_{fm} \quad (6)$$

For a given joint match and firm productivity, more productive workers sample more jobs than less productive workers as long as  $\alpha_1, (\alpha_2 + \alpha_3) > 0$  corresponding to the production function being strictly supermodular.

We can summarize the findings above in the following proposition:

**Proposition 1** *When the production function  $f(p_w, p_{fm})$  admits supermodularity such that  $\alpha_1, (\alpha_2 + \alpha_3) > 0$ , more productive workers sample more jobs conditional on their current joint firm and match productivity  $n'_{p_w}(p_w, p_{fm}) > 0$ .*

**Proof.** See the text above. ■

Since workers are employed at  $p_{fm} \geq \left(\frac{b}{\beta}\right)^{\frac{1}{\alpha_2 + \alpha_3}}$  they have smaller expected gains of searching than unemployed workers with the same productivity and consequently they search less. Therefore, it is not necessarily the case that more productive employed workers search more than less productive employed workers since, on average, they will be employed in more productive matches already in the first match after being unemployed.

## 2.2 The Firm-Side

Unemployed workers choose the vacancy with the highest productivity among the sampled vacancies given  $p_{fm} \geq p_{fm}^r$ , while employed workers only accept to join a vacancy of productivity  $p_{fm}$  if their current productivity is lower and if  $p_{fm}$  is the highest productivity sampled. The vacancy picks the worker at random given that the worker's productivity together with the

drawn match effect is above a reservation threshold. We will express the reservation threshold in terms of the match effect, but make it depend on the worker productivity, that is  $p_m^r(p_w)$ . The firm's reservation productivity is decreasing in  $p_w$ , such that the highest reservation match effect is at the lower support of the worker distribution. To make the model tractable we assume that workers are accepted at any firm. More formally,

**Assumption 1**  $p_m^r(\underline{p}_w) \leq \underline{p}_m$  for all  $p_f \in [\underline{p}_f, \bar{p}_f]$ , where  $\underline{p}_m$  is the lowest possible match effect.

At the time when the firm posts a vacancy it only knows its own firm effect  $p_f$ . Assume that the match effect is distributed with  $\Upsilon(\cdot)$ . If the firm randomly selects a worker with productivity  $p_w$  currently employed at  $p_{fm}$  the probability that the firm of productivity  $p_f$  offers the highest wage is  $\int_{p_m^r(p_w)}^{\bar{p}_m} I \left\{ p_f^{\frac{\alpha_2}{\alpha_2+\alpha_3}} \cdot (p'_m)^{\frac{\alpha_3}{\alpha_2+\alpha_3}} > p_{fm} \right\} \Gamma \left( p_f^{\frac{\alpha_2}{\alpha_2+\alpha_3}} \cdot (p'_m)^{\frac{\alpha_3}{\alpha_2+\alpha_3}} \right)^{n(p_w, p_{fm})-1} d\Upsilon(p'_m)$ , where  $I\{\cdot\}$  is an indicator function making sure that the worker prefers the new match to the incumbent match. Using this, the value of vacancy  $V(p_f)$  is given by

$$\begin{aligned} rV(p_f) = & -c_v + \int_{\underline{p}_{fm}}^{\bar{p}_{fm}} \int_{\underline{p}_w}^{\bar{p}_w} \int_{p_m^r(p_w)}^{\bar{p}_m} I \left\{ p_f^{\frac{\alpha_2}{\alpha_2+\alpha_3}} \cdot (p'_m)^{\frac{\alpha_3}{\alpha_2+\alpha_3}} > p'_{fm} \right\} \Gamma \left( p_f^{\frac{\alpha_2}{\alpha_2+\alpha_3}} \cdot (p'_m)^{\frac{\alpha_3}{\alpha_2+\alpha_3}} \right)^{n(p_w, p'_{fm})-1} \\ & \times \left[ \frac{uh(p'_w) n(p'_w, p'_{fm}) +}{(1-u)g(p'_w, p'_{fm}) n(p'_w, p'_{fm})} \right] \left[ J \left( p'_w, p_f^{\frac{\alpha_2}{\alpha_2+\alpha_3}} \cdot (p'_m)^{\frac{\alpha_3}{\alpha_2+\alpha_3}} \right) - V(p_f) \right] dp'_w dp'_{fm} \end{aligned} \quad (7)$$

where  $J(p_w, p_{fm})$  is the value of filled job,  $c_v$  is the flow cost of having a vacancy and  $u$  denotes the unemployment rate, which is constant across worker type.

Job separations can happen as the worker is offered a job with a higher joint firm and match productivity or matches can be dissolved exogenously with rate  $\delta$ . The Bellman equation for a filled job is

$$rJ(p_w, p_{fm}) = (1-\beta)p_w^{\alpha_1} p_{fm}^{\alpha_2+\alpha_3} + \left[ \lambda \left( 1 - \Gamma(p_{fm})^{n(p_w, p_{fm})} \right) + \delta \right] [V(p_f) - J(p_w, p_{fm})] \quad (8)$$

Rather than matching with a worker of a given  $p_w$ , a firm may actually prefer to match with workers of lower productivity since workers with higher productivity sample more jobs and, hence, are more likely to draw a better firm and leave. In other words the expected value of a match may not be an increasing function of worker productivity. Nevertheless, since a firm selects its workers randomly it will be willing to fill its vacancy with a high productivity worker, since this is better than keeping the job vacant.

## 2.3 Steady State

Since firms choose workers randomly, we can express the inflow to and outflow from unemployment as in usual search models. In steady-state the inflow and outflow must balance

$$\delta(1 - u) = \lambda u \quad (9)$$

The mass  $G(p_w, p_{fm})$  is the share of the employed workers with a worker productivity less or equal to  $p_w$  working at a joint firm and match productivity less or equal to  $p_{fm}$ . The flow into  $G(p_w, p_{fm})$  must equal the outflow in steady-state. The outflow, on the l.h.s. below, consists of two terms, the exogenous destruction which happens at the rate  $\delta$  and the endogenous job quits. When considering outflow from  $G(p_w, p_{fm})$  in the form of quits, we - by definition - only consider workers with productivity  $p_w$  or less, who leaves a job with productivity equal or below  $p_{fm}$  and gets a job with productivity above  $p_{fm}$ . Since workers only change to more productive matches, inflow into  $G(p_w, p_{fm})$  only comes from unemployment, where the number of jobs sampled is  $n(p_w, p_{fm}^r)$ . The steady-state condition is given by

$$\begin{aligned} & \delta(1 - u) G(p_w, p_{fm}) + (1 - u) \lambda \int_{p_w}^{p_w} \int_{p_{fm}}^{p_{fm}} \left( \Gamma(\bar{p}_{fm})^{n(p'_w, p'_{fm})} - \Gamma(p_{fm})^{n(p'_w, p'_{fm})} \right) g(p'_w, p'_{fm}) dp'_{fm} dp'_w \\ = & u \lambda \int_{p_w}^{p_w} \left( \Gamma(p_{fm})^{n(p'_w, p_{fm}^r)} - \Gamma(p_{fm})^{n(p'_w, p_{fm}^r)} \right) h(p'_w) dp'_w \end{aligned} \quad (10)$$

Rearranging and using the equilibrium equation for unemployment gives us

$$\int_{p_w}^{p_w} \int_{p_{fm}}^{p_{fm}} \left[ \delta + \lambda \left( 1 - \Gamma(p_{fm})^{n(p'_w, p'_{fm})} \right) \right] g(p'_w, p'_{fm}) dp'_{fm} dp'_w = \delta \int_{p_w}^{p_w} \Gamma(p_{fm})^{n(p'_w, p_{fm}^r)} h(p'_w) dp'_w$$

Differentiating this with respect to  $p_w$  gives

$$\int_{p_{fm}}^{p_{fm}} \left[ \delta + \lambda \left( 1 - \Gamma(p_{fm})^{n(p_w, p'_{fm})} \right) \right] g(p_w, p'_{fm}) dp'_{fm} = \delta \Gamma(p_{fm})^{n(p_w, p_{fm}^r)} h(p_w) \quad (11)$$

Evaluating this expression in  $\bar{p}_{fm}$  obviously gives  $\int_{p_{fm}}^{\bar{p}_{fm}} g(p_w, p'_{fm}) dp'_{fm} = h(p_w)$ , and when combining this with equation (11), we obtain

$$\int_{p_{fm}}^{p_{fm}} \tilde{g}(p_w, p'_{fm}) dp'_{fm} = \frac{\delta}{\delta + \lambda} \Gamma(p_{fm})^{n(p_w, p_{fm}^r)} + \frac{\lambda}{\delta + \lambda} \int_{p_{fm}}^{p_{fm}} \Gamma(p_{fm})^{n(p_w, p'_{fm})} \tilde{g}(p_w, p'_{fm}) dp'_{fm} \quad (12)$$

where  $\int_{p_{fm}}^{p_{fm}} \tilde{g}(p_w, p'_{fm}) dp'_{fm} \equiv \int_{p_{fm}}^{p_{fm}} g(p_w, p'_{fm}) dp'_{fm} \left( \int_{p_{fm}}^{\bar{p}_{fm}} g(p_w, p'_{fm}) dp'_{fm} \right)^{-1}$  is the cumulative distribution function of firm productivities conditional on worker skill.

We want to examine whether the allocation of workers in the economy reflects positive sorting. While previous studies on assortative models have studied the sets of matches that are acceptable by both workers and firms, this approach is not useful with on-the-job search. Instead, we compare the worker distribution over different firms conditional on worker type similarly to Lentz (2008). For this purpose we use the following definition:



**Definition 1** Consider two workers  $A$  and  $B$ , where  $p_w^A > p_w^B$ . Assortative matching implies that  $G^B(p_{fm}) \equiv \int_{p_{fm}}^{p_{fm}} \tilde{g}(p_w^B, p'_{fm}) dp'_{fm} \geq \int_{p_{fm}}^{p_{fm}} \tilde{g}(p_w^A, p'_{fm}) dp'_{fm} \equiv G^A(p_{fm})$  for  $p_{fm} \in [p_{fm}; p_{fm}]$ .

In the present model set-up, it is not immediately clear on the grounds of equation (12) whether or not the model framework implies assortative matching. Before we more formally prove this, we can gain some intuition by assuming that the number of jobs sampled is independent of the current firm and match productivity, that is  $n(p_w, p_{fm}) = n(p_w)$ . With this assumption it is clear that we have

$$\int_{p_{fm}}^{p_{fm}} \tilde{g}(p_w, p_{fm} | n(p_w) = n(p_w, p_{fm})) dp'_{fm} = \frac{\delta \Gamma(p_{fm})^{n(p_w)}}{\delta + \lambda (1 - \Gamma(p_{fm})^{n(p_w)})} \quad (13)$$

which for the number of jobs sampled being constant across worker type, that is  $n(p_w) = 1$  gives us the usual distribution of realized matches (see e.g. Postel-Vinay and Robin (2002)). If equation (13) is differentiated with respect to  $p_w$ , we see that the r.h.s. becomes negative implying assortative matching. However, assuming that  $n(p_w, p_{fm}) = n(p_w)$  will overvalue the degree of assortative matching since it does not take into account that workers in better matches searches less.

A formal proposition for assortative matching is below. The proof uses a discretized version of equation (12) and is in Appendix A.<sup>5</sup>

**Proposition 2** When the production function  $f(p_w, p_{fm})$  admits supermodularity such that  $\alpha_1, (\alpha_2 + \alpha_3) > 0$ , and the workers are allowed to sample  $n = 0, 1, 2$  jobs the model features assortative matching.

**Proof.** See appendix A. ■

Furthermore, the steady-state equilibrium is a tuple  $\{p_{fm}^r, n(p_w, p_{fm}), n(p_w, p_{fm}^r), G(p_w, p_{fm}), u\}$  satisfying equations (4), (5), (6), (9) and (10), which leads us to the following proposition.

**Proposition 3** There exists a unique steady-state.

**Proof.** See appendix B. ■

---

<sup>5</sup>This proposition only encompass  $n = 0, 1, 2$  since allowing for higher  $n$  makes the math very cumbersome. By computer simulation it is fairly straight-forward to show that this property of assortative matching holds as we let the maximum number of jobs sampled increase far above 2. These programs are available from the authors upon request.

### 3 Econometric Methodology

#### 3.1 The Two-Way Fixed Effects Model

Our theoretical model implies a log-linear wage equation where the log of worker productivity and the log of firm productivity are additively separable. This property is very convenient, since it aligns perfectly with the leading empirical model for estimating the degree of assortative matching in the labor market developed by Abowd, Kramarz and Margolis (1999) (henceforth AKM). Before we exploit this direct link between the theoretical and empirical model, we will give a brief introduction to the AKM model which takes the following form

$$y_{it} = x_{it}\beta + \theta_i + \psi_{J(i,t)} + \varepsilon_{it} \quad i = 1, \dots, N; \quad t = 1, \dots, T_i \quad (14)$$

where  $y_{it}$  is the log of the hourly wage rate for individual  $i$  in period  $t$ ,  $x_{it}$  is a  $1 \times k$  vector of time-varying explanatory variables that may both relate to the individual and the firm,  $\beta$  is the parameter vector,  $\theta_i$  is the unobserved person effect,  $\psi_{J(i,t)}$  is the unobserved firm effect, and  $\varepsilon_{it}$  is the error term with  $E(\varepsilon_{it}|x_{it}, \theta_i, \psi_{J(i,t)}) = 0$ . The function  $J(i, t)$  associates an employer, indexed by  $J$ , with an individual  $i$  at time  $t$ .

Since most empirical applications relate to data with more individuals than firms ( $N > J$ ), we begin by making a within-individual transformation that sweeps away  $\theta_i$ . Expressing the model in matrix form, using  $\sim$  to denote within transformed variables and letting  $D$  be the matrix of firm dummies gives us the following model to estimate

$$\tilde{Y} = \tilde{X}\beta + \tilde{D}\Psi + \tilde{\varepsilon} \quad (15)$$

where  $\Psi$  is a vector of firm effects for every firm in the sample.<sup>6</sup> The parameter estimates can be found by solving

$$\begin{bmatrix} \hat{\beta} \\ \hat{\Psi} \end{bmatrix} = \begin{bmatrix} \tilde{X}'\tilde{X} & \tilde{X}'\tilde{D} \\ \tilde{D}'\tilde{X} & \tilde{D}'\tilde{D} \end{bmatrix}^{-1} \begin{bmatrix} \tilde{X}'\tilde{Y} \\ \tilde{D}'\tilde{Y} \end{bmatrix} \quad (16)$$

The problem of estimating the resulting model is that the cross-product matrix is potentially very high-dimensional due to  $\tilde{D}'\tilde{D}$  containing a dummy for each firm. However, with use of sparse matrix algebra we can estimate the  $\begin{bmatrix} \hat{\beta} \\ \hat{\Psi} \end{bmatrix}$  and afterwards recover  $\hat{\theta}$ .

One key aspect of this estimator worth noticing is that the firm coefficient is only identified by workers moving between firms in the sample period. Hence, looking only at a worker employed in the same firm in all years there is no way for the econometrician to disentangle

---

<sup>6</sup>Identification of firm effects is in principle only possible within a group, where a group is defined by the movement of workers between firms. For a thorough discussion see Abowd, Creedy and Kramarz (2002). For expositional simplicity we assume that we already have identified the groups, dropped one firm dummy for each group, and normalized the mean in each group to zero to allow for cross-group comparison. All while redefined  $\tilde{D}$  accordingly.

the person and firm fixed element of log wages.

As in all fixed effects models the variances of the fixed effects have a positive bias. Furthermore, due to the additive structure the covariance of the estimated worker and firm effects will be biased, since an over-estimate of the one fixed effect will lead to an under-estimate of the other. Andrews, Gill, Schank and Upward (2007) develop the formulae to correct for these biases. We use their method of correcting the estimates under the assumption that the explanatory variables are uncorrelated with the worker and firm effects.<sup>7</sup>

### 3.2 Woodcock's Hybrid Mixed Effects Estimation

Woodcock (2007) argues that the presence of a match effect will bias the correlation between worker and firm effects, but his agenda is broader than this, since omitted match effects will bias all estimates unless the match effect is completely orthogonal. Estimating an AKM model which also includes a match effect is impossible and, therefore, Woodcock suggest using the mixed effects model. Instead of estimating all the individual effects, Woodcock's estimation procedure implies estimating the variances of the worker, firm, match effects and error term and subsequently predicting all the individual effects. Woodcock needs to assume that the three random effects are uncorrelated with each other, when estimating the variances. However, there is no such restriction on the predicted individual effects. Woodcock's model is

$$y_{it} = x_{it}\beta + \theta_i + \psi_j + \phi_{ij} + \varepsilon_{it} \quad i = 1, \dots, N; \quad t = 1, \dots, T_i; \quad j = 1, \dots, J$$

where  $\phi_{ij}$  is the match effect. It is easy to estimate  $\beta$  even if the worker effect  $\theta_i$ , the firm effect  $\psi_j$ , and the match effect  $\phi_{ij}$  are fixed effects, since  $\beta$  is the within-match estimator. However, separately identifying the worker, firm, and match effects in a fixed effects context is impossible since we from, say,  $M$  matches cannot estimate  $M + N + J$  effects. However, if we are willing to assume that the worker, firm and match effects are orthogonal random effects, we can estimate the model. Obviously, the orthogonality assumption is a strong assumption - especially since we are mainly interested in the correlation between the worker and firm effects.

Woodcock suggests the following 3-step estimation procedure: First, estimate  $\hat{\beta}$  as the within-match estimator in the first stage and compute  $(y_{it} - x_{it}\hat{\beta})$ . In the second stage, the variance of the random effects  $(\sigma_\theta^2, \sigma_\psi^2, \sigma_\phi^2)$  and the error variance  $\sigma_\varepsilon^2$  are estimated by Restricted Maximum Likelihood (REML) on  $(y_{it} - x_{it}\hat{\beta})$ . These REML estimates are computed with the use of the average information algorithm of Gilmour, Thompson and Cullis (1995), which exploits the sparsity of the matrix design. In the third and final stage, Woodcock makes the

---

<sup>7</sup>This assumption is made since without it we need too invert a  $N \times N$  matrix to solve for the biases, and this is not feasible with our current computational power. Note also that unlike in the empirical estimation we have no explanatory variables when we simulate data from our theoretical model. Hence, in that case the assumption is met by definition.

Best Linear Unbiased Predictor (BLUP) of the random effects and estimate the correlations between the various terms.

## 4 Simulating of the Search Model

Since our theoretical model delivers a log-linear wage equation it seems as a natural starting point to solve and simulate data from the theoretical model and estimate the AKM model as well as Woodcock's mixed effect model on this simulated data.

To simulate our model we need a number of functional assumptions. In the following we assume that worker productivity  $p_w$ , firm productivity  $p_f$  and match productivity  $p_m$  all are log-normal distributed;  $p_w \sim LN(\mu_w, \sigma_w^2)$ ,  $p_f \sim LN(\mu_f, \sigma_f^2)$ ,  $p_m \sim LN(\mu_m, \sigma_m^2)$  and specify the search cost function as  $c(n) = c_1 n^{c_2}$ .

Before we can simulate data from our model, we need to approximate the function  $n(p_w, p_{fm})$ . To do this, we solve equations (5) and (6) for  $n$  using quadrature methods to approximate the integrals. The function  $n(p_w, p_{fm})$  is stepwise increasing in  $p_w$  and decreasing in  $p_{fm}$ , as illustrated in Figure 2, so we just need to know precisely in what values of  $(p_w, p_{fm})$  that  $n$  changes. We use an algorithm that determines the number of points where  $n$  changes in the  $(p_w, p_{fm})$  space with a precision such that the maximum deviation in  $p_{fm}$  and  $p_w$  from their true values is 0.01.<sup>8</sup> Next, we use cubic splines to approximate a curve for each change in  $n$  in the  $(p_w, p_{fm})$  space. These cubic splines are then use to draw  $n(p_w, p_{fm})$  in the actual simulation.

Notice that since the production function is given by  $f(p_w, p_{fm}) = p_w^{\alpha_1} p_f^{\alpha_2} p_m^{\alpha_3}$  our assumption of log-normality in all inputs implies that the joint firm and match productivity  $p_{fm} = p_f^{\frac{\alpha_2}{\alpha_2+\alpha_3}} p_m^{\frac{\alpha_3}{\alpha_2+\alpha_3}}$  is also log-normally distributed  $p_{fm} \sim LN(\mu_{fm}, \sigma_{fm}^2)$  with  $\mu_{fm} = \frac{\alpha_2}{\alpha_2+\alpha_3} \mu_f + \frac{\alpha_3}{\alpha_2+\alpha_3} \mu_m$  and  $\sigma_{fm} = \sqrt{(\frac{\alpha_2}{\alpha_2+\alpha_3} \sigma_f)^2 + (\frac{\alpha_3}{\alpha_2+\alpha_3} \sigma_m)^2}$ . This again implies that when we want to simulate from a model without a match effect, we can simply let  $\alpha_3 \equiv 0$  which implies that  $\mu_{fm} = \mu_f$  and  $\sigma_{fm} = \sigma_f$  such that  $p_{fm} = p_f$  and  $f(p_w, p_{fm}) = f(p_w, p_f)$ .

To facilitate comparison between simulations with and without match effect below in the simulations with match effect we always choose  $\mu_m$  and  $\sigma_m$  such that we have  $\mu_{fm} = \mu_w$  and  $\sigma_{fm} = \sigma_w$ , and in the simulations without the match effect we simply choose  $\mu_f = \mu_w$  and  $\sigma_f = \sigma_w$ .

We wish to simulate an economy inhabited with firms whose size is log-normal distributed. Given  $\mu_f$  and  $\sigma_f$  we define the minimum and maximum  $p_f$  as the values corresponding to the 0.05 percentile and the 99.5 percentile. In between the minimum and maximum values, we let each firm productivity be equally spaced, whereas each firm's share of the job offers is the log-normal density. Hence, the firm productivity is only approximately log-normal, but will

---

<sup>8</sup>First, we set  $p_{fm} = 0$  and determine for which values of  $p_w$   $n$  changes. Then for  $p_w$ , each of these points in  $p_w$ ,  $\bar{p}_w$ , and two additional values evenly distributed among each of these points we determine all values of  $p_{fm}$  where  $n$  changes.

as the number of firms increases, converge to the log-normal distribution. Given our initial guess of a correlation between worker and the joint firm and match effect, the model runs for 30 periods before the worker allocation is completely stable and, hence, we discard the first 29 simulated periods.

We also need to choose values for our parameters. The parameters describing flows in labor market are fixed at  $\lambda = 0.9$  and  $\delta = 0.1$ , which implies an equilibrium unemployment of 10 per cent. We have set the parameters of the log normal distributions such that  $\alpha_3 = 0.25$  implying that the match effect constitutes roughly 25 per cent of the explained variation in log wages. Obviously, the influence of the match effect that we find below will be smaller (larger) if the match effect constitutes a smaller (larger) share of the wage than the assumed 25 per cent. The rest of the parameters in the two simulations are given in Table 3.

| TABLE 1: PARAMETER VALUES  |            |            |                    |                          |         |            |         |            |         |       |       |      |
|----------------------------|------------|------------|--------------------|--------------------------|---------|------------|---------|------------|---------|-------|-------|------|
| Match Effect Included:     |            |            |                    |                          |         |            |         |            |         |       |       |      |
| $\alpha_1$                 | $\alpha_2$ | $\alpha_3$ | $\mu_w = \mu_{fm}$ | $\sigma_w = \sigma_{fm}$ | $\mu_f$ | $\sigma_f$ | $\mu_m$ | $\sigma_m$ | $\beta$ | $c_1$ | $c_2$ | $r$  |
| 0.40                       | 0.35       | 0.25       | 5.00               | 0.60                     | 5.00    | 0.84       | 5.00    | 0.84       | 0.50    | 5.50  | 1.20  | 0.05 |
| Match Effect Not Included: |            |            |                    |                          |         |            |         |            |         |       |       |      |
| $\alpha_1$                 | $\alpha_2$ | $\alpha_3$ | $\mu_w = \mu_{fm}$ | $\sigma_w = \sigma_{fm}$ | $\mu_f$ | $\sigma_f$ | $\mu_m$ | $\sigma_m$ | $\beta$ | $c_1$ | $c_2$ | $r$  |
| 0.40                       | 0.60       | 0.00       | 5.00               | 0.60                     | 5.00    | 0.60       | .       | .          | 0.50    | 5.50  | 1.20  | 0.05 |

To complete the link between the theoretical model and empirical model we add a normal distributed error term to the log linear wage equation. We set the variance of the error term, such that it contributes with 5-10 per cent of the total wage variation.

With the assumed parameter values, the maximum number of jobs that any worker samples is 3. In Figure 2 a surface plot of the  $n$ -function is shown. Unemployed workers with productivity above approximately 225, corresponding to 25 per cent of the workers, sample 3 jobs. Since almost no unemployed workers sample just one job, almost 75 per cent sample 2 jobs. The figure also shows that as workers climb the firm and match productivity ladder they reduce the number of jobs they sample and when they reach sufficiently far, they stop searching.

Since the workers in the economy without a match effect and in the economy with a match effect draw productivities from the same distribution the  $n$ -function in the two scenarios is identical.

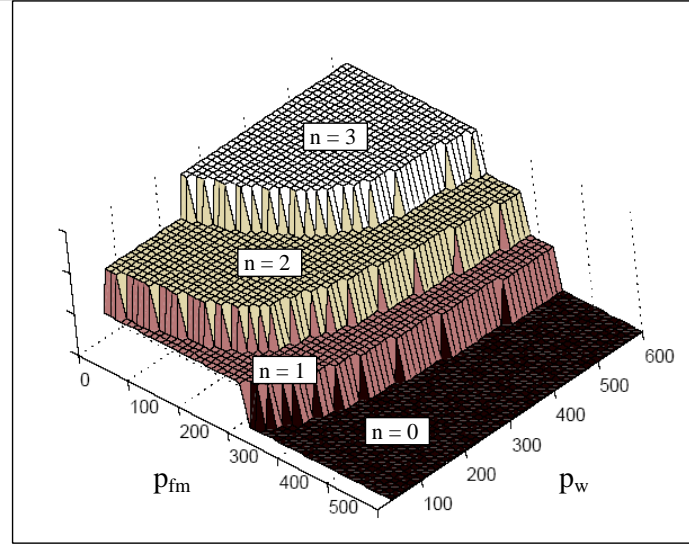
---



---

FIGURE 2: THE OPTIMAL JOB SAMPLE SIZE

---



In Table 2 we show the results from the AKM estimation on the simulated data. There are only small differences in the overall labor market between the two scenarios. The differences in the dispersion of wages arise, since whereas we assume a discrete distribution of firm productivities which is cut off, the match effect is allowed to be continuous. Therefore, the joint firm and match distribution will have a larger dispersion than the firm productivity in the case without match effect. Furthermore, in the economy with a match effect workers can get a better job within a firm by drawing an offer from the exact same firm, but with a higher match effect. This might have a small positive effect on both the mean wage and the dispersion of wages.

TABLE 2: MONTE-CARLO ESTIMATIONS

|  | Match effect included |        |        | Match effect not included |       |       |
|--|-----------------------|--------|--------|---------------------------|-------|-------|
| No. of replications  | 100                   |        |        | 100                       |       |       |
| No. time periods   | 6                     |        |        | 6                         |       |       |
| No. of observations  | 66,760                |        |        | 66,760                    |       |       |
| No. of persons   | 12,500                |        |        | 12,500                    |       |       |
| No. of firms   | 495                   |        |        | 473                       |       |       |
| Average of wages   | 124.7                 |        |        | 124.4                     |       |       |
| Variance of wages  | 47.1                  |        |        | 41.2                      |       |       |
| Ave. no. of obs per firm   | 135                   |        |        | 141                       |       |       |
|  | Min                   | Max    | Mean   | Min                       | Max   | Mean  |
| AKM, Estimated $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$            | -0.086                | -0.035 | -0.064 | 0.107                     | 0.140 | 0.125 |
| AKM, Corrected $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$            | -0.076                | -0.023 | -0.052 | 0.112                     | 0.146 | 0.131 |
| MIXED, Estimated $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$          | 0.014                 | 0.042  | 0.029  | .                         | .     | .     |
| True $cor(\alpha_1 * \ln(p_w), \alpha_2 * \ln(p_f))$                 | 0.079                 | 0.115  | 0.095  | 0.112                     | 0.147 | 0.131 |
| True $cor(\alpha_1 * \ln(p_w), (\alpha_2 + \alpha_3) * \ln(p_{fm}))$ | 0.093                 | 0.135  | 0.112  | 0.112                     | 0.147 | 0.131 |
| Mean influence on $var(Y)$ :   |                       |        |        |                           |       |       |
|  | True                  | AKM    | Mixed  | True                      | AKM   |       |
| <i>Firm effect</i>   | 0.208                 | 0.194  | 0.193  | 0.392                     | 0.392 |       |
| <i>Person effect</i>   | 0.442                 | 0.678  | 0.444  | 0.543                     | 0.555 |       |
| <i>Match effect</i>  | 0.272                 | .      | 0.285  | 0.000                     | .     |       |
| <i>Error term</i>  | 0.077                 | 0.128  | 0.078  | 0.065                     | 0.052 |       |

In the right panel of the table we show the results for the case without a match effect. The estimated correlation is very close to the true correlation. With the bias correction we obtain the true correlation.

In the left panel of the table we include the match effect. Here, workers change jobs on the grounds of the composite firm and match productivity rather than just the firm productivity. This implies that the true correlation between the worker and firm productivities, on average, is 0.095. However, with the presence of the match effect both the estimated and corrected correlations from the fixed effects estimation are severely biased and even negative with mean values of  $-0.064$  and  $-0.052$  respectively. Therefore, existing studies finding a negative correlation

between worker and firm effects may actually reflect a labor market with positive assortative matching. Moreover, the bias from the match effect seems to be more important than the statistical bias. Woodcock’s mixed effects model does considerably better with a positive correlation of 0.029 although it is also biased downwards.

The assumed wage setting in our theoretical model is the piece-rate contract. Cahuc, Postel-Vinay and Robin (2006) and Lentz (2008) use an alternative bargaining mechanism, in which employers are allowed to respond to an outside bid for its workers. Besides the worker’s own productivity and her current firm’s productivity, the worker’s current wage also depends on the productivity of the previous firm. Thereby, this wage-setting mechanism would compared to the piece-rate contract *ceteris paribus* imply a lower correlation between the worker and firm productivities. To some extent the match effect plays a similar role here, and it is also apparent that the correlation between the worker productivity and the firm productivity is lower when there is a match component in the wages.

Woodcock (2007) argues that a match effect, which is positively correlated with the worker effect and negatively correlated with the firm effect, will imply that the AKM model overestimates the proportion of variation attributable to the worker effect and underestimates the proportion attributable to the firm effect. Our simulation results show that this is certainly true; while the true worker effect amounts 44 per cent of the variation, the estimated is 68 per cent. In this perspective Woodcock’s model performs much better since it attributes exactly 44 per cent of variation to the worker effect.

Andrews, Gill, Schank and Upward (2007) argue that the negative correlation between worker and firm effects to a large extent is due to limited mobility bias. Perhaps, limited mobility bias and the bias due to match effects are the same. In other words, will the match effect bias disappear if we consider firms with more worker mobility? Due to the lognormal firm size distribution firms with the highest firm productivity advertise the fewest jobs. Thus, if we only estimate the AKM model using a 6 period sample of firms with more than 100 workers, we are essentially restricting the range of firm productivities and the estimated correlation will be biased due to the selection on an endogenous variable. Hence, for the simulated data the sample selection bias makes such exercise useless.

Instead of estimating on a sample of large firms, as we will do for the empirical estimation in the next section, we extend the sample length. Table 3 shows that more estimation periods imply that the gap between the true and the corrected estimate narrows since as the number of observations per firm increases, the firm effects become more precisely estimated. With 20 periods the estimated correlation from the AKM estimation turns positive, but even with 50 periods the bias still amounts to approximately 20 per cent. Nevertheless, we can conclude that the match effect bias is a cause of the limited mobility bias. Furthermore, Table 3 reveals that the correlation from the mixed effects estimation in all simulations lies in between the true



correlation and the correlation from the AKM estimation.

TABLE 3: LIMITED MOBILITY BIAS

| No.of timeperiods | No. of obs. | Ave. obs. per firm | True correlation | AKM corrected | MIXED |
|-------------------|-------------|--------------------|------------------|---------------|-------|
| 6                 | 66,760      | 135                | 0.095            | −0.052        | 0.029 |
| 10                | 111,281     | 224                | 0.096            | −0.013        | 0.033 |
| 20                | 222,523     | 447                | 0.095            | 0.026         | 0.050 |
| 30                | 333,746     | 670                | 0.095            | 0.045         | 0.063 |
| 50                | 555,296     | 1115               | 0.096            | 0.062         | 0.075 |

Note: The complete set of results for the simulations can be found in Table 2 and Tables 8-11 in Appendix C.

## 5 Empirical Results

We have access to a population register data set from Statistics Denmark and we restrict attention to all workers aged 25-59 years and employed in the private sector. The data set is an unbalanced panel data set for 1999-2004 and the variables originate from three databases and include detailed information on a wide range of variables. Due to the nature of a fixed effect estimator, which precludes the use of time-invariant explanatory variables, we only include a small number of explanatory variables. The dependent variable is the log of hourly wages taken from the IDA database. We use two groups of explanatory variables. Firstly, we include a second order polynomial in the actual labor market experience and dummies for whether the individual lives in a rural area or in a large city. These variables are also drawn from the IDA database. Secondly, firm variables including value added per employee, capital stock per employee, the ratio of males in the firm’s workforce and log of number of employees drawn from the IDA and FIDA databases. Furthermore, we include time dummies in the regression. All nominal variables are deflated with the GDP deflator.

Since firm effects are only identified by movers we have chosen to restrict our estimation to firms with more than 50 worker observations in the 6-year sample window. The resulting data set has 4 million observations on 925,000 persons employed in approximately 15,000 firms.

| TABLE 4: AKM PARAMETER ESTIMATES           |                      |                      |
|--|----------------------|----------------------|
|  | AKM Estimator        | MIXED Estimator      |
| Experience                                 | 0.0187<br>(80.20)    | 0.0200<br>(237.22)   |
| (Experience) <sup>2</sup>                  | -0.0062<br>-(233.40) | -0.0041<br>-(190.91) |
| Large cities <sup>(*)</sup>                | -0.0022<br>-(3.66)   | -0.0273<br>-(52.22)  |
| Rural area <sup>(*)</sup>                  | 0.0027<br>(7.65)     | -0.0269<br>-(83.70)  |
| Value added per employee (mill. DKK)       | 0.0085<br>(33.55)    | 0.0189<br>(85.74)    |
| Capital stock per employee (thousands DKK) | 0.0049<br>(1.89)     | 0.0000<br>(6.42)     |
| Male ratio                                 | -0.0175<br>-(7.74)   | 0.1379<br>(116.44)   |
| ln(employees)                              | 0.0194<br>(54.02)    | 0.0127<br>(90.53)    |
| $R^2$                                      | 0.8939               | 0.8874               |
| No. of observations                        |                      | 4,003,929            |
| No. of persons                             |                      | 925,011              |
| No. of firms                               |                      | 15,455               |
| No. of worker-firm spells                  |                      | 1,350,944            |
| No. of groups                              |                      | 95                   |

Note: <sup>(\*)</sup> The omitted category is the greater Copenhagen area. t-values are in parenthesis.

Table 4 presents the parameter estimates. All coefficients are significant besides the coefficient for the capital stock per employee <sup>9</sup>, and all have the expected signs. As our main focus is assortative matching we proceed to look at the estimated correlation between worker and firm fixed effects.

<sup>9</sup>In Appendix D it is shown that the coefficient to capital stock per employee is significantly positive when restricting the sample to firms with more than 300 observations, where the firm effect is better identified.

TABLE 5: AKM ESTIMATOR, STANDARD DEVIATIONS AND CORRELATION MATRIX (OBS PER FIRM &gt;50)

|  | Standard<br>deviation | Correlations |                    |                    |                 |                       |                  |  |                                     |                    |
|--|-----------------------|--------------|--------------------|--------------------|-----------------|-----------------------|------------------|--|-------------------------------------|--------------------|
|  |                       | $Y$          | $X_w\hat{\beta}_w$ | $X_f\hat{\beta}_f$ | $\hat{T}_{dum}$ | $\hat{\psi}_{J(i,t)}$ | $\hat{\theta}_i$ | $X_f\hat{\beta}_f + \hat{\psi}_{J(i,t)}$ | $X_w\hat{\beta}_w + \hat{\theta}_i$ | $\varepsilon_{it}$ |
| $Y$                                      | 0.351                 | 1.000        | -0.049             | 0.044              | 0.010           | 0.281                 | 0.886            | 0.294                                    | 0.905                               | 0.326              |
| $X_w\hat{\beta}_w$                       | 0.068                 | -0.049       | 1.000              | -0.018             | -0.042          | 0.003                 | -0.256           | -0.004                                   | -0.051                              | 0.000              |
| $X_f\hat{\beta}_f$                       | 0.037                 | 0.044        | -0.018             | 1.000              | 0.009           | -0.165                | -0.018           | 0.235                                    | -0.022                              | 0.000              |
| $\hat{T}_{dum}$                          | 0.017                 | 0.010        | -0.042             | 0.009              | 1.000           | -0.001                | -0.032           | 0.003                                    | -0.042                              | 0.000              |
| $\hat{\psi}_{J(i,t)}$                    | 0.009<br>(0.008)      | 0.281        | 0.003              | -0.165             | -0.001          | 1.000                 | 0.036<br>(0.064) | 0.920                                    | 0.037                               | 0.000              |
| $\hat{\theta}_i$                         | 0.107<br>(0.102)      | 0.886        | -0.256             | -0.018             | -0.032          | 0.036<br>(0.064)      | 1.000            | 0.028                                    | 0.978                               | 0.000              |
| $X_f\hat{\beta}_f + \hat{\psi}_{J(i,t)}$ | 0.094                 | 0.294        | -0.004             | 0.235              | 0.003           | 0.920                 | 0.028            | 1.000                                    | 0.028<br>(0.056)                    | 0.000              |
| $X_w\hat{\beta}_w + \hat{\theta}_i$      | 0.316                 | 0.905        | -0.051             | -0.022             | -0.042          | 0.037                 | 0.978            | 0.028<br>(0.056)                         | 1.000                               | 0.000              |
| $\varepsilon_{it}$                       | 0.114                 | 0.326        | 0.000              | 0.000              | 0.000           | 0.000                 | 0.000            | 0.000                                    | 0.000                               | 1.000              |

Note: Lower case parenthesis denotes the correlation corrected for statistical bias.  $X_w$  includes experience, (experience)<sup>2</sup>, large cities and rural areas.  $X_f$  includes value added per employee, capital stock per employee, male ratio and ln(employees).

The resulting correlation matrix from the AKM model is shown in the Table 5. The estimated correlation between the unobserved worker and firm effects is 0.036, while the bias corrected correlation, shown in parenthesis, is 0.064. Taking account of both observed and unobserved effects, we estimate the correlation between the overall worker effect and the overall firm effect to be 0.028, while the corrected is 0.056.<sup>10</sup> With the two-way fixed effects model we explain 89 per cent of the variation of the log wages, and approximately 3/4 of this variation is due to observed and unobserved worker characteristics.

The positive correlation is in contrast to existing international studies which have almost all found negative correlations. Hence, the evidence from the AKM estimation implies that there is positive assortative matching in the Danish labor market. It turns out that the positive correlation is not robust to inclusion of persons aged 18-24 years. In this case the estimated correlation is -0.0047 while the corrected correlation is 0.0155. This result suggests that the process of sorting takes time.

In addition to the statistical bias, both Abowd, Kramarz, Lengermann and Perez-Duarte (2004) and Andrews, Gill, Schank and Upward (2007) argue that there might also exist a

<sup>10</sup>To compute the corrected correlation we simply subtract the bias in the  $cov(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$  from  $cov(X_w\hat{\beta}_w + \hat{\theta}_i, X_f\hat{\beta}_f + \hat{\psi}_{J(i,t)})$ , and subtract the biases in  $var(\hat{\theta}_i)$  and  $var(\hat{\psi}_{J(i,t)})$  from respectively  $var(X_w\hat{\beta}_w + \hat{\theta}_i)$  and  $var(X_f\hat{\beta}_f + \hat{\psi}_{J(i,t)})$ .

negative bias due to poorly identified firm effects, when there is limited mobility. We can quantify this bias by only estimating the AKM model on larger firms.<sup>11</sup> As Andrews, Gill, Schank and Upward we also find that this bias is more important than the statistical bias, and as shown in Appendix D the corrected correlation between the unobserved effects becomes 0.092 and 0.111 when we estimate on samples, where the minimum number of observations per firm are respectively 100 and 300. The correlation between the overall worker and firm effects are respectively 0.085 and 0.113.

TABLE 6: MIXED ESTIMATOR, STANDARD DEVIATIONS AND CORRELATION MATRIX (OBS PER FIRM >50)

|  | Standard<br>deviation | Y     | Correlations       |                    |                 |                       |                  |                   |  |                                     |                    |
|--|-----------------------|-------|--------------------|--------------------|-----------------|-----------------------|------------------|-------------------|--|-------------------------------------|--------------------|
|  |                       |       | $X_w\hat{\beta}_w$ | $X_f\hat{\beta}_f$ | $\hat{T}_{dum}$ | $\hat{\psi}_{J(i,t)}$ | $\hat{\theta}_i$ | $\hat{\phi}_{ij}$ | $X_f\hat{\beta}_f + \hat{\psi}_{J(i,t)}$ | $X_w\hat{\beta}_w + \hat{\theta}_i$ | $\varepsilon_{it}$ |
| Y  | 0.351                 | 1.000 | 0.145              | 0.155              | 0.027           | 0.477                 | 0.837            | 0.706             | 0.492                                    | 0.851                               | 0.398              |
| $X_w\hat{\beta}_w$                       | 0.055                 | 0.145 | 1.000              | 0.066              | -0.039          | -0.009                | -0.019           | -0.011            | 0.008                                    | 0.228                               | 0.001              |
| $X_f\hat{\beta}_f$                       | 0.037                 | 0.155 | 0.066              | 1.000              | -0.011          | 0.069                 | 0.025            | 0.001             | 0.320                                    | 0.041                               | -0.007             |
| $\hat{T}_{dum}$                          | 0.012                 | 0.027 | -0.039             | -0.011             | 1.000           | 0.003                 | -0.002           | 0.001             | 0.000                                    | -0.012                              | 0.000              |
| $\hat{\psi}_{J(i,t)}$                    | 0.137                 | 0.477 | -0.009             | 0.069              | 0.003           | 1.000                 | 0.119            | 0.038             | 0.967                                    | 0.114                               | 0.004              |
| $\hat{\theta}_i$                         | 0.217                 | 0.837 | -0.019             | 0.025              | -0.002          | 0.119                 | 1.000            | 0.690             | 0.119                                    | 0.969                               | 0.114              |
| $\hat{\phi}_{ij}$                        | 0.072                 | 0.706 | -0.011             | 0.001              | 0.001           | 0.038                 | 0.690            | 1.000             | 0.036                                    | 0.670                               | 0.216              |
| $X_f\hat{\beta}_f + \hat{\psi}_{J(i,t)}$ | 0.144                 | 0.492 | 0.008              | 0.320              | 0.000           | 0.967                 | 0.119            | 0.036             | 1.000                                    | 0.118                               | 0.002              |
| $X_w\hat{\beta}_w + \hat{\theta}_i$      | 0.223                 | 0.851 | 0.228              | 0.041              | -0.012          | 0.114                 | 0.969            | 0.670             | 0.118                                    | 1.000                               | 0.111              |
| $\varepsilon_{it}$                       | 0.099                 | 0.398 | 0.001              | -0.007             | 0.000           | 0.004                 | 0.114            | 0.216             | 0.002                                    | 0.111                               | 1.000              |

Note: Lower case parenthesis denotes the correlation corrected for statistical bias.  $X_w$  includes experience, (experience)<sup>2</sup>, large cities and rural areas.  $X_f$  includes value added per employee, capital stock per employee, male ratio and ln(employees).

Table 6 presents the correlation matrix when estimating using Woodcock's hybrid mixed effects model. We obtain a correlation of 0.119 on the sample where the minimum number of observations per firm is 50. In Table 7 we compute the mean influence of each term on the variance of the log of the wage rate. While the AKM estimation suggests that roughly 80 per cent of the variance in the wages can be attributed to the individual heterogeneity, the mixed effects estimation only suggests about 50 per cent are due to worker heterogeneity. This repeats the finding from the simulated data and is due to the high positive correlation of 0.69 between the match effect and the worker effect. From the mixed effects estimation we find that the match effect explains 14.5 per cent of the variation in the log wages, which is of the same magnitude as Woodcock finds using US data.

<sup>11</sup> Andrews, Gill, Schank and Upward examine this by estimating on a sample of plants with 30 or more workers moving during the sample period.

| TABLE 7: MEAN INFLUENCE ON $var(Y)$ |               |                 |
|-------------------------------------|---------------|-----------------|
|                                     | AKM Estimator | MIXED Estimator |
| $X_w \hat{\beta}_w$                 | (0.0097)      | 0.0226          |
| $X_f \hat{\beta}_f$                 | 0.0049        | 0.0161          |
| $\hat{T}_{dum}$                     | 0.0008        | 0.0009          |
| $\hat{\psi}_{J(i,t)}$               | 0.0745        | 0.1854          |
| $\hat{\theta}_i$                    | 0.8235        | 0.5173          |
| $\hat{\phi}_{ij}$                   | .             | 0.1450          |
| $\hat{\varepsilon}_{it}$            | 0.1061        | 0.1126          |

The correlation from Woodcock’s mixed effects estimation is higher than the estimated correlation from the AKM model. Still our simulation results from section 4 combined with the sizeable match effect found using the Woodcock estimator show that the true correlation in the Danish labor market will be above the estimated 11.9 per cent.

## 6 Conclusion

In this paper we argue that the presence of a match effect in the wages will imply that the estimated correlation in an AKM estimation will be negatively biased. In order to analyze this we develop a theoretical search model with continuous heterogeneity on both worker and firm sides. Like the empirical model, the theoretical model implies a log-linear wage equation which is additively separable in the worker effects and the firm effects. Besides this, the theoretical model also provides the opportunity of having an additively separable match effect. Importantly for our agenda, the model implies assortative matching even though we only use a strictly supermodular production function. We achieve this by letting the workers choose how many jobs they want to sample. Compared to Shimer and Smith (2000) we can as Lentz (2008) relax the assumption of log supermodularity and re-instate Becker’s frictionless result.

Our model shares similarities with Lentz (2008), but has the desirable feature that more productive workers, on average, leave unemployment or any given employment level to find better matches than their less productive colleagues. However, compared to Lentz’ model this is at the expense of no differences in unemployment durations. A model that could combine the differences in expected unemployment duration and that more productive workers leave unemployment to find more productive matches than less productive workers would be most appealing. It seems to be the case that such a model can be achieved by allowing not only workers to choose the sample, but also firms to choose the optimal sample of job candidates.

Thus, for future research on assortative matching the discrete time sampling approach seems to be more relevant than its continuous approximation.

In the case of Denmark the correlation between the worker and firm effects is estimated to be 0.12. We argue that it is most likely still a downward biased estimate, since from simulations of the search model we show that we can obtain the standard negative correlation estimate from an economy where there is indeed positive assortative matching.

In conclusion, although researches have found negative correlations from estimating the AKM model for a series of countries, labor markets might after all be characterized by positive assortative matching.

## References

- [1] Abowd, J. M., Creedy, R. & Kramarz, F. (2002), Computing person and firm effects using linked longitudinal employer-employee data, Technical Paper 2002-06, U.S. Census Bureau.
- [2] Abowd, J. M., F. Kramarz and D.N. Margolis (1999): High Wage Workers and High Wage Firms, *Econometrica* **67-2**, pp. 251-333. Abowd, J. M., F. Kramarz and D.N. Margolis (1999): High Wage Workers and High Wage Firms, *Econometrica* **67-2**, pp. 251-333.
- [3] Abowd, J. M., F. Kramarz, P. Lenger mann and S. Perez-Duarte (2004): Are Good Workers Employed by Good Firms? A Test of a Simple Assortative Matching Model for France and the United States, Mimeo, Cornell University.
- [4] Acemoglu, D. and R. Shimer (2000): Wage and Technology Dispersion, *Review of Economic Studies* **67**, pp. 585-607.
- [5] Andrews, M., L. Gill, T. Schank and R. Upward (2007): High Wage Workers and Low Wage Firms: Negative Assortative Matching or Limited Mobility Bias?, *Journal of the Royal Statistical Society (forthcoming)*.
- [6] Atakan, A.E. (2006): Assortative Matching with Explicit Search Costs, *Econometrica* **74-3**, pp. 667-680.
- [7] Bagger J., F. Fontaine, F. Postel-Vinay and J.-M. Robin (2007): A Tractable Equilibrium Search Model of Individual Wage Dynamics with Experience Accumulation, working paper.
- [8] Barth, E. and H. Dale-Olsen (2003): Assortative Matching in the Labour Market? Stylised facts about workers and plants, working paper.
- [9] Becker, G.S. (1973): A Theory of Marriage: Part I, *Journal of Political Economy* **81**, pp. 813-846.

- [10] Burdett, K. and M.G. Coles (1999): Long Term Partnership Formation: Marriage and Employment, *Economic Journal* **109**, pp. F307-F334.
- [11] Cahuc, P. F. Postel-Vinay and J.-M. Robin (2006): Wage Bargaining with On-the-Job Search: Theory and Evidence, *Econometrica* **74-2**, pp. 323-364.
- [12] Chade, H. (2001): Two-Sided Search and Perfect Segregation with Fixed Search Costs, *Mathematical Social Sciences* **42**, pp. 31-51.
- [13] Gilmour, A. R., R. Thompson, and B. R. Cullis (1995): Average information REML: An Efficient Algorithm for Variance Parameter Estimation in Linear Mixed Models, *Biometrics* **51**, pp. 1440-1450.
- [14] Gruetter, M. and R. Lalive (2004): The Importance of Firms in Wage Determination, IZA Discussion Paper No. 1367.
- [15] Jovanovic, B (1979): Job Matching and the Theory of Turnover, *Journal of Political Economy* **87-5**, pp. 972-990.
- [16] Lentz, R. (2008): An Equilibrium Model of Wage Dispersion with Sorting, working paper, University of Wisconsin-Madison.
- [17] Mortensen, D.T. (2003): *Wage Dispersion: Why are Similar Workers Paid Differently?*, Zeuthen Lectures Bookseries, MIT Press.
- [18] Piekola, H. (2005): Knowledge Capital as the Source of Growth, working paper.
- [19] Postel-Vinay, F. and J.-M. Robin (2002): Equilibrium Wage Dispersion with Worker and Employer Heterogeneity, *Econometrica* **70-6**, pp. 2295-2350.
- [20] Sattinger, M. (1975): Comparative Advantages and the Distribution of Earnings and Abilities, *Econometrica* **43-3**, pp. 455-468.
- [21] Shimer, R. (2005): The Assignment of Workers to Jobs in an Economy with Coordination Frictions, *Journal of Political Economy* **113-5**, pp. 996-1025.
- [22] Shimer, R. and L. Smith (2000): Assortative Matching and Search, *Econometrica* **68-2**, pp. 343-369.
- [23] Smith, L. (2006): The Marriage Model with Search Frictions, *Journal of Political Economy* **114-6**, pp. 1124-1144.
- [24] Stigler, G.J. (1961): The Economics of Information, *Journal of Political Economy* **69-3**, pp. 213-225.

[25] Woodcock, S.D. (2007): Match Effects, working paper, Simon Fraser University.

## Appendix

### Appendix A: Proof of Proposition 2

**Proof.** The number of jobs sampled is necessarily discrete and recognizing this, it is useful for us to work with segments of  $p_{fm}$  for which a given worker with productivity  $p_w$  does not change her number of jobs sampled  $n(p_w, p_{fm})$ . Defining  $\hat{g}(p_w, p_{fm}^j) \equiv \int_{p_{fm}^{j-1}}^{p_{fm}^j} \tilde{g}(p_w, p'_{fm}) dp'_{fm}$  and  $p_{fm}^0 \equiv p_{fm}^r$  we can express equation (12) evaluated in  $p_{fm}^i$  as

$$\sum_{j=1}^i \hat{g}(p_w, p_{fm}^j) = \frac{\delta}{\delta + \lambda} \Gamma(p_{fm}^i)^{n(p_w, p_{fm}^0)} + \frac{\lambda}{\delta + \lambda} \sum_{j=1}^i \Gamma(p_{fm}^i)^{n(p_w, p_{fm}^{j-1})} \hat{g}(p_w, p_{fm}^j) \quad (17)$$

Rearranging to solve for  $\hat{g}(p_w, p_{fm}^i)$  we get

$$\hat{g}(p_w, p_{fm}^i) = \frac{\frac{\delta}{\delta + \lambda} \Gamma(p_{fm}^i)^{n(p_w, p_{fm}^0)}}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^i)^{n(p_w, p_{fm}^{i-1})}} - \{i > 1\} \sum_{j=1}^{i-1} \frac{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^i)^{n(p_w, p_{fm}^{j-1})}}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^i)^{n(p_w, p_{fm}^{i-1})}} \hat{g}(p_w, p_{fm}^j) \quad (18)$$

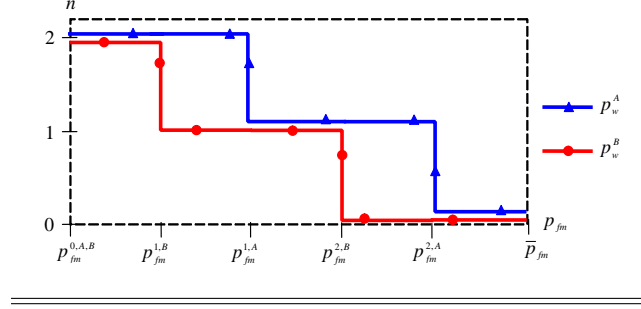
Next, for some workers of productivity  $p_w^X$  we have that

$$\hat{G}^X(p_{fm}^I) = \sum_{i=1}^I \frac{\frac{\delta}{\delta + \lambda} \Gamma(p_{fm}^I)^{n(p_w^X, p_{fm}^{0,X})}}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^I)^{n(p_w^X, p_{fm}^{I-1,X})}} - \{I > 1\} \sum_{i=2}^I \sum_{j=1}^{i-1} \left( \frac{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^I)^{n(p_w^X, p_{fm}^{j-1,X})}}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^I)^{n(p_w^X, p_{fm}^{i-1,X})}} \cdot \hat{g}(p_w^X, p_{fm}^j) \right) \quad (19)$$

Consider two workers  $A$  and  $B$ , where  $p_w^A > p_w^B$ , so that we by proposition 1 have that  $n(p_w^A, p_{fm}) \geq n(p_w^B, p_{fm})$ . Furthermore, assume that  $n = 0, 1, 2$ . Using Definition 1, we wish to compare the allocation of the two worker types to show that  $G^B(p_{fm}^I) \geq G^A(p_{fm}^I)$ . The proof is in two parts. In part A we show that for the particular example depicted in Figure 3  $G^B(p_{fm}^I) \geq G^A(p_{fm}^I)$  for any  $p_{fm}^I \in [0, 1]$ . In part B of the proof, we show that all other possible scenarios are special cases of the example in part A.



FIGURE 3



Part A: The discreteness of the number of jobs sampled implies that  $n$  in the interval  $[0, 2]$  is a decreasing step-wise function of  $p_{fm}$  with five segments. As illustrated in Figure 3, the considered example implies that  $p_w^A$  and  $p_w^B$  are sufficiently close so that workers  $A$  and  $B$  are sampling the same number of jobs for some ranges of  $p_{fm}$ . Next, we will use that if  $n(p_w^A, p_{fm}) = n(p_w^B, p_{fm})$  it must be the case that person  $B$  will decrease her  $n$  at some firm productivity  $p_{fm}$  lower than the firm productivity where  $A$  will decrease her  $n$ .

By the use of equation (18) and (19) we have that  $\hat{G}^B(p_{fm}^I) - \hat{G}^A(p_{fm}^I) \geq 0$  no matter which segment  $p_{fm}^I$  is situated on in Figure 3. The solutions for each segment are:

$$\left( \hat{G}^B(p_{fm}^I) - \hat{G}^A(p_{fm}^I) \right) |_{0 \leq p_{fm}^I < p_{fm}^{1,B}} = 0 \quad (20)$$

$$\begin{aligned} & \left( \hat{G}^B(p_{fm}^I) - \hat{G}^A(p_{fm}^I) \right) |_{p_{fm}^{1,B} \leq p_{fm}^I < p_{fm}^{1,A}} = \\ & \frac{\lambda \delta}{(\delta + \lambda)^2} \Gamma(p_{fm}^I) \left( \frac{\Gamma(p_{fm}^I)^2}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^I)^2} - \frac{\Gamma(p_{fm}^{1,B})^2}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^{1,B})^2} \right) \frac{1 - \Gamma(p_{fm}^I)}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^I)} > 0 \end{aligned} \quad (21)$$

$$\begin{aligned} & \left( \hat{G}^B(p_{fm}^I) - \hat{G}^A(p_{fm}^I) \right) |_{p_{fm}^{1,A} \leq p_{fm}^I < p_{fm}^{2,B}} = \\ & \frac{\lambda \delta}{(\delta + \lambda)^2} \Gamma(p_{fm}^I) \left( \frac{\Gamma(p_{fm}^{1,A})^2}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^{1,A})^2} - \frac{\Gamma(p_{fm}^{1,B})^2}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^{1,B})^2} \right) \frac{1 - \Gamma(p_{fm}^I)}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm}^I)} > 0 \end{aligned} \quad (22)$$

$$\begin{aligned}
& \left( \hat{G}^B(p_{fm}^I) - \hat{G}^A(p_{fm}^I) \right) \Big|_{p_{fm}^{2,B} \leq p_{fm}^I < p_{fm}^{2,A}} = \\
& \frac{\delta\lambda}{(\delta+\lambda)^2} \frac{1 - \Gamma(p_{fm}^I)}{1 - \frac{\lambda}{\delta+\lambda}} \frac{1}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{1,A})^2} \left( \frac{\Gamma(p_{fm}^I)^2 - \Gamma(p_{fm}^{1,A})^2}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^I)} - \frac{\Gamma(p_{fm}^{2,B})^2 - \Gamma(p_{fm}^{1,A})^2}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{2,B})} \right) \\
& + \frac{\delta\lambda}{(\delta+\lambda)^2} \frac{1 - \Gamma(p_{fm}^I)}{1 - \frac{\lambda}{\delta+\lambda}} \left( \frac{\Gamma(p_{fm}^{1,A})^2}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{1,A})^2} - \frac{\Gamma(p_{fm}^{1,B})^2}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{1,B})^2} \right) \left( \frac{1 - \Gamma(p_{fm}^I)^2}{1 - \Gamma(p_{fm}^I)} - \frac{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{2,B})^2}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{2,B})} \right) \\
& > 0
\end{aligned} \tag{23}$$

$$\begin{aligned}
& \left( \hat{G}^B(p_{fm}^I) - \hat{G}^A(p_{fm}^I) \right) \Big|_{p_{fm}^{2,A} \leq p_{fm}^I < 1} = \\
& \frac{\delta\lambda}{(\delta+\lambda)^2} \frac{1 - \Gamma(p_{fm}^I)}{1 - \frac{\lambda}{\delta+\lambda}} \frac{1}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{1,A})^2} \left( \frac{\Gamma(p_{fm}^{2,A})^2 - \Gamma(p_{fm}^{1,A})^2}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{2,A})} - \frac{\Gamma(p_{fm}^{2,B})^2 - \Gamma(p_{fm}^{1,A})^2}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{2,B})} \right) \\
& + \frac{\delta\lambda}{(\delta+\lambda)^2} \frac{1 - \Gamma(p_{fm}^I)}{1 - \frac{\lambda}{\delta+\lambda}} \left( \frac{\Gamma(p_{fm}^{2,A})^2}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{2,A})^2} - \frac{\Gamma(p_{fm}^{1,B})^2}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{1,B})^2} \right) \left( \frac{1 - \Gamma(p_{fm}^I)^2}{1 - \Gamma(p_{fm}^I)} - \frac{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{2,B})^2}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{2,B})} \right) \\
& > 0
\end{aligned} \tag{24}$$

where the only term not immediately seen to be positive is

$$\left( \frac{1 - \Gamma(p_{fm}^I)^2}{1 - \Gamma(p_{fm}^I)} - \frac{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{2,B})^2}{1 - \frac{\lambda}{\delta+\lambda} \Gamma(p_{fm}^{2,B})} \right)$$

But since  $\frac{\partial \frac{1-x^2}{1-x}}{\partial x} = 1 > 0$  this term as well is clearly positive. Hence, we conclude that

$$\hat{G}^B(p_{fm}^I) \geq \hat{G}^A(p_{fm}^I) \quad \forall p_{fm}^I \in [0, 1]$$

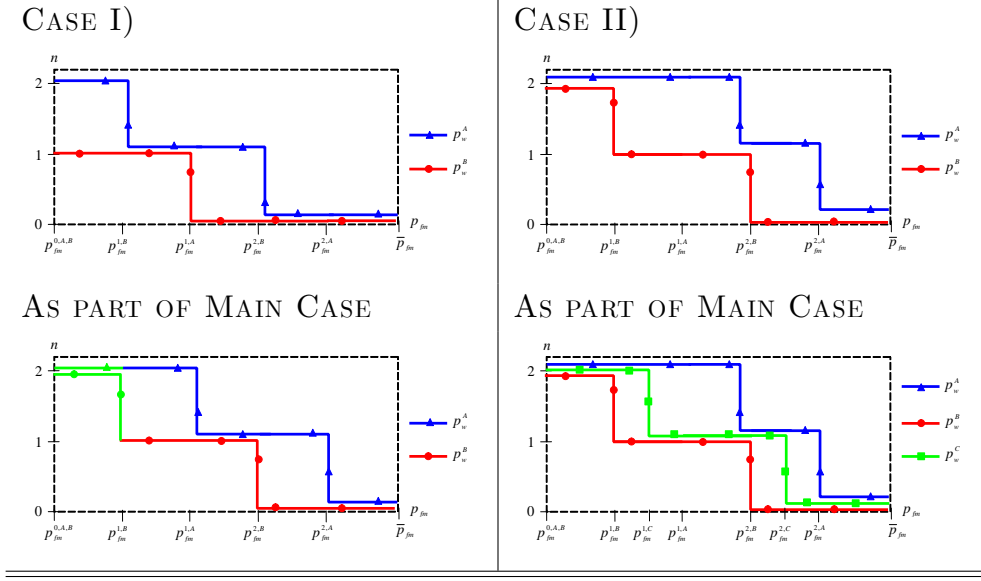
Part B: Since we know that

$$p_w^A > p_w^B, \quad n'_{p_w}(p_w, p_{fm}) > 0 \quad \implies \quad n(p_w^A, p_{fm}) \geq n(p_w^B, p_{fm}) \tag{25}$$

it is straightforward to show that every possible scenario satisfying (25) can be included either directly as part of the main case above or be re-stated as combinations of a number of sub-cases, all part of the main case above.

To illustrate consider the two examples in Figure 4.

FIGURE 4



Case I) just parallels the last four segments of the main case from part A since from (20)  $\hat{G}^B(p_{fm}^I) = \hat{G}^A(p_{fm}^I)$  for  $0 \leq p_{fm}^I < p_{fm}^1$ . In case II) one can include a worker  $C$  with  $p_w^A > p_w^C > p_w^B$  (as illustrated with the middle line). By the proof in part A we know that  $\hat{G}^B(p_{fm}^I) \geq \hat{G}^C(p_{fm}^I)$  and  $\hat{G}^C(p_{fm}^I) \geq \hat{G}^A(p_{fm}^I)$ , whereby we also have that  $\hat{G}^B(p_{fm}^I) \geq \hat{G}^A(p_{fm}^I)$ . By the same line of argument, all cases in the  $n \in [0, 1, 2]$  space can be showed to have assortative matching by using only part A of this proof. ■

## Appendix B: Proof of Proposition 3

**Proof.** Existence of a unique reservation productivity  $p_w^r$  and a unique unemployment rate  $u$  follows trivially from equations (4) and (9). The l.h.s. of equations (5) and (6) is increasing in  $n$ , while the r.h.s. is decreasing in  $n$ , which implies that there is a unique solution for each of the equations. If this value is not an integer, it is possible that the two integers adjacent to the solution of first-order condition imply the same value of the value function. In this case, we assume that the worker chooses the lowest  $n$ . Under this assumption there exist a unique  $n(p_w, b)$  and  $n(p_w, p_{fm})$  for any  $p_w \in [\underline{p}_w, \bar{p}_w]$  and any  $p_{fm} \in [\underline{p}_f, \bar{p}_{fm}]$ . Differentiating (12) with respect to  $p_{fm}$  gives

$$\begin{aligned}
\hat{g}(p_w, p_{fm}) &= \frac{\delta}{\delta + \lambda} n(p_w, b) \Gamma(p_{fm})^{n(p_w, b) - 1} + \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm})^{n(p_w, p_{fm})} \hat{g}(p_w, p_{fm}) \\
&\quad + \frac{\lambda}{\delta + \lambda} \int_{\underline{p}_{fm}}^{p_{fm}} n(p_w, p'_{fm}) \Gamma(p_{fm})^{n(p_w, p'_{fm}) - 1} \hat{g}(p_w, p'_{fm}) dp'_{fm} \\
&\Leftrightarrow \\
\hat{g}(p_w, p_{fm}) &= \frac{\frac{\delta}{\delta + \lambda} n(p_w, b) \Gamma(p_{fm})^{n(p_w, b) - 1}}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm})^{n(p_w, p_{fm})}} + \frac{\frac{\lambda}{\delta + \lambda} \int_{\underline{p}_{fm}}^{p_{fm}} n(p_w, p'_{fm}) \Gamma(p_{fm})^{n(p_w, p'_{fm}) - 1} \hat{g}(p_w, p'_{fm}) dp'_{fm}}{1 - \frac{\lambda}{\delta + \lambda} \Gamma(p_{fm})^{n(p_w, p_{fm})}}
\end{aligned}$$

which is an inhomogenous Volterra equation of second kind with an everywhere continuous and uniformly bounded integral kernel. Given uniqueness of  $n(p_w, b)$  and  $n(p_w, p_{fm})$  we also have a unique solution for  $\hat{g}(p_w, p_{fm})$  for any  $p_w \in [\underline{p}_w, \bar{p}_w]$  and any  $p_{fm} \in [\underline{p}_{fm}, \bar{p}_{fm}]$ . ■

## Appendix C: Tables from Simulation

TABLE 8: MONTE-CARLO ESTIMATIONS WITH 10 PERIODS

|  | Match effect included |       |        | Match effect not included |       |       |
|--|-----------------------|-------|--------|---------------------------|-------|-------|
| No. of replications  | 100                   |       |        | 100                       |       |       |
| No. time periods   | 10                    |       |        | 10                        |       |       |
| No. of observations  | 111,281               |       |        | 111,281                   |       |       |
| No. of persons   | 12,500                |       |        | 12,500                    |       |       |
| No. of firms   | 496                   |       |        | 477                       |       |       |
| Average of wages   | 124.7                 |       |        | 124.4                     |       |       |
| Variance of wages  | 47.2                  |       |        | 41.3                      |       |       |
| Ave. no. of obs per firm   | 224                   |       |        | 233                       |       |       |
|  | Min                   | Max   | Mean   | Min                       | Max   | Mean  |
| AKM, Estimated $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$            | -0.035                | 0.004 | -0.018 | 0.114                     | 0.145 | 0.130 |
| AKM, Corrected $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$            | -0.031                | 0.010 | -0.013 | 0.116                     | 0.147 | 0.132 |
| MIXED, Estimated $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$          | 0.019                 | 0.049 | 0.033  | .                         | .     | .     |
| True $cor(\alpha_1 * \ln(p_w), \alpha_2 * \ln(p_f))$                 | 0.082                 | 0.110 | 0.096  | 0.116                     | 0.146 | 0.132 |
| True $cor(\alpha_1 * \ln(p_w), (\alpha_2 + \alpha_3) * \ln(p_{fm}))$ | 0.097                 | 0.128 | 0.113  | 0.116                     | 0.146 | 0.132 |
| Mean influence on $var(Y)$ :   |                       |       |        |                           |       |       |
|  | True                  | AKM   | Mixed  | True                      | AKM   |       |
| <i>Firm effect</i>   | 0.208                 | 0.189 | 0.191  | 0.392                     | 0.392 |       |
| <i>Person effect</i>   | 0.443                 | 0.642 | 0.448  | 0.543                     | 0.551 |       |
| <i>Match effect</i>  | 0.272                 | .     | 0.284  | 0.000                     | .     |       |
| <i>Error term</i>  | 0.078                 | 0.169 | 0.078  | 0.065                     | 0.057 |       |

TABLE 9: MONTE-CARLO ESTIMATIONS WITH 20 PERIODS

|  | Match effect included |       |       | Match effect not included |       |       |
|--|-----------------------|-------|-------|---------------------------|-------|-------|
| No. of replications  | 100                   |       |       | 100                       |       |       |
| No. time periods   | 20                    |       |       | 20                        |       |       |
| No. of observations  | 222,523               |       |       | 222,523                   |       |       |
| No. of persons   | 12,500                |       |       | 12,500                    |       |       |
| No. of firms   | 498                   |       |       | 481                       |       |       |
| Average of wages   | 124.7                 |       |       | 124.4                     |       |       |
| Variance of wages  | 47.2                  |       |       | 41.4                      |       |       |
| Ave. no. of obs per firm   | 447                   |       |       | 462                       |       |       |
|  | Min                   | Max   | Mean  | Min                       | Max   | Mean  |
| AKM, Estimated $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$            | 0.007                 | 0.038 | 0.024 | 0.118                     | 0.143 | 0.131 |
| AKM, Corrected $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$            | 0.009                 | 0.040 | 0.026 | 0.118                     | 0.144 | 0.131 |
| MIXED, Estimated $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$          | 0.035                 | 0.061 | 0.050 | .                         | .     | .     |
| True $cor(\alpha_1 * \ln(p_w), \alpha_2 * \ln(p_f))$                 | 0.080                 | 0.109 | 0.095 | 0.118                     | 0.144 | 0.131 |
| True $cor(\alpha_1 * \ln(p_w), (\alpha_2 + \alpha_3) * \ln(p_{fm}))$ | 0.099                 | 0.124 | 0.113 | 0.118                     | 0.144 | 0.131 |
| Mean influence on $var(Y)$ :   |                       |       |       |                           |       |       |
|  | True                  | AKM   | Mixed | True                      | AKM   |       |
| <i>Firm effect</i>   | 0.208                 | 0.181 | 0.187 | 0.392                     | 0.392 |       |
| <i>Person effect</i>   | 0.442                 | 0.592 | 0.453 | 0.544                     | 0.547 |       |
| <i>Match effect</i>  | 0.272                 | .     | 0.282 | 0.000                     | .     |       |
| <i>Error term</i>  | 0.078                 | 0.227 | 0.078 | 0.065                     | 0.061 |       |

TABLE 10: MONTE-CARLO ESTIMATIONS WITH 30 PERIODS

|  | Match effect included |       |       | Match effect not included |       |       |
|--|-----------------------|-------|-------|---------------------------|-------|-------|
| No. of replications  | 100                   |       |       | 100                       |       |       |
| No. time periods   | 30                    |       |       | 30                        |       |       |
| No. of observations  | 333,746               |       |       | 333,746                   |       |       |
| No. of persons   | 12,500                |       |       | 12,500                    |       |       |
| No. of firms   | 498                   |       |       | 484                       |       |       |
| Average of wages   | 124.8                 |       |       | 124.4                     |       |       |
| Variance of wages  | 47.3                  |       |       | 41.4                      |       |       |
| Ave. no. of obs per firm   | 670                   |       |       | 689                       |       |       |
|  | Min                   | Max   | Mean  | Min                       | Max   | Mean  |
| AKM, Estimated $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$            | 0.032                 | 0.060 | 0.043 | 0.120                     | 0.143 | 0.131 |
| AKM, Corrected $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$            | 0.034                 | 0.062 | 0.045 | 0.120                     | 0.143 | 0.132 |
| MIXED, Estimated $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$          | 0.052                 | 0.076 | 0.063 | .                         | .     | .     |
| True $cor(\alpha_1 * \ln(p_w), \alpha_2 * \ln(p_f))$                 | 0.084                 | 0.108 | 0.095 | 0.119                     | 0.143 | 0.132 |
| True $cor(\alpha_1 * \ln(p_w), (\alpha_2 + \alpha_3) * \ln(p_{fm}))$ | 0.101                 | 0.124 | 0.112 | 0.119                     | 0.143 | 0.132 |
| Mean influence on $var(Y)$ :   |                       |       |       |                           |       |       |
|  | True                  | AKM   | Mixed | True                      | AKM   |       |
| <i>Firm effect</i>   | 0.208                 | 0.177 | 0.185 | 0.391                     | 0.391 |       |
| <i>Person effect</i>   | 0.443                 | 0.564 | 0.458 | 0.544                     | 0.546 |       |
| <i>Match effect</i>  | 0.271                 | .     | 0.279 | 0.000                     | .     |       |
| <i>Error term</i>  | 0.078                 | 0.259 | 0.078 | 0.065                     | 0.063 |       |

TABLE 11: MONTE-CARLO ESTIMATIONS WITH 50 PERIODS

|  | Match effect included |       |       | Match effect not included |       |       |
|--|-----------------------|-------|-------|---------------------------|-------|-------|
| No. of replications  | 100                   |       |       | 100                       |       |       |
| No. time periods   | 50                    |       |       | 50                        |       |       |
| No. of observations  | 556,296               |       |       | 556,296                   |       |       |
| No. of persons   | 12,500                |       |       | 12,500                    |       |       |
| No. of firms   | 499                   |       |       | 487                       |       |       |
| Average of wages   | 124.8                 |       |       | 124.5                     |       |       |
| Variance of wages  | 47.3                  |       |       | 41.3                      |       |       |
| Ave. no. of obs per firm   | 1115                  |       |       | 1142                      |       |       |
|  | Min                   | Max   | Mean  | Min                       | Max   | Mean  |
| AKM, Estimated $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$            | 0.051                 | 0.070 | 0.061 | 0.124                     | 0.140 | 0.132 |
| AKM, Corrected $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$            | 0.052                 | 0.070 | 0.062 | 0.124                     | 0.140 | 0.132 |
| MIXED, Estimated $cor(\hat{\theta}_i, \hat{\psi}_{J(i,t)})$          | 0.066                 | 0.084 | 0.075 | .                         | .     | .     |
| True $cor(\alpha_1 * \ln(p_w), \alpha_2 * \ln(p_f))$                 | 0.086                 | 0.104 | 0.096 | 0.124                     | 0.141 | 0.132 |
| True $cor(\alpha_1 * \ln(p_w), (\alpha_2 + \alpha_3) * \ln(p_{fm}))$ | 0.102                 | 0.123 | 0.113 | 0.124                     | 0.141 | 0.132 |
| Mean influence on $var(Y)$ :   |                       |       |       |                           |       |       |
|  | True                  | AKM   | Mixed | True                      | AKM   |       |
| <i>Firm effect</i>   | 0.208                 | 0.173 | 0.183 | 0.392                     | 0.392 |       |
| <i>Person effect</i>   | 0.442                 | 0.534 | 0.462 | 0.543                     | 0.545 |       |
| <i>Match effect</i>  | 0.272                 | .     | 0.276 | 0.000                     | .     |       |
| <i>Error term</i>  | 0.078                 | 0.294 | 0.078 | 0.065                     | 0.063 |       |



## Appendix D: Tables from Empirical Estimation

| TABLE 12: AKM PARAMETER ESTIMATES          |                     |                     |
|--|---------------------|---------------------|
|  | (obs per firm >100) | (obs per firm >300) |
| Experience                                 | 0.0168              | 0.0137              |
|  | (67.34)             | (47.76)             |
| (Experience) <sup>2</sup>                  | -0.0061             | -0.0060             |
|  | -(219.63)           | -(191.50)           |
| Large cities <sup>(*)</sup>                | -0.0018             | -0.0022             |
|  | -(2.92)             | -(3.18)             |
| Rural area <sup>(*)</sup>                  | 0.0024              | 0.0014              |
|  | (6.41)              | (3.25)              |
| Value added per employee (mill. DKK)       | 0.0082              | 0.0067              |
|  | (31.23)             | (19.12)             |
| Capital stock per employee (thousands DKK) | 0.0047              | 0.4968              |
|  | (1.82)              | (18.63)             |
| Male ratio                                 | -0.0190             | -0.0260             |
|  | -(6.87)             | -(6.89)             |
| ln(employees)                              | 0.0182              | 0.0211              |
|  | (47.64)             | (45.37)             |
| $R^2$                                      | 0.8986              | 0.9045              |
| No. of observations                        | 3,458,066           | 2,596,705           |
| No. of persons                             | 820,883             | 645,302             |
| No. of firms                               | 7,585               | 2,293               |
| No. of groups                              | 11                  | 1                   |

Note: <sup>(\*)</sup> The omitted category is the greater Copenhagen area.

TABLE 13: AKM ESTIMATOR, STANDARD DEVIATIONS AND CORRELATION MATRIX (OBS PER FIRM &gt;100)

|  | Standard<br>deviation | Correlations |                    |                    |                 |                       |                  |  |                                     |                    |
|--|-----------------------|--------------|--------------------|--------------------|-----------------|-----------------------|------------------|--|-------------------------------------|--------------------|
|  |                       | $Y$          | $X_w\hat{\beta}_w$ | $X_f\hat{\beta}_f$ | $\hat{T}_{dum}$ | $\hat{\psi}_{J(i,t)}$ | $\hat{\theta}_i$ | $X_f\hat{\beta}_f + \hat{\psi}_{J(i,t)}$ | $X_w\hat{\beta}_w + \hat{\theta}_i$ | $\varepsilon_{it}$ |
| $Y$                                      | 0.351                 | 1.000        | -0.067             | 0.020              | 0.009           | 0.286                 | 0.891            | 0.296                                    | 0.916                               | 0.318              |
| $X_w\hat{\beta}_w$                       | 0.079                 | -0.067       | 1.000              | -0.009             | -0.048          | -0.001                | -0.303           | -0.004                                   | -0.070                              | 0.000              |
| $X_f\hat{\beta}_f$                       | 0.033                 | 0.020        | -0.009             | 1.000              | 0.013           | -0.210                | -0.024           | 0.183                                    | -0.027                              | 0.000              |
| $\hat{T}_{dum}$                          | 0.020                 | 0.009        | -0.048             | 0.013              | 1.000           | 0.001                 | -0.038           | 0.007                                    | -0.052                              | 0.000              |
| $\hat{\psi}_{J(i,t)}$                    | 0.007<br>(0.007)      | 0.286        | -0.001             | -0.210             | 0.001           | 1.000                 | 0.071<br>(0.092) | 0.923                                    | 0.075                               | 0.000              |
| $\hat{\theta}_i$                         | 0.110<br>(0.106)      | 0.891        | -0.303             | -0.024             | -0.038          | 0.071<br>(0.092)      | 1.000            | 0.063                                    | 0.972                               | 0.000              |
| $X_f\hat{\beta}_f + \hat{\psi}_{J(i,t)}$ | 0.083                 | 0.296        | -0.004             | 0.183              | 0.007           | 0.923                 | 0.063            | 1.000                                    | 0.064<br>(0.085)                    | 0.000              |
| $X_w\hat{\beta}_w + \hat{\theta}_i$      | 0.317                 | 0.916        | -0.070             | -0.027             | -0.052          | 0.075                 | 0.972            | 0.064<br>(0.085)                         | 1.000                               | 0.000              |
| $\varepsilon_{it}$                       | 0.112                 | 0.318        | 0.000              | 0.000              | 0.000           | 0.000                 | 0.000            | 0.000                                    | 0.000                               | 1.000              |

Note: Lower case paranthesis denotes the correlation corrected for statistical bias.  $X_w$  includes experience, (experience)<sup>2</sup>, large cities and rural areas.  $X_f$  includes value added per employee, capital stock per employee, male ratio and ln(employees).

TABLE 14: AKM ESTIMATOR, STANDARD DEVIATIONS AND CORRELATION MATRIX (OBS PER FIRM &gt;300)

|  | Standard<br>deviation | Correlations |                    |                    |                 |                       |                  |  |                                     |                    |
|--|-----------------------|--------------|--------------------|--------------------|-----------------|-----------------------|------------------|--|-------------------------------------|--------------------|
|  |                       | $Y$          | $X_w\hat{\beta}_w$ | $X_f\hat{\beta}_f$ | $\hat{T}_{dum}$ | $\hat{\psi}_{J(i,t)}$ | $\hat{\theta}_i$ | $X_f\hat{\beta}_f + \hat{\psi}_{J(i,t)}$ | $X_w\hat{\beta}_w + \hat{\theta}_i$ | $\varepsilon_{it}$ |
| $Y$                                      | 0.350                 | 1.000        | -0.081             | -0.005             | 0.007           | 0.282                 | 0.887            | 0.299                                    | 0.926                               | 0.309              |
| $X_w\hat{\beta}_w$                       | 0.099                 | -0.081       | 1.000              | 0.000              | -0.051          | -0.008                | -0.367           | -0.009                                   | -0.083                              | 0.000              |
| $X_f\hat{\beta}_f$                       | 0.033                 | -0.005       | 0.000              | 1.000              | 0.016           | -0.356                | -0.023           | 0.079                                    | -0.025                              | 0.000              |
| $\hat{T}_{dum}$                          | 0.022                 | 0.007        | -0.051             | 0.016              | 1.000           | 0.004                 | -0.048           | 0.011                                    | -0.067                              | 0.000              |
| $\hat{\psi}_{J(i,t)}$                    | 0.006<br>(0.006)      | 0.282        | -0.008             | -0.356             | 0.004           | 1.000                 | 0.099<br>(0.111) | 0.904                                    | 0.104                               | 0.000              |
| $\hat{\theta}_i$                         | 0.116<br>(0.112)      | 0.887        | -0.367             | -0.023             | -0.048          | 0.099<br>(0.111)      | 1.000            | 0.095                                    | 0.957                               | 0.000              |
| $X_f\hat{\beta}_f + \hat{\psi}_{J(i,t)}$ | 0.073                 | 0.299        | -0.009             | 0.079              | 0.011           | 0.904                 | 0.095            | 1.000                                    | 0.099<br>(0.113)                    | 0.000              |
| $X_w\hat{\beta}_w + \hat{\theta}_i$      | 0.318                 | 0.926        | -0.083             | -0.025             | -0.067          | 0.104                 | 0.957            | 0.099<br>(0.113)                         | 1.000                               | 0.000              |
| $\varepsilon_{it}$                       | 0.108                 | 0.309        | 0.000              | 0.000              | 0.000           | 0.000                 | 0.000            | 0.000                                    | 0.000                               | 1.000              |

Note: Lower case paranthesis denotes the correlation corrected for statistical bias.  $X_w$  includes experience, (experience)<sup>2</sup>, large cities and rural areas.  $X_f$  includes value added per employee, capital stock per employee, male ratio and ln(employees).

# Exposure to Low-Wage Country Imports and Skill-Upgrading at the Firm Level<sup>1</sup>

MIKAEL B. ANDERSEN

*Centre for Economic and Business Research (CEBR)*

CHRISTIAN SCHEUER

*Department of Economics, Copenhagen Business School, and  
Centre for Economic and Business Research (CEBR)*

ANDERS SØRENSEN

*Department of Economics, Copenhagen Business School, and  
Centre for Economic and Business Research (CEBR).*

AND

MICHAEL ROSHOLM

*Department of Economics, Aarhus School of Business,*

June 2009

<sup>1</sup>Acknowledgements: We are grateful to Guy Michaels and John Van Reenen for helpful comments; and to the Tuborg Foundation for financial support.

## **Abstract**

This paper investigates the impact of imports on the demand for skills in Danish manufacturing companies. We find that it is of crucial importance to distinguish imports by country-of-origin. The main finding is that increasing imports from low-wage countries and skill-upgrading in Danish manufacturing firms are positively and significantly correlated. Especially, this is the case for the external firm effect as measured by imports of product types that is used to proxy import competition in product markets; but also for the internal firm effect for larger firms as measured by firm imports. Since import competition by construction is an aggregate measure it is considered external to the firm, which implies that the correlation can be given an causal interpretation.

*Keywords:* Skill-upgrading, firm imports, import competition, low-wage countries

*JEL:* F14, J24, L60

# 1 Introduction

This paper investigates the implications of imports for skill-upgrading in Danish manufacturing firms, i.e., increasing demand for skilled labor. We analyze two distinct mechanisms through which imports potentially influences firms' demand for skilled and unskilled labor. The first mechanism is an *internal firm effect* based on the increasing possibility for firms to import cheap inputs from low-wage countries. The second mechanism is an *external product effect* based on firms meeting stronger competition in domestic product markets through increasing imports from low-wage countries. We refer to the latter effect as import competition.

The internal firm effect investigates whether there is a significant correlation between skill-upgrading and firm imports. What we have in mind is the standard story of decreases costs of purchasing inputs from abroad leading firms either to produce fewer inputs themselves or to buy fewer inputs from domestic producers. Since production of the relevant inputs are intensive in unskilled labor this leads to lower shares of unskilled workers in production.

The external product effect investigates whether skill-upgrading is caused by aggregate imports of a particular product type. The mechanism that we have in mind is that firms as a consequence of increasing import competition gradually move into more skill-intensive production to avoid increasing foreign competition from low-wage countries. Import competition in domestic product markets is a measure of aggregate imports of the product types that the firm produces. Because the measure by construction is an aggregate measure, it is considered external to the firm, which implies that the identified effects can be given a causal interpretation.

The main finding is that increasing import competition from low-wage countries leads to within-firm skill-upgrading. This finding is robust to different definitions of import competition relevant for the single firm and with respect to the details of the applied product classifications. Moreover, the internal firm effect, i.e., firm imports from low-wage countries, is found to be positively and significantly correlated with skill-upgrading within larger firms.

The finding that import competition from low-wage countries leads to skill-upgrading is of interest because of the big increases in trade with countries like India and China, which means that studies of globalization effects with this newer form of trade are high on the research agenda.<sup>1</sup> In the past, economists have not found much evidence for import competition to play a major role in the changing demand for skills. Instead the primarily focus has been on firm imports that are sometimes referred to as international outsourcing. However, there begin to be a renewed interest in the effects of imports on the labor market. This interest has been absent for some time since there has been a consensus that imports has not been important.<sup>2</sup> This is

---

<sup>1</sup>China became member of WTO in late 2001 and India has grown to become an important player in the world markets.

<sup>2</sup>In the Journal of Economic Perspectives, summer 1995, there was a symposium on income inequality and trade. For example, Wood (1995) "...argue[s] for what is still a minority view among economists: that the main cause of the deteriorating situation of unskilled workers in developed countries has been expansion of trade with

due to the existing literature that has not found much evidence for trade to be a major cause of increasing inequality. This consensus is, however, problematic, because it is based on studies that use data that to a high degree are outdated. This argument is put forward by Krugman (2008), who states: "Until recently .. surprisingly little attention was given to the increasingly out-of-date nature of data behind the reassuring consensus that trade has only modest effects on income distribution". This was also noted by Bernanke (2007): "Unfortunately, much of the available empirical research on the influence of trade on inequality dates from the 1980s and 1990s and thus does not address later developments".

This paper offers an analysis that solves some of the issues pointed out above. First, the empirical study is based on recent data covering the period 1999-2003. Second, imports are split-up after country-of-origin; more precisely, imports are divided after low-wage and high-wage countries. In addition to the two data improvements, we construct firm-specific measures of import competition by combining external trade information with industrial sales broken-down after product categories. More precisely, we construct our base measure of import competition after product types and use weights based on sales broken-down after product types to obtain measures of import competition relevant for the individual firm. To illustrate the measure, imagine that sales in a firm are constituted by 30 percent of product type A and 70 percent of product type B, then the firm-specific measure of import competition is determined as the sum of aggregate imports of product A weighted by 30 percent and aggregate imports of product B weighted by 70 percent. In this sense, import competition is firm-specific. We also apply an alternative measure of import competition that is defined as aggregate imports of the product type for which the firm has the largest sales share; i.e., import competition is equal to aggregate imports of product type B in the example. The latter measure of import competition is closer to the standard measure as used by Bernard, Jensen, and Schott (2006), because this measure is constructed for the US manufacturing industries and because firms are assigned to an industry according to the product type with the largest sales share.

According to our best knowledge this paper is novel since it is the first firm-level study of the relative importance of firm imports and import competition for skill-upgrading that distinguishes imports after country-of-origin, and applies firm-specific measures of import competition.

The study is based on a unique combination of data sets yielding a matched employer-employee sample of manufacturing firms containing information on output, sales broken-down after product types, labor inputs, and imports, all measured at the firm level, and covering the period 1999-2003. This data set enables us to develop measures of cost shares for workers of different education categories and imports both for the single firm and for product types after country-of-origin. We estimate labor demand functions derived from a translog cost

---

developing countries."

function and all regressions are performed using fixed effects estimation techniques, implying that the model parameters are identified using variation within firms over time. This reflects our hypothesis that a change in imports causes a change in the cost share between skilled and unskilled workers.

As mentioned, the international trade literature has mainly focussed on the influence of imports of intermediate inputs on skill-upgrading; thereby to a large extent ignoring the impact from import competition. Since the work of Feenstra and Hanson (1996), the idea that firms offshore production activities that use unskilled labor intensively to low-wage countries has been investigated intensively. Empirically, international trade in intermediate inputs is often found to be of significant importance for skill-upgrading, see Feenstra and Hanson (1999), and Feenstra (2004). The relationship between trade in intermediate inputs and skill-upgrading is usually investigated using industry data from input-output tables, and hence, there is no distinction between country-of-origin, i.e., the approach does not allow a decomposition of trade in intermediate inputs in low- and high-wage countries; exceptions are Ekholm and Hakkala (2006), and Hijzen, Görg and Hine (2005). Moreover, using data from input-output tables exclude the possibility of investigating the importance of imports of the final stage of production for skill-upgrading, e.g., assembly; an activity where many low-wage countries have a comparative advantage, see Ng and Yeats (1999).

In the empirical literature, the hypothesis that industries shift towards more skill-intensive activities as a consequence of increasing import competition is investigated using measures based on overall imports. That is, the measures are based on aggregate imports from *all* countries. There has only been weak support for this hypothesis. See for example, Autor, Katz, and Krueger (1998). The finding that import competition is without importance for skill-upgrading is also based on shift-share analyses. Using this method it is found that within-industry effects dominate skill-upgrading, whereas between-industry effects are rather modest. The interpretation is that import competition is without importance for skill-upgrading, because industry imports - according to this view - should affect the composition of skills through a changing industry structures, see for example Berman, Bound, and Griliches (1994).

The view that import competition mainly affects the composition of skills through changing industry structures is only valid as long as firms or products are homogeneous within industries. There is, however, room for firms to adjust the product-mix towards skill-intensive production without switching industry if firms or products to a larger extent are heterogeneous within industries. Sørensen (2008) finds industry level evidence that import competition from low-wage countries is important for within industry skill-upgrading in Danish Manufacturing. It is shown that the break-down into low- and high-wage countries is of crucial importance, implying that imports from low-wage countries leads to comprehensive skill-upgrading. Due to the nature of the study, it is however not clear whether skill-upgrading takes place between firms and within

industries; or whether it takes place within firms. This issue is addressed in the present paper. If it takes place within firms, this suggests that increasing foreign competition in product markets makes firms change their product mix.<sup>3</sup>

Exceptions from using industry data are Biscourp and Kramarz (2007) and Bernard, Jensen and Schott (2006) that use firm data. The former paper is focused on the relationship between firm imports and labor market outcomes in domestic firms. In other words, the focus is on the internal firm effect of internationalization and skill-upgrading. The authors find that increased imports especially of finished goods have a negative association with the demand for production workers, as well as for unskilled workers. This is consistent with our findings for the internal firm effect. Bernard, Jensen, and Schott (2006) finds support for import competition from low-wage countries to play an important role for firms to adjust their product mix in order to avoid trade pressures. This suggests that firms shift towards more skill-intensive activities as a consequence of increasing international competition from low-wage countries and that this shift may take place within industries. Moreover, the authors study skill-upgrading using the cost shares of production workers but do not establish any significant correlations. However, measures of skill-intensity based on educational attainment should be better indicators of those most likely to be affected by trade; and such measures are not available to the authors. Finally it is worth noticing that our data is much more recent since Bernard, Jensen, and Schott (2006) use data for the period 1977-1997, whereas Biscourp and Kramarz (2007) use data for 1986-1992.

Another studies relevant for the present paper is Harrison and McMillan (2006), where the dependent variable is employment; not relative demand for skills. The focus is on the importance of firm imports for reductions of employment in US multinationals. The authors argue that offshoring play a minor role for firm employment, whereas import competition from low-wage countries are of greater importance. A finding similar to our results for skill-upgrading.

The next section describes the main idea of the analysis in a simple theoretical model. After this we present the basic equations in the translog cost model and discusses the econometric strategy. Section 4 describes the data set applied in the analysis, as well as the constructed measures of international trade. Section 5 presents the baseline empirical results, while section 6 and 7 further analyses the robustness of these results. Section 8 concludes.

## 2 Factor Proportions Framework

We have the factor proportions framework in mind when theoretically approaching the importance of imports from low-wage countries for skill-upgrading. Three products can potentially

---

<sup>3</sup>A more radical consequence of import competition is that domestic firms may be pressured out of business and exit the market. This is not an issue that we address in this paper. The issue of plant survival and import competition is addressed in Bernard, Jensen, and Schott (2006).



be produced in the skill-abundant domestic economy; two final products and a pure intermediate product. We assume that production of final product 1 is more skill-intensive than the other products, whereas the intermediate input is more skill-intensive than final product 2. The model is presented in the Appendix.

Prices are determined in the world market and exogenous to the high-wage country under investigation. The prices relevant for the domestic economy are the world price multiplied by a product specific transportation cost of the "iceberg" type. What we have in mind is that unskilled-intensive final product 2 has a higher transportation cost than the intermediate input and final product 1, whereas the intermediate input has a higher transportation cost than final product 1. When the degree of internationalization increases, we assume that the transportation costs for the products fall in similar proportions implying that relative prices for products leads to higher relative prices of skill-intensive products in the skill-abundant country. These assumptions capture that the largest effect from increasing internationalization is on unskilled-intensive products. A numerical example of the consequences of increased internationalization in this setup is presented in appendix A.

In this model increased internationalization in the form of decreasing transportation costs imply that the skill-abundant country will specialize further in the skill-intensive final product compared to both the intermediate input and the unskilled-intensive final product. The change in the specialization pattern also implies that imports of intermediate inputs will increase. Moreover, the economy will specialize more in the production of intermediate products compared to the unskilled intensive products. Actually, the home country will even restrain from producing final product 2 if  $\theta$  is above a threshold level. In other words, production of final product 2 becomes unprofitable when internationalization increases and consumption of final product 2 equals imports of the product. This is another mechanism that leads firms to specialize in skill-intensive production as a consequence of increasing internationalization.

One difficulty in using the factor proportion framework to analyze effects of internationalization on firm behavior is that the model focuses on products or industries. We follow Bernard, Jensen and, Schott (2006) and use the interpretation that firms produce in bundles of disaggregate products. Following this interpretation, firms in the domestic economy both produce the final products and the intermediate input. When internationalization increases firms have the incentive to shift towards skill-intensive production. The first mechanism above can be thought of as an effect related to what we label for the internal firm effect in the empirical section, which focuses on decreases costs of purchasing inputs from abroad. The second mechanism focuses on foreign firms having a cost advantage in unskilled-intensive products, implying that production is unprofitable in the skill-abundant country. This will lead firms to move into more skill-intensive production and therefore upgrade the employed skills. This mechanism can be thought of as import competition.

Based on the above discussion, we consider two testable hypotheses from the factor proportions framework:

- **Hypothesis 1:** The relative demand for skilled labor at the firm level increases with the extent of firm imports from low-wage countries.
- **Hypothesis 2:** Exposure to import competition from low-wage countries increases the relative demand for skilled labor at the firm level.

### 3 Econometric Framework

Our empirical specification is based on the translog cost function. We follow Brown and Christensen (1981) assuming that the different types of labor are variable inputs, whereas physical capital is quasi fixed. We add firm imports and import competition that are assumed to be quasi fixed inputs (or cost shifters). Finally, we add a technology measures. Below the model for two labor types is described.

Using Shephard's lemma, the translog cost function generates a wage cost share equation of the following form:

$$\begin{aligned}
S_{\text{skilled},i,t} = & \beta_0 + \beta_1 \ln \left( \frac{w_{\text{skilled},i,t}}{w_{\text{unskilled},i,t}} \right) + \beta_2 \ln (Y_{i,t}) + \beta_3 \ln (K_{i,t}) \\
& + \beta_4 \ln \left( M_{i,t}^{\text{firm, LW}} \right) + \beta_5 \ln \left( M_{i,t}^{\text{firm, HW}} \right) \\
& + \beta_6 \ln \left( M_{i,t}^{\text{product, LW}} \right) + \beta_7 \ln \left( M_{i,t}^{\text{product, HW}} \right) \\
& + \beta_8 \ln (TECH_{i,t}) + \alpha_{\text{skilled},i} + \varepsilon_{\text{skilled},i,t}
\end{aligned}$$

where  $S_{\text{skilled},i,t}$  is the cost share of skilled labor to total labor costs in firm  $i$  observed at time  $t$ .  $w_{\text{skilled}}/w_{\text{unskilled}}$  is the relative wage of skilled labor to unskilled labor,  $Y$  is total production,  $K$  is the capital stock,  $M$  is imports. 'firm' denotes firm imports, whereas 'product' denotes import competition; 'LW' and 'HW' denote low-wage and high-wage countries, respectively.  $\alpha_{\text{skilled},i}$  is a firm fixed effect, and  $\varepsilon_{\text{skilled},i,t}$  is an *i.i.d.* error component.

In general a translog cost function generates a series of wage cost share equations, one for each type of variable labor input. Imposing the standard restrictions of symmetry and homogeneity of degree 1 in prices allows us to reach the specification above where one of the equations becomes redundant. In the case of two labor inputs, the estimates of the similar equation for the wage cost share of unskilled labor can be recovered from the symmetry restrictions without estimating the equation.

In a latter subsection, the labor demand functions are estimated for three skill levels. In this case, the restrictions of symmetry and homogeneity of degree one in prices are imposed on

the model. This model is estimated using restricted maximum likelihood, incorporating all the structural parameter restrictions.

## 4 Data

The applied data set originate from administrative registers maintained by Statistics Denmark. Using these data we construct a matched employer-employee database covering the entire population. The sampling unit is the "private manufacturing firm with more than 10 employees", and we observe these annually over the period 1999 to 2003. Specifically, the applied data sets are the Danish Firm Integrated Database for Labor Market Research (FIDA), the External Trade Statistics, and the Industrial Sales of Product Types from Statistics Denmark. Moreover, the OECD ANBERD database is applied to construct a proxy for technical changes. Below we discuss the variables applied in the empirical analysis and our sampling strategy.

### 4.1 Skill-Upgrading

The FIDA database includes variables for individual firms. It is possible to identify all workers in each firm for each year, and for each worker we have access to detailed information on educational attainment and wages. The data thus permit us to construct wage cost shares for different types of labor at the firm level. We mainly perform the analyses for two skill types by classifying labor into unskilled labor and skilled labor that includes all workers with formal qualifying education.

We also perform the analysis for three types of labor. This latter classification groups labor in unskilled labor, labor with vocational training, and labor with academic education. The choice of dividing labor into three skill groups is motivated by the educational system of Denmark, which consists of a vocational track and an academic track. Moreover, this additional decomposition of the educated labor group enables us to study the nature and composition of skill-upgrading in more details. Vocational education is a mix of schooling and training in firms with a typical duration of approximately 3 years and this category also includes workers with a short academic education. Labor with academic education includes workers with medium or long academic education. Medium academic education corresponds to the bachelor level, whereas long academic education corresponds to the master level or more.

We include firms with more than 10 employees because this is the minimum size for data collected in the Industrial Sales of Product Types. When the focus is on three labor types, we restrict the sample to firms with more than 50 employees. This additional sampling restriction is made to avoid the technical problem of small firms with zero employees of a specific skill type. This would result in a corner solution in the model for relative labor demand. The vast majority of firms with more than 10 employees employ unskilled workers as well as workers

with formal skills. Moreover, we find that most firms with more than 50 employees employ all three labor types, i.e., unskilled, vocational, and academically educated workers. The few firms that do not employ all labor types are excluded from our sample.

The FIDA database provides background information such as turnover and the value of fixed assets from the firms' balance sheet. Table 1 shows descriptive statistics for the samples. The average number of Manufacturing firms over the period 1999-2003 is around 5,000 firms with more than 10 employees and 1,400 firms with more than 50 employees. For both samples there is a falling tendency of the number of firms over time. Our samples represent approximately 95 and 80 percent of total manufacturing turnover and around 95 and 85 percent of the total fixed assets in manufacturing.

Table 1 also presents total wage cost share composition and its development over the sampling period for the different samples. The main impression is that skill-upgrading takes place over time and the cost share of workers without formal education falls with approximately 3 percentage point over the five year period.

| TABLE 1: TOTAL WAGE COST SHARES COMPOSITION IN DANISH MANUFACTURING |         |         |         |         |         |
|---|---------|---------|---------|---------|---------|
|   | 1999    | 2000    | 2001    | 2002    | 2003    |
| —— Manufacturing Firms with 10 or More Employees ——                 |         |         |         |         |         |
| <b>Wage: No Education</b>   | 33.9%   | 33.6%   | 32.7%   | 32.0%   | 31.0%   |
| <b>Wage: All Educations</b>   | 66.1%   | 66.4%   | 67.3%   | 68.0%   | 69.0%   |
| <b>Total Number of Firms</b>  | 5,192   | 5,131   | 5,004   | 4,800   | 4,664   |
| <b>Total Number of Workers</b>                                      | 391,711 | 397,042 | 390,589 | 379,857 | 361,337 |
| <b>Total Turnover, Billions DKK</b>                                 | 435.4   | 487.6   | 520.5   | 520.5   | 514.8   |
| <b>Total Capital, Billions DKK</b>                                  | 413.8   | 456.6   | 467.4   | 474.5   | 485.3   |
| —— Manufacturing Firms with 50 or More Employees ——                 |         |         |         |         |         |
| <b>Wage: No Education</b>   | 34.4%   | 34.0%   | 33.1%   | 32.3%   | 31.3%   |
| <b>Wage: Vocational or Short Academic Education</b>                 | 48.2%   | 48.8%   | 49.2%   | 49.3%   | 49.4%   |
| <b>Wage: Medium or Long Academic Education</b>                      | 17.4%   | 17.2%   | 17.7%   | 18.4%   | 19.3%   |
| <b>Total Number of Firms</b>  | 1,415   | 1,451   | 1,405   | 1,345   | 1,289   |
| <b>Total Number of Workers</b>                                      | 310,766 | 317,990 | 312,751 | 304,211 | 288,723 |
| <b>Total Turnover, Billions DKK</b>                                 | 361.8   | 412.4   | 443.6   | 443.1   | 439.0   |
| <b>Total Capital, Billions DKK</b>                                  | 363.3   | 405.8   | 415.6   | 421.6   | 430.4   |

## 4.2 Measuring Imports

We apply two measures of internationalization; firm imports and product imports. The differences between firm imports and product imports is the level of aggregation where firm imports is a firm specific measure and product imports is an product specific aggregate. However, there is another important difference between the two measures, namely, that firm imports measure imports *of all foreign produced products to a particular firm*, whereas product imports measure

*aggregate imports of a particular foreign produced product over all domestic industries and final use categories.* The interpretation is that firm imports is a measure focusing on input markets of the firm; i.e., the higher is firm imports the better possibility has the firm to take advantage of cheaper foreign produced inputs in the production process. On the other hand, product imports is a measure focused on the competitive state on the domestic product marked of the firm in the sense that a higher value implies that the firm faces increased competition from abroad. Therefore, the relevant imports is imports of products that the firm produces.

Table 2 presents the overall import data for Danish firms. Despite the short time span, imports from low and middle-income countries have increased from 36.1 to 53 billions DKK from 1999 to 2003, an increase of almost 50 percent, and a pattern we see repeated in both samples of manufacturing firms.

| TABLE 2: IMPORTS IN DANISH FIRMS BY COUNTRY-OF-ORIGINS INCOME PER CAPITA |   |       |       |       |       |
|--|---|-------|-------|-------|-------|
|  | 1999  | 2000  | 2001  | 2002  | 2003  |
|  | ———— Billion DKK ————                             |       |       |       |       |
|  | — All Firms —                                     |       |       |       |       |
| Low and Middle Income Countries  | 36.1  | 45.0  | 49.4  | 48.9  | 53.0  |
| High Income Countries  | 272.1   | 311.2 | 279.0 | 294.7 | 276.6 |
|  | — All Manufacturing Firms —                       |       |       |       |       |
| Low and Middle Income Countries  | 10.9  | 12.7  | 14.6  | 14.2  | 15.3  |
| High Income Countries  | 61.2  | 69.7  | 79.6  | 80.3  | 77.0  |
|  | — Manufacturing Firms with 10 or More Employees — |       |       |       |       |
| Low and Middle Income Countries  | 10.5  | 12.3  | 14.0  | 13.8  | 14.7  |
| High Income Countries  | 60.1  | 68.5  | 77.8  | 79.0  | 75.8  |
|  | — Manufacturing Firms with 50 or More Employees — |       |       |       |       |
| Low and Middle Income Countries  | 8.9   | 10.5  | 12.3  | 12.2  | 13.3  |
| High Income Countries  | 54.6  | 62.1  | 71.2  | 72.1  | 69.2  |

Firm imports is based on imports in individual manufacturing firms from the External Trade Statistics of Statistics Denmark, which contains information on the value, type, and origin for every product imported to Denmark from countries outside the EU and for products imported from countries within EU by firms with total EU imports exceeding 1.8 million DKK.

Import competition is an aggregate measure of imports of foreign produced product types. This measure includes all import to Denmark, that means, also import of firms outside manufacturing, e.g., trading companies located in the service sector. We apply two alternative measures of import competition; one is proportional to sales broken-down after product types in the single firm; the other is related to the product with the largest sales share for the single

firm. More precisely, the first measure is defined as:

$$M_{i,t}^{\text{product}}(1) = \sum_{p=1}^P \gamma_{p,i,t} M_{p,t}^{\text{product}}$$

where  $M_{p,t}^{\text{product}}$  is total imports of product  $p$  at time  $t$  and  $\gamma_{p,i,t}$  is product  $p$ 's share of sales in firm  $i$  at time  $t$ , i.e.,  $\gamma_{p,i,t} = \text{sales}_{p,i,t} / \sum_{p=1}^N \text{sales}_{p,i,t}$ . The second measure is defined as

$$M_{i,t}^{\text{product}}(2) = M_{p,i,t}^{\text{product}} \text{ with } p = \max(\gamma_{1,i,t}, \dots, \gamma_{P,i,t}).$$

The calculation of measures of import competition is based on the External Trade Statistics for  $M_{p,i,t}^{\text{product}}$  and Industrial Sales of Product Types for  $\gamma_{p,i,t}$ . The second measure comes closest to the measure applied by Bernard, Jensen, and Schott (2006). They use a measure of import competition for the industry level. However, the way firms are assigned to specific industry is precisely using the product with the largest sales share.

The measures of import competition is calculated for different levels of aggregation. For the most detailed level, we use SITC 5 digit including 2915 products in the data set, whereas SITC 4 and SITC 3 include respectively 998 and 260 products in the data set.

Both firm imports and import competition are calculated separately for low-wage and high-wage countries. The country-split that we apply are low and middle income countries (LW) versus high income countries (HW) according to 2005 GNI per capita, calculated using the World Bank Atlas method. Hence, the groups are divided at \$10,726 2005 GNI per capita.

### 4.3 Other Variables

We use relative wages measured at the municipality level. The municipality group-specific wage measures are calculated from information on individual wage for all workers of all types. We do this because using the relative wage measure at the firm level may be problematic. Endogeneity of firms' wage policies is an issue that we cannot neglect, since wage policies are a crucial part of the strategic positioning of the firm in the context of internationalization.<sup>4</sup>

We do not have technology measures at the firm level. However, given the role of technological change as a potential confounding variable, it is important to try to include a measure of it. In the literature, different variables have been used to capture the increasing efficiency of skilled and educated labor. Autor, Katz, and Krueger (1998) show that the diffusion of computers and related technologies is an important source of changes in the relative demand of

---

<sup>4</sup>Data on individual wages and working hours are aggregated to the municipality level for individuals working in the firms that are included in our sample. These aggregates are used to calculate the relevant hourly wage rate for each labor type in each of Denmark's 271 municipalities.

skills and thereby in the relative efficiency of skilled labor. We follow Machin and Van Reenen (1998), who use R&D intensities to explain skill-upgrading. Hence, R&D intensities are used as measures of the technological stage of development using the OECD ANBERD database. R&D data that are compatible with the applied databases, i.e., industry-structure ISIC Revision 3 within manufacturing, only exist at the 13 industry level. R&D intensities are defined as R&D expenditures in an industry divided by industry production.<sup>5</sup>

## 5 Results

The empirical results presented in this section are all regressions performed using fixed effects estimation techniques, implying that the model parameters are identified using only variation in the explanatory variables within firms over time. In this sense, we investigate the importance of increasing imports for skill-upgrading within firms; not between. Hence, our hypothesis is that increasing imports is associated with increasing cost share of skilled workers within firms.

Table 3 presents the main results that is based on the first measure of import competition,  $M_{i,t}^{\text{firm}}(1)$ , where aggregated imports are allocated proportional to sales broken-down after product types in each firm, and the most disaggregate product code, i.e., SITC 5 digit. Models 1-2 include measures of firm imports only. No significant correlation between skill-upgrading as measured by the wage share of skilled labor and firm imports is detected; neither when total firm imports are included nor when firm imports is decomposed after country-of-origin.

---

<sup>5</sup>The technology indicator is linked to the single firm using information on industry attachment, whereas measures of import competition is linked to firms using information on attachment to product types.

TABLE 3: CHANGE IN SKILLED WAGE SHARE AS DEPENDENT VARIABLE, 1999-2003, FIXED EFFECTS ESTIMATION TWO EDUCATION GROUPS, FIRM AND INDUSTRY IMPORT.

|   | (1)                   | (2)                   | (3)                   | (4)                   | (5)                   | (6)                   |
|---|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| <b>Relative wage<sub>mun</sub>,<br/>Skilled</b> | -0.0521***<br>(3.903) | -0.0515***<br>(3.852) | -0.0534***<br>(3.998) | -0.0477***<br>(3.566) | -0.0514***<br>(3.851) | -0.0456***<br>(3.411) |
| $\ln(Y_i)$                                      | -0.0032**<br>(2.079)  | -0.0033**<br>(2.147)  | -0.0029*<br>(1.897)   | -0.0032**<br>(2.149)  | -0.0034**<br>(2.239)  | -0.0038**<br>(2.492)  |
| $\ln(K_i)$                                      | 0.0007<br>(0.895)     | 0.0007<br>(0.922)     | 0.0007<br>(0.870)     | 0.0007<br>(0.862)     | 0.0006<br>(0.845)     | 0.0007<br>(0.865)     |
| $\ln(Firm\_imp)$                                | 0.0002<br>(0.457)     |                       |                       |                       | 0.0001<br>(0.349)     |                       |
| $\ln(LW\_Firm\_imp)$                            |                       | 0.0005<br>(1.162)     |                       |                       |                       | 0.0004<br>(1.014)     |
| $\ln(HW\_Firm\_imp)$                            |                       | -0.0001<br>(0.395)    |                       |                       |                       | -0.0002<br>(0.492)    |
| $\ln(Indu\_imp)$                                |                       |                       | 0.0013<br>(1.397)     |                       | 0.0013<br>(1.334)     |                       |
| $\ln(LW\_Indu\_imp)$                            |                       |                       |                       | 0.0028***<br>(6.162)  |                       | 0.0027***<br>(5.938)  |
| $\ln(HW\_Indu\_imp)$                            |                       |                       |                       | -0.0030***<br>(3.087) |                       | -0.0029**<br>(2.966)  |
| $\ln(TECH)$                                     | 0.0059***<br>(7.105)  | 0.0058***<br>(7.025)  | 0.0061***<br>(7.377)  | 0.0061***<br>(7.385)  | 0.0058***<br>(7.040)  | 0.0058***<br>(7.005)  |
| <b>Firms</b>                                    | 6932                  | 6932                  | 6932                  | 6932                  | 6932                  | 6932                  |
| <b>Obs.</b>                                     | 24615                 | 24615                 | 24615                 | 24615                 | 24615                 | 24615                 |

T-value in parentheses

\* significant at 10 per cent; \*\* significant at 5 per cent; \*\*\* significant at 1 per cent

Next we turn to product imports in Models 3-4. In Model 3, it is seen that total product imports have a positive but insignificant impact on the relative demand for skilled labor. The point estimate is consistent with our expectations, namely, that firms susceptible to import competition tend to reduce demand for skills when import competition increases. Moreover, the result supports the consensus that import competition is not important for changing demand for skilled labor.

When decomposing the measure of import competition after high- and low-wage countries in Model 4, we see that the overall picture in Model 3 hides important heterogeneity. Firms producing product types exposed to extensive product imports from low-wage countries increase the relative demand for skilled labor more than other firms, while firms producing products exposed to extensive import competition from high-wage countries lower their relative demand for skilled labor, that is, product imports from high-wage countries leads to skill-downgrading. Overall, this picture suggests that Danish manufacturing firms have comparative advantages in skill-intensive production when compared to low-wage countries and comparative advantages in production intensive in unskilled labor when compared to other high-wage countries.

Finally, both measures of firm and product imports are included in Models 5-6. The results are robust to the inclusion of both measures, implying that skill-upgrading is affected positively



by product imports from low-wage countries. Moreover, there is some indications that product imports from high-wage countries lead to skill-downgrading. Firm imports do not display important correlations with relative demand for skills. In the following we apply Model 6 as our baseline model.

In conclusion this supports Hypothesis 2; that relative demand for skilled labor increases with the extent of import competition from low-wage countries. On the contrary, we do not find significant support for Hypothesis 1 that the relative demand for skilled labor increases with the extent of manufacturing firm imports from low-wage countries. In the following section, we analyze the robustness of these conclusions.

Other explanatory variables also affect the relative demand for skilled labor. The relative demand decreases in the relative wage of skilled labor and by the size of the firm in terms of output. The measure of physical capital enters with a positive but insignificant effect on relative demand for skilled. The positive point estimate is consistent with capital-skill complementarity. The insignificant correlation is potentially explained by the nature of time series for physical capital that are smooth and therefore it is difficult statistically to distinguish between a time trend and the development in physical capital, see for example Islam (1995). In all models presented in Table 3, the TECH variable capturing technological progress has a significant positive effect on the relative demand for skilled to unskilled labor.

To evaluate the importance of imports for skill-upgrading at the firm level, we compute elasticities for each firm and take the mean over all firms. The average elasticity for the wage share of changing import competition are around 0.005 for low wage countries and -0.005 from high wage countries. For firm imports the elasticities are insignificant. The significance of the elasticities follows the results presented in Table 3. These elasticities translate into an explained variation in the skilled wage share of  $\sim 30\%$  percent for import competition from low wage countries and an explained variation in the skilled wage share of  $\sim 15\%$  percent for import competition from high wage countries<sup>6</sup>. This suggests that product imports from low-wage countries have an important impact on skill-upgrading in the average firm.

## 6 Robustness

The purpose of the present section is to investigate the robustness of the results established in Table 3. We check the results under three modifications: (i) alternative measure of import competition, (ii) restriction of the samples by firms size, and (iii) firms with dominating home market sales share.

---

<sup>6</sup>Computed as (for low wage countries):

$$\left[ \text{mean}_{i,t} \left( \varepsilon_{i,t}^{LW\_Firm\_imp} \right) * \text{mean}_{i,t} (\% \text{ increase in } LW\_Firm\_imp) \right] / \text{mean}_{i,t} (\% \text{ increase in skilled wage share}),$$

where the few firms with outlying % increase in  $LW\_Firm\_imp$  are disregarded

## 6.1 Alternative Measures

An important objection to the main finding is that the association between skill-upgrading and import competition from low-wage countries may not represent a causal relationship, or expressed differently import competition may be endogenous. This could be the case due to omitted variables that affect both skill-upgrading and import competition or, due to incentives causing firms to simultaneously change the cost share of skilled labor and import competition. E.g., imagine that the firm wins a patent for a new and promising skill intensive product, and hence, decides to expand production and thereby sales of skill-intensive product types. Such a choice would increase the cost share of skilled labor and affect the measure of import competition relevant to the firm because shares of sales, i.e.,  $\gamma_{p,i,t}$ , will change, thus rendering import competition endogenous.

We try to adress this problem by introducing other import competition measures that potentially are less prone to endogeneity. Firstly, we apply the alternative measure as defined by  $M_{i,t}^{\text{product}}(2)$ , where import competition is measured only by the dominating product of each firm, which can be argued to be less sensitive to the issue described above. Moreover, we develop two additional measures of import competition for higher levels of aggregation, since the higher the level of aggregation, the less each firm influences the measure of import penetration. Where SITC 5 Digit are based on 2915 products, SITC 4 Digit are based on 998 and SITC 3 on 260 products.

In Table 4 column (1), we present our baseline model. In the remainder of the columns alternative measures of import competition are applied. In Column 2, we apply,  $M_{i,t}^{\text{product}}(2)$ . It is evident that, we find a similar conclusion with respect to import competition from low-wage countries leading to skill-upgrading. The parameter value is a little lower when the alternative measure of import competition is applied.

TABLE 4: CHANGE IN SKILLED WAGE SHARE AS DEPENDENT VARIABLE, 1999-2003, FIXED EFFECTS ESTIMATION TWO EDUCATION GROUPS, ALTERNATIVE MEASURES OF FIRM IMPORT

|                      | (1)                   | (2)                   | (3)                   | (4)                   | (5)                   | (6)                   |
|----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
|                      | Baseline              |                       |                       |                       |                       |                       |
|                      | M(1)                  | M(2)                  | M(1)                  | M(2)                  | M(1)                  | M(2)                  |
|                      | 5 Digit               | 5 Digit               | 4 Digit               | 4 Digit               | 3 Digit               | 3 Digit               |
| $\ln(LW\_Firm\_imp)$ | 0.0004<br>(1.014)     | 0.0004<br>(1.046)     | 0.0004<br>(0.890)     | 0.0004<br>(0.895)     | 0.0003<br>(0.858)     | 0.0004<br>(0.955)     |
| $\ln(HW\_Firm\_imp)$ | -0.0002<br>(0.492)    | -0.0002<br>(0.510)    | -0.0002<br>(0.450)    | -0.0002<br>(0.426)    | -0.0002<br>(0.420)    | -0.0002<br>(0.408)    |
| $\ln(LW\_Indu\_imp)$ | 0.0027***<br>(5.938)  | 0.0021***<br>(5.380)  | 0.0040***<br>(6.817)  | 0.0031***<br>(6.198)  | 0.0059***<br>(6.888)  | 0.0053***<br>(6.773)  |
| $\ln(HW\_Indu\_imp)$ | -0.0029***<br>(2.966) | -0.0024***<br>(3.060) | -0.0060***<br>(4.489) | -0.0043***<br>(3.863) | -0.0097***<br>(5.274) | -0.0073***<br>(4.556) |
| <b>Firms</b>         | 6932                  | 6932                  | 6932                  | 6932                  | 6932                  | 6932                  |
| <b>Obs.</b>          | 24615                 | 24615                 | 24615                 | 24615                 | 24615                 | 24615                 |

T-value in parentheses

\* significant at 10 per cent; \*\* significant at 5 per cent; \*\*\* significant at 1 per cent

Our baseline model is also estimated for two measures of import competition at higher levels of aggregation. The main impression of Table 4, Columns 3-6, is that the result, that increasing import competition from low-wage countries lead to skill-upgrading carries through for all specifications.

## 6.2 Firm size

In Table 3 all firms with more than 10 employees are included in our regressions. This may not be appropriate because it could be the case that small firms do not have the capacity to identify the foreign produced inputs relevant for their production and thereby choose not to exploit the benefits from cheap imports *directly*. Instead it may be the case that smaller firms utilize advantages from imports *indirectly* through the purchase of cheaper inputs from domestic trading companies/firms located in the service sector. If this is an important channel, the cheaper foreign imports will be deliveries from domestic trading firms to domestic manufacturing firms; deliveries that do not show up in firm imports. These considerations suggests that firm size may play an important role in relation to skill-upgrading and firm imports in manufacturing firms and, consequently, we check the robustness of the main results presented in Table 3 by estimation the labor demand functions for different restrictions on firm size.

TABLE 5: CHANGE IN SKILLED WAGE SHARE AS DEPENDENT VARIABLE, 1999-2003, FIXED EFFECTS ESTIMATION TWO EDUCATION GROUPS, BY MAXIMUM ANNUAL NUMBER OF EMPLOYEES IN SAMPLE PERIOD

|                      | (1)<br>Baseline       | (2)<br><50           | (3)<br>+50-100       | (4)<br>+100           |
|----------------------|-----------------------|----------------------|----------------------|-----------------------|
| $\ln(LW\_Firm\_imp)$ | 0.0004<br>(1.014)     | 0.0004<br>(0.579)    | -0.0014**<br>(2.032) | 0.0016***<br>(3.575)  |
| $\ln(HW\_Firm\_imp)$ | -0.0002<br>(0.492)    | -0.0004<br>(0.676)   | 0.0015**<br>(2.074)  | -0.0007<br>(1.119)    |
| $\ln(LW\_Indu\_imp)$ | 0.0027***<br>(5.938)  | 0.0028***<br>(4.255) | 0.0038***<br>(4.181) | 0.0021***<br>(3.171)  |
| $\ln(HW\_Indu\_imp)$ | -0.0029***<br>(2.966) | -0.0031**<br>(2.278) | -0.0012<br>(0.584)   | -0.0041***<br>(3.051) |
| <b>Firms</b>         | 6932                  | 5055                 | 922                  | 955                   |
| <b>Obs.</b>          | 24615                 | 16748                | 3845                 | 4022                  |

T-value in parentheses

\* significant at 10 per cent; \*\* significant at 5 per cent; \*\*\* significant at 1 per cent

The results are presented in Table 5 Models 2-4; Column 1 presents Model 6, Table 3. It is evident that there is a positive and significant correlation between the change in relative demand for labor and firm imports from low-wage countries when the firm size is larger than or equal to 100 employees. This suggests that firm imports are important for skill-upgrading and that a small firm bias towards domestic deliveries (of foreign produced inputs) hide the correlation when such firms are included. Thus, looking only on larger firms Hypothesis 1 is supported.

### 6.3 Dominating Home Market

A last objection is that the main result that more foreign competition in the home market leads to more skill-upgrading may be picking up an effect from exports markets. It may well be that exporting firms are forced to skill-upgrade and move into niche products to stand up to competition from low-wage countries in the world market. Battu et al. (2003) finds positive externalities at the workplace from hiring certain types of human capital, and so do Munch and Skaksen (2008) using Danish data. Moreover, they find that the human capital spillovers are stronger, the more the firm is exporting. They interpret this as evidence of exporting firms using high-skilled workers to escape the intense competition at international markets.

If the world markets experience the same change in the supply from low-wage countries as those that lead to the changes in the applied measures of import competition from low-wage countries, we cannot rule out that skill-upgrading is a consequence of changing competition in export markets; not home markets. We approach this potential critique by splitting up the sample of manufacturing firms into a group that depends heavily on the home market in terms

of the share of sales delivered to the home market and a group that are more internationally oriented.

TABLE 6: CHANGE IN SKILLED WAGE SHARE AS DEPENDENT VARIABLE, 1999-2003, FIXED EFFECTS ESTIMATION TWO EDUCATION GROUPS, BY MAXIMUM ANNUAL EXPORT/SALES RATIO

|                      | (1)                   | (2)                  | (3)                   | (4)                 | (5)                  |
|----------------------|-----------------------|----------------------|-----------------------|---------------------|----------------------|
|                      | Baseline              | 0-25                 | +25-50                | +50-75              | +75-100              |
| $\ln(LW\_Firm\_imp)$ | 0.0004<br>(1.014)     | -0.0012<br>(1.497)   | -0.0003<br>(0.278)    | 0.0008<br>(0.788)   | 0.0017***<br>(2.860) |
| $\ln(HW\_Firm\_imp)$ | -0.0002<br>(0.492)    | -0.0002<br>(0.293)   | -0.0002<br>(0.275)    | -0.0003<br>(0.330)  | -0.0002<br>(0.326)   |
| $\ln(LW\_Indu\_imp)$ | 0.0027***<br>(5.938)  | 0.0022***<br>(3.465) | 0.0039***<br>(2.979)  | 0.0035**<br>(2.325) | 0.0030***<br>(3.379) |
| $\ln(HW\_Indu\_imp)$ | -0.0029***<br>(2.966) | -0.0022<br>(1.517)   | -0.0074***<br>(2.937) | -0.0014<br>(0.452)  | -0.0023<br>(1.449)   |
| <b>Firms</b>         | 6932                  | 5,341                | 1,265                 | 1,103               | 965                  |
| <b>Obs.</b>          | 24615                 | 16,727               | 2,747                 | 2,458               | 2,683                |

T-value in parentheses

\* significant at 10 per cent; \*\* significant at 5 per cent; \*\*\* significant at 1 per cent

The results are presented in Table 6 Columns 2-5; Column 1 presents Model 6, Table 3. Firstly it can be seen that total product imports from low wage countries have significant positive effect for skill upgrading across all groups of firm. Secondly the effect is somewhat increasing in firm export/sale's ratios. Hence this may be some support for the hypothesis that exporting firms are forced to skill-upgrade and move into niche products to stand up to competition from low-wage countries. But as we also see significant positive effects for firms with low export/sale ratios this is not the only explanation.

## 7 Three Education Types

Until now, we have investigated the skill-upgrading using two skill types. In the following, we apply 3 education types; unskilled, vocational, and academically educated workers. This division is interesting because it can be investigated if skill-upgrading takes place between unskilled labor and vocationally skilled labor or between unskilled labor and academically educated labor.

TABLE 7: CHANGE IN VOCATIONAL AND EDUCATED WAGE SHARES AS DEPENDENT VARIABLES, 1999-2003, FIXED EFFECTS ESTIMATION THREE EDUCATION GROUPS, FIRM AND INDUSTRY IMPORT

|  | Baseline              |                       | Firm Size 100+        |                       |
|--|-----------------------|-----------------------|-----------------------|-----------------------|
|  | VOC<br>(1)            | EDU<br>(2)            | VOC<br>(3)            | EDU<br>(4)            |
| <b>Relative wage<sub>mun</sub>, vocational</b> | 0.0107<br>(0.749)     | -0.0256***<br>(4.573) | 0.0189<br>(1.063)     | -0.0411***<br>(5.810) |
| <b>Relative wage<sub>mun</sub>, education</b>  | -0.0256***<br>(4.573) | 0.0272***<br>(5.349)  | -0.0411***<br>(5.810) | 0.0421***<br>(5.802)  |
| $\ln(Y_i)$                                     | 0.0038**<br>(2.005)   | -0.0153***<br>(9.250) | 0.0053**<br>(2.507)   | -0.0201***<br>(9.435) |
| $\ln(K_i)$                                     | 0.0004<br>(0.268)     | 0.0064***<br>(4.898)  | -0.0007<br>(0.428)    | 0.0080***<br>(4.977)  |
| $\ln(LW\_Firm\_imp)$                           | 0.0003<br>(0.908)     | 0.0004<br>(1.470)     | 0.0006*<br>(1.787)    | 0.0004<br>(1.261)     |
| $\ln(HW\_Firm\_imp)$                           | 0.0004<br>(1.088)     | 0.0003<br>(0.811)     | -0.0001<br>(0.316)    | 0.0001<br>(0.164)     |
| $\ln(LW\_Indu\_imp)$                           | 0.0012***<br>(2.953)  | 0.0012***<br>(3.460)  | 0.0010**<br>(2.039)   | 0.0013***<br>(2.628)  |
| $\ln(HW\_Indu\_imp)$                           | 0.0009<br>(1.051)     | -0.0035***<br>(4.642) | 0.0004<br>(0.397)     | -0.0044***<br>(4.624) |
| $\ln(TECH)$                                    | 0.0008<br>(1.043)     | 0.0053***<br>(7.646)  | 0.0009<br>(0.969)     | 0.0071***<br>(7.721)  |
| <b>Obs.</b>                                    | 6905                  | 6905                  | 3994                  | 3994                  |

T-value in parentheses

\* significant at 10 per cent; \*\* significant at 5 per cent; \*\*\* significant at 1 per cent

The main results are presented in Table 7, columns 1-2. Interestingly, the relative demand for both vocationally and academically educated labor is positively affected by increasing import competition from low-wage countries, whereas import competition from high-wage countries leads to skill-downgrading only for academically educated workers. When it comes to firm imports, there is no correlation between the relative demand for vocationally and academically educated labor and firm imports. Finally, technological progress and physical capital are seen to increase the demand for academically educated labor in relations to unskilled labor only, whereas workers with vocational education are almost unaffected.<sup>7</sup>

Column 3-4 presents the same estimations for firms with more than 100 employees. The main finding is that this restrictions have no major impact on the overall results from the full sample presented in columns 1-2,

<sup>7</sup>Higher wages of vocational and academically educated workers in relation to wages of unskilled workers lead to higher demand for vocational and academic skills, respectively. The results can arise because the relative wage enters in the wage cost share. When the relative wage rate increases, this can result in a higher wage cost share even when the employment share decreases. We have estimated the models of Table 7 using employment shares, rather than wage cost shares, as the dependent variable and find that higher relative wages of both vocationally and academically educated workers lead to lower employment shares for both types. Moreover, the effect on skill-upgrading from changing relative cross wages are negative. Our regressions based on the employment share as dependent variable suggest that this is due to correlation between the two relative wages.

## 8 Conclusion

The relation between skill-upgrading and imports from low-wage countries is studied in this paper. The broader idea is that firms can follow two strategies to stand up to increasing internationalization. One strategy is to lower production costs, which can be accomplished through firm imports of cheap unskilled-labor intensive production from low-wage countries. Another strategy is to switch towards skill-intensive production and avoid import competition from low-wage countries by moving into products markets that are less exposed to imports from low-wage countries.

The study is based on data for Danish Manufacturing that enables us to develop measures of firm imports and product imports that focus on where imports originate rather than on their overall level. The main finding suggests that it is of crucial importance to distinguish import by country-of-origin. It is found that imports from low-wage countries lead to skill-upgrading. Especially, this is the case for product imports, and for imports for larger firms. Moreover, we find that product imports from high-wage countries lead to skill-downgrading.

In order to evaluate the importance of internationalization for skill-upgrading, we estimate the elasticities in the mean of the data. It is found that the elasticity on the relative demand for skilled labor of import competition are around 0.005 for low-wage countries. This elasticities translate into an explained variation in the skilled wage share of  $\sim 30\%$  percent for import competition from low wage countries

The present analysis raises new questions worth exploring in future research. Since the demand for skilled labor, especially, workers with academic education, increases as a consequence of product imports from low-wage countries, it is of interest to understand the tasks that skilled labor performs. If related to more skill-intensive production, it is important to know whether more qualified labor work as production workers or whether they work on tasks such as different types of managers, research and development workers, innovation, marketing personnel, etc. This type of knowledge is of crucial importance to understand how firms in the developed world compete in the world market. In a broader perspective, it is also important, for example, for education policy within the tertiary education.

## References

- [1] Autor, D.H., L.F. Katz, and A.B. Krueger (1998), “Computing Inequality: Have Computers Changed the Labor Market?” *Quarterly Journal of Economics*, 113 (4), 1169-1213
- [2] Batra, R.N., and F.R. Casas (1973), “Intermediate Products and the Pure Theory of International Trade: A Neo-Heckscher-Ohlin Framework,” *American Economic Review*, 63(3), 297-311
- [3] Battu, H., C.R. Belfield and P.J. Sloane (2003), “Human Capital Spillovers Within the Workplace: Evidence for Great Britain”, *Oxford Bulletin of Economics and Statistics*, 65, 575-594.
- [4] Berman, E., J. Bound and Z. Griliches (1994), “Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures,” *Quarterly Journal of Economics*, 109(2), 367-398
- [5] Bernanke, B. (2007), “The Level and Distribution of Economic Well-Being,” <http://www.federalreserve.gov/newsevents/speech/Bernanke20070206a.htm>
- [6] Bernard, A.B., J.B. Jensen, and P.K. Schoot (2006), “Survival of the Best Fit: Exposure to Low-Wage Countries,” *Journal of International Economics*
- [7] Biscourp, Pierre and Francis Kramarz (2007), “Employment, Skill Structure and International Trade: Firm-Level Evidence for France,” *Journal of International Economics*, 72, 22–51.
- [8] Brown, R. S., and L. R. Christensen, (1981), “Estimates of elasticities of substitution in a model of partial static equilibrium: An application to US agriculture”, 1947-1974, in E. R. Berndt and B. C. Field (eds.): *Modelling and measuring natural resource substitution*, 209-229, MIT Press
- [9] Doms, M., T. Dunne, K.R. Troske (1997): “Workers, Wages, and Technology,” *Quarterly Journal of Economics*, 112(1), 253-90
- [10] Ekholm, K., and K. Hakkala (2006), “The Effect of Offshoring on Labor Demand: Evidence from Sweden”, CEPR working paper #5648
- [11] Feenstra, R.C. (2004), *Advanced International Trade: Theory and Evidence*, Princeton University Press
- [12] Feenstra, R.C. and G.D. Hanson (1996), “Globalization, Outsourcing, and Wage Inequality”, *American Economic Review*, 86(2), Papers and Proceedings, 240-245



- [13] Feenstra, R.C. and G.D. Hanson (1999), "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-1990", *Quarterly Journal of Economics*, 114, 907-41
- [14] Harrison, Ann and Margaret McMillan, "Outsourcing Jobs? Multinational and U.S. Employment," July 2006. NBER Working Paper No. 12372.
- [15] Hijzen, A., H. Görg and R.C. Hine (2005), "International Outsourcing and the Skill Structure of Labor Demand in the United Kingdom", *Economic Journal*, 115, 506, 860-878
- [16] Islam, N. (1995), "Growth Empirics: A Panel Data Approach", *Quarterly Journal of Economics*, 443, 1127-1170
- [17] Krugman, P. (2008) "Trade and Wages, Reconsidered", Mimeo Princeton University
- [18] Machin, S., and J. Van Reenen (1998), "Technology and Changes in Skill Structure: Evidence from Seven OECD Countries," *Quarterly Journal of Economics*, 113(4), 1215-1244
- [19] Munch, J.R. and J.R. Skaksen (2008), "Human Capital and Wages in Exporting Firms", *Journal of International Economics*, 75, 363-372.
- [20] Ng, F., and A.J. Yeats (1999), "Production Sharing in East Asia – Who Does What for Whom and Why?", Policy Research Working Paper 2197, World Bank
- [21] Riedel, J. (1976), "Intermediate Inputs and the Theory of International Trade: A Generalization of the Pure Intermediate Good Case", *American Economic Review*, 68(3), 441-447.
- [22] Sørensen, A (2008), "Skill-Upgrading and Internationalization: Country-of-Origin or End-Use of Products", *Economics Letters*, 101(1), 9-12
- [23] Schweinberger, A.G., (1975), "Pure Traded Intermediate Products and The Heckscher-Ohlin Theorem," *American Economic Review*, 65(4), 634-43
- [24] Wood, A. (1995), "How Trade Hurt Unskilled Workers", *Journal of Economic Perspectives*, 9(3), 57-80

## A Appendix 1: The Factor Proportions Framework

In this appendix we present a simple model that analyzes effects on the specialization pattern in a simple setting of 2 final products and 1 pure intermediate input produced using 2 primary production factors. The two primary production factors are skilled labor,  $S$ , and unskilled labor,  $U$ , whereas the pure intermediate input is labelled  $I$ . The domestic economy is abundant in skilled labor.

Production of the two final products  $Q_1$  and  $Q_2$  are determined by production functions

$$\begin{aligned} Q_1 &= AS_1^\alpha U_1^{1-\alpha} + Q_{I_1}, \quad 0 < \alpha < 1 \\ Q_2 &= BS_2^\beta U_2^{1-\beta} + Q_{I_2}, \quad 0 < \beta < 1. \end{aligned} \quad (1)$$

where  $Q_{I_i}$  measures the use of intermediate input in the production of final product  $i$ . The production of pure intermediate input  $Q_I$  is determined by the production function

$$Q_I = CS_I^\gamma U_I^{1-\gamma}, \quad 0 < \gamma < 1 \quad (2)$$

We apply the following simplifying assumptions: (i) the two skill types determine value added according to a Cobb-Douglas aggregate, (ii) the pure intermediate input and value added determines gross output according to a Leontief technology, and (iii)  $Q_{I_i}$  are determined according to  $Q_{I_i} = a_{3i}Q_i$  where  $a_{3i}$  is constant,  $i \in 1, 2$ .

We assume that production of product 1 is more intensive in the use of skilled labor than other products, whereas the intermediate product is more skill intensive than product 2, i.e.,  $\alpha > \gamma > \beta$ .

Prices are determined in the world market and are given by  $p_1$ ,  $p_2$ , and  $p_I$ . Given that the intermediate product is produced in the skill intensive economy, cost minimizing behavior implies that unit costs equal:

$$\begin{aligned} c_1 &= \frac{(1 - a_{31}) w_U^{1-\alpha} w_S^\alpha}{\bar{A}} + a_{31} \frac{w_U^{1-\gamma} w_S^\gamma}{\bar{C}} \\ c_I &= \frac{w_U^{1-\gamma} w_S^\gamma}{\bar{C}} \\ c_2 &= \frac{(1 - a_{32}) w_U^{1-\beta} w_S^\beta}{\bar{B}} + a_{32} \frac{w_U^{1-\gamma} w_S^\gamma}{\bar{C}} \end{aligned} \quad (3)$$

where  $\bar{A} \equiv A\alpha^\alpha (1 - \alpha)^{(1-\alpha)}$ ,  $\bar{B} \equiv B\beta^\beta (1 - \beta)^{(1-\beta)}$  and  $\bar{C} \equiv C\gamma^\gamma (1 - \gamma)^{(1-\gamma)}$ .

Prices are determined in the world market and exogenous to the high-wage country under investigation. Implementing product specific transportation costs of the "iceberg" type,  $\tau_i$ ,

implies that the domestic economy has to supply  $(1 + \tau_i)$  units of product  $i$  for each unit demand of the product in the foreign economy. Likewise, the foreign economy has to supply  $(1 + \tau_i)$  units of each product type per unit demand in the domestic economy. The prices relevant for the domestic economy are the world price multiplied by a product specific transportation cost of the "iceberg" type.

We assume that the skill-intensive products are produced in the country, implying that wages are solved by:

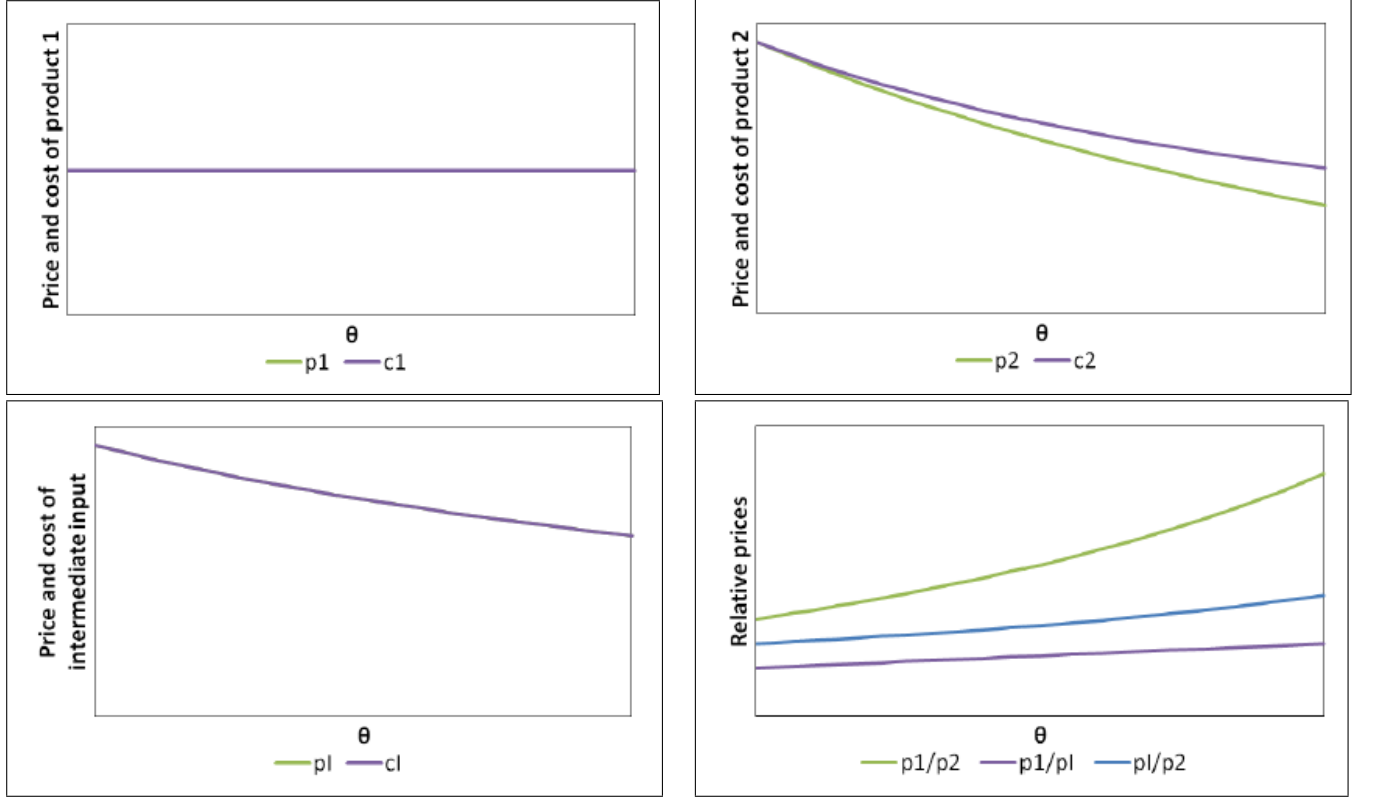
$$\begin{aligned}(1 + \tau_I)p_I &= \frac{w_U^{1-\gamma}w_S^\gamma}{\bar{C}} \\ (1 + \tau_1)p_1 &= \frac{(1 - a_{31})w_U^{1-\alpha}w_S^\alpha}{\bar{A}} + \frac{a_{31}w_U^{1-\gamma}w_S^\gamma}{\bar{C}}\end{aligned}$$

Product 2 is produced if  $(1 + \tau_2)p_2 = c_2$ .

What we have in mind is that unskilled-intensive final product 2 has a higher transportation cost than the intermediate input and final product 1, whereas the intermediate input has a higher transportation cost than final product 1 ( $\tau_1 < \tau_I < \tau_2$ ). When the degree of internationalization increases, we assume that the transportation costs for the products fall in similar proportions implying that relative prices for products leads to higher relative prices of skill-intensive products in the skill-abundant country. These assumptions capture that the largest effect from increasing internationalization is on unskilled-intensive products.

A numerical example is presented in Figure 1, where we let  $\theta = \frac{1}{1+\tau_I}$  measure the degree of internationalization. The figure illustrate a possible change in the production pattern as the degree of internationalization increases:

FIGURE 1: PRODUCT PRICES, PRODUCTION COSTS AND THE DEGREE OF INTERNATIONALIZATION



Note: The panels are derived for the parameters  $\alpha = 0.6$ ,  $\beta = 0.4$ ,  $\gamma = 0.5$ ,  $a_{31} = 0.3$ ,  $a_{32} = 0.25$ ,  $A = 1.96$ ,  $B = 4$ ,  $C = 2$ ,  $p_1 = 2$ ,  $p_I = 1$ ,  $p_2 = 0.3$ , and  $\tau_2 = 3\tau_I$ ,  $\theta = \frac{1}{1+\tau_I}$

# Imports Effects on Skill-Upgrading, New Insights from Firm Level Evidence<sup>1</sup>

CHRISTIAN SCHEUER

*Department of Economics, Copenhagen Business School, and  
Centre for Economic and Business Research (CEBR)*

June 2009

<sup>1</sup>Acknowledgements: The author gratefully acknowledges financial support from the Tuborg Foundation. Further I am grateful for the comments I have received from Daniel le Maire, Nikolaj Malkov Møller, Esben Schultz, Jan Rose Skaksen, Anders Sørensen, and Participants at CBS graduate program workshop. Finally, I thank Christian Gormsen Schmidt for research assistance. All remaining errors are mine. Address: Department of Economics, Copenhagen Business School and Centre for Economic and Business Research, Porcelaenshaven 16A, 2000 Frederiksberg, Denmark.

## **Abstract**

This paper analyzes the implications of imports for skill-upgrading in Danish manufacturing firms. The ability to decompose firm level imports combined with the information contained in a full panel of matched employer-employee data are utilized to show that it is of crucial importance to distinguish imports by country-of-origin and level of processing when analyzing skill-upgrading. It is shown that pooling imports from all countries and disregarding import of final products, as is the case when using input-output tables, will significantly bias the influence of imports on skill-upgrading, leading to an under-evaluation of the role of imports. Furthermore, the empirical evidence suggests that import's explanatory power for skill-upgrading increases with firm size.

*Keywords:* Skill-upgrading, firm import, low-wage country outsourcing, comparative advantage

*JEL:* F14, F16, J21, J24, L60

# 1 Introduction

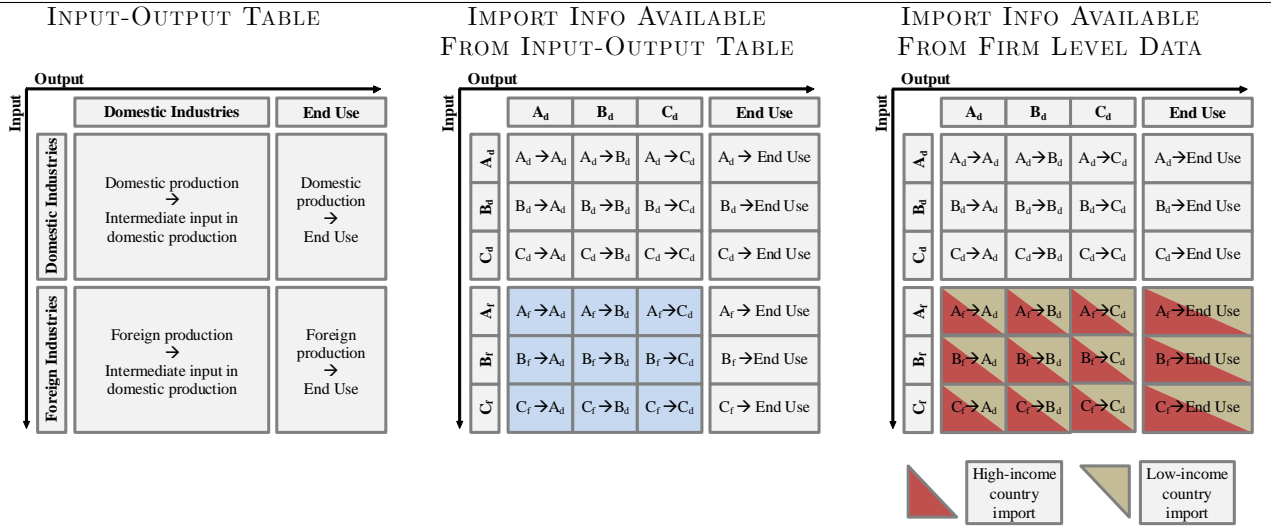
The purpose of this paper is to analyze the implications of imports for skill-upgrading in Danish manufacturing firms. Based on high quality micro level evidence the novel approach applied allow for several new and important insights. Firstly, disregarding imports of final products significantly bias the results and lead to under-evaluation of import's role for skill-upgrading. Secondly, the ability to distinguish imports according to country of origin and level of processing is shown to be of vital importance for understanding the implications of imports on skill-upgrading. Thirdly, it is shown that the explanatory power of import of final goods for skill-upgrading is increasing with firm size.

In the seminal paper by Feenstra and Hanson (1996), the authors investigate the idea that US firms offshore production activities that use unskilled labor intensively. Feenstra and Hanson use input-output data to show that trade in intermediate inputs between countries plays an important role as driving mechanism for skill-upgrading. Since then, their method has been widely applied to establish evidence that skill-upgrading is affected by imports for many developed countries, see e.g. Feenstra and Hanson (1999) and Feenstra (2004) for US, and Hijzen, Görg and Hine (2005) for UK.

Nevertheless, using import information from input-output data has two potential pitfalls as illustrated in figure 1<sup>1</sup>:

1. It does not distinguish imports by country-of origin.<sup>2</sup>
2. It does not include import of final products.

FIGURE 1: POTENTIAL PITFALLS WHEN USING INPUT-OUTPUT TABLES



<sup>1</sup>For simplification, the illustration is made for a three sector economy.

<sup>2</sup>An exception are Ekholm and Hakkala (2006) who address the issue using input-output tables for Sweden combined with Swedish trade statistics to construct proxies of import from low- or high-income countries.

The current paper contributes by addressing both of these problems.

The left panel of figure 1 illustrates the basic principle behind an input-output table. That is, how domestic and foreign industries supply intermediate input to domestic industries and final products for domestic end-use.

The middle panel illustrates how an input-output table only contains industry level information on import of intermediate goods. Such information is limited to analysis on industry level, e.g. how is domestic industry  $A_d$  affected by total imports from foreign industry  $A_f$ , or how is domestic industry  $B_d$  affected by total imports from foreign industry  $C_f$ , etc.

Finally, the right panel illustrates how firm level evidence, as used in this study, contributes by adding additional information on import of end products, and the ability to distinguish import according to country of origin. Hence, offering the following advantages over input-output data:

1. As the data used contain information on the exact country of origin of almost every good imported to every firm in Denmark, one can split imports by country of origin and analyze its importance for skill-upgrading for different countries or group of countries. Section 2 of this paper presents a theoretical argument why trading with foreign countries with lower income levels and abundance of unskilled labor will lead to domestic skill-upgrading. However, it is not immediately clear why trade with similar countries in respect to income levels and skill distribution should have the same effects. Hence, this paper splits imports according to whether it originates from low- or high-income countries. And, as a matter of fact, it is shown that pooling trade from all countries will significantly bias the empirical effect of imports on skill upgrading.
2. Firm level evidence allows adding import of final goods to the analysis. This may potentially be of great importance, as economies today become more integrated leading to increased trade, also in final goods, and as we actually observe lot of import of final goods in Danish manufacturing firms in the sample period.
3. Firm level evidence will capture any within industry differences in import's effect on skill-upgrading neglected in industry level data. Hence, adding potential important effects from firms or groups of firms within industries adjusting their product-mix without changing industry.
4. Employer-employee data can be used to identify and analyze groups or types of firms across the traditional industry classification where the effects of import on skill-upgrading are especially pronounced. More specifically, this paper examines three sources of variation that may cause manufacturing firms' skill-upgrading to be exposed to a varying extent to changes in imports; difference in trade patterns, industry stability and firm size.



This paper is not the first study to depart from the traditional use of input-output tables. Bernard, Jensen, and Schott (2006), Biscourp and Kramarz (2007) and Scheuer et al (2008) all use micro level evidence.

Bernard, Jensen, and Schott (2006) have a rather different perspective than the current study, since their focus are on the effect of import competition measured at the firm level as domestic total import of goods from the particular industry of the given firm. Their main result is that import competition from low-income countries imposes trade pressure, which leads firms to adjust their product mix.

Biscourp and Kramarz (2007) are more closely related to the present study and are based on French micro data for the period 1986-1992 in many ways similar to data used here. Biscourp and Kramarz (2007) find a strong correlation between import of final goods and job destruction of production jobs. Also in line with the findings here, they find the relation between job destruction and imports to be stronger for larger firms. Besides the somewhat different framework they use, the two major differences to the present study are the period covered, and the availability of educational attainment of workers. The period covered in the present study (1999-2003) is a period of increased trade with low-income countries that has been taking place due to the opening of the markets in Russia, East Europe, India and China. Also here, the data allows for a distinguishing of workers according to their education instead of the usual production/ non-production categorization. This may be of importance as the correlation between educational level and production/ non-production is low (see e.g. Doms, Dunne, and Troske (1997)), and since education is a better measure of workers' skills.

Scheuer et al (2008) use the same data as the present study to compare two distinct mechanisms through which internationalization potentially influences firms' relative demand for skilled labor. The first mechanism is "the internal firm effect" which is based on firm level imports and captures the increasing possibility for firms to lower production costs by taking advantage of cheap inputs produced in low-income countries. The second mechanism is "the external product effect" which is based on import competition and seeks to capture the effect that firms meet stronger competition in their domestic product markets when imports from low-wage countries of products they themselves produce, increase. Scheuer et al (2008) conclude that the external industry effect is the most important for explaining skill-upgrading. This paper contributes by rethinking how to use information on the internal firm effect, and shows that accounting for level of processing, especially in the case of larger firms, reintroduces the internal firm effect as an important determinant for skill-upgrading in Denmark.

The remainder of this paper is organized as follows. Section 2 outlines the main hypothesis tested. Section 3 presents the basic econometric specification used and discusses the econometric strategy. Section 4 describes the data set applied in the analysis. Section 5 presents empirical results, while section 6 concludes.

## 2 Model

The following model leading to the main hypothesis tested *"that the relative demand for skilled labor in high-income countries increases with the extent of manufacturing firm imports from low-income countries"* is based on the factor proportions framework. The full model is explained and derived in the appendix to Scheuer et al (2008).

The model is a two-country model with a domestic and a foreign (denoted by a  $*$ ) country. The economy has two final goods and one intermediate input  $(1, 2, I)$  and two primary inputs; skilled and unskilled workers  $(S, U)$ . The ranking of skill intensity in production is such that the production of good 1 is most skill intensive, and the product of good 2 least skill intensive:  $\left(\frac{S^1}{U^1} > \frac{S^I}{U^I} > \frac{S^2}{U^2}\right)$ . Furthermore, it is assumed that the home country is endowed with more skilled labor than the foreign country  $\left(\frac{S^d}{U^d} > \frac{S^*}{U^*}\right)$ . Finally price is assumed exogenous to the domestic economy (determined in the world market), and hence, the prices relevant for the domestic economy are the world price plus a product specific transportation cost of the "iceberg" type. In the initial setting these "iceberg"-type transportation costs are assumed inversely related to skilled intensity such that

$$\tau_2 > \tau_I > \tau_1$$

When the degree of internationalization increases, it is assume that the transportation costs for the products fall in similar proportions implying that relative prices for products leads to higher relative prices of skill-intensive products in the skill-abundant country. These assumptions capture that the largest effect from increasing internationalization is on unskilled-intensive products.

Under these conditions it is shown that an increase in internationalization will lead the skill-abundant economy to specialize further in skill-intensive product 1, implying that imports of intermediate inputs will increase, and that the skill-abundant country also will specialize in skill-intensive product 1 over unskill-intensive product 2. It is further shown that at a threshold level the home country will restrain from producing product 2.

Departing from the traditional factor proportion framework and interpreting the results as if domestic firms produce in bundles of disaggregate products allowing them to potentially produce both the final products and the intermediate input, means that increasing internationalization as measured by the lower transportation costs will cause domestic firms to shift production towards more skill-intensive product bundles. I.e., lower transportation cost will lead domestic firms to alter their product mix, and eventually switch completely away from producing certain products - here final product 2.

Hence, leading us to the following testable hypothesis:

**Hypothesis:** *The relative demand for skilled labor at the firm level increases with the extent*

of firm imports from low-wage countries.

### 3 Econometric Framework

The empirical specification is based on the translog cost function.<sup>3</sup> The cost function is log-linearized and following the framework in Brown and Christensen (1981), the different types of labor are assumed to be variable inputs whereas capital is assumed to be a quasi fixed input. The specification here applies to the firm level rather than the industry level.

Next, measures of international trade and technology are included as shift share variables. Imports at the firm level are included defined as intensities and split according to country of origin (*LIC*: low-income countries, *HIC*: high-income countries) and level of processing (*INT*: Intermediate goods, *FIN*: Final goods). Unfortunately, no technology measures are available in the data at the firm level, so instead an industry measure *tech* is used (as explained in more details in next section).

In the model for two labor types the translog cost function generates a wage cost share equation of the following form:

$$\begin{aligned}
S_{\text{skilled},i,j,t} = & \beta_0 + \beta_1 \ln \left( \frac{w_{\text{skilled},i,t}}{w_{\text{unskilled},i,t}} \right) + \beta_2 \ln(Y_{i,t}) + \beta_3 \ln(K_{i,t}) \\
& + \beta_4 \frac{\text{imp}_{i,t}^{LIC,INT}}{Y_{i,t}} + \beta_5 \frac{\text{imp}_{i,t}^{HIC,INT}}{Y_{i,t}} \\
& + \beta_6 \frac{\text{imp}_{i,t}^{LIC,FIN}}{Y_{i,t}} + \beta_7 \frac{\text{imp}_{i,t}^{HIC,FIN}}{Y_{i,t}} \\
& + \beta_8 \frac{\text{tech}_{j,t}}{Y_{j,t}} + \alpha_{\text{skilled},i} + \varepsilon_{\text{skilled},i,t}
\end{aligned}$$

where  $S_{\text{skilled},i,j,t}$  is the cost share of skilled labor to total labor costs in firm  $i$ , located in industry  $j$ , observed at time  $t$ . The cost share of skilled labor measures the firm's demand for skilled labor, which is derived using Shephard's lemma.  $w_{\text{skilled}}/w_{\text{unskilled}}$  is the relative wage of skilled labor to unskilled labor,  $Y$  is total production,  $K$  is the capital stock,  $\alpha_{\text{skilled}}$  is a firm fixed effect and  $\varepsilon_{\text{skilled}}$  is assumed to be an i.i.d. error component.

In general, estimating a translog cost function generates a series of wage cost share equations, one for each type of variable input. Imposing the standard restrictions of symmetry and homogeneity of degree 1 in prices allows for reaching the specification above where one of the equations is redundant. In the case of two labor inputs, the estimates of the similar equation for the wage cost share of unskilled labor can be recovered from the symmetry restrictions without actually estimating the equation.

---

<sup>3</sup>The transcendental logarithmic function was developed in Kmenta (1967) to approximate the CES-function, but this study is more closely related to Christensen and Greene (1976) and Berndt (1991).

All regressions are performed using fixed effects estimation, implying that the model parameters are identified using only variation *within* firms over time. Thus, the hypothesis tested is whether *change* in imports will cause a *change* in the cost share between skilled and unskilled workers. Or put differently, this paper does not test the absolute hypothesis that firms with the highest imports from low-income countries have the highest share of skilled labor. The latter is disregarded since empirically there are several examples of very high-skilled industries with no or little low-income country imports, and vice-versa, e.g. caused by lack of production facilities or workers in low-income countries qualified for very skill intensive production. Such patterns would cause omitted variable bias and/or endogeneity issues if estimating our model using a linear specification.

## 4 Data

The data used in this study is primarily drawn from Statistics Denmark's registers. A matched employer-employee dataset with yearly information on workers and firms covering the period 1999-2003 is constructed from the Danish Firm Integrated Database for Labor Market Research (FIDA), the Danish Integrated Database for Labor Market Research (IDA) and the External Trade Statistics.

Since the External Trade Statistics are limited to trade in goods and not services the sample used is restricted to *private manufacturing firms*. Furthermore, the attention is restricted to firms with more than 10 employees in any given year to avoid the technical problem of many small firms having zero employees of a given skill type which would represent a corner solution in a model of relative labor demand.<sup>4</sup>

From the databases it is possible to identify any workers in any firm in all the years covered. The IDA database contains variables for every worker in the Danish labor market and the FIDA database contains variables for every active firm in the Danish labor market.

The analysis here is performed on the basis of two types of labor; skilled and unskilled. Skilled labor is defined as persons with a qualifying education above high-school level, which in Denmark includes the following categories: Vocational education, most often a mix of schooling and training in firms with a typical duration around 3 years. Short academic education; typically up to two years on top of high school and with a practical focus. Medium academic education corresponds to the bachelor level. Long academic education corresponds to the master level or more.

The dependent variable in the analysis, wage cost share, is constructed for each type of labor at the firm level using information on education and wages.

---

<sup>4</sup>Finally, the few firms that still do not employ both labor types are excluded from the sample. A restriction, that represents well below a one per cent reduction in the sample for any of the two labor types in any sample year.

Table 1 compares the sample used to the sample of all manufacturing firms and illustrates the development of key variables over the sampling period.

| TABLE 1: TOTAL WAGE COST SHARES COMPOSITION IN DANISH<br>MANUFACTURING |        |        |        |        |        |
|--|--------|--------|--------|--------|--------|
|  | 1999   | 2000   | 2001   | 2002   | 2003   |
| <b>All Manufacturing Firms</b>   |        |        |        |        |        |
| <b>No education</b>  | 34.0%  | 33.6%  | 32.8%  | 32.0%  | 31.0%  |
| <b>Vocational Education</b>  | 44.4%  | 44.6%  | 44.8%  | 44.6%  | 44.2%  |
| <b>Short Academic Education</b>  | 6.4%   | 6.5%   | 6.8%   | 7.1%   | 7.6%   |
| <b>Medium Academic Education</b>                                       | 10.1%  | 10.0%  | 10.2%  | 10.4%  | 10.7%  |
| <b>Long Academic Education</b>   | 5.2%   | 5.2%   | 5.5%   | 6.0%   | 6.5%   |
| <b>Firms</b>   | 13,335 | 13,130 | 12,787 | 12,374 | 12,100 |
| <b>Workers / 1000</b>  | 433.0  | 436.8  | 430.3  | 416.9  | 397.2  |
| <b>Turnover, DKK Billions</b>  | 465.0  | 517.7  | 551.9  | 550.2  | 543.7  |
| <b>Capital, DKK Billions</b>   | 434.2  | 477.9  | 488.5  | 495.8  | 506.5  |
| <b>Full Sample</b>   |        |        |        |        |        |
| <b>No education</b>  | 33.9%  | 33.6%  | 32.7%  | 32.0%  | 31.0%  |
| <b>All Educations</b>  | 66.1%  | 66.4%  | 67.3%  | 68.0%  | 69.0%  |
| <b>Firms</b>   | 5,192  | 5,131  | 5,004  | 4,800  | 4,664  |
| <b>Workers / 1000</b>  | 391.7  | 397.0  | 390.6  | 379.9  | 361.3  |
| <b>Turnover, DKK Billions</b>  | 435.4  | 487.6  | 520.5  | 520.5  | 514.8  |
| <b>Capital, DKK Billions</b>   | 413.8  | 456.6  | 467.4  | 474.5  | 485.3  |

It is evident from table 1 that skill-upgrading has taken place in Denmark over the relative short time span covered by the sample, as the wage cost share of unskilled workers have fallen with almost three percentage points over the five years from 1999-2003.

Moreover, the sample is seen to contain annual observations for slightly less than 400,000 workers in around 5,000 Danish manufacturing firms.

Comparing the full sample with all manufacturing firms, one sees, that although the restrictions imply an exclusion of approximately 7,000 of the smallest firms, the full sample still represents the vast majority of manufacturing covering more than 90 per cent of total manufacturing turnover and more than 90 per cent of manufacturing workers.

Having defined the sample used, the remainder of this section is devoted to the development of the explanatory variables needed for the analysis as outlined in the econometric framework in section 3.

First variable needed is the relative wage between skilled and unskilled workers in each year in each firm in the sample. This variable is immediately available, but since wage policies are a crucial part of the strategic positioning of firms in the context of globalization one may rightfully fear that firm level relative wages are potentially endogenous. Therefore, the empirical analysis is carried out using the relative wage measured at the municipality level (*mun*). The municipality skill-specific wage measures are calculated from information on individual wage

for all workers of all types.<sup>5</sup>

The next set of variables, the log of total production and the capital stock at the firm level are readily available. Firm level information on turnover and capital stock measured by the value of fixed assets from the firms' balance sheet are drawn from the FIDA database.

Next group of variables to be constructed are firm level imports. Imports are split in two dimensions according to country of origin and the level of processing of the goods traded. Information on imports at the firm level is drawn from the External Trade Statistics, which contains information on the value, origin and type of all goods imported to Denmark. The database contains information on all goods imported from outside the EU but is limited to all products imported from within the EU by firms with total EU-imports of more than 1.8 million DKK (or around \$300,000). This restriction is fairly unproblematic since the limit is fairly low considering that the sample only contains firms with more than 10 employees.

The first split on country of origin is done separating imports in two groups according to which countries trade takes place with; low and middle income countries (*LMIC*) or high income countries (*HIC*) according to 2005 GNI per capita, calculated using the World Bank Atlas method.<sup>6</sup>

The next split according to the level of processing is done separating imported goods according to whether they are intermediate or final goods. This split is done using the available product codes in the External Trade Statistics to group goods according to the UN BEC classification.<sup>7</sup>

Table 2 presents import data for Danish firms.

---

<sup>5</sup>Data on individual wages and working hours are aggregated to the municipality level for all workers in all firms included in the sample. These aggregates are used to calculate the relevant hourly wage rate for each labor type in each of the 271 municipalities.

<sup>6</sup>These groups are defined as: low income, \$875 or less; lower middle income, \$876 - \$3,465; upper middle income, \$3,466 - \$10,725; and high income, \$10,726 or more. For the exact method, see <http://go.worldbank.org/IEH2RL06U0>.

<sup>7</sup>See <http://unstats.un.org/unsd/class/intercop/expertgroup/2007/AC124-8.PDF>. More specifically the BEC coding described on page 9 of the document is used. 5 BEC codes are not directly classified according to intermediate/ consumptions goods. These are: Capital goods (41 & 521), Motor spirit (321), Passenger motor cars (51) and Goods not elsewhere specified (7). Here, they are all categorized as consumption goods. The sensitivity of the placement of these groups of goods has been tested and it is of minor importance for the results reported in this paper.

| TABLE 2: IMPORT IN DANISH FIRMS BY COUNTRY OF ORIGINS INCOME PER CAPITA,<br>DKK BILLIONS |       |       |       |       |       |       |       |       |       |
|--|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Countries by<br>Income Group:  | Year  |       |       |       |       |       |       |       |       |
|  | 1995  | 1996  | 1997  | 1998  | 1999  | 2000  | 2001  | 2002  | 2003  |
| <b>All Firms</b>   |       |       |       |       |       |       |       |       |       |
| <b>Total</b>   | 256.1 | 261.0 | 293.1 | 309.8 | 310.6 | 358.9 | 331.0 | 346.4 | 332.2 |
| <b>High OECD</b>   | 220.9 | 223.8 | 249.8 | 264.8 | 263.3 | 299.1 | 269.2 | 284.8 | 264.4 |
| <b>High Non-OECD</b>   | 7.1   | 7.0   | 8.0   | 8.3   | 8.8   | 12.1  | 9.8   | 9.9   | 12.2  |
| <b>Upper Middle</b>  | 13.5  | 14.5  | 16.4  | 17.8  | 19.0  | 24.0  | 28.4  | 28.0  | 28.9  |
| <b>Lower Middle</b>  | 9.7   | 10.3  | 13.7  | 13.5  | 14.1  | 17.3  | 17.1  | 16.7  | 19.7  |
| <b>Low</b>   | 2.7   | 3.2   | 2.9   | 3.2   | 3.0   | 3.7   | 3.9   | 4.2   | 4.4   |
| <b>Unknown</b>   | 2.1   | 2.1   | 2.3   | 2.3   | 2.4   | 2.7   | 2.7   | 2.7   | 2.5   |
| <b>All Manufacturing Firms</b>   |       |       |       |       |       |       |       |       |       |
| <b>Low &amp; Middle</b>  |       |       |       |       | 10.9  | 12.7  | 14.6  | 14.2  | 15.3  |
| <b>High</b>  |       |       |       |       | 61.2  | 69.7  | 79.6  | 80.3  | 77.0  |
| <b>Full Sample</b>   |       |       |       |       |       |       |       |       |       |
| <b>Low &amp; Middle</b>  |       |       |       |       | 10.5  | 12.3  | 14.0  | 13.8  | 14.7  |
| <b>High</b>  |       |       |       |       | 60.1  | 68.5  | 77.8  | 79.0  | 75.8  |

The table shows that imports from low and middle-income countries have increased by nearly 50 per cent from 36 to 53 billion DKK in the time span (1999-2003) covered in this study. Furthermore, it is evident that the imports included in the sample represents the vast majority of all manufacturing firms' imports in the period covered.

The last variable needed for the analysis is a technology measure, but unfortunately Statistics Denmark's data does not contain such a measure at the firm level. Since technological change is a potential confounding variable in explaining skill-upgrading the solution here is to include an industry level measure. In the existing literature, different measures have been used in pursuit of capturing the increase in efficiency of skilled and educated labor. Autor, Katz, and Krueger (1998) show that the diffusion of computers and related technologies is an important source of changes in the relative demand of skills and, thereby, in the relative efficiency of skilled labor. This paper follows Machin and Van Reenen (1998) in using R&D intensities to explain skill-upgrading.

The data on R&D intensities is taken from the OECD ANBERD database. R&D intensities are included as R&D expenditures within each industry divided by the industry production. R&D intensities compatible with the applied databases, i.e., industry-structure ISIC Revision 3 within manufacturing, only exist on an aggregated 13 manufacturing industry level, and thus, these are used in the analysis.

## 5 Results

This section presents and analyzes the empirical estimations.

First subsection contains full sample estimates of the empirical effects on skill-upgrading in the form of changing wage share in the sample period 1999-2003. Most importantly, the section addresses the empirical importance of distinguishing the effect of imports on skill-upgrading according to country of origin and level of processing of the goods imported.

The second and final subsection explores the mechanisms behind skill-upgrading in further details, seeking to find the groups or types of firms within manufacturing, that are especially prone to skill-upgrading as a consequence of imports. Here, a number of subsamples are identified according to appropriate measures and the resulting estimates for each subsample are analyzed in more detail.

### 5.1 The Importance of Distinguishing Between Country of Origin and Level of Processing

Table 3 presents full sample estimates (including approximately 7,000 firms and 25,000 workers) of four models all with the dependent variable being the wage share of skilled workers. The models are arranged according to the level of details in the imports information used.



TABLE 3: CHANGE IN SKILLED WAGE SHARE,  
1999-2003, DIFFERENT MEASURES OF FIRM IMPORT

|                                       | (1)      | (2)      | (3)      | (4)      |
|---------------------------------------|----------|----------|----------|----------|
| <b>Relative wage,<br/>Skilled</b>     | -0.057   | -0.057   | -0.056   | -0.057   |
|                                       | (4.25)** | (4.26)** | (4.25)** | (4.26)** |
| $\ln(Y_i)$                            | -0.003   | -0.003   | -0.003   | -0.003   |
|                                       | (1.87)   | (1.90)   | (1.90)   | (1.84)   |
| $\ln(K_i)$                            | 0.001    | 0.002    | 0.002    | 0.002    |
|                                       | (1.04)   | (1.06)   | (1.07)   | (1.06)   |
| $\frac{\text{Imp}_i}{Y_i}$            | 0.002    |          |          |          |
|                                       | (0.59)   |          |          |          |
| $\frac{\text{Imp\_int}_i}{Y_i}$       |          | -0.002   |          |          |
|                                       |          | (0.38)   |          |          |
| $\frac{\text{Imp\_fin}_i}{Y_i}$       |          | 0.006    |          |          |
|                                       |          | (1.18)   |          |          |
| $\frac{\text{Imp\_int\_lmic}_i}{Y_i}$ |          |          | 0.043    | 0.041    |
|                                       |          |          | (2.31)*  | (2.23)*  |
| $\frac{\text{Imp\_int\_hic}_i}{Y_i}$  |          |          | -0.009   | -0.009   |
|                                       |          |          | (1.54)   | (1.52)   |
| $\frac{\text{Imp\_fin\_lmic}_i}{Y_i}$ |          |          |          | 0.011    |
|                                       |          |          |          | (1.76)   |
| $\frac{\text{Imp\_fin\_hic}_i}{Y_i}$  |          |          |          | -0.004   |
|                                       |          |          |          | (0.43)   |
| $\frac{\text{R\&D}_j}{Y_j}$           | 0.382    | 0.382    | 0.378    | 0.377    |
|                                       | (7.63)** | (7.63)** | (7.56)** | (7.53)** |
| <b>Firms</b>                          | 6970     | 6970     | 6970     | 6970     |
| <b>Obs.</b>                           | 24791    | 24791    | 24791    | 24791    |

Standard errors in parentheses

\* significant at 5 per cent; \*\* significant at 1 per cent

The first reported model (model 1) mimics the information contained in an ordinary input-output table and, hence, the only measure of firm import intensities included is total import of intermediate goods. This model shows only small and insignificant effects of changes in the intermediate import intensity on skill-upgrading.

Furthermore, it is seen, that there are only two significant explanatory variables for skill-upgrading in model 1. Firstly, ceteris paribus, increasing relative wages for skilled workers leads to lower wage shares for skilled workers, which points to a substitution between skilled and unskilled workers according to their relative price. Secondly, industry R&D is positively related to the wage share of skilled workers, which is in line with the general idea that skilled workers are complementary to new technology.

Next, neither the log of output nor the log of the measure of firm capital stock appears to affect the relative demand for skilled labor. That output does not affect the relative cost shares, is in line with constant returns to scale. A potential explanation for the latter effect, that capital stock has no effect on skill-upgrading, is that the time series for physical capital is smooth and therefore it is difficult statistically to distinguish between a time trend and the

development in physical capital, see for example Islam (1995).

The next model (model 2) investigates the effect of adding import intensities of final goods as an additional explanatory variable. Neither of the import intensities have significant effects on skill-upgrading. In conclusion, simply adding final goods do not aid the empirical explanatory power of imports on skill-upgrading.

Model 3 includes information on imports of intermediate goods. Splitting the intermediate imports according to country of origin has interesting implications. Intermediate import intensities from low- and middle-income countries are now seen to have significant positive effect on skill-upgrading, whereas there is no significant effect from intermediate import intensities from high-income countries. These results are fully in line with the theoretical framework that predicts positive impact on skill-upgrading in a high-income country as a consequence of trade with low- and middle-income countries. Thus, this points to the fact, that pooling imports from all countries contaminates this positive effect on skill-upgrading from low- and middle-income country import of intermediate goods.

This suggests that Danish manufacturing firms have comparative advantages in skill-intensive production when compared to low- and middle-income countries and no special comparative advantages in production when compared to other high-income countries.

In model 4 final good import intensities are split according to country of origin and added as explanatory variables. Estimating on the full sample there is no significant effect on skill-upgrading from import of final goods from neither low- and middle- nor high-income countries, although the final good import intensity from low- and middle-income countries is close to borderline significance.

In conclusion, *the results of table 3 support the hypothesis that the relative demand for skilled labor in high-income countries (in this case Denmark) increases with the extent of manufacturing firm imports from low-income countries*

Hence, it is of crucial importance to distinguish imports by country of origin, since pooling imports from all countries will significantly bias the results and lead to under-evaluation of the effect of imports on skill-upgrading. However, including final goods have not yet shown to be of high importance. The latter result is somewhat puzzling and, hence, the next subsection is devoted to investigating these results in more details and, especially, to explore to what extent the results of this section hold for different subsamples of manufacturing firms.

## 5.2 For Whom Imports Really Matters

In this subsection three sources of potential importance for manufacturing firm's exposure to skill-upgrading are investigated in detail; difference in trade patterns, industry stability and firm size (here approximated by the number of employees). For each of these factors in turn, potential subsamples within all manufacturing firms are selected, and the degree of skill-

upgrading in each subsample due to changing import intensities according to country of origin and level of processing is examined.

First it is tested whether firms more engaged in international trade are especially prone to skill-upgrading caused by firm level imports. This is investigated by constructing three subsamples with respectively firms engaged in imports, firms engaged in export and firms engaged in both.

Secondly, the subsample of firms who stay within the same industry in the period covered is investigated.<sup>8</sup> Changing industry is not very pronounced. Almost 90 per cent of the firms in the sample stay within the same industry during the period covered. There are two main reasons to focus on firms staying within the same industry. One may argue that a firm actually changing industry is much more likely to be influenced by external factors not controlled for in this analysis, e.g. environmental or legal regulation etc. And, when a firm changes industry it will potentially (depending on the degree of change) also get assigned a new industry specific R&D intensity, which potentially may conflict with the interpretation of the results.

Thirdly it is tested whether firm size matters for import's effect on skill-upgrading. There are several reasons to expect different empirical evidence according to firm size.

One could imagine that smaller firms are not rewarded to the same degree as larger firms for finding their own foreign suppliers, simply due to differences in scale. Furthermore, import of final goods may be a stage of production (e.g. assembly) where many low- and middle-income countries have a comparative advantage, see Ng and Yeats (1999). However, the most obvious way for firms to utilize this advantage is to set up own plants in the foreign country, an activity that predominantly takes place in the case of larger firms.

Besides this, the available data is likely to be less informative for smaller firms. The reason is that smaller firms do not have the same possibility for finding low- and middle-income country suppliers and, therefore, smaller firms are likely to a larger extent to choose to buy their intermediate inputs or final goods from a third part trading company located in Denmark outside the manufacturing sector. Hence, these goods do not show up as imports in the data used.

Both hypotheses suggest that estimating using samples of larger firms, the effect of low- and middle-income country imports on skill-upgrading should increase. Therefore, all estimations are performed for groups of firms according to size, where size is defined as the maximum annual number of employees from the five year sample period. The firms are split into five groups; firms with a maximum of 10-50 employees, 51-100 employees, 101-200 employees, 201-500 employees and above 500 employees.

Before presenting the estimation results, table 4 and 5 introduce characteristics of the chosen

---

<sup>8</sup>Here industry is defined using the DB nomenclature, which is Statistics Denmark's more disaggregated version of NACE rev. 1 industrial classification. The classification is used in its most disaggregated version implying 316 different manufacturing industries (DB03).

subsamples. Table 4 presents the number of workers covered by the subsamples as well as the developments in wage share composition over the sample period and table 5 the pattern of imports by country of origin over the sample period.

| TABLE 4: TOTAL WAGE COST SHARES COMPOSITION, SELECTED GROUPS WITHIN DANISH MANUFACTURING |       |       |       |       |       |                          |       |       |       |       |
|--|-------|-------|-------|-------|-------|--------------------------|-------|-------|-------|-------|
|  | Year  |       |       |       |       | Year                     |       |       |       |       |
|  | 1999  | 2000  | 2001  | 2002  | 2003  | 1999                     | 2000  | 2001  | 2002  | 2003  |
| <b>Full Sample</b>   |       |       |       |       |       | <b>10-50 Employees</b>   |       |       |       |       |
| <b>Workers / 1000</b>  | 391.7 | 397.0 | 390.6 | 379.9 | 361.3 | 72.9                     | 72.2  | 70.2  | 66.9  | 64.3  |
| <b>No Education</b>  | 33.9% | 33.6% | 32.7% | 32.0% | 31.0% | 32.0%                    | 31.4% | 30.6% | 30.0% | 29.3% |
| <b>All Educations</b>  | 66.1% | 66.4% | 67.3% | 68.0% | 69.0% | 68.0%                    | 68.6% | 69.4% | 70.0% | 70.7% |
| <b>Importing Firms</b>   |       |       |       |       |       | <b>51-100 Employees</b>  |       |       |       |       |
| <b>Workers / 1000</b>  | 359.0 | 364.1 | 359.1 | 349.9 | 330.3 | 48.5                     | 49.0  | 46.7  | 45.1  | 43.0  |
| <b>No Education</b>  | 34.2% | 33.8% | 32.9% | 32.2% | 31.3% | 34.0%                    | 33.7% | 32.6% | 32.0% | 31.2% |
| <b>All Educations</b>  | 65.8% | 66.2% | 67.1% | 67.8% | 68.7% | 66.0%                    | 66.3% | 67.4% | 68.0% | 68.8% |
| <b>Exporting Firms</b>   |       |       |       |       |       | <b>101-200 Employees</b> |       |       |       |       |
| <b>Workers / 1000</b>  | 355.0 | 360.4 | 353.7 | 344.9 | 328.7 | 49.9                     | 51.1  | 50.3  | 47.7  | 44.4  |
| <b>No Education</b>  | 34.1% | 33.8% | 32.9% | 32.2% | 31.2% | 35.2%                    | 34.8% | 34.3% | 33.5% | 32.5% |
| <b>All Educations</b>  | 65.9% | 66.2% | 67.1% | 67.8% | 68.8% | 64.8%                    | 65.2% | 65.7% | 66.5% | 67.5% |
| <b>Im- and Exporting Firms</b>   |       |       |       |       |       | <b>201-500 Employees</b> |       |       |       |       |
| <b>Workers / 1000</b>  | 342.6 | 348.1 | 341.9 | 334.5 | 316.7 | 75.3                     | 77.1  | 76.5  | 74.2  | 69.5  |
| <b>No Education</b>  | 34.2% | 33.9% | 33.1% | 32.3% | 31.4% | 35.0%                    | 34.6% | 33.0% | 32.6% | 32.2% |
| <b>All Educations</b>  | 65.8% | 66.1% | 66.9% | 67.7% | 68.6% | 65.0%                    | 65.4% | 67.0% | 67.4% | 67.8% |
| <b>Same Industry Firms</b>   |       |       |       |       |       | <b>+500 Employees</b>    |       |       |       |       |
| <b>Workers / 1000</b>  | 347.4 | 350.2 | 343.1 | 334.9 | 320.4 | 145.0                    | 147.7 | 146.9 | 146.0 | 140.0 |
| <b>No Education</b>  | 34.3% | 33.9% | 33.0% | 32.3% | 31.3% | 33.9%                    | 33.5% | 32.9% | 32.0% | 30.6% |
| <b>All Educations</b>  | 65.7% | 66.1% | 67.0% | 67.7% | 68.7% | 66.1%                    | 66.5% | 67.1% | 68.0% | 69.4% |

Naturally there will be a high degree of overlap between firms importing, firms exporting and firms engaged in both. Table 4 shows that the majority of workers are employed in firms both importing and exporting and in firms not changing industry, and that the wage share patterns for all three subsamples of firms with distinct trade patterns and those firms not changing industry all resemble the full sample pattern.

Also for the subsamples of firms of different sizes similar wage share patterns are observed, although with slightly more variation. Further, it is seen that almost 20 per cent of workers are employed in the groups of firms with either 10-50 or 201-500 employees, around 12 per cent are employed in the groups of firms with either 51-100 or 101-200 employees and the remaining 35-40 per cent in firms with + 500 employees.

Table 5 presents the pattern of imports by country of origin for all the subsamples over the sample period.

| TABLE 5: IMPORTS IN DANISH FIRMS BY COUNTRY OF ORIGINS INCOME PER CAPITA,<br>SELECTED GROUPS WITHIN DANISH MANUFACTURING, DKK BILLIONS |      |      |      |      |      |      |      |      |      |      |
|--|------|------|------|------|------|------|------|------|------|------|
| Countries by<br>Income Group:  | Year |      |      |      |      | Year |      |      |      |      |
|  | 1999 | 2000 | 2001 | 2002 | 2003 | 1999 | 2000 | 2001 | 2002 | 2003 |
| <b>Full Sample</b>   |      |      |      |      |      |      |      |      |      |      |
| <b>10-50 Employees</b>   |      |      |      |      |      |      |      |      |      |      |
| <b>Low &amp; Middle</b>  | 10.5 | 12.3 | 14.0 | 13.8 | 14.7 | 1.6  | 1.8  | 1.7  | 1.6  | 1.5  |
| <b>High</b>  | 60.1 | 68.5 | 77.8 | 79.0 | 75.8 | 5.6  | 6.5  | 6.6  | 6.9  | 6.6  |
| <b>Importing Firms</b>   |      |      |      |      |      |      |      |      |      |      |
| <b>51-100 Employees</b>  |      |      |      |      |      |      |      |      |      |      |
| <b>Low &amp; Middle</b>  | 10.5 | 12.3 | 14.0 | 13.8 | 14.7 | 1.6  | 2.2  | 1.9  | 1.9  | 1.8  |
| <b>High</b>  | 60.1 | 68.5 | 77.8 | 79.0 | 75.8 | 6.4  | 7.3  | 7.3  | 7.5  | 7.4  |
| <b>Exporting Firms</b>   |      |      |      |      |      |      |      |      |      |      |
| <b>101-200 Employees</b>   |      |      |      |      |      |      |      |      |      |      |
| <b>Low &amp; Middle</b>  | 10.4 | 12.3 | 13.9 | 13.7 | 14.7 | 1.5  | 1.8  | 2.4  | 2.4  | 2.2  |
| <b>High</b>  | 59.8 | 68.1 | 77.3 | 78.4 | 75.3 | 8.5  | 10.1 | 10.8 | 10.8 | 10.1 |
| <b>Im- and Exporting Firms</b>   |      |      |      |      |      |      |      |      |      |      |
| <b>201-500 Employees</b>   |      |      |      |      |      |      |      |      |      |      |
| <b>Low &amp; Middle</b>  | 10.4 | 12.3 | 13.9 | 13.7 | 14.7 | 2.0  | 2.4  | 2.7  | 2.9  | 3.6  |
| <b>High</b>  | 59.8 | 68.1 | 77.3 | 78.4 | 75.3 | 16.2 | 18.3 | 19.1 | 18.3 | 18.7 |
| <b>Same Industry Firms</b>   |      |      |      |      |      |      |      |      |      |      |
| <b>+500 Employees</b>  |      |      |      |      |      |      |      |      |      |      |
| <b>Low &amp; Middle</b>  | 9.9  | 11.4 | 12.7 | 12.5 | 13.7 | 3.7  | 4.2  | 5.2  | 5.0  | 5.6  |
| <b>High</b>  | 55.1 | 62.3 | 71.5 | 72.3 | 69.3 | 23.5 | 26.3 | 34.0 | 35.5 | 33.0 |

As expected the group of importing firms exactly resembles the overall pattern. Slightly more surprising, the group of exporting firms also account for almost the entire imports within Danish manufacturing firms. This underlines the fact, that importing and exporting activities are closely related within Danish manufacturing firms. The group of firms staying within the same industry is seen to account for more than 90 per cent of the overall imports in manufacturing firms, and the pattern of low- and middle-income and high-income imports is seen to resemble the full sample pattern.

For the subsamples of firms of different sizes two observations are worth noticing. Firstly, although the amount of imports for each subsample relative to the overall imports are seen to be related to the share of workers in each subsample, the imports per worker increases with firm-size (at least up until the group with 200-500 employees). Secondly, the increase in imports over the sample period, especially for imports from low- and middle-income countries, is clearly positively correlated with firm size.

Having introduced the most important characteristics of the subsamples table 6 and 7 present estimates for all subsamples. Both tables only present the model that fully utilizes the import information and includes import intensities by country of origin and level of processing.<sup>9</sup>

<sup>9</sup>The remaining models for all subsamples (1-3 in table 3 above) are available from the author upon request.

| TABLE 6: CHANGE IN SKILLED WAGE SHARE, 1999-2003, TRADE & INDUSTRY PATTERNS |             |                 |                 |                         |                     |
|---|-------------|-----------------|-----------------|-------------------------|---------------------|
|   | Full Sample | Importing Firms | Exporting Firms | Im- and Exporting Firms | Same Industry Firms |
| <b>Relative wage, Skilled</b>   | -0.057      | -0.046          | -0.051          | -0.047                  | -0.058              |
|   | (4.26)**    | (3.02)**        | (3.42)**        | (3.01)**                | (3.97)**            |
| $\ln(Y_i)$  | -0.003      | -0.007          | -0.006          | -0.007                  | -0.002              |
|   | (1.84)      | (3.39)**        | (3.30)**        | (3.58)**                | (1.13)              |
| $\ln(K_i)$  | 0.002       | 0.004           | 0.002           | 0.004                   | 0.001               |
|   | (1.06)      | (2.46)*         | (1.48)          | (2.41)*                 | (0.33)              |
| $\frac{\text{Imp\_int\_lmic}_i}{Y_i}$                                       | 0.041       | 0.039           | 0.044           | 0.043                   | 0.070               |
|   | (2.23)*     | (2.22)*         | (2.45)*         | (2.46)*                 | (3.22)**            |
| $\frac{\text{Imp\_int\_hic}_i}{Y_i}$  | -0.009      | -0.010          | -0.014          | -0.014                  | -0.013              |
|   | (1.52)      | (1.73)          | (2.37)*         | (2.36)*                 | (2.13)*             |
| $\frac{\text{Imp\_fn\_lmic}_i}{Y_i}$  | 0.011       | 0.010           | 0.011           | 0.011                   | 0.011               |
|   | (1.76)      | (1.77)          | (1.79)          | (1.81)                  | (1.84)              |
| $\frac{\text{Imp\_fn\_hic}_i}{Y_i}$   | -0.004      | -0.005          | -0.005          | -0.005                  | -0.006              |
|   | (0.43)      | (0.54)          | (0.56)          | (0.60)                  | (0.66)              |
| $\frac{\text{R\&D}_j}{Y_j}$   | 0.377       | 0.401           | 0.359           | 0.398                   | 0.629               |
|   | (7.53)**    | (7.68)**        | (6.87)**        | (7.42)**                | (9.14)**            |
| <b>Firms</b>  | 6970        | 4453            | 4597            | 3895                    | 6114                |
| <b>Obs.</b>   | 24791       | 17530           | 18016           | 15620                   | 21027               |

Standard errors in parentheses

\* significant at 5 per cent; \*\* significant at 1 per cent

The first observation from table 6 is that focusing only on importing manufacturing firms does not change the magnitude or significance of how imports affects skill-upgrading.

Next, restricting to exporting or im- and exporting firms the significance and magnitude of intermediate import intensities from low- and middle-income countries increases slightly and intermediate import intensities from high-income countries becomes significantly negative. The latter indicates that Danish manufacturing firms that export have comparative advantages in production processes that are intensive in unskilled labor when compared to other high-income countries.

Finally, restricting to firms staying in the same industry the significance and magnitude of intermediate import intensities from low- and middle-income countries increase considerably and as for the exporting firms the intermediate import intensities from high-income countries becomes significantly negative. Also, the R&D intensities become much larger and more significant. Combined, these factors suggest either the wage share composition within this group is more affected by import patterns, or data considerations make the effects easier recoverable.

| TABLE 7: CHANGE IN SKILLED WAGE SHARE, 1999-2003, FIRM SIZE PATTERNS |                |               |                |                 |                 |              |
|--|----------------|---------------|----------------|-----------------|-----------------|--------------|
|  | Full<br>Sample | 10-50<br>Emp. | 51-100<br>Emp. | 101-200<br>Emp. | 201-500<br>Emp. | +500<br>Emp. |
| <b>Relative wage,<br/>Skilled</b>                                    | -0.057         | -0.056        | -0.062         | -0.084          | -0.031          | -0.061       |
| $\ln(Y_i)$   | (4.26)**       | (3.25)**      | (2.27)*        | (2.33)*         | (0.74)          | (0.96)       |
| $\ln(K_i)$   | -0.003         | 0.001         | -0.008         | -0.013          | -0.011          | -0.034       |
|  | (1.84)         | (0.60)        | (2.23)*        | (2.89)**        | (2.84)**        | (4.84)**     |
| $\frac{\text{Imp\_int\_lmic}_i}{Y_i}$                                | 0.002          | 0.000         | 0.000          | -0.001          | 0.009           | 0.008        |
|  | (1.06)         | (0.11)        | (0.10)         | (0.13)          | (3.33)**        | (1.02)       |
| $\frac{\text{Imp\_int\_hic}_i}{Y_i}$                                 | 0.041          | 0.016         | 0.071          | 0.116           | 0.106           | 0.094        |
|  | (2.23)*        | (0.64)        | (1.48)         | (2.47)*         | (3.33)**        | (1.78)       |
| $\frac{\text{Imp\_fin\_lmic}_i}{Y_i}$                                | -0.009         | -0.008        | 0.028          | -0.007          | 0.004           | -0.057       |
|  | (1.52)         | (1.08)        | (1.85)         | (0.43)          | (0.28)          | (1.66)       |
| $\frac{\text{Imp\_fin\_hic}_i}{Y_i}$                                 | 0.011          | 0.010         | -0.022         | 0.070           | 0.183           | 0.498        |
|  | (1.76)         | (1.45)        | (0.63)         | (2.05)*         | (3.01)**        | (3.09)**     |
| $\frac{\text{R\&D}_j}{Y_j}$  | -0.004         | -0.012        | 0.006          | 0.083           | -0.044          | 0.049        |
|  | (0.43)         | (1.01)        | (0.38)         | (3.32)**        | (1.81)          | (1.05)       |
| <b>Firms</b>   | 6970           | 5084          | 929            | 479             | 330             | 148          |
| <b>Obs.</b>  | 24791          | 16876         | 3880           | 1994            | 1418            | 623          |

Standard errors in parentheses

\* significant at 5 per cent; \*\* significant at 1 per cent

Table 7 presents the results for the subsamples of firms of different sizes, and a number of new and interesting insights appear.

For the two subsamples of firms with less than 100 employees, constituting the majority of firms, no measures of import intensities have significant effects.

Next, it is seen that intermediate import intensities from low- and middle-income countries are more significant and have much larger effects for larger firms compared to the full sample (although borderline insignificant for the firms with +500 employees).

Finally, final good import intensities from low- and middle-income countries are also significant for larger firms, and the magnitude increase rapidly with firm size, suggesting that import of final goods is very important in explaining skill-upgrading for larger firms within Danish manufacturing.

The last fact ties in with the discussion of why the empirical evidence of import's effect on skill-upgrading may vary according to firm size. The results can be interpreted as supporting the hypothesis either that larger firms have advantage in utilizing the import of final goods production from low- and middle-income countries due to scale (e.g. by setting up own production) or that smaller firms to a larger degree utilize third party trading companies, whereby, their "imports" simply do not show up in the data.

## 6 Conclusion

The main focus of the current paper has been to study the relation between imports and skill-upgrading using a high quality employeeer-employee sample from Danish manufacturing firms covering the period from 1999-2003. In the paper it is argued how the micro level evidence applied presents the following improvements over the traditional use of input-output tables:

- The ability to distinguish imports according to whether it originates from low- or high-income countries
- The possibility of adding import of final goods
- The capability to capture within industry differences
- The ability to identify and analyze groups firms across industry classification

The paper proceeds by presenting a theoretical argument why *the relative demand for skilled labor in high-income countries increases with the extent of manufacturing firm imports from low-income countries*. Next an empirical estimation strategy is formulated to test this hypothesis.

It is found that all improvements are of vital importance as the three main conclusions of the paper are:

1. Pooling imports from all countries and disregarding import of final products is showed to render the effect of imports on skill-upgrading close to zero and insignificant (see model 1 in table 3). Thus, limiting data in this way (*similar to the limits imposed when using figures from input-output tables*) *will significantly bias the results and lead to under-evaluation of import's role for skill-upgrading*.
2. When imports are split according to country of origin and level of processing import of intermediate goods from low- and middle-income countries is found to have a significant effect on skill-upgrading for the full sample of manufacturing firms and import of final goods from low- and middle-income countries is found to have a significant effect on skill-upgrading for several subsamples within manufacturing firms. Hence, *distinguishing imports according to country of origin and level of processing are of vital importance*.
3. Although import of final goods from low- and middle-income countries is found to be borderline insignificant in the overall sample of manufacturing firms, the analysis showed (see table 7) that when grouping firms according to their size, import of final goods from low- and middle-income countries has a large and significant impact on skill-upgrading for firms with more than 100 employees. And interestingly, *the explanatory power and magnitude of import of final goods from low- and middle-income countries for skill-upgrading increases with firm size*.



These are all empirical facts adding to the understanding of how international trade affects skill-upgrading. And, as current research seeks to develop theoretical models that to a higher extent allow us to understand and test the causal relations of trade, this paper suggests, that one should consider in details how and why larger firms are more affected by international trade, and especially, why final good imports seems to be so much more important for this group of firms.

## References

- [1] Autor, D.H., L.F. Katz, and A.B. Krueger (1998), “Computing Inequality: Have Computers Changed the Labor Market?” *Quarterly Journal of Economics*, 113 (4), 1169-1213
- [2] Bernard, A.B., J.B. Jensen, and P.K. Schoot (2006), “Survival of the Best Fit: Exposure to Low-Wage Countries,” *Journal of International Economics*, 68(1), 219-237
- [3] Biscourp, Pierre and Francis Kramarz (2007), “Employment, Skill Structure and International Trade: Firm-Level Evidence for France,” *Journal of International Economics*, 72, 22–51.
- [4] Berndt, E. R. (1991), *The Practice of Econometrics Classic and Contemporary*, Addison-Wesley Publishing Company
- [5] Brown, R. S., and L. R. Christensen, (1981), “Estimates of elasticities of substitution in a model of partial static equilibrium: An application to US agriculture”, 1947-1974, in E. R. Berndt and B. C. Field (eds.): *Modelling and measuring natural resource substitution*, 209-229, MIT Press
- [6] Christensen, L. R. and W. H. Greene (1976), “Economics of scale in U.S. Electric Power Generation”, *The Journal of Political Economy*, 84, 655-676
- [7] Doms, M., T. Dunne, K.R. Troske (1997): “Workers, Wages, and Technology,” *Quarterly Journal of Economics*, 112(1), 253-90
- [8] Ekholm, K., and K. Hakkala (2006), “The Effect of Offshoring on Labor Demand: Evidence from Sweden”, CEPR working paper #5648
- [9] Feenstra, R.C. (2004), *Advanced International Trade: Theory and Evidence*, Princeton University Press
- [10] Feenstra, R.C. and G.D. Hanson (1996), “Globalization, Outsourcing, and Wage Inequality”, *American Economic Review*, 86(2), Papers and Proceedings, 240-245
- [11] Feenstra, R.C. and G.D. Hanson (1999), “The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-1990”, *Quarterly Journal of Economics*, 114, 907-41
- [12] Hijzen, A., H. Görg and R.C. Hine (2005), “International Outsourcing and the Skill Structure of Labor Demand in the United Kingdom”, *Economic Journal*, 115, 506, 860-878
- [13] Islam, N. (1995), “Growth Empirics: A Panel Data Approach”, *Quarterly Journal of Economics*, 443, 1127–1170

- [14] Kmenta, J. (1967), “On Estimation of the CES Production Function”, *International Economic Review* 8, 180-189
- [15] Machin, S., and J. Van Reenen (1998), “Technology and Changes in Skill Structure: Evidence from Seven OECD Countries,” *Quarterly Journal of Economics*, 113(4), 1215-1244
- [16] Ng, F., and A.J. Yeats (1999), “Production Sharing in East Asia – Who Does What for Whom and Why?”, Policy Research Working Paper 2197, World Bank
- [17] Scheuer, C., A. Sørensen and M. Rosholm (2008) “Exposure to Low-Wage Country Trade and Skill-Upgrading at the Firm Level”, Working Paper, CEBR.

## TITLER I PH.D.SERIEN:

– a Field Study of the Rise and Fall of a Bottom-Up Process

### 2004

1. Martin Grieger  
*Internet-based Electronic Marketplaces and Supply Chain Management*
2. Thomas Basbøll  
*LIKENESS  
A Philosophical Investigation*
3. Morten Knudsen  
*Beslutningens vaklen  
En systemteoretisk analyse af moderniseringen af et amtskommunalt sundhedsvæsen 1980-2000*
4. Lars Bo Jeppesen  
*Organizing Consumer Innovation  
A product development strategy that is based on online communities and allows some firms to benefit from a distributed process of innovation by consumers*
5. Barbara Dragsted  
*SEGMENTATION IN TRANSLATION AND TRANSLATION MEMORY SYSTEMS  
An empirical investigation of cognitive segmentation and effects of integrating a TM system into the translation process*
6. Jeanet Hardis  
*Sociale partnerskaber  
Et socialkonstruktivistisk casestudie af partnerskabsaktørers virkelighedsopfattelse mellem identitet og legitimitet*
7. Henriette Hallberg Thygesen  
*System Dynamics in Action*
8. Carsten Mejer Plath  
*Strategisk Økonomistyring*
9. Annemette Kjærgaard  
*Knowledge Management as Internal Corporate Venturing*
10. Knut Arne Hovdal  
*De professionelle i endring  
Norsk ph.d., ej til salg gennem Samfundslitteratur*
11. Søren Jeppesen  
*Environmental Practices and Greening Strategies in Small Manufacturing Enterprises in South Africa  
– A Critical Realist Approach*
12. Lars Frode Frederiksen  
*Industriel forskningsledelse  
– på sporet af mønstre og samarbejde i danske forskningsintensive virksomheder*
13. Martin Jes Iversen  
*The Governance of GN Great Nordic  
– in an age of strategic and structural transitions 1939-1988*
14. Lars Pynt Andersen  
*The Rhetorical Strategies of Danish TV Advertising  
A study of the first fifteen years with special emphasis on genre and irony*
15. Jakob Rasmussen  
*Business Perspectives on E-learning*
16. Sof Thrane  
*The Social and Economic Dynamics of Networks  
– a Weberian Analysis of Three Formalised Horizontal Networks*
17. Lene Nielsen  
*Engaging Personas and Narrative Scenarios – a study on how a user-centered approach influenced the perception of the design process in the e-business group at AstraZeneca*
18. S.J Valstad  
*Organisationsidentitet  
Norsk ph.d., ej til salg gennem Samfundslitteratur*

19. Thomas Lyse Hansen  
*Six Essays on Pricing and Weather risk in Energy Markets*
  20. Sabine Madsen  
*Emerging Methods – An Interpretive Study of ISD Methods in Practice*
  21. Evis Sinani  
*The Impact of Foreign Direct Investment on Efficiency, Productivity Growth and Trade: An Empirical Investigation*
  22. Bent Meier Sørensen  
*Making Events Work Or, How to Multiply Your Crisis*
  23. Pernille Schnoor  
*Brand Ethos*  
*Om troværdige brand- og virksomhedsidentiteter i et retorisk og diskursteoretisk perspektiv*
  24. Sidsel Fabech  
*Von welchem Österreich ist hier die Rede?*  
*Diskursive forhandlinger og magtkampe mellem rivaliserende nationale identitetskonstruktioner i østrigske pressediskurser*
  25. Klavs Odgaard Christensen  
*Sprogpolitik og identitetsdannelse i flersprogede forbundsstater*  
*Et komparativt studie af Schweiz og Canada*
  26. Dana B. Minbaeva  
*Human Resource Practices and Knowledge Transfer in Multinational Corporations*
  27. Holger Højlund  
*Markedets politiske fornuft*  
*Et studie af velfærdens organisering i perioden 1990-2003*
  28. Christine Mølgaard Frandsen  
*A.s erfaring*  
*Om mellemværendets praktik i en transformation af mennesket og subjektiviteten*
  29. Sine Nørholm Just  
*The Constitution of Meaning – A Meaningful Constitution? Legitimacy, identity, and public opinion in the debate on the future of Europe*
- 2005**
1. Claus J. Varnes  
*Managing product innovation through rules – The role of formal and structured methods in product development*
  2. Helle Hedegaard Hein  
*Mellem konflikt og konsensus – Dialogudvikling på hospitalsklinikker*
  3. Axel Rosenø  
*Customer Value Driven Product Innovation – A Study of Market Learning in New Product Development*
  4. Søren Buhl Pedersen  
*Making space*  
*An outline of place branding*
  5. Camilla Funck Ellehave  
*Differences that Matter*  
*An analysis of practices of gender and organizing in contemporary workplaces*
  6. Rigmor Madeleine Lond  
*Styring af kommunale forvaltninger*
  7. Mette Aagaard Andreassen  
*Supply Chain versus Supply Chain Benchmarking as a Means to Managing Supply Chains*
  8. Caroline Aggestam-Pontoppidan  
*From an idea to a standard*  
*The UN and the global governance of accountants' competence*
  9. Norsk ph.d.
  10. Vivienne Heng Ker-ni  
*An Experimental Field Study on the*

- Effectiveness of Grocer Media Advertising*  
*Measuring Ad Recall and Recognition, Purchase Intentions and Short-Term Sales*
11. Allan Mortensen  
*Essays on the Pricing of Corporate Bonds and Credit Derivatives*
  12. Remo Stefano Chiari  
*Figure che fanno conoscere*  
*Itinerario sull'idea del valore cognitivo e espressivo della metafora e di altri tropi da Aristotele e da Vico fino al cognitivismo contemporaneo*
  13. Anders McIlquham-Schmidt  
*Strategic Planning and Corporate Performance*  
*An integrative research review and a meta-analysis of the strategic planning and corporate performance literature from 1956 to 2003*
  14. Jens Geersbro  
*The TDF – PMI Case*  
*Making Sense of the Dynamics of Business Relationships and Networks*
  15. Mette Andersen  
*Corporate Social Responsibility in Global Supply Chains*  
*Understanding the uniqueness of firm behaviour*
  16. Eva Boxenbaum  
*Institutional Genesis: Micro – Dynamic Foundations of Institutional Change*
  17. Peter Lund-Thomsen  
*Capacity Development, Environmental Justice NGOs, and Governance: The Case of South Africa*
  18. Signe Jarlov  
*Konstruktioner af offentlig ledelse*
  19. Lars Stæhr Jensen  
*Vocabulary Knowledge and Listening Comprehension in English as a Foreign Language*
  20. Christian Nielsen  
*Essays on Business Reporting*  
*Production and consumption of strategic information in the market for information*
  21. Marianne Thejls Fischer  
*Egos and Ethics of Management Consultants*
  22. Annie Bekke Kjær  
*Performance management i Proces-innovation*  
*– belyst i et social-konstruktivistisk perspektiv*
  23. Suzanne Dee Pedersen  
*GENTAGELSENS METAMORFOSE*  
*Om organisering af den kreative gøren i den kunstneriske arbejdspraksis*
  24. Benedikte Dorte Rosenbrink  
*Revenue Management*  
*Økonomiske, konkurrencemæssige & organisatoriske konsekvenser*
  25. Thomas Riise Johansen  
*Written Accounts and Verbal Accounts*  
*The Danish Case of Accounting and Accountability to Employees*
  26. Ann Fogelgren-Pedersen  
*The Mobile Internet: Pioneering Users' Adoption Decisions*
  27. Birgitte Rasmussen  
*Ledelse i fællesskab – de tillidsvalgte fornyende rolle*
  28. Gitte Thit Nielsen  
*Remerger*  
*– skabende ledelseskrafter i fusion og opkøb*
  29. Carmine Gioia  
*A MICROECONOMETRIC ANALYSIS OF MERGERS AND ACQUISITIONS*

30. Ole Hinz  
*Den effektive forandringsleder: pilot, pædagog eller politiker?*  
*Et studie i arbejdslederes meningstilskrivninger i forbindelse med vellykket gennemførelse af ledelsesinitierede forandringsprojekter*
  31. Kjell-Åge Gotvassli  
*Et praksisbasert perspektiv på dynamiske læringsnettverk i toppidretten*  
Norsk ph.d., ej til salg gennem Samfundslitteratur
  32. Henriette Langstrup Nielsen  
*Linking Healthcare*  
*An inquiry into the changing performances of web-based technology for asthma monitoring*
  33. Karin Tweddell Levinsen  
*Virtuel Uddannelsespraksis*  
*Master i IKT og Læring – et casestudie i hvordan proaktiv proceshåndtering kan forbedre praksis i virtuelle læringsmiljøer*
  34. Anika Liversage  
*Finding a Path*  
*Labour Market Life Stories of Immigrant Professionals*
  35. Kasper Elmquist Jørgensen  
*Studier i samspillet mellem stat og erhvervsliv i Danmark under 1. verdenskrig*
  36. Finn Janning  
*A DIFFERENT STORY*  
*Seduction, Conquest and Discovery*
  37. Patricia Ann Plackett  
*Strategic Management of the Radical Innovation Process*  
*Leveraging Social Capital for Market Uncertainty Management*
- 2006**
1. Christian Vintergaard  
*Early Phases of Corporate Venturing*
  2. Niels Rom-Poulsen  
*Essays in Computational Finance*
  3. Tina Brandt Husman  
*Organisational Capabilities, Competitive Advantage & Project-Based Organisations*  
*The Case of Advertising and Creative Good Production*
  4. Mette Rosenkrands Johansen  
*Practice at the top*  
*– how top managers mobilise and use non-financial performance measures*
  5. Eva Parum  
Corporate governance som strategisk kommunikations- og ledelsesværktøj
  6. Susan Aagaard Petersen  
*Culture's Influence on Performance Management: The Case of a Danish Company in China*
  7. Thomas Nicolai Pedersen  
*The Discursive Constitution of Organizational Governance – Between unity and differentiation*  
*The Case of the governance of environmental risks by World Bank environmental staff*
  8. Cynthia Selin  
*Volatile Visions: Transactions in Anticipatory Knowledge*
  9. Jesper Banghøj  
*Financial Accounting Information and Compensation in Danish Companies*
  10. Mikkel Lucas Overby  
*Strategic Alliances in Emerging High-Tech Markets: What's the Difference and does it Matter?*
  11. Tine Aage  
*External Information Acquisition of Industrial Districts and the Impact of Different Knowledge Creation Dimensions*

- A case study of the Fashion and Design Branch of the Industrial District of Montebelluna, NE Italy*
12. Mikkel Flyverbom  
*Making the Global Information Society Governable*  
*On the Governmentality of Multi-Stakeholder Networks*
  13. Anette Grønning  
*Personen bag*  
*Tilstedevær i e-mail som interaktionsform mellem kunde og medarbejder i dansk forsikringskontekst*
  14. Jørn Helder  
*One Company – One Language?*  
*The NN-case*
  15. Lars Bjerregaard Mikkelsen  
*Differing perceptions of customer value*  
*Development and application of a tool for mapping perceptions of customer value at both ends of customer-supplier dyads in industrial markets*
  16. Lise Granerud  
*Exploring Learning*  
*Technological learning within small manufacturers in South Africa*
  17. Esben Rahbek Pedersen  
*Between Hopes and Realities: Reflections on the Promises and Practices of Corporate Social Responsibility (CSR)*
  18. Ramona Samson  
*The Cultural Integration Model and European Transformation.*  
*The Case of Romania*
- 2007**
1. Jakob Vestergaard  
*Discipline in The Global Economy*  
*Panopticism and the Post-Washington Consensus*
  2. Heidi Lund Hansen  
*Spaces for learning and working*  
*A qualitative study of change of work, management, vehicles of power and social practices in open offices*
  3. Sudhanshu Rai  
*Exploring the internal dynamics of software development teams during user analysis*  
*A tension enabled Institutionalization Model; "Where process becomes the objective"*
  4. Norsk ph.d.  
Ej til salg gennem Samfundslitteratur
  5. Serden Ozcan  
*EXPLORING HETEROGENEITY IN ORGANIZATIONAL ACTIONS AND OUTCOMES*  
*A Behavioural Perspective*
  6. Kim Sundtoft Hald  
*Inter-organizational Performance Measurement and Management in Action*  
*– An Ethnography on the Construction of Management, Identity and Relationships*
  7. Tobias Lindeberg  
*Evaluative Technologies*  
*Quality and the Multiplicity of Performance*
  8. Merete Wedell-Wedellsborg  
*Den globale soldat*  
*Identitetsdannelse og identitetsledelse i multinationale militære organisationer*
  9. Lars Frederiksen  
*Open Innovation Business Models*  
*Innovation in firm-hosted online user communities and inter-firm project ventures in the music industry*  
*– A collection of essays*
  10. Jonas Gabrielsen  
*Retorisk toposlære – fra statisk 'sted' til persuasiv aktivitet*



11. Christian Moldt-Jørgensen  
*Fra meningsløs til meningsfuld evaluering.*  
*Anvendelsen af studentertilfredsheds-målinger på de korte og mellemlange videregående uddannelser set fra et psykodynamisk systemperspektiv*
12. Ping Gao  
*Extending the application of actor-network theory*  
*Cases of innovation in the telecommunications industry*
13. Peter Mejlby  
*Frihed og fængsel, en del af den samme drøm?*  
*Et phronetisk baseret casestudie af frigørelsens og kontrollens sam-eksistens i værdibaseret ledelse!*
14. Kristina Birch  
*Statistical Modelling in Marketing*
15. Signe Poulsen  
*Sense and sensibility:*  
*The language of emotional appeals in insurance marketing*
16. Anders Bjerre Trolle  
*Essays on derivatives pricing and dynamic asset allocation*
17. Peter Feldhütter  
*Empirical Studies of Bond and Credit Markets*
18. Jens Henrik Eggert Christensen  
*Default and Recovery Risk Modeling and Estimation*
19. Maria Theresa Larsen  
*Academic Enterprise: A New Mission for Universities or a Contradiction in Terms?*  
*Four papers on the long-term implications of increasing industry involvement and commercialization in academia*
20. Morten Wellendorf  
*Postimplementering af teknologi i den offentlige forvaltning*  
*Analyser af en organisations kontinuerlige arbejde med informations-teknologi*
21. Ekaterina Mhaanna  
*Concept Relations for Terminological Process Analysis*
22. Stefan Ring Thorbjørnsen  
*Forsvaret i forandring*  
*Et studie i officerers kapabiliteter under påvirkning af omverdenens forandringspres mod øget styring og læring*
23. Christa Breum Amhøj  
*Det selvskabte medlemskab om managementstaten, dens styringsteknologier og indbyggere*
24. Karoline Bromose  
*Between Technological Turbulence and Operational Stability*  
*– An empirical case study of corporate venturing in TDC*
25. Susanne Justesen  
*Navigating the Paradoxes of Diversity in Innovation Practice*  
*– A Longitudinal study of six very different innovation processes – in practice*
26. Luise Noring Henler  
*Conceptualising successful supply chain partnerships*  
*– Viewing supply chain partnerships from an organisational culture perspective*
27. Mark Mau  
*Kampen om telefonen*  
*Det danske telefonvæsen under den tyske besættelse 1940-45*
28. Jakob Halskov  
*The semiautomatic expansion of existing terminological ontologies using knowledge patterns discovered*

- on the WWW – an implementation and evaluation
29. Gergana Koleva  
*European Policy Instruments Beyond Networks and Structure: The Innovative Medicines Initiative*
  30. Christian Geisler Asmussen  
*Global Strategy and International Diversity: A Double-Edged Sword?*
  31. Christina Holm-Petersen  
*Stolthed og fordom  
Kultur- og identitetsarbejde ved skabelsen af en ny sengeafdeling gennem fusion*
  32. Hans Peter Olsen  
*Hybrid Governance of Standardized States  
Causes and Contours of the Global Regulation of Government Auditing*
  33. Lars Bøge Sørensen  
*Risk Management in the Supply Chain*
  34. Peter Aagaard  
*Det unikkes dynamikker  
De institutionelle mulighedsbetingelser bag den individuelle udforskning i professionelt og frivilligt arbejde*
  35. Yun Mi Antorini  
*Brand Community Innovation  
An Intrinsic Case Study of the Adult Fans of LEGO Community*
  36. Joachim Lynggaard Boll  
*Labor Related Corporate Social Performance in Denmark  
Organizational and Institutional Perspectives*
- 2008**
1. Frederik Christian Vinten  
*Essays on Private Equity*
  2. Jesper Clement  
*Visual Influence of Packaging Design on In-Store Buying Decisions*
  3. Marius Brostrøm Kousgaard  
*Tid til kvalitetsmåling?  
– Studier af indrulleringsprocesser i forbindelse med introduktionen af kliniske kvalitetsdatabaser i speciallægepraksissektoren*
  4. Irene Skovgaard Smith  
*Management Consulting in Action  
Value creation and ambiguity in client-consultant relations*
  5. Anders Rom  
*Management accounting and integrated information systems  
How to exploit the potential for management accounting of information technology*
  6. Marina Candi  
*Aesthetic Design as an Element of Service Innovation in New Technology-based Firms*
  7. Morten Schnack  
*Teknologi og tværfaglighed  
– en analyse af diskussionen omkring indførelse af EPJ på en hospitalsafdeling*
  8. Helene Balslev Clausen  
*Juntos pero no revueltos – un estudio sobre emigrantes norteamericanos en un pueblo mexicano*
  9. Lise Justesen  
*Kunsten at skrive revisionsrapporter.  
En beretning om forvaltningsrevisions beretninger*
  10. Michael E. Hansen  
*The politics of corporate responsibility: CSR and the governance of child labor and core labor rights in the 1990s*
  11. Anne Roepstorff  
*Holdning for handling – en etnologisk undersøgelse af Virksomheders Sociale Ansvar/CSR*

12. Claus Bajlum  
*Essays on Credit Risk and Credit Derivatives*
  13. Anders Bojesen  
*The Performative Power of Competence – an Inquiry into Subjectivity and Social Technologies at Work*
  14. Satu Reijonen  
*Green and Fragile  
A Study on Markets and the Natural Environment*
  15. Ilduara Busta  
*Corporate Governance in Banking  
A European Study*
  16. Kristian Anders Hvass  
*A Boolean Analysis Predicting Industry Change: Innovation, Imitation & Business Models  
The Winning Hybrid: A case study of isomorphism in the airline industry*
  17. Trine Paludan  
*De uvidende og de udviklingsparate  
Identitet som mulighed og restriktion  
blandt fabriksarbejdere på det aftayloriserede fabriksgulv*
  18. Kristian Jakobsen  
*Foreign market entry in transition economies: Entry timing and mode choice*
  19. Jakob Elming  
*Syntactic reordering in statistical machine translation*
  20. Lars Brømsøe Termansen  
*Regional Computable General Equilibrium Models for Denmark  
Three papers laying the foundation for regional CGE models with agglomeration characteristics*
  21. Mia Reinholt  
*The Motivational Foundations of Knowledge Sharing*
  22. Frederikke Krogh-Meibom  
*The Co-Evolution of Institutions and Technology  
– A Neo-Institutional Understanding of Change Processes within the Business Press – the Case Study of Financial Times*
  23. Peter D. Ørberg Jensen  
*OFFSHORING OF ADVANCED AND HIGH-VALUE TECHNICAL SERVICES:  
ANTECEDENTS, PROCESS DYNAMICS AND FIRMLEVEL IMPACTS*
  24. Pham Thi Song Hanh  
*Functional Upgrading, Relational Capability and Export Performance of Vietnamese Wood Furniture Producers*
  25. Mads Vangkilde  
*Why wait?  
An Exploration of first-mover advantages among Danish e-grocers through a resource perspective*
  26. Hubert Buch-Hansen  
*Rethinking the History of European Level Merger Control  
A Critical Political Economy Perspective*
- 2009**
1. Vivian Lindhardsen  
*From Independent Ratings to Communal Ratings: A Study of CWA Raters' Decision-Making Behaviours*
  2. Guðrið Weihe  
*Public-Private Partnerships: Meaning and Practice*
  3. Chris Nøkkentved  
*Enabling Supply Networks with Collaborative Information Infrastructures  
An Empirical Investigation of Business Model Innovation in Supplier Relationship Management*
  4. Sara Louise Muhr  
*Wound, Interrupted – On the Vulnerability of Diversity Management*

5. Christine Sestoft  
*Forbrugeradfærd i et Stats- og Livsformsteoretisk perspektiv*
6. Michael Pedersen  
*Tune in, Breakdown, and Reboot: On the production of the stress-fit self-managing employee*
7. Salla Lutz  
*Position and Reposition in Networks – Exemplified by the Transformation of the Danish Pine Furniture Manufacturers*
8. Jens Forssbæck  
*Essays on market discipline in commercial and central banking*
9. Tine Murphy  
*Sense from Silence – A Basis for Organised Action*  
*How do Sensemaking Processes with Minimal Sharing Relate to the Reproduction of Organised Action?*
10. Sara Malou Strandvad  
*Inspirations for a new sociology of art: A sociomaterial study of development processes in the Danish film industry*
11. Nicolaas Mouton  
*On the evolution of social scientific metaphors: A cognitive-historical enquiry into the divergent trajectories of the idea that collective entities – states and societies, cities and corporations – are biological organisms.*
12. Lars Andreas Knutsen  
*Mobile Data Services: Shaping of user engagements*
13. Nikolaos Theodoros Korfiatis  
*Information Exchange and Behavior*  
*A Multi-method Inquiry on Online Communities*
14. Jens Albæk  
*Forestillinger om kvalitet og tværfaglighed på sygehuse*  
*– skabelse af forestillinger i læge- og plejegrupperne angående relevans af nye idéer om kvalitetsudvikling gennem tolkningsprocesser*
15. Maja Lotz  
*The Business of Co-Creation – and the Co-Creation of Business*
16. Gitte P. Jakobsen  
*Narrative Construction of Leader Identity in a Leader Development Program Context*
17. Dorte Hermansen  
*“Living the brand” som en brandorienteret dialogisk praksis: Om udvikling af medarbejdernes brandorienterede dømmekraft*
18. Aseem Kinra  
*Supply Chain (logistics) Environmental Complexity*
19. Michael Nørager  
*How to manage SMEs through the transformation from non innovative to innovative?*
20. Kristin Wallevik  
*Corporate Governance in Family Firms*  
*The Norwegian Maritime Sector*
21. Bo Hansen Hansen  
*Beyond the Process*  
*Enriching Software Process Improvement with Knowledge Management*
22. Annemette Skot-Hansen  
*Franske adjektivisk afledte adverbier, der tager præpositionssyntagmer indledt med præpositionen à som argumenter*  
*En valensgrammatisk undersøgelse*
23. Line Gry Knudsen  
*Collaborative R&D Capabilities*  
*In Search of Micro-Foundations*

24. Christian Scheuer  
*Employers meet employees  
Essays on sorting and globalization*

#### **TITLER I ATV PH.D.-SERIEN**

##### **1992**

1. Niels Korum  
*Servicesamkørsel – organisation, økonomi og planlægningsmetoder*

##### **1995**

2. Verner Worm  
*Nordiske virksomheder i Kina  
Kulturspecifikke interaktionsrelationer  
ved nordiske virksomhedsetableringer i Kina*

##### **1999**

3. Mogens Bjerre  
*Key Account Management of Complex  
Strategic Relationships  
An Empirical Study of the Fast Moving  
Consumer Goods Industry*

##### **2000**

4. Lotte Darsø  
*Innovation in the Making  
Interaction Research with heterogeneous  
Groups of Knowledge Workers  
creating new Knowledge and new  
Leads*

##### **2001**

5. Peter Hobolt Jensen  
*Managing Strategic Design Identities  
The case of the Lego Developer Network*

##### **2002**

6. Peter Lohmann  
*The Deleuzian Other of Organizational  
Change – Moving Perspectives of the  
Human*

7. Anne Marie Jess Hansen  
*To lead from a distance: The dynamic  
interplay between strategy and strategizing – A case study of the strategic  
management process*

##### **2003**

8. Lotte Henriksen  
*Videndeling  
– om organisatoriske og ledelsesmæssige  
udfordringer ved videndeling i  
praksis*
9. Niels Christian Nickelsen  
*Arrangements of Knowing: Coordinating  
Procedures Tools and Bodies in  
Industrial Production – a case study of  
the collective making of new products*

##### **2005**

10. Carsten Ørts Hansen  
*Konstruktion af ledelsesteknologier og  
effektivitet*

#### **TITLER I DBA PH.D.-SERIEN**

##### **2007**

1. Peter Kastrup-Misir  
*Endeavoring to Understand Market  
Orientation – and the concomitant  
co-mutation of the researched, the  
researcher, the research itself and the  
truth*

##### **2009**

1. Torkild Leo Thellefsen  
*Fundamental Signs and Significance-effects  
A Semeiotic outline of Fundamental  
Signs, Significance-effects, Knowledge  
Profiling and their use in Knowledge  
Organization and Branding*