Economic Studies 208

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Structural Change, Match Quality, and Integration in the Labor Market

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ECONOMICS AT UPPSALA UNIVERSITY

The Department of Economics at Uppsala University has a long history. The first chair in Economics in the Nordic countries was instituted at Uppsala University in 1741.

The main focus of research at the department has varied over the years but has typically been oriented towards policy-relevant applied economics, including both theoretical and empirical studies. The currently most active areas of research can be grouped into six categories:

* Labour economics
* Public economics
* Macroeconomics
* Microeconometrics
* Environmental economics
* Housing and urban economics

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Dissertation presented at Uppsala University to be publicly examined in Hörsal 2, Ekonomikum, Kyrkogårdsgatan 10, Uppsala, Friday, 21 April 2023 at 13:15 for the degree of Doctor of Philosophy. The examination will be conducted in English. Faculty examiner: Professor Maarten Goos (Utrecht University, School of Economics).

Abstract

Ek, S. 2023. Structural Change, Match Quality, and Integration in the Labor Market. *Economic studies* 208. 176 pp. Uppsala: Department of Economics, Uppsala University. ISBN 978-91-506-2991-0.

Essay I: Are workers with poor outside opportunities less responsive and more susceptible to negative demand shifts in routine occupations? To answer this, I create and estimate an occupation specialization index (OSI) using Swedish register data and machine learning tools. It measures the expected difference in utility between a worker's occupation and his best non-routine outside option. This determines the loss he is willing to tolerate to avoid switching. Low-OSI employees disproportionately left routine work. Their future wage growth was akin to comparable workers initially in non-routine occupations. By contrast, routine specialists largely stayed put and experienced lower wage growth than generalists and non-routine specialists.

Essay II (with Adrian Adermon, Georg Graetz, and Yaroslav Yakymovych): Using a new identification strategy, we jointly estimate the growth in occupational wage premia and time-varying occupation-specific life-cycle profiles for Swedish workers 1996–2013. We document a substantial increase in between-occupation wage inequality due to differential growth in premia. The association of wage premium growth and employment growth is positive, suggesting that premium growth is predominantly driven by demand side factors.

Essay III (with Peter Fredriksson, Lena Hensvik, and Oskar Nordström Skans): We provide two pieces of evidence that workers' capacity to extract rents from match-specific productivity hinges on their outside options. Using a measure of match quality, derived from the relationship between workers' multidimensional skills and job-specific skill requirements, we show that: (i) wages within ongoing matches are more closely aligned with match quality following an improvement of local labor market conditions; (ii) wages of job-to-job movers are positively related to the match quality in the previous job, even when controlling for previous wage.

Essay IV (with Mats Hammarstedt, and Per Skedinger): In a field experiment we study the causal effects of previous work experience and language skills when Syrian refugees in Sweden apply for low-skilled jobs. We find no evidence of sizeable effects from experience or completed language classes on the probability of receiving callback from employers. However, female applicants were more likely than males to receive a positive response. As a complement to the experiment, we interview a select number of employers.

Keywords: Structural change, Outside options, Match quality, Integration of immigrants

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ISSN 0283-7668
ISBN 978-91-506-2991-0
URN urn:nbn:se:uu:diva-497751 (http://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-497751)

To my mother, Ihréne, and grandmother, Elly

Acknowledgements

Writing a thesis is no small feat, nor can it be accomplished swiftly. I am typically a rather restless person and used to things in life moving faster. I still vividly remember my first day in the PhD program, awkwardly consuming breakfast sandwiches at an introductory meeting while failing to memorize any names. Back then, there appeared to be a vast ocean of time between me and graduation. Now that ocean has been reduced to a few droplets, and I cannot comprehend how quickly time has passed.

This journey has been very rewarding, and I am grateful for having had the opportunity to write this thesis. I have had the privilege of interacting with many brilliant scholars in several exceptional academic environments. I have also had the freedom to pursue whatever research I deemed meaningful while having access to extensive support and resources. At the same time, it has been very challenging. I always enjoyed playing the role of student, enthusiastically absorbing material meticulously selected and conveyed by a teacher. Writing a dissertation is a different affair entirely. In doing so, one must do substantial groundwork in order to comprehend what we already know, what we ought to know, what is even knowable, and how one can convincingly bring about the knowledge that is missing. Given this formidable task, I am very glad for having had great people at my side throughout the entire process.

I am perhaps most grateful to my supervisors, Peter Fredriksson and Georg Graetz. Thank you Peter not only for your excellent, painstaking academic guidance, but also for your emotional support during spells of stress and doubt. Your door was always open, your office armchairs felt comfortable no matter the level of thesis progression, and you always had a joke up your sleeve that spoke perfectly to my sense of humour. Thank you Georg for all the help. I am impressed and humbled by your ability to perform sound economic thinking on the spot, the extent of your knowledge, and your dedication to research. Your feedback has been consistently precise and to the point.

My work has also benefited greatly from competent co-authors. In addition to my supervisors, I have the joy of working with Adrian Adermon, Mats Hammarstedt, Lena Hensvik, Oskar Nordström Skans, Per Skedinger, and Yaroslav Yakymovych. At times, I find it hard to see the big picture and deciding how to best advance a project. Thank you Lord for co-authors! In addition, they have all been great sources of inspiration. This thesis is in all respects (at least) a nine-person job.

I hold the Uppsala University economics department in high regard. This may be interlinked with me having obtained all my tertiary education at this department; I am what you could call an in-house product. Researchers who have been particularly helpful and generous with their time include Mikael Carlsson, Stefan Eriksson, Oscar Erixson, Christoph Hedtrich, Luca Repetto, Olof Åslund, and Erik Öberg. Moreover, the department would not function without our excellent administration. All the auxiliary work has been smooth thanks to you, be it registering for courses at other departments, applying for a research visit, or convincing banks that I may presumably be trusted with a mortgage (thank you Ulrika Öjdeby!).

Writing a thesis would be awfully dull without fellow PhD students. My cohort consisted of Anton, Edvin, Elin, Fei, Jan, Maxi, and Zeynep. It has been a delight spending time with you all these years! You also helped me through all the initial coursework. A special thank you to Edvin for being the best of office mates and for introducing me to Ester and Gunnar. Thanks also to all other PhD students, past and present, including some at SLU. Both Sofia and Raoul have functioned as role models and provided helpful feedback on my work. I have had many interesting conversations about economics with Adam, Alice, Akib, Alexander, Bahre, Dogan, Erik, Jacob, Jonathan, Josefin, Lillit, Malin, Melinda, Olle, Rinni, and Xiao, to name a few. Others that made the PhD experience more enjoyable include Adrian, Daniel, Erika, Gaëlle, Hanfeng, Henning, Ida, Jakob, Majken, Markus, Polina, Sebastian, Tianze, Tram, and Tsz Chun.

During my penultimate year of the PhD program, I carried out a brief but inspiring research visit to the Centre for Economic Performance (CEP) at the London School of Economics, generously funded by *Jan Wallanders och Tom Hedelius stiftelse*. Thanks to Stephen Machin for inviting me, to my host Guy Michaels, and to the PhD students I shared offices with at the CEP.

I also wish to extend my gratitude to my former employers Lars Calmfors and Magnus Henrekson. You taught me to care as much about the questions as the methods, the importance of policy relevance, and how rewarding practical economic thinking can be. I do not think I would have pursued a PhD had it not been for my time working for you at the Research Institute of Industrial Economics and the Swedish Labour Market Policy Council in Stockholm. During this period, I also learned much from Niclas Berggren, Fredrik Heyman, Ann-Sofie Kolm, Pehr-Johan Norbäck, Martin Olsson, Tuomas Pekkarinen, Lars Persson, Per Skedinger, Roger Svensson, Björn Tyrefors, and Joacim Tåg.

My family is truly irreplaceable. My partner Hanna has been extraordinary during the last four or so years, lending support whenever I felt overwhelmed and making sure I did not take myself or my work too seriously. I love you. My sister and father are also outstanding. Buying a cottage with you is one of the best decisions I have made, because it means spending more time together. I also appreciate that you care little for what I do professionally. I have therefore never felt much external pressure to perform well in academia, enabling me to do things solely because I find them interesting. I am also blessed with a brilliant extended family through Annette, Birgit, Ebba, Mathias, Molly, Monica, Rikard, and Örjan. Thank you for all the Christmases and birthday celebrations throughout the years. Finally, I want to name a few close friends: Anton and Gabriella, thank you for always making me feel welcome whenever I visit. Spending time with you, Noel, and Isak has provided much-needed distraction from my work; Sebastian, despite the long periods of time in between, when we see each other, it feels like no time has passed. I appreciate our solid friendship; Annika, Alf, Ellen, and Klara, thank you for the many midsummer parties and get-togethers.

Uppsala, March 2023
Simon Ek

Contents

Introduction

The market for labor is crucial in many respects. Nearly all persons interact with it throughout much of their lives. Moreover, individuals make significant life choices and substantial investments in order to succeed in this market. Due to its importance, the labor market warrants much attention and research.

I firmly maintain that, as researchers, we have an obligation to improve knowledge about questions that (we at least believe) have value beyond academia, not least for making sound policy. I think many scholars within the field of labor economics are doing just that: Identifying questions that non-academics and policy makers deem important, and answering them the best they can, whether they concern structural change, education, wage setting, labor market power, the consequences of job loss, discrimination, (in)equality of opportunity and outcomes, social security, or the labor market integration of immigrants. I have tried my best to focus on policy-relevant topics that I believe are of such merit. In doing so, this thesis has come to concern three main themes: Labor market structural change, wage bargaining in matches between firms and workers, and the labor market integration of immigrants.

Throughout history, new technological advancements and ways of organizing work have transformed the market for labor. This has led to continuing advancements in welfare and wealth. But technological transitions have not been seamless, and far from everyone has benefited from them (e.g., Autor, 2015). Still today, there is much concern about how workers will handle future shifts in demand for labor across different types of jobs. The ability to cope will determine both their life-time earnings and the value created in the labor market. Although previous automation mainly concerned routine (i.e., easily codifiable and repetetive) tasks typically found in manufacturing, future technology is expected to be able to perform a broader repertoire of both lower- and higher-skilled work (e.g., Brynjolfsson and McAfee, 2014). Halting technological progress and structural change is neither feasible, nor desirable. But mitigating negative consequences of such shifts for workers should be a priority for policy makers. One key to doing so is to identify which occupations are likely to see negative shifts in demand. Indeed, there exists numerous forecasts on future employment and labor demand at the occupation level (e.g., Frey and Osborne, 2017; Arntz et al., 2017; Webb, 2019). But we do not care about occupations per se, but rather the workers in them. Many workers will likely do well following such shifts, while others will struggle. Thus, it is not sufficient to identify the occupations that will decline. One also needs to identify the workers in them that are vulnerable to negative structural shifts. Despite its importance, there is little work on this topic. This is what the first chapter of my thesis is about. In it, I develop and substantiate a theory-consistent way of characterizing worker susceptibility to negative shifts in labor demand at the occupation level.

Even after a shift in, say, occupation employment has occurred, it is neither straightforward to determine what the underlying causes of it were, nor is it uncomplicated to gauge the consequences for workers. Key to understanding the causes is the relationship between such shifts and the changes over time in the wage returns paid in different occupations. These wage returns are also critical for outcomes such as wage inequality. But they are notoriously difficult to estimate. One peculiarity that has puzzled researchers is the absence of any clear relationship between the growth in employment and average wages at the occupation level across industrialized countries (see the discussion in, e.g., Böhm et al., 2023). For instance, even though employment has declined substantially, average wages paid in routine occupations in manufacturing have remained relatively high. This is a conundrum considering that the employment changes appear to be mainly caused by shifts in demand, which should result in lower wages. But a recent literature suggests that systematic occupation switching behaviour of workers may be concealing shifts in the wages paid for a unit of skill in these occupations, i.e., the occupation wage premium (Cortes, 2016; Böhm, 2020; Cavaglia and Etheridge, 2020; Böhm et al., 2023). The second chapter adds to this literature by developing a new method for estimating these occupational wage premia.

Another important topic that has received much attention recently is that of employer labor market power (e.g., Lamadon et al., 2022; Berger et al., 2022). The degree to which firms can exert power over wage setting is important for, e.g., the labor share of value added. How then can a worker obtain as high a wage as possible? Sorting into jobs for which a worker is a good match is pivotal. But firms may not have to pay the full value of a worker's labor. A strand of search and matching theory (e.g., Postel-Vinay and Robin, 2002; Cahuc et al., 2006) makes an intuitive proposition: In order for workers to extract rents from a relationship with an employer, it is necessary but not sufficient for that relationship to be of high value. Workers also need strong outside offers to use as a bargaining chip. The current employer will then be forced to bargaining (directly or indirectly) with the employer who gave the outside offer in order to hope to retain the worker, resulting in a higher wage. Anecdotally, this is a common scenario: Workers can bring job offers to their current employer to get a better wage deal. This type of bargaining also has implications at the aggregate level: If outside offers are abundant, for instance when the labor market is tight, workers can extract more value from strong matches. The third chapter presents two sharp tests of this hypothesis.

Finally, for a long time, I have taken an interest in the public debate regarding the labor market integration of immigrants in Sweden. This is one of the major challenges that Swedish policy makers currently face, and it is interlinked with many other public concerns. Two of the questions that have dominated this debate are how to enable immigrants to successfully enter the labor market as quickly as possible, with the hope that this results in long-term establishment, and what role language skills play in facilitating this. The main tool for improving language proficiency among immigrants is language training, specifically the Swedish for Immigrants (SFI) program. Generally, immigrants who enter the labor market soon after arrival with a good proficiency in Swedish tend to do better in the long term. But due to, e.g., unobserved ability, it is difficult to determine to what extent this is caused by labor market experience and language proficiency in itself. The fourth chapter of this thesis studies how much emphasis employers put on previous experience and completed SFI in recruitment processes.

1 The essays

1.1 Worker Specialization and the Consequences of Occupational Decline

According to a standard Roy model, when demand for labor in an occupation declines, the utility loss of an incumbent worker is determined by the initial difference between the utility associated with his current occupation and his best outside option in the set of occupations unaffected by the shock. I refer to this difference as his degree of occupation specialization. Generalist workers with good outside options will leave quickly and be better off, while highly specialized workers willingly remain and tolerate the full effect of the demand shift through lower wages.

This essay shows that under certain distributional assumptions on occupation utility, the expected value of the above utility difference can be inferred from the *ex ante* probability of a worker being observed in the set of unaffected outside occupations, given his traits. I name this function the occupation specialization index (OSI). To construct it empirically, I train an artificial neural network to predict occupation choice probabilities using data from Sweden on detailed worker characteristics, including multidimensional abilities, age, education, region of residence, and industry-specific work experience.

The index is then used to shed light on the historical decline in employment in routine-intensive occupations. I compare the difference in long-run occupation switching behaviour and career outcomes between workers initially employed in routine and non-routine occupations across the specialization distribution by means of a difference-in-differences-styled specification. This allows for holding fixed any general effect of being specialized that is not related to negative demand shifts. The probability of leaving one's initial occupation depends strongly on initial OSI. This suggests that the choice of leaving routine-intensive occupations were often voluntary and guided by outside options. Moreover, the long-run earnings growth penalty of working in a routine-intensive occupation increases with the OSI. This effect acts through wages rather than employment.

Understanding better the historical shift in demand for routine work and its consequences for incumbent workers is important in its own right. But the results also substantiate the general usefulness of the specialization index in determining which workers are susceptible to negative demand shifts. The index is solely based on current information. Therefore, it could be used to characterize workers employed in occupations today that are believed to decline or even disappear in the future by susceptibility to such shifts.

1.2 Understanding Occupational Wage Growth

Co-authored with Adrian Adermon, Georg Graetz, and Yaroslav Yakymovych.

We develop a novel method for estimating occupation-specific wage premium growth—that is, the growth in the return per unit of skill or productivity—which can be applied to relatively small amounts of data. It relies on two fundamental ideas: Observing the wage growth of occupation stayers between two adjacent years in order to address issues with selection in occupation switching; and the notion of a “flat spot” in the experience profiles in each occupation where the return to an additional year of experience equals zero. The method allows for both estimating the wage premium growth between one year and the next as well as the wage-experience profiles at the occupation level. We then accumulate the year-on-year wage premium growth estimates to obtain the long-run growth in wage premia.

We implement our method on data for Sweden for the years 1996–2013. There is a modest, yet clear positive relationship between estimated wage premium growth and employment growth at the occupation level. Moreover, by means of a decomposition exercise, we find that the relative premia changes contributed substantially to the increase in overall wage inequality, but that this is masked by worker sorting. Finally, we document large heterogeneity in life-cycle profiles across occupations, which have also seen substantial shifts across time.

1.3 Outside Options and the Sharing of Match-Specific Rents

Co-authored with Peter Fredriksson, Lena Hensvik, and Oskar Nordström Skans.

A relatively recent strand of search and matching models (e.g., Postel-Vinay and Robin, 2002, Cahuc et al., 2006, Yamaguchi, 2010, Bagger and Lentz, 2019) suggests that workers in productive matches can use outside offers to pit employers against each other, thereby bidding up their wage. Thus, a valuable match and outside options are jointly necessary to reach a high wage, and well-matched workers can extract more rents when outside offers are abundant. Put differently, we should expect a positive interaction effect between workers' match quality and expected outside options on wages. Is this type of bargaining an important feature of the labor market? Although there exists some structural econometric work and survey evidence on bargaining regimes, to the best of our knowledge, there are no reduced-form tests of this theory.

This chapter provides two pieces of evidence on how outside options affect the transmission from match-specific productivity to wages. We begin by constructing an empirical measure of the quality of a match between a job and a worker. To this end, we follow Fredriksson et al. (2018) by leveraging Swedish enlistment data on multidimensional abilities and comparing the conformity between a worker's skill set and those of his tenured co-workers. This metric has multiple desirable empirical traits.

In a first exercise, we show that there is a positive, economically significant interaction effect on wages between match quality and several proxies of labor market tightness, which theoretically governs the probability of receiving outside offers. These proxies include local unemployment, a shift-share instrument based on changes in industry employment and local industry composition, and occupation-specific employment, to name a few. Secondly, we home in on job switchers. Here, our theoretical framework provides a sharp prediction: If workers are able to pit employers against each other, not only should the previous wage matter for the wage following a job transition, previous match quality should also contribute to the new wage. We find that even when conditioning on previous wage, prior match quality increases the wage in the new job. But this is only true in the absence of any interruption in the employment spell. Contrary to canonical bargaining models, these results suggest that match-specific factors and outside options are not additively separable in wage formation.

1.4 Low-skilled Jobs, Language Proficiency and Job Opportunities for Refugees

Co-authored with Mats Hammarstedt, and Per Skedinger.

This chapter focuses on two central aspects of the labor market integration of immigrants with low levels of education: The value of previous labor market experience, and language training. A common idea is that, in itself, entering the labor market improves the subsequent outlook of immigrants by, e.g., providing valuable experience and acting as a productivity signal to other employers. The fact that there is a positive association between language proficiency and employment is not seldom taken as proof of the importance of language training. Despite the relevance for policy, causal evidence on how these factors influence the integration process is scant.

One way to better understand what role they play is by studying employers' assessment of job candidates with varying characteristics. More specifically, we analyze the emphasis employers put on completing the full set of courses in the Swedish for Immigrants (SFI) program and having previous work experience as a restaurant assistant by means of a field experiment. We created eight fictitious refugee job seekers with different CV:s who immigrated from Syria in 2016. These were randomly assigned to apply to advertised low-skilled job vacancies. We also complement the experiment with interviews with a handful of employers experienced in handling applications for low-skilled jobs from immigrants.

Previous work experience and completed SFI seem to provide at best a small positive signal when refugees apply for low-skilled jobs through formal channels. This indicates that any potential positive effects must act through other mechanisms such as human capital accumulation, professional networks, or a better comprehension of the Swedish labor market. Moreover, our most salient result is that female applicants receive substantially more callbacks than male ones. This suggests that the lower employment rate among immigrant women compared to men may not be explained by worse employment prospects.

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Essay I. Worker Specialization and the Consequences of Occupational Decline

Acknowledgements: I am very grateful to my supervisors Peter Fredriksson and Georg Graetz for their continued support. I also thank Adrian Adermon, Teodora Borota Milicevic, Michael Böhm, Lars Calmfors, Mikael Carlsson, Tiernan Evans, Christoph Hedtrich, Magnus Henrekson, Sofia Hernnäs, Edvin Hertegård, Raoul van Maarseveen, Alan Manning, Guy Michaels, Oskar Nordström Skans, Per Skedinger, Joacim Tåg, Yaroslav Yakymovych, Olof Åslund, Özge Öner, and participants at workshops and seminars at the Department of Economics at Uppsala University, the Centre for Economic Performance at London School of Economics, the Institute for Evaluation of Labour Market and Education Policy (IFAU), the Research Institute of Industrial Economics (IFN), and the Department of Economics and Statistics, Linnaeus University for valuable comments and discussions. Any errors are my own.

1 Introduction

Many developed economies have experienced large occupational structure shifts in recent decades. Generally, routine-intensive occupations with codifiable tasks have declined in favor of non-routine work. This is partly due to advancements in labor-replacing technologies. The occupations that declined were commonly located in the middle of the wage distribution. These shifts have therefore contributed to wage polarization. Moreover, a recent literature finds that the growth over time in occupation wage premia and employment are positively correlated. This strongly suggests that these occupation structure shifts, including the substantial decline in routine work, were caused by changing demand.[1]

There are strong public concerns regarding how well incumbent workers will cope with future shifts in labor demand across occupations.[2] This paper develops a method grounded in theory for identifying which workers are particularly vulnerable to negative shifts in occupation labor demand.[3] It is based on estimating how much value a worker puts on his current occupation relative to his outside options. This difference is referred to as workers' degree of occupation specialization. I then ask two questions: First, how does specialization relate to the career consequences of incumbent employees following the historical decline in routine work? This query is important in its own right. But it is also a means of substantiating the general usefulness of my method for predicting worker susceptibility. Second, what is the nature of worker flows out of routine occupations? This is informative about the process by which these occupations decreased in size. It also speaks to whether mobility was voluntary for workers lacking good alternatives.

I begin by setting up a Roy-style discrete choice model with deterministic (which depend on workers' characteristics) and idiosyncratic utility terms. When a demand shock lowers the wage premium in a worker's occupation, his utility loss is determined by the difference between his utility in that occupation and his best non-shocked outside option, i.e., his specialization. Workers with little specialization move to a now-more attractive option. Highly specialized workers remain, losing more utility. I hypothesize that this effect is work-

[1]See, e.g., Goos et al. (2014) and Goos et al. (2019) for occupation structure shifts across countries; Autor et al. (2003), Goos and Manning (2007), Autor et al. (2008), and Adermon and Gustavsson (2015) for the literature on routine-biased technological change and wage polarization; Cortes (2016), Böhm (2020), Cavaglia and Etheridge (2020), and Böhm et al. (2023) for studies on occupational wage premium and employment growth.

[2]See, e.g., Brynjolfsson and McAfee (2014), Mokyr et al. (2015), Frey and Osborne (2017), and OECD (2019). For example, future technology is envisioned to be able to perform many tasks previously considered impossible, such as writing news articles and driving cars.

[3]There exists many projections (e.g., the U.S. Bureau of Labor Statistics Occupation Projections) and ample work (e.g., The OECD Future of Work initiative, Frey and Osborne, 2017, Arntz et al., 2017, and Webb, 2019) on future occupation employment. I am not aware of any predictions at the worker level. This paper provides a framework for making such projections.

ing partly through wages rather than only through amenities. For workers in occupations that did not experience any negative demand shift, specialization should be less important for future outcomes. Next, I show that under Gumbel distributed idiosyncratic preferences, expected specialization is a function of workers' *ex ante* probability of working in a non-shocked outside option. I name this expected value the occupation specialization index (OSI). I also demonstrate that ordering workers by the OSI is equivalent to ordering them by the expected utility loss from a negative wage premium shock of any size.

To construct the OSI empirically, I train an artificial neural network (ANN). The network predicts occupation choice probabilities using Swedish register data on male worker characteristics. These include multidimensional abilities (collected during the Swedish enlistment process), educational attainment, region of residence, age, and industry-specific experience. The ANN uses the same formula as the multinomial logit, consistent with the theoretical framework. But it requires less strict functional form assumptions on utility and can accommodate important but unknown non-linear and interaction effects. I use Autor and Dorn (2013)'s routine task intensity index (RTI) to classify occupations as either routine (above) or non-routine (below-median RTI). Between 2001 and 2013, non-routine occupations remained stable or grew while routine occupations declined (by 6 percentage points on average).

The OSI is expected to be more negatively related to occupation switching and wage growth for routine than non-routine workers. To test this, the OSI is related to the long-run (up to twelve years into the future) career outcomes of workers observed in 1997-2001 separately by initial routine and non-routine low- to middle-skilled occupations.[4] The probability of leaving routine work depends strongly on initial OSI. I interpret this as switching typically being voluntary, guided by the attractiveness of workers' outside options. The wage growth penalty of initially working in a routine occupation increases in the OSI. On average, routine specialists experienced lower wage and earnings growth than both low-OSI workers in either type of occupation and non-routine specialists. These results are consistent with the prediction that low-OSI "generalists" are better able to avoid losses from declining demand by transitioning to more attractive occupations.

The paper contributes to the literature on routine-biased technological change. Several previous papers in this literature highlight that susceptibility to negative demand shifts is determined by the difference between a worker's current utility and potential utility in his non-shocked options. My addition is to show that, under certain assumptions, my occupation specialization index measures the expected value of this difference. The index is simply a monotone transfor-

[4]With only one exception, the routine occupations are classified as low- or middle-skilled. To obtain a more comparable comparison group of non-routine occupations, I exclude higher-skilled occupations in the main analysis. But these are included in robustness checks. The low- to middle-skilled routine occupations are mainly concentrated in manufacturing while the non-routine are found in, e.g., services, construction, and transportation.

mation of the *ex ante* propensity for working in a non-shocked outside option. To the best of my knowledge, this closed-form solution has not been utilized before. I also demonstrate that the index predicts well which incumbents lost from the historical decline in demand for routine work. Hence, the Roy (1951) model seemingly provides an accurate representation of who loses when occupation labor demand declines. Moreover, the observable worker attributes at hand can be used to characterize workers' occupation options well.

There exists a few studies on the consequences of working in declining or routine occupations. Edin et al. (2022a) follow workers in occupations that later experienced arguably unanticipated decline using both Swedish and U.S. data. Ross and Ukil (2021) relate future industry employment to the future earnings of workers in the NLSY. Böhm (2020) and Jaimovich et al. (2021) use cross-sectional AFQT data to study changes in outcomes of workers with skill bundles fit for routine work. Cortes et al. (2017) describe which demographic groups in the U.S. contributed to the decline in routine employment. Bachmann et al. (2019) demonstrate that working in routine occupations in Germany is associated with low job stability and a high risk of unemployment. Cortes et al. (2020) find that the decline in routine work can to a large extent be accounted for by changing transition rates from non-employment to routine occupations.

More generally, there is a large literature explaining occupation switching behaviour (e.g., Jovanovic and Nyarko, 1997; Gathmann and Schönberg, 2010; Groes et al., 2015; Cortes and Gallipoli, 2018). I also relate to research using direct measures of worker attributes to infer job-specific match quality (e.g., Fredriksson et al., 2018; Guvenen et al., 2020; Lise and Postel-Vinay, 2020) and to the literature on the importance of different types of skills (e.g., Lindqvist and Vestman, 2011; Deming, 2017; Roys and Taber, 2022; Edin et al., 2022b). Finally, there are some studies of the role of occupation-specific human capital (often proxied by the distance between the task content of their initial and other occupations) for the ability to adjust to, e.g., mass layoffs (Robinson, 2018) and trade shocks (Traiberman, 2019; Eggenberger et al., 2022).

Section 2 describes the discrete choice model, the specialization index, and the econometric framework for the empirical analysis. Section 3 presents the data. Section 4 reports the empirical results. Section 5 concludes. Appendix A presents the derivation of the specialization index. The Neural Network is described in detail in Appendix B. Additional tables and figures are found in Appendix C.

2 Conceptual framework

2.1 A discrete occupation choice model

Setup

Consider a setting where workers are characterized by multiple attributes collected in the vector $\boldsymbol{x}$. There exists a finite number of occupations collected in the set K that are either classified as routine ($R \subset K$) or non-routine ($N \subset K$). The utility of worker i in occupation k is:

$$u_{ik} = \pi_k + m_k(\boldsymbol{x}) + q_k(\boldsymbol{x}) + \varepsilon_{ik}. \tag{1}$$

π_k represents the wage premium in k for a unit of skill, $m_k(\boldsymbol{x})$ determines productivity in k and $q_k(\boldsymbol{x})$ captures any amenities. ε_{ik} is an idiosyncratic term that may influence both the wage and amenities. Define deterministic utility as $u_k(\boldsymbol{x}) \equiv \pi_k + m_k(\boldsymbol{x}) + q_k(\boldsymbol{x})$. Workers choose the occupation with the highest utility. Denote a worker's initial choice by j.

Utility loss following a routine wage premium shock

Due to automation, there is a wage premium shock to all routine occupations of size $-\delta$, with $\delta > 0$. Define $d_j \equiv \delta \mathbb{1}[j \in R]$. Workers in R will choose whether to switch to another occupation. The initial occupation, j, yields a higher utility than any other occupation in R both before and after the shock. Therefore, the only relevant options are the non-shocked occupations in N. Since $d_j = 0$ for workers in N, their outside options do not matter. But if their occupation would experience the shock, the relevant option is the best choice in the set of non-routine occupations excluding j, i.e., $N \backslash \{j\}$.

The utility loss from staying in j is $-d_j$. The loss from switching is the difference between the initial utility in j and the best, non-shocked, outside option, i.e., the initial utility surplus. The worker will choose the option with the smallest associated loss. Thus, the change in utility is:

$$\Delta u_{ij} = \max\left\{-d_j,\ -\left(u_{ij} - \max_{n \in N \backslash \{j\}} u_{in}\right)\right\} \leq 0. \tag{2}$$

The loss, in absolute terms, is bounded above by workers' utility surplus relative to their best non-routine outside option. I call this their degree of occupation specialization. Specialists with a large surplus remain and tolerate the full effect of the wage premium shock. Workers with a small surplus will instead move and experience a smaller utility loss.

For routine workers, $N \backslash \{j\}$ equals N. Thus, the surplus is defined slightly different for routine and non-routine workers. But it captures the difference between current utility and the utility associated with the best non-routine outside option for both groups.

Gumbel distributed idiosyncratic terms

I henceforth assume that all ε_{ik} are IID standard extreme value type I (or Gumbel) distributed. Although the utility surplus in (2) is never observed, four key properties of the Gumbel distribution allow me to characterize the distribution of this surplus: First, the occupation choice probabilities follow the multinomial logit (see McFadden, 1973):

$$p_k(\boldsymbol{x}) = \frac{e^{u_k(\boldsymbol{x})}}{\sum\limits_m e^{u_m(\boldsymbol{x})}}. \tag{3}$$

Second, the distribution of maximum utility before conditioning on occupation choice is also Gumbel distributed, with known location and scale. Third, using results from Hanemann (1984), the maximum utility conditional on any optimal choice j can be shown to be distributed the same as the unconditional maximum. Fourth, the difference between two same-scaled Gumbels is known to be logistic distributed. The details of characterizing the utility surplus distribution are reported in Appendix A.

2.2 The occupation specialization index

I now turn to finding a closed-form expression for the expected value of the utility surplus. I name this expression the occupation specialization index, or OSI. It reveals the expected utility a worker would lose if leaving his current occupation. Thus, one may interpret the OSI as how dependent, on average, workers are on their occupation for utility. The derivation of the OSI, and its properties, is described in Appendix A.

The index

First, define the *ex ante* probability of working in a non-routine outside option as follows. It is determined by a worker's characteristics, his observed occupation, and the set of non-routine occupations:

$$\rho(\boldsymbol{x}, j, N) \equiv \sum_{n \in N \setminus \{j\}} p_n(\boldsymbol{x}). \tag{4}$$

The expected value of the utility surplus can then be shown to be a monotonically decreasing function of $\rho(\boldsymbol{x}, j, N)$. This is the occupation specialization index:

$$\text{OSI}(\boldsymbol{x}, j, N) \equiv \mathbb{E}\left[u_{ij} - \max_{n \in N \setminus \{j\}} u_{in} \;\middle|\; \boldsymbol{x}, j\right] = -\frac{\ln(\rho(\boldsymbol{x}, j, N))}{1 - \rho(\boldsymbol{x}, j, N)}. \tag{5}$$

To the best of my knowledge, this metric has neither been used previously in any work on occupation decline as well as routine-biased technological change, nor been derived in the theoretical discrete choice literature. The OSI is more general than in my application: It can be used to infer the expected utility surplus of any observed choice relative to a subset of alternatives.

Relationship with expected loss

The expected value of the utility change following the wage premium shock in (2) is a function of only d_j and $\rho(\boldsymbol{x}, j, N)$:

$$\mathbb{E}\left[\Delta u_{ij} \,\middle|\, \boldsymbol{x},\ j\right] = -\frac{d_j - \ln\left(1 + \left(e^{d_j} - 1\right)\rho(\boldsymbol{x}, j, N)\right)}{1 - \rho(\boldsymbol{x}, j, N)}. \tag{6}$$

For any value of $d_j = \delta > 0$, it is monotonically increasing (i.e., the absolute loss becomes smaller) in $\rho(\boldsymbol{x}, j, N)$. Since the OSI is decreasing in $\rho(\boldsymbol{x}, j, N)$, ordering workers by the OSI is equivalent to ordering them by absolute expected loss for any shock size.

Interpretation of the index

To summarize, the utility loss from an occupation wage shock is determined by the difference between a worker's utility in his occupation and his best non-shocked outside option. The expected value of this difference can be inferred from his *ex ante* probability of working in an outside, non-shocked occupation via the OSI. The OSI can also be used to order workers by expected loss from a shock of unknown size.

Intuitively, the OSI can be comprehended as follows. The extent to which a worker's peers with similar characteristics are observed in outside non-routine occupations carries a signal about his non-routine options. If no other workers with, say, a comparable skill set and education background works in an occupation other than his, these options are likely unattractive or unavailable to him. This idea is similar in spirit to the widely used revealed comparative advantage metric by Balassa (1965). It is also related to, e.g., Fredriksson et al. (2018) who measure match quality by the similarity of the skills of workers and their co-workers, Coraggio et al. (2022) who define match quality as the probability of being observed in an occupation-industry cell, and the outside options index developed by Caldwell and Danieli (2022).

Although this framework concerns utility, the empirical section deals with, e.g., wages and earnings. Workers that remain in occupations with decreasing wage premia will experience the effect on utility through wages. For switchers, however, utility may be influenced through wages or amenities. These are difficult to disentangle. But in Section 4.1, I show that specialization correlates positively with the wage surplus that a worker enjoys in his occupation.

Estimation

To construct the OSI empirically, I estimate occupation choice probabilities using the formula from (3). This is also known as the softmax activation function. Instead of using a multinomial logit, it can be used to estimate $p_k(\boldsymbol{x})$

by an artificial neural network (ANN; Described in detail in appendix B). This flexible machine learning algorithm requires less strict functional form assumptions on $u_k(\boldsymbol{x})$ regarding non-linear and interaction effects. But to attest that the results are robust to choice of method, I also estimate $p_k(\boldsymbol{x})$ using a multinomial logit assuming that $u_k(\boldsymbol{x}) = \boldsymbol{\vartheta}'_k\boldsymbol{x}$. I then calculate $\rho(\boldsymbol{x}, j, N)$ in (4) using the predicted probabilities. Finally, $\rho(\boldsymbol{x}, j, N)$ is inserted into the OSI formula in (5). To avoid outliers, I censor the OSI at the 1st and 99th percentile. The OSI is difficult to interpret in levels, and is therefore standardized to mean zero, standard deviation one.

2.3 Specialization based on observed wages

Definition

As a complement to the OSI, I estimate the expected difference between a worker's log wage in j and $N\backslash\{j\}$. I refer to this as the wage surplus, or WOSI. Let $\mathbb{E}[w_{ia} \mid \boldsymbol{x}, b]$ be the expected log wage in occupation set a of workers in set b. $\mathbb{E}[w_{iN\backslash\{j\}} \mid \boldsymbol{x}, j]$ is not observed. But one can assume to what extent workers in $N\backslash\{j\}$ are representative of workers in j with similar characteristics. The expected log wage surplus can be written as:

$$\begin{aligned} \mathrm{WOSI}(\boldsymbol{x}, j, N) &= \mathbb{E}[w_{ij} - w_{iN\backslash\{j\}} \mid \boldsymbol{x}, j] \\ &= \mathbb{E}[w_{ij} \mid \boldsymbol{x}, j] - \sum_{n\in N\backslash\{j\}} \frac{p_n(\boldsymbol{x})}{\sum_{m\in N\backslash\{j\}} p_m(\boldsymbol{x})} \mathbb{E}[w_{in} \mid \boldsymbol{x}, n] + e(\boldsymbol{x}, j, N), \end{aligned} \tag{7}$$

where $e(\boldsymbol{x}, j, N) = \mathbb{E}[w_{iN\backslash\{j\}} \mid \boldsymbol{x}, N\backslash\{j\}] - \mathbb{E}[w_{iN\backslash\{j\}} \mid \boldsymbol{x}, j]$ is the error with which a worker's wage in $N\backslash\{j\}$ is predicted.

Estimation

To construct the WOSI empirically, I first demean w_{ijt} separately by year. I then estimate $w_{ijt} = \boldsymbol{\omega}'_j\boldsymbol{x}_{it} + \varepsilon_{ijt}$ using OLS. Next, I substitute all expected values in (7) with $\hat{\boldsymbol{\omega}}'_k\boldsymbol{x}_{it}$ and the choice probabilities with the ANN predictions. The bias will depend on $e(\boldsymbol{x}, j, N)$, which is omitted. The key assumption for using the WOSI is that it carries a positive and equally strong signal of the true wage surplus for workers in routine and non-routine occupations. As with the OSI, I censor the WOSI at the 1st and 99th percentile and standardize it.

2.4 Predictions

From the above framework, I highlight two predictions:

1. Expected loss: The expected loss from a negative demand shift in routine occupations increases in an incumbent's expected degree of specialization. Workers in non-routine occupations will be less affected by such a shock

and their specialization matters less than for workers initially observed in routine work. The difference in the average loss between the two groups will therefore increase in specialization. I hypothesize that the loss in utility works partly through wages rather than only through amenities.

2. Expected worker flows: There is negative selection on the OSI in who leaves the routine occupations: Highly specialized workers will to a larger extent remain and tolerate the full effect of the negative shock. Again, specialization should matter less for the probability of switching to another occupation for workers initially in non-routine work; It should primarily be routine generalists that engage in occupation switches.

2.5 Econometric framework

The framework outlined above motivates a difference-in-differences-styled specification comparing the effect of the OSI on the outcomes of workers initially in routine and non-routine work. This holds constant any common effect of being specialized relative to the non-routine outside options by using non-routine workers as a comparison group to the "treated" routine workers.

Main regression model

Let $y_{ijt+\tau}$ represent an outcome in year $t+\tau$ of individual i observed in occupation j in t. The following model is considered the main specification:

$$\begin{aligned} y_{ijt+\tau} = & \psi \widehat{\text{OSI}}(\boldsymbol{x}_{it}, j, N) + \mathbb{1}\left[j \in R\right] \left[\beta + \phi \widehat{\text{OSI}}(\boldsymbol{x}_{it}, j, N)\right] \\ & + \boldsymbol{\lambda}' \boldsymbol{z}_{it} + \varepsilon_{ijt+\tau}. \end{aligned} \tag{8}$$

β captures the difference between routine and non-routine workers at average OSI, and ψ captures the common effect of the OSI. The difference in the effect between the two occupation groups is captured by ϕ. The vector $\boldsymbol{z}$ includes year FE and the variables used to estimate the OSI, i.e., $\boldsymbol{x}$. At times it also includes occupation FE, but then β is no longer identified. The model then mainly relies on workers with similar characteristics sorting into different occupations for identification.

Semi-parametric model

To obtain non-parametric estimates of the effect of specialization, I will also estimate models with indicators for the decile groups of the OSI distribution separately for routine and non-routine workers. The model is:

$$\begin{aligned} y_{ijt+\tau} = & \sum_q \theta_q^R g_q^R \left(\widehat{\text{OSI}}(\boldsymbol{x}_{it}, j, N)\right) + \sum_q \theta_q^N g_q^N \left(\widehat{\text{OSI}}(\boldsymbol{x}_{it}, j, N)\right) \\ & + \boldsymbol{\lambda}' \boldsymbol{z}_{it} + \varepsilon_{ijt+\tau}. \end{aligned} \tag{9}$$

g_q^R and g_q^N are indicators for belonging to OSI decile group q^R and q^N, respectively. The reference category is the lowest non-routine decile group. The θ_q^R, θ_q^N coefficients will be plotted against the average OSI within each decile group. After estimation, I add the mean of the outcome for the reference category to all θ_q^R, θ_q^N coefficients. In some exercises, I also estimate a version of (9) with only one set of decile group indicators.

Standard errors
Since the OSI is an estimate, I cannot obtain correct standard errors for the coefficients in (8) and (9). Bootstrapping is not feasible due to the laboriousness of constructing the metrics. Nevertheless, I report standard errors clustered at the individual level.

3 Data

3.1 Variables

Background characteristics
I collect data on individual characteristics from Swedish population-wide administrative registers. I use 13 different levels of educational attainment,[5] and 25 different fields of study,[6] according to the 2-digit categories of the Swedish Standard Classification of Education (SUN, based on ISCED). I also calculate work experience between $t-13$ and $t-1$ (t = year of observation) in 14 industries according to the Swedish Standard Industry Classification (SNI).[7]

Wage and occupation information
I use workers' full-time equivalent monthly wages from the Swedish Wage Structure Statistics (*Lönestrukturstatistiken*; WSS) survey. I also collect information on occupation at the two-digit level of the Swedish Classification of Occupations (SSYK, based on ISCO). A few, very small, occupations are

[5]Preschool; compulsory < 9 or 9-10 years; secondary < 2, 2, or 3 years; post-secondary < 2, 2, 3, 4 or ≥ 5 years; licentiate or similar degree; doctoral degree.
[6]Basic; literacy and numeracy; personal skills; teacher training and education science; arts and media; humanities; social and behavioural science; journalism and information; business and administration; law; life science; physical science; mathematics and statistics; computing; engineering and engineering trades; manufacturing and processing; architecture and building; agriculture, forestry, fishery; veterinary; health; social services; personal services; transport services; environmental protection; security services.
[7]Agriculture and related; mining and quarrying; manufacturing; electricity, gas and water supply; construction; wholesale and retail trade; hotels and restaurants; transport, storage and communication; financial intermediation; real estate and renting; public administration; education; health care and social services; other services.

excluded. I also exclude managers and politicians. The final data include 22 occupations.[8]

Survey weights

Sampling in the WSS occurs at the firm/organization level. All public and almost 50 percent of private sector employees are sampled each year. The data include weights used to make any constructed moments representative of the full employee population.[9] To mitigate issues with extreme weights being put on a few very small firms in certain industries, I censor the weights at the 99th percentile. I use these survey weights for all empirical exercises, including training the ANN.

Multidimensional skills

I utilize information on cognitive and non-cognitive skills from the Swedish War Archive. These data were collected during the Swedish draft process in 1969-1994. They are available for around 90 percent of males born in 1951-1976 who underwent the draft at the age of 18 or 19.[10] The draftees performed four standardized cognitive tests on: Inductive reasoning; verbal comprehension; spatial ability, and; technical understanding. They also took part in a 25 minute interview with a psychologist. The psychologist evaluated the profile of the draftee and scored them along four dimensions. Mood et al. (2012) interprets these as: Social maturity; psychological energy, focus or perseverance; intensity or activation without pressure; emotional stability or tolerance to stress. The detailed scores were used by the military to produce two aggregate measures of cognitive and non-cognitive ability. I utilize these aggregate metrics in some descriptive exercises. The scaling of the scores varies by test type and draft cohorts. I standardize the skill measures within each cohort following Fredriksson et al. (2018) and Edin et al. (2022b).

Variables used to estimate the OSI

To estimate the OSI, I incorporate a second-order polynomial for each of the eight cognitive and non-cognitive abilities and for experience in the 14 industries in $\boldsymbol{x}$.[11] I also include 28 age, 13 education level, 25 education field, and 21 region of residence indicators. These variables proxy abilities at labor market entry, human capital acquired through education, experience and age, and differences in, i.a., occupation demand across local labor markets.

[8] Occupation and full-time wages refer to a reference week in September for the private sector and November for the public sector.

[9] All firms with at least 500 employees as well as the whole public sector are sampled. In smaller firms, the sampling probability is positively related to size and stratified by industry.

[10] These skill measures are described in detail by Lindqvist and Vestman (2011).

[11] Individual occupation histories are not observable as occupation information is from a survey.

Occupation routine task intensity

To distinguish between routine and non-routine occupations, I use the routine task intensity (RTI) index from Autor and Dorn (2013). It is based on the five measures of task requirements in 1980 from the U.S. dictionary of occupation titles (DOT) used by Autor et al. (2003): Eye-hand-foot coordination (classified as manual); set limits, tolerances and standards (routine cognitive) and finger dexterity (routine manual), the average of which is routine task requirement; direction control and planning, and GED math, the average of which is abstract task requirement. The RTI for occupation k is:

$$\text{RTI}_k = \ln(\text{routine input}_k) - \ln(\text{manual input}_k) - \ln(\text{abstract input}_k). \quad (10)$$

I classify occupations as either routine ($r_k = 1$) or non-routine ($r_k = 0$) based on the RTI_k relative to the median M at the worker level: $r_k = \mathbb{1}\left[\text{RTI}_k \geq M\right]$.

3.2 Sample

My sample for which I aim to predict the OSI consists of approximately 1.7 million observations of male employees observed in 1997-2001, who are sampled in the WSS, for which information on skills is available and who are therefore aged 23-50. 1997-2001 can be thought of as a pre-period. 2001 is chosen as the final year somewhat arbitrarily. I need a sufficiently large sample to train the Neural Network. Moreover, aggregate statistics on occupation employment are published by Statistics Sweden from this year forward.

I draw a random 30 percent sample of individuals (and not observations) from the pre-period sample. This subsample is used as training data for the ANN, multinomial logit and wage regression underlying the WOSI. The remaining 70 percent are used for out-of-sample evaluation and the empirical analysis in Section 4.

For the empirical analysis, I follow the individual associated with each observation in the pre-period up to twelve years forward in time and collect information on wages, annual earnings, employment and occupation.[12] To obtain better coverage, future occupation and log wage from the WSS are measured in $t+10$ through $t+12$. I use the most recent observation if available or move back otherwise. As survey weights, I use the inverse of the probability of being observed in t and at least in one year between $t+10$ and $t+12$.[13] To account for differences in when workers are observed, I always control for initial $\times$ future year of observation FE.

[12] In one exercise, I also follow workers five years back in time from the pre-period year of observation and collect information on previous wages.

[13] More precisely, I use the observed initial weight$_t$ and future weight$_{t+\tau}$ and calculate the inverse of the probability of being observed in both t and at least one year between $t+10$ and $t+12$ as $\text{weight}_t \times 1/\left(1-\left(1-\frac{1}{\text{weight}_{t+\tau}}\right)^3\right)$.

4 Empirical analysis

This section reports the empirical results. Section 4.1 presents validation exercises. Section 4.3 describes how different characteristics relate to the OSI. Section 4.3 reports the results on long-run worker outcomes.

4.1 Validation exercises

I begin by discussing, e.g., how well the ANN can predict occupation choices. I then describe how the OSI is related to alternative metrics of specialization and to log wage. Finally, I show that the routine indicator predicts well which occupations declined during the studied period.

Explanatory power of the choice and wage models

The neural network has an out-of-sample accuracy, i.e., assigns the highest probability to the actual occupation choice, of 47.9 percent. This is a slight advantage over the accuracy of the multinomial logit, 43.5 percent. These numbers can be compared to when including only a constant in the vector $\boldsymbol{x}$. The guess would then be the largest occupation in the training data set (physical and engineering associate professionals), with an accuracy of 11.3 percent.

The ANN acuracy does not matter per se for the OSI. The critical aspect is instead the validity of the probabilities it assigns to *all* potential choices. Figure C3 in the appendix shows that the probabilities assigned by the ANN on average correspond well to the choices of workers in the evaluation sample. In contrast, the multinomial logit predictions slightly overestimate the true probabilities.

The wage regression underlying the WOSI in (7) has a coefficient of determination of 0.56 out-of-sample; occupation FE interacted with age, skills, education, region, and previous experience can explain around half of the variation in log wage (after residualization by year).[14]

The alternative specialization indices and wages

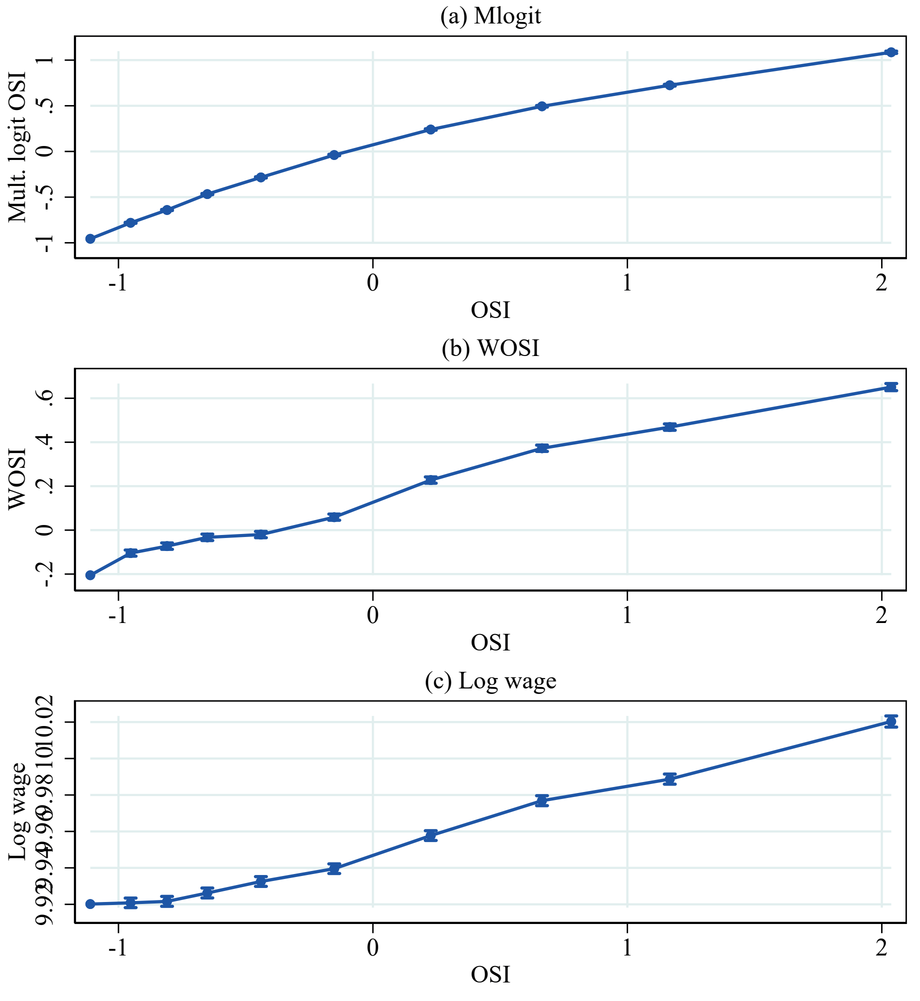
Next, I relate the OSI to the metric based on the multinomial logit, the WOSI, and workers' log wages.[15] Figure 1 reports non-parametric estimates from the version of the model from (9) with a common set of decile group indicators. I control for occupation and year FE as well as all variables in $\boldsymbol{x}$ used to construct the OSI (i.e., abilities, industry experience, education level and field, region, and age).

According to panel (a), there is a strong relationship between the two probability based metrics. Panel (b) reveals a positive relationship between the OSI

[14] The accuracy and coefficient of determination are very similar for the training and test sample, indicating that the models are not prone to overfitting.

[15] Figure C2 reports histograms of these metrics.

Figure 1. Non-parametric relationship between the OSI, alternative specialization metrics and log wage



Notes: The figure relates the OSI based on the neural network to the OSI using the multinomial logit estimates (Panel a), the WOSI which measures the expected wage difference between workers' current and outside options (panel b) and log wage (panel c). The vertical axis reports the decile group coefficients from the version of equation (9) with a common set of indicators. The regressions include controls for a second-order polynomial in the eight skill dimensions and 14 previous industry experience variables as well as age, education and field, region, year, and occupation FE. To all decile group coefficients, I add the average outcome of the lowest decile group reference category. The horizontal axis plots the average OSI within each decile group.

and WOSI. This means that, when a worker's expected wage surplus in an occupation is high, so is his propensity to work there. A one-standard deviation (sd) increase in the OSI is associated with a 0.3-sd higher WOSI. There is also a positive relationship with log wage: A sd increase in the OSI results in 3 percent higher wages.[16] Importantly, this implies that the wage loss associated with leaving one's occupation is increasing in the OSI.

Destinations of occupation switchers

The model assumes that worker characteristics are intrinsically linked to occupation specific utility and therefore occupation choices. One way to corroborate this is to study the choices of workers that transition from their original occupation. Figure C4 shows that the assigned probabilities are highly informative about which outside occupations are the most likely destinations of long-run switchers.

Relationship between routine task intensity and employment growth

Figure 2 ranks all occupations according to their routine task intensity. This rank is then plotted against growth in the employment share between 2001 and 2013 according to Statistics Sweden. The vertical line shows the routine/non-routine cutoff. The occupations that saw the lowest employment growth are routine-intensive. In fact, no routine occupation experienced an increasing employment share and only one non-routine occupation (teaching professionals)[17] saw declining relative employment.

The figure also plots the employment share growth by occupation for my sample of workers for which I observe occupation in both t and $t+10$ to $t+12$. The results are quite similar. With the exception of high-skilled physical and engineering professionals and stationary plant operators, all routine occupations that experienced negative employment growth also saw size decreases in my sample of incumbent workers. Overall, routine decline cannot be accounted for only by labor market entrants and leavers.

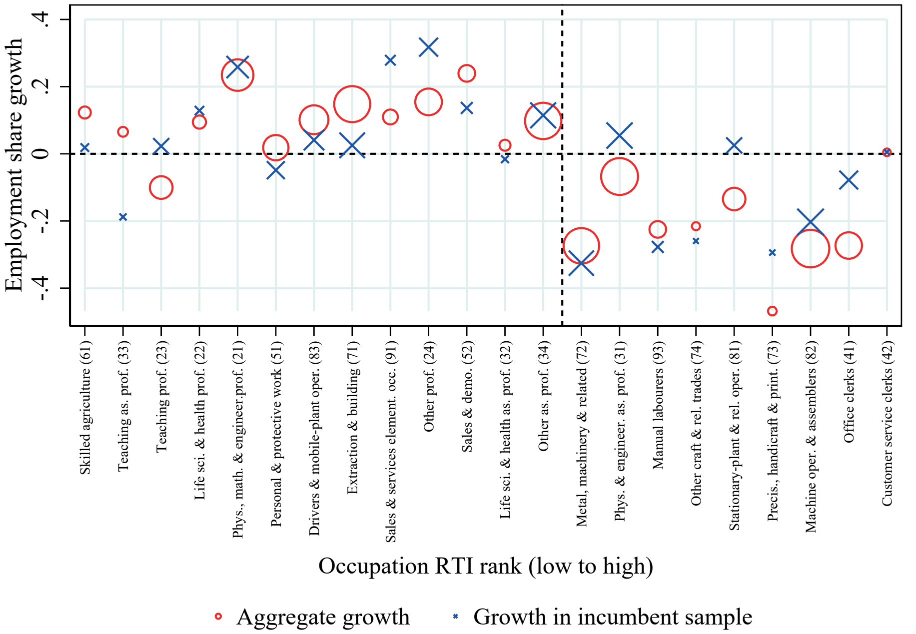
Education requirements of routine and non-routine occupations

In SSYK, occupations with the leading number 1-3, 4-8, and 9 can be considered high-, medium- and low-skilled, respectively. As evident from Figure 2, with only one exception, routine occupations are low- to middle-skilled. To be able to better compare these to non-routine occupations, I focus on workers initially observed in low- to middle-skilled occupations in Sections 4.2 and 4.3. These are listed in Table 1. Apart from clerks and manual labourers, the routine occupations are concentrated in manufacturing. The non-routine occu-

[16] Thus, in line with, e.g., Fredriksson et al. (2018), being well matched (i.e., likely to sort into the chosen occupation) is also associated with an absolute premium.

[17] However, associate teaching professionals exhibit a substantial increase in size, suggesting that workers' occupations may have been reclassified.

Figure 2. Occupation employment share growth by routine-intensity rank



Notes: The figure plots the employment share growth at the occupation level on the vertical axis. On the horizontal axis, the occupations are ranked by their routine task intensity (from low to high). The vertical dashed line represents the cutoff between routine and non-routine occupations. "Aggregate growth" refers to relative employment growth between 2001 and 2013 according to Statistics Sweden. "Growth in incumbent sample" instead refers to my sample of workers for which I observe occupation in both t (1997-2001) and $t+10$ to $t+12$ (depending on when workers are observed in the WSS). The size of the markers is determined by initial employment share.

pations are instead mainly found in construction, services, transportation, and agriculture.[18]

4.2 Characteristics associated with specialization

I now briefly describe which characteristics are associated with specialization. Figures C5 and C6 relates the OSI to the variables that are used to construct the OSI for workers in low- to middle-skilled occupations.

For routine occupations, both cognitive and non-cognitive ability is strongly negatively related to specialization. The story for educational attainment is similar. The education fields associated with the highest specialization are general (which includes primary) education and, unsurprisingly, engineering, manufacturing and construction. Regarding regions, average OSI is relatively low in the Stockholm region and other densely populated areas. Specialization is also relatively low in the least populated regions. Specialization is decreasing slightly in age. At the same time, experience in manufacturing is one of the strongest predictors of specialization for routine workers.

For non-routine workers, the ability relationships are not as stark as for routine occupations. But the relationship with education level and age are more pronounced. Specialization is also high for workers with an education related to services, teaching, and construction (classified together with engineering and manufacturing). The results for region of residence are similar as for routine workers. Finally, workers with experience in construction, transportation, public administration, education and health care all exhibit high specialization levels.

4.3 Specialization and long-run career outcomes

How does the OSI relate to the future career outcomes of workers in routine and non-routine occupations? From the theory, I expect routine workers to be more likely to switch to a non-routine outside option than non-routine workers. This difference should be caused primarily by low-OSI workers. Moreover, I expect average wage/earnings growth to be lower for workers in routine than non-routine occupations. This growth penalty should be increasing in the OSI.

Two occupation outcomes are analyzed: Making any occupation transition between t and $t+10$ to $t+12$, and transitioning to a non-routine outside option. I then analyze three additional outcomes: log wage growth between t and $t+10$ to $t+12$, annual earnings growth in t to $t+12$ relative to the initial level, i.e., $\Delta_{t,t+12}\text{earnings}/\text{earnings}_t$, and an employment indicator for $t+12$. Earnings and wages are adjusted for CPI.

[18] Higher-skilled occupations still enter as outside occupations when calculating the OSI. In robustness checks, I show that the results are similar when including all occupations.

Table 1. *Low- to middle-skilled routine and non-routine occupations*

Routine			Non-routine		
SSYK	Name	N	SSYK	Name	N
74	Other craft & related trades	3,098	61	Skilled agriculture work	9,364
42	Customer service clerks	4,825	52	Sales & demo.	15,596
73	Precision, handicraft & printing	5,103	91	Sales & services elementary occupations	22,010
93	Manual labourers	29,411	83	Drivers & mobile-plant operators	52,904
81	Stationary-plant & related operators	56,923	51	Service, care & protective work	77,605
41	Office clerks	66,488	71	Extraction & building	91,859
72	Metal, machinery & related	101,206			
82	Machine operators & assemblers	116,862			

Notes: The table reports the number of observations in the pre-period test sample for all low- to middle-skilled occupations (excluding the high-skilled categories 1-3 at the broadest level of SSYK) separately by occupations below and above median routine intensity.

Non-parametric estimates

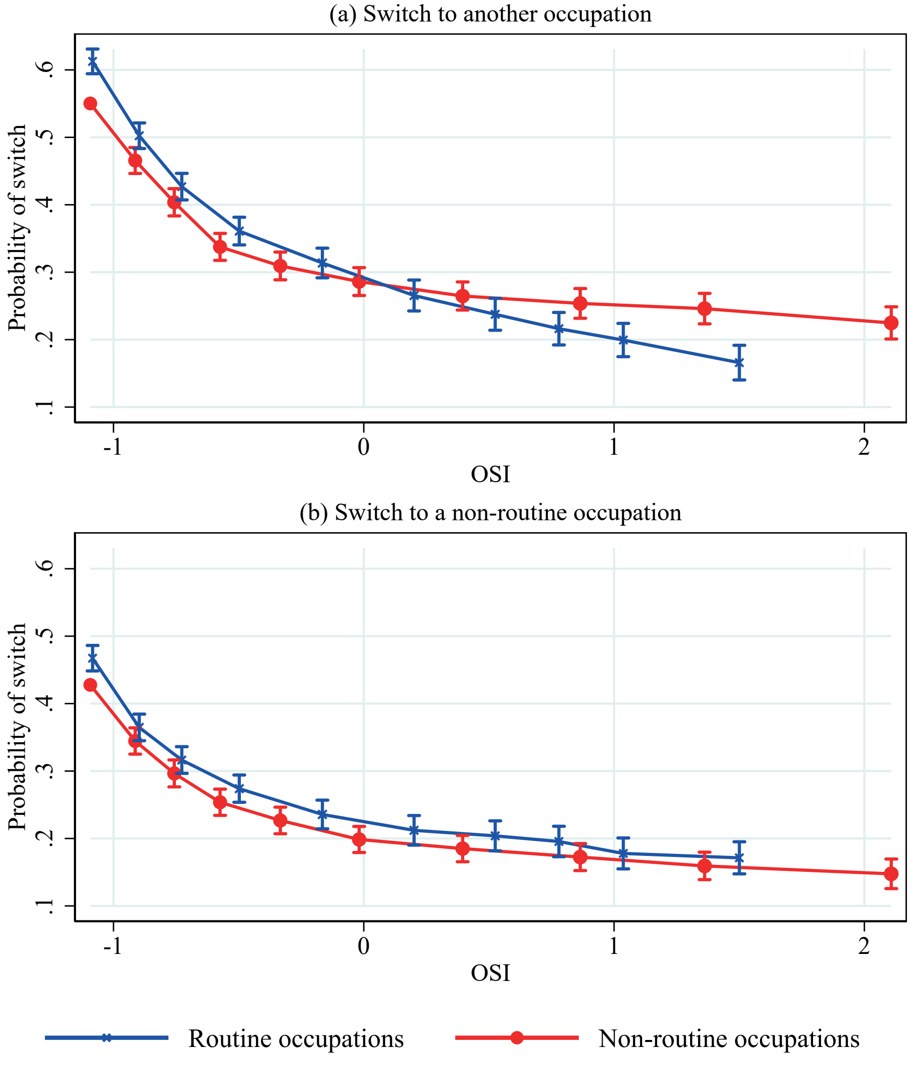
Figure 3 reports non-parametric estimates from equation (9) for the OSI and the switching outcomes. Panel (a) shows that leaving the initial occupation is strongly negatively related to specialization for both routine and non-routine occupations. Results are similar when only considering switches to other non-routine occupations in panel (b). Almost half of the least specialized workers in routine occupations left for a non-routine occupation. This is around three times the mobility rate of the highest-OSI workers. In (a), the relationship is somewhat stronger for routine compared to non-routine workers. But this is to a lesser extent the case in (b). Thus, the OSI indeed predicts which workers leave the set of routine occupations. My interpretation of this is that workers were typically not forced out of routine work; Highly specialized routine were largely able to remain in their initial occupations. However, the hypothesis that primarily routine (and not non-routine) generalists are engaged in occupation switches is not consistently borne out.

Figure 4 instead reports results for wage growth, earnings growth, and employment. Specialization is negatively related to wage and earnings growth. These relationships are markedly stronger for workers in routine compared to non-routine work. At the bottom of the OSI distribution, there is no discernible difference in wage and earnings growth between the two occupation groups. At the top of the distribution, the difference in wage (earnings) growth is around five log points (six percentage points). These results indicate that routine specialists experienced substantial negative consequences of the demand shift.[19] By contrast, routine workers with the lowest OSI levels appear to have been largely shielded from it. There is a slight positive relationship between the OSI and future employment for both occupation groups. This relationship appears marginally stronger for non-routine workers, but the difference in the effect is never significant. The absence of any employment effect suggests that the quality of workers' future jobs is the important margin for future outcomes.

Wage growth can be analyzed separately for occupation stayers and switchers. However, specialization influences the decision to switch. Selection is therefore a key issue to bear in mind. Figure C7 reports non-parametric estimates for log wage growth separately for workers that remained in the same occupation and moved to an outside non-routine occupation. The relationship between the OSI and wage growth is similar for routine and non-routine switchers. However, specialization is more negatively related to wage growth for routine compared to non-routine stayers. This may be due to selection: If the wage premium in routine work decreases, generalists with good outside options should stay only if there is some counteracting idiosyncratic effect in the future that leads to acceptable wage growth. A more troubling explana-

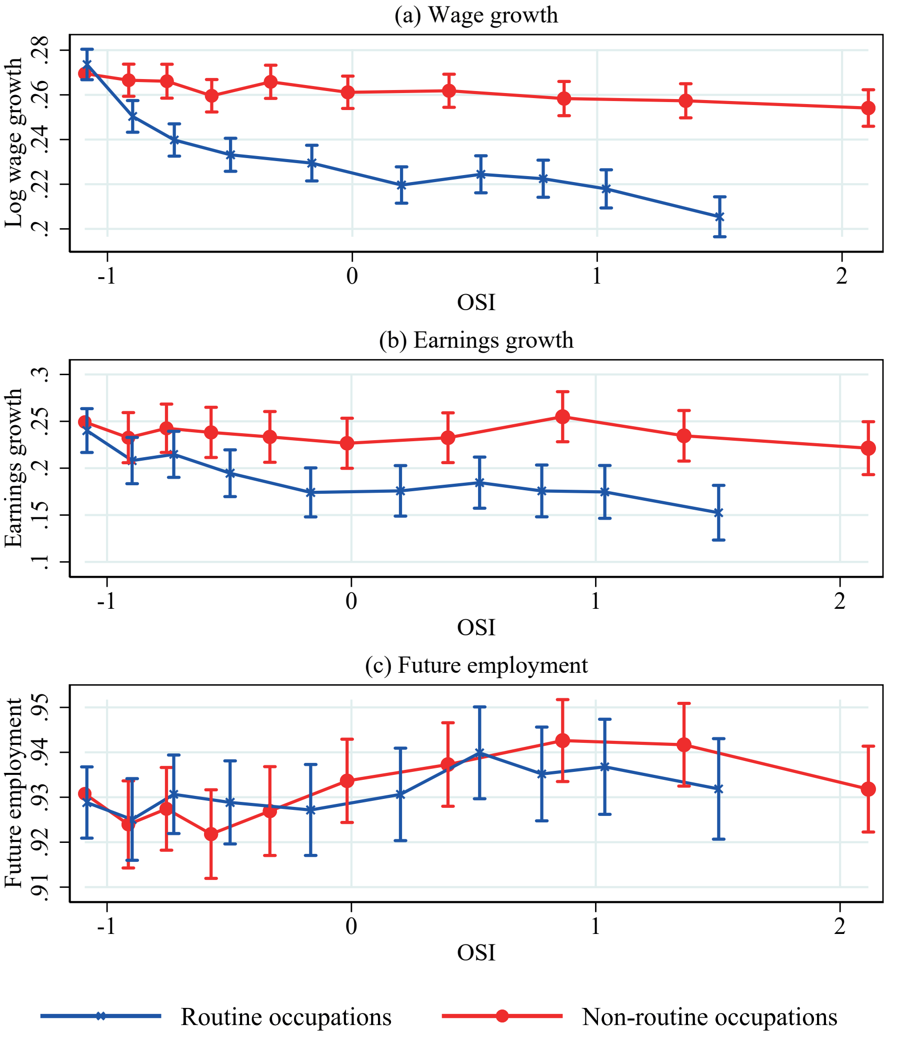
[19] This is consistent with the findings for workers who stay in routine occupations in Cortes (2016).

Figure 3. Non-parametric relationship between specialization and leaving the initial occupation by routine and non-routine occupations



Notes: The vertical axis reports the decile group coefficients from equation (9) for separate occupation switching outcomes. All regressions include controls for a second-order polynomial in the eight skill dimensions and 14 previous industry experience variables as well as age, education and field, region, and initial $\times$ future year fixed effects. To all decile group coefficients, I add the average outcome of the lowest OSI non-routine reference category. The horizontal axis plots the average OSI within each decile group. Panel (a) relates the OSI to the probability of being observed in a different occupations in t and $t+10$ to $t+12$ separately for workers initially observed in routine and non-routine occupations. Panel (b) instead reports the relationship between specialization and switching to another, non-routine occupation.

Figure 4. Non-parametric relationship between specialization and labor market outcomes by routine and non-routine occupations



Notes: The figure relates the OSI to log wage growth between t and $t+10$ to $t+12$, growth in annual earnings between t and $t+12$ divided by initial earnings, and the probability of being classified as employed in $t+12$. See Figure 3 for additional information.

tion is if the OSI is related differently to career wage profiles for routine and non-routine occupations. To account for this, I control for age and industry experience fully interacted with the routine indicator in subsequent robustness checks.

Alternative specifications, samples and specialization metrics

Next, I explore the robustness of my results to the choice of specification and specialization metric. To this end, I estimate different versions of the main regression model from equation (8).

Table 2 reports results for the main OSI metric. The first model uses the same controls as in Figures 3-4: Year FE and all variables used to estimate the OSI. The second model additionally controls for occupation FE, thus relying on variation within each occupation. The third model adds a second-order polynomial in initial log wage fully interacted with the routine indicator. This allows for comparing workers with similar absolute productivity yet different relative occupation advantage. The fourth model includes workers in higher-skilled occupations. In all models, the OSI is negatively associated with occupation switching and earnings and wage growth. The effect is consistently more negative for workers in routine than non-routine work, as captured by the interaction. In the first model, a standard deviation increase in the OSI is associated with around 1.4 percent lower wage growth and 2 percentage points lower earnings growth for routine relative to non-routine workers. These effects decrease slightly when controlling for occupation FE, but remain statistically significant. Moreover, there are no significant effects on future employment.

Table 3 reports results for alternative specialization metrics. All models include controls for the variables used to estimate the OSI and year and occupation FE. The first model uses the OSI based on the multinomial logit. It exhibits very similar results to the comparable model in Table 2. The WOSI used in the second model yields qualitatively similar results, but the effect sizes are more modest. The third model uses the percentile groups of the OSI distribution within each occupation instead of the OSI. I standardize the metric for ease of comparison. This corroborates that the results are not caused by how the OSI scales across occupations. Finally, the metric in the fourth model includes all outside occupations when calculating the OSI. This implies summing over $n \in K \setminus \{j\}$ in equation (5). The effects are much starker than for the baseline OSI. However, this is because a subset of the routine occupations are very similar and could be classified as the same occupations. This leads to much less variation in specialization for routine workers.

Interacted controls

Figure C8 reports estimates from models where subsets of the variables used to estimate the OSI (i.e., $\boldsymbol{x}$) are fully interacted with the routine indicator. The subsets are: All skill measures; Region of residence FE; Education level and

Table 2. *Regressions using the main specialization index with varying controls and samples*

	Switch to a non-routine occ.	Growth in log wage	Growth in rel. earnings	Future employment
	(1)	(2)	(3)	(4)
(a) Controls for all characteristics				
Routine	0.0483***	-0.0271***	-0.0441***	-0.00170*
	(0.00190)	(0.000808)	(0.00200)	(0.000919)
OSI	-0.0681***	-0.00419***	-0.00490***	0.00287***
	(0.00133)	(0.000568)	(0.00132)	(0.000605)
OSI × Routine	-0.0124***	-0.0144***	-0.0214***	-0.00126
	(0.00180)	(0.000766)	(0.00191)	(0.000878)
N	446,921	446,921	639,007	639,896
R^2	0.078	0.119	0.054	0.036
(b) Additional controls for occupation				
OSI	-0.0451***	-0.00257***	-0.00404***	0.00115*
	(0.00143)	(0.000612)	(0.00143)	(0.000655)
OSI × Routine	-0.0138***	-0.0108***	-0.0189***	-0.000819
	(0.00187)	(0.000801)	(0.00200)	(0.000916)
N	446,921	446,921	639,007	639,896
R^2	0.095	0.127	0.056	0.037
(c) Additional controls for occupation and initial log wage				
OSI	-0.0435***	0.00929***	0.000219	0.000494
	(0.00143)	(0.000530)	(0.00143)	(0.000656)
OSI × Routine	-0.0135***	-0.0122***	-0.0187***	-0.000845
	(0.00187)	(0.000692)	(0.00199)	(0.000915)
N	446,921	446,921	639,007	639,896
R^2	0.097	0.349	0.061	0.039
(d) Additional controls for occupation, including all occupations				
OSI	-0.0864***	-0.0138***	-0.0159***	0.00293***
	(0.000856)	(0.000380)	(0.000895)	(0.000377)
OSI × Routine	-0.00219	-0.00687***	-0.0142***	-0.00172***
	(0.00144)	(0.000637)	(0.00150)	(0.000636)
N	831,991	831,991	1,149,195	1,172,526
R^2	0.100	0.205	0.079	0.034

Notes: The table reports results from estimating equation (8) for different outcomes, sets of controls, and samples. All regressions include controls for a second-order polynomial in the eight skill dimensions and 14 previous industry experience variables as well as age, education and field, region, and initial × future year fixed effects. Models (b)-(d) additionally include occupation FE. Model (c) includes controls for a second-order polynomial in initial log wage fully interacted with the indicator for routine occupations. Model (d) is estimated using observations of workers in all, and not only low- to middle-skilled, occupations. Standard errors clustered at the individual level are in parenthesis. *, ** and *** represent statistical significance at the 10-, 5- and 1-percent level, respectively.

Table 3. *Regressions using alternative specialization indices*

	Switch to a non-routine occ.	Growth in log wage	Growth in rel. earnings	Future employment
	(1)	(2)	(3)	(4)
(a) Specialization based on multinomial logit				
OSI	-0.0376***	-0.00205***	0.00224	0.00180**
	(0.00178)	(0.000763)	(0.00179)	(0.000819)
OSI × Routine	-0.0278***	-0.0126***	-0.0289***	-0.00128
	(0.00220)	(0.000942)	(0.00233)	(0.00107)
N	446,915	446,915	639,001	639,890
R^2	0.094	0.127	0.056	0.037
(b) Specialization based on predicted log wage (WOSI)				
OSI	-0.0129***	-0.00908***	0.00179	0.000769
	(0.00153)	(0.000652)	(0.00158)	(0.000727)
OSI × Routine	-0.00912***	-0.00223***	-0.00777***	0.00143*
	(0.00175)	(0.000750)	(0.00185)	(0.000848)
N	446,921	446,921	639,007	639,896
R^2	0.092	0.127	0.056	0.037
(c) Specialization based on OSI percentiles within occupation				
OSI	-0.0500***	-0.000825	-0.00418***	0.000690
	(0.00125)	(0.000535)	(0.00125)	(0.000574)
OSI × Routine	-0.00134	-0.00829***	-0.0115***	-0.00137*
	(0.00145)	(0.000622)	(0.00153)	(0.000702)
N	446,921	446,921	639,007	639,896
R^2	0.097	0.127	0.056	0.037
(d) Including routine outside options in OSI				
OSI	-0.0774***	-0.00243***	-0.00230	0.00285***
	(0.00176)	(0.000754)	(0.00181)	(0.000829)
OSI × Routine	-0.0769***	-0.0531***	-0.0304***	0.0135***
	(0.00568)	(0.00243)	(0.00617)	(0.00283)
N	446,919	446,919	639,005	639,894
R^2	0.097	0.128	0.056	0.037

Notes: The table reports results from estimating equation (8) for different outcomes and specialization metrics. All regressions include controls for a second-order polynomial in the eight skill dimensions and 14 previous industry experience variables as well as age, education and field, region, initial × future year, and occupation fixed effects. Model (a) uses the OSI metric based on the multinomial logit. (b) uses the WOSI based on predicted wage surplus. (c) uses as specialization the within-occupation percentile groups of the OSI. This metric is standardized to mean zero, standard deviation one for ease of comparison. (d) uses a version of the OSI based on all (and not only non-routine) outside options. See Table 2 for additional information.

field FE; Age FE and industry experience. This exercise reveals if the estimated effect of the OSI is caused by any subset of $\boldsymbol{x}$. Controlling for age and experience also addresses concerns about whether differences in wage growth is due to differing career wage profiles. Most coefficients are highly similar to the second model in Table 2. The exception is when controlling for interacted age and experience. The interaction effect on wage growth then increases from -0.01 to around -0.005. Thus, age and experience appears to contribute disproportionately to this effect. But the other characteristics are still important. Moreover, the interaction effect on earnings growth is resilient to this set of controls.

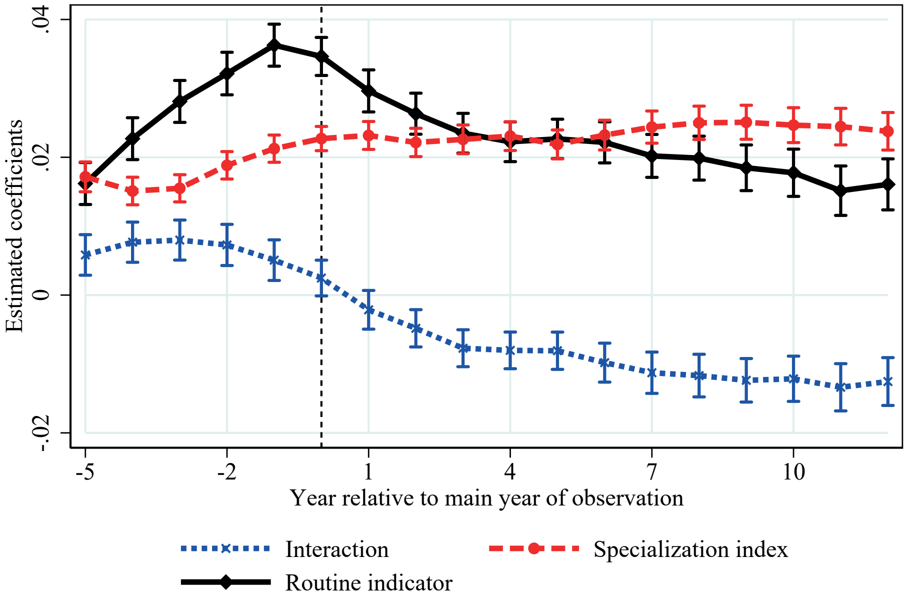
Occupation-specific effects
To better understand what role specialization plays in each occupation, I estimate occupation-specific effects of the OSI on outcomes. These are reported in Figure C9. Without exception, the probability of switching to another non-routine occupation declines with specialization. Furthermore, the OSI is typically negatively associated with both wage and earnings growth. This is especially true for routine occupations, in line with the previous results.

Trends in the returns to specialization
When in workers' careers does the effect of specialization on wage growth arise? To study this, I estimate equation (8) separately for log wage level in $t+\tau$ for all $\tau \in \{-5,\ldots,12\}$ where t is the year when the OSI and occupation choice is measured. Figure 5 plots the main coefficients against τ. Routine workers enjoyed a high initial wage premium, which was increasing until t. This coefficient then decreases from 0.04 to 0.02 in $t+12$. There is a positive relationship between specialization and wages: For all relative years, the common effect of the OSI is positive. On average, the estimate is around 0.02 and increases marginally over time. The additional OSI premium of routine relative to non-routine workers is positive at first, but declines to around -0.015 in $t+12$. Thus, being specialized in routine occupations used to yield a higher return. Over time, this effect turns into a relative penalty for workers initially observed in routine work.

5 Conclusions

In this paper, I create and estimate an index of worker occupation specialization (OSI) using detailed individual characteristics and machine learning tools. The OSI is derived from a Roy (1951)-styled discrete choice model. Theoretically, it measures the expected difference between a worker's utility in his occupation and his best outside option. The index is simply a monotone transformation of the *ex ante* propensity for working in an outside occupation. This determines the worker's utility loss from a negative wage premium

Figure 5. Estimated effect of occupation specialization on log wage by routine and non-routine occupations and year relative to year of observation



Notes: The figure reports estimates and 95-percent confidence intervals for the routine indicator, the OSI, and the interaction between the two from equation (8) estimated on log wage in different years relative to the year of observation. I follow individuals five years back and 12 years forward in time and estimate a separate model for each time horizon. All regressions include controls for a second-order polynomial in the eight skill dimensions and 14 previous industry experience variables as well as age, education and field, region, and year fixed effects. Standard errors are clustered at the individual level.

shock: Low-OSI workers with attractive non-shocked options are able to alleviate losses by moving. High-OSI specialists instead willingly remain and experience the full consequences of the shock.

The paper then analyzes to what extent the OSI can explain the consequences for incumbent employees of the falling employment in routine occupations, likely caused by shifting demand, during the period 1997–2013. I find that routine and non-routine generalists with low levels of OSI were highly mobile and did approximately equally well in terms of future earnings growth. Routine specialists instead by and large remained in routine work despite the overall employment decline in these occupations. They also experienced significantly lower earnings growth than both generalists and non-routine specialists.

These findings are broadly consistent with the predictions from the Roy-style discrete choice model from which the specialization index is derived. Overall, the results indicate that the Roy (1951) model can characterize which workers lose from negative demand shifts. Moreover, the observable worker attributes at hand can be used to infer how dependent workers are on their current occupations.

Exploring the consequences of the historical decline in routine work is important in its own right. But the ability of the OSI to predict which workers experienced negative consequences from this shift also substantiates the general usefulness of the index for describing worker susceptibility. Currently, policy makers have very few tools at hand for forecasting individual consequences of future shifts in occupation demand. The OSI is solely based on current information. It could therefore be used to characterize workers employed in occupations today that we believe will experience negative demand shifts in the future.

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Appendix A Derivations

This section shows the full derivation of the results discussed in Section 2.1 and 2.2. I begin by discussing some useful properties of the Gumbel distribution. I then characterize the distribution of the utility surplus in equation (2). Using these results, I proceed to derive the occupation specialization index. Finally, I derive a closed-form expression for the expected value of the utility loss following the wage premium in equation (2).

A.1 Properties of the Gumbel distribution

All ε_{ik} are assumed to be IID standard extreme value type I (or Gumbel) distributed. The occupation choice probabilities then follow the multinomial logit formula expressed in equation (3).

Moreover, the maximum utility of a worker (see equation (1)) before conditioning on occupation choice is distributed as:

$$\max_{k \in K} u_{ik} \sim \text{Gumbel}\left(\ln\left(\sum_{k \in K} e^{u_k(\boldsymbol{x})}\right), 1\right). \tag{A1}$$

The location parameter in this equation is commonly referred to as the logsum. The expected utility takes the form $\mathbb{E}\left[\max_{k \in K} u_{ik}\right] = \ln\left(\sum_{k \in K} e^{u_k(\boldsymbol{x})}\right) + C$, where C is an unknown constant reflecting that absolute utility cannot be measured. See, e.g., Small and Rosen (1981), Train (2009) for a textbook treatment, and De Jong et al. (2007) for a literature review of applications of this expected value.

Using results from Hanemann (1984),[20] the maximum utility can be shown to be independent of the chosen occupation j. More specifically, Hanemann (1984) shows that the idiosyncratic term of the best choice j is distributed as:

$$\varepsilon_{ij} \mid \arg\max_{k \in K} u_{ik} = j \sim \text{Gumbel}\left(\ln\left(\sum_{k \in K} e^{u_k(\boldsymbol{x})}/e^{u_j(\boldsymbol{x})}\right), 1\right). \tag{A2}$$

Next, let $F(.)$ be the CDF of this distribution and s be some value. Then:

$$\begin{aligned}
\Pr(u_{ij} < s) &= F(s - u_j(\boldsymbol{x})) \\
&= \exp\left\{-\exp\left\{-(s - u_j(\boldsymbol{x})) + \ln\left(\sum_{k \in K} e^{u_k(\boldsymbol{x})}/e^{u_j(\boldsymbol{x})}\right)\right\}\right\} \\
&= \exp\left\{-\exp\left\{-s + \ln\left(\sum_{k \in K} e^{u_k(\boldsymbol{x})}\right)\right\}\right\}.
\end{aligned} \tag{A3}$$

[20] His framework focuses on consumption and incorporates heterogeneous goods prices and a budget constraint.

This is the CDF associated with the distribution in (A1). Thus, the maximum utility conditional on any optimal choice j is distributed the same as the unconditional maximum in (A1).

A final useful property of the Gumbel distribution is that the difference between two independent Gumbel distributed variables with location parameters a, b and common scale parameter c is known to follow a Logistic$(a-b,\ c)$ distribution.

A.2 Characterizing the distribution of the utility surplus

Finding the distribution of the utility surplus in (2) is done in four steps.

Step 1: Rewriting the utility surplus

I begin by defining $P(s)$ as the probability that the utility surplus in (2) conditional on worker characteristics $\boldsymbol{x}$ and occupation choice j is smaller than the value s. This represents the CDF of the utility surplus for which I want to obtain an closed-form expression:

$$P(s) \equiv \Pr\left(u_{ij} - \max_{n \in N \setminus \{j\}} u_{in} \leq s \;\middle|\; \boldsymbol{x},\ \arg\max_{k \in K} u_{ik} = j\right). \tag{A4}$$

Next, K can be partitioned into two subsets: One including R and a worker's chosen occupation j, and one with his non-routine outside options. The probability may then be rewritten in terms of the difference between the maximum utility in each set conditional on the first maximum being larger, and on the choice in the first set being j:

$$P(s) = \Pr\left(\max_{r \in R \cup \{j\}} u_{ir} - \max_{n \in N \setminus \{j\}} u_{in} \leq s \;\middle|\; \boldsymbol{x},\ \max_{r \in R \cup \{j\}} u_{ir} - \max_{n \in N \setminus \{j\}} u_{in} \geq 0,\ \arg\max_{r \in R \cup \{j\}} u_{ir} = j\right). \tag{A5}$$

Thus, I recast the maximization problem as a two-step problem where the worker finds the best local options in the two subsets, and then compares them to each other. Notice here that j changes interpretation from the best option in K to the best option in the set $R \cup \{j\}$.

Step 2: Removing the argmax condition from $P(s)$

Both $\max_{r \in R \cup \{j\}} u_{ir}$ and $\max_{n \in N \setminus \{j\}} u_{in}$ are Gumbel distributed according to (A1). According to (A3), $\max_{r \in R \cup \{j\}} u_{ir}$ does not depend on $\arg\max_{r \in R \cup \{j\}} u_{ir} = j$. Conditional on the value of $\max_{r \in R \cup \{j\}} u_{ir}$, $\max_{n \in N \setminus \{j\}} u_{in}$ must also be independent of the argmax condition. Hence, this condition can be removed from the set of conditions in (A5):

$$P(s) = \Pr\left(\max_{r \in R \cup \{j\}} u_{ir} - \max_{n \in N \setminus \{j\}} u_{in} \;\middle|\; \boldsymbol{x},\ \max_{r \in R \cup \{j\}} u_{ir} - \max_{n \in N \setminus \{j\}} u_{in} \geq 0\right). \tag{A6}$$

One may now think of j as a regular occupation rather than as the optimal choice, although it still represents the observed occupation of worker i. Finally, define v_{ij} as the difference between the two maxima in (A6):

$$v_{ij} \equiv \max_{r \in R \cup \{j\}} u_{ir} - \max_{n \in N \setminus \{j\}} u_{in}. \tag{A7}$$

One may then write:

$$P(s) = \Pr\left(v_{ij} \leq s \,\middle|\, \boldsymbol{x}, v_{ij} \geq 0\right). \tag{A8}$$

Step 3: Determining the distribution of v_{ij}

By (A1), $\max_{r \in R \cup \{j\}} u_{ir}$ and $\max_{n \in N \setminus \{j\}} u_{in}$ are both gumbel with scale one. Since by (A6) one may now think of j as a regular occupation, they must also be independent. Hence, by the final property of the Gumbel distribution stated in Section A.1, v_{ij} is Logistic distributed with scale one.

From equation (A1), one can also infer the location parameter μ of v_{ij}. It equals the difference between the location parameters of the two Gumbels. Using the multinomial logit formula from (3), μ can then readily be rewritten as a function of only choice probabilities. Finally, recall that equation (4) defines $\rho(\boldsymbol{x}, j, N)$ as the *ex ante* probability of working in a non-routine outside option, i.e.,

$$\rho(\boldsymbol{x}, j, N) \equiv \sum_{n \in N \setminus \{j\}} p_n(\boldsymbol{x}).$$

The location parameter of the distribution of v_{ij} is:

$$\begin{aligned}
\mu = \mu(\boldsymbol{x}, j, N) &= \ln\left(\sum_{r \in R \cup \{j\}} e^{u_r(\boldsymbol{x})}\right) - \ln\left(\sum_{n \in N \setminus \{j\}} e^{u_n(\boldsymbol{x})}\right) \\
&= \ln\left(\sum_{r \in R \cup \{j\}} e^{u_r(\boldsymbol{x})} \Big/ \sum_{n \in N \setminus \{j\}} e^{u_n(\boldsymbol{x})}\right) \\
&= \ln\left(\frac{\sum_{r \in R \cup \{j\}} e^{u_r(\boldsymbol{x})}}{\sum_{k \in K} e^{u_k(\boldsymbol{x})}} \Big/ \frac{\sum_{n \in N \setminus \{j\}} e^{u_n(\boldsymbol{x})}}{\sum_{k \in K} e^{u_k(\boldsymbol{x})}}\right) \\
&= \ln\left(\sum_{r \in R \cup \{j\}} p_r(\boldsymbol{x}) \Big/ \sum_{n \in N \setminus \{j\}} p_n(\boldsymbol{x})\right) \\
&= \ln\left(\frac{1}{\sum_{n \in N \setminus \{j\}} p_n(\boldsymbol{x})} - 1\right) \\
&= \ln\left(\frac{1}{\rho(\boldsymbol{x}, j, N)} - 1\right).
\end{aligned} \tag{A9}$$

Step 4: Finding the distribution function of the utility surplus
Next, I turn to finding an expression for the CDF and PDF of the utility surplus. First, denote the PDF and CDF of the Logistic$(\mu(\boldsymbol{x},j,N),1)$ distribution by $F'(.)$ and $F(.)$, respectively. These are:

$$\begin{aligned} F'(s \mid \boldsymbol{x},j,N) &= \frac{e^{-s+\mu(\boldsymbol{x},j,N)}}{\left(1+e^{-s+\mu(\boldsymbol{x},j,N)}\right)^2} \\ F(s \mid \boldsymbol{x},j,N) &= \frac{1}{1+e^{-s+\mu(\boldsymbol{x},j,N)}} \end{aligned} \tag{A10}$$

Next, by properties of conditional probabilities, one can write the CDF of the utility surplus in terms of $F(.)$:

$$\begin{aligned} P(s) &= \Pr\left(v_{ij} \leq s \,\middle|\, \boldsymbol{x}, v_{ij} \geq 0\right) \\ &= \frac{\Pr\left(0 \leq v_{ij} \leq s \,\middle|\, \boldsymbol{x}\right)}{1-\Pr\left(v_{ij} \leq 0 \,\middle|\, \boldsymbol{x}\right)} \\ &= \begin{cases} \frac{F(s \mid \boldsymbol{x},j,N)-F(0 \mid \boldsymbol{x},j,N)}{1-F(0 \mid \boldsymbol{x},j,N)} & \text{for } s \geq 0 \\ 0 \text{ otherwise} \end{cases} \end{aligned} \tag{A11}$$

Finally, to obtain the PDF of the utility surplus, differentiate (A11) with respect to s:

$$P'(s) = \begin{cases} \frac{F'(s \mid \boldsymbol{x},j,N)}{1-F(0 \mid \boldsymbol{x},j,N)} & \text{for } s \geq 0 \\ 0 \text{ otherwise} \end{cases} \tag{A12}$$

A.3 Deriving the occupation specialization index

Let S represent the utility surplus. Using the PDF of the logistic distribution from (A10) and its relationship with the utility surplus PDF in (A12), one can obtain a closed-form solution to the expected value of the surplus. Finally, plugging in the location parameter from (A9) and simplifying gives the OSI:

$$\begin{aligned} \mathrm{OSI}(\boldsymbol{x},j,N) &\equiv \mathbb{E}\left[u_{ij} - \max_{n \in N\setminus\{j\}} u_{in} \,\middle|\, \boldsymbol{x},\, \operatorname*{arg\,max}_{k \in K} u_{ik} = j\right] \\ &= \left(1 - \frac{1}{1+e^{\mu(\boldsymbol{x},j,N)}}\right)^{-1} \int_0^\infty S \frac{e^{-S+\mu(\boldsymbol{x},j,N)}}{\left(1+e^{-S+\mu(\boldsymbol{x},j,N)}\right)^2} dS \\ &= \frac{1+e^{\mu(\boldsymbol{x},j,N)}}{e^{\mu(\boldsymbol{x},j,N)}} \ln\left(1+e^{\mu(\boldsymbol{x},j,N)}\right) \\ &= -\frac{\ln\left(\rho(\boldsymbol{x},j,N)\right)}{1-\rho(\boldsymbol{x},j,N)} \end{aligned} \tag{A13}$$

Both $\ln(\rho(\boldsymbol{x},j,N))$ and $1/(1-\rho(\boldsymbol{x},j,N))$ are increasing in $\rho(\boldsymbol{x},j,N)$. Therefore, the OSI is a monotonically decreasing function of $\rho(\boldsymbol{x},j,N)$.

A.4 Deriving the expected utility loss

The expected value of the utility change following the wage premium shock in (2) can be written as a probability-weighted average of d_j and a conditional expected value of S. A closed-form solution can then be derived in a similar way as in (A13). Again, let S represents the utility surplus random variable. Then:

$$\begin{aligned}
\mathbb{E}\left[\Delta u_{ij} \mid \boldsymbol{x},\ j\right] &= \mathbb{E}\left[\max\left\{-d_j, -\left(u_{ij} - \max_{n\in N\setminus\{j\}} u_{in}\right)\right\} \mid \boldsymbol{x},\ \arg\max_{k\in K} u_{ik} = j\right] \\
&= -d_j - \Pr(S \le d_j)\left(\mathbb{E}\left[S \mid S \le d_j\right] - d_j\right) \\
&= -\frac{\left(1 - \frac{1}{1+e^{-d_j+\mu(\boldsymbol{x},j,N)}}\right) d_j + \int\limits_0^{d_j} S \frac{e^{-S+\mu(\boldsymbol{x},j,N)}}{\left(1+e^{-S+\mu(\boldsymbol{x},j,N)}\right)^2} dV}{1 - \frac{1}{1+e^{\mu(\boldsymbol{x},j,N)}}} \\
&= -\frac{d_j - \ln\left(1 + \left(e^{d_j} - 1\right)\rho(\boldsymbol{x}, j, N)\right)}{1 - \rho(\boldsymbol{x}, j, N)}. \qquad \text{(A14)}
\end{aligned}$$

For any value of $d_j = \delta > 0$, (A14) is monotonically increasing (i.e., the absolute loss becomes smaller) in $\rho(\boldsymbol{x}, j, N)$. To see this, differentiate (A14) with respect to ρ which is used as shorthand for $\rho(\boldsymbol{x}, j, N)$:

$$\begin{aligned}
\frac{\partial \mathbb{E}\left[\Delta u_{ij} \mid \boldsymbol{x},\ j\right]}{\partial \rho} &= -\frac{d_j - \ln\left(1 + \left(e^{d_j} - 1\right)\rho\right)}{(1-p)^2} + \frac{\frac{e^{d_j}-1}{1+\left(e^{d_j}-1\right)\rho}}{1-\rho} \\
&= \frac{1}{(1-p)^2}\left[-\left(d_j - \ln\left(1 + \left(e^{d_j} - 1\right)\rho\right)\right) + \frac{(1-\rho)\left(e^{d_j}-1\right)}{1+\left(e^{d_j}-1\right)\rho}\right] \\
&= \frac{1}{(1-p)^2}\left[-\left(\ln\left(e^{d_j}\right) - \ln\left(1 + \left(e^{d_j} - 1\right)\rho\right)\right) + \frac{e^{d_j} - \left(1+\left(e^{d_j}-1\right)\rho\right)}{1+\left(e^{d_j}-1\right)\rho}\right] \\
&= \frac{1}{(1-p)^2}\left[-\ln\left(\frac{e^{d_j}}{1+\left(e^{d_j}-1\right)\rho}\right) + \frac{e^{d_j}}{1+\left(e^{d_j}-1\right)\rho} - 1\right]
\end{aligned} \qquad \text{(A15)}$$

This may be rewritten as:

$$\frac{\partial \mathbb{E}\left[\Delta u_{ij} \mid \boldsymbol{x},\ j\right]}{\partial \rho} = a\left[b - 1 - \ln(b)\right],$$
$$\text{where } a = \frac{1}{(1-\rho)^2} \text{ and } b = \frac{e^{d_j}}{\left(1+\left(e^{d_j}-1\right)\rho\right)}. \qquad \text{(A16)}$$

$a > 1$ for any $0 < \rho < 1$. For routine workers with $d_j = \delta > 0$, $e^{d_j} \ge 1 + (e^{d_j} - 1)\rho > 1$. This implies that $b > 1$. In turn, $b - 1 - \ln(b) > 0$. Thus, the derivative is positive, implying monotonicity.

Appendix B The artificial neural network

B.1 Sample and variables

As discussed in Section 3, 30 percent of observations in my full pre-period sample are used for training the neural network. Twenty percent of this subsample is used for validation when choosing the specific features of the network, while 80 percent are used for training.

The vector of input variables, $\boldsymbol{x}$, is of length 129. It incorporates the following variables: Age fixed effects (FE); A second-order polynomial in all ability measures; Education level FE; Education field FE; Region of residence FE; Separate second-order polynomials in experience between $t-13$ and $t-1$ in 14 industry categories.

The vector of output variables, $\boldsymbol{y}$, includes indicators for the 22 different occupations.

B.2 Neural network

The neural network consists of an input layer, a single hidden layer and an output layer. Each layer includes a number of neurons, or variables. The input layer consists of the explanatory variables. Each input neuron is associated with a set of weights (coefficients) to be estimated that map to the second, hidden, layer of neurons, the length of which is discussed below. The value of the jth hidden neuron for a particular observation i is determined by $z_i^j = \boldsymbol{w'}_j^z \boldsymbol{x}_i + b_j^z$, where $\boldsymbol{w}_j^z$ is a vector of all the weights mapping the input neurons to the jth hidden neuron, $\boldsymbol{x}_i$ is a vector of the inputs for observation i and b_j is the bias (intercept) for j. z_i^j is then transformed using a non-linear activation function $f(.)$ before being passed forward to the next layer, i.e., the input into the output layer from the jth hidden node for the ith observation is $a_i^j = f(z_i^j)$. This process is then repeated for all hidden nodes j, and the resulting values are collected in the vector $\boldsymbol{a}_i$. To find the value of the mth neuron in the output layer, I calculate $y_i^m = \boldsymbol{w}_m'^y \boldsymbol{a}_i + b_m^y$ Finally, I also apply an activation function $g(.)$ to the values of the output layer neurons.

The network can be described in matrix notation as:

$$\boldsymbol{Y} = g\left(\boldsymbol{W}^{output} \times f\left(\boldsymbol{W}^{hidden} \times \boldsymbol{X} + \boldsymbol{b}^{hidden}\right) + \boldsymbol{b}^{output}\right). \tag{B1}$$

where $g(.)$ and $f(.)$ are activation functions which operate on the individual cells of the matrices and return matrices of the same dimensions. $\boldsymbol{X}$ is a $v^{input} \times N$ matrix, where v^{input} is the length of the input vector and N represents the number of observations. $\boldsymbol{W}^{hidden}$ is a $v^{hidden} \times v^{input}$-dimensional matrix containing all the weights that link the inputs to the hidden layer and where v^{hidden} is the number of hidden neurons. For instance, $\boldsymbol{W}_{j,k}^{hidden}$ refers to the weight linking the jth hidden neuron and kth input. $\boldsymbol{b}^{hidden}$ is a vector of length v^{hidden} containing the biases (intercepts) for each hidden neuron.

$\boldsymbol{W}_{i,j}^{output}$ contain the $v^{output} \times v^{hidden}$ weights mapping the values of the hidden neurons to the output neurons and $\boldsymbol{b}^{output}$ contains all the output neuron biases.

For the hidden layer, I use a leaky rectified linear unit (RELU) activation function. More specifically, $f(x) = \max\{0.001x,\ x\}$. The inclusion of such an activation function allows the neural network to accommodate important non-linear effects and interactions between multiple variables. I set the number of hidden neurons to 150.

The output layer is activated using the softmax function, $p_k = e^{x_k}/\sum_m e^{x_m}$, where x_k is the value of the kth output neuron and the denominator sums over all output layer neurons.

The loss function used to train the network is the categorical cross-entropy loss:

$$Loss = -\sum_{i \in N} \sum_{k \in K} I_{ik} \times \ln\left(\hat{p}_{ik}\right). \tag{B2}$$

where I_{ik} is an indicator for if the true choice of observation i is occupation k and zero otherwise. Thus, the loss function is based on the sum of the log propensities assigned to the true choice of all observations.

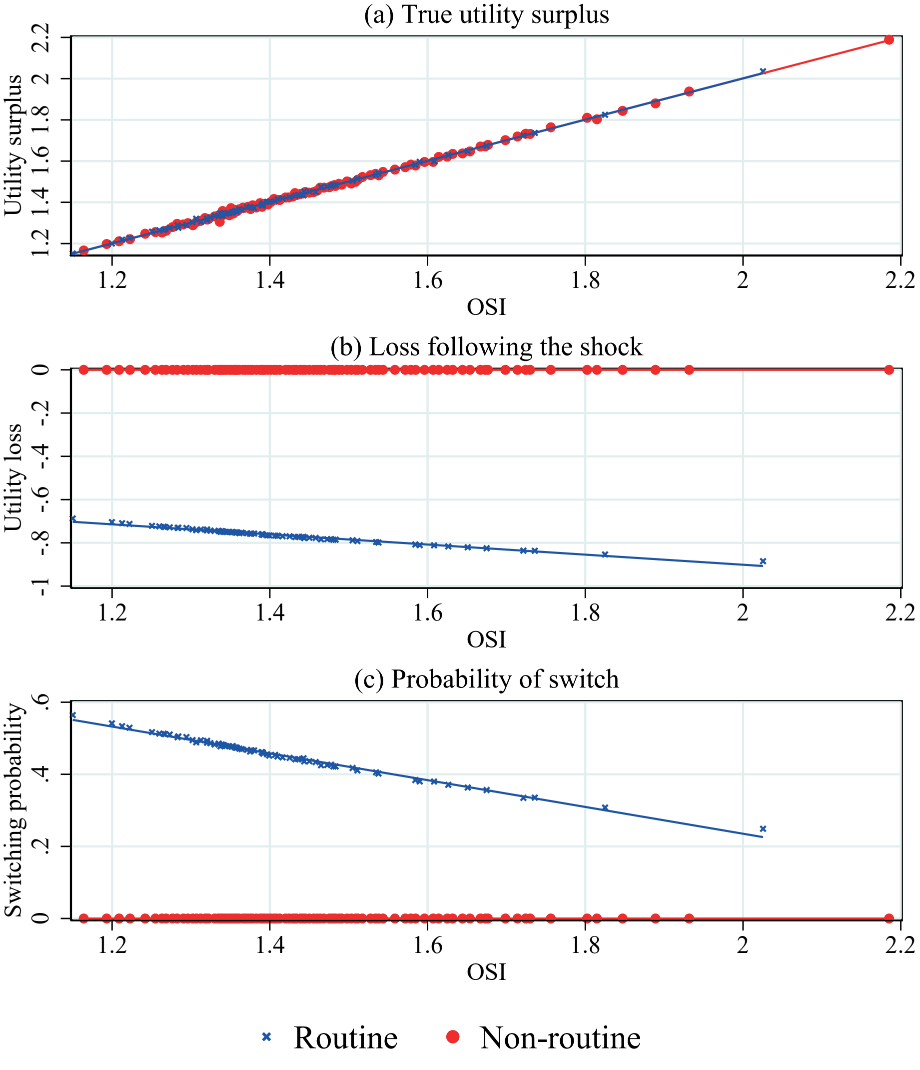
The network is trained using the Adam optimization algorithm (Kingma and Ba, 2014), which is an extension of stochastic gradient descent. Training is done for a maximum of 100 epochs (cycling through all observations in the training data) with a batch size (the number of observations passed through the network at each step) of 1000. But to avoid overfitting, I utilize what is known as an early stopping rule: When the loss in the validation sample has not decreased for 10 subsequent epochs, I stop the training algorithm and restore the model from all previous epochs that is associated with the smallest loss in the validation sample. Moreover, I apply dropout on the hidden layer at a rate of 50 percent: Between each weight update cycle, half of all the neurons are randomly chosen and set to zero. This forces the network to be less reliant on a small set of neurons for predictions.

To implement the network, I use the Keras API for R, which uses the Tensorflow machine learning platform.

Appendix C Additional figures

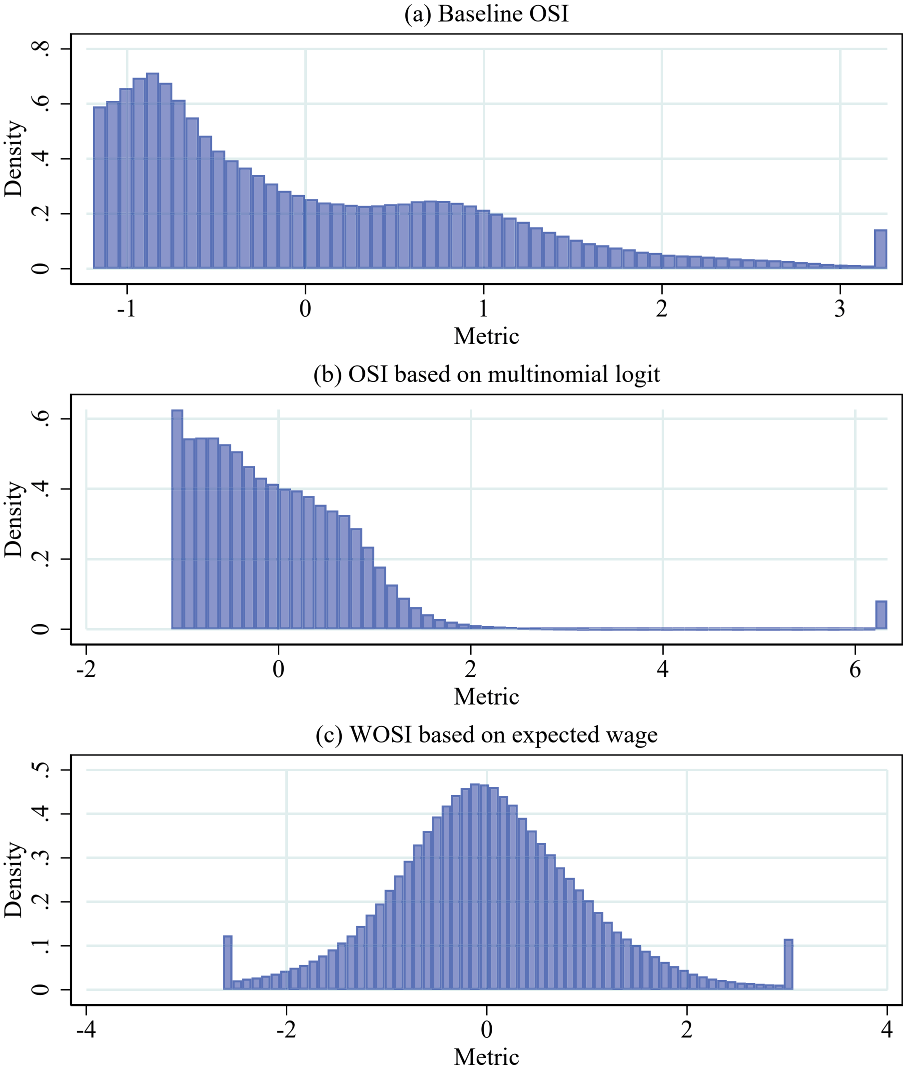
This section presents all the additional figures that are referenced in the empirical analysis section. Please see the main text for a description of the results from each figure.

Figure C1. Simulated relationship between outcomes and the OSI



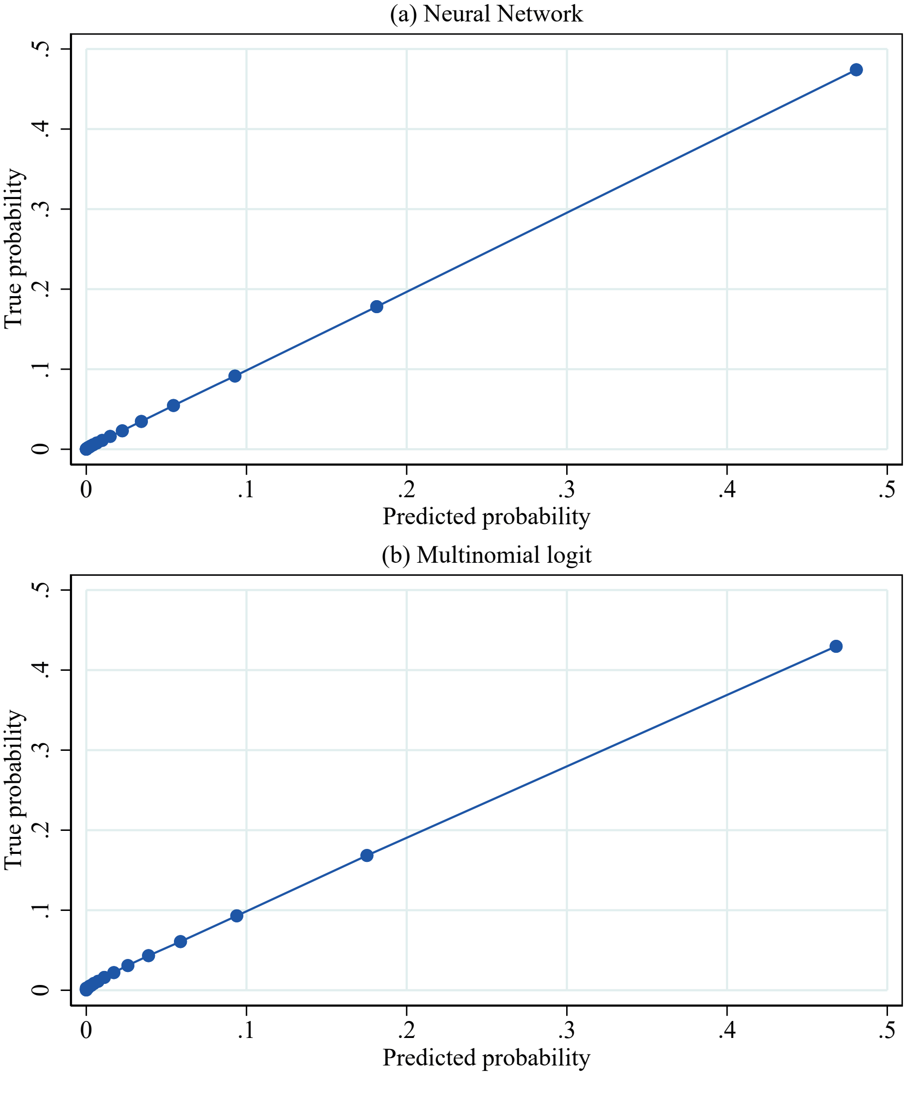
Notes: To verify the predictive properties of the OSI for the loss, I simulate the model in Section 2 for 10 routine and 10 non-routine occupations. I generate 10 million workers i with individual standard Gumbel draws for each occupation. All workers belong to one of 100 equally-sized groups $g \in \{1,\ldots,100\}$. Each group draws a deterministic utility term u_{gk} for each occupation k from the standard normal distribution. The wage premium shock is set to $\delta = 1$. For each worker, I find $\max_{k\in K}\{u_{ik}\} - \max_{n\in N\setminus\{j\}}\{u_{in}\}$. Next, I calculate group-specific probabilities as the number of workers in g in k (N_{gk}) divided by the total size of g (N_g); $p_{gk} = N_{gk}/N_g$. Workers are classified as either routine or non-routine depending on whether $\arg\max_{k\in K}\{u_{ik}\} \in R$. To construct the OSI, I use the group-specific probabilities. Finally, I calculate $\max\Big\{-d_j, -\big(\max_{k\in K}\{u_{ik}\} - \max_{n\in N\setminus\{j\}}\{u_{in}\}\big)\Big\}$ and $\mathbb{1}\Big[\big(\max_{k\in K}\{u_{ik}\} - \max_{n\in N\setminus\{j\}}\{u_{in}\}\big) < d_j\Big]$.

Figure C2. Histograms of the occupation specialization indices



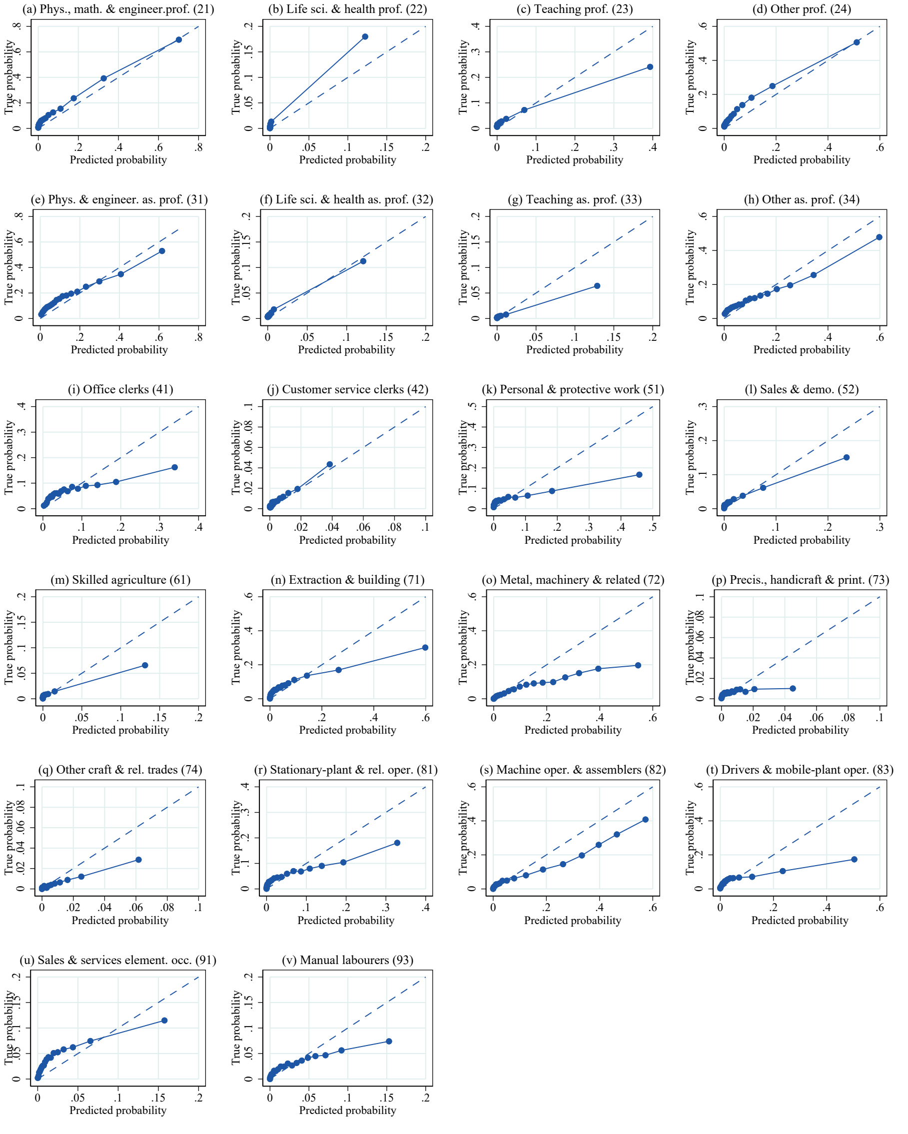
Notes: The figure reports histograms of the main OSI metric based on predictions from the neural network, the alternative OSI based on the multinomial logit, and the WOSI which measures the estimated wage surplus in worker's occupations. All the metrics are censored at the 1st and 99th percentile and standardized to mean zero, standard deviation one.

Figure C3. Relationship between predicted and actual occupation choice probabilities



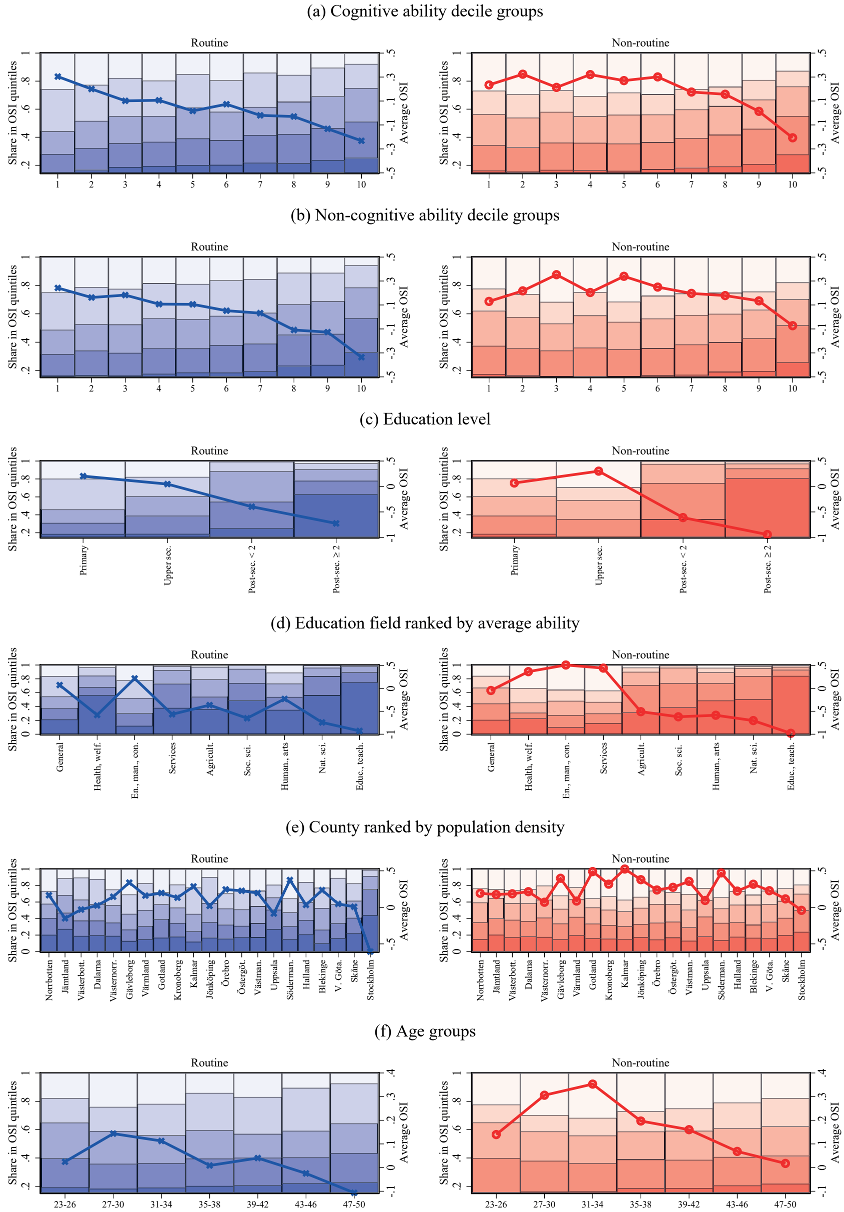
Notes: The figure plots the assigned occupation choice probability against the true out-of-sample probability. Let I_{ik} represent an indicator for if the true choice of individual i is occupation k. First, an observation containing $(I_{ik}, \hat{p}_{ik})$ is constructed for each individual observation i $\times$ potential occupation choice k. I then divide them into 100 bins based on the percentiles of the distribution of $\hat{p}_{ik}$ at this level of observation. Finally, I plot the average $\hat{p}_{ik}$ against the actual probability, i.e., the average of the indicator I_{ik}, for each bin.

Figure C4. Predicted and actual choice probabilities for switchers by destination



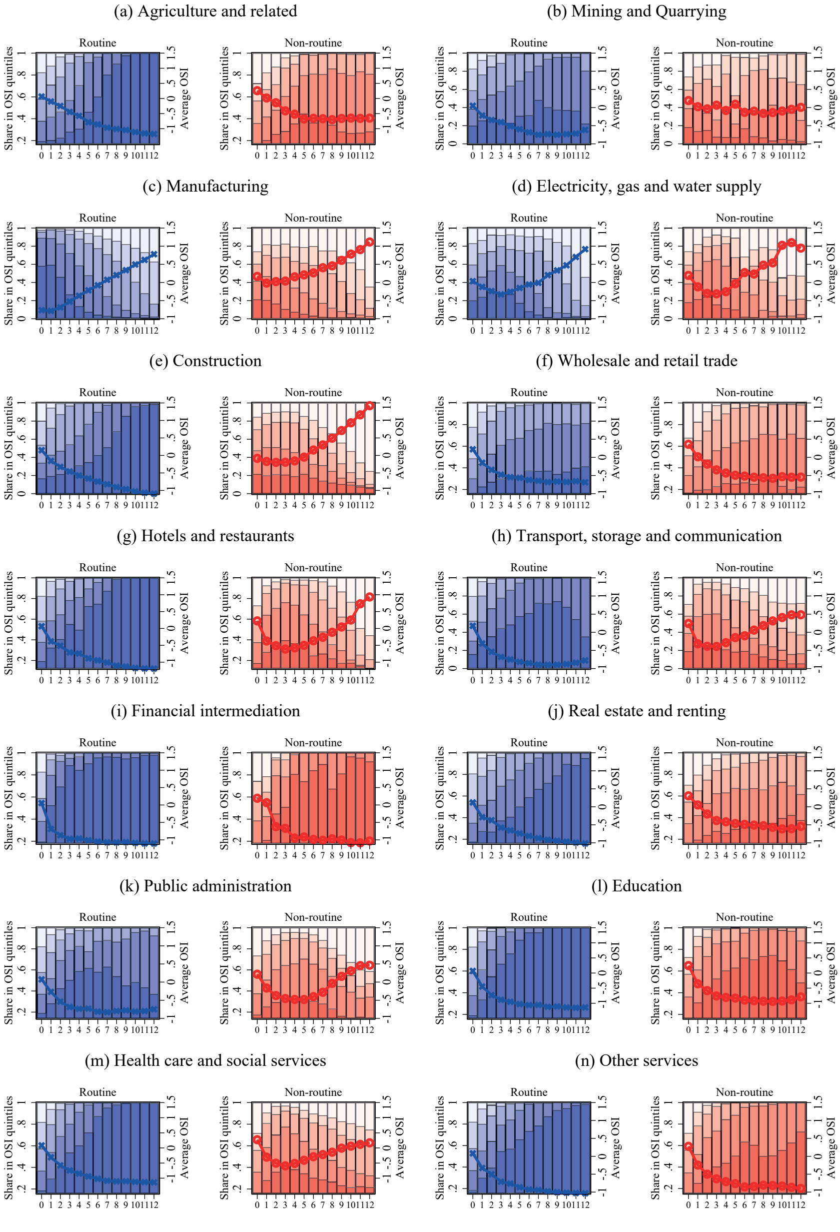
Notes: The figure is based on data for occupation switchers between t and $t+10$ to $t+12$. Separately by destination occupation, I produce binned scatterplots of the relationship between actual probability to switch to a certain occupation and the predicted choice probability conditional on not choosing the source occupation j. More specifically, I use the predicted propensities from the neural network for all outside occupations, rescale them to sum to one, create bins based on the assigned probabilities, and relate them to the actual destination choice probabilities of occupation switchers. For all occupations, there is a strong positive relationship between the predicted probabilities and the actual choices, albeit typically lower than one-to-one.

Figure C5. Occupation specialization by skill level, education, county and age for low- to middle-skilled occupations



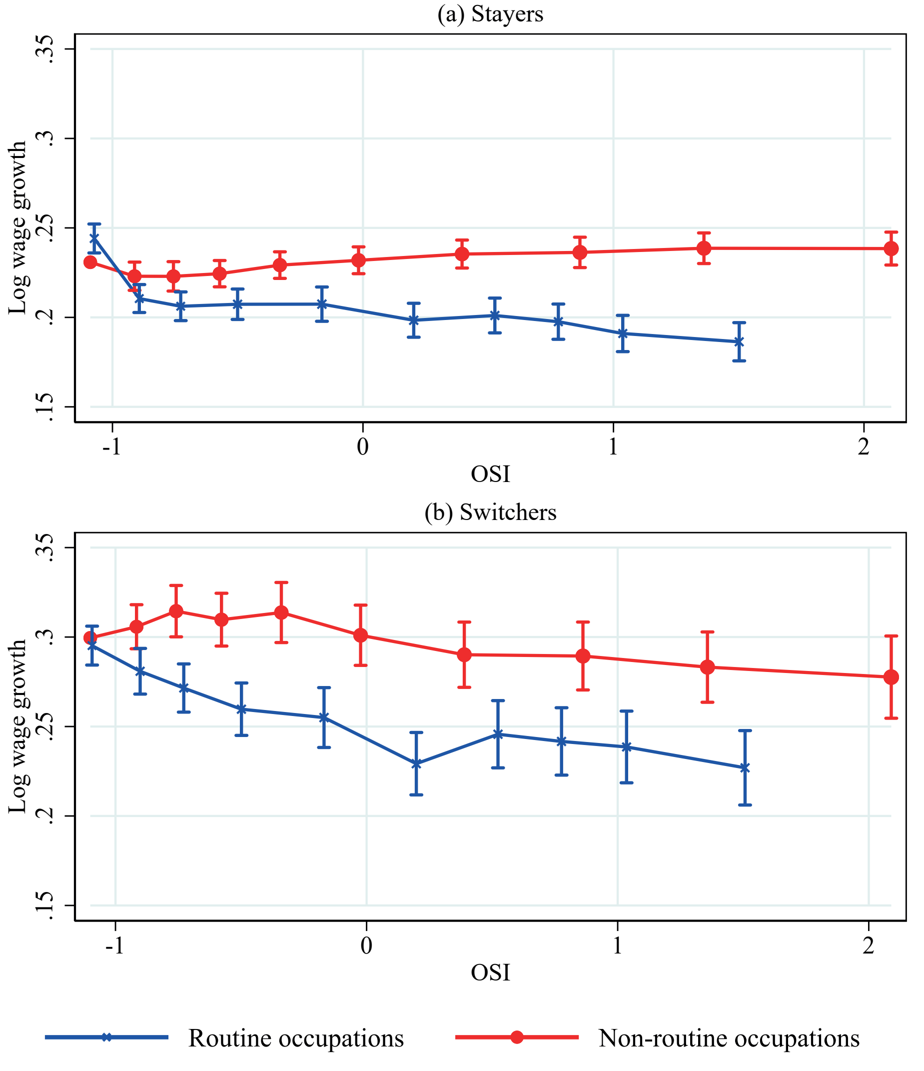
Notes: The figures report the share of workers in a certain subgroup based on worker characteristics (e.g., the lowest decile group of cognitive ability) that belong to different OSI quintile groups on the left vertical axis. The right vertical axis instead plots the average OSI for the different groups. This is done separately for workers in routine (left column) and non-routine (right column) occupations.

Figure C6. Occupation specialization by previous industry experience for low- to middle-skilled occupations



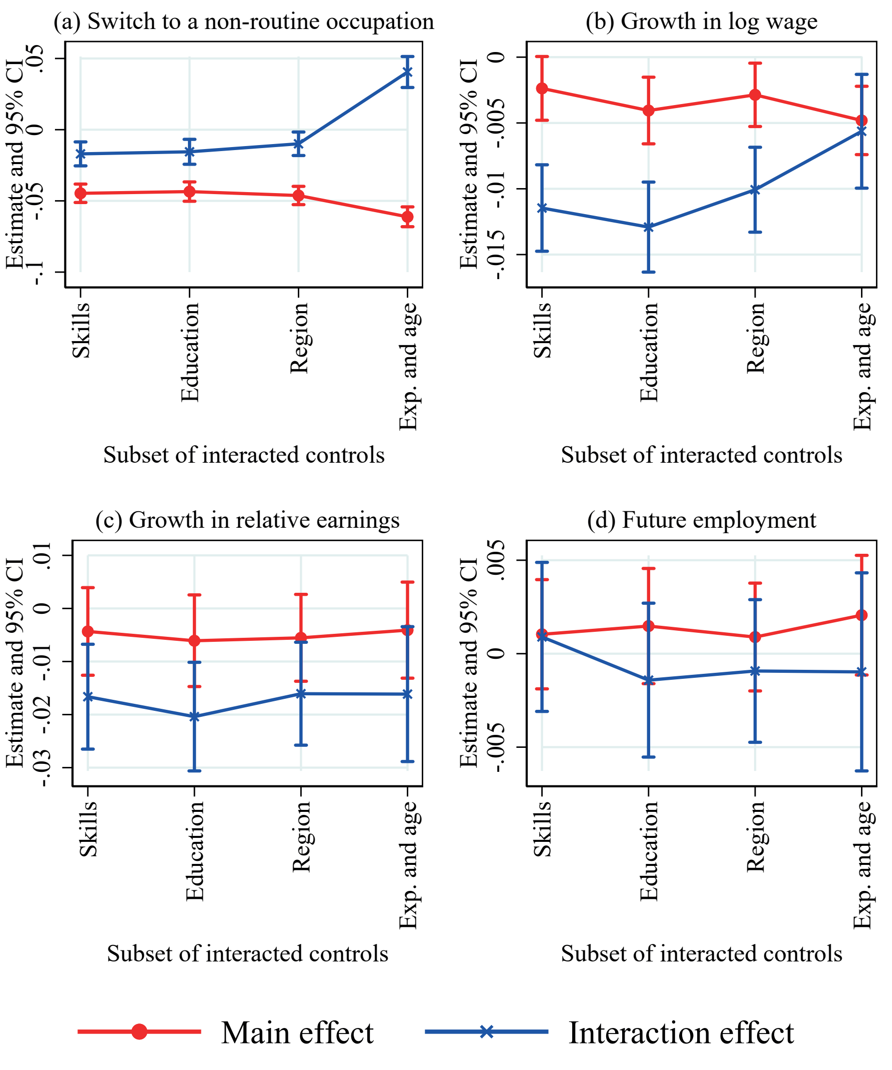
Notes: The figures report the share of workers with different years of industry-specific experience that belong to different OSI quintile groups on the left vertical axis. The right vertical axis instead plots the average OSI for the different experience levels. This is done separately for workers in routine (left figure) and non-routine (right figure) occupations.

Figure C7. Non-parametric relationship between specialization and log wage growth by routine and non-routine occupation switchers and stayers



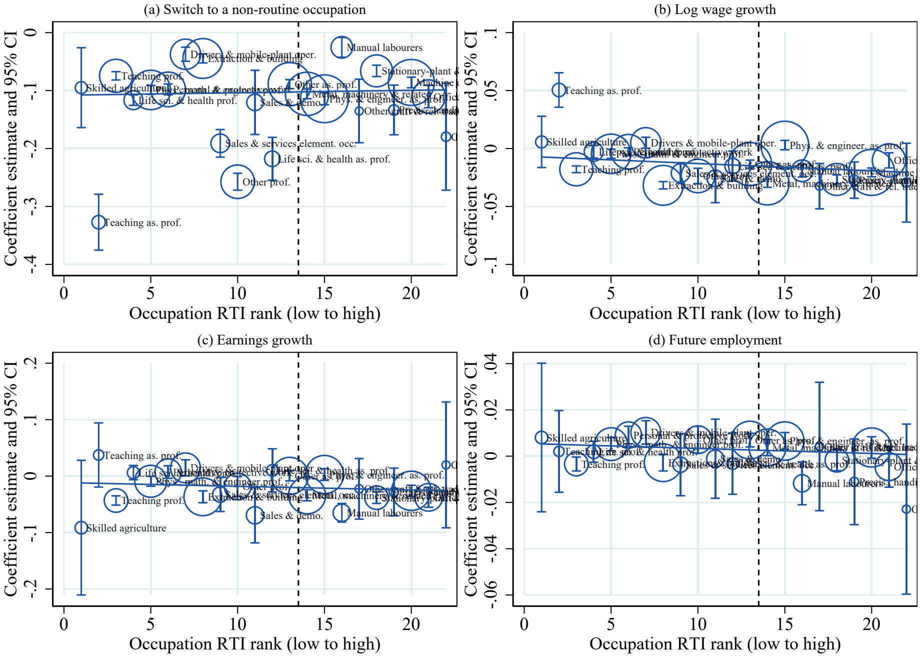
Notes: The figure relates the OSI to log wage growth between t and $t+10$ to $t+12$ separately for workers initially in routine and non-routine occupations. In panel (a) this is done for workers who remained in the same detailed occupation. Panel (b) instead does so for workers who moved to another, non-routine occupation. See Figure 3 for additional information.

Figure C8. Estimated effect of specialization for different sets of interacted controls



Notes: The figure reports estimates and corresponding 95 percent CIs for the OSI and interaction between OSI and the routine indicator from different versions of equation (8). All regressions include controls for a second-order polynomial in the eight skill dimensions and 14 previous industry experience variables as well as age, education and field, region, initial × future year, and occupation fixed effects. Each point on the horizontal axis represents a separate model which interacts the routine indicator with one of four sets of control variables: A second-order polynomial in all skill variables; education level and field FE; region of residence FE; age FE and a second-order polynomial in the previous industry experience variables.

Figure C9. Occupation-specific estimates of occupation specialization on labor market outcomes



Notes: The figure reports point estimates and 95-percent confidence intervals separately by occupation for different outcomes from a version of equation (8) which instead of the routine indicator interacts the OSI with all occupations to obtain occupation-specific OSI estimates. All regressions include controls for a second-order polynomial in the eight skill dimensions and 14 previous industry experience variables as well as age, education and field, region, initial $\times$ future year, and occupation fixed effects. Standard errors are clustered at the individual level. On the horizontal axis, the occupations are ranked by their routine task intensity (from low to high). The vertical dashed line represents the cutoff between routine and non-routine occupations. Marker size is determined by the size of each occupation.

Essay II. Understanding Occupational Wage Growth

Co-authored with Adrian Adermon, Georg Graetz, and Yaroslav Yakymovych

Acknowledgements: We thank Michael Böhm, Stefan Eriksson, Peter Fredriksson, Lena Hensvik, Lisa Laun, Oskar Nordström Skans, as well as seminar participants at the Uppsala Center for Labor Studies, the Future of Labor workshop in Berlin, and the Swedish Conference in Economics for helpful suggestions.

1 Introduction

The past four decades have seen systematic shifts in occupational employment across industrialized countries, with high- and low-paying occupations gaining at the expense of the middle. This is commonly interpreted as reflecting labor demand shifts induced by technological change, consumer demand, or offshoring. However, the impact of such occupation-level demand shifts on the wage structure is far from clear. First, occupations appear to play a minor role in driving changes in wage inequality, at least in terms of descriptive decomposition exercises. Second, occupational employment and wage growth typically do not feature a strong positive correlation. Finally, wage inequality trends differ substantially across countries, while occupational employment shifts are highly similar.[1]

In this paper, we shed light on these puzzles by studying occupational wage growth in Sweden 1996–2013. Swedish employment shifts are similar to those elsewhere (Adermon and Gustavsson, 2015), but the wage structure is dramatically compressed compared to most other industrialized countries, and growth in inequality has been moderate and episodic (Graetz, 2020). We show that, as elsewhere, occupations do not appear to play an important role in basic decompositions of changes in wage inequality.

However, as has long been recognized, any analysis of occupational demand shifts and wages must address selection problems arising from workers' systematic sorting into occupations (see for instance Roy, 1951; Acemoglu and Autor, 2011; Böhm, 2020). For example, a positive demand shock to computer programmers may manifest itself as an increase in the price paid for a unit of programming output. At the same time, this increased *occupational wage premium* draws in workers from other occupations, who may be less productive than incumbents, thus leaving *observed* wages approximately unchanged.

Our starting point for overcoming the selection problem is to focus on occupation stayers, whose wage growth comes closer to the growth in premia as time-invariant skills are differenced out and the composition of workers is left unchanged (Cortes, 2016). We address attenuation bias stemming from selection on idiosyncratic shocks using the method developed by Böhm et al. (2023).

The second challenge we face is that occupations may differ in how workers accumulate skills over the life-cycle, so that differential wage growth among

[1]The polarization of occupational employment in the US and elsewhere has been documented by Wright and Dwyer (2003), Goos and Manning (2007), and Autor et al. (2006); and Goos et al. (2014). See in particular Adermon and Gustavsson (2015) for the Swedish case. Goos et al. (2014) provide evidence in favor of a technological explanation. Barany and Siegel (2018) emphasize structural change and consumer demand instead. In a decomposition exercise, Hoffmann et al. (2020) find only a minor role for occupations in driving rising wage inequality. Roys and Taber (2019), Böhm (2020), and Böhm et al. (2023) highlight the lack of a strong positive correlation between occupational employment and wage growth in the US and Germany.

occupation stayers may reflect not only differential premium growth (Deming, 2021). Moreover, occupational experience profiles may have shifted over time, for instance due to technology-induced obsolescence of skills (Deming and Noray, 2020). A theoretically motivated restriction that has been suggested as a solution to this identification problem is the concept of a "flat spot", a point in the life-cycle when the derivative of human capital with respect to experience is zero (Heckman et al., 1998; Bowlus and Robinson, 2012). We propose a novel approach for implementing this restriction, namely to re-center the experience profiles around the flat spot. This leaves us with greater statistical power as we are not forced to restrict the sample to workers near the flat spot. More importantly, it allows us to estimate experience profiles for each occupation and point in time.[2]

Finally, we explore to what extent our estimated premium growth is driven by changes in occupation-specific skill returns. A growing literature documents changing skill returns in the aggregate, and suggests that occupations may be important drivers of such trends (Deming, 2017; Edin et al., 2022). Given the availability of cognitive and psycho-social skill measures from the Swedish military enlistment, we are able to control for differential changes in skill returns in our estimation.

Our findings are as follows. First, premium growth is positively correlated with employment growth (and more strongly so than is raw wage growth). Second, premium growth is also positively correlated with initial wages. These two findings together imply our third finding, namely that in the absence of compositional changes between-occupation wage inequality would have increased more than it actually has. Fourth, experience profiles vary strongly across occupations at any given point in time, and while they are stable in some occupations, in others they show large changes. These results are robust to allowing for changes in specific returns to cognitive and psycho-social skills.

The positive association between premium growth and employment shifts suggests that variation in premium growth is mostly due to demand side factors. At the same time, our results suggest that there is an important life-cycle component to shifts in the occupational wage structure.

Our findings are consistent with a recent and growing literature documenting the importance of compositional changes in counteracting occupation-level demand shifts (Cortes, 2016; Böhm, 2020; Cavaglia and Etheridge, 2020; Böhm et al., 2023). Our contribution compared to these studies is first, to provide comparable evidence for the Swedish economy, which at first glance features a very different wage structure. Second, to estimate time-varying

[2]Böhm et al. (2023) assume that experience profiles are constant—following much of the theoretical literature on task-biased technological change—and use a pre-period of uniform premium growth to estimate these profiles. Our data do not go back in time sufficiently to make this approach feasible.

occupation-specific experience profiles. And third, to allow for time-varying occupation-level skill returns when estimating wage premium growth.

To the best of our knowledge, the joint estimation of premium growth and experience profiles has only been attempted by one other paper, Böhm et al. (2023). Their identification assumption is that the profiles are fixed over time, and that during the decades prior to 1985 any differential wage premium growth was negligible, so that experience profiles can be estimated using a prior period. Our assumptions and identification strategy differ from Böhm et al. (2023), and we view our approach as complementary.[3]

The remainder of the paper is structured as follows. Section 2 presents our theoretical framework, discusses identification challenges as well as our proposed solutions, and develops counterfactual scenarios. We describe our data in Section 3. Section 4 contains our results, and Section 5 concludes.

2 Theoretical framework and empirical strategy

The theoretical motivation for our empirical exercise is the standard Roy model in which workers sort into occupations based on comparative advantage. Rather than estimating a completely specified model, our point of departure is an assumption about the data-generating process for potential wages. In Section 2.1, we explore how key parameters of this wage equation can be identified under different assumptions about occupational choice. In Section 2.2, we show how changes in overall wage inequality can be attributed to occupation-level driving forces, and develop counterfactual scenarios based on our estimated wage equation.

2.1 Identifying the parameters of the wage function

Suppose that individual worker i's log wage in occupation k and year t, w_{ikt}, is given by

$$w_{ikt} = \pi_{kt} + \alpha_{ik} + \beta_k \mathbf{s}_i + g_k(x_{ikt} - x^*) + \varepsilon_{ikt}, \tag{1}$$

where π_{kt} is a potentially time-varying occupation-specific wage premium; α_{ik} is an unobserved worker-occupation fixed effect; $\mathbf{s}_i$ is a vector of observable skills with its associated occupation-specific returns β_k; x_{ikt} is the worker's experience in the occupation measured in years and centered around x^*, to be

[3] Using unusual rich data, Böhm et al. (2023) are able to estimate across-occupation experience profiles, that is, the extent to which a year of work experience in one occupation increases the worker's productivity in this and all other occupations. In contrast, we estimate how wage growth in each occupation and at each point in time varies with overall potential labor market experience. (Given the limited length of our panel, we cannot construct workers' occupational histories.) Therefore, our estimates have a different structural interpretation from those in Böhm et al. (2023).

discussed below; g_k is an occupation-specific experience profile; and ε_{ikt} is an i.i.d. shock. Our main goal is to estimate π_{kt} for each occupation, or at least its *change relative to a reference occupation*.

For the moment, let us assume that workers choose the occupation in which they earn the highest wage in each period, abstracting from dynamic considerations. Furthermore, let us assume for now that the shock ε_{ikt} is realized *after* workers have made their choice. These assumptions are the same as in Cortes (2016). This leaves us with two potential threats to identification: Selection on unobserved time-invariant characteristics, and occupation-specific experience profiles. We address these in turn.

Selection on time-invariant characteristics

Consider the first difference of Equation (1),

$$\Delta w_{ik} = \Delta \pi_k + g_k(x_{ikt} - x^*) - g_k(x_{ikt} - 1 - x^*) + \Delta \varepsilon_{ik}, \tag{2}$$

where Δ is the first difference operator, so that $\Delta X = X_t - X_{t-1}$. If we estimate Equation (2) using the sample of occupation stayers, we can be sure that selection on time-invariant skills α_{ik} and $\mathbf{s}_i$ is accounted for, since these terms are differenced out. An alternative method accomplishing this is of course to estimate Equation (1) in levels and to include worker-by-occupation fixed effects, as in Cortes (2016). We prefer the first difference specification for two reasons. First, it allows us to run separate regressions for each year, and thus work with datasets of manageable size. Second, our data on wages and occupations come from repeated cross-sectional samples, so that it is difficult to construct long panels of individuals workers, and to accurately capture longer occupational spells (see Section 3).

Occupation-specific experience profiles

For concreteness, we approximate the profile by a polynomial of order M, $g_k(x) = \sum_{m=1}^{M} \gamma_{km}(x - x^*)^m$. Under this assumption, the component of wage growth due to experience—among occupation stayers—now becomes

$$g_k(x_{ikt} - x^*) - g_k(x_{ikt} - 1 - x^*) = \gamma_{k1} + \sum_{m=2}^{M} \gamma_{km} \left\{ (x_{ikt} - x^*)^m - (x_{ikt} - 1 - x^*)^m \right\}.$$

The wage growth equation to be estimated is thus

$$\Delta w_{ik} = \Delta \pi_k + \gamma_{k1} + \sum_{m=2}^{M} \gamma_{km} \left\{ (x_{ikt} - x^*)^m - (x_{ikt} - 1 - x^*)^m \right\} + \Delta \varepsilon_{ik}. \tag{3}$$

Estimation of Equation (3) for a given occupation yields a constant term $\theta_{kt} = \Delta \pi_k + \gamma_{k1}$. Thus, the challenge is to separate out changes in premia from the constant term of the experience profile. Note that γ_{k1} is the effect of additional experience at the point $x_{it} = x^*$. Human capital theory (Ben-Porath, 1967; Heckman et al., 1998) suggests that there comes a point in a worker's life cycle when human capital accumulation stops, or even reverses due to depreciation—a so-called flat spot where the marginal effect of experience on wages is zero. Thus, if x^* is set to be at the flat spot, then $\gamma_{k1} = 0$, solving the identification problem as we now have $\theta_{kt} = \Delta\pi_k$.[4]

We illustrate this strategy using a concrete example: The wage growth of *physical and engineering science technicians* from 2005–06. Figure 1 plots changes in log wages, together with the fitted polynomial, against potential experience re-centered around different values—the assumed locations of the flat spot. The fitted polynomial comes from estimating Equation (3) choosing $m = 4$. Grey dashed lines mark the constant term estimated by the regressions, equal to premium growth under the assumption $\gamma_{k1} = 0$. The data reveal a strong downward trend in wage growth, consistent with faster skill accumulation among inexperienced workers, as well as a flattening of this relationship at higher levels of potential experience. The top-left panel does not re-center the data, thus yielding a large estimated premium growth of around 8 percent. But an assumption of zero skill accumulation for labor market entrants is of course highly implausible. Assuming flat spots at higher values such as 25, 30, or 35 all yield estimated premium growth around 2 percent, as shown in the remaining panels.

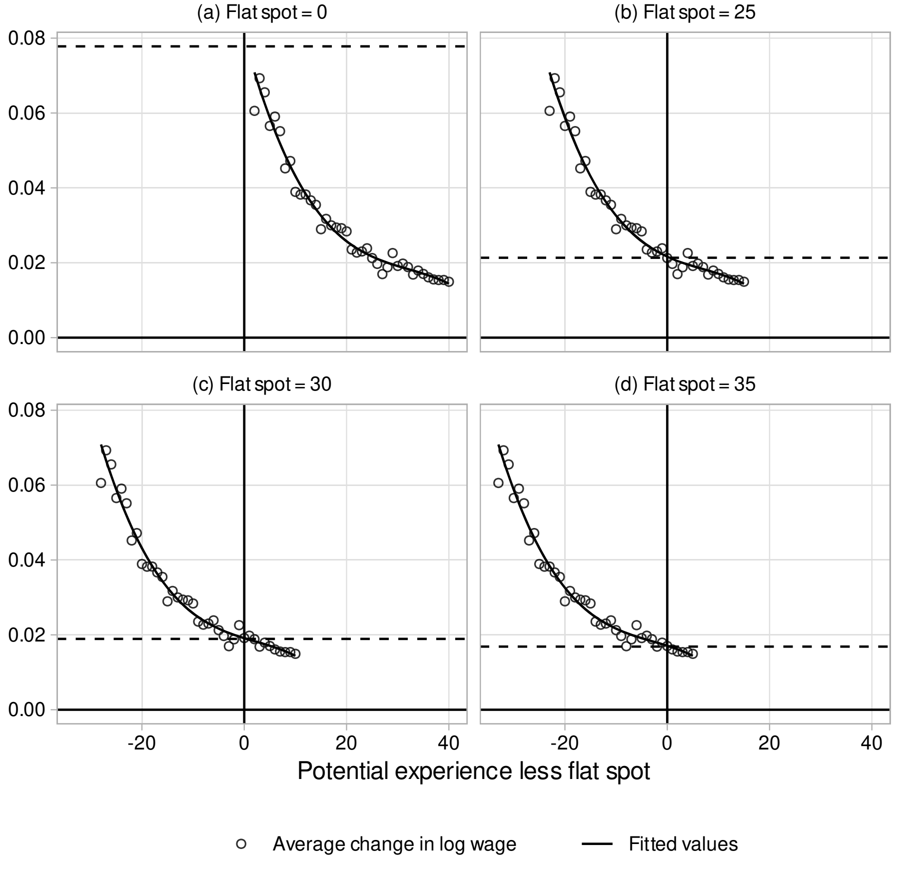
Figure 1 illustrates that choosing the flat spot means picking a point on the fitted first-differenced experience profile and attributing all wage growth at that point to growth in the premium.[5] Relying on a parametric prediction for the profile yields greater statistical power compared to simply using average wage growth at the flat spot.

Figure 1 also raises the question whether the flat spot can be determined in a data-driven way. In general, the answer is no. Consider three hypothetical experience-wage profiles plotted in the top row of Figure 2. As we do not observe workers' time-invariant occupation-specific skills, we cannot estimate the profiles in levels. We thus first-difference the profiles, shown in the bottom row. The challenge remains to separate premium growth from skill accumulation. Consider first column (a). The differenced profile reproduces the nearly flat region of the original in-levels profile. While it may not be easy to determine the *exact* location of the flat spot, this would also not matter greatly for the estimated premium growth. However, recall that the econometrician cannot see the top row. As column (b) shows, a flat region in first differences

[4]Our approach is related to Fosse and Winship (2019), who address the identification problem arising in the presence of age, cohort, and time effects. They highlight that it is only linear effects that are unidentified, and explain how one can bound these. However, a single restriction is often sufficient for point identification, as is the case in our context.

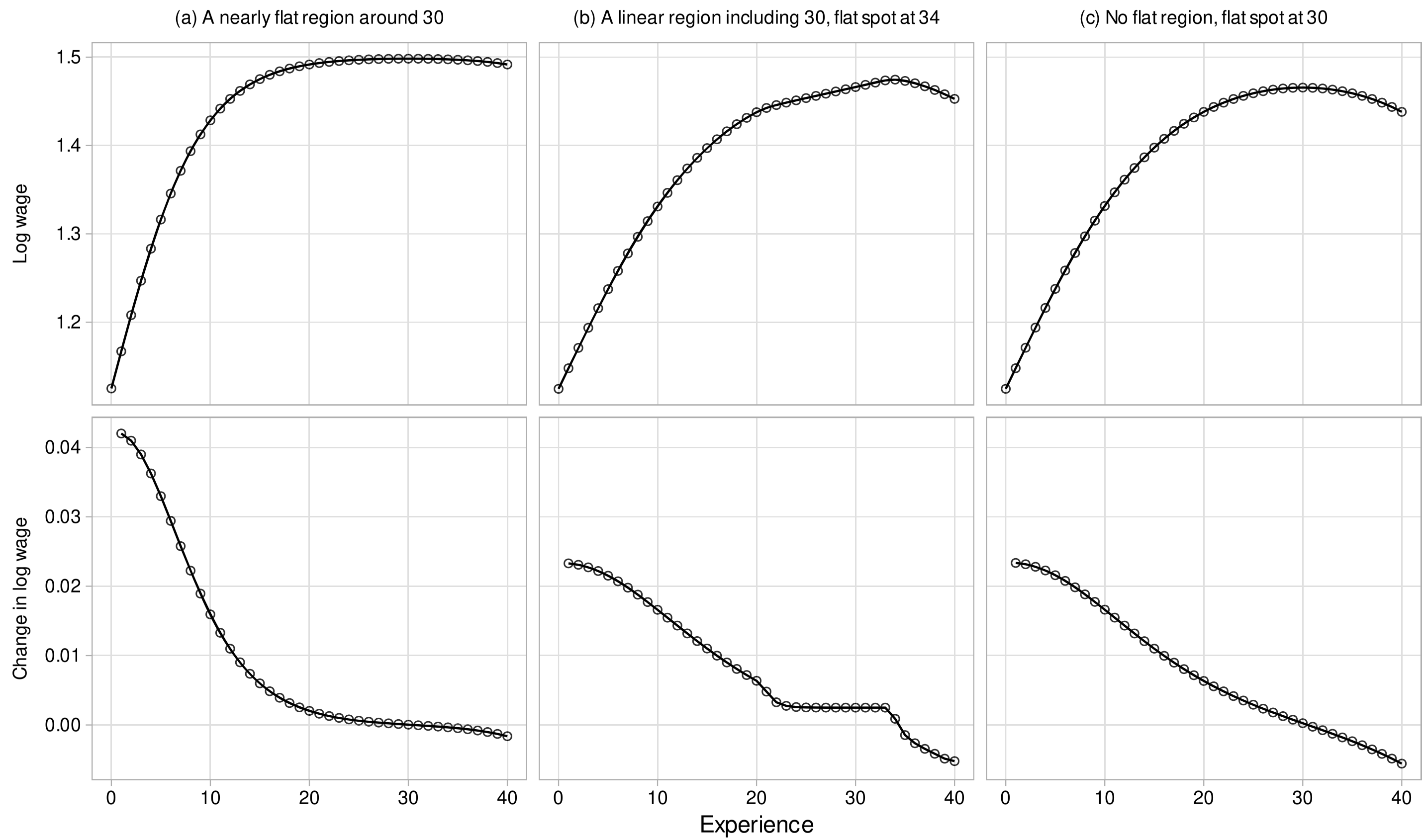
[5]To be precise, the flat spot assumption says that $g'_k(x^*) = 0$. In the polynomial case, $g'_k(x^*) = \sum_{m=1}^{M} \gamma_{km} m(x - x^*)^{m-1} = \gamma_{k1}$. Here, the flat spot assumption $\gamma_{k1} = 0$ does not imply that $\Delta w_{ik}|_{x=x^*} = \Delta\pi_k$ exactly, which requires $\sum_{m=2}^{M} \gamma_{km} \{-(-1)^m\} = 0$. However, in practice these equations will hold approximately, as is the case in Figure 1.

Figure 1. Illustration of flat spot identification



Notes: Grey dashed lines mark the constant term from estimating the experience profiles, equal to wage premium growth under the respective flat spot assumptions. The data include all individuals who worked as physical and engineering science technicians in 2005 and 2006. See Section 3 for further details on sample selection.

Figure 2. Simulated wage-experience profiles



Notes: The top row shows various simulated experience profiles. The bottom row plots first differences of the profiles above, assuming wage premium growth of two percent.

can also result from a locally log-linear profile in levels. In this case, the true flat spot at 34 cannot be detected based on first differences. Finally, consider column (c), which shows a profile of roughly constant curvature and hence no flat region. Again, it is not obvious how to choose the flat spot based on the first-differenced profile.

Given that the flat spot cannot be identified without further assumptions, our approach is to set it at 30 for all occupations, while also reporting results for alternative values. In a further robustness check, we estimate flat spots under the additional assumption that the true profiles are strictly concave except for possible flat sections (that is, linear segments with non-zero slope, as in the middle column of Figure 2, are prohibited). In this case, the second derivative of the profile will be maximized (closest to zero) at the flat spot, so that any statistic of interest should change by the least amount—in absolute value—at the true flat spot. See Section A for further details.

A key advantage of our method is that it allows us to jointly estimate experience profiles and premium growth. Moreover, as we estimate separate models for each year, we essentially estimate time-varying experience profiles.[6] A third advantage is that we retain greater statistical power than existing approaches in the literature which implement the flat spot idea using only data on workers near the flat spot (Bowlus and Robinson, 2012; Cavaglia and Etheridge, 2020).[7]

We note that the interpretation of our estimated profiles is affected by the measurement of occupation-specific experience. With a panel that is relatively short (20 years) relative to the typical length of working lives, it is not possible to construct complete occupational histories for each worker.[8] In our baseline specification we therefore use potential overall labor market experience, based on age and years of schooling. Given this, the occupation-specificity of the γ_{km}'s means that experience is differently valued across occupations, but it does not matter in which occupation this experience was gained. Alternatively, one can simply interpret the estimated profiles as describing the wage growth in a given occupation and year as a function of potential overall labor market experience. This function will depend not only on deep structural parameters, but also on the characteristics—such as occupational histories—of the workers staying in that occupation in that year (and the year before).

[6] Strictly speaking, the experience profile in *levels* must be constant across the two adjacent years. This would not matter if we had specified the profile in changes in the first place. However, starting with a levels specification is arguably more natural given the Roy framework.

[7] It is also possible to implement flat spot identification via an iterative procedure (Lagakos et al., 2017).

[8] Another challenge is that private sector workers in Sweden are sampled, as we discuss in the data section.

Time-varying skill returns

A key finding in recent research on inequality is that wage returns to various skills have evolved differently over time, with occupations seemingly playing an important role. While this is interesting in its own right, here we are mainly concerned with the impact of such changes on our ability to estimate changes in occupational wage premia. Suppose, then, that returns to portable skills vary over time,

$$w_{ikt} = \pi_{kt} + \alpha_{ik} + \beta_{kt}\mathbf{s}_i + g_k(x_{ikt} - x^*) + \varepsilon_{ikt},$$

so that wage growth now becomes

$$\Delta w_{ik} = \Delta\pi_k + (\Delta\beta_{kt})\,\mathbf{s}_i + \sum_{m=2}^{M} \gamma_{km}\left\{(x_{ikt} - x^*)^m - (x_{ikt} - 1 - x^*)^m\right\} + \Delta\varepsilon_{ik}. \quad (4)$$

For selected cohorts of Swedish men we actually have at our disposal the skill measures for which changing wage returns have been documented. We can thus assess whether our baseline estimates of $\Delta\pi_k$ are robust to controlling for these measures, by estimating Equation (4) where the vector $\mathbf{s}_i$ contains cognitive and psycho-social skills, as described further in the data section.

Selection on idiosyncratic shocks

Let us now allow for selection on the idiosyncratic shock ε_{ikt}, as well. The constant term from estimating Equation (3), imposing the flat spot assumption $\gamma_{k1} = 0$, now becomes $\theta_{kt} = \Delta\pi_k + \mathrm{E}[\Delta\varepsilon_{ik}|k_{it} = k_{i,t-1} = k]$. The second term no longer equals zero, due to selection. Other things equal, occupations experiencing relatively fast premium growth will retain more workers with a bad realization of the shock, while occupations in which premia decline only retain those workers with very good realizations. Therefore, selection on idiosyncratic shocks biases downward the between-occupation variance in premium growth. This bias is more severe the larger is the variance of ε_{ikt}. A method to correct for this bias, developed by Böhm et al. (2023), is to include occupation switchers in a regression of wage growth on workers' average choices. We implement this method as a robustness check.

Remaining issues

There are a number of issues which are beyond the scope of this paper. These include forward-looking occupational choice, amenities, search frictions, and long-term wage contracts. We believe that addressing any one of these requires estimation of a fully specified structural model (for recent examples, see Roys and Taber, 2019; Traiberman, 2019).

2.2 Occupational drivers of changes in wage inequality

A key objective of this paper is to assess the importance of occupations for changes in wage inequality. Therefore, we need to formally characterize how changes in inequality relate to occupation-level changes such as differential premium growth and worker re-allocation. We closely follow Böhm et al. (2023).

First, by the Law of Total Variance, $\mathrm{Var}(w_{it}) = \mathrm{E}[\mathrm{Var}(w_{it}|k)] + \mathrm{Var}(\mathrm{E}[w_{it}|k])$. That is, overall wage inequality can be decomposed into a within-occupation and a between-occupation component. Without specifying the distribution of skills, it is difficult to say much about how changes in premia affect the within component, so we focus on the between component.

To ease notation, let us from now on write $w_{kt} \equiv \mathrm{E}[w_{it}|k]$ and $\Delta w_k \equiv \Delta\mathrm{E}[w_i|k]$, and similarly for other variables. The difference operator $\Delta X \equiv X_1 - X_0$ denotes changes between two points in time 0 and 1, not necessarily adjacent years.

Note, to integrate out the conditioning variable—occupational choice—we must specify a distribution of occupational employment. When decomposing the variance at a given point in time, the obvious choice is to use the distribution at that point. But when considering changes over time, we need to be explicit about the distribution. We use subscripts to do so.

The change in between-occupation wage inequality can be written as

$$\mathrm{Var}_1(w_{k1}) - \mathrm{Var}_0(w_{k0}) = \underbrace{\mathrm{Var}_0(w_{k1}) - \mathrm{Var}_0(w_{k0})}_{\text{change at initial employment}} + \underbrace{\mathrm{Var}_1(w_{k1}) - \mathrm{Var}_0(w_{k1})}_{\text{re-allocation}}. \tag{5}$$

Define $y_{kt} \equiv w_{kt} - \pi_{kt}$, which captures workers' skills in the broadest sense—all parts of log wages not determined by the occupation premium. The first component on the right-hand side of Equation (5) can be broken down as

$$\begin{aligned} \mathrm{Var}_0(w_{k1}) - \mathrm{Var}_0(w_{k0}) &= \mathrm{Var}_0(\Delta w_k) + 2\mathrm{Cov}_0(w_{k0}, \Delta w_k) \\ &= \mathrm{Var}_0(\Delta\pi_k) + \mathrm{Var}_0(\Delta y_k) + 2\mathrm{Cov}_0(\Delta\pi_k, \Delta y_k) \\ &\quad + 2\mathrm{Cov}_0(w_{k0}, \Delta\pi_k) + 2\mathrm{Cov}_0(w_{k0}, \Delta y_k). \end{aligned} \tag{6}$$

From Equation (6), we see how differential changes in premia may affect changes in wage inequality, and at the same time, how their effects may be offset by opposing forces. In particular, all the components of the decomposition involving changes in average skills Δy_k, as well as the re-allocation term from Equation (5), can be seen as potentially countervailing effects due to workers' re-sorting. In contrast, all terms only involving $\Delta\pi_k$ and initial mean wages w_{k0} can be interpreted as giving the counterfactual increase in between-occupation wage inequality in the absence of re-sorting. That is, with worker composition unchanged, we have

$$\mathrm{Var}_0(w_{k1}) - \mathrm{Var}_0(w_{k0}) = \mathrm{Var}_0(\Delta\pi_k) + 2\mathrm{Cov}_0(w_{k0}, \Delta\pi_k), \tag{7}$$

which is a key object of interest in our analysis. Equation (7) shows that, holding worker composition constant, changes in wage premia have a large effect on wage inequality if they are very dispersed, or if they are positively correlated with initial mean wages.

3 Data description

3.1 Data sources

We obtain demographic information (year of birth, sex, municipality of residence, education, immigration status) from Statistics Sweden's LISA database, covering the population of Swedish residents 1985-2016. LISA also contains employment status in November each year, annual salary income, as well as industry and municipality of workplace.

Some information that is key for our purposes is absent from LISA. In particular, LISA does not contain weeks and hours worked, nor occupation. For this, we turn to a database called Swedish Wage Structure Statistics (henceforth WSS). WSS contains three-digit occupation codes according to the *SSYK96* classification 1996–2013, and according to the *SSYK2012* classification 2014-2016.[9] The two classifications cannot be mapped unambiguously, and breaks in employment trends are apparent even at higher levels of aggregation. We therefore end our main analysis in 2013.

WSS also contains contractual monthly wage rates. This in combination with annual salary income allows us to determine annual labor supply. Most importantly, these contractual wage rates are the main outcome of interest for our analysis, since we are interested in the price of labor.

A drawback of WSS is that outside the public sector, only a sample of workers is available. Sampling is stratified by firms, with large firms being more likely to be drawn. This does not pose any problems for cross-sectional analysis—sampling weights are provided—but makes it more difficult to analyze dynamic phenomena such as occupational mobility. We discuss this issue further in the next sub-section.

For some of our analysis, we use test scores collected during military enlistment in the last decades of the 20th century, after which conscription was gradually phased out. Among birth cohorts 1952-1981, more than 90 percent of Swedish-born males are covered by these data. We use a combined measure of cognitive skills based on four different standardized tests of inductive, verbal and spatial skills, and technical comprehension, and a measure of psychosocial skills (sometimes called "non-cognitive skills") based on a half-hour, semi-structured interview with a certified psychologist.[10] We standardize the

[9]SSYK stands for *Standard för Svensk Yrkesklassificering*, literally "Standard for Swedish occupation classification", a version of the International Standard Classification of Occupations (ISCO).

[10]The intent of the interview was to evaluate the psychological fitness for coping with military service. See Lindqvist and Vestman (2011) and Fredriksson et al. (2018) for more details on these data.

two measures within each draft cohort to have mean zero and standard deviation one. To ensure comparability, we estimate our main specification also for the sub-sample of male cohorts for which enlistment data are available.

3.2 Sample selection and construction of variables

Our population of interest includes all Swedish employees aged 18–64 during the years 1996–2013 (sometimes extended to 2016). Employees are individuals who are employed in November and whose annual labor earnings are no less than three times the 10th-percentile monthly wage. We calculate individual wage growth for all adjacent years, dropping anyone with wage growth below the first or above the 99th percentile for each pair of years.[11]

We calculate potential labor market experience as years elapsed since year of graduation, based on highest education attained and a school starting age of six. To reduce noise, we drop observations with potential experience below two and greater than 40 years. Due to the limited length of the panel as well as due to sampling, we are unable to construct actual occupation-specific experience.

We use sampling weights to adjust for stratification. The raw weights supplied in WSS feature some extremely large values, and this may introduce noise, especially when multiplying the weights for a first-difference analysis using a two-year panel. Whenever we work with individual, two-year panel data, we therefore trim the weights following the procedure of Potter (1990).[12] However, when computing aggregate moments, we use the original weights.

For our baseline analysis we use the 3-digit-level *SSYK96* occupational classification, which includes 101 occupations. However, we sometimes use a coarser classification for descriptive and other purposes.

4 Results

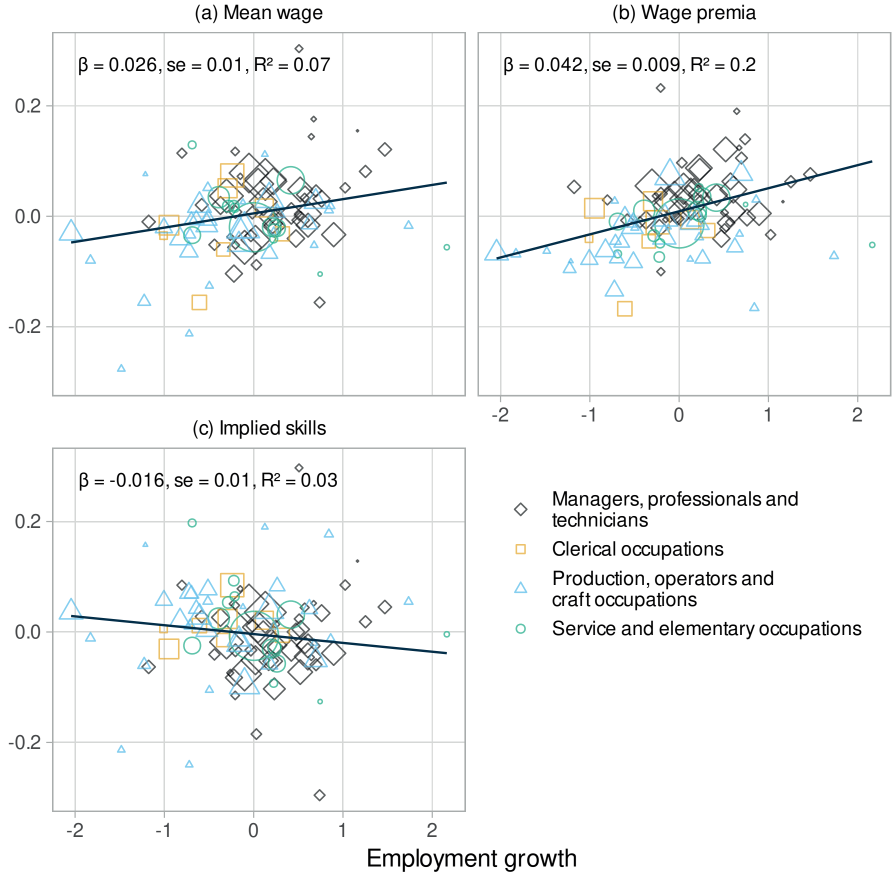
4.1 Raw wages, wage premia, and employment

To set the stage, we document the relationship between growth in averages wages and growth in employment as well as initial wages, across occupations for the period 1996–2013. Panel (a) of Figure 3 plots the long difference in log wages against the long difference in the log of employment, with each marker

[11] Extreme values of wage growth — five or more standard deviations away from the mean — may occur because individuals enter into and exit from executive positions (Skans et al., 2009). We drop extreme values as these can have a large impact on the results.

[12] The procedure is as follows. We first fit a Beta(α,β) distribution to the weights. Second, weights whose estimated cumulative probability is above 99 percent are trimmed to the estimated 99th percentile. Third, weights are re-scaled such that their sum is unchanged. This procedure is repeated ten times.

Figure 3. Growth in wages, premia, and skills against employment growth, 1996–2013



Notes: The figure plots the growth mean log wages, cumulative estimated wage premia, as well as the implied change in mean skills, against the change in log employment. Wage premia are estimated according to our baseline specification Equation (8). Each marker represents one of 101 occupations. The size of each marker is determined by the employment share in the first year and the regression line is weighted accordingly. We use original survey weights when calculating occupation size and mean log wage.

representing one occupation. First, by moving along the horizontal axis, we see much variation in employment growth. Production, operators, and craft occupations tend to see low (often negative) employment growth, while on average, employment growth appears highest among managers, professionals, and technicians. Clerical and services occupations fall somewhere in between. However, there is much variation even within these broad categories. Turning to wage growth, there is a positive but rather weak relationship with employment growth. Panel (a) of Figure 4 reveals an even weaker relationship of average wage growth with initial (1996) average wages.

However, as discussed in Section 2, average wage growth captures both changes in occupational wage premia and changes in worker composition and hence average skills. In order to isolate changes in wage premia, we operationalize Equation (2) by estimating separate regressions of year-on-year changes in individual log wages on occupation fixed effects and a polynomial in potential experience:

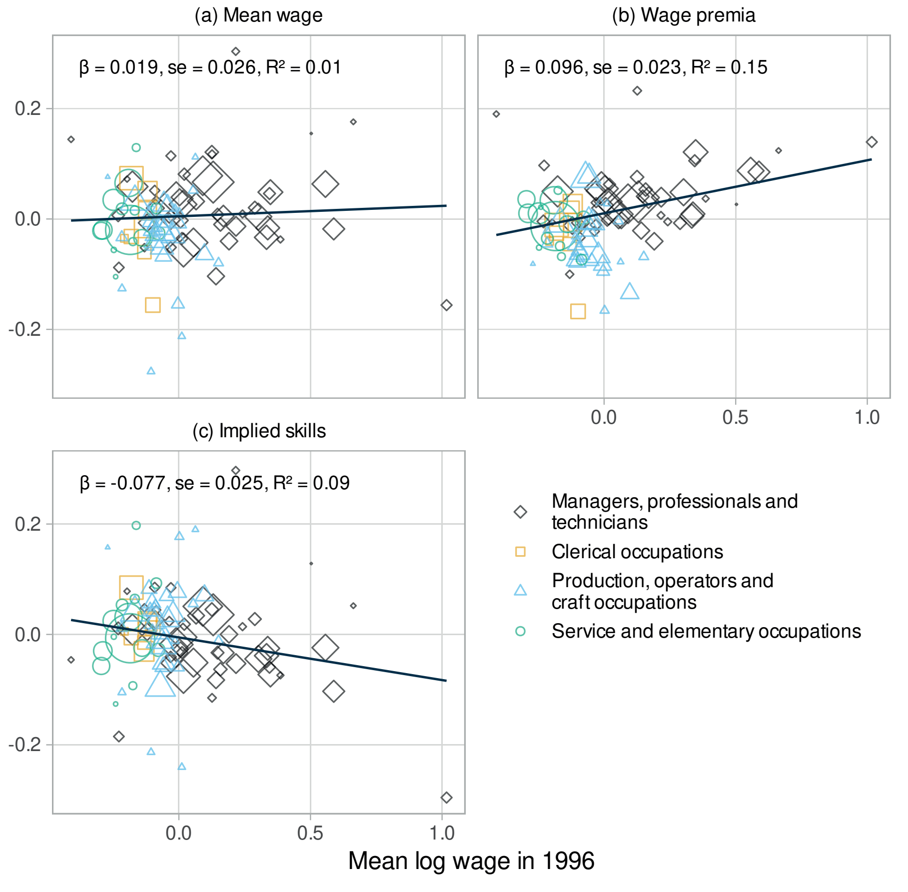
$$\Delta w_{it} = \varphi_{kt} + \sum_{m=2}^{4} \gamma_{km} \{\tilde{x}_{it}^{m} - (\tilde{x}_{it} - 1)^{m}\} + u_{it}, \tag{8}$$

where φ_{kt} are occupation-specific fixed effects; $\tilde{x}_{it} \equiv x_{it} - x^{*}$ is potential experience re-centered around the assumed flat spot in the experience profile; and γ_{km} are polynomial coefficients allowed to vary by occupation. In our main specification, we use a fourth-order polynomial and re-center potential experience at 30 years. We report robustness checks with respect to these choices below. We estimate separate regressions for each pair of adjacent years in our sample. In order to control for changes in worker composition, we use only individuals who remained in the same occupation across both years, $k_{it} = k_{i,t-1}$.

Under the assumption that there is no selection on idiosyncratic shocks and that $\gamma_{m1} = 0$ (the flat spot assumption), the fixed effects φ_{kt} consistently estimate premium growth $\Delta_{t-1}^{t}\pi_k$ for an adjacent pair of years. We estimate premium growth over the full period by simply accumulating the estimated year-on-year changes, $\widehat{\Delta_{1997}^{2013}\pi_k} = \sum_{t=1997}^{2013} \widehat{\varphi}_{kt}$.

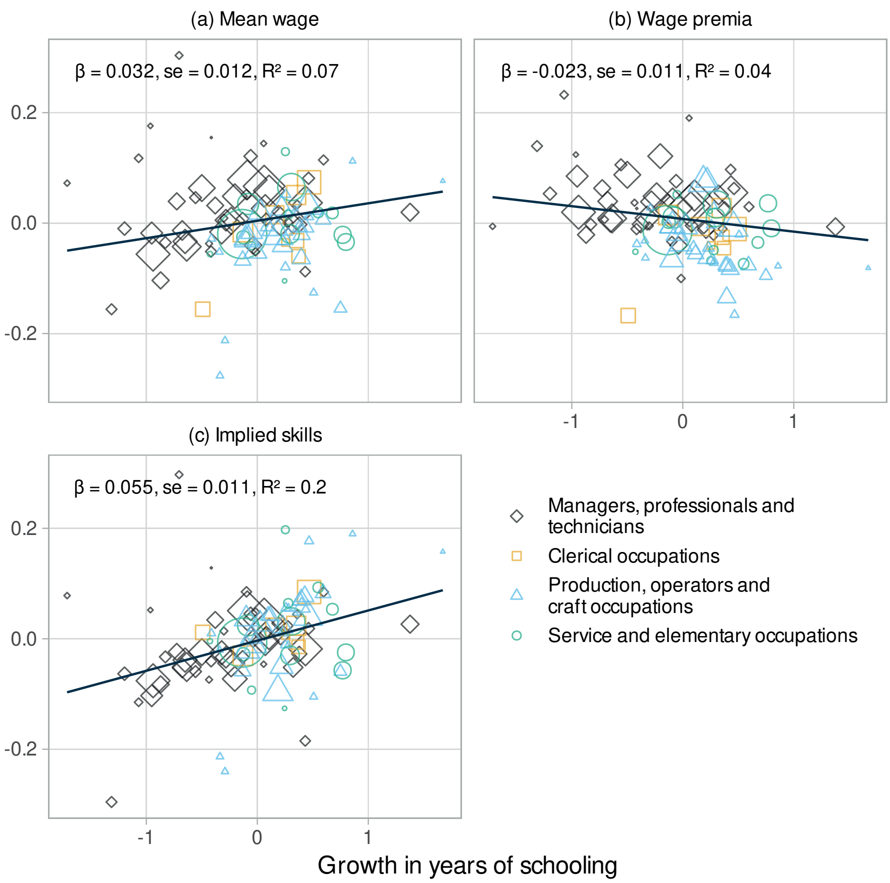
Our premium growth estimates are plotted against employment growth in Panel (b) of Figure 3. The relation between premium growth and employment growth is stronger than that of mean wage growth—the slope is steeper, and R^2 almost triples. This pattern implies that while demand factors were pushing up wage premia during this period, changes in the skill composition of workers acted as a counteracting force, resulting in the tempered trend we see in average wage growth. This is consistent with a situation where growing labor demand in certain occupations attracts new workers with lower productivity than the incumbents—and conversely, occupations with falling labor demand might let their lower-productivity workers go first. The implied change in skill composition can be backed out from our estimates by simply subtracting the estimated changes in premia from the observed changes in average wages.

Figure 4. Growth in wages, premia, and skills against initial wages, 1996–2013



Notes: The figure plots the growth mean log wages, cumulative estimated wage premia, as well as the implied change in mean skills, against initial mean log wages. Wage premia are estimated according to our baseline specification Equation (8). Each marker represents one of 101 occupations. The size of each marker is determined by the employment share in the first year and the regression line is weighted accordingly. We use original survey weights when calculating occupation size and mean log wage.

Figure 5. Growth in wages, premia, and skills against growth in schooling, 1996–2013



Notes: The figure plots the growth mean log wages, cumulative estimated wage premia, as well as the implied change in mean skills, against initial the growth in average years of schooling. Wage premia are estimated according to our baseline specification Equation (8). Each marker represents one of 101 occupations. The size of each marker is determined by the employment share in the first year and the regression line is weighted accordingly. We use original survey weights when calculating occupation size and mean log wage.

This is shown in Panel (c) of Figure 3. As expected, faster growing occupations have seen falling implied skill levels in their workforce, although this relationship is not very strong.

Panel (b) of Figure 4 shows that premium growth is strongly positively associated with initial wages. Given Equation (6), this suggests that premium growth would cause an increase in between-occupation wage inequality in the absence of compositional changes. However, panel (c) of Figure 4 already gives an idea of how strong these compositional changes might be—growth in average skills are strongly negatively related to initial wages. We explore these issues in detail in Section 4.2.

One way to assess the plausibility of the estimated growth in skills is to check its association with changes in years of schooling. Panel (c) Figure 5 shows that there is indeed a positive relationship, with a fairly high R^2 of 0.2. On the other hand, panel (b) of the same figure shows a negative association between premium growth and changes in years of schooling, consistent with lower educated workers moving into occupations experiencing positive demand changes.[13]

While the evidence presented so far suggests that the forces predicted by the Roy model are at work, it remains to assess their quantitative importance for the evolution of wage inequality in Sweden. We do so next.

4.2 Decomposing changes in between-occupation wage inequality

To quantify the role of differential premium growth for changes in between-occupation inequality in Sweden, we use our estimates to calculate the counterfactual scenarios developed in Section 2.2. We first focus on the long difference 1996–2013 and then examine changes at annual frequency.

The first three lines in column (1) of Table 1 show the change in the observed variance of log wages, the change in between-occupation variance, as well as the change in between-occupation variance holding occupational employment fixed at 1996. The variance of log wages increased by 0.026 between 1996–2013, from 0.073 in 1996. (To avoid excessive decimal places, we multiply the variance and its components by 100 from here on.) Although the wage distribution in Sweden is still highly compressed compared to other countries (Graetz, 2020), this increase is large in relative terms.

Between-occupation wage inequality accounts for just over half of the increase in overall variance. But this is allowing for the employment weights in the calculation of variance to change over time. If employment shifts from

[13]For completeness, Figure B2 displays the respective bi-variate associations of wage growth, premium growth, and implied skill growth, showing positive correlations between wage growth and premium growth, and wage growth and skill growth, and a negative correlation between premium growth and skill growth.

Table 1. *Decomposition of changes in between-occupation wage inequality*

	(1)	(2)	(3)	(4)
	Baseline	Common flat spot		Occ.-spec.
		25	35	flat spot
Total				
$\Delta\text{Var}(w_{ik})$	2.57			
Between				
$\Delta\text{Var}(w_k)$	1.31			
$\Delta\text{Var}_0(w_k)$	.39			
Components				
$\text{Var}_0(\Delta\pi_k) + 2\text{Cov}_0(w_{k0}, \Delta\pi_k)$	.94	2.03	.29	.66
$\text{Var}_0(\Delta\pi_k)$	.23	.43	.17	.27
$2\text{Cov}_0(w_{k0}, \Delta\pi_k)$	.71	1.59	.12	.4
$\text{Var}_0(\Delta y_k)$	.26	.37	.24	.25
$2\text{Cov}_0(w_{k0}, \Delta y_k)$	-.57	-1.45	.02	-.26
$2\text{Cov}_0(\Delta\pi_k, \Delta y_k)$	-.24	-.55	-.16	-.27

Notes: The table reports results from a decomposition of the change in the between-occupation variance in wages between 1996 and 2013 for different flat spot levels. See Equation (6) for the formal statement of the decomposition. Column (1) uses a common flat spot for all occupations, at 30 years of potential experience, when estimating growth in wage premia. Columns (2)–(3) vary this common flat spot as indicated. Column (4) estimates a flat spot for each occupation using the procedure described in Section A. All figures have been multiplied by 100 for readability.

middle- to both high- and low-paying occupations, we should expect between-occupation inequality to increase even if wage premia do not grow differentially. The phenomenon of job polarization has been extensively documented in the literature (Goos et al., 2014; Adermon and Gustavsson, 2015), and Figure B1 confirms that it is present also in our sample period.

Our main interest, however, is in occupation-level drivers of wage inequality that are due to differential changes in compensation for a fixed set of workers. The third row in Table 1 shows that holding employment fixed at 1996 levels, the contribution of between-occupation variance shrinks by more than two thirds. But, as discussed above, changes in observed wages at the occupation level may mask changes in composition. To assess the role of differential growth in occupational wage premia, we perform the decomposition given by Equation (6).

Column (1) of Table 1 presents our baseline results, with the flat spot set at 30 for all occupations. Holding worker composition constant, the increase in between-occupation variance would have been 0.94 based on our decomposition. This is more than twice the increase in the between-occupation variance of raw wages (at constant employment), and almost 40 percent of the increase in the overall variance of log wages. Most of this effect is due to a positive covariance between initial wages and premium growth, while the variance in premium growth plays a relatively minor role. The last two rows in column (1) of Table 1 show the attenuating forces: Changes in worker skills are negatively correlated with both initial wages and growth in wage premia.

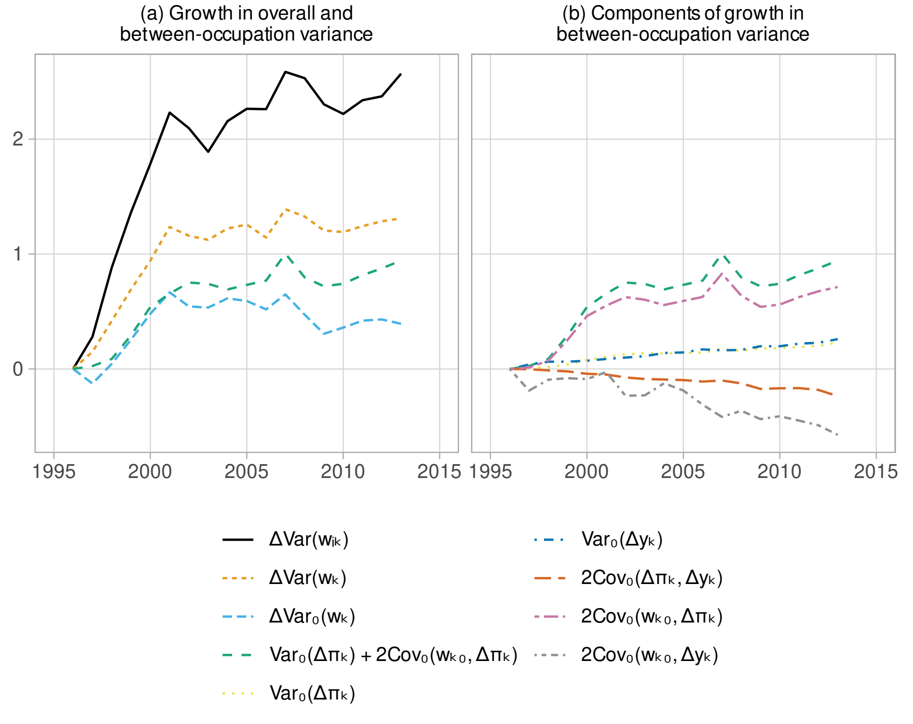
Figure 6 shows the evolution of the variance components year-on-year. Interestingly, during the period 1996–2001, which saw the fastest growth in wage inequality, the attenuating forces of a changing skill composition are absent, and the no-sorting counterfactual closely tracks between-occupation inequality in raw wages (at constant employment). The attenuating forces emerge only after 2001.[14]

4.3 Robustness checks

We conduct a number of robustness checks for the results that depend on the estimation of wage premium growth. First, we vary the location of the flat spot. As expected given the shape of wage-experience profiles and the above discussion of Figure 1, the decomposition results are sensitive to the choice of flat spot, as seen in columns (3) and (4) of Table 1. The sensitivity varies

[14]Column (1) in panel B of Table B1 displays the decomposition results for the sub-period 2001–2013. Figures B3 and B4 display the relationships between growth in wages, premia, and implied skills on the one hand, and employment growth and initial wages on the other, for 2001–2013. While overall inequality changed little during this time, the pattern of premium growth and compositional changes is qualitatively very similar to that for the whole sample period.

Figure 6. Decomposition of changes in between-occupation inequality 1996-2013



Notes: The figure plots the results from the decomposition given by Equation (6) for every year pair $\{1996, t\} \; \forall \, t \in \{1996, \dots, 2013\}$.

by component: The variance of premium growth appears more stable than the covariance of premium growth and initial wages.[15]

However, when we attempt to determine occupation-specific flat spots in a data-driven way—based on the assumption of strictly concave wage-experience profiles (except for possible flat regions) as discussed in Section A—we obtain results quite similar to our baseline specification (column (4)). Note also that setting the flat spot at zero, which would be implied if we simply added higher-order terms of potential experience without re-centering them, yields clearly unreasonable results (column (2) of Table B2).

Table B2 displays the decomposition components for a set of further robustness checks. These include changing the order of the polynomial in potential experience; adjusting for endogenous mobility using the method of Böhm et al. (2023); allowing for differential growth in wage premia at the level of regions and industries; pooling the data to estimate time-invariant experience profiles; restricting the data to men with non-missing enlistment scores; controlling for time-varying returns to cognitive and non-cognitive skills within this restricted sample; and dividing the data by gender. The results are robust in the sense that the no-sorting counterfactual in the majority of cases is of similar or even larger magnitude compared to the baseline.[16]

Finally, we probe the robustness of the associations of premium growth and implied skills with employment growth, initial wages, and years of schooling. The results are shown in Figures B5 and B6, and once again are largely similar to the baseline specification.

4.4 Changes in occupational experience profiles

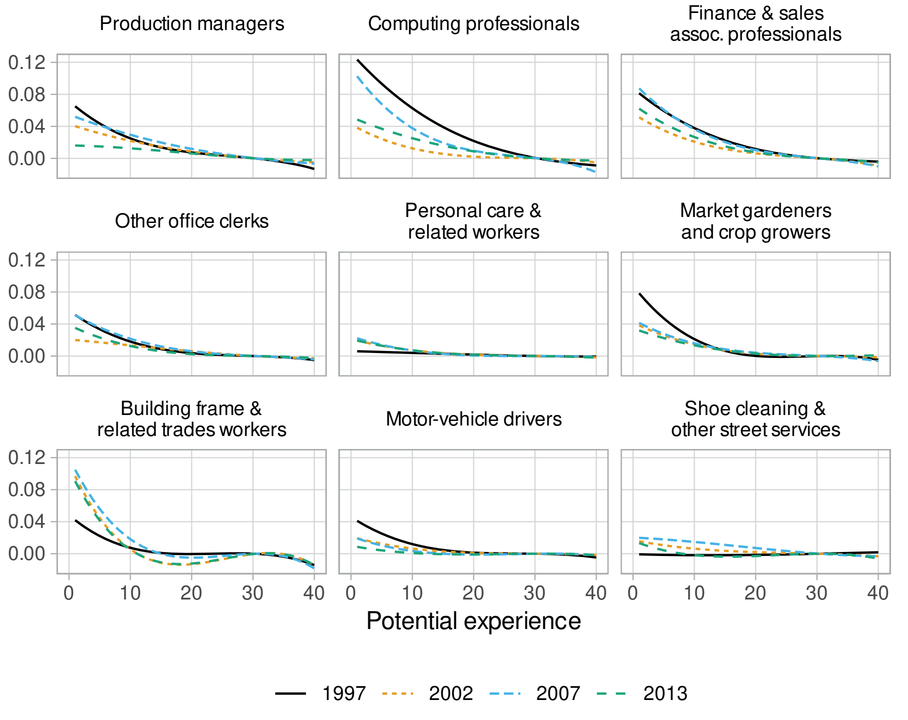
A key advantage of our empirical approach is that we are able to estimate occupational experience profiles that vary over time. We estimate profiles for 101 occupations and each pair of years from 1996–2013. Due to space constraints, we only show estimated profiles for the largest (in terms of average employment 1996–2013) 3-digit occupation in each of nine main categories, for the years 1997, 2002, 2008, and 2013.

The estimated profiles are shown in Figure 7. There are several noteworthy findings. First, in all occupations wage growth is fastest for inexperienced workers, but this pattern is much more pronounced in some occupations (finance & sales professionals, building frame workers) than in others (personal care workers). Second, while in some occupations the profiles are stable (building frame workers), in others they show large changes over time (com-

[15] As premium growth and skill growth are strongly negatively correlated, this difference in sensitivity is mirrored by the other components.

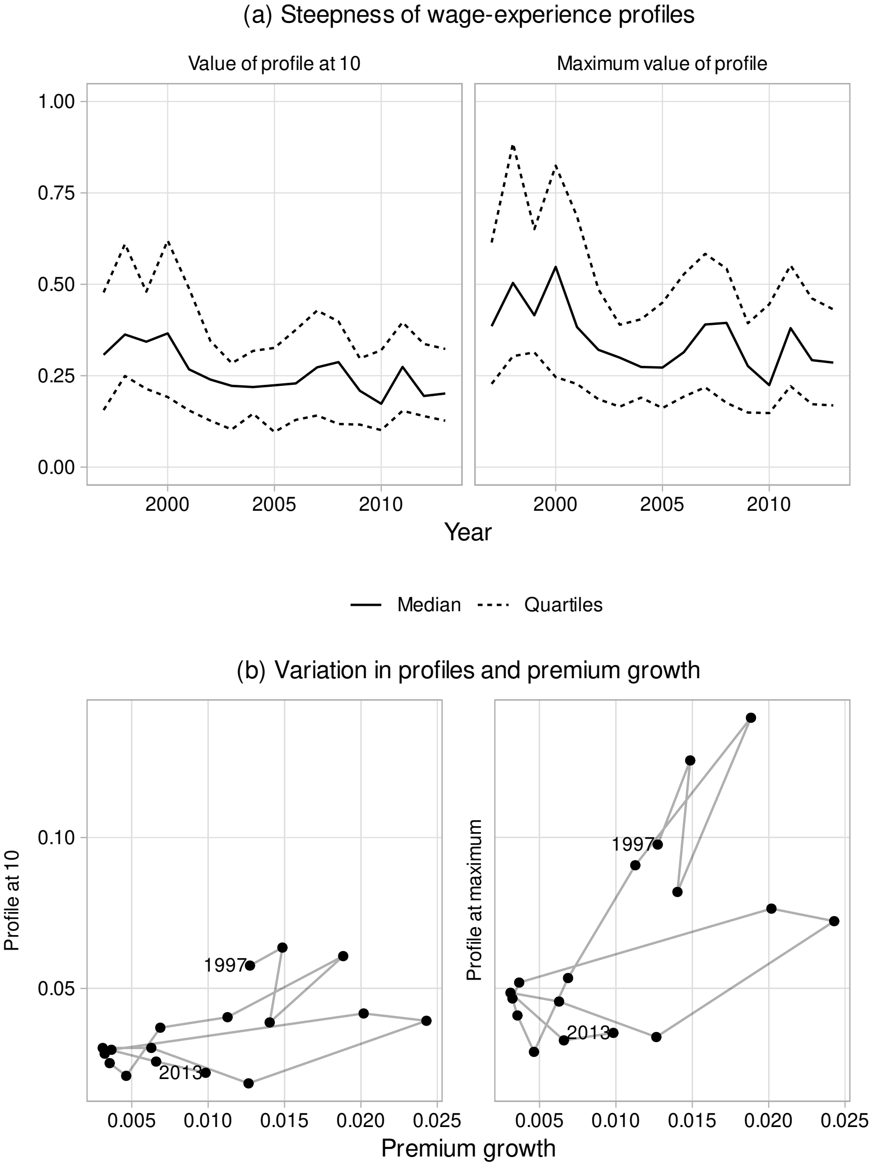
[16] Note that using a polynomial of order one or forcing the experience profiles to be constant over time are more restrictive and thus inferior to our baseline specification.

Figure 7. Estimated occupational experience profiles for selected occupations and years



Notes: The figure plots the estimated experience profiles from Equation (8) for the indicated occupations and years.

Figure 8. Wage-experience profiles over time



Notes: The figure characterizes the distribution of the experience profiles estimated by Equation (8) over time (panel (a)) and shows how variance in selected characteristics of experience profiles is related to variance in premium growth (panel (b)).

puting professionals). Third, profiles are steepest in the late 1990s in several cases, but this is not a universal pattern.

To further investigate changes over time, we plot the median as well as quartiles of two measures capturing the steepness of the profiles, namely, the value of the profile at ten years of potential experience as well as the maximum value (both in levels). Panel (a) of Figure 8 reveals that, by both measures, profiles were indeed somewhat steeper in the late 1990s. But even more striking is that the steepness of the profiles was much more dispersed in that period.

Finally, we explore if there is a systematic relationship between dispersion in wage-experience profiles and dispersion in wage premium growth. Panel (b) of Figure 8 plots the variances of the two steepness measures along with the variance of premium growth against time. It appears that years with higher dispersion in profiles also tend to see higher dispersion in premium growth.

5 Conclusion

We contribute to the literature on shifts in the wage structure by jointly estimating growth in occupational wage premia and occupation-specific life cycle wage profiles. We document substantial changes in occupations' relative premia in Sweden in recent decades, which are masked in the raw wage data due to worker sorting. There is a positive association between premium growth and employment growth, suggesting that workers have been responsive to changes in occupational demand. The relative premia changes are estimated to have substantially contributed to the increase in overall wage inequality. We also document large heterogeneity in life-cycle profiles across occupations, as well as substantial shifts of the profiles over time. Allowing for occupation-level changes in returns to cognitive and psycho-social skills has little effect on the results.

Our results suggest that although the overall wage structure in Sweden is highly compressed, forces related to technological change do influence the wage structure and drive workers' occupational choices. An open question is why the increase in Swedish wage inequality was concentrated in the late 1990s. This could be due to a temporary rise in the flexibility of collective bargaining, or it may reflect uneven technological change, for instance a transitional period of technology adoption (Beaudry et al., 2016).

The method we propose to estimate changes in occupational wage premia may fruitfully be applied to other settings, especially those in which experience profiles appear to change over time, and in cases where only short (two-year) panels of workers are available.

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Appendix A Procedure for estimating occupation-specific flat spots

Suppose that experience profiles are strictly concave except for possible flat regions. That is, linear segments with non-zero slope, as in the middle column of Figure 2, are prohibited. Formally, $g''(x) \leq 0$, $g''(x) = 0 \Rightarrow g'(x) = 0$. This implies that the second derivative of the profile will be maximized (closest to zero) at the flat spot, so that any statistic of interest should change by the least amount—in absolute value—at the true flat spot. We use this insight to pin down the flat spot in a data-driven way.

Recall from Section 2.2 that the change in between-occupation variance of log wages, at constant employment, can be decomposed as

$$\begin{aligned}
\mathrm{Var}_0(w_{k1}) - \mathrm{Var}_0(w_{k0}) &= \mathrm{Var}_0(\Delta w_k) + 2\mathrm{Cov}_0(w_{k0}, \Delta w_k) \\
&= \mathrm{Var}_0(\Delta \pi_k) + \mathrm{Var}_0(\Delta y_k) + 2\mathrm{Cov}_0(\Delta \pi_k, \Delta y_k) \\
&\quad + 2\mathrm{Cov}_0(w_{k0}, \Delta \pi_k) + 2\mathrm{Cov}_0(w_{k0}, \Delta y_k).
\end{aligned} \tag{A1}$$

Denote by μ the components of the decomposition,

$$\mu \in \mathscr{M} \equiv \{\mathrm{Var}_0(\Delta \pi_k), \mathrm{Var}_0(\Delta y_k), 2\mathrm{Cov}_0(w_{k0}, \Delta \pi_k), 2\mathrm{Cov}_0(\Delta \pi_k, \Delta y_k)\}.$$

Each of the elements of $\mathscr{M}$ depends on the change in the premia $\Delta \pi_k$, which in turn depend on the chosen flat spots. However, the sum of all components on the right-hand side of Equation (A1) is constant, so we exclude $2\mathrm{Cov}_0(w_{k0}, \Delta y_k)$ from the set $\mathscr{M}$.

Let $\boldsymbol{\varpi}$ denote the vector of changes in premia, and let $\tilde{\mathbf{x}}$ denote the vector of candidate flat spots. Both vectors contain K elements, where K is the total number of occupations, indexed by k. We denote the above-mentioned functional dependence by $\mu \equiv \mu(\boldsymbol{\varpi}(\tilde{\mathbf{x}}))$. Using the chain rule, we define the sensitivity of μ to changing the flat spot, in absolute terms, as

$$|d\mu(\boldsymbol{\varpi}(\tilde{\mathbf{x}}))| \equiv \left| \sum_k \frac{\partial \mu}{\partial(\Delta \pi_k)} \times \sum_{k'} \frac{\partial(\Delta \pi_{k'})}{\partial \tilde{x}_{k'}} \times d\tilde{x}_{k'} \right|.$$

Under strictly concave experience profiles, we conjecture that $|d\mu(\boldsymbol{\varpi}(\tilde{\mathbf{x}}))|$ attains its minimum at or near the vector of true flat spots $\mathbf{x}^*$, and similarly for the sum over $|d\mu(\boldsymbol{\varpi}(\tilde{\mathbf{x}}))|$,

$$\mathbf{x}^* = \arg\min_{\tilde{\mathbf{x}}} \sum_{\mu \in \mathscr{M}} |d\mu(\boldsymbol{\varpi}(\tilde{\mathbf{x}}))|. \tag{A2}$$

We implement the optimization problem given by Equation (A2) in practice by solving

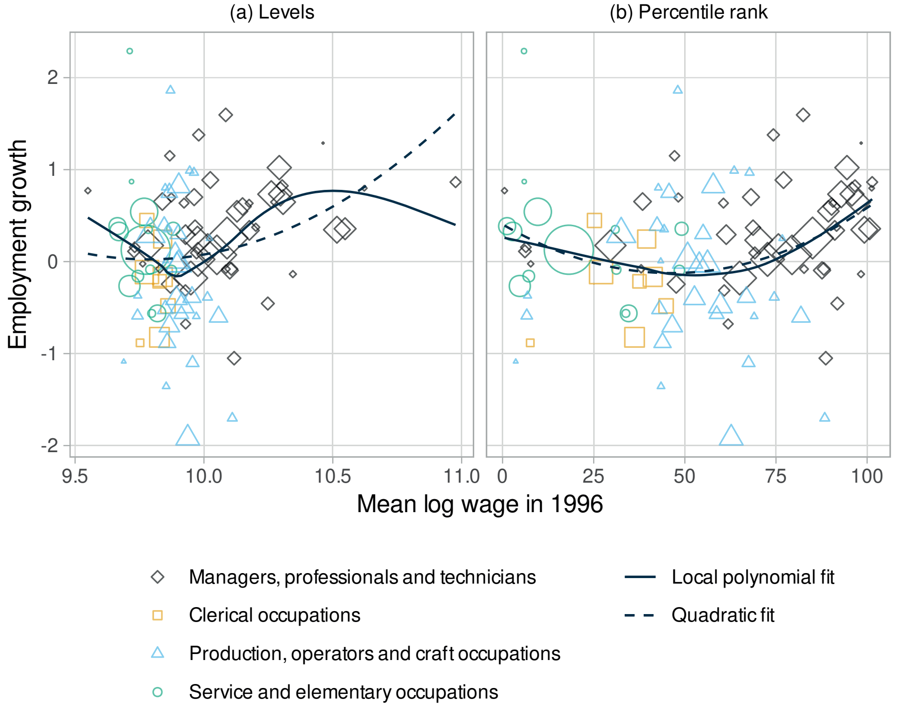
$$\mathbf{x}^* = \arg\min_{\tilde{\mathbf{x}}} S \times \sum_{\widehat{\mu} \in \mathscr{M}} \left[(\widehat{\mu}(\tilde{\mathbf{x}} + \tau) - \widehat{\mu}(\tilde{\mathbf{x}}))^2 + (\widehat{\mu}(\tilde{\mathbf{x}} - \tau) - \widehat{\mu}(\tilde{\mathbf{x}}))^2 \right],$$

where $\widehat{\mu}$ denote the estimated moments, τ is size-k vector with constant elements representing step size, and S is a scaling factor chosen for numerical stability. We set the elements of τ to equal 0.01 and $S = 1\text{e+}7$. We use the L-BFGS-B method (Liu and Nocedal, 1989) implemented by the `optim` package in R. We impose $\tilde{x}_k \in [25, 40]\ \forall k$. As the procedure appears to be sensitive to initial values, we draw initial values at random from the continuous uniform distribution $U(26, 39)$ for each $\tilde{x}_k$. This process is repeated 100 times. We then choose the $\mathbf{x}^*$ with the lowest associated loss.

Note that in principle, given strictly concave profiles one should be able to find the flat spots by minimizing the sensitivity of the $\Delta\pi_k$'s instead of a moment that is a function of them. However, approximating the experience profiles by a polynomial does not guarantee that the estimated profiles are actually strictly concave. Alternatively, one could impose a functional form on the profiles that does guarantee strict concavity. We attempted to do this, but the estimation turned out to be highly unstable.

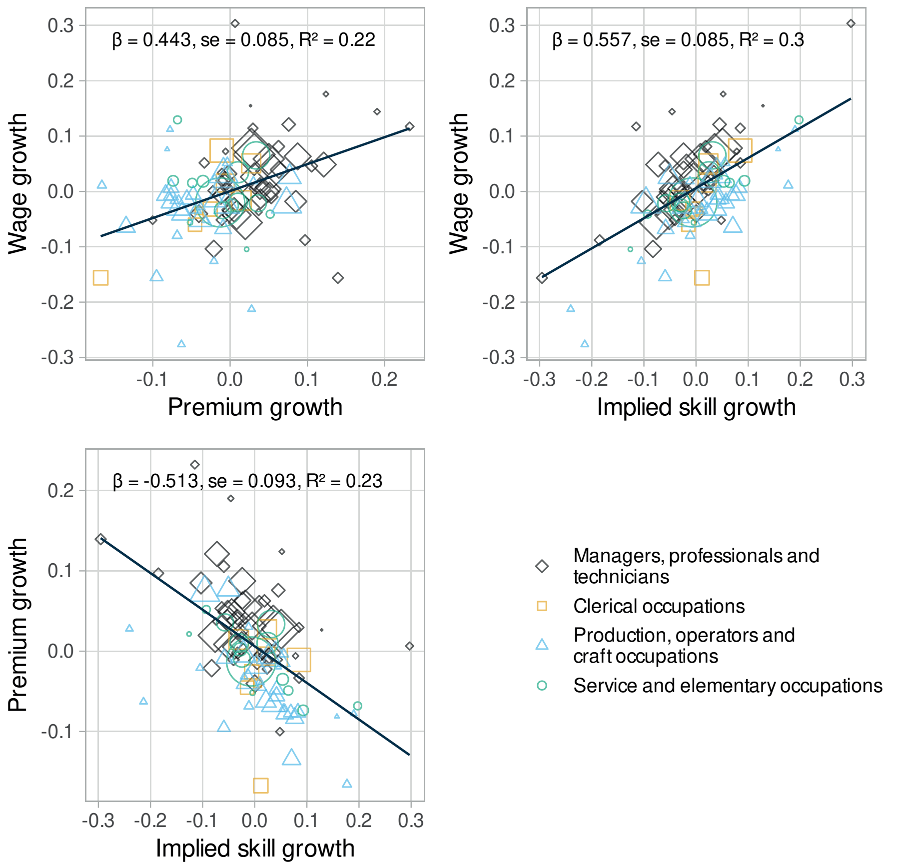
Appendix B Additional figures and tables

Figure B1. Job polarization



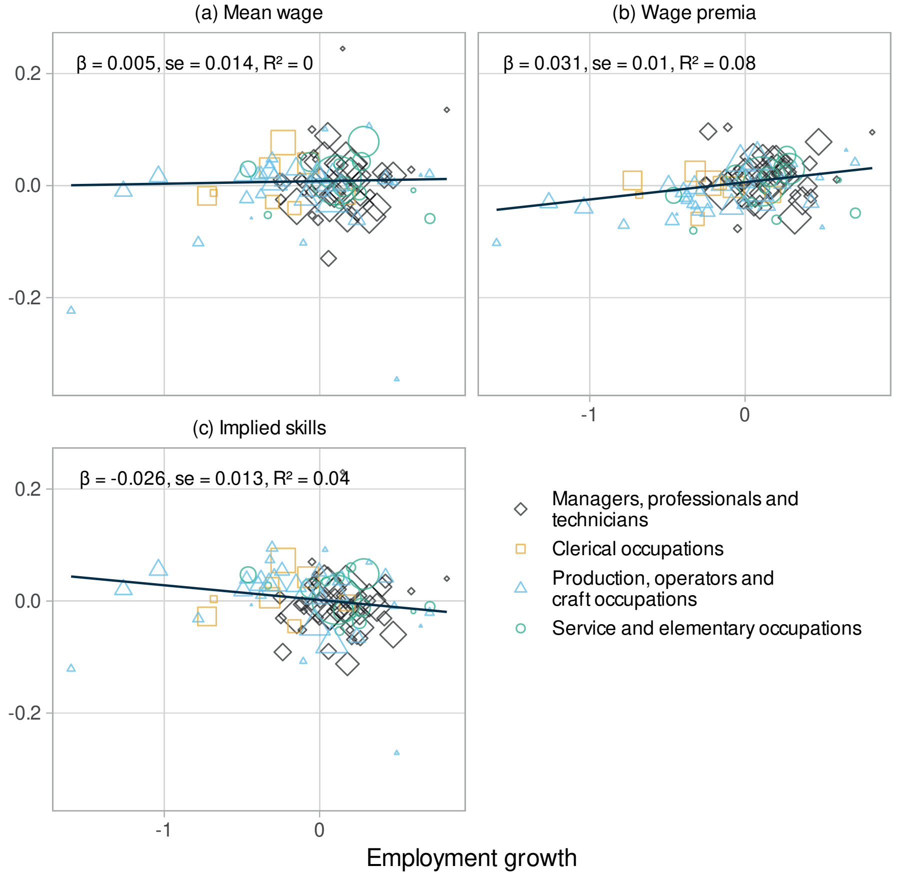
Notes: The figure plots the growth in log employment against mean log wages in 1996. In Panel (b), log wages have been percentile-ranked, weighted by initial employment. Each marker represents one of 101 occupations. The size of each marker is determined by the employment share in the first year and the regression lines are weighted accordingly. We use original survey weights when calculating occupation size and mean log wage.

Figure B2. Relations between growth rates



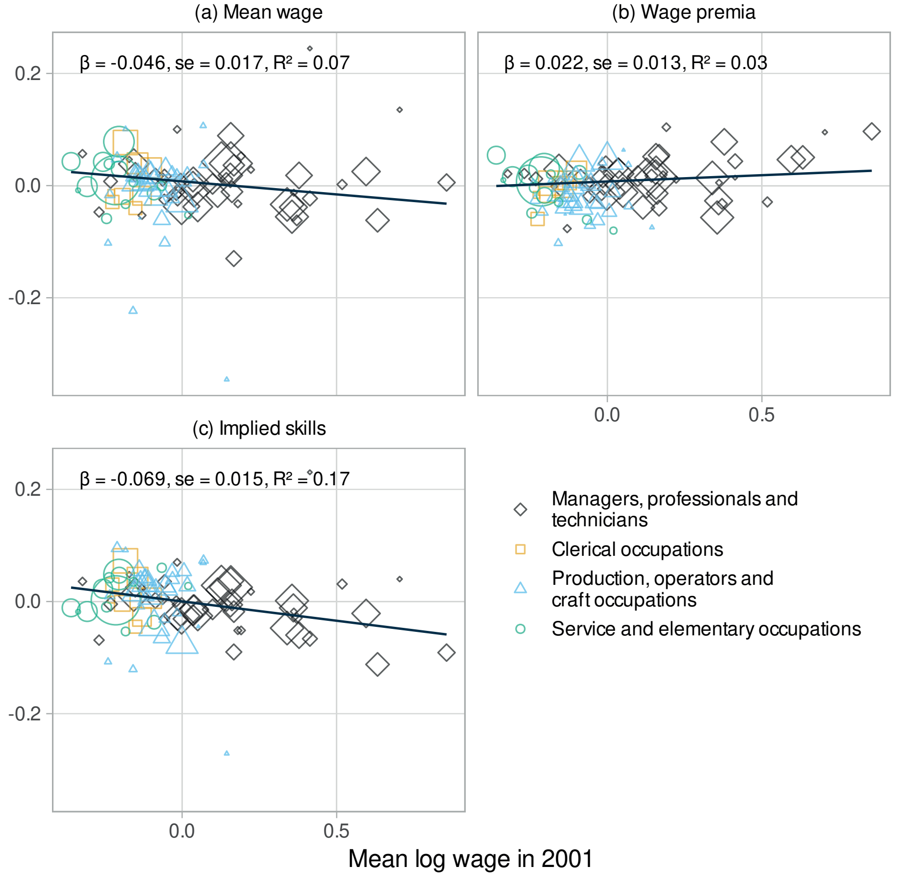
Notes: The figure plots the bivariate relationships between the growth in mean log wages, cumulative estimated wage premia, and the implied change in mean skills. Each marker represents one of 101 occupations. The size of each marker is determined by the employment share in the first year and the regression lines are weighted accordingly. We use original survey weights when calculating occupation size and mean log wage.

Figure B3. Growth in wages, premia, and skills against employment growth, 2001–2013



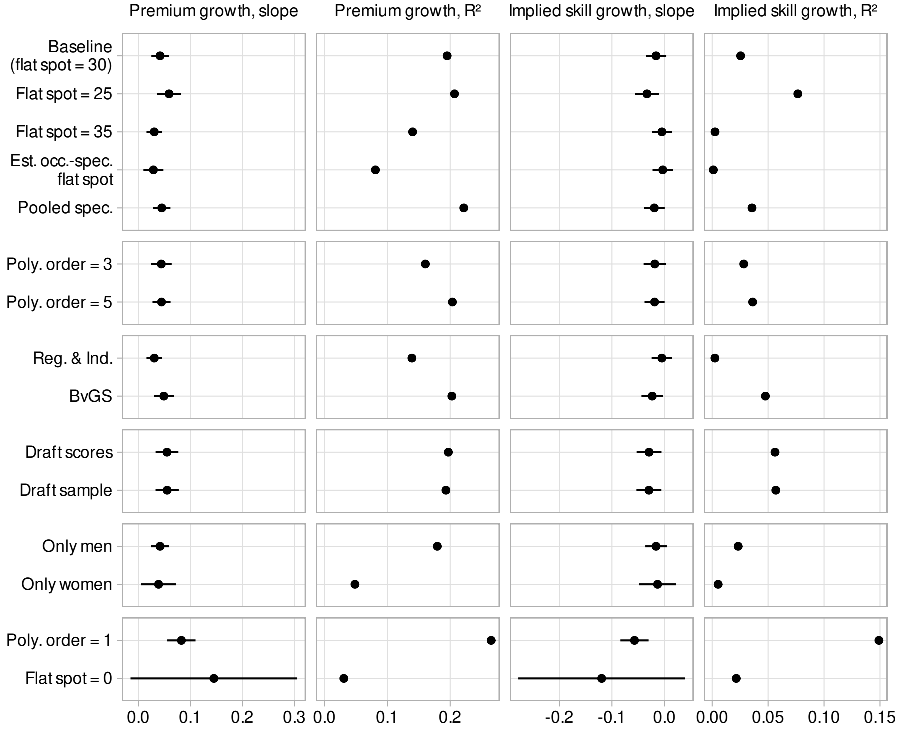
Notes: The figure plots the growth mean log wages, cumulative estimated wage premia, as well as the implied change in mean skills, against the change in log employment. Wage premia are estimated according to our baseline specification Equation (8). Each marker represents one of 101 occupations. The size of each marker is determined by the employment share in the first year and the regression line is weighted accordingly. We use original survey weights when calculating occupation size and mean log wage.

Figure B4. Growth in wages, premia, and skills against initial wages, 2001–2013



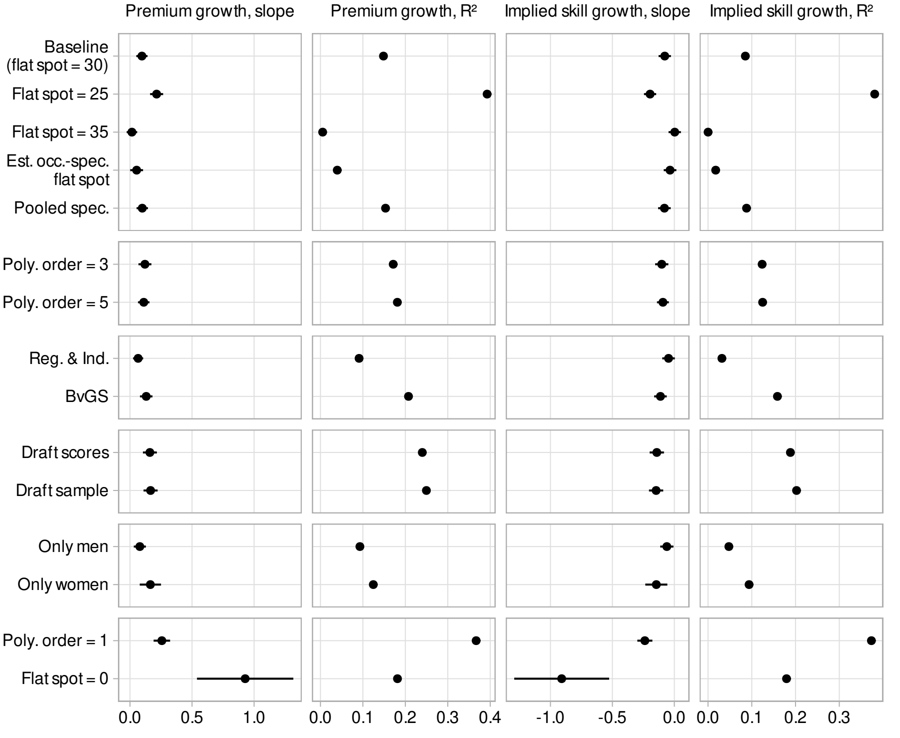
Notes: The figure plots the growth mean log wages, cumulative estimated wage premia, as well as the implied change in mean skills, against initial mean log wages. Wage premia are estimated according to our baseline specification Equation (8). Each marker represents one of 101 occupations. The size of each marker is determined by the employment share in the first year and the regression line is weighted accordingly. We use original survey weights when calculating occupation size and mean log wage.

Figure B5. Premia, skills, and employment growth—robustness checks



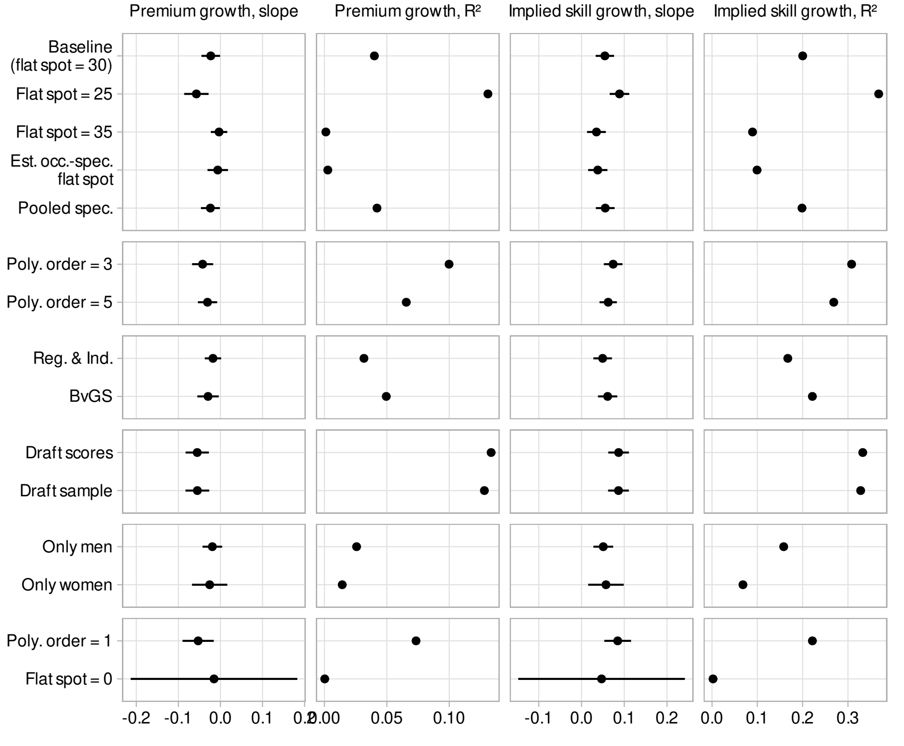
Notes: The table reports the coefficients, 95 percent confidence intervals, and coefficients of determination from separately regressing cumulative estimated wage premia and the implied change in mean skills (growth in average wage minus premium growth) against the change in log employment at the occupation level for different sets of premia estimates. See the text for descriptions of how these estimates are produced. The weight assigned to each occupation is determined by the employment share in the first year. We use original survey weights when calculating occupation size and mean log wage.

Figure B6. Premia, skills, and initial wages—robustness checks



Notes: The figure reports the coefficients, 95 percent confidence intervals, and coefficients of determination from separately regressing cumulative estimated wage premia and the implied change in mean skills (growth in average wage minus premium growth) against initial mean log wage at the occupation level for different sets of premia estimates. See also the notes to Figure B5.

Figure B7. Premia, skills, and schooling—robustness checks



Notes: The figure reports the coefficients, 95 percent confidence intervals, and coefficients of determination from separately regressing cumulative estimated wage premia and the implied change in mean skills (growth in average wage minus premium growth) against growth in average years of schooling at the occupation level for different sets of premia estimates. See also the note to Figure B5.

Table B1. *Decomposition results—sub-periods*

	(1) Baseline	(2) Common flat spot	(3)	(4) Occ.-spec.
		25	35	flat spot
(a) 1996–2013				
Total				
$\Delta \text{Var}(w_{ik})$	2.57			
Between				
$\Delta \text{Var}(w_k)$	1.31			
$\Delta \text{Var}_0(w_k)$	.39			
Components				
$\text{Var}_0(\Delta\pi_k) + 2\text{Cov}_0(w_{k0}, \Delta\pi_k)$	.94	2.03	.29	.66
$\text{Var}_0(\Delta\pi_k)$	.23	.43	.17	.27
$2\text{Cov}_0(w_{k0}, \Delta\pi_k)$	.71	1.59	.12	.4
$\text{Var}_0(\Delta y_k)$	.26	.37	.24	.25
$2\text{Cov}_0(w_{k0}, \Delta y_k)$	-.57	-1.45	.02	-.26
$2\text{Cov}_0(\Delta\pi_k, \Delta y_k)$	-.24	-.55	-.16	-.27
(b) 2001–2013				
Total				
$\Delta \text{Var}(w_{ik})$	.34			
Between				
$\Delta \text{Var}(w_k)$	.07			
$\Delta \text{Var}_0(w_k)$	-.31			
Components				
$\text{Var}_0(\Delta\pi_k) + 2\text{Cov}_0(w_{k0}, \Delta\pi_k)$	.31	.93	-.08	.15
$\text{Var}_0(\Delta\pi_k)$	.09	.13	.08	.1
$2\text{Cov}_0(w_{k0}, \Delta\pi_k)$	.22	.79	-.16	.05
$\text{Var}_0(\Delta y_k)$	.14	.18	.12	.15
$2\text{Cov}_0(w_{k0}, \Delta y_k)$	-.68	-1.25	-.3	-.51
$2\text{Cov}_0(\Delta\pi_k, \Delta y_k)$	-.08	-.17	-.06	-.1

Notes: The table reports results from a decomposition of the change in the between-occupation variance in wages for different flat spot levels and periods. See Equation (6) for the formal statement of the decomposition. Column (1) uses a common flat spot for all occupations, at 30 years of potential experience, when estimating growth in wage premia. Columns (2)–(3) vary this common flat spot as indicated. Column (4) estimates a flat spot for each occupation using the procedure described in Section A. All figures have been multiplied by 100 for readability.

Table B2. *Decomposition results—further specifications*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline	Flat spot = 0	Poly. order			BvGS	Reg. &	Pooled	Draft	Draft	Men	Women
			1	3	5		ind.	spec.	sample	scores		
(a) 1996–2013												
Total												
$\Delta\mathrm{Var}(w_{ik})$	2.57											
Between												
$\Delta\mathrm{Var}(w_k)$	1.31											
$\Delta\mathrm{Var}_0(w_k)$	.39											
Components												
$\mathrm{Var}_0(\Delta\pi_k) + 2\mathrm{Cov}_0(w_{k0}, \Delta\pi_k)$	.94	24.49	2.57	1.21	1.07	1.28	.66	.97	1.64	1.59	.84	2.02
$\mathrm{Var}_0(\Delta\pi_k)$	.23	17.6	.67	.31	.25	.31	.17	.24	.41	.4	.25	.8
$2\mathrm{Cov}_0(w_{k0}, \Delta\pi_k)$	.71	6.89	1.9	.89	.82	.97	.49	.73	1.23	1.19	.59	1.22
$\mathrm{Var}_0(\Delta y_k)$	.26	17.09	.56	.31	.25	.29	.25	.27	.4	.39	.28	.83
$2\mathrm{Cov}_0(w_{k0}, \Delta y_k)$	-.57	-6.75	-1.77	-.75	-.68	-.83	-.35	-.59	-1.09	-1.05	-.45	-1.08
$2\mathrm{Cov}_0(\Delta\pi_k, \Delta y_k)$	-.24	-34.44	-.98	-.37	-.25	-.35	-.18	-.25	-.55	-.54	-.28	-1.38
(b) 2001–2013												
Total												
$\Delta\mathrm{Var}(w_{ik})$	.34											
Between												
$\Delta\mathrm{Var}(w_k)$	.07											
$\Delta\mathrm{Var}_0(w_k)$	-.31											
Components												
$\mathrm{Var}_0(\Delta\pi_k) + 2\mathrm{Cov}_0(w_{k0}, \Delta\pi_k)$	.31	14.5	1.22	.45	.41	.58	.17	.1	.51	.53	.26	.84
$\mathrm{Var}_0(\Delta\pi_k)$	.09	9.31	.22	.12	.09	.13	.07	.11	.09	.08	.11	.29
$2\mathrm{Cov}_0(w_{k0}, \Delta\pi_k)$	.22	5.19	1	.33	.32	.45	.1	-.01	.41	.45	.15	.55
$\mathrm{Var}_0(\Delta y_k)$	.14	9.69	.29	.16	.13	.16	.12	.14	.12	.13	.15	.35
$2\mathrm{Cov}_0(w_{k0}, \Delta y_k)$	-.68	-5.65	-1.45	-.79	-.78	-.91	-.56	-.45	-.87	-.91	-.61	-1.01
$2\mathrm{Cov}_0(\Delta\pi_k, \Delta y_k)$	-.08	-18.85	-.36	-.13	-.08	-.14	-.04	-.1	-.07	-.06	-.11	-.5

Notes: The table reports results from a decomposition of the change in the between-occupation variance in wages for different specifications and periods. See Equation (6) for the formal statement of the decomposition and the text for details on the different specifications. All figures have been multiplied by 100 for readability.

Essay III. Outside Options and the Sharing of Match-Specific Rents

Co-authored with Peter Fredriksson, Lena Hensvik, and Oskar Nordström Skans

Acknowledgements: We thank seminar participants at EALE Padua 2021, IFAU, BI Norwegian Business School, and SOLE Minneapolis 2022 for comments and discussions.

1 Introduction

Wage inequality is shaped by how labor markets operate and how wages are set. Equally skilled workers earn different wages across workplaces because of imperfect competition and frictions. Furthermore, on-the-job search can generate dispersion across equally productive workers in the same job, *and* make within-job wage inequality responsive to the aggregate cycle. But the impact of on-the-job search on wage inequality crucially depends on how wages respond to outside offers. If workers in productive matches can use outside offers to bid up their current wage, as in Postel-Vinay and Robin (2002), well-matched workers will tend to extract a greater share of their match surplus when the state of the labor market improves. In canonical wage bargaining models (e.g. Pissarides, 2000), wages are instead set as weighted averages between match productivity and aggregate conditions with fixed weights. In this case, wages will increase with market tightness without affecting within-job dispersion. This empirical paper sheds light on this issue by providing direct evidence on how outside options affect the transmission from match-specific productivity to wages.

We derive a measure of job-level match quality using Swedish enlistment data on eight distinct skills, following Fredriksson et al. (2018). Consistent with most wage bargaining models, well-matched workers earn higher wages. But what role do outside options play? Our stylized theoretical framework, building on Postel-Vinay and Robin (2002), predicts that, if outside offers are used in bargaining, then match quality for *job stayers* will matter more for wages when the aggregate arrival rate of offers is higher, i.e., when local labor market conditions are favorable. Moreover, for *job movers*, match quality in the previous job should matter for the current wage, but only if the transition was direct (i.e., without intermittent non-employment).

Our empirical results confirm these predictions. The wage returns to match quality are pro-cyclical for workers who remain in their jobs; The return to wages in levels increases by 50 percent of the average return when moving from the highest to the lowest ventile of the local unemployment distribution. The results are qualitatively similar for wages in logs and levels. They are independent of how we define the local labor market, and remain unaltered when we replace unemployment by other indicators of local labor market conditions, including shift-share instruments and occupation-specific employment.

For job-to-job movers, match quality in the previous job is more important for the current wage than current match quality. This holds even when conditioning on the previous wage. By contrast, prior match quality is unrelated to the new wage among workers with interim non-employment.

Our results imply that internal (match quality) and external (outside options) factors are not additively separable as in canonical bargaining models. Instead, workers' returns to match productivity increase when market conditions improve and there are more counteroffers, or when they move directly from a position where they were already well-matched as originally proposed by Postel-Vinay and Robin (2002).

Our main contribution is to offer direct evidence on how outside offers affect wages, an issue which previously exclusively has been studied with structural models. Earlier reduced-form studies (surveyed by Jäger et al., 2020) have analyzed how match-specific factors and outside options affect wages, but not how they interact. Fredriksson et al. (2018) study match quality and wages at the job-level whereas Guvenen et al. (2020) and Lise and Postel-Vinay (2020) use occupations. Studies of outside options analyze unemployment (Blanchflower and Oswald, 1994), outside firms (Lamadon et al., 2022), networks (Caldwell and Harmon, 2019), dual jobs (Lachowska et al., 2022), and benefits (Jäger et al., 2020).[1] Di Addario et al. (2022), study how the previous firm effect (as in Abowd et al., 1999) affect the new wages of job-to-job movers, and find very small effects.

Many papers have used structural approaches to compare wage-setting mechanisms in models with two-sided heterogeneity. Mortensen (2003) found support for wage bargaining over wage-posting in many market segments. Cahuc et al. (2006) embeds outside offers and traditional bargaining, finding more support for the former. Hagedorn and Manovskii (2013) argue that counteroffers do not add additional information once match quality (proxied by previous tightness) is accounted for. More recently, Bagger and Lentz (2019) and Yamaguchi (2010) allow for both endogenous search and human capital accumulation.[2]

Section 2 presents a theoretical framework. Section 3 describes data and measurement. Section 4 reports the results. Section 5 concludes.

2 Theoretical framework

We outline a stylized theoretical framework that highlights how and why counteroffers can provide an important link between outside options and returns to individual match productivity. The labor market is segmented by skill levels. To simplify, the value of unemployment, b, is homogeneous across workers within each skill segment. For ease of exposition, we focus on a single segment, and let b remain a constant.[3] Productivity (p) differs across matches (worker-job pairs) since workers' have different skill bundles and jobs have

[1] On Swedish data, see Carlsson et al. (2019) (unemployment), Carlsson et al. (2016) (outside firms), and Fredriksson and Söderström (2020) (benefits).

[2] A different set of studies have used surveys to directly measure how wages are set (e.g., Barron et al., 2006, Hall and Krueger, 2012, Brenzel et al., 2014). Barron et al. (2006) find that 44 percent of firms would consider making a counteroffer. Hall and Krueger (2012) notes that around 40 percent of workers bargained for a new job while maintaining the option to go back to their previous job.

[3] Our empirical analysis holds the main effects of skills constant.

different skill requirements. Workers search for jobs randomly and match quality is revealed after they meet.

Consider a two-period set-up. In period 1, unemployed workers meet a firm with probability λ, draw idiosyncratic match quality p from a differentiable distribution $F(p)$, decide on whether to match, and bargain over the wage, $w = w(b, p)$. In period 2, employed workers meet with other firms (again at rate λ), and draw match quality, p'. Since unemployed and employed workers draw matches at the same rate, the reservation wage (and reservation match quality) in period 1 is b.

Workers move if $p' > p$. When $b < p' \leq p$, offers are instead used to bid up the wage in the current match *if* the worker can use the alternative offer in negotiations with the current employer. There are three scenarios when meeting a firm in period 2:

1. If $p' \leq b$, nothing happens and the worker retains $w(b, p)$;
2. If $b < p' \leq p$, the worker (potentially) renegotiates the wage to $w(p', p)$; and
3. If $p' > p$, the worker moves and earns $w(p, p')$.

Following Cahuc et al. (2006), we let wages be affected by Nash bargaining and by counteroffers. Without counteroffers, workers obtain a share η of the (flow) surplus. If employers can respond to counteroffers, wages are instead:

1. $w(b, p) - b = \eta(p - b)$ for $p' \leq b$ (and entrants from unemployment);
2. $w(p', p) - p' = \eta(p - p')$ for $p' \in (b, p]$; and
3. $w(p, p') - p = \eta(p' - p)$ for $p' > p$.

With a slight change of notation, define p_1 and p_2 as the first and second most productive relationship the worker has found during his current employment spell. Then p_1 is match quality with the current employer and p_2 is the best outside offer. The wage-setting rule becomes:

$$w = w(p_1, p_2, b) = \eta p_1 + (1 - \eta) \max(b, p_2), \tag{1}$$

where $p_2 = 0$ if the worker has received no alternative wage offer. This rule is more general than it may appear. It is derived by Cai (2020) as the result of a strategic alternating bargaining game (of the Rubinstein (1982) type) when the risk of an exogenous break-up of the bargain is ignorable.

In our empirical work, we estimate separate wage regressions for stayers and movers. We begin by considering the wage for a stayer in the second period.

Define θ as the probability of receiving an outside offer that is higher than b conditional on remaining in the initial job:

$$\theta = \frac{\lambda(F(p) - F(b))}{1 - \lambda + \lambda F(p)}. \tag{2}$$

The expected wage for stayers may then be written in terms of the first-period wage, the expected wage conditional on receiving a useful outside offer, and θ:

$$\begin{aligned}\mathbb{E}[w \mid p' \leq p, p, \lambda] &= w(p,b) + \theta\left(\mathbb{E}[w(p,p') \mid p' \leq p, p] - w(p,b)\right) \\ &= \eta p + (1-\eta)b + (1-\eta)\theta\left(\mathbb{E}[p' \mid b \leq p' \leq p] - b\right),\end{aligned} \tag{3}$$

where the second line uses (1).

To see how the expected second-period wage is influenced by initial match quality, we differentiate (3) with respect to p:

$$\frac{\partial \mathbb{E}[w \mid p' \leq p, p, \lambda]}{\partial p} = \eta + (1-\eta)\left[\underbrace{\frac{\partial \theta}{\partial p}\left(\mathbb{E}(p'_s) - b\right)}_{\substack{\text{Effect due to} \\ \text{offer probability}}} + \underbrace{\theta \frac{\partial \mathbb{E}(p'_s)}{\partial p}}_{\substack{\text{Effect due to} \\ \text{offer quality}}}\right] \geq \eta, \tag{4}$$

where we have introduced the notation $\mathbb{E}(p'_s) = \mathbb{E}[p' \mid b \leq p' \leq p]$

Both θ and $\mathbb{E}(p'_s)$ are increasing in p. Hence, the derivative is larger than the direct effect of increasing match quality on shared surplus, captured by η. This implies that workers receive higher rents when outside offers can be used in bargaining. The difference in the effect of an increase in p on the expected wage between workers that did and did not receive outside offers equals:

$$\begin{aligned}&\left.\frac{\partial \mathbb{E}[w \mid p' \leq p, p, \lambda]}{\partial p}\right|_{\lambda=1} - \left.\frac{\partial \mathbb{E}[w \mid p' \leq p, p, \lambda]}{\partial p}\right|_{\lambda=0} \\ &= (1-\eta)\frac{F'(p)}{F(p)}\left[\frac{F(b)}{F(p)}\left(\mathbb{E}(p'_s) - b\right) + p - \mathbb{E}(p'_s)\right] \geq 0.\end{aligned} \tag{5}$$

Thus, remaining workers with higher match quality on average benefit more from receiving outside offers.

How does the effect of initial match quality on expected second-period wage change when the arrival rate of offers increases? To determine this, (4) is differentiated with respect to λ:

$$\frac{\partial^2 \mathbb{E}[w \mid p' \leq p, p, \lambda]}{\partial p \partial \lambda} = (1-\eta)\left[\underbrace{\frac{\partial \theta}{\partial \lambda}\frac{\partial \mathbb{E}(p'_s)}{\partial p}}_{\substack{\text{Direct interaction} \\ \text{effect}}} + \underbrace{\frac{\partial^2 \theta}{\partial p \partial \lambda}\left(\mathbb{E}(p'_s) - b\right)}_{\substack{\text{Interaction effect on} \\ \text{offer probability}}}\right]. \tag{6}$$

The direct interaction effect is clearly positive: Workers become more likely to receive useful offers, and, on average, such offers grow more valuable with the quality of the initial match. However, the derivative also depends on the interaction effect on the probability of receiving a useful outside offer. This term is in principle ambiguous in sign, essentially because probabilities are bounded.

To find a closed-form expression for (6), we first calculate the relevant derivatives:

$$\begin{aligned}
\frac{\partial \theta}{\partial \lambda} &= \frac{F(p)-F(b)}{(1-\lambda+\lambda F(p))^2} \geq 0, \\
\frac{\partial \mathbb{E}(p_s')}{\partial p} &= \frac{F'(p)}{F(p)-F(b)}(p-\mathbb{E}(p_s')) \geq 0, \\
\frac{\partial^2 \theta}{\partial p \partial \lambda} &= \frac{F'(p)}{(1-\lambda+\lambda F(p))^2}(1-2\theta).
\end{aligned} \tag{7}$$

Inserting these into (6) and simplifying yields:

$$\frac{\partial^2 \mathbb{E}[w \mid p' \leq p, p, \lambda]}{\partial p \partial \lambda} = \frac{(1-\eta)F'(p)}{(1-\lambda+\lambda F(p))^2}\Big[(p-\mathbb{E}(p_s')) + (1-2\theta)(\mathbb{E}(p_s')-b)\Big]. \tag{8}$$

A sufficient condition for this expression to be positive is that $\theta \leq 0.5$. This is true for all values of p if $\lambda(1-F(b)) \leq 0.5$. In other words, as long as the probability that the best matched worker can use an outside offer to renegotiate the wage is less than 50 percent, the sign of equation (8) is positive.

Of course, (8) can be positive under more general circumstances. To see this write $\mathbb{E}(p_s')$ as a weighted average of p and b:

$$\mathbb{E}(p_s') = \omega p + (1-\omega)b, \tag{9}$$

where the weight ω depends on the shape of the density function on the (b,p) interval. Use (9) in (8):

$$\frac{\partial^2 \mathbb{E}[w \mid p' \leq p, p, \lambda]}{\partial p \partial \lambda} = \frac{2(1-\eta)F'(p)(p-b)}{(1-\lambda+\lambda F(p))^2}\Big[\frac{1}{2} - \theta\omega\Big]. \tag{10}$$

Thus, $\theta\omega \leq 1/2$ implies that (8) is unambiguously positive. In a uniform distribution, for example, $\omega = 1/2$, and thus (8) is positive for all values of λ and b.

In the appendix, we explore which values of p, λ, and b lead to a non-positive value of (8) under various distributional assumptions. We find that this almost never occurs. For example, when the distribution of match quality is log-normal, (8) is positive for all values of λ and b. When the distribution is normal, we find that (8) can become negative only if $\lambda > 0.9$ and $F(b) < 0.05$. Since this is an extreme case, it seems safe to surmise that an increase in the job-offer arrival rate will benefit well-matched workers more than other workers, i.e., that (8) is positive.

This prediction contrasts with implications of a standard Nash-bargaining sharing framework (e.g., Pissarides, 2000) where $w = \eta p + (1-\eta)b(\lambda)$. In this case, the only relevant outside option is the aggregate state $(b(\lambda))$; and the wage effects of idiosyncratic productivity would remain constant if λ changes.

Our first empirical part studies whether the wage impact of idiosyncratic productivity is pro-cyclical among workers who remain in their job.

Now, consider the wage for a worker who has moved to a new job in period 2 because $p' > p$. Then, bargaining revolves around the quality of the old match, regardless of the arrival rates of outside offers:

$$\mathbb{E}\left[w \mid p' > p,\ p,\ p'\right] = \eta p' + (1-\eta)p. \tag{11}$$

This wage equation has an extremely simple form. The key prediction is that previous match productivity matters for wages also in the new job. This is, again, different from the standard sharing framework where the outside option *at the market-level* would replace the previous match productivity, p, in equation (11).

Only workers that match with an alternative job before separating from their initial job can use p as an outside option. If leaving/quitting *before* finding alternative employment, the wage equation instead reverts back to $w(p', b)$.

The second empirical part estimates the wage-impact of previous match quality for job-to-job (or EE) movers and for (ENE) movers with an interim non-employment spell.

To summarize, our empirical work tests three predictions:

Prediction 1 (Stayers)
For stayers, the wage return to match quality in the current job is increasing in the probability of obtaining an outside offer.

Prediction 2 (EE movers)
Match quality in the previous job has a positive impact on wages in the current job for workers who have made an employment-to-employment move.

Prediction 3 (ENE movers)
Match quality in the previous job has no impact on wages in the current job for workers who have moved to a new job with an intermittent spell of non-employment.

3 Data, variables and sample selection

3.1 Data sources and information

Our data are drawn from population-wide Swedish administrative registers. They include linked information on individuals, workplaces and firms, and basic individual characteristics such as age, education and municipality. Employment status in November is drawn from tax returns. Data cover 1985-2013. Employment status is used to infer labor market experience (years observed in employment, censored at 12).

The Wage Structure Statistics (WSS), covering 1997-2013, record hours-adjusted wages and three-digit occupations (SSYK-96, corresponding to ISCO-88) annually for half of the private and all public sector employees. Data cover all the workers in sampled firms. The sampling probability increases in firm size and all firms with 500 or more employees are sampled.

From the Swedish War archives, we add detailed measures of cognitive and non-cognitive ability. These were collected during the Swedish military draft procedure and are available for nearly all males in the 1951-1976 cohorts. These were enlisted during 1969-1994 at age 18 or 19.

Finally, we collect aggregate data on unemployment from Statistics Sweden and the Swedish Public Employment Service.

3.2 Variables and definitions

The definition of a job

We focus on match quality at the worker-job level. A *job* is an occupation at a workplace.[4] This allows skill requirements to vary between different occupations in a given workplace, as well as between different workplaces for a given occupation.[5]

Local unemployment

Unemployment is measured at the workplace municipality level.[6] It is computed from individual-level information on non-employed job seekers (including participants in active labor market programs) registered at the public employment service. We define *unemployment* as the annual incidence of registered job-seekers among all residents aged 20-64 (i.e., not just labor force participants). Our results remain robust if we use other measures (see the appendix).

[4]Data cover 113 occupations. Our used sample cover 30,000 workplaces and 70,000 jobs.

[5]Sorting across both margins appear empirically relevant, see, e.g., Fredriksson et al. (2018) and Choné et al. (2022).

[6]Sweden has 10 million residents, 290 municipalities and 21 counties.

Multidimensional skills

Mood et al. (2012) and Lindqvist and Vestman (2011) provide extensive details on the test scores. Four skills are based on written tests. These capture *inductive reasoning*, *verbal comprehension*, *spatial ability* and *technical understanding* (jointly *cognitive ability*). The remaining four are assessed during a 25-minute interview with a trained psychologist. These capture *social maturity*, *psychological energy*, *intensity*, and *emotional stability* according to Mood et al. (2012) (jointly *non-cognitive ability*). We standardize the data to mean zero and standard deviation one for each skill and cohort.

For our purposes, a key aspect of these scores is that workers with similar types of skills tend to be clustered into the same jobs as shown by, e.g., Fredriksson et al. (2018). Workers systematically sort into jobs where the return to their particular skill endowments are higher than in the average job.[7]

Match quality

Our measure of job-specific match quality builds on insights from Fredriksson et al. (2018). The objective is to compare the skill set of a worker to the skill requirements of the job. We use other workers who remain within the same job to measure skill requirements. The presumption is that workers who remain within a job are well matched, i.e., their skill set is likely to be well aligned with the skill requirements of the job. We do not use coworkers who remain for less than three years when calculating the skill requirements as these are likely to be poorly matched.

For each worker i in job j, we calculate the average skill level along a particular dimension k among other, tenured, incumbents in j. We denote this average by $\tilde{s}_{j,k}^{-i}$ where "$-i$" represents all individuals except i. In contrast to Fredriksson et al. (2018), we keep $\tilde{s}_{j,k}^{-i}$ constant across time within jobs to ensure that the skill-requirement is not endogenous to the cycle.

For each skill-dimension k, we calculate the absolute difference between individual skills $s_{i,k}$ and $\tilde{s}_{j,k}^{-i}$, and then sum over the eight dimensions. We let $D_{i,j}$ denote worker i's deviation from the skills of tenured co-workers in job j:

$$D_{i,j} = \sum_{k=1}^{8} \left| s_{i,k} - \tilde{s}_{-i,j,k} \right|$$

For ease of interpretation we construct our measure of match quality (M) as the negative of the standardized distance D. This implies that a positive one-unit change in our match quality measure is equivalent to a standard deviation reduction in the distance to the skills of the coworkers:

[7] Fredriksson et al. (2018) also estimate significant wage returns to each of the different skills, even conditional on education.

$$M_{i,j} = -\left(\frac{D_{i,j} - \text{mean}\,(D_{i,j})}{\text{sd}(D_{i,j})}\right)$$

To assess the wage impact of match quality, net of constant skill differences across workers and jobs, we always analyze $M_{i,j}$ conditional on controls for worker skills and job fixed effects.

The returns to skills

To understand our measure of match quality, consider a generic version of our wage regressions:

$$w_{i,j} = \alpha_j + \boldsymbol{\beta'}\boldsymbol{s}_i + \mu M_{i,j} + \varepsilon_{i,j} \tag{12}$$

where α_j is a job-specific fixed effects and $\boldsymbol{s}_i$ is a vector comprising all individual skills. A marginal increase in $s_{i,k}$ will have an effect through the market (via β_k) and an effect from job-match quality (through μ). Assume that *market returns* to skills are positive ($\beta_k > 0 \;\forall\; k$) and that wages are increasing in match quality ($\mu > 0$).[8]

Match quality can either become better or worse if we increase $s_{i,k}$. Match quality will increase if the worker is underskilled at job j in dimension k (i.e. if $s_{i,k} < \tilde{s}^{-i}_{j,k}$) which will generate an additional wage gain. But match quality will deteriorate if worker i is overskilled, i.e. if $s_{i,k} > \tilde{s}^{-i}_{j,k}$ and we add further skills. The overall wage impact (market returns + match-quality effects) of additional skills for overskilled workers is therefore lower than the market returns.

The key takeaway is that the model allows the overall wage return to additional skills to *kink* at the point of optimal match quality (i.e., at the point where $s_{i,k} = \tilde{s}^{-i}_{j,k}$).

3.3 Sample and descriptive statistics

Our sample consists of workers who were i) employed in year t, ii) sampled in the WSS, iii) Swedish residents during $[t-1, t+1]$ and iv) in our skills data. We use data for 1997-2012 (to allow for a 1 year follow-up). We only use jobs with at least five tenured coworkers to get a reasonable measure of average skills within jobs.

Column (1) in Table 1 reports means and standard deviations in the used sample. For comparison, column (2), describes all workers in the WSS. The differences between columns (which are mainly driven by firm size) arise because we require jobs to have at least five male workers with skills within each

[8]For the general returns to skills, see Fredriksson et al. (2018). For the returns to match quality, see the next section.

job. The larger firm size makes both job stability and wages somewhat higher than in the overall sample. Reassuringly (for external validity), the distribution of occupations is similar across columns.

4 Empirical analysis

4.1 The overall impact of match quality and unemployment

We first show how match quality relates to wages and the probability of leaving the initial workplace between year t and $t+1$ (separations). We then relate local unemployment to wages and to the probability of doing a job-to-job move (among all separations). For wages, we use unemployment during the observed year t. For separations, we instead use unemployment in $t+1$ since this better reflects the applicable market conditions between November in years t and $t+1$. We illustrate the patterns graphically after removing the impact of key controls.[9]

The top left panel of Figure 1 shows that there is a strong positive relationship between the match quality of a worker and his wage. Moving from the 10th to the 90th percentile of the (residualized) match-quality distribution is associated with approximately two percent higher wages. Similarly, a well-matched worker has a significantly lower risk of separating from his current workplace than poorly matched co-workers. The separation probability is 0.5 percentage points lower for a worker on the 90th percentile compared to a worker on the 10th percentile of the match quality distribution (the average probability is approximately 10 percent). The two lower panels show the relationship between wages and the probability of separating to another employer, respectively, and unemployment. Local unemployment is associated with lower wages—wages are 0.6 percent lower at the 90th percentile than at the 10th percentile of the unemployment distribution—and less employment-to-employment separations—an increase from the 10th to the 90th percentile of the unemployment distribution reduces the job-to-job share by 0.6 percentage points.

4.2 Outside options and the sharing of rents with remaining workers

This section examines Prediction 1 of Section 2. We thus ask how the returns to workers' match quality vary with local unemployment (our proxy for the arrival rate of outside offers). Guided by the theory, we only include workplace

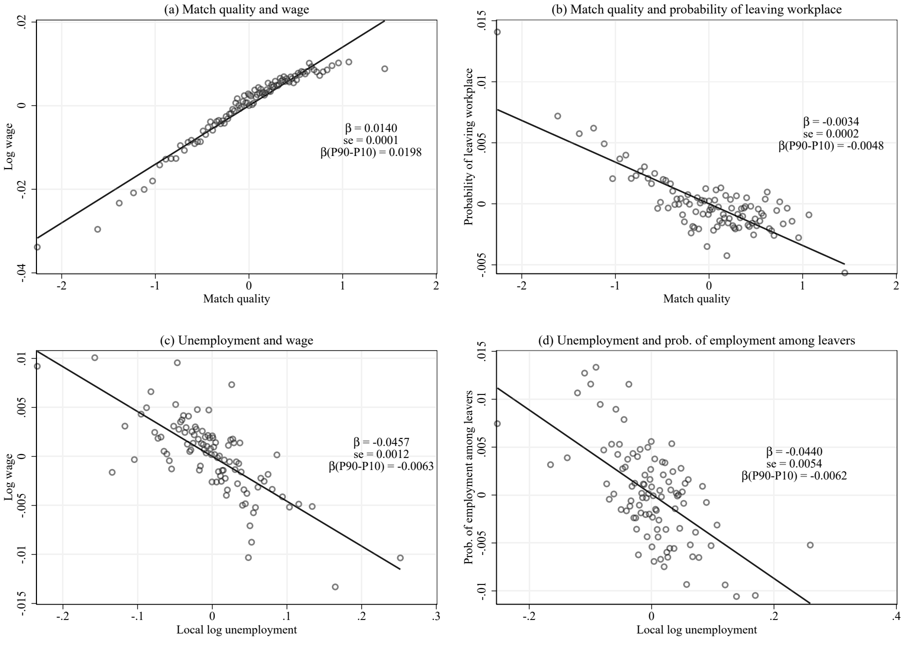
[9] We residualize wages, separations, match quality, and unemployment using: A 2nd order polynomial in each skill, age, education, and experience fixed effects (FEs). In addition, the upper two panels of Figure 1 control for job-by-year FEs (making local unemployment redundant); the lower two panels use additive job and year FEs.

Table 1. *Characteristics of the main sample and all workers sampled in the WSS*

	Main sample	All male workers in WSS
	(1)	(2)
Probability of separation	.096	.137
log wage	10.181 (.363)	10.127 (.357)
Age	41.684 (8.285)	42.868 (11.721)
Years of schooling	12.477 (2.399)	12.37 (2.454)
Establishment size	534.1 (1035.7)	410.5 (948.0)
Years of workplace tenure		
—1 to 3	.253	.345
—4 to 6	.193	.188
—7 to 9	.139	.121
—10 or more	.415	.346
Occupation category (one-digit level)		
—Legislators, senior officials, and managers	.068	.084
—Professionals	.229	.214
—Technicians and associate professionals	.216	.204
—Clerks	.05	.062
—Service workers and shop sales workers	.053	.084
—Skilled agricultural and fishery workers	.005	.007
—Craft and related trades workers	.127	.119
—Plant machine operators and assemblers	.215	.172
—Elementary occupations	.038	.054
N	4,315,746	13,359,613

Notes: Column (1) reports the mean and (when relevant) the standard deviation of key variables in the main sample. For comparison, column (2) reports descriptive statistics for all male workers for which we observe wages and occupation in the Wage Structure Statistics (WSS).

Figure 1. How wages and separations relate to match quality and unemployment



Notes: Panels (a) and (b) relate log wages and the probability of separating from the current workplace between t and $t+1$, respectively, to match quality. Panel (c) plots log wages against unemployment, while panel (d) relates the probability of being employed in $t+1$, for workers that left the workplace between t and $t+1$, to unemployment in $t+1$. We have residualized all variables with respect to a 2nd order polynomial in each of the eight included skills, age, as well as education and experience fixed effects (FEs). In addition, panels (a) and (b) control for job-by-year FEs; panels (c) and (d) hold job and year FEs constant.

stayers (at least one year of tenure), but this is not crucial for the results. Job movers are analyzed in the next section.

We regress wages (w) on match quality (M), local unemployment (u), and the interaction between the two, while accounting for job fixed effects and the direct impact of skills. More specifically, we estimate different versions of the following model:

$$w_{i,j,l,t} = \alpha_{j,t} + \phi\, u_{l,t} + \delta M_{i,j} + \mu\, (u_{l,t} \times M_{i,j}) + g(\boldsymbol{s}_i) + u_{l,t} \times h(\boldsymbol{s}_i) + \boldsymbol{\gamma}\boldsymbol{x}_{i,t} + \varepsilon_{i,j,l,t}, \tag{13}$$

where i, j, l and t indexes individual, job, local labor market (municipality) and year, respectively. We include fixed effects ($\alpha_{j,t}$) for each job (separately by year in the tightest specification), which implies that we only identify the return to match quality from within job variation. $g(\boldsymbol{s}_i)$ and $h(\boldsymbol{s}_i)$ are second-order polynomials in each of the eight skill measures. we control flexibly for skills to account for changes in market-wide returns to skills (through $g(\boldsymbol{s}_i)$) and variation across the business cycle in skill returns (through $u_{l,t} \times h(\boldsymbol{s}_i)$). Finally, $\boldsymbol{x}_{i,t}$ includes a linear control for age, as well as experience and education fixed effects.

For testing Prediction 1, μ is the key parameter of interest. We expect it to be negative such that workers receive a smaller share of the surplus associated with match quality when the arrival rate of job offers is low (i.e., when unemployment is high).[10]

The first three columns of Table 2 report the results from estimating different versions of equation (13) using log wages as the outcome. Column (1) uses additive job and year fixed effects, for which the main effect of unemployment is identified. As previously shown, wages are on average lower when local unemployment is high. Moreover, there is a positive (and precisely estimated) return to match quality.

Crucially, the estimates on the interaction between match quality and unemployment are all negative (and precise). When local unemployment falls, the return to a good match thus grows. The magnitudes are non-trivial. For ease of interpretation, Figure 2 (panel a), *inter alia*, plots the estimated return to match quality (from column 2) along the distribution of local unemployment. The estimates suggest that if unemployment falls from the top to the bottom end of the distribution, the return to a standard deviation increase in match quality rises by 0.275 percent. This increase corresponds to 20 percent ($= 0.275/1.38$) of the average return to match quality.

A possible concern is that the interaction between match quality and unemployment picks up national trends, or time-invariant differences across munic-

[10]To facilitate interpretation of the estimates, we demean unemployment allowing us to interpret the estimates for δ and ϕ as the average effect of match quality and unemployment, respectively. Note, that ϕ is not identified when job-by-year fixed effects are included in the regression.

ipalities, in the returns to match quality that are not caused by unemployment. To address such issues, we interact $M_{i,j}$ with year as well as municipality fixed effects. These interactions imply that the model only relies on variation within municipalities over time when identifying μ. Reassuringly, the estimate on the interaction term is robust to allowing the returns to match quality to vary across municipality and years (see column (3)). If anything, the coefficient on the interaction term increases in absolute size.

In addition to using log wages as the outcome variable—the standard practice in reduced-form empirical work—equation (13) is also estimated using wage levels—in better agreement with the standard theoretical formulation. To make the wage measure comparable across time, and for ease of interpretation, we standardize it (mean = 0, standard deviation = 1) separately by year. Columns (4) to (6) of Table 2 report the results. The results are qualitatively similar to those for log wages, and, thus the results do not depend on functional form. But the interaction effect is more important relative to the average return to match quality in columns (4)-(6) than in columns (1)-(3). Figure 2 (panel b) illustrates this point by showing the estimated return to match quality (from column 5) along the distribution of local unemployment. If unemployment falls from the top to the bottom end of the distribution, the return to an increase in match quality rises by 2.3 percentage points relative to the standard deviation in wages. This increase corresponds to 52 percent (=2.3/4.42) of the average return to match quality.

Figure 2 also provides non-parametric estimates of the return to match quality. Here, we group observations into 20 bins based on the ventiles of the unemployment distribution. The return to match quality is then estimated using a version of equation (13) which, instead of interacting match quality with unemployment, interacts match quality with the dummies for each ventile bin. The non-parametric estimates are well aligned with the predicted returns from the main specification (which we take to be columns 2 and 5 in Table 2).

In the appendix, we report a large number of robustness checks for the relationships presented in this section. Among other things, we vary how standard errors are calculated, use alternative definitions of local labor markets, use alternative proxies for the arrival rate of offers (local employment instrumented by a shift-share instrument, occupation-specific local employment, labor market tightness), relate the return to match quality to the average unemployment during workers' tenure spells, give each municipalities equal weight irrespective of size, and incorporate individual $\times$ job fixed effects in our main specification to hold fixed time-invariant match-specific non-observables. Our results are robust across all these specifications.

Table 2. *Wage regressions for job stayers*

	Log wage			Standardized wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Match quality × log unemployment	-0.00534	-0.00264	-0.00393	-0.00997	-0.0217	-0.0332
	(0.000488)	(0.000497)	(0.00112)	(0.00194)	(0.00194)	(0.00378)
Match quality	0.0134	0.0138		0.0472	0.0442	
	(0.000136)	(0.000135)		(0.000545)	(0.000533)	
log unemployment	-0.0455			-0.0579		
	(0.00123)			(0.00447)		
Year fixed effects	✓			✓		
Job fixed effects	✓			✓		
Job × year fixed effects		✓	✓		✓	✓
M × municipality interactions			✓			✓
M × year interactions			✓			✓
N	3,938,598	3,938,598	3,938,598	3,938,598	3 938 598	3 938 598
R^2	0.806	0.834	0.834	0.604	0.661	0.661

Notes: The table reports versions of the model represented by equation (13). In addition to the control variables listed in the table, all regressions control for education and experience fixed effects as well as age (linearly) and, for each of the eight skills, a second-order polynomial for the skill level of individual i. All models also include interactions between each of the individual skill polynomials and unemployment. Standard errors are heteroskedasticity-robust.

4.3 Match quality in the previous job and the wages of job movers

One key prediction from multilateral wage bargaining is that workers who voluntary move to a new job can use the old job as a distinct outside option in order to bid up the wage in the new job. Thus, the wage in the new job should be a function of match quality in the previous job; see Prediction 2 of Section 2. Moreover, if there is some additional sharing motives, i.e., if the new firm shares more of the surplus than what is required to outbid the old, competing, firm, the quality of the new match should also influence starting wages. The difference between the effects of previous and current match quality, which are measured in the same way, will indicate the relative importance of counteroffers versus generic sharing motives.

However, previous match quality should only be useful for workers whose previous jobs remain available. For workers that are laid off, or quit before finding a new job, we therefore expect previous match quality to play no role in bargaining; see Prediction 3 of Section 2.

To test these predictions, we identify all workers who switched to a new firm between $t-1$ and t.[11] We refer to this set of workers as job-to-job (or EE) movers. We also identify employed workers in t who were classified as non-employed in $t-1$—and were thus likely hired from non-employment—for whom we observe match quality and wages in $t-2$.[12] We refer to these workers as movers with an interim non-employment spell (or ENE movers).

For the two groups, $r \in \{EE, ENE\}$, we estimate joint wage regressions with controls for current and previous match quality interacted with indicators for the two groups. The regressions also include the same controls for skills and individual characteristics as the regressions in Table 2, as well as year fixed effects. In addition, for each of our eight skill dimensions, we include a second-order polynomial in the average skill level of the coworkers—for the new job ($g^m_{j'}(\tilde{\boldsymbol{s}}^{-i}_{j'})$) as well as the previous job ($g^m_j(\tilde{\boldsymbol{s}}^{-i}_j)$).[13] We thus estimate different versions of the following model:

$$\begin{aligned} w_{i,j',j,t} = &\rho_t + \omega I^{EE}_{i,t} + \sum_{r \in \{EE,ENE\}} I^r_{i,t}\left(\kappa^r M_{i,j'} + \nu^r M_{i,j}\right) \\ &+ g^m(\boldsymbol{s}_i) + \boldsymbol{\psi'}\boldsymbol{x}_{it} + g^m_{j'}(\tilde{\boldsymbol{s}}^{-i}_{j'}) + g^m_j(\tilde{\boldsymbol{s}}^{-i}_j) + \varepsilon_{i,j',j,t}, \end{aligned} \tag{14}$$

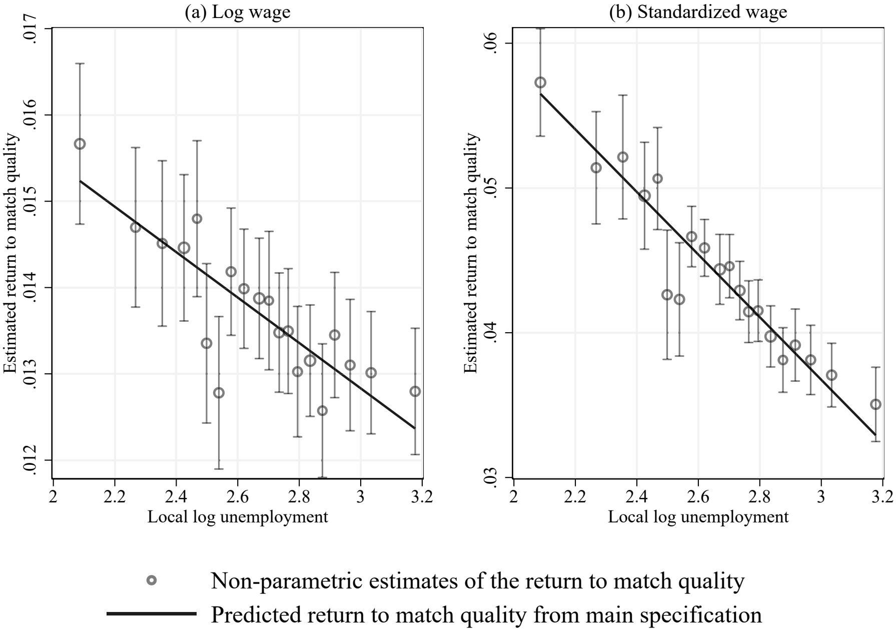
where j' and j indexes the current and previous job, respectively. $I^r_{i,t}$ is an indicator for belonging to group r. We restrict the background controls to have

[11] In addition, we require that they have no previous experience from the new workplace, and that we observe match quality and wages in both periods.

[12] We also require that they did not return to their old firm in t.

[13] This is a parsimonious way of controlling for the features of the new and the previous job. In the appendix, we show that the results are robust to instead using unrestricted fixed effects for the old and the new firm.

Figure 2. The return to match quality along the unemployment distribution



Notes: Non-parametric estimates are obtained by grouping data into 20 bins based on the ventiles of the distribution of $u_{j,t}$. The return to match quality is then estimated using a version of equation (13) which interacts match quality with the indicators for each bin. Panel (a) shows the estimates, and the 95-percent confidence intervals based on robust standard errors, for log wages while (b) presents the same information for wage levels standardized (mean = 0, standard deviation = 1) separately by year. The solid lines show the predicted return to match quality based on the estimates in columns (2) and (5) from Table 2.

the same impact across the two groups. ω corresponds to the average wage premium of being hired from employment compared to non-employment; κ^r and ν^r informs us about the importance of new and previous match quality for group r.

The results are reported in Table 3. Columns (1)-(3) report results for log wages while the results for standardized wages are reported in columns (4)-(6). In columns (1) and (4), we start by relating wages to current match quality. We then introduce previous match quality in columns (2) and (5). Note, we have 58,053 workers which we classify as EE movers, while (only) 1,784 workers are classified as ENE movers.

The estimated return to match quality for the group of EE movers is large and statistically significant. When we add previous match quality to the regression, the estimated effect of current match quality approximately halves in size. Through the lens of the model, this can be interpreted as current match surplus being shared between workers and firms. The implied estimate of the sharing parameter (η of Section 2) is 0.41.[14] Most importantly, there is a significant and even stronger relationship between previous match quality and the current wage, conditional on current match quality. This strongly suggests that counteroffers from the old employer play an important role in wage setting.

On average, job-to-job movers have a substantially higher wage in their new job compared to movers with interim non-employment (see the coefficient on "EE mover"). For ENE movers, current match quality appears to be important. In relation to Prediction 3, we note that previous match quality for the ENE group appear irrelevant; the estimate for ENE $\times$ previous match quality—i.e., ν^{ENE}—is virtually zero (see column 2).[15]

The impact of the previous match quality may, in principle, be mediated by the previous wage. To see what role previous match quality plays, conditional on previous wages, columns (3) and (6) report results from an augmented version of equation (14) where we introduce group-specific effects of the wage in the previous job. These specifications naturally reduce the impact of match quality, since wages depend on match productivity. Nevertheless, previous match quality is still significant for EE movers.

[14] This is obtained as $0.0112/(0.0112+0.0164)$, where the normalization takes into account that we only observe a proxy for match quality rather than match productivity. In columns (3), (5), and (6), an analogous exercise produces estimates of η equaling 0.26, 0.44, and 0.40, respectively.

[15] In the appendix, we report estimates from separate regressions for the two groups. Overall, the results are qualitatively robust, with one exception: Current match quality does not seem to be as important as indicated by the pooled regression. With that said, one should keep in mind that there are only 1,784 workers in the ENE group.

Table 3. *Wage regressions for job movers*

	Log wage			Standardized wage		
	(1)	(2)	(3)	(4)	(5)	(6)
EE mover	0.130 (0.00544)	0.130 (0.00548)	0.115 (0.00864)	0.240 (0.0129)	0.240 (0.0130)	0.250 (0.0408)
EE × new match quality	0.0201 (0.00163)	0.0112 (0.00198)	0.00109 (0.00129)	0.0657 (0.00517)	0.0395 (0.00614)	0.00793 (0.00401)
ENE × new match quality	0.00908 (0.00492)	0.0144 (0.00683)	0.00303 (0.00554)	0.0434 (0.0115)	0.0420 (0.0161)	0.0105 (0.0112)
EE × prev. match quality		0.0164 (0.00191)	0.00305 (0.00127)		0.0493 (0.00596)	0.0117 (0.00399)
ENE × prev. match quality		-0.00121 (0.00673)	0.00102 (0.00559)		0.0201 (0.0159)	0.00527 (0.0110)
EE × prev. wage			0.773 (0.00425)			0.745 (0.0187)
ENE × prev. wage			0.455 (0.0219)			0.420 (0.0565)
N	59,837	59,837	59,837	59,837	59,837	59,837
R^2	0.612	0.612	0.844	0.367	0.368	0.740

Notes: "EE movers" are workers who changed firms between $t-1$ and t. "ENE movers" are workers who changed firms between $t-2$ and t with an intermittent spell of non-employment in November $t-1$. We also require that we observe wages and match quality in the current and previous job. All regressions include controls for education and experience fixed effects, a linear control for age, and a second-order polynomial for each of the eight skills. In addition, we control for a second-order polynomial for the average in each skills among tenured workers in the previous as well as current job. The sample includes 58,053 EE movers, and 1,784 ENE movers. Robust standard errors in parentheses.

5 Conclusions

We offer two pieces of evidence that workers can use outside offers to extract rents from match productivity. Using a match quality measure based on the alignment between workers' multidimensional abilities and the skill requirements of their jobs, we show that: (i) Wages within ongoing matches are more closely aligned with match quality following an improvement of local labor market conditions; (ii) Wages of job movers are positively related to the match quality in the previous job, even when controlling for previous wage, while wages of workers who are hired after a non-employment spell are unrelated to the match quality in the last job.

These finding run counter to the standard wage bargaining framework, as well as the typical reduced form rent-sharing set-up, which are based on the assumption that the impact of idiosyncratic rents and outside options are additively separable in the wage equation.

Our findings have clear implications for wage inequality: When firms are prepared to make counteroffers, there will be wage dispersion among workers who are equally productive within a given match. Moreover, since the wage returns to match quality grow larger, within-firm wage inequality due to variation in match productivity among incumbent workers increases when the state of the labor market improves.

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Appendix A Simulations

This section analyzes the derivative of the expected wage for job stayers with respect to the arrival rate of offers and match quality, i.e., the sign of:

$$\frac{\partial^2 \mathbb{E}[w \mid p' \leq p, p, \lambda]}{\partial p \partial \lambda} = \frac{(1-\eta)F'(p)}{(1-\lambda+\lambda F(p))^2}\Big[(p-\mathbb{E}(p'_s)) + (1-2\theta)(\mathbb{E}(p'_s)-b)\Big]. \tag{A1}$$

More specifically, we investigate which distributional assumptions, as well as values of λ, b and p, that lead to a negative sign of equation (A1).

To this end, we simulate the model in Section 2 using three different distributions for match quality: The Normal(5, 1); The Log-Normal(0, 1); And the Uniform(0, 1). For each distribution, the simulation considers values of $\lambda, F(b) \in \{0.01, 0.02, \ldots, 0.99\}$.

For all possible values of $\lambda, F(b)$, we randomly generate a value of p_i for 10 000 individuals indexed by i, discarding those with $p_i < b$. Each individual is then given the chance of drawing an outside offer in the second period. More specifically, we calculate the best outside option as $\max\{b, -\alpha + \mathrm{B}(\lambda) \times (p'_i + \alpha)\}$, where the Bernoulli trial $\mathrm{B}(\lambda)$ determines whether the worker matched with a new firm, p'_i is the random value of that match, and α is a large value such that $-\alpha < b$. Observations with outside options outside the range $[b, p_i]$ are removed, i.e., we only retain job stayers.

We proceed by calculating $F(p_i)$, $F'(p_i)$ and $\mathbb{E}(p'_{si}) = \mathbb{E}[p'_i \mid b < p'_i < p_i, p_i]$ for all individuals. These values are then plugged into (A1). Finally, for all combinations of $\lambda, F(b)$, we calculate the average derivative over the simulated p_i distribution for stayers. This average is a close approximation of the empirical estimate on the interaction between the arrival rate and match quality in the wage regression for stayers.

For both the uniform and the lognormal distributions, equation (A1) is positive for all values of $\lambda, F(b)$, and $F(p)$. In fact, this can be proven analytically for the uniform distribution, as briefly discussed in Section 2. Moreover, the right skewness of the lognormal distribution typically causes $\mathbb{E}[p'_i \mid b < p'_i < p_i, p_i]$ to be closer to b than to p_i. In turn, this implies that (A1) is positive as also noted in Section 2. It is only for the normal distribution that (A1) can turn negative. But this only happens at extreme values of the arrival rate—values which are not observed empirically (see Faberman et al., 2022, and Hornstein et al., 2011)[16]—and low levels of b.

The dark (light) squares in Figure A1 show combinations of $F(b)$ and λ where (A1) is negative (positive) when averaged over the distribution of p.

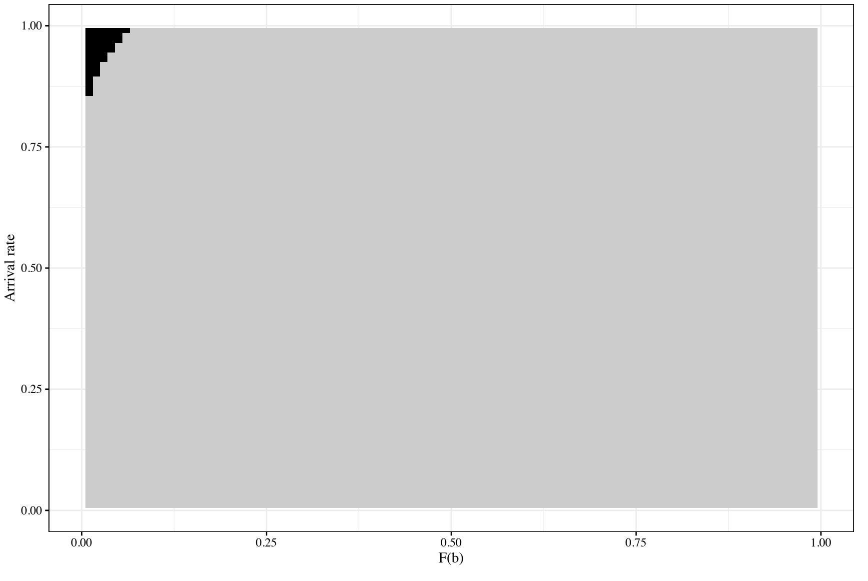
[16]Faberman et al. (2022)'s analysis suggests a monthly arrival rate for employed workers of 0.081. The probability of receiving at least one offer in a year can then be calculated as $(1-(1-0.081)^{12})$. Thus, converted to an annual frequency, this implies $\lambda = 0.637$.

Figure A2 presents the analogous information for different decile groups of the simulated $F(p_i)$ distribution.

Figure A1 shows that a negative sign of (A1) requires $\lambda \geq 0.88$ when $F(b) = 0.01$. With a slight increase in b to $F(b) = 0.05$, the requirement is $\lambda \geq 0.97$.

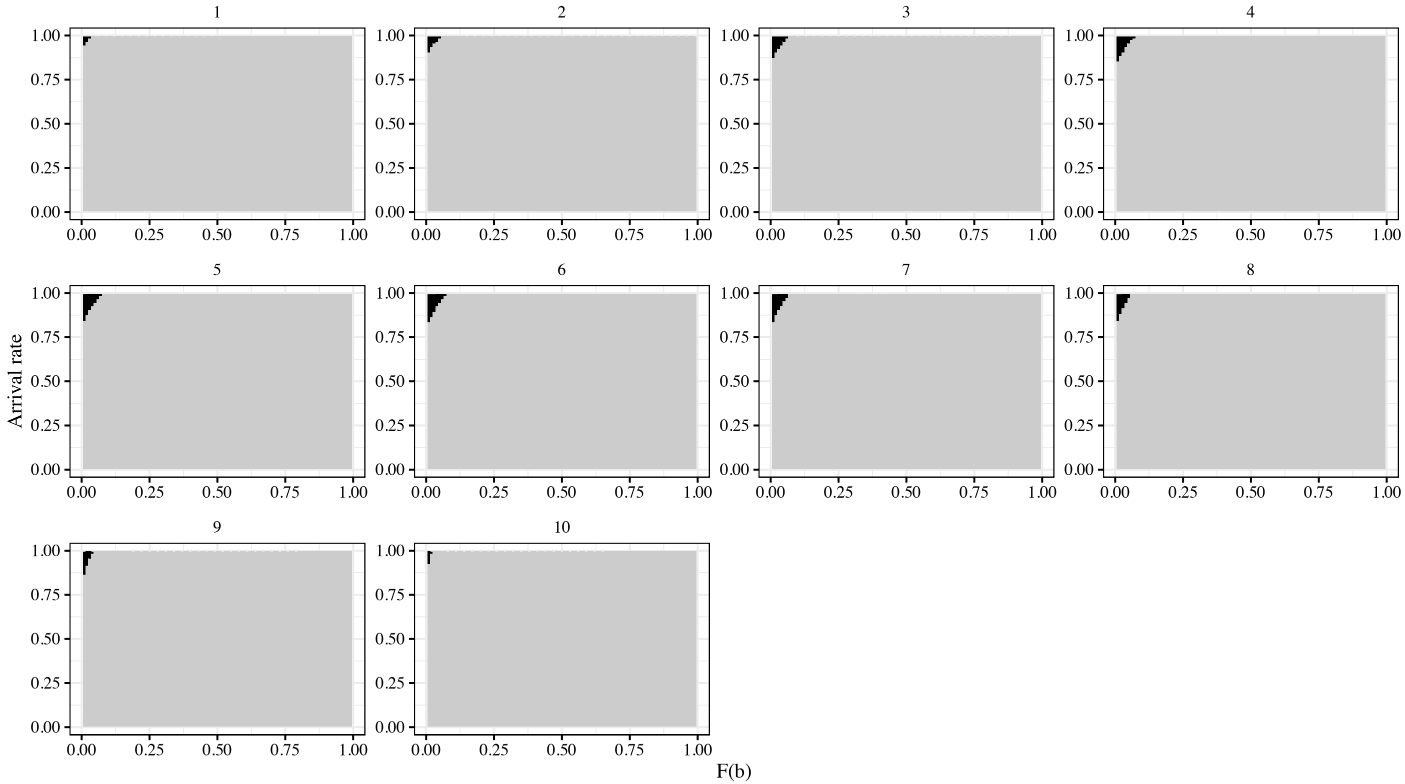
Figure A2 shows that the middle deciles of the $F(p)$ distribution drive the average illustrated in Figure A1. For decile groups with relatively low and high match quality, however, a negative value of (A1) is associated with even more extreme values of λ and $F(b)$.

Figure A1. Sign of equation (A1), averaged over the distribution of p, for different values of λ and $F(b)$



Notes: The figure reports the sign of the second-order derivative of the expected wage with respect to match quality (p) and the arrival rate (λ) by $F(b)$ and λ, averaged over the distribution of p. Dark (light) squares indicate a negative (positive) derivative.

Figure A2. Sign of equation (A1) for different values of λ and $F(b)$, by match quality decile groups



Notes: The figure reports the sign of the second-order derivative of the expected wage with respect to match quality (p) and the arrival rate (λ) by $F(b)$ and λ, separately by decile groups of $F(p)$. Dark (light) squares indicate a negative (positive) derivative.

Appendix B Robustness checks for remaining workers

This section describes a battery of robustness checks, the majority of which are reported in Table B1, in order to determine the sensitivity of the results reported in Section 4.2. Among other things, we produce different standard errors, vary at which level local unemployment is measured, introduce alternative proxies for local labor market tightness/expected outside option relevant for each individual, and vary the controls and fixed effects that are included in the main specification (see equation (13)). If not stated otherwise, all regressions include the same controls as columns (2) and (5) in Table 2, i.e., job $\times$ year fixed effects as well as the controls that are shared across all models.

Table B1 reports the estimate and standard error for the interaction between match quality and applicable proxy for workers' expected outside options (the equivalent of μ from equation (13)). The table also reports the difference between the 90th and 10th percentile of the outside option proxy distribution, and for ease of interpretation and comparison, the estimated difference in match quality returns between these points, i.e., $\hat{\mu} \times (P90 - P10)$.

Alternative definitions of local labor markets

The main analysis utilizes workplace municipality unemployment. Measuring unemployment at a more aggregate level does not call into question our main results; if anything, the heterogeneity in returns to mismatch with respect to unemployment is marginally larger when using unemployment in the workplace local labor market or county. Moreover, using the annual unemployment incidence in the residential municipality of each worker, which may vary within each job $\times$ year cell, yields very similar results.[17]

Actual and instrumented municipality employment

We've also substituted unemployment for the logarithm of the number of employed workers in the workplace municipality. Naturally, employment is expected to have the opposite influence on the return to match quality as unemployment.

Next, we construct a plausibly exogenous measure of local labor market conditions by instrumenting log employment using a shift-share/Bartik (1991) style instrument. The instrument is based on the national deviation in industry s and year t from the industry average logarithm of employment. The employment in each municipality and year is then predicted based on the local industry composition in 1997 using the following formula:

$$\ln(\text{employment})_{l,t}^{Instr.} = \sum_{s} \text{Share}_{l,s,1997} \times \left(\ln(\text{employment})_{s,t} - \overline{\ln(\text{employment})}_{s}\right), \quad \text{(B1)}$$

[17]The main effect of residential municipality unemployment on wages, which is not reported in any table, is also both statistically and economically significant, which suggests that cross-municipality-border commuters may be influenced by their residential municipality conditions.

where $\text{Share}_{l,s,1997}$ is the fraction of all workers in municipality l in 1997 that were employed in industry s. We use the highest level of aggregation in the Swedish Standard Industrial Classification, which includes 21 different industry categories.

Regressing standardized employment, $\ln(\text{employment})_{l,t} - \overline{\ln(\text{employment})}_l$, onto the instrumented standardized log employment using 4913 observations at the municipality-year level returns a coefficient of around 0.9 with a t-value of 64, and so the first stage equation is sufficiently precise. Instead of performing the full two-stage least squares analysis, we settle for the reduced form, i.e., we directly substitute unemployment with the instrument in equation (13). The return to match quality increases with both the actual and instrumented normalized logarithm of employment. The interaction effect estimates are also similar in size.

Occupation-specific local employment

The benefit of using occupation-specific local employment is that it is arguably a more relevant measure for each worker of available jobs and proxy of labor market tightness, and that it also exhibits within-municipality and year variation.

We use occupation categories at the three-digit level of SSYK-96 to be consistent with our previously described definition of a job.[18]

First, we use the logarithm of the number of employees in each occupation $\times$ municipality $\times$ year cell as the proxy for tightness. Next, we residualize this measure by running a regression at the same level of observation which incorporates municipality $\times$ year and occupation $\times$ year fixed effects, which implies that the variation in the residuals will stem from the deviation from the national occupation-specific employment and local overall employment in a given year. Both variants are reported in Table B1, and in both cases the return to match quality is increasing in occupation-specific employment. Moreover, there is more heterogeneity in match quality returns across the occupation-municipality log employment distribution compared to local unemployment.

Vacancies relative to unemployment

To construct an additional proxy of tightness, we use the number of new vacancies that have been added to the Swedish Public Employment Service job portal *Platsbanken* in a municipality during a particular year and divide it by the number of openly unemployed. The measure is then standardized to mean

[18] We have also investigated whether the local unemployment-specific returns to match quality vary by occupation by, in our main specification, interacting M and $M \times u$ (where u is either unemployment or occupation-specific local employment) by broad occupation group (one-digit level) indicators. The match quality and interaction term estimates have the expected sign, and are both statistically and economically significant, in most occupation groups. This suggests that the return to match quality is responsive to workers' outside options across broad occupation categories.

zero, standard deviation one. Again, we find that, when the relative number of vacancies is low, so is the return to match quality. One issue here is that the vacancies likely only represent a subset of available jobs in the local economy.

Share of separations to employment

The final alternative proxy of the arrival rate of outside offers is the share of workers that separate from their initial workplace between $t-1$ and t that are categorized as employed in t. The share is calculated at the workplace municipality in $t-1$ and year level, and workers are allowed to transition between municipalities. This is equivalent to the measure used in panel (d) in Figure 1.

Unemployment during tenure spell

One may argue that it is the history of unemployment that a worker has experienced while in a particular job that should affect to what extent his match quality can be converted into a high wage. Therefore, we have calculated the average municipality log unemployment during each worker's tenure spell, censored at 15 years. Unfortunately, municipality-level data on unemployment is only available from 1997, and so we're forced to exclude around half of all observations, especially with long tenure and in the early years of our sample.[19]

An alternative match quality proxy

To see whether our results are sensitive to how we define match quality, we have constructed an alternative proxy based on the wage returns to abilities within each job compared to the market-wide returns for the same abilities. The idea is that the job-specific returns are informative about the importance of each ability. However, one disadvantage to this method is the noisiness of the estimates for small job cells. To construct the measure, for each job j, we estimate a regression of the following form:

$$w_{i,j,t} = \alpha_{j,t} + \boldsymbol{\beta'}_j^{\text{Job}} \boldsymbol{s}_i + \varepsilon_{i,j,t}, \tag{B2}$$

where $\alpha_{j,t}$ is a set of job-times year fixed effects, the vector $\boldsymbol{s}_i$ comprises the eight skill measures, and the vector $\boldsymbol{\beta'}_j^{\text{Job}}$ contains the returns to each skill for job j.

We also estimate the same regression for all workers simultaneously, treating the whole market as a single job, to obtain market-wide returns, $\boldsymbol{\beta'}^{\text{Market}}$.

Our wage-based match quality metric, $M_{i,j}^{\text{wage}}$, is calculated as follows. To remove outliers, we exclude observations below the 1st and above the 99th

[19]To be able to compare these estimates to the baseline estimates, we have also re-estimated our main specification for this subset of observations. The interaction estimates for log wage and standardized wage are around -0.00177 and -0.0256, respectively.

percentile of the $M_{i,j}^{\text{wage}}$ distribution. We also standardize it to mean zero, standard deviation one, to make it comparable to our baseline match quality proxy:

$$M_{i,j}^{\text{wage}} = \frac{\left(\hat{\boldsymbol{\beta}}'^{\text{ Job}}_{j} - \hat{\boldsymbol{\beta}}'^{\text{ Market}}\right)\boldsymbol{s}_i - \text{mean}\left(\left(\hat{\boldsymbol{\beta}}'^{\text{ Job}}_{j} - \hat{\boldsymbol{\beta}}'^{\text{ Market}}\right)\boldsymbol{s}_i\right)}{\text{sd}\left(\left(\hat{\boldsymbol{\beta}}'^{\text{ Job}}_{j} - \hat{\boldsymbol{\beta}}'^{\text{ Market}}\right)\boldsymbol{s}_i\right)}. \tag{B3}$$

The interaction term between $M_{i,j}^{\text{wage}}$ and unemployment reveals to what extent the relationship between predicted skill-bundle return in workers' jobs relative to the market and their actual wages relates to unemployment.

Alternative specifications

To verify that our results are not driven solely by large municipalities (e.g., Stockholm), and hold also in smaller settings, we have weighted the regressions with the inverse of the number of observations in each municipality $\times$ year cell, thus putting equal weight on each cell. The interaction effect remains highly statistically significant and similar in size.

Finally, individual $\times$ job fixed effects have been added to the specification which also incorporates job $\times$ year fixed effects. This removes any constant wage differences between individuals and jobs. Put differently, we then rely on within individual and job variation in wages and local unemployment across time to identify the interaction between match quality and unemployment. The resulting interaction estimate for log wages is somewhat more negative, while the estimate for standardized wages is less negative, than the preferred specifications reported in Table 2, columns (2) and (5).[20]

[20] In unreported regressions, we have also included individual and job $\times$ year fixed effects as well as only individual $\times$ job fixed effects.

Table B1. *Robustness checks for job stayers*

	Log wage		Standardized wage	
	Coef. (SE)	Coef.×(P90 - P10) [P90 - P10]	Coef. (SE)	Coef.×(P90 - P10) [P90 - P10]
	(1)	(2)	(3)	(4)
(a) Standard errors				
Clustering at municipality × year level	-0.00263 (0.00072)	-0.00177 [0.67315]	-0.02162 (0.00432)	-0.01455 [0.67315]
Clustering at job level	-0.00263 (0.00126)	-0.00177 [0.67315]	-0.02162 (0.00535)	-0.01455 [0.67315]
Twoway clustering at muni. × year and job	-0.00263 (0.00131)	-0.00177 [0.67315]	-0.02162 (0.00635)	-0.01455 [0.67315]
(b) Alternative local labor markets				
Residential municipality	-0.00425 (0.00049)	-0.00316 [0.74497]	-0.03706 (0.00243)	-0.02761 [0.74497]
Workplace local labor market	-0.00458 (0.00055)	-0.00296 [0.64581]	-0.03301 (0.00239)	-0.02132 [0.64581]
Workplace county	-0.00473 (0.00059)	-0.00291 [0.61468]	-0.03637 (0.00258)	-0.02236 [0.61468]
(c) Alternative proxies of expected outside option				
$\ln(\text{employment})_{l,t} - \overline{\ln(\text{employment})_l}$	0.01968 (0.00203)	0.00331 [0.16817]	0.02585 (0.00879)	0.00435 [0.16817]
Instrumented $\ln(\text{employment})_{l,t}$	0.02309 (0.00276)	0.00297 [0.12858]	0.02435 (0.01205)	0.00313 [0.12858]
Occupation-specific ln(employment)	0.00167 (0.00009)	0.00770 [4.60852]	0.00996 (0.00047)	0.04592 [4.60852]
Residualized occ. ln(employment)	0.00137 (0.00012)	0.00373 [2.72120]	0.00558 (0.00041)	0.01517 [2.72120]
# New vacancies$_{l,t}$ / # Unemployed$_{l,t}$	0.00046 (0.00016)	0.00094 [2.04292]	0.00727 (0.00082)	0.01485 [2.04292]
Share of separations to employment	0.01841 (0.00256)	0.00235 [0.12793]	0.11400 (0.00995)	0.01458 [0.12793]
Mean local unemployment during tenure spell	-0.00309 (0.00082)	-0.00200 [0.64791]	-0.02851 (0.00297)	-0.01847 [0.64791]
(d) Alternative match quality proxy				
Wage-based match quality	-0.00361 (0.00052)	-0.00243 [0.67315]	-0.02611 (0.00209)	-0.01757 [0.67315]
(e) Alternative specifications				
Weighted using $1/N$ at muni. × year level	-0.00334 (0.00080)	-0.00225 [0.67315]	-0.00937 (0.00190)	-0.00631 [0.67315]
Individual × job and job × year FE	-0.00598 (0.00056)	-0.00403 [0.67315]	-0.01409 (0.00248)	-0.00948 [0.67315]

Notes: Columns (1) and (3) report the estimates and standard errors (in parenthesis) for the interaction between match quality and proxy of workers' expected outside options. Columns (2) and (4) report the predicted difference in the effect of match quality between the 90th and 10th percentile of the outside option proxy distribution, and the difference between the 90th and 10th percentile (in brackets). See also the description of Table 2. All regressions include the same controls as the model reported in column (2) in that table. See the description of the robustness checks in the main text.

Appendix C Robustness checks for workplace movers

This section reports results from robustness checks for the wages of workplace and firm switchers. Table C1 reports estimates from regressions estimated separately for job-to-job switchers between $t-1$ and t and switchers between $t-2$ and t with interim non-employment in $t-1$ of the following form:

$$w_{i,j',j,t} = \rho_t + \kappa M_{i,j'} + \nu M_{i,j} + g^m(\boldsymbol{s}_i) + \boldsymbol{\psi}'\boldsymbol{x}_{it} + g^m_{j'}(\tilde{\boldsymbol{s}}^{-i}_{j'}) + g^m_j(\tilde{\boldsymbol{s}}^{-i}_j) + \varepsilon_{i,j',j,t}. \tag{C1}$$

See the description of equation (C1) in the main text for definitions of each variable and subscript.

The results from these regressions are reported in Table C1. Again, we see that previous match quality is more important for EE relative to ENE switchers. However, now match quality in the new firm does not appear to be important for ENE switchers either, which is different from when estimating joint regressions for the two switcher groups. However, given the small sample of ENE switchers, we are cautious regarding how to interpret these results.

We have also estimated joint regressions for EE and ENE switchers where we augment the model from equation (C1) by introducing job fixed effects. Whenever such job fixed effects are included, the average skill controls for co-workers are rendered superfluous. These results are presented in Table C2. The regressions are again estimated both for log wages (columns (1)-(3)) and standardized wages (columns (4)-(6)). In columns (1) and (4), we control for fixed effects for the new job of the worker, in (2) and (4) we instead include fixed effects for the previous job, and both types of fixed effects are included in columns (3) and (6). In the last version of the model, we rely on variation stemming from multiple workers leaving the same job with different destinations and multiple workers entering into the same job from multiple sources. In this model, around one third of our sample is in effect lost due to lack of variation.

The results are well in line with those from Table 3: For EE switchers, both new and previous match quality is important for wages, and the estimate for previous match quality is larger than that for current match quality throughout the table. For ENE switchers, previous match quality appears to mostly play a minor role for wages, while the estimate for current match quality is often relatively large and on par with the estimate for EE switchers.

Table C1. *Separate regressions for EE and ENE job movers*

	Log wage				Standardized wage			
	EE		ENE		EE		ENE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New match quality	0.0194	0.0112	0.00119	-0.000739	0.0645	0.0392	0.0112	0.00577
	(0.00166)	(0.00199)	(0.00613)	(0.00637)	(0.00530)	(0.00619)	(0.0133)	(0.0138)
Previous match quality		0.0158		0.00653		0.0481		0.0184
		(0.00192)		(0.00687)		(0.00600)		(0.0150)
N	58 053	58 053	1 784	1 784	58 053	58 053	1 784	1 784
R^2	0.609	0.610	0.501	0.501	0.363	0.364	0.316	0.317

Notes: The table reports the results from separate regressions on wage in t for workers that moved between workplaces and firms between $t-1$ and t (EE switchers) and workers who moved between $t-2$ and t who were classified as non-employed in November in $t-1$ (ENE switchers) for which we observe wages and match quality in the last job and current job. All regressions include controls for education and experience fixed effects, a linear control for age, a second-order polynomial for each of the eight skills and skills squared, and a second-order polynomial for the average of all skills among tenured workers in the previous as well as new job. Robust standard errors in parenthesis.

Table C2. *Robustness checks for job movers*

	Log wage			Standardized wage		
	(1)	(2)	(3)	(4)	(5)	(6)
EE switcher	0.0659	0.0696	0.0631	0.134	0.106	0.138
	(0.00658)	(0.00768)	(0.00790)	(0.0177)	(0.0190)	(0.0244)
EE × new match quality	0.00593	0.00426	0.00576	0.0190	0.0183	0.0233
	(0.00228)	(0.00240)	(0.00242)	(0.00759)	(0.00756)	(0.00892)
ENE × new match quality	0.0216	0.0103	0.00118	0.0611	0.0255	0.0184
	(0.00888)	(0.0103)	(0.0104)	(0.0249)	(0.0250)	(0.0290)
EE × prev. match quality	0.0101	0.0119	0.0107	0.0320	0.0354	0.0260
	(0.00209)	(0.00227)	(0.00233)	(0.00711)	(0.00734)	(0.00884)
ENE × prev. match quality	-0.00783	-0.00415	0.00950	-0.0166	0.0101	0.0168
	(0.00791)	(0.0104)	(0.0111)	(0.0195)	(0.0252)	(0.0303)
New job FE	✓		✓	✓		✓
Prev. job FE		✓	✓		✓	✓
N	50 625	49 723	39 540	50 625	49 723	39 540
R^2	0.866	0.856	0.889	0.715	0.710	0.743

Notes: The table reports the results from regressions on wage in t for workers that moved between workplaces and firms between $t-1$ and t and workers who moved between $t-2$ and t who were classified as non-employed in November in $t-1$ for which we observe wages and match quality in the last job and current job. All regressions include controls for education and experience fixed effects, a linear control for age, a second-order polynomial for each of the eight skills and skills squared, and a second-order polynomial for the average of all skills among tenured workers in the previous as well as new job. Each column incorporates fixed effects for the current job, previous job or both. Whenever fixed effects are incorporated, the average skill controls are rendered superfluous. The sample includes 58 053 observations with employment in $t-1$ and 1 784 observations with non-employment in $t-1$. Standard errors are clustered at the current job level in columns (1), (3), (4) and (6) and at the previous job level in columns (2) and (5).

Essay IV. Low-Skilled Jobs, Language Proficiency and Job Opportunities for Refugees

Co-authored with Mats Hammarstedt, and Per Skedinger

Acknowledgements: We thank Gabriella Chirico Willstedt, Stefan Eriksson, Peter Fredriksson, Georg Graetz, Edvin Hertegård, seminar participants at IFN and Uppsala University, the editor and three referees for helpful comments, the employers who kindly participated in our interviews, and Emma Gunnarsson, Jörgen Nilson, Kasper Nilson and Sara Norbäck for excellent research assistance. The experiment was registered at the American Economic Association (for more details, see https://www.socialscienceregistry.org/trials/4832).

1 Introduction

The refugee crisis of 2015–16 resulted in large immigrant inflows from countries in the Middle East and Africa to Europe. It is well documented in several countries that refugees, and especially female refugees, experience poorer labor market outcomes—e.g., lower employment and higher unemployment rates—than both natives and other groups of foreign born (see, e.g., Brell et al., 2020). In many cases it takes a long time after arrival for both refugees and their relatives to find stable employment. A large share of immigrants from the Middle East and Africa lack higher levels of education, preventing them from entering the skilled segments of the labor market. Poor language proficiency may also be an obstacle for labor market integration.

There is an ongoing discussion, both in policy circles and in academia, regarding the value of labor market experience and language skills for the labor market integration of immigrants (see, e.g., OECD, 2018). A key idea is that the first job significantly improves labor market prospects, making a worker better suited for, and more able to find, subsequent employment opportunities. The question then becomes how to facilitate labor market entry as soon after arrival as possible. The fact that language skills are strongly correlated with favorable labor market outcomes is often used as confirmation of the importance of language training. However, despite the obvious policy relevance of these issues, causal evidence on the impact of labor market experience and language training on the integration of immigrants is scarce.

This article studies job opportunities for refugee immigrants in Sweden, a country which has experienced a very large inflow of refugee immigrants in recent years. We focus on the effects of language training provided via the Swedish for Immigrants (SFI) program and labor market experience in low-skilled jobs in a field experiment. In the experiment, we investigate the impact of experience from jobs as restaurant assistants and completed SFI for foreign-born job seekers. Applications were sent from randomly assigned fictitious Syrian refugees with different levels of previous experience and language training, to employers who advertised low-skilled job vacancies. Syrians constitute the largest group of foreign born in Sweden. This allows us to put more focus on the effects of skill variation within a particular refugee group.

We complement the field experiment with interviews with a select number of employers with extensive experience of handling applications for low-skilled jobs from persons originating from Middle Eastern and African countries. While this evidence is only suggestive in nature, it nevertheless provides some insights into what employers look for when judging job candidates. It is also informative about how actual applications are typically written. In these respects, the interviews serve as a check on our results from the field experiment. But they should also be of interest in their own right.

In the econometric analysis, we are unable to demonstrate sizeable effects of previous experience or completed language training on the probability of callback from employers. However, females were more likely than males to receive a positive response on their applications. Most of the respondents in our employer interviews reported that they do not attach much value to previous experience and completed SFI. When judging applicants, the respondents had a very functional approach, considering the requirements of the task at hand and the potential for a long-term relationship rather than formal qualifications. They also put much emphasis on how motivated job candidates are. Moreover, some of the employers disclosed a preference for hiring females over males, because the former were regarded as more conscientious and adaptable. These qualitative results support our findings in the experiment.

Our study contributes to several literatures on the impact of work experience and language skills on labor market prospects for immigrants. Economic theory suggests that low-skilled jobs may lead to more qualified jobs if individuals increase their human capital by means of on-the-job-training or learning-by-doing (Becker, 1962). The transferability of skills between jobs is then of crucial importance. Moreover, such jobs may improve social capital through an expanded professional network (see, e.g., Calvo-Armengol and Jackson, 2004). Previous experience may also serve as a productivity signal when applying for other jobs (see, e.g., Spence, 1973). This may be so even if a worker's human capital is unaffected—simply exhibiting sufficient skills to handle a certain job may make a worker more attractive to other firms. Language skills can be considered an investment in the individual's human capital, and may also signal higher productivity (Chiswick and Miller, 2015). Taken together, these theories suggest that foreign-born persons, and especially refugee immigrants, may be disadvantaged by poor language skills, little work experience and inadequate professional networks.

The role of labor market experience, occupational sorting, and job mobility for the labor market assimilation process has been studied extensively in empirical work (see, e.g., Husted et al., 2001, Chiswick et al., 2005, Barth et al., 2012, and Brenzel and Reichelt, 2018). Other observational studies show that proficiency in the language spoken in the host country is associated with higher employment and higher wages for immigrants (see, e.g., Chiswick and Miller, 2015, and Yao and Ours, 2015, for surveys). There is also some evidence indicating that a large part of the difference in labor market outcomes between immigrants and natives can be explained by differences in language proficiency, as measured by tests, and not by differences in returns to these skills (see Ferrer et al., 2006, and Himmler and Jäckle, 2018). Consequently, it should be of great policy interest to investigate the labor market effects of government-sponsored, formal language training for adult immigrants. However, there are few such studies that allow a causal interpretation. Two recent exceptions are Lochmann et al. (2019) and Arendt et al. (2020), utilizing regression discontinuity designs to show that language classes improve the labor market integration of immigrants.

In general, though, the findings in the literatures that we have discussed cannot be interpreted as necessarily reflecting causal relationships. Labor market experience and language skills may be correlated with other unobserved characteristics that influence outcomes under investigation. Unlike previous observational studies on immigrants, our experimental approach enables us to identify causal relationships between, on the one hand, experience from a low-skilled job and language skills, and, on the other hand, employment prospects. Our design also allows for examining the impact of combinations of the two qualifications.

Our most salient result is that female applicants receive more callbacks than males. This is in line with other correspondence studies for the Swedish labor market, documenting that, compared to females, male applicants with foreign-sounding names are less likely to receive a positive response from employers (Arai et al., 2016; Vernby and Dancygier, 2019; Erlandsson, 2022). This evidence appears to be consistent with theories in social psychology postulating that mainly males are subject to stereotypes about foreign nationalities (see Manzi, 2019, for a literature survey). But it is inconclusive as to whether gendered ethnic discrimination is more pervasive in female-dominated occupations.[1]

Previous correspondence studies dealing with assimilation in the labor market typically do not concern refugee immigrants (but native-born persons with foreign or minority background), rarely consider variations in work experience, usually do not focus on typical entry occupations for immigrants, and typically do not examine the impact of variations in language skills within a minority group. However, some correspondence studies compare the returns to work experience for foreign born or a minority group to those of natives or members of the majority group (see, e.g., Bertrand and Mullainathan, 2004, Vernby and Dancygier, 2019, and Adermon and Hensvik, 2022). The typical finding in these studies is that experience is less rewarded, in terms of callback rates, for foreign born or minority groups. However, Baert et al. (2017) find that differences in returns to experience diminish and eventually disappear with longer experience in skilled jobs. To the best of our knowledge, the only comparable previous correspondence study on language proficiency is Edo et al. (2019), which, unlike our experiment, focuses on skilled jobs and has job applicants in France signaling language skills by participation in language related activities other than language classes, such as tutoring in French and membership in reading clubs. The results indicate that signal inclusion

[1]There are also Swedish correspondence studies with native applicants only that document higher callback rates for females in female-dominated occupations (Carlsson, 2011; Carlsson and Eriksson, 2019).

reduces discrimination against females with non-French-sounding names, but not against male minorities.

Based on our findings, we conclude that previous experience and completed SFI seem to provide at best a small positive signaling value when refugees apply for low-skilled jobs through formal channels. Effects of low-skilled job experience and language training may, however, be driven by other mechanisms outside our experimental setting, such as better access to informal career paths or personal networks. The fact that females from Middle Eastern and African countries have lower employment rates than males from these regions cannot be explained by females being less likely to be contacted for an interview, according to our experimental data. This indicates that the integration of foreign-born females could be improved if they apply for jobs to a greater extent—and more so than for males.

The remainder of the paper is organized as follows. The next section provides a background on the labor market situation for immigrants in Sweden. The correspondence study, involving newly arrived immigrants from Syria, is presented in Section 3. Section 4 reports the findings from the employer interviews and Section 5 concludes the paper.

2 The immigrant population in Sweden

During recent decades, immigration to Sweden has consisted mainly of refugees and their relatives, most of them originating from countries outside Europe. Of Sweden's total population of somewhat more than 10 million in 2021, around 2 million, or about 20 percent, are foreign born. The foreign-born population has doubled in size during the last 20 years, but Sweden has a fairly long history of immigration and its characteristics have changed over time. (For an overview of Sweden's immigration history, see, e.g., Boguslaw, 2012.) Since the turn of the millennium, immigration from certain countries in the Middle East (Syria and Iraq) and Africa (Somalia) have accounted for most of the migration to Sweden. The increase of people with background in non-European countries has been considerable during the 2000s. In 2000, about 220,000 and 55,000 individuals in the Swedish population were born in Asian and African countries, respectively. In 2021, the corresponding numbers have increased to about 780,000 and 230,000 individuals. The refugee immigration reached historically high levels in 2015 and 2016 when refugee immigration from countries in the Middle East, with Syria and Iraq as the dominating countries, increased as a result of the civil wars in the region. During the peak of what is known as the "refugee crisis" in 2016, more than 70,000 individuals were granted residence permit as refugees in Sweden and an additional 40,000 were granted such permit as "tied movers". Most of the residence permits during 2016 were admitted to refugees from Syria, and around 60 percent to males. Today, Syria is the dominating immigrant country in Sweden and about 200,000 individuals in Sweden are born in Syria. Furthermore, around 150,000 individuals are born in Iraq and 70,000 are born in Somalia.

2.1 Educational attainment

Table 1 shows the educational attainment for the entire immigrant population in Sweden and for immigrants originating from Iraq, Somalia and Syria, respectively, in the age span 25 to 64 years. The foreign-born population are overrepresented among individuals with nine years of compulsory schooling or shorter education. This picture is most pronounced for individuals from Iraq, Somalia and Syria. Among immigrants from Syria and Iraq, around 30 percent had nine years of compulsory schooling or less and the corresponding figure for immigrants from Somalia is over 50 percent. This can be compared to 10 percent in the native-born population. Table 1 also highlights the fact that only 5 percent of the immigrants from Somalia have a university education that is three years or longer. For immigrants from Syria this share amounts to 15 percent. The figures can be compared to 27 percent in the native population.

2.2 Labor market integration

Several studies have documented differences in labor market outcomes between groups of immigrants in Sweden (see, e.g., Aldén and Hammarstedt, 2015, and Calmfors et al., 2018, for an overview). While immigrants originating from countries in Western Europe are doing about as well as natives on the labor market, low employment rates and high rates of unemployment characterize immigrants born in the Middle East and Africa. Table 2 shows the labor market situation for immigrants from the Middle East and Africa and also for immigrants originating from the three major non-European immigrant countries in 2017. Employment rates are considerably lower for immigrants from these regions than for natives, and this pattern is even more pronounced for females. For male immigrants, the employment rate differential to natives ranges between 25 (Iraqis) and 46 percentage points (Syrians), whereas the corresponding interval for females is 35 (Iraqis) to 61 percentage points (Syrians). A similarly bleak picture emerges for unemployment. It should be noted that the figures refer to 2017, i.e., immediately after the "refugee crisis", implying that a large number of immigrants from especially Syria only have been resident in Sweden for a very short time when we observe them in the data. This contributes to the employment rate being much lower and the unemployment rate considerably higher for Syrian immigrants than for immigrants from Iraq and Somalia in this particular year.

Table 1. *Educational attainment, by region of birth, percent, 2016*

	Educational attainment (percent)				
	$\leq$9 years schooling	Upper secondary	University $<$3 years	University $\geq$3 years	Unknown
Born in Sweden	10	47	16	27	0
Foreign born	20	33	14	26	7
Born in:					
—Iraq	29	30	15	22	3
—Somalia	52	29	7	5	7
—Syria	35	22	21	15	6

Notes: The data refer to 25-64-year-olds. *Source:* Statistics Sweden.

Table 2. *Labor market status by region of birth, percent, 2017*

	Sweden	Africa	Middle East	Iraq	Somalia	Syria
(a) Males:						
Employment rate	86.9	60.9	55.9	62.0	57.6	40.6
Share in unemployment	5.5	33.7	39.2	27.0	38.3	68.1
(b) Females:						
Employment rate	85.5	48.8	45.6	50.2	34.7	24.3
Share in unemployment	4.4	31.5	33.6	24.7	41.1	60.5

Notes: The data refer to 25-64-year-olds. The definition of employment is based on annual income taxation records. The cutoff for being classified as employed is based on a model which incorporates taxation records and data from the Swedish Labor Force Surveys for October-November. The method is designed to produce an employment measure that corresponds to the definition of employment according to the International Labour Organization as closely as possible. Unemployment is defined as "total" unemployment, i.e., being registered at the Swedish Public Employment Service as full-time unemployed or participating in any labor market program, including subsidized employment, on the 30th of November. *Source:* Own calculations, based on register data from Statistics Sweden.

2.3 Employment in low-skilled jobs

Approximately one in twenty employees in Sweden work in elementary occupations, which typically do not require more than primary education. These include, i.a., cleaners, restaurant assistants and home care assistants. It can be concluded from Figure 1 that immigrants from Africa and the Middle East are strongly overrepresented in these jobs. This is especially true for males, and for individuals who immigrated recently; despite representing only around five percent of all jobs in Sweden, elementary occupations employ about 40 percent of male immigrant employees in the studied group who immigrated the year before. After four years, the number is still above 25 percent. Even after ten years, the share of employees in elementary occupations is still around three times larger than the share for all workers in Sweden. Our data indicate that elementary occupations are an important gateway to the labor market for newly arrived immigrants from Africa and the Middle East and continue to be of significance long after immigration.

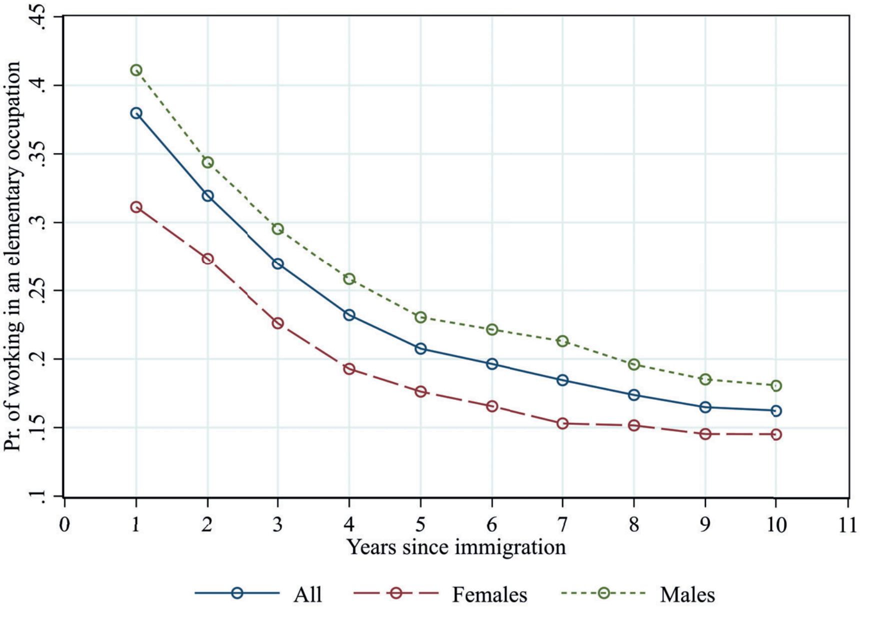
To what extent are low-skilled jobs female dominated? Table 3 reports the percentage of female workers in the largest low-skilled occupations by region of birth. The highest share of female workers is in cleaning and related services and restaurant jobs, where, e.g., three-quarters of native workers are women. Elementary occupations in construction, manufacturing and transportation instead exhibit the lowest overall shares. The female share is notably lower for workers born in Africa and the Middle East than for natives. This is particularly true for restaurant and café assistants, where only around a third of workers from Africa and the Middle East are women.

3 The field experiment

The aim of the experiment is to study the impact of language training and experience from low-skilled jobs for foreign-born persons who apply for low-skilled jobs in the Swedish labor market. Eight fictional job applicants are included in the experiment: Four males and four females, all of whom with unique Arabic-sounding names, born in Syria, 23 years old, single, living in the same suburb of Stockholm, with a high school diploma from their country of origin and with a residence permit granted in 2016. As we noted in the Introduction, a very large number of the refugees who were granted residence permits in Sweden in recent years have a Syrian background.[2] In order to

[2]It is not explicitly stated in the applications that the applicants have been refugees. Strictly speaking, they could have been granted residence permits also as "tied movers" (see Section 2). (Around 24 percent of granted residence permits for Syrians during 2015-16 were for "tied movers" and very few, if any, were for work or studies, according to the Swedish Migration Agency.) The distinction between refugees and "tied movers" is not likely to matter much for employers in our experiment. For simplicity, we use the term "refugees" forthwith to include also migrants for family reasons.

Figure 1. Probability to be in elementary occupation for employees born in Africa and the Middle East, by gender and years since immigration



Notes: The data refer to individuals aged 20 to 64, observed between the years 2000 and 2013. Occupation based on the 1996 version of SSYK. *Source:* Own calculations, based on register data from Statistics Sweden.

Table 3. *Share of females in low-skilled jobs, by occupation and region of birth, 2017*

Occupation	N	Native	Foreign born	Africa	Middle East	Iraq	Somalia	Syria
Cleaning and related services (91)	87,392	75.1	68.6	47.6	38.1	37.9	43.7	34.9
Construction, manufacturing and transport (93)	22,395	20.0	22.4	8.7	12.7	16.5	2.4	8.9
Restaurant and café assistants (94)	59,781	77.9	44.6	29.3	34.7	41.9	34.9	23.2
Other service workers (96)	47,757	30.7	31.5	21.2	26.6	25.8	23.7	22.0
All low-skilled occupations	220,505	54.5	53.2	36.6	33.0	36.6	36.7	24.9

Notes: The data refer to 25-64-year-olds. Elementary occupations, as defined by the International Standard Classification of Occupations, require at most primary education. Occupation based on the 2012 version of SSYK. Each cell reports the percentage of females of all workers by occupation and region of birth. The figures for all low-skilled occupations include the minor occupations “Berry pickers and planters” and “Market salespersons”. *Source:* Own calculations, based on register data from Statistics Sweden.

avoid having job applicants with a long work history, we have chosen them to be relatively young. The experiment was carried out during the period January to December 2019 (i.e., before the Covid-19 pandemic broke out).

3.1 Design of the experiment

All eight job applicants were registered at the Swedish Public Employment Service in August 2016. Four of them signaled work experience by stating employment in a low-skilled job—restaurant assistant in a well-known fast-food restaurant chain (starting in November 2017)—in their applications, while the other four instead continued to be registered at the employment service. Four of the applicants signaled language proficiency by stating that they had completed the entire Swedish for immigrants (SFI) program, while the other four did not mention anything about such training. The applicants were randomly distributed to advertisements for low-skilled jobs. Through this procedure, we thus get the following four types of applicants of each gender:

1. One who has been registered with the Public Employment Service until the time of application and who does not mention anything about completed SFI.
2. One who has been registered with the Public Employment Service until the time of application and who claims to have completed SFI.
3. One who, after being registered with the Public Employment Service, worked in a low-skilled job until the time of application and who does not mention anything about completed SFI.
4. One who, after being registered with the Swedish Public Employment Service, worked in a low-skilled job until the time of application and who claims to have completed SFI.

Our hypothesis is that experience from a low-skilled job and completed SFI should increase the probability that employers respond positively to an application, as these two characteristics should signal higher productivity, relative to continued unemployment and not having completed language training, respectively.

We chose to signal labor market experience by having the applicants refer to a well-known fast food chain since the majority of people in Sweden should understand roughly what tasks are performed and what level of effort is required to carry out a low-skilled job in such a restaurant. Thus, the employer should relatively easily be able to infer the value of such experience for the advertised job at hand.

The purpose of the SFI education, which is the responsibility of municipalities and is free of charge, is to provide basic proficiency in the Swedish language to adult immigrants (Swedish National Agency for Education, 2018). SFI is structured in three different paths depending on the individual student's prior general skill level. Within each path, students can advance to courses with a gradually higher degree of difficulty (courses A to D for path 1, B to D for path 2 and C to D for path 3), but with the same knowledge requirements regardless of the path. The courses deal with listening and reading comprehension, oral proficiency and writing skills. While courses A and B focus on informal language in everyday situations, courses C and D also teach students more formal language used in workplaces, educational institutions and the wider community. SFI can be vocationally oriented, with courses sandwiched with practical work, but it seems that only a minority of students—data at the national level are not available—get access to these vocational orientations (Swedish Schools Inspectorate, 2010).

Although SFI is a compulsory part of the Establishment program (*etableringsprogrammet*) that certain refugee immigrants are supposed to participate in, a substantial share do not complete the training.[3] During the period 2014–18, only between 35 and 37 percent of the participants completed the SFI courses, according to statistics published by the Swedish National Agency for Education. Participants drop out for various reasons, not necessarily detrimental to the individual. Some may have found a job, while others may have entered other types of education, moved to another part of Sweden or returned to their home country. Notwithstanding, it seems plausible that an explicit reference to having actually completed the language training can be perceived as a positive signal regarding language proficiency by the employers.

Employers responded to applications via email or phone message. We distinguish between two types of callback: (i) Invitation to an interview or request for more information about the applicant (than what appears from the cover letters and attached resumés), and; (ii) Invitation to an interview. As expected, no employers responded with direct job offers, so no such callbacks are categorized. To minimize the inconvenience for employers, we promptly declined any callback offers. In line with other correspondence studies, we interpret requests for more information from the applicant as a positive signal from the employer, even if it does not lead to an interview or a job offer.

The application letters were designed to be simple and rather short, but were written in grammatically correct Swedish without spelling mistakes. We decided not to signal language proficiency by variations in how correct the language in the application letters was. Arguably, this signal can be weak, for several reasons. First, checks for grammatical and spelling errors are integral parts of most word processing programs. Second, templates of correctly formulated applications are readily available on the Internet. Finally, relatives and friends with good language skills may assist in the formulation of the applications. As we show in Section 4, employers seem well aware of these possibilities, implying that they are inclined not to draw strong conclusions

[3]The Establishment program is organized by the Public Employment Service and consists of support in the form of activities and education, directed to newly arrived refugee immigrants aged 20–64 with residence permits.

regarding language proficiency from an application in correct Swedish until they have talked to the applicant in person. There are also other concerns with varying the quality of the language in the application letters. Such variation may, apart from language proficiency, signal other personal characteristics like ambition and conscientiousness, making the interpretation of any effects on callback complicated. Focusing on language training only is arguably also more policy relevant.

An example of an application with cover letter and resumé, translated to English, is shown in Appendix. The brief letters may also have motivated some employers to request additional information instead of forthwith inviting the applicant for an interview.

The eight applicants were randomly assigned to low-skilled job openings across the country, which were advertised on the Swedish Public Employment Service's portal *Platsbanken*. We selected five occupations at the lowest skill level (i.e., elementary occupations) according to the Swedish Standard Classification of Occupations (SSYK): Restaurant/café assistant, cleaner, newspaper/leaflet deliverer, home care assistant and hand packer. At this skill level, these occupations are among the most common among foreign-born, according to Statistics Sweden. These occupations are also characterized by lower language requirements than more skilled occupations (Ek et al., 2020).

Advertised jobs were not applied for if qualifications were explicitly required that were not clear in all applications (for example, previous work experience, good knowledge of Swedish or other languages, special training, driving license or local knowledge) or if information about applicants were requested that we could not provide (for example, social security number or photo). We also excluded jobs advertised by staffing firms, as we lack the necessary information about the client firm in which the employee will work. In addition, we excluded jobs in the fast-food chain at which some of the fictitious applicants were already employed.

It turned out that many jobs in three of the occupations—newspaper/leaflet deliverer, home care assistant and hand packer—could not be applied for, to a large extent for the reasons stated above, and they were also relatively few in number. Consequently, almost all applications concerned jobs as restaurant/café assistants or cleaners. However, these occupations account for a very large proportion of the low-skilled jobs among foreign born, 86 percent for males and 61 percent for females in 2017 (Ek et al., 2020). In practice, the restrictions also meant that only jobs in the private sector could be applied for, as social security numbers are requested in job advertisements in the public sector.

The experiment was registered with the *American Economic Association's* registry for randomized controlled trials before performing any analyses using the collected data, which means that we specified in advance the regressions to be estimated and for which groups. We also performed some power calculations (to be discussed in Section 3.4), although the sample size was not determined by these, but rather by a predetermined start and end date of the trial. Moreover, we submitted the experimental design in advance to *Etikprövningsnämnden* (the Ethics Review Board) in Stockholm for ethical approval, which is standard procedure for research projects involving experimental subjects in Sweden. They decided that no ethical review was necessary.

In total, we sent out 2,184 applications. For 1,958 of these, we were able to determine the geographical location (municipality) of the job and whether the advertisements referred to an open-ended or fixed-term contract and/or a full-time or part-time job and in the analyses below we only include these observations.[4]

3.2 Descriptive results

Table 4 displays descriptive statistics for the variables included in our analysis. A first observation is that the callback rates were low: 3.9 percent for interview or more information and 1.4 percent for interview. However, the callback rates are fairly similar to those for non-European immigrants in other Swedish correspondence studies, although these results are not strictly comparable.[5] Furthermore, 63.3 (44.5) percent of the jobs were open-ended contracts (full-time), whereas the corresponding figure for the labor market as a whole is 83.4 (78.5) percent, according to Statistics Sweden. The jobs in the experiment are thus not only low-skilled, employment contracts are also atypical to a greater extent than is the case for the labor market as a whole. Some jobs could only be applied for via the employer's own web portal, and not by email. However, only 9 percent of applications were made through such online forms.

Table 5 reports balancing checks, where the characteristics of the job vacancies are related to those of the fictitious applicants. Since applicants are randomly assigned to each vacancy, there should be no systematic differences in job characteristics across them. We include indicators for open-ended and full-time contracts, if jobs were applied to via online forms, if the job was as a cleaner or restaurant assistant, if the job was located in the Stockholm local labor market area, and the distance from job to home. The upper part of the table reports averages for each of the eight applicants, while the lower part shows coefficients and standard errors from regressing the job character-

[4]The qualitative results regarding the randomized variables (SFI completion, experience and gender) are not affected by this choice, and the regression estimates are very similar when instead using all 2,184 observations and not including controls for job characteristics.

[5]There is no previous Swedish study that is fully comparable to ours, in terms of applicant groups and types of jobs. Some of the results in Carlsson (2010) and Vernby and Dancygier (2019) come closest. The former study reports a callback rate of 7 percent for persons born in the Middle East applying for low-skilled jobs in the restaurant sector. In the latter study, callback rates for Iraqi- and Somali-born turn out to be 10 and 5 percent, respectively, but the restaurant and café jobs applied for include not only low-skilled ones, as in our study, but also higher-skilled jobs.

Table 4. *Descriptive statistics for the experiment*

	Mean	Standard deviation
(a) Type of callback:		
Interview/more information	0.039	0.194
Interview	0.014	0.117
(b) Characteristics of job applicants:		
Completed language training (SFI)	0.508	0.500
Experience as restaurant assistant	0.500	0.500
Female	0.508	0.500
(c) Characteristics of jobs applied for:		
Open-ended contract	0.633	0.482
Full-time schedule	0.445	0.497
Online form	0.089	0.285
Distance to job from home	284.0	249.3
Stockholm area market	0.369	0.483
Hand packer	0.006	0.078
Home care assistant	0.002	0.045
Restaurant/café assistant	0.697	0.460
Cleaner	0.291	0.454
Newspaper/leaflet deliverer	0.004	0.060

Notes: 1,958 observations. Distance is in kilometers between the residential municipality and the municipality in which the job is located, as indicated by Google Maps.

istics onto indicators for having previous labor market experience, completed language training, and for being female, separately for each outcome and explanatory variable. Overall, the treatment is balanced over job characteristics. The only exception is that applicants with previous experience are four percentage points less likely to apply for jobs as restaurant assistants, with an average probability of just below 70 percent, which is mirrored in the higher probability of applying to jobs as cleaners.

Figure 2 shows the callback rates in our experiment by gender and type of job applicant, together with 95 percent confidence intervals, for the broad definition of callback (interview or request for more information), while Figure 3 shows corresponding rates for the narrow definition (interview).[6] The callback rate for females (around six percent) is three times as large as for male applicants (two percent). Within genders, there are no apparent differences across types, suggesting no large returns in the form of higher callback rates for applicants with completed language training, work experience or with both of these qualifications, relative to those with neither of them.

3.3 Econometric framework

The econometric analysis is based on linear probability models estimated with OLS. As the main dependent variable, we use an indicator variable for if there was a callback from the employer, either regarding invitation to an interview or a request for more information. We will also conduct analyses with just invitation to an interview as the dependent variable.

In the econometric analysis, our basic model is represented by the following equation:

$$y_i = \beta_0 + \beta_1 \times SFI_i + \beta_2 \times EXP_i + \beta_3 \times FEMALE_i + \boldsymbol{\gamma}'\boldsymbol{X}_i + \varepsilon_i, \qquad (2)$$

where y is the outcome of interest, *SFI* is an indicator for whether the applicant successfully finished language training, *EXP* is an indicator for whether the job applicant has experience from a low-skilled occupation, *FEMALE* is an indicator for female applicants, and ε is the error term. Job applications are indexed by i. Although not necessary for identification, the model also includes a vector of additional, non-randomized controls, $\boldsymbol{X}$, which comprises indicator variables for whether the employment contract is open-ended or fixed-term, for whether the job is full-time or part-time, the distance from job to home, using data from Google Maps and scaled to lie between 0 and 1, as well as indicator variables for the occupations. As hand packers, home care assistants and newspaper/leaflet deliverers accounted for very few observations, these occupations have been merged into a single category, "Other occupations".

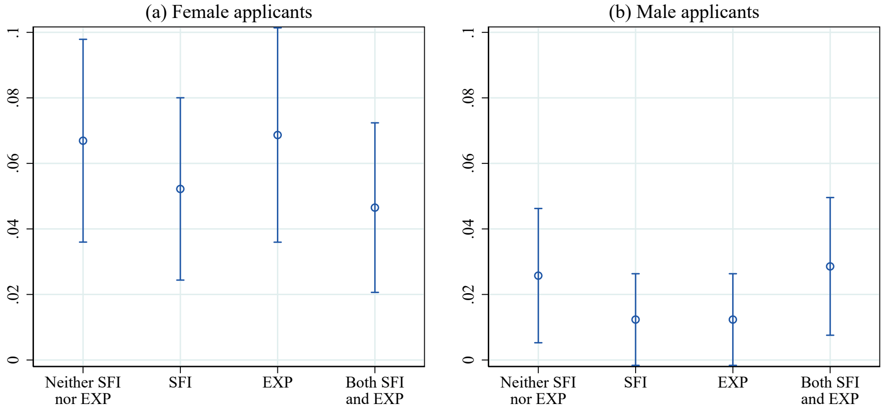
[6]This is equivalent to estimating a fully saturated, non-parametric model of callback for each of the eight applicants.

Table 5. *Characteristics of vacancies, by applicant type*

	(1) Open-ended	(2) Full-time	(3) Online form	(4) Cleaner	(5) Restaurant ass.	(6) Stockholm	(7) Distance to job
(a) Applicants:							
Male	0.631	0.416	0.077	0.266	0.717	0.348	301
Male with language training (SFI)	0.617	0.424	0.074	0.288	0.700	0.329	300
Male with experience as restaurant assistant	0.658	0.440	0.115	0.272	0.720	0.395	263
Male with SFI and experience	0.669	0.429	0.118	0.294	0.682	0.376	276
Female	0.606	0.469	0.095	0.276	0.720	0.331	297
Female with language training (SFI)	0.639	0.430	0.100	0.265	0.731	0.430	257
Female with experience as restaurant assistant	0.627	0.464	0.047	0.326	0.652	0.356	299
Female with SFI and experience	0.620	0.488	0.081	0.341	0.655	0.388	279
(b) Estimated effect of:							
Female	-0.021	0.035	-0.015	0.022	-0.014	0.014	-2.242
	(0.022)	(0.022)	(0.013)	(0.021)	(0.021)	(0.022)	(11.272)
EXP	0.020	0.020	0.004	0.035*	-0.040*	0.019	-9.376
	(0.022)	(0.022)	(0.013)	(0.021)	(0.021)	(0.022)	(11.267)
SFI	0.006	-0.004	0.009	0.013	-0.012	0.024	-12.392
	(0.022)	(0.022)	(0.013)	(0.021)	(0.021)	(0.022)	(11.264)

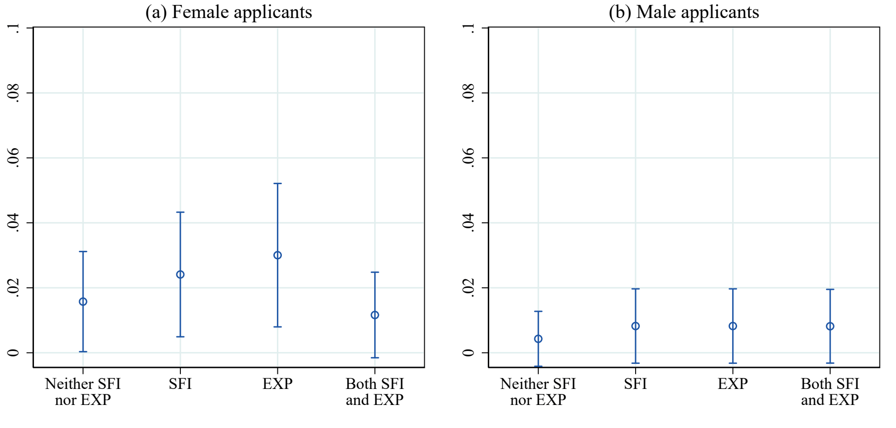
Notes: The upper part of the table reports average job characteristics of the applications sent from the eight applicants, while the lower part shows estimates from separately regressing the job characteristics onto the characteristics of the applicants. Distance is in kilometers between the residential municipality and the municipality in which the job is located, as indicated by Google Maps. Robust standard errors in parentheses. * indicates statistical significance at the 10-percent level.

Figure 2. Callback rates for broad definition of callback, by gender and type of job applicant



Notes: Callback refers to invitation to an interview from the employer or enquiry for more information about the applicant. SFI and EXP stands for completed education in Swedish for immigrants and experience as restaurant assistant, respectively. 994 observations for female applicants and 964 for male. 95 percent confidence intervals.

Figure 3. Callback rates for narrow definition of callback, by gender and type of job applicant



Notes: Callback refers to invitation to an interview from the employer. SFI and EXP stands for completed education in Swedish for immigrants and experience as restaurant assistant, respectively. 994 observations for female applicants and 964 for male. 95 percent confidence intervals.

In alternative specifications, we add an interaction between *SFI* and *EXP* to the model above, in order to capture heterogeneous effects for different combinations of qualifications. Later on, we also examine if there are heterogeneous effects with regard to gender, occupation, the region in which the job is located, and mode of application, i.e., whether the job could be applied for by email or only by using the employer's own web portal.

3.4 Econometric results

In the registered analysis plan, our point of departure for the power calculations was a sample of 3,000 applications, a callback rate of 5 percent and a 5 percent significance level, implying that we can detect an effect of about 2.5 percentage points with an 80 percent probability (the standard power level used in experimental studies). The actual number of observations in our study turned out to be lower (2,184).[7] The actual callback rate for all applicants was slightly below 4 percent (for interview or more information). With that as the correct underlying baseline, the real effect of any intervention would need to be around 2.6 percentage points in order for us to reject with 80 percent probability the null hypothesis that there is no effect of, for example, completed SFI.

The first set of regressions, for all job applicants and both definitions of callback, is shown in Table 6, while Table 7 reports regressions by gender, using the broader response measure only. Neither *SFI* nor *EXP* contributes significantly to higher (or lower) callback rates and this is true also for the interaction *SFI* $\times$ *EXP*, although the latter is borderline significant in the sample with male job applicants. In some of the regressions, the estimated effects are even negative, but they are never significant. The only variable that seems to systematically affect callback rates is the applicant's gender: Females are about 3.8 percentage points more likely than males to be asked for an interview or for more information. The difference is 1.3 percentage points for the narrower measure of invitation to an interview. Relatively speaking, the gender difference is very large; the probability of being invited to an interview or asked for more information increases by approximately 190 percent if the applicant is female instead of male, while the corresponding increase for invitation to an interview amounts to around 180 percent.[8] The higher callback rate for females is also consistent with our finding in the employer interviews

[7] Basically all jobs were applied for that appeared on *Platsbanken* during the period of study and fulfilled our selection criteria.

[8] To obtain the relative effects, we divide the estimated coefficient for the *FEMALE* indicator by the average probability of receiving a callback for male applicants. The average callback rate for invitation to an interview or request for more information was 2.0 percent for males and 5.8 percent for females, while the corresponding rate for invitation to interview was 0.7 and 2.0 percent, respectively.

that some employers prefer hiring females over males in the low-skilled jobs we study (see Section 4).

With all applicants included and without interaction between *SFI* and *EXP*, the confidence interval for *SFI* ranges from -0.027 to 0.009, while that for *EXP* is between -0.018 and 0.018. Since the overall callback is only 4 percent, we cannot rule out sizeable relative effects. In absolute terms, however, the effects appear small; based on the upper bound of the confidence intervals, when signaling experience one would receive at most one additional positive callback per $\frac{1}{0.018} \approx 56$ applications and when signaling *SFI* the corresponding number is $\frac{1}{0.009} \approx 111$. With separate regressions by gender and with interaction effects the confidence intervals become even larger, since we are then in effect comparing either four or eight groups.

What about the control variables in the regressions? It should be noted that job characteristics were not randomized in the experiment, so it is not possible to interpret our findings for these variables in causal terms out of hand. If the advertisement refers to an open-ended contract, the callback rate for the more broadly defined response decreases by 1.9 percentage points, but the coefficient is close to zero for the interview alone. The fact that jobs with open-ended contracts are associated with lower callback rates may reflect that these positions are more attractive to apply for, but employers may also become more demanding when recruiting to such jobs as costs of dismissal are substantially higher. The mode of application could reflect unobserved employer characteristics correlated with callback rates, such as size, the number of expected applicants and the resources devoted to the screening of applicants. However, neither for full-time jobs nor online forms do we see a relationship with callback. While full-time jobs may also be more attractive to apply for, they are not associated with higher dismissal costs than part-time positions. Since all applicants resided in the Stockholm area but applied for jobs all over the country, we examine whether geographical distance affects callback rates. For example, the low callback rates in general may reflect that many jobs (over 60 percent) were located outside of Stockholm. The distance variable is rescaled to run between 0 and 1, so the coefficient can be interpreted as the difference between applying for jobs in the residential municipality and the municipality farthest from this municipality. We find a negative effect of the distance variable, but it is significant only for the narrow definition of callback. Employers may be reluctant to directly invite faraway applicants to interviews for low-skilled jobs, out of misgivings that the applicants are not genuinely interested in the position (see Section 4, where this matter is discussed in more detail).

Examination of heterogeneous effects with regard to independent variables is rendered somewhat problematic because of low power, but outlines of such analyses were part of our pre-registration plan and the results are provided in

Table 6. *Callback regressions, by type of response*

	(1)	(2)	(3)	(4)
	Interview/more information		Interview	
Language training (SFI)	-0.009	-0.014	-0.002	0.006
	(0.009)	(0.012)	(0.005)	(0.007)
Experience as restaurant assistant	-0.000	-0.006	0.001	0.009
	(0.009)	(0.013)	(0.005)	(0.008)
SFI × Experience		0.012		-0.015
		(0.018)		(0.011)
Female	0.038***	0.038***	0.013**	0.013**
	(0.009)	(0.009)	(0.005)	(0.005)
Open-ended	-0.019*	-0.019*	-0.006	-0.006
	(0.010)	(0.010)	(0.006)	(0.006)
Full-time	-0.010	-0.011	-0.008	-0.008
	(0.009)	(0.009)	(0.005)	(0.005)
Online form	-0.010	-0.010	0.010	0.011
	(0.016)	(0.016)	(0.012)	(0.012)
Scaled distance to job from home	-0.022	-0.022	-0.034***	-0.034***
	(0.021)	(0.021)	(0.012)	(0.012)
Cleaner	-0.006	-0.006	0.015**	0.015**
	(0.043)	(0.044)	(0.006)	(0.006)
Restaurant/café assistant	-0.010	-0.010	0.015***	0.015***
	(0.043)	(0.043)	(0.005)	(0.006)
Constant	0.056	0.059	0.007	0.003
	(0.044)	(0.044)	(0.007)	(0.007)
Number of observations	1,958	1,958	1,958	1,958
R^2	0.014	0.015	0.009	0.010

Notes: The regression models are estimated with OLS. The reference category for the occupations is Other occupations (hand packers, home care assistants and newspaper/leaflet deliverers). Robust standard errors in parentheses. *, ** and *** indicate statistical significance at the 10-, 5- and 1-percent level, respectively.

Table 7. *Callback regressions for broad definition of callback, by gender*

	(1)	(2)	(3)	(4)
	Female applicants		Male applicants	
Language training (SFI)	-0.018	-0.015	0.002	-0.014
	(0.015)	(0.021)	(0.009)	(0.013)
Experience as restaurant assistant	-0.003	0.000	0.002	-0.013
	(0.015)	(0.023)	(0.009)	(0.013)
SFI × Experience		-0.006		0.031*
		(0.030)		(0.018)
Open-ended	-0.027	-0.027	-0.012	-0.012
	(0.017)	(0.017)	(0.011)	(0.011)
Full-time	-0.013	-0.013	-0.009	-0.008
	(0.015)	(0.015)	(0.010)	(0.010)
Online form	-0.008	-0.008	-0.012	-0.012
	(0.031)	(0.031)	(0.013)	(0.013)
Scaled distance to job from home	-0.019	-0.018	-0.028	-0.028
	(0.038)	(0.038)	(0.020)	(0.020)
Cleaner	-0.058	-0.057	0.017*	0.020*
	(0.118)	(0.118)	(0.009)	(0.010)
Restaurant/café assistant	-0.070	-0.069	0.022***	0.025***
	(0.118)	(0.118)	(0.007)	(0.008)
Constant	0.162	0.160	0.016	0.022
	(0.120)	(0.120)	(0.014)	(0.015)
Number of observations	994	994	964	964
R^2	0.008	0.008	0.005	0.008

Notes: The regression models are estimated with OLS. The reference category for the occupations is Other occupations (hand packers, home care assistants and newspaper/leaflet deliverers). Robust standard errors in parentheses. *, ** and *** indicate statistical significance at the 10-, 5- and 1-percent level, respectively.

Table 8. All regressions use the broader measure of callback as the dependent variable.

Separate regressions for cleaners and restaurant/café assistants reveal no sizeable positive effects from signaling SFI or experience for any occupation. The coefficient for *SFI* is significantly negative for the latter group. (Given the large number of estimates in the table, we are of course likely to find some significant effects just by chance.) Surprisingly, we find no positive effect of non-trivial magnitude on callback from signaling previous experience as a restaurant/café assistant even when such jobs were applied for.

We have examined heterogeneity relating to geographical distance in two ways. First, we have added interactions between the measure of the traveling distance between job and home and the *SFI*, *EXP* and *FEMALE* indicators. Second, we estimate separate models for job postings inside and outside the Stockholm local labor market as well as a joint model where the randomized explanatory variables are interacted with an indicator for if the job was located in Stockholm. However, we find no relationship between, on the one hand, the traveling distance from the residential municipality and whether the jobs are in Stockholm and, on the other hand, effect sizes for the randomized variables. Furthermore, we find no difference in the returns from signaling completed SFI or experience with respect to the mode of application, but there is a negative effect of the distance variable when only online forms were used.

Finally, in unreported regressions (available on request from the authors) we investigated whether the month of application during the year-long experiment and repeat applications to the same employer matter. The month of application reflects pure calendar effects, on the one hand, as well as effects stemming from the fact that both length of previous experience and duration of unemployment increases over time, on the other hand. It is not possible to distinguish between the two effects with our data. We divided the sample according to month of application and estimated the regressions corresponding to Table 6, column 1, separately for each month. We see no clear trends in the estimates for *SFI* or *EXP*, but there is a weak tendency for the estimates for females to be somewhat smaller in the second half-year. Moreover, it turned out that many employers received more than one application—38 percent of all applications were made to an employer whose name and/or contact details appear multiple times in our sample. However, a large number of these occurrences were due to applications being sent to jobs at large chains/firms with multiple establishments across the country, hiring locally. Only about half of the occurrences (21 percent) in our main sample were associated with an email address that appears multiple times. These were often addresses used specifically for recruitment purposes. Although the applications were for different job postings and over the course of a year, it is conceivable that these firms discovered that an experiment was going on and consequently differ from other firms in their response. However, separate regressions, corresponding to Table 6, columns 1-2, for applications to employers who received only one application throughout the experiment show only small differences to the regressions using the full sample in the estimates for *SFI*, *EXP* and *FEMALE*.

4 The employer interviews

After the field experiment was completed, we conducted interviews with employers with extensive experience of handling and judging applications for low-skilled jobs from persons of non-European origin. The purpose of the interviews was to shed additional light on what employers look for in such applications and how these are typically written. Contact information to suitable employers was provided by two Swedish employer associations, *Visita* and *Almega*. The former consists of firms in the hospitality industry and the latter directs itself to various other service industries, including cleaning firms.

In total, we contacted ten employers, five of whom did not respond or declined to participate. We carried out interviews with four employers from the hospitality industry and one cleaning firm. These were conducted via Zoom and recorded (with the consent of the interviewees) and lasted between 30 minutes and one hour. After the Zoom interviews, some follow-up questions were communicated via email. All the respondents were directly involved in recruitment, either as owners of the firms, chief operating officers or heads of human resources departments. The participating firms were located in different geographical areas of Sweden and of different size in terms of the number of employees: One small firm (49 employees or less), two medium-sized firms (50–249 employees) and two large firms (250 employees or more).

Before the interviews, the respondents were informed about the purpose of the interviews and that the identity of the firms would not be revealed. The interviews were semi-structured, and based on a questionnaire (that the respondents were given access to in advance), but allowing for follow-up questions depending on the answers given.

The number of interviews is small and the employers were not chosen randomly, implying that the evidence we collected should be regarded as suggestive in nature. Our respondents were, however, quite unanimous in several important respects.

All firms except one (a former user) reported that they use the web portal of the Public Employment Service, *Platsbanken*, as the main recruitment channel. Some interviewees also use social media, e.g., Facebook and LinkedIn, or the firm's own website. The type of low-skilled jobs our respondents advertise include restaurant assistants, cleaners and, in one firm, janitors/park-tenders.

All of the employers stated that they receive many applications for low-skilled jobs: From 30–40 applications for a single position in one firm up to 1,500 applications for a couple of hundred positions in another firm. Handling such large amounts of applications obviously require a great deal of resources on part of the firms. Some employers argued that the task is made more diffi-

Table 8. *Robustness regressions for broad definition of callback*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Stockholm vs. other local labor market				Heterogeneous effects by occupation			Applications via online forms		
	Distance interaction	Stockholm interaction	Stockholm only	Other only	Rest. ass. interaction	Rest. ass. only	Cleaners only	Online form interaction	Other applications	Online forms
Language training (SFI)	-0.015	-0.008	-0.007	-0.007	0.021	-0.021**	0.027	-0.011	-0.011	0.013
	(0.013)	(0.011)	(0.014)	(0.011)	(0.016)	(0.010)	(0.017)	(0.009)	(0.009)	(0.027)
Experience as restaurant assistant	-0.001	0.001	-0.003	0.001	-0.005	0.001	-0.008	-0.003	-0.003	0.029
	(0.013)	(0.011)	(0.014)	(0.011)	(0.016)	(0.010)	(0.018)	(0.009)	(0.009)	(0.029)
Female	0.034**	0.045***	0.030**	0.045***	0.055***	0.032***	0.052***	0.037***	0.037***	0.072**
	(0.013)	(0.011)	(0.014)	(0.011)	(0.016)	(0.010)	(0.017)	(0.009)	(0.009)	(0.033)
Open-ended	-0.019*	-0.018*	-0.042*	-0.008	-0.019*	-0.014	-0.034*	-0.019*	-0.022**	0.014
	(0.010)	(0.010)	(0.022)	(0.012)	(0.010)	(0.012)	(0.019)	(0.010)	(0.011)	(0.027)
Full-time	-0.010	-0.010	0.003	-0.012	-0.011	-0.006	-0.016	-0.011	-0.009	-0.014
	(0.009)	(0.009)	(0.014)	(0.012)	(0.009)	(0.010)	(0.019)	(0.009)	(0.010)	(0.028)
Online form	-0.010	-0.011	0.047	-0.026*	-0.012	0.004	-0.031	-0.049**		
	(0.016)	(0.016)	(0.047)	(0.015)	(0.016)	(0.022)	(0.024)	(0.023)		
Scaled distance to job from home	-0.049	-0.053	0.728	-0.060*	-0.018	-0.028	0.004	-0.022	-0.006	-0.184**
	(0.043)	(0.037)	(0.504)	(0.035)	(0.022)	(0.023)	(0.045)	(0.021)	(0.022)	(0.080)
Cleaner	-0.006	-0.006	0.065**	-0.019	-0.011			-0.006	-0.024	0.029
	(0.041)	(0.041)	(0.031)	(0.056)	(0.041)			(0.044)	(0.065)	(0.028)
Restaurant/café assistant	-0.011	-0.010	0.068**	-0.030	0.015			-0.010	-0.030	0.045*
	(0.041)	(0.041)	(0.030)	(0.056)	(0.044)			(0.043)	(0.064)	(0.024)
Stockholm area		-0.005								
		(0.022)								
SFI interaction	0.029	-0.001			-0.042**			0.021		
	(0.044)	(0.018)			(0.019)			(0.028)		
EXP interaction	0.003	-0.005			0.007			0.037		
	(0.044)	(0.018)			(0.019)			(0.031)		
Female interaction	0.022	-0.017			-0.023			0.020		
	(0.044)	(0.018)			(0.019)			(0.032)		
Number of observations	1,958	1,958	723	1,235	1,958	1,365	570	1,958	1,784	174
R^2	0.015	0.015	0.025	0.019	0.018	0.013	0.030	0.015	0.015	0.078

Notes: The table reports the results of variations of the regression model reported in the first column of Table 6, estimated by OLS. In column (1), we add interactions between the distance between the residential municipality and the municipality in which the job is located and language training, work experience and female indicators (henceforth the randomized indicators). The distance measure is rescaled to run between 0 and 1. Column (2) adds interactions between an indicator for if a job is located in the Stockholm area and the randomized indicators. Column (3) and (4) only include jobs located in and outside the Stockholm area, respectively. Column (5) interacts the randomized indicators with an indicator for if the job is as a restaurant assistant. Column (6) and (7) only include jobs as restaurant assistants and cleaners, respectively. In column (8), the randomized indicators are interacted with an indicator for if the job was applied to via a web portal instead of by sending a letter and a resumé via email. Column (9) excludes all applications made via web portals, while Column (10) only includes such applications. The reference category for the occupations is Other occupations (hand packers, home care assistants and newspaper/leaflet deliverers). Robust standard errors in parentheses. *, ** and *** indicate statistical significance at the 10-, 5- and 1-percent level, respectively.

cult by the perception that some applications are not seriously intended, only serving as a means to fulfill requirements for unemployment benefits or activity support, i.e., monetary compensation for those participating in active labor market programs, sometimes resulting in no-shows for job interviews. These difficulties were also the reason why the former user of *Platsbanken* stopped using it entirely.

A clear majority of the applications for low-skilled jobs come from persons with perceived origin in non-European countries, according to all but one of our respondents. Estimated shares range between 50 and 90 percent. Regarding the share of applications from females, responses were more dispersed, between 20 and 80 percent. Three of the firms were of the opinion that there are no important differences in job performance between females and males, but two respondents regarded females as being more conscientious and adaptive. One of these respondents, with only 20 percent of the applications from females, would like to see the share of females in the firm increase. This respondent also claimed that females are more meticulous than males in cleaning jobs, and that this possibly reflects habits from their home countries, where females traditionally assume full responsibility for household chores.

Two respondents reported that, on average, there are differences in social skills between females and males. One of them stated that women can be relatively quiet and unobtrusive, in line with traditional gender roles. Another respondent was of the opinion that males connect faster to co-workers than females.

Without exception, the firms reported that job applications from non-Europeans tend to be very short and simple, containing only basic information. A length of six to seven sentences in the cover letter is typical for persons from Africa and the Middle East and some applicants do not even include a letter, only the resumé. Some applications are more standardized and formal than others, and appear to be written using templates, from SFI or the Internet, or with the assistance of a job coach from the Public Employment Service. While our respondents informed us that grammatical and spelling errors are common in the application letters, not much emphasis seems to be put on this in the screening process.

Most of the firms did not regard completed SFI as important. A common view was that proficiency in Swedish varies a great deal among those who have completed SFI, implying that the language skills signal is rather weak. The best way to assess language proficiency is to meet the applicant in person. One interviewee claimed that the quality of SFI is not always first-rate and that there are other ways to learn Swedish. Another one mentioned that many positions do not require advanced knowledge of Swedish. A third respondent observed that completed SFI does not necessarily imply good communication skills—some employees with fluency in Swedish do worse when it comes to communicating with co-workers and customers, while some employees lacking in language skills are better at this. One respondent, however, had a more positive attitude toward the merit of completing SFI and argued that it shows dedication to and ability for learning. There is little to suggest that the responses were due to the interviewees being completely ignorant about SFI or lacking in interest; two employers had personal experience of SFI, as a visitor to language classes and co-arranger of vocationally oriented SFI, respectively. The extent to which our respondents put emphasis on proficiency in Swedish seems to vary with occupation. For jobs requiring direct contact with customers basic knowledge of Swedish is seen as quite important, while other jobs are less demanding in this respect (but some proficiency in English, at least, is desirable).

Regarding the value attributed to previous labor market experience in Sweden, opinions differed. Three of the firms do not attach much importance to this when recruiting, be it from the same type of job as the vacant position or not and regardless of length. One respondent emphasized the importance of on-the-job training. Under supervision from an experienced co-worker, it is possible to learn the job from scratch within a couple of weeks. Another interviewee noted that many positions in the firm pertain to summer or weekend jobs, which typically are applied for by new entrants in the labor market. Fostering an employee into a valuable member of a working team is not dependent on previous experience, according to a third respondent. For instance, in his/her firm, some of the restaurant staff are former carpenters. Two respondents reported that at least some labor market experience is valuable, but not necessarily from the same occupation as the one advertised.

Overall, our respondents regarded personal traits and attitudes—something that they try to figure out from the application letters but is better assessed during a job interview—as more important than formal qualifications. Being motivated, service minded, conscientious, interested in a long-term employment relationship with the firm, and able to fit in with the workplace culture, are characteristics highly sought after by employers in our survey.

Although strong conclusions cannot be drawn from our small survey, the findings do lend support to our simple design of the application letters in the field experiment. They also contribute to the understanding of the reasons behind the low callback rates in general, why they were higher for females than males, and why applicants with completed SFI and previous experience did not receive more callbacks than applicants without these qualifications. Our findings suggest that employers hiring applicants from the Middle East and Africa in low-skilled jobs view SFI and experience as weak signals of productivity. When judging such applicants, employers seem to have a functional approach, considering the requirements of the task at hand and the potential for a long-term relationship rather than formal qualifications.

5 Conclusions

Using a correspondence test, we have investigated the impact of completed language training in Swedish (SFI) and experience from low-skilled jobs for recently arrived foreign-born job applicants in the Swedish labor market. Applications were sent from fictitious Syrian refugees with different language skills and previous work experiences to employers advertising low-skilled job vacancies. We are unable to demonstrate large positive effects of SFI or previous experience on callback rates. However, female job applicants were significantly more likely than male applicants to receive callback from employers. We have complemented the correspondence study with interviews with a select number of employers, in order to shed light on potential mechanisms behind our experimental results.

A review of previous research indicates that initial labor market experience is associated with improved long-term labor market outcomes for foreign-born individuals. Language proficiency also seems to be related to better prospects in the labor market for immigrants according to the literature. But employers in our experiment did not pay all that much attention to whether or not a job applicant has completed language training in Swedish or have any previous work experience. Neither completed SFI nor a low-skilled job thus seems to provide any significant positive signaling value when refugees from Syria apply for low-skilled jobs through formal channels. One interpretation of these findings is that the positive effects suggested in the literature of these qualifications are driven by other mechanisms than signaling, which are not possible to account for in our experimental setting, such as better access to informal career paths, information, human capital accumulation, or improved professional networks. The respondents in our employer interviews reported that they regard the link between completed SFI and language proficiency as being rather weak and that applicants' personal traits, like motivation and conscientiousness, are more important than previous experience. Applications for low-skilled jobs are typically very short and simple, according to our respondents, and more information about the personal characteristics that employers are looking for could contribute to higher callback rates.

The observation (in Section 2) that females from Middle Eastern and African countries exhibit lower employment rates compared to men from these regions does not seem to be explained by females being less likely to be contacted for an interview. The two most important occupations in our experiment, restaurant assistant and cleaner, are dominated by females and there are also other correspondence studies that find that females have a higher callback rate than males in female-dominated occupations, as discussed in the Introduction. The interviews revealed that some employers regard females as more conscientious and adaptable than males. Disregarding any general equilibrium effects and differences in selection into employment for males and females, our results indicate that the integration of foreign-born females would be improved if they to a greater extent apply for jobs.

As is usual in correspondence studies, a number of caveats are in order. It should be emphasized that we do not test the effect of language skills per se, but the signal from completed language training. It is not obvious how employers interpret the formulation that the job applicant has completed "the entire SFI program" in terms of language skills, as employers may be ill-informed about the contents and structure of SFI (although the employer interviews showed that some of them were practically involved in the program). We cannot distinguish between effects due to ignorance or misconceptions regarding SFI on part of employers and effects based on actual knowledge. Moreover, given previous experience, completed formal language training may not be seen as a large additional advantage. It is also conceivable that SFI has no positive effect on the callback rate if an explicit reference to such training reminds the employer that the applicant belongs to a group with a perceived low productivity (foreign born) or if the employer is reminded of a training to which he or she is skeptical, even if completed by the applicant. This skepticism may be due to the requirements or quality in SFI perceived as being too low.

The fact that unemployment is assigned such a small role by employers in our study may be related to the fact that the group we examine has a generally low employment rate. For the group we are investigating, it may be that the work experience is considered to be too short (between 14 and 25 months, depending on time of application) or not sufficiently qualified. However, it is not possible to distinguish between effects of different lengths of work experience and calendar effects in our experiment.

Furthermore, the labor market we study is characterized by stronger competition for available jobs than in more skilled occupations, according to the Swedish Public Employment Service (2019), whose regularly published indices indicate the extent of labor shortages or excess supply in various jobs. The observation that competition for low-skilled jobs can be fierce is also supported by our employer interviews, in which the respondents reported that they receive a large number of applications per vacant position, and by public statements from other employers (Bergfors, 2011; Jureskog, 2022). Fierce competition may have particularly negative consequences for the vulnerable group included in the experiment and not only lead to a generally low callback rate, but also to a small return on the signals of Swedish language proficiency and productivity acquired through work experience in the applications.

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Appendix A Application letter and resume

Job application, with cover letter and resumé. [ ] indicates text not shown here. Text without { } refers to applicant 1 (see Section 3.1) and text with { } added refers to the other applicants.

Page 1

To: [Employer]

In your ad, I read that you are looking for a [Professional role]. I'm very interested in the job. I'm 23 years old. I was born in Damascus in Syria and received a residence permit in Sweden in 2016. I currently live in Stockholm. {I have completed the entire education in Swedish for immigrants (SFI).}[1]

I have a high school diploma from my home country. {I currently work as a restaurant assistant at [Fast-food chain] in Stockholm (references provided on request).}[2]

I'm single and in my spare time I like to work out, listen to music and meet friends.

I hope to meet you in person and send my application.

Page 2

Resumé

Personal Information:
Name: [Name]
Date of birth: [Date of birth]
Place of birth: Damascus, Syria
Address: [Residential address]
Email: [Email address]
Telephone: [Telephone number]

Education:
High school diploma from Damascus, Syria
{Completed the entire education Swedish for immigrants (SFI)}[1]

Work experience:
201608 - Registered at the Swedish Public Employment Service
{201711 - Employed as a restaurant assistant at [Fast food chain]}[2]

[1]{ } indicates text included for applicant 2 and 4, see Section 3.1.
[2]{ } indicates text included for applicant 3 and 4, see Section 3.1.

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