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INDIVIDUAL CONSEQUENCES OF OCCUPATIONAL DECLINE*

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We assess the career earnings losses that individual Swedish workers suffered when their occupations' employment declined. High-quality data allow us to overcome sorting into declining occupations on various attributes, including cognitive and non-cognitive skills. Our estimates show that occupational decline reduced mean cumulative earnings from 1986–2013 by no more than 2%–5%. This loss reflects a combination of reduced earnings conditional on employment, reduced years of employment and increased time spent in unemployment and retraining. While on average workers successfully mitigated their losses, those initially at the bottom of their occupations' earnings distributions lost up to 8%–11%.

What are the career earnings losses that workers suffer when demand for their occupations declines? This question is important for policy debates on responses to technologies that replace workers (Acemoglu and Restrepo, 2019), and is relevant for broader discussions on labour market transformations due to technological change (see, for instance, Brynjolfsson and McAfee, 2014, Autor, 2015 and Caselli and Manning, 2019). New labour-replacing technologies no longer threaten only machine operatives and clerical workers. Self-driving vehicles may reduce the employment of drivers (Campbell, 2018), and artificial intelligence software challenges professionals such as lawyers and financial investors (Susskind and Susskind, 2015) and even fashion designers (Scheiber, 2018). This is causing considerable angst. It is therefore important to understand how costly occupation-replacing technologies are for workers, since this informs our thinking about individual welfare, inequality and human capital investments. It is

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The data and codes for this paper are available on the Journal repository. They were checked for their ability to reproduce the results presented in the paper. The authors were granted an exemption to publish parts of their data because access to these data is restricted. However, the authors provided the Journal with temporary access to the data, which enabled the Journal to run their codes. The codes for the parts subject to exemption are also available on the Journal repository. The restricted access data and these codes were also checked for their ability to reproduce the results presented in the paper. The replication package for this paper is available at the following address: https://doi.org/10.5281/zenodo.7756112.

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also important for public policy decisions on taxation, redistribution, retirement and education, and may even have broader political consequences (Marx, 1867; Caprettini and Voth, 2017; Bo *et al.*, 2023).

In this paper, we investigate the consequences for the career earnings and employment of individual Swedish workers of large declines in demand for their occupations, which are driven by technological change. We assemble high-quality population-level administrative data spanning several decades with a highly detailed occupational classification and a rich set of control variables. Using these, we regress workers' career earnings on an indicator for (large) occupational declines, controlling for potential confounders as discussed below. We show that the coefficient on the occupational decline indicator can be decomposed into the mean effect of occupational decline on workers whose occupation declines relative to those whose occupation does not, plus a selection term.

This selection term represents the mean difference in outcomes between workers whose occupation declines and other workers in the absence of any occupational decline. To address this selection problem, we show that adding individual-level controls addresses individual-level selection on cognitive and non-cognitive skills and parental backgrounds. We also control for occupation-level characteristics, to address the concern that declining occupations would have delivered different outcomes in the absence of occupational decline.

To learn more about the mean effect of occupational decline on workers in declining occupations, we consider how the underlying processes affect workers whose occupations do not decline. Workers in non-declining occupations are likely to gain, at least on average, through two channels: first directly, as demand increases for occupations that drive technological change; and second indirectly, as rising incomes increase demand more broadly. Some workers in non-declining occupations may still lose from technological change if their occupations experience small falls in demand, a possibility we address by considering different cutoffs for declining and non-declining occupations. Overall, we expect technological change to benefit the average worker (Caselli and Manning, 2019; Humlum, 2021). During the period of our study, Swedish workers' incomes rose substantially (for example, Graetz, 2020 reported that the real growth of median wages in Sweden was around 1.8% per year). Moreover, mean wages (and earnings) in Sweden increased over the period we study, not only in the aggregate, but also for all subgroups formed by age-by-gender-by-education cells. In sum, therefore, our regression estimates likely provide an upper bound on the magnitude of the losses incurred by workers whose occupations decline. Across a range of specifications and robustness checks, we find that this bound is around 2%–5% of earnings from 1985–2013. This indicates that at least on average, Swedish workers in declining occupations were able to avoid large income losses.

As our main measure of occupational decline, we use the US Occupational Outlook Handbooks (Bureau of Labor Statistics, 1986; 2018, henceforth OOH), which allows us to identify which occupations declined in the United States since the mid-1980s, to check whether occupational declines had likely technology drivers and to gauge expectations of employment growth at the time. For reasons that we discuss below, our baseline definition of occupational decline requires that employment contracted by at least 25% since the mid-1980s, though we also explore many alternative definitions, including declines using a range of thresholds as well as measure computed using only the Swedish data. We match the occupational information from the OOH to individual-level panel data on the entire Swedish population. Thus, we utilise the best aspects of both countries' data: the US data allow us to characterise occupational employment growth and control for anticipated changes in demand, while the Swedish data let us follow individuals who differ in their exposure to occupational declines, but were otherwise very similar.

Focusing on cohorts that were in prime working age from the mid-1980s till the mid-2010s, we study how cumulative long-run outcomes (such as earnings and employment) differ for those who in 1985 worked in occupations that subsequently declined. We control the initial selection of workers into declining occupations by gender, age, education, income, and location in 1985. We show that, conditional on these controls, those in occupations that subsequently declined had similar cognitive and non-cognitive skills and parental education and earnings, and similar pre-1985 earnings, as other workers. In some specifications we add other controls, including measures of occupation-varying life-cycle profiles and predictors of occupational employment growth, as well as broad occupation and industry dummies. We show using pre-period data that our rich set of controls plausibly addresses the occupation-level differences in outcomes in the absence of occupational decline.

We confirm that both our OOH-based measure of occupational decline and the predicted changes in US employment correlate strongly with the employment changes in Sweden. Specifically, Swedish workers who started out in occupations that subsequently declined were exposed to employment growth that was 20–40 log points lower than in non-declining occupations. We find that, relative to workers with similar characteristics in non-declining occupations, those in declining occupations lost about 5% of mean cumulative pre-tax earnings and 2% of mean cumulative employment. And compared to similar workers in similar occupations and industries, the cumulative earnings losses were only around 2%, and the cumulative employment losses were around 1%. The implied elasticity of relative employment losses with respect to occupational employment growth ranges from 0.04–0.05, and that for earnings losses ranges from 0.08–0.13.[1,2]

We also find that those in declining occupations were significantly less likely to still work in their 1985 occupation in 2013, and the implied elasticity of remaining with respect to employment growth ranges from 0.71–0.95. If occupational demand curves slope downward, such a strong mobility response likely mitigated the earnings losses for those who remained in declining occupations.

While mean relative earnings losses from occupational decline were around 2%–5%, those in the bottom tercile of their occupation's earnings distribution in 1985 suffered larger relative losses, amounting to 8%–11%. Those at the bottom (and possibly also the top) of their occupation's earnings distribution were also less likely to remain in their starting occupation than the median worker.

We further find that occupational decline increased the cumulative time spent in unemployment (accounting for roughly a third of lost employment) and retraining (accounting for just under 10%

[1] Our paper focuses on changes that result in large-scale occupational declines, rather than task-replacing technologies that change the work done within occupations. Nevertheless, we note that workers performing similar tasks may be exposed to similar demand changes. Indeed, we find that the difference in occupational employment growth between declining and non-declining occupations decreases in magnitude when we control for broad occupational categories. This is reflected in the implied elasticities. There may also be spillovers as workers move from declining occupations into other occupations requiring similar tasks. In a robustness check, we find that spillovers matter to an extent, but do not overturn our main conclusions.

[2] We estimate mean earnings and employment losses from occupational decline that are similar in magnitude or possibly even smaller using micro data from the United States (National Longitudinal Survey of Youth 1979); the NLSY estimates are, however, noisier than those using Swedish data. Nevertheless, these findings suggest that our estimates of losses from occupational decline may generalise to settings beyond Sweden. See the earlier working paper version for details (Edin *et al.*, 2019).

of lost employment). Moreover, occupational decline led to slightly earlier retirement among middle-aged (in 1985) workers. While most of our analysis focuses on overall occupational decline, we also investigate variation stemming from technological replacement using three distinct methods, none of which is mechanically related to the other. We find that all three measures of technological replacement are associated with employment and earnings losses for individual workers that are broadly similar to those in our main estimates.

To frame our empirical analysis of the consequences of occupational decline, we construct a qualitative Roy (1951) model with occupational demand shocks. As discussed above, we find that the largest earnings losses from occupational decline in Sweden are incurred by those who earned the least within their initial occupations. This finding is inconsistent with the frictionless Roy model, but it is consistent with a version where occupational switching costs decline in the workers' ability in the destination occupation. Moreover, our empirical analysis sheds light on the nature of the occupational switching costs, as almost half of the employment losses we estimate are accounted for by a combination of increased retraining and especially unemployment.

Our model can account for additional empirical findings when we also allow for worker displacement. In this case, those with lower initial within-occupation earnings rank suffer larger earnings losses from occupational decline; switchers' earnings losses may be larger than those of stayers; and switching probabilities are U-shaped in initial earnings, whereby low-earning workers switch occupations if displaced, while high-earning workers switch regardless of displacement when faced with occupational decline.

Taken together, our results suggest that most workers have coped well with occupational decline, in part through successful occupational switching, which is an encouraging message for workers facing the risk of technological displacement today. One exception to this generally positive finding is that low-ranked workers suffer larger losses from occupational decline.

Occupational decline is a salient feature of the evolution of labour markets (Goldin, 2000). But despite its importance, past work provides relatively little evidence about its consequences for individuals' careers. While there is a large literature on the costs of occupational mobility, we are not aware of previous estimates of workers' earnings losses from negative occupation-level demand changes.[3]

Our paper is distinct from panel studies of workers who differ in the routineness of their jobs.[4] A key difference is that we can compare similar workers, even doing similar work, with different exposure to occupational decline.[5]

Our paper also differs conceptually from studies of mass layoffs. Occupational decline can sometimes be managed through retirement and reduced hiring, allowing workers to change jobs without leaving employment; and occupational decline need not entail severe spillovers for local labour markets, unlike mass layoffs (Gathmann *et al.*, 2018). While magnitude comparisons across studies should be interpreted with caution, the mean loss that we find from occupational

[3] Kambourov and Manovskii (2009), Sullivan (2010), Pavan (2011) and Cortes and Gallipoli (2017) estimated the human capital losses associated with switching occupations. An older literature, including Neal (1995) and Parent (2000), studied the cost of moving across industries, while in other related work Poletaev and Robinson (2008) and Gathmann and Schönberg (2010) focused on task-specific human capital. Changes in the task content of existing occupations (for instance, Spitz-Oener, 2006), while also potentially relevant, are outside the scope of our study due to data limitations.

[4] See, for example, Autor and Dorn (2009), Cortes (2016) and Bachmann *et al.* (2019).

[5] Also related is independent work by Schmillen (2019), who studied employment shocks faced by German apprentices, although our paper differs in its research question, econometric inference and outcomes.

decline is generally lower than the loss from mass layoffs.[6] Finally, our paper also differs from studies of trade shocks, which affect import-competing firms and industries, while the changes we study typically affect individual workers within firms.

Our paper is also related to Dauth *et al.* (2021), who explored how workers who were exposed to industrial robots fared; and to Battisti *et al.* (2017), who investigated how firm-level technological and organisational change affects workers' careers. Our paper differs by exploring the consequences of a broader set of changes in occupational employment. Furthermore, our paper is related to the literature on possible future displacement due to technological changes. Forecasts of occupational displacement range from almost 50% (Frey and Osborne, 2017) to around 10% (Arntz *et al.*, 2017, who obtained a lower estimate by taking into account within-occupation heterogeneity in tasks). At the same time, Bessen (2016) concluded that technology has, at least so far, not been a net destroyer of jobs. Even if this benign aggregate trend continues, however, some occupations may be replaced by technology, and our study offers a way to assess the losses from occupational displacement.

We conclude the introduction with brief remarks on the setting we study. Sweden's economy and labour market institutions constitute the backdrop to most of our empirical analysis. During the period of our study, the Swedish economy experienced a deep recession in the early 1990s and a milder one in 2008 (Lindbeck, 1997; Gottfries, 2018), and we find that earnings losses in declining occupations were worse during those recessions. Wage inequality in Sweden increased during the 1980s and 1990s, and remained relatively stable thereafter (Skans *et al.*, 2009). Swedish labour market institutions have been characterised by strong labour unions and substantial public spending on labour market policies. Unions have generally embraced technological changes to promote productivity and wage gains, while expecting that active labour market policy will help displaced workers find work (Edin and Holmlund, 1995). There is, indeed, some evidence that Sweden's occupational retraining programs raise earnings (Vikström and van den Berg, 2017), so they may have contributed to the modest losses from occupational decline that we find.[7] At the same time, our finding of noisier but similarly modest mean earnings and employment losses from occupational decline in the United States (Edin *et al.*, 2019) suggests that workers find ways to mitigate losses from occupational decline even in other settings.

The remainder of our paper is organised as follows. Section 1 presents our model, Sections 2 and 3 discuss our data and empirical strategy, respectively, Section 4 presents our results, and Section 5 concludes.

1. Occupational Decline in a Roy Model

This section presents a simple model to help us frame our empirical investigation. We consider two occupations, one of which is hit by a negative demand shock, and we qualitatively

[6] Studies of mass layoffs in Sweden find losses of 4%–6% of annual earnings in the 5–10 years following displacement (Eliason and Storrie, 2006; OECD, 2015). In the United States losses from displacement are generally larger and range from 7%–14% of earnings (Davis and Von Wachter, 2011), or possibly even higher for workers who were highly attached to their firms (Jacobson *et al.*, 1993). Galaasen and Kostøl (2018) and Bana (2021) explored how mass layoffs' effects differ for occupations facing negative demand shocks, but their focus is still on mass layoffs.

[7] Another feature of Swedish labour market institutions are so-called employment security agreements reached between labour unions and business associations, and administered by works councils. These agreements stipulate counselling of laid-off workers to minimise the duration of their unemployment. We do not consider these agreements important in driving our results because, first, private sector blue-collar workers were only covered from 2004 onwards, and second, a careful evaluation of these agreements does not find strong support for positive treatment effects (Andersson, 2017).

study the resulting sorting of workers and the costs they incur. We investigate how workers' likelihood of leaving the affected occupation, and their earnings losses, depend on their initial earnings. Starting from a standard frictionless Roy (1951) model, we successively introduce positive and potentially heterogeneous costs of switching occupation, as well as the possibility that workers are displaced from their jobs and incur a cost to find a new job even when remaining in their initial occupation. Finally, we consider how workers' sorting differs when the negative demand shock is anticipated in advance. A complete, self-contained exposition of the model is given in the Online Appendix. Here we only summarise the main elements.[8]

We consider a competitive economy with a continuum of individuals indexed by i who live for two periods $t \in \{1, 2\}$ and each supplies a unit of labour inelastically each period. There are two occupations indexed by $k \in \{A, B\}$ for the workers to choose from. Workers' per-period log earnings are given by $y_{ikt} = \pi_{kt} + \alpha_{ik} - c_{ikt}$, where π_{kt} is the time-varying and stochastic (log) price of a unit of output in occupation k, α_{ik} is the time-invariant (log) amount of output that worker i produces in occupation k and $c_{ikt} \geq 0$ is a time cost related to occupational switching, which we discuss below.[9] There are no saving opportunities and earnings are consumed immediately. We define the life-time expected utility function as $\mathbb{E}[y_{ik1} + \beta y_{ik2}]$, where $\beta > 0$ is a discount factor. In each period, workers choose the occupation that maximises their expected utility. As a normalisation, we assume that workers always choose occupation A if indifferent. Since we focus our analysis on relative wages, we define $\widetilde{\pi}_t \equiv \pi_{Bt} - \pi_{At}$ and assume for simplicity that $\widetilde{\pi}_1 = 0$. As we discuss in Section 3.1, our empirical analysis proceeds in two steps. First, we characterise conditions for identifying the effect of occupational decline on those in declining occupations relative to others. And second, we discuss the additional assumptions required to identify a bound on the absolute losses of those in declining occupations. The model is focused on the first part. Prices are determined in equilibrium by supply and demand. However, here we take them as given, and analyse the consequences of a change to prices occurring in period 2 for occupational sorting and earnings. Note that the second period may be interpreted as all periods following this change, so β could be larger than one. For simplicity, we assume that α_{iA} and α_{iB} are independent and both uniformly distributed between zero and some finite, but possibly large number $\overline{\alpha}$. We explain in the Online Appendix that our main results are robust to alternative assumptions about the joint skills distribution.

In period 2, there is a negative demand shock to occupation A such that $\pi_{A2} - \pi_{A1} = -d$ and $\widetilde{\pi}_2 = d$, $d > 0$. This may be due to labour-replacing technology becoming available, or cheaper, in occupation A. We are interested in the consequences of the shock for the earnings of workers who start out in occupation A, under various assumptions about switching costs and anticipation of the price change. Formally, let $l_i \equiv \mathbb{E}[y_{i2}|\alpha_{iA}, k_{i1} = A, D_A = 0] - \mathbb{E}[y_{i2}|\alpha_{iA}, k_{i1} = A, D_A = 1]$ be the expected earnings loss in period 2 that results from the shock, conditional on worker i starting out in occupation A, and conditional on her ability (and hence earnings rank) α_{iA}, where the occurrence of the shock is indicated by $D_A \in \{0, 1\}$. Similarly, l_i^{switch} and l_i^{stay} denote the earnings losses further conditioned on leaving and staying, respectively, and p_i is the probability

[8] Gola (2021) provided a different, but related theoretical analysis of technological change in a two-sector model.

[9] The time cost may reflect search or retraining (or both); we assume throughout that a worker's wage equals the value of her marginal product, $e^{\pi_{kt}+\alpha_{ik}}$. We thus abstract from any job-level rents that may arise in the presence of search frictions.

of switching.[10] The overall loss is given by

$$l_i = l_i^{\text{stay}} - p_i(l_i^{\text{stay}} - l_i^{\text{switch}}).$$

As long as there is no displacement then $l_i^{\text{stay}} = d$ and, by revealed preference, $l_i^{\text{switch}} \leq d$, so that $l_i \leq d$. Thus, switching enables workers to mitigate the losses from occupational decline. In the Online Appendix we show that in each version of our model, $\partial p_i/\partial d \geq 0$, $\partial l_i/\partial d \geq 0$ (with strict inequalities for some i): the larger the drop in demand, the more workers switch, and the higher are earnings losses. Furthermore, $\partial l_i/\partial \alpha_{iA} = -\partial p_i(l_i^{\text{stay}} - l_i^{\text{switch}})/\partial \alpha_{iA} + p_i \partial l_i^{\text{switch}}/\partial \alpha_{iA}$. In other words, losses decrease with initial within-occupation earnings rank if the switching probability is increasing and the loss of switchers decreasing in initial earnings rank, $\partial p_i/\partial \alpha_{iA} > 0$ and $\partial l_i^{\text{switch}}/\partial \alpha_{iA} < 0$.

We start with the simplest case, where occupational prices π_{kt} are revealed at the start of each period and there are no switching costs. Hence, occupational choice is a sequence of static decisions that can be analysed in isolation. Panel (a) of Figure 1 illustrates occupational choices in the two periods as a function of workers' skills. The set of workers who start out in occupation A, but then switch to B is indicated by the blue area in the figure. Given uniformly distributed skills, the figure shows that $\partial p_i/\partial \alpha_{iA} \leq 0$. We show in the Online Appendix that $\partial l_i^{\text{switch}}/\partial \alpha_{iA} \geq 0$ also, and that $\partial l_i/\partial \alpha_{iA} > 0$: mean losses from occupational decline increase with initial earnings.

To understand the intuition for these results, call occupation A 'typist' and occupation B 'cashier', where typists suffer a negative demand shock. The worst typists could only become the worst cashiers; otherwise, they would have chosen to be cashiers in period 1. But the best typists can at most become the best cashiers, and in general they will not all be the best cashiers. Therefore, the best typists are less able to mitigate their earnings losses by becoming cashiers, and they suffer larger losses than the worst typists. This argument suggests that switching probabilities are decreasing and earnings losses are increasing in ability under a large set of alternative assumptions on the skill distributions.

Next, we assume that there is a constant switching cost $c \in (0, d)$ for moving between occupations. Occupational choice is no longer a period-by-period decision. Instead, workers choose in period 1 the occupation with the highest expected present discounted value of log earnings, net of switching costs. Let us assume that occupational log prices follow a random walk, $\mathbb{E}[\widetilde{\pi}_2] = \widetilde{\pi}_1 = 0$, where the last equality is due to our earlier simplifying assumption.[11] Panel (b) of Figure 1 shows that occupational choices are qualitatively similar to the baseline model, except that the blue region marking the workers who switch is smaller than in panel (a). Again we have $\partial l_i/\partial \alpha_{iA} > 0$.

Instead of a constant switching cost, let us now assume that the cost for moving from A to B equals $C - \alpha_{iB}$, with $C > \overline{\alpha}$ (symmetrically, the cost of moving from B to A equals

[10] Formally,

$$\begin{aligned}
l_i &\equiv \quad l_i(\alpha_{iA}, d) &&\equiv \mathbb{E}[y_{i2}|\alpha_{iA}, k_{i1} = A, D_A = 0] - \mathbb{E}[y_{i2}|\alpha_{iA}, k_{i1} = A, D_A = 1],\\
l_i^{\text{switch}} &\equiv l_i^{\text{switch}}(\alpha_{iA}, d) &&\equiv \mathbb{E}[y_{i2}|\alpha_{iA}, k_{i1} = A, D_A = 0] - \mathbb{E}[y_{i2}|\alpha_{iA}, k_{i1} = A, k_{i2} = B, D_A = 1],\\
l_i^{\text{stay}} &\equiv \quad l_i^{\text{stay}}(\alpha_{iA}, d) &&\equiv \mathbb{E}[y_{i2}|\alpha_{iA}, k_{i1} = A, D_A = 0] - \mathbb{E}[y_{i2}|\alpha_{iA}, k_{i1} = A, k_{i2} = A, D_A = 1],\\
p_i &\equiv \quad p_i(\alpha_{iA}, d) &&\equiv \mathbb{P}(k_{i2} = B|k_{i1} = A, \alpha_{iA}, D_A = 1).
\end{aligned}$$

[11] The random walk assumption is consistent with our scenario of occupation A experiencing an adverse shock in period 2. Since occupations are completely symmetric ex ante, this is without loss of generality. Instead of the random walk assumption we could impose that demand changes are somehow otherwise perfectly unforeseen, for instance due to adaptive expectations.

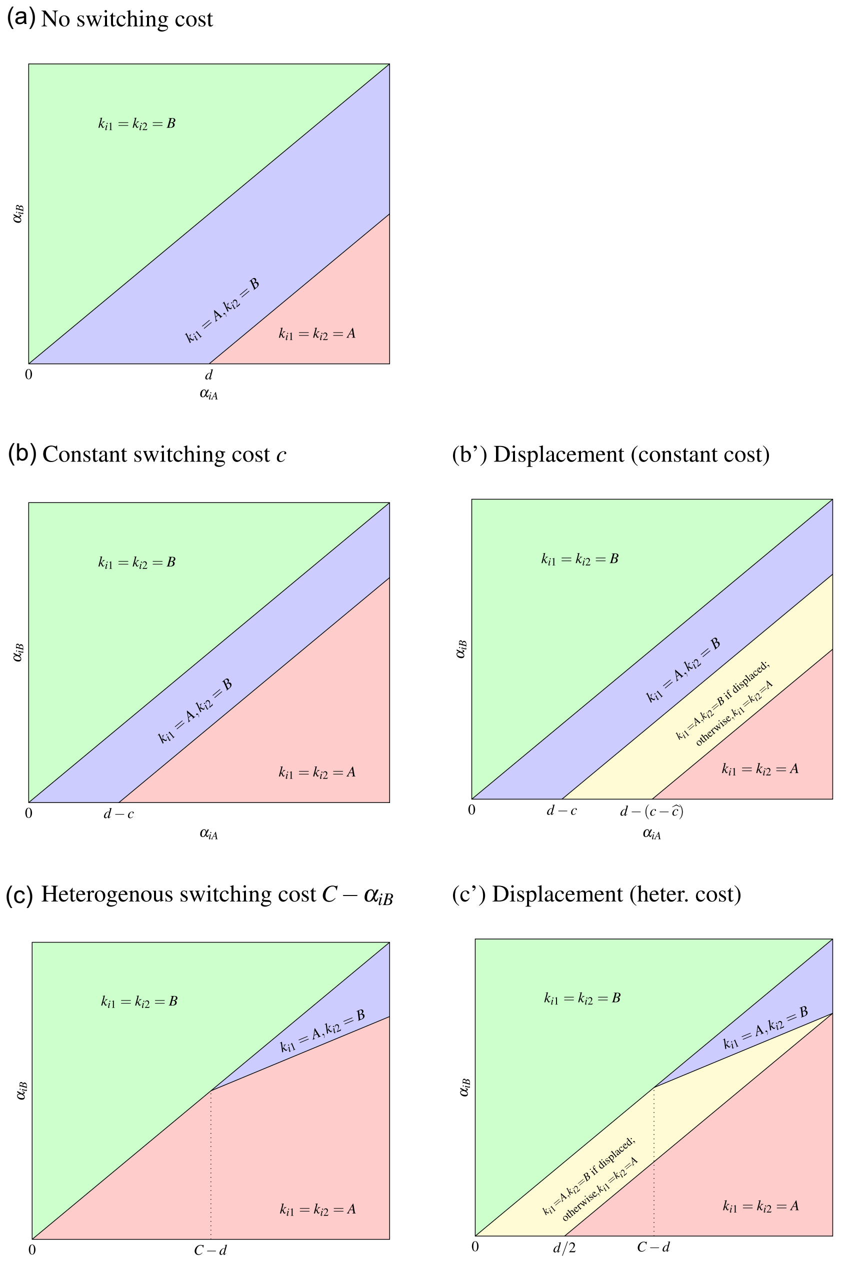

Fig. 1. *Sorting in a Two-Period Roy Model.*

Notes: Here k_{it} denotes the occupation chosen by worker i in period t; α_{ik} denotes log productivity of worker i in occupation k; and d is the amount by which the relative occupational log price declines from period 1 to period 2. The parameter values chosen are $(\overline{\alpha}, d, c, \widehat{c}, C) = (1, 0.5, 0.25, 0.25, 1)$. Panel (a) shows the simplest case, where occupational prices are revealed at the start of each period and there are no switching costs. In panel (b), constant switching costs are added, and in panel (c) the switching costs instead decline in their output in t the new occupation. Panels (b') and (c') show the results adding displacement to the models shown in panels (b) and (c), respectively.

$C - \alpha_{iA}$). This structure of switching costs captures in a reduced-form way the frictions that occupational moves may entail: for example, job search may take time, and those more able in the new occupation may find a job more quickly. We continue to assume that occupational log prices follow a random walk. Panel (c) of Figure 1 shows that low-ability workers do not leave occupation A, and among high-ability workers, $\partial p_i/\partial \alpha_{iA} > 0$. We show in the Online Appendix that $\partial l_i^{\text{switch}}/\partial \alpha_{iA} < 0$ (taking into account earnings losses due to the time cost of switching), so that $\partial l_i/\partial \alpha_{iA} \leq 0$: mean losses from occupational decline (weakly) decrease with initial earnings.

In terms of the example above, in this case the worst typists do not switch, because their initial choice of occupation A reveals, not only low earnings potential in occupation B, but also a large switching cost. Among the best typists, however, many possess substantial earnings potential as cashiers, as well as low switching costs. Therefore, the best typists are on average better able to mitigate their earnings losses by becoming cashiers, and hence the earnings losses from the demand shock are smaller for the best typists than for the worst typists.[12]

Building on the previous case, we now explore a version of the model that includes involuntary job displacement. Suppose that workers experience job displacement with some probability that is independent of skill, and incur a time cost $C - \alpha_{ik}$ to find a job in occupation k, be it the starting occupation or a different one. Here we have in mind exogenous job losses, for instance due to plant closure, which are a standard feature of search models (see, for instance, Pissarides, 2000). There is a fraction of high-ability workers who switch occupation regardless of displacement. In addition, now a fraction of low-ability workers also switch, but only if they are displaced. This is illustrated by the yellow area in panel (c') of Figure 1. Moreover, the earnings losses experienced by these displaced movers are larger than those of non-displaced, comparable stayers. This is by revealed preference: a worker in the yellow region prefers to remain if not displaced, so her non-displaced counterpart (with the same period-1 earnings) necessarily incurs a lower earnings loss. We show in the Online Appendix that $\partial l_i/\partial \alpha_{iA} \leq 0$, as before. Unlike in the case without displacement, however, p_i is U-shaped in initial earnings. This is because the probability of a displacement-induced switch is decreasing, and that of a voluntary one is increasing in initial earnings. The earnings loss l_i is again decreasing in initial earnings, as the costs of moving jobs—both within and across occupations—decrease with initial earnings.[13]

As a final variation on our model, we consider a case where period-2 prices are revealed to be $\widetilde{\pi}_2 = d$ at the start of period 1. In the presence of switching costs, some workers that would otherwise have chosen occupation A in period 1 instead start out in occupation B. This means that the fraction of workers switching after period 1 is smaller, and it could even be zero if switching costs are large. Since there is less switching, earnings losses are larger than in the case of unanticipated shocks, for a given d.

[12] While our model excludes occupation-specific human capital, it does allow us to think about some of its potential implications. For example, if all workers accumulate occupation-specific human capital additively (in logarithms), the effects are similar to adding constant switching costs, since switching means foregoing this capital. And if the accumulation of occupation-specific human capital is faster for those with higher ability in the occupations they initially select, they become less mobile, in contrast to the case of heterogeneous switching costs discussed above. Either way, adding occupation-specific human capital does not help to rationalise our empirical findings.

[13] We have also analysed displacement under constant switching costs, that is, when workers incur a time cost $\widehat{c} > 0$ to find a new job in A, or a cost c to find a job in B. This case is illustrated by panel (b') of Figure 1, and details are given in the Online Appendix.

We conclude this section by summarising the main results from our model. The baseline frictionless model makes three predictions: the probability of leaving a declining occupation is decreasing in initial earnings; earnings losses due to occupational decline are increasing in initial earnings, and earnings losses of those who leave a declining occupation are less than the losses of those who remain. Anticipating that these predictions are inconsistent with our empirical findings, we consider how occupational switching costs can reconcile our results. Introducing an occupational switching cost that is decreasing in the worker's earnings in the destination occupation leads to a positive relationship between switching probabilities and initial earnings, and a negative relationship between earnings losses and initial earnings. Allowing for displacement, together with a cost of switching jobs within an occupation, implies that switchers' earnings losses may be larger than those of stayers. Moreover, displacement can cause switching probabilities to be U-shaped in initial earnings, whereby low-earning workers switch involuntarily if displaced, while high-earning workers switch voluntarily regardless of displacement.[14]

2. Data

Our main empirical analysis uses individual-level longitudinal administrative data covering the entire population of Sweden for several decades, and various editions of the OOH published by the Bureau of Labor Statistics (BLS). Here we discuss key elements of the data we use, and leave many of the details to the Online Appendix.

2.1. *Data Sources*

Our primary sources for measuring occupational decline are the 1986–7 and the 2018–19 editions of the OOH (Bureau of Labor Statistics, 1986; 2018). The OOH describes the nature of work, the number of jobs and the projected employment growth for hundreds of occupations. For a subset of these occupations, more details are reported, including (among much else) data on whether technology is expected to affect—or has already affected—the occupation in question, and if so, in what way. In the 1986–7 edition, 401 occupations are described, covering about 80% of US employment. Detailed information is available for 196 of these occupations, covering about 60% of employment.[15]

Our main outcomes of interest come from Swedish micro data. We obtain basic demographic (year of birth, gender, education and county of residence) and labour market (employment status, annual earnings and industry) variables from the Integrated Database for Labour Market Research (LISA), a collection of administrative registers. For 1985–2013, LISA contains one observation per year for every individual aged 16–64 living in Sweden. Key variables, such as employment status and industry (as well as county of residence) are measured each November. We also use individual data from the Swedish Public Employment Service (PES), which contain

[14] An alternative model of occupational decline is the hierarchical Roy model of Cortes (2016). There are three occupations that differ by skill intensity—there is only one dimension of skill—and the declining occupation is assumed to be the middle-skilled one. Among middle-skilled workers, both the lowest and highest paid leave the occupation, while the medium paid workers stay. As in any frictionless Roy model, stayers incur the largest earnings losses when an occupation declines. Therefore, the model of Cortes (2016) cannot explain our finding that the lowest paid within the occupation incur the largest losses. And naturally, that model cannot speak to our findings about unemployment and retraining.

[15] The number of distinct occupations in the OOH, as well as the number of occupations covered in detail, increased over time, so our crosswalk from the 1986–7 to the 2018–19 OOH is mostly, though not always, one too many.

information on the number of days registered as unemployed, and the number of days spent in retraining programs administered by the PES, for all individuals ever registered with the PES from 1992–2013.

To assess balance between treatment and control groups in terms of pre-determined characteristics, we use information on cognitive skills (an IQ-type measure) and non-cognitive skills (capturing psychological traits such as the ability to cope with stress) from the military enlistment. These data are described in detail by Lindqvist and Vestman (2011). We also use information on parents' education and income from the 1985 version of LISA.

Our data on workers' occupations come from the population censuses, which were conducted every five years from 1960–90, and from the Wage Structure Statistics (WSS) for the years 1996–2013.[16] The WSS contains the population of public sector workers and a sample of about 50% of private sector workers. We apply sampling weights when working with the occupation variable from the WSS.

A useful feature of our data is that in the 1985 and 1990 censuses, workers' occupations are coded using a five-digit classification, YRKE5, containing about 1,400 distinct occupations. This allows us to accurately merge occupation-level information from the United States, as we describe below. Unfortunately, such detailed occupation codes are not available after 1990. From 1996–2013, a three-digit classification containing 172 distinct codes, SSYK96, is available in the WSS. This classification is different from YRKE5, and the crosswalk between YRKE5 and SSYK96 likely introduces measurement error in workers' occupations after 1990. This limits our analysis of occupational employment shifts and individual workers' occupational mobilities during 1985–2013.

Finally, we use information from the 1960 census, which allows us to calculate prior occupational employment changes at the three-digit level using the YRKE3 classification, a coarser version of YRKE5 (there are 229 distinct codes that cover the period 1960–85).

2.2. *Construction of Key Variables*

To construct our measure of occupational decline, we begin with the OOH data. Mapping occupations across the 1986–7 and 2018–19 editions of the OOH, we calculate the percentage growth in employment 1984–2016.[17] If, after a careful search, a 1986–7 occupation has no counterpart in the 2018–19 edition, we classify it as having vanished, and assign a percentage growth of -100.[18] While few occupations actually disappeared, some occupations declined sharply, including both white-collar (typists, drafters and telephone operators) and blue-collar (precision assemblers, welders and butchers) jobs.

We also record the projected employment growth of each occupation from the 1986–7 OOH.[19] The BLS constructs these predictions using a careful and lengthy procedure.[20] In the 1986–7 OOH, forecasts were reported in categories: 'declining', 'little or no change', 'increasing slower than average', 'increasing about as fast as average' and 'increasing faster than average'. We

[16] We also use individual-level earnings data for 1975 and 1980 from the population censuses.

[17] The 1986–7 OOH reports employment for 1984, while the 2018–19 edition reports 2016 employment.

[18] Between the 1986–7 and 2018–19 editions of the OOH, some occupations were split or merged, which we take into account when computing the percentage growth. See the Online Appendix for details.

[19] We use US rather than Swedish employment forecasts, since the Swedish forecasts from the relevant time period are only at the one-digit occupation level (Statistics Sweden, 1990).

[20] Veneri (1997) evaluated the ex post accuracy of the projections used in the 1986–7 OOH, and concluded that it correctly foresaw most occupational trends, although there were non-trivial cases of error.

create a cardinal predicted growth index assigning these categories the numbers 1–5 (where higher numbers correspond to more positive predicted employment changes). We report results both from using this index and using the categorical outlook variable.

In order to merge the OOH-based variables to the Swedish data, we map the 401 1986–7 OOH occupations to the 1,396 five-digit Swedish occupation codes available in the 1985 census. We successfully map 379 US occupations to 1,094 Swedish occupations—we are able to find corresponding US occupations for 91% of Swedish workers in 1985. We map percentage changes in US employment 1984–2016, as well as 1986–7 OOH predictions (categorical and index), to Swedish five-digit occupations using our crosswalk, applying weights (OOH 1984 employment shares) in the case of many-to-one matches.

We define a Swedish five-digit occupation as declining if the weighted employment growth of its corresponding OOH occupations is negative and larger (in absolute magnitude) than 25%. We regard this as a sensible threshold: smaller observed declines may result from measurement error from matching OOH occupations over time. At the same time, we report robustness checks using several alternative thresholds. We also use information from the OOH to determine whether technology likely played a role in the decline, as we further explain in the Online Appendix. In 1985, 13% of Swedish employees worked in subsequently declining occupations, and 8% worked in subsequently declining occupations where the decline is linked to technological change. Examples of sharply declining occupations in Sweden include both blue-collar (vehicle fitter, assembler of metal products, machine fitter and clothing seamstress) and white-collar occupations (office telephone operator, data reader, data machinist and typist).[21]

We also classify occupations as having been susceptible to replacement by specific technologies. Unlike the declines linked to technological change, these occupations were categorised without relying on actual employment changes in the United States (nor Sweden). We identify relevant technologies using two approaches: a ‘manual’ one and an ‘algorithmic’ one. For the manual approach, we consider whether we know of a technology that replaced all or nearly all of tasks in the occupation. For the algorithmic approach, we use a pre-specified Google search query to identify mentions of technology replacing workers in the occupation. An occupation is considered to have been replaced if the technology identified was commercially viable during the period we study. In both cases, technological replacement is strongly positively correlated with occupational decline. In 1985, 5.4% (3.7%) of Swedish employees worked in occupations that were replaced, as classified using the algorithmic (manual) approach.

We construct several left-hand side variables that characterise workers’ career outcomes spanning the years 1986–2013, that is, starting with the first year after we measure treatment and ending with the last year available in our data. We start by summing up years observed as employed and real annual labour earnings, obtaining the variables cumulative years employed and cumulative earnings. Following Autor *et al.* (2014), we measure normalised cumulative earnings, which is the ratio of cumulative earnings to predicted initial earnings.[22] We consider further earnings

[21] This list includes occupations with at least 5,000 workers in 1985, whose decline measure fell by 50% or more and with distinct names, as opposed to ‘Other within [a broader category]’.

[22] The prediction comes from a regression of log earnings on a quartic in age and dummies for gender, county and seven education categories, run separately for each three-digit SSYK96 occupation in 1985. We divide by predicted rather than actual initial earnings to eliminate transitory earnings variation, which would introduce an important role for mean reversion into the distribution of normalised cumulative earnings. Autor *et al.* (2014) divided cumulative earnings by earnings averaged across four pre-treatment years for the same reason. Since we do not have annual earnings information prior to 1985, we normalise by predicted earnings instead.

measures—such as rank, discounted cumulative earnings and earnings growth—in robustness checks.

Our measure of long-run occupational mobility is a dummy variable that equals one if the individual worked in the same three-digit SSYK96 occupation in 2013 as 1985. It equals zero if the individual works in a different occupation or is not employed.[23] Using the PES data, we calculate cumulative days spent unemployed and cumulative days spent in retraining during 1992–2013. We define dummy variables for ever unemployed and ever having participated in retraining. Finally, we calculate the retirement age, where we define retirement as a continuous spell of zero annual earnings up to and including age 64.[24]

2.3. *Sample Restrictions*

Our starting sample contains all individuals born between 1921–69 and hence aged 16–64 (at some point) in 1985, who were employed in November 1985, whose annual earnings in 1985 were no less than the 'base amount' (Swedish: *basbelopp*) specified by the social security administration and for whom we have the relevant demographic and labour market information.[25] There are 3,061,051 individuals fulfilling the above criteria.[26] Our *baseline sample* further restricts the sample to those aged 25–36 in 1985. We drop younger workers, who are less likely to have settled on an occupation. And we drop middle-aged and older workers from our baseline sample because we want to focus on workers who did not reach retirement age by 2013, the end of our period of study, in our main analysis. We analyse these older workers separately.

3. Empirical Strategy

3.1. *The Estimating Equations and Their Interpretation*

Our objective is to estimate the consequences of occupational decline for individual workers' careers. To fix ideas, we consider occupational decline brought about by technological change, and later consider other potential drivers of occupational decline.

Consider a regression of cumulative career outcomes—such as cumulative years employed, or cumulative earnings—on an indicator for working in 1985 in occupations that subsequently declined, conditional on a set of controls. The probability limit of the regression coefficient on the declining indicator can be expressed as a difference in conditional means, which in turn can be decomposed into the difference between a treatment effect on workers in declining occupations

[23] Our measure of occupational mobility does not capture any temporary exits during the intervening years if workers returned to their initial occupation. A limitation of our data is that they are not conducive to studying high-frequency occupational mobility: During the years 1986–9 and 1991–5, we do not observe workers' occupation. And during 1996–2004, the SSYK96 variable contains substantially fewer distinct codes than from 2005 onwards.

[24] The LISA database includes individuals older than 64 only during later years. Since we do not consistently observe individuals beyond age 64, we assume for all years that individuals aged 65 or older have retired.

[25] The base amount is used as an accounting unit when calculating benefits, and it is typically equal to about three months' worth of full-time work at the median wage. As we do not observe hours worked or full-time status, we use the base amount to exclude individuals with little labour market attachment.

[26] There were 5,281,382 individuals aged 16–64 in Sweden in 1985. Of those, 4,186,512 were employed in November 1985, and among them, 3,648,034 earned no less than the base amount during 1985. The reduction to 3,061,051 is due to missing education, industry or occupation information, including cases where YRKE5 occupations do not have matches in the OOH. Online Appendix Table OA1 shows that dropping observations with missing education, occupation and industry has very little effect on the sample composition in terms of gender, age and base earnings.

and a treatment effect on workers in non-declining occupations, and selection bias:

$$\begin{aligned}
&\underbrace{\mathbb{E}[y_{i2}|k_{i1} \in A, D_A = 1, D_B = 0, \mathbf{x}_{i1}] - \mathbb{E}[y_{i2}|k_{i1} \in B, D_A = 1, D_B = 0, \mathbf{x}_{i1}]}_{\text{Observed difference in means}} \\
&= \underbrace{\mathbb{E}[y_{i2}|k_{i1} \in A, D_A = 1, D_B = 0, \mathbf{x}_{i1}] - \mathbb{E}[y_{i2}|k_{i1} \in A, D_A = 0, D_B = 0, \mathbf{x}_{i1}]}_{\text{Effect of occupational decline on } A \text{ workers}} \\
&\quad - \underbrace{(\mathbb{E}[y_{i2}|k_{i1} \in B, D_A = 1, D_B = 0, \mathbf{x}_{i1}] - \mathbb{E}[y_{i2}|k_{i1} \in B, D_A = 0, D_B = 0, \mathbf{x}_{i1}])}_{\text{Effect of occupational decline on } B \text{ workers}} \\
&\quad + \underbrace{\mathbb{E}[y_{i2}|k_{i1} \in A, D_A = 0, D_B = 0, \mathbf{x}_{i1}] - \mathbb{E}[y_{i2}|k_{i1} \in B, D_A = 0, D_B = 0, \mathbf{x}_{i1}]}_{\text{Selection bias}}. \quad (1)
\end{aligned}$$

Here, y_{i2} is the outcome of interest, such as cumulative earnings of individual i (who is employed in occupation k_{i1} in 1985) in period 2 (1986 through 2013). Our notation separates declining occupations (A) from non-declining ones (B). Variable D is an indicator for occupational decline, which allows us to consider the hypothetical situation where occupational decline did not take place. We motivate our use of an indicator for occupational decline in Section 3.2 below. We denote by $\mathbf{x}_{i1}$ a set of (yet unspecified) controls, which we also revisit below.

In our model, the selection term equals zero due to the symmetry assumptions we make, and there is no need for controls. In practice, the identifying assumption for the regressions without controls is too strong, because the selection term reflects both differences in individuals sorting across occupations as well as differences between occupations A and B even in the absence of occupation decline. Our empirical strategy aims to mitigate both types of selection concerns.

Our first step towards addressing the sorting of individuals is to control for a rich vector of individual characteristics in period 1, that is, in 1985: gender, age, educational attainment and county of residence dummies, and earnings. To address potential concerns about sorting on other dimensions of skill, we investigate whether individuals differ in terms of cognitive and non-cognitive skills from the military enlistment, which are available for men of a subset of cohorts for whom military service was compulsory. We also check whether workers in declining occupations differ in other background characteristics, namely parental education and pre-1985 earnings.

But even if the controls resolve concerns about sorting on individuals' characteristics, the selection term may still be non-zero if earnings growth in occupations A and B would have been different in the absence of occupational decline—that is, if a worker's occupation affects her earnings growth even without occupational decline. To mitigate this concern, we use data from 1985 to estimate expected occupation-specific lifetime earnings profiles, which we add as controls to the regressions.

To further control for differences between declining and non-declining occupations, we use information from the 1986–7 OOH. The BLS authors went to great lengths to accurately forecast occupational employment changes. Once we condition on predicted occupational growth, we likely remove much of the differences between declining and non-declining occupations that are related to workers' sorting in anticipation of future demand. Since the occupational decline and the forecasts that we use rely on US data, we also control for each occupation's level of employment and pre-existing employment growth trends in Sweden. Together, this set of controls removes predictable variation in the declining indicator, and in this sense gets us closer to isolating unanticipated declines. In some specifications we use two additional sets of controls:

broad (one-digit) occupation dummies and (two-digit) industry dummies. Adding these controls comes at the cost of reducing the variation in occupational decline, since it only uses variation in occupational decline between very similar occupations.

Addressing the selection concerns allows us to identify the net effect of occupational decline on workers who start out in occupations that subsequently decline, relative to the effect of occupational decline on workers who start out in non-declining occupations (the difference of the two middle terms in (1)). This difference is equivalent to $-\mathbb{E}[l_i]$ in the model and is interpretable as the effect of occupational decline on inequality between occupations.

To view (1) as informing us about the effect on earnings of occupational decline on workers who start out in declining occupations, we need to make further assumptions about its effect on workers in non-declining occupations. There are reasons to think that this effect would be at least weakly positive, even if not all non-declining occupations gain. Increased demand due to technological change may raise demand for workers in non-declining occupations and may open new employment opportunities (Autor, 2015), and technological change should lead to higher average wages under general conditions (Caselli and Manning, 2019). On the other hand, there may be a secondary effect due to an inflow of workers from declining occupations to non-declining ones, but its magnitude is likely to be modest (for calculations based on structural models that are consistent with this intuition, see Humlum, 2021 and Acemoglu and Restrepo, 2022). Finally, we note that real earnings and wages in Sweden have indeed increased substantially during our sample period (Graetz, 2020), and the most likely explanation for such growth over long periods of time is a technology-driven increase in productivity. Moreover, mean wages (and earnings) in Sweden increased over the period we study, not only in the aggregate, but also for all subgroups formed by age-by-gender-by-education cells.[27] Under the assumption that workers in non-declining workers do not, on average, lose from occupational decline, we get an inequality:

$$\underbrace{\mathbb{E}[y_{i2}|k_{i1} \in A, D_A = 1, D_B = 0, \mathbf{x}_{i1}] - \mathbb{E}[y_{i2}|k_{i1} \in B, D_A = 1, D_B = 0, \mathbf{x}_{i1}]}_{\text{Observed difference in means}}$$
$$\leq \underbrace{\mathbb{E}[y_{i2}|k_{i1} \in A, D_A = 1, D_B = 0, \mathbf{x}_{i1}] - \mathbb{E}[y_{i2}|k_{i1} \in A, D_A = 0, D_B = 0, \mathbf{x}_{i1}]}_{\text{Effect of occupational decline on } A \text{ workers}}.$$

In other words, the observed difference in conditional earnings means is a lower bound for the effect of occupational decline on workers in declining occupations. Since, as we discuss below, we find that the observed difference is moderate in magnitude, the loss for those in declining occupations is even more moderate.

To implement the empirical methodology outlined above, our estimating equation takes the form

$$y_{i2} = \beta D_{k_{i1}} + \gamma \mathbf{x}_{i1} + \delta \widetilde{\mathbf{x}}_{k_{i1}} + \varepsilon_i, \tag{2}$$

where $D_{k_{i1}}$ is an indicator for working in 1985 in an occupation that subsequently declined; $\mathbf{x}_{i1}$ is a vector of individual characteristics, measured in 1985, as discussed above; $\widetilde{\mathbf{x}}_k$ is a vector of occupational characteristics and ε_i is the error term, which we conservatively cluster by three-digit Swedish occupations.[28]

[27] Specifically, we break the population of workers into three age groups (25–36, 37–48 and 49–60, as we do elsewhere in this paper), by five education groups and by gender. For all the resulting 30 groups, real earnings and real wage rates increased by at least 1.2% and 1.4% per year, respectively, from 1985–2013.

[28] As discussed above, some specifications also control for industry fixed effects.

We provide further evidence that our identification strategy plausibly addresses the selection issues by considering two additional sets of outcomes. First, we examine the earnings of workers in the years before the occupational decline that we study. Second, we study the cumulative earnings during the first few years of our study, when the effect of occupational decline was likely limited.

A different question regarding our approach is whether occupational decline that is specifically linked to labour-replacing technologies has distinct consequences from demand-driven occupational decline in general. To provide evidence on the role of technology, we restrict some of the analysis to occupational declines that are explicitly linked to concrete new technologies, such as personal computers and robots. We also examine measures of technological replacement that are solely based on an occupation's exposure to labour-replacing technologies without incorporating any information on employment changes.

Returning to the potential causes of occupational decline, we note that losses due to increased international trade or offshoring are likely to follow a similar logic to that outlined above for technological changes, although admittedly there is less evidence on this.

One final step in our empirical analysis is to consider how the costs of occupational decline may fall differently on workers with different initial earnings rank within their occupations, in line with the discussion in the model section.

3.2. *Rationale for Measuring Occupational Decline Using US Data*

Prior literature has documented that shifts in occupational employment are strongly correlated across countries; see, for instance, Goos *et al.* (2014) documenting job polarisation across European countries and, in particular, Adermon and Gustavsson (2015) on job polarisation in Sweden. Here we explain why using measures of occupational decline from the OOH is not only feasible, but also desirable.

We begin by explaining why we prefer this measure of decline to an alternative measure using the SSYK96 codes. First, there are 401 OOH codes compared to just 172 (three-digit) SSYK96 codes, and having more codes affords us more variation from small and declining occupations. For example, it lets us separate typists, whose employment fell sharply, from secretaries, whose employment grew. To use the OOH codes, we match them to YRKE5 codes, but since the YRKE5 are more numerous, we do not lose much variation. Second, since the SSYK96 codes were introduced from 1996, they reflect a judgement on an occupation's importance made after the start of the occupational decline that we study. Consequently, SSYK96 codes are more likely to pool occupations with low employment in 1996 (including declining ones) with non-declining occupations. Because the 2018–19 OOH separately describes even occupations with very low employment, this is less of a problem for our approach. Finally, using occupational declines measured in Sweden as a regressor where the dependent variable is the change in earnings creates a problem of simultaneity. This problem is mitigated by using the OOH measure.

At this stage readers may also ask: why do we report reduced-form results using the OOH decline measure rather than use it as an instrument for occupational decline measured in Sweden using SSYK96? Our rationale for the reduced-form approach is that it preserves much more of the variation that we are interested in, for several reasons. First, as noted above, if we use measures based on SSYK96 codes, we lose much of the variation in occupational decline because of the coarseness of the classifications and the lower likelihood of separating occupations in decline. Second, 2SLS would exacerbate this problem, since it only uses part of the variation in the decline. Finally, as we show below, while we still have power to detect changes in occupational decline in Sweden, once we control for predicted changes we are left with a weak instrument.

Nonetheless, we sometimes report the implied elasticities of our outcome variables with respect to occupational employment growth in Sweden as an additional way of assessing magnitudes. Given the caveats just mentioned, these elasticities are likely upper bounds, as the measured Swedish employment change is biased towards zero due to the absorption of declining occupations into broader categories in the SSYK96 classification.

Still another question is why we focus only on occupational declines instead of using the full variation in OOH occupational change. Again, there are several factors that influence our choice. First, declines are interesting from the perspective of their social costs and policy implications. Second, large declines in employment are likely driven by declines in labour demand, and we use several alternative measures of technological replacement to corroborate our findings. Finally, as we explain below, we use different cutoffs in the regressions as well as graphical evidence, to show that the costs of occupational change are concentrated among those who experience substantial occupational declines; increases or moderate declines seem to matter little relative to each other. Nevertheless, for completeness, we also report estimates using the full variation in occupational changes.

To conclude, we note that in order to better assess the quantitative importance of the estimated earnings losses, we relate them to the estimated impacts on occupational mobility, as well as to Swedish occupational employment growth.

4. Empirical Analysis

In this section we present the findings from our empirical analysis. First, we quantify occupational decline in Sweden and discuss sorting into declining occupations. Second, we study how employment, earnings and occupational mobility differed for workers in declining occupations. Third, we investigate how the consequences of occupational decline differed by workers' initial within-occupation earnings rank. Fourth, we explore some of the mechanisms through which occupational decline operates, including unemployment, retraining and early retirement. Fifth, we examine whether occupational declines with observed links to technology has distinct consequences. At the end of this section, we interpret our findings through the lens of the theoretical model from Section 1.

4.1. *Occupational Decline and Sorting across Occupations*

We begin by quantifying workers' exposure to occupational decline. In Table 1 we report estimates of (2), where the dependent variable is the log employment change from 1985–2013 in each worker's three-digit occupation. Panel A shows estimates for workers aged 16–64 in 1985, and panel B focuses on our main sample of workers—those aged 25–36 in 1985. The results, which are similar across panels, suggest that workers in declining occupations are exposed to a log employment change that is about 50 log points lower than for workers in non-declining ones, about 40 log points lower when we compare observationally similar workers, and lower by about 20–30 log points when we also include occupation and industry controls. It is important to keep these results in mind when interpreting our findings from putting individual-level career outcomes on the left-hand side of (2). While adding more controls reduces the risk of omitted variable bias, the results in Table 1 show that this also leaves less variation in exposure to occupational change.

Table 1. *Quantifying Workers' Exposure to Occupational Decline.*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Workers aged 16–64 in 1985 (3,061,051 observations)						
Declining	−0.49	−0.44	−0.43	−0.31	−0.28	−0.22
	(0.12)	(0.11)	(0.11)	(0.10)	(0.11)	(0.10)
Panel B. Workers aged 25–36 in 1985 (877,324 observations)						
Declining	−0.47	−0.40	−0.39	−0.28	−0.27	−0.22
	(0.11)	(0.11)	(0.11)	(0.10)	(0.12)	(0.10)
Demographics & earnings		✓	✓	✓	✓	✓
Life-cycle profiles			✓	✓	✓	✓
Predictors of growth				✓	✓	✓
Occupation dummies					✓	✓
Industry dummies						✓

Notes: Results from regressions of occupational log employment changes on a dummy for working in a declining occupation are shown. Regressions are run on individual-level data. However, the dependent variable is the difference in aggregate log employment in Swedish three-digit occupations between 2013 and 1985, matched to each worker's 1985 five-digit occupation using a crosswalk. A Swedish five-digit occupation is classified as 'Declining' if there are employment losses of more than 25% between 1986–2016 in the corresponding US occupation(s). In the regressions reported here, the 'Declining' variable indicates that an individual worked in such an occupation in 1985. Demographic controls include female, cohort, county and education dummies. Occupation-level life-cycle profiles are cumulative earnings calculated for each individual based on their 1985 occupation. Predictors of growth include 1985 employment shares, 1960–85 occupational employment growth and the predicted growth index. Occupation and industry dummies are at the one-digit and two-digit levels, respectively. Robust standard errors, clustered by 1985 three-digit occupation, are given in parentheses.

We also note, as discussed in Section 3.2, that these estimates likely understate the employment decline for five-digit occupations, which we are unable to measure.[29] Online Appendix Table OA2 reports similar estimates, aggregated by three-digit occupations and weighted by 1985 Swedish employment shares, using our main sample of workers.

Having described the extent of occupational declines, we turn to the sorting of individuals in 1985 into subsequently declining occupations. Table 2 presents results from regressions of several individual characteristics on an intercept and the declining indicator. The top panel considers the entire working-age population with non-missing demographic and labour market information, and the bottom panel focuses on our main sample. In both cases, the sorting patterns are similar: those in occupations that subsequently declined were of similar age, and more likely to be male, less educated, and more likely to be employed in manufacturing. Coincidentally, the gender gap in earnings is offset by the differences in schooling, and on net, the workers in subsequently declining occupations had similar earnings to others in 1985.

We next investigate whether there is sorting into declining occupations based on cognitive skills, non-cognitive skills, and parental attributes, and if so, whether any differences in these variables disappear once we control for the individual characteristics described in the previous paragraph. Columns (1) and (4) in panel A of Table 3 show that in 1985, the cognitive and non-cognitive skills of men in subsequently declining occupations were lower than those of the other men by about 0.2–0.25 SDs. But the table also shows that our set of demographic

[29] The difference of 50 log points translates into an employment decline of about 18%. Let y_i be the log employment change assigned to each individual based on her 1985 five-digit occupation, and let D_i be the declining indicator. From the regression $y_i = \alpha + \beta D_i + \varepsilon_i$ we obtain $\mathbb{E}[\exp\{y_i\}|D_i = 1] = \exp\{\alpha + \beta\}\mathbb{E}[\exp\{\varepsilon_i\}|D_i = 1]$, and plugging in our estimates, $\exp\{0.06 - 0.49\} \times 1.26 = 0.82$. As we argue in the text, this likely understates the actual average decline in the five-digit occupations.

Table 2. *Baseline Characteristics of Workers in Subsequently Declining Occupations.*

	(1) Female	(2) age	(3) Compulsory school	(4) High school	(5) College	(6) Earnings	(7) Manufacturing
Panel A. Workers aged 16–64							
Intercept	0.52	39.5	0.33	0.56	0.11	191.3	0.25
	(0.078)	(0.41)	(0.030)	(0.033)	(0.027)	(10.8)	(0.050)
Declining	−0.25	−0.89	0.13	−0.063	−0.070	−0.23	0.38
	(0.088)	(0.63)	(0.035)	(0.034)	(0.028)	(11.0)	(0.085)
Panel B. Workers aged 25–36							
Intercept	0.51	30.8	0.23	0.64	0.13	182.8	0.23
	(0.078)	(0.078)	(0.022)	(0.033)	(0.032)	(9.28)	(0.050)
Declining	−0.26	−0.19	0.15	−0.065	−0.082	12.0	0.38
	(0.085)	(0.091)	(0.030)	(0.034)	(0.034)	(9.40)	(0.084)

Notes: Results from OLS regressions of various baseline (1985) characteristics on a constant and an indicator for working in a declining occupation are shown (see the notes to Table 1 for the definition of the declining indicator). Earnings are measured in thousand Swedish crowns inflated to 2014 levels. The sample includes all individuals of the indicated ages who were employed and earned at least the base amount in 1985, and whose education, occupation, and industry are observed. The number of observations is 3,061,051 in panel A and 877,324 in panel B. Robust standard errors, clustered by 1985 3-digit occupation, in parentheses.

Table 3. *Balance of Pre-Determined Characteristics.*

	(1)	(2)	(3)		(4)	(5)	(6)
Panel A. Military test scores							
	Cognitive skills				Non-cognitive skills		
Declining	−0.24	−0.015	0.022		−0.20	−0.077	−0.022
	(0.084)	(0.035)	(0.022)		(0.062)	(0.041)	(0.021)
Individual controls		✓	✓			✓	✓
Occupation & industry controls			✓				✓
Mean of dep. var.		0.06				0.06	
Observations				272,350			
Panel B. Mother's characteristics							
	Mother finished high school				Mother's earnings (1985)		
Declining	−0.059	−0.012	0.0033		−6.73	−2.31	0.079
	(0.020)	(0.0100)	(0.0058)		(2.41)	(1.29)	(0.84)
Individual controls		✓	✓			✓	✓
Occupation & industry controls			✓				✓
Mean of dep. var.		0.35				97.4	
Observations				609,075			
Panel C. Father's characteristics							
	Father finished high school				Father's earnings (1985)		
Declining	−0.069	−0.0088	0.0075		−13.7	−1.38	2.26
	(0.027)	(0.012)	(0.0067)		(6.67)	(2.85)	(1.99)
Individual controls		✓	✓			✓	✓
Occupation & industry controls			✓				✓
Mean of dep. var.		0.43				174.2	
Observations				451,301			

Notes: Results from regressions of various pre-determined characteristics on a dummy for working in 1985 in a subsequently declining occupation are shown. Test scores from the military enlistment are standardised to have mean zero and unit variance within enlistment cohorts. The sample in panel A includes men born in Sweden from 1952−9 with non-missing test scores (more than 85% of men in each cohort), who were employed and earned at least the base amount in 1985, and whose education, occupation and industry are observed. The samples in panels B and C are the same as that in panel B of Table 2, except that individuals with missing information on their mother's or father's education and income were dropped. Individual-level controls include female, cohort, county and education dummies, as well as earnings in 1985. Occupation and industry controls include predicted lifetime income, predictors of occupational growth, occupation dummies and industry dummies. Robust standard errors, clustered by 1985 three-digit occupation, are given in parentheses.

Table 4. *Occupational Decline and Individual-Level Cumulative Employment and Earnings 1986–2013.*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Cumulative years employed 1986–2013 (mean: 23.4)						
Declining	−0.73	−0.49	−0.49	−0.30	−0.24	−0.19
	(0.26)	(0.20)	(0.20)	(0.20)	(0.18)	(0.14)
Panel B. Cumulative real earnings ('000 2014 SEK) 1986–2013 (mean: 6,926)						
Declining	−354	−347	−241	−117	−63	−126
	(419)	(120)	(81)	(76)	(71)	(58)
Panel C. Cumulative real earnings divided by predicted initial earnings (mean: 38.7)						
Declining	−4.29	−2.10	−2.21	−1.52	−0.98	−1.11
	(0.91)	(0.53)	(0.54)	(0.54)	(0.41)	(0.36)
Demographics & earnings		✓	✓	✓	✓	✓
Life-cycle profiles			✓	✓	✓	✓
Predictors of growth				✓	✓	✓
Occupation dummies					✓	✓
Industry dummies						✓

Notes: Results from regressions of the indicated outcomes on a dummy for working in 1985 in a subsequently declining occupation are shown. Demographic controls include female, cohort, county and education dummies. Occupation-level life-cycle profiles are cumulative earnings calculated for each individual based on their 1985 occupation. Predictors of growth include 1985 employment shares, 1960–85 occupational employment growth and the predicted growth index. Occupation and industry dummies are at the one-digit and two-digit levels, respectively. The number of observations is 877,324. The sample is the same as that in panel B of Table 2. Robust standard errors, clustered by 1985 three-digit occupation, are given in parentheses.

controls (columns (2) and (5)) and additional controls largely solves the selection problem, as the estimates with controls are small and not statistically significant. Panels B and C repeat the analysis for mothers' and fathers' schooling and earnings in 1985, which have the advantage of being available for women as well as men. The pattern is qualitatively very similar to that of the military skill measures: working in a subsequently declining occupation is associated with lower parental schooling and earnings, but these differences disappear once adding controls. In sum, Table 3 suggests that, although there is negative selection into occupations that later decline, most of this selection can be mitigated using suitable controls such as education and 1985 earnings. To the extent that minor negative selection persists in the regressions with individual controls, these regressions may slightly overstate the negative effect of occupational decline on workers, but this is not a concern once we add all the controls.

As a final check for sorting into declining occupations, we investigate earnings in 1980 for the older cohorts in our baseline sample (individuals aged 25–31 in 1980).[30] Again, we find that conditional on individual-level characteristics, there are essentially no differences in prior earnings, as seen in Online Appendix Figure OA2. Taken together, the results in this section suggest that concerns about sorting into declining occupations are largely alleviated when we include suitable controls.

4.2. *Main Results on Employment, Earnings and Occupational Mobility*

Table 4 reports results from estimating (2) using our main sample of workers aged 25–36 in 1985. Panel A shows that workers in declining occupations spent about nine fewer months (0.73 fewer years) in employment from 1986–2013 (column (1)). Once we add individual controls, this

[30] Earnings data for the population of Swedish workers are not available at annual frequency prior to 1985. We obtain prior earnings from the population censuses, which were carried out every five years until 1990.

estimate reduces to about six months, or about 2% of the sample mean of about 23 years (column (2)). Next, we add more controls and compare those who experienced occupational declines to observationally similar workers in similar occupations and industries. These specifications suggest that the losses from occupational decline averaged about two months (0.2 years) of employment, or about 1% of the sample mean (columns (3)–(6)).

Panel B of Table 4 reports results from using cumulative earnings 1986–2013 as the outcome. Column (1) shows that working in a declining occupation was associated with 350,000 Swedish krona (SEK) lower cumulative earnings, or about 5% of the sample mean.[31] When including individual controls, the estimated loss is similar, though the confidence interval is much tighter (column (2)). Further adding occupational controls cuts the loss to less than 2% of the sample mean.

In panel C we examine earnings losses from occupational decline using an alternative earnings measure: cumulative earnings divided by predicted initial earnings (see Section 2.2 for details on the construction of this variable). Depending on the controls included, the estimated losses in cumulative earnings range from around 100% to 220% of initial annual earnings, or from 2.5%–5.7% in terms of the sample mean, quite similar to the results in panel B.[32]

In Figure 2, we present a dynamic counterpart to the results reported in panel B, columns (2) and (6) of Table 4. Here we use as outcomes each year's earnings and cumulative earnings from 1986 up to the year indicated on the horizontal axis of each chart. The top right panel of Figure 2 is suggestive of a smooth process of occupational decline, with earnings losses building up gradually. However, the top left panel reveals that losses in annual earnings suffered by workers in declining occupations were larger during the 1990s and late-2000s recessions.[33] The picture is similar when we divide the coefficients by the mean of cumulative earnings at each horizon (bottom panels). As before, the losses are smaller when we include occupation and industry controls.

Next, we investigate occupational mobility. Table 5 reports estimates of equation (2) with indicators for working in 2013 in the same occupation as in 1985 (or in a similar ones) as outcomes. As we do not want to condition the sample on being employed in 2013 (which is also an outcome), we have that 'not remaining' in the same occupation could reflect either occupational switching or non-employment, a point to which we return below.

Column (1) in panel A of Table 5 shows that the probability of remaining in the same three-digit occupation was around 14 percentage points lower in declining occupations, compared to a mean of 29% in our sample. In other words, by 2013 a little over 70% of all workers had left their 1985 occupations (or left employment altogether), and the probability of staying in the same occupation was roughly halved for those starting in declining occupations. When we compare observationally similar workers, occupational decline appears to reduce the probability of remaining in the 1985 occupation by 11 percentage points, and when further restricting the comparison to similar occupations and industries, the estimate falls to 4.5 percentage points. Panels B and C of Table 5 show similar, albeit somewhat smaller, coefficients when we look at

[31] We inflate all SEK figures to 2014 levels. Average annual earnings of Swedish workers, conditional on being employed in November and earning at least the base amount during the year, were SEK 190,200 in 1985 and SEK 330,800 in 2013, in terms of 2014 SEK. We do not express these amounts in USD due to exchange rate fluctuations. For instance, SEK 1,000 were worth about USD 150 in January 2014, but about USD 130 in December 2014 and about USD 110 in October 2018.

[32] Below we discuss results using alternative functional forms for cumulative earnings.

[33] These results are related to Jaimovich and Siu (2020), who found that recessions hit routine employment particularly hard.

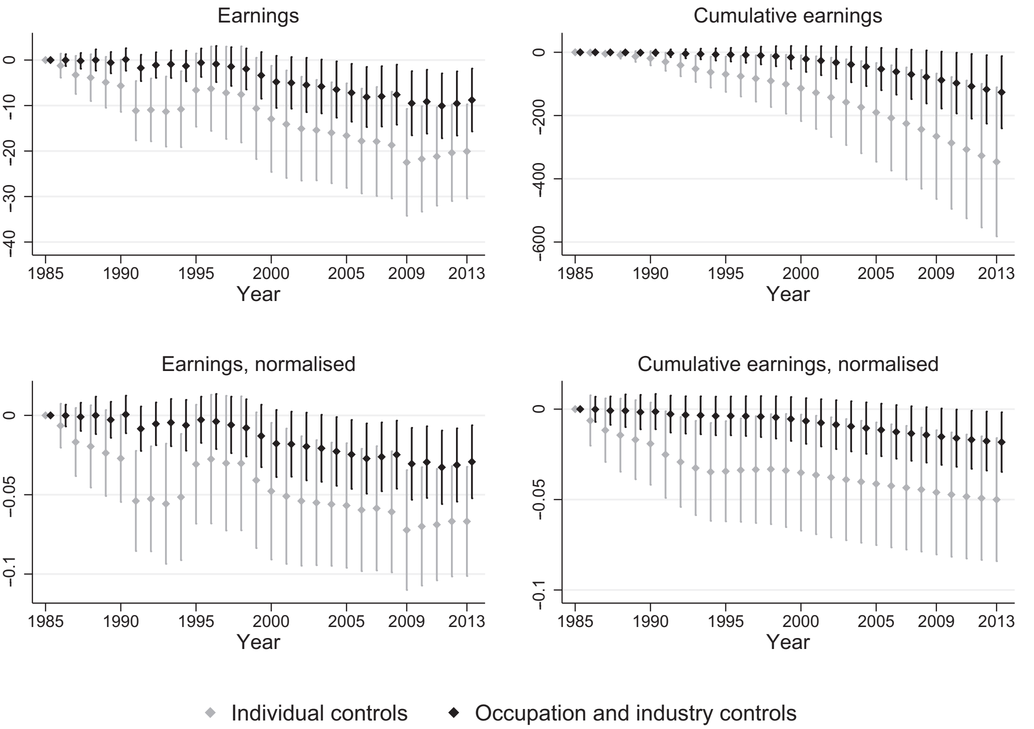

Fig. 2. *Differences in Earnings and Cumulative Earnings by Exposure to Occupational Decline, over Time.*
Notes: Diamonds mark the coefficients on the declining indicator from regressions of annual earnings or cumulative earnings on the indicator, including the same controls as in columns (2) ('Individual controls') and (6) ('Occupation and industry controls') of Table 4, separately for each year 1986–2013. Bars indicate 95% confidence intervals.

Table 5. *Occupational Decline and Individual Occupational Stability.*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Probability of working in the same three-digit occupation in 2013 as in 1985 (mean: 0.29)						
Declining	−0.14	−0.11	−0.11	−0.065	−0.086	−0.045
	(0.043)	(0.041)	(0.042)	(0.032)	(0.035)	(0.020)
Panel B. Probability of working in the same two-digit occupation in 2013 as in 1985 (mean: 0.35)						
Declining	−0.12	−0.088	−0.087	−0.051	−0.071	−0.037
	(0.034)	(0.034)	(0.035)	(0.030)	(0.030)	(0.019)
Panel C. Probability of working in the same one-digit occupation in 2013 as in 1985 (mean: 0.40)						
Declining	−0.098	−0.070	−0.069	−0.039	−0.060	−0.031
	(0.030)	(0.031)	(0.032)	(0.029)	(0.027)	(0.018)
Demographics & earnings		✓	✓	✓	✓	✓
Life-cycle profiles			✓	✓	✓	✓
Predictors of growth				✓	✓	✓
Occupation dummies					✓	✓
Industry dummies						✓

Notes: Results from regressions of the indicated outcomes on a dummy for working in 1985 in a subsequently declining occupation are shown. See the notes to Tables 1 and 4 for the definition of the declining indicator and a description of control variables, respectively. The number of observations is 553,169. The sample is the same as that in panel B of Table 2, except that individuals who were employed in 2013, but not sampled in the Wage Structure Statistics had to be excluded, as it is unknown whether they work in the same occupation in 2013 as in 1985. Sampling weights are applied. Robust standard errors, clustered by 1985 three-digit occupation, are given in parentheses.

the probability of remaining in more broadly defined (two-digit or one-digit) occupations. It is noteworthy that even when we consider one-digit occupations, only about 40% of the sample remained in the same broadly defined occupation over the 28-year period that we study.[34]

Having presented our main results on career employment, career earnings and occupational mobility, we now return to the issues of interpretation alluded to in Section 3.1 and the question of magnitudes discussed in Section 3.2. Our results from including individual, occupation and industry controls (column (6) in Tables 4 and 5) plausibly provide us with conservative estimates of the losses from occupational decline—about 2% of mean cumulative earnings over 28 years—given the balance of pre-determined characteristics conditional on these controls, as well as the fact that no earnings losses appear in the first 5–10 years (Figure 2). As argued in Section 4.1, the specification only controlling for individual characteristics (column (2) in Tables 4 and 5) may slightly overstate the losses from occupational decline—5% of mean cumulative earnings—as it leaves minor differences in some of the pre-determined characteristics. In addition, Figure 2 shows earnings losses based on this specification already in the years immediately after 1985. On the other hand, we have also seen that the extent of occupational decline is much reduced when including occupation and industry controls (columns (2) and (6) in Table 1). This brings us to the discussion of magnitudes.

We calculate the elasticities of our outcome variables with respect to occupational employment growth in Sweden by taking the reduced-form estimates reported in Tables 4 and 5 (expressed in percent of the outcome mean), and dividing them by the difference in occupational employment growth between declining and non-declining occupations reported in Table 1. This yields elasticities of 0.04–0.05 for cumulative employment, 0.08–0.13 for cumulative earnings and 0.71–0.95 for remaining in the initial occupation (the ranges again refer to columns (2) and (6) in the relevant tables). Recall from the discussion in Section 3.2 that these numbers are likely upper bounds on the true elasticities. Nonetheless, they support the interpretation that, on average, occupational decline results in a modest loss in career employment, a somewhat larger, but still modest loss in career earnings and, in contrast, a strong occupational mobility response. These estimates potentially mask substantial heterogeneity, however, which we investigate in Section 4.3.

4.2.1. *Robustness of main results*

Our first set of robustness checks relates to the choice of functional form of occupational decline. The declining indicator is based on a 25% cutoff, conservatively identifying occupations whose (US) employment fell substantially since the mid-1980s. We also explore a range of alternative cutoffs, and find that higher cutoffs (in the sense of isolating larger employment declines) usually result in larger estimated losses and mobility responses. In addition, our results are very similar when we exclude occupations that grew rapidly from the control group (see Online Appendix Table OA3 for both sets of results). While we focus on a binary definition of occupational decline as motivated in Section 3.2, we also explore the relationships between our key outcomes of interest and the full variation in US and Swedish employment growth. The (residualised) associations of cumulative earnings and occupational mobility with occupational employment growth are mostly flat, apart from a drop in occupations that declined substantially (see Online Appendix Figures OA3 and OA4, and corresponding regression results in Online Appendix Table OA4).

[34] For related discussions of the importance of switching occupations in the presence of technological change, see Cortes (2016) and Caselli and Manning (2019).

Table 6. *Heterogeneity by within-Occupation Earnings Rank.*

	Employment		Earnings		Earnings, normalised		Remain	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Linear interaction								
Declining	−0.51	−0.23	−353.5	−131.0	−2.16	−1.19	−0.11	−0.046
	(0.21)	(0.15)	(110.7)	(55.8)	(0.55)	(0.37)	(0.041)	(0.020)
Declining × rank	1.17	1.17	441.5	449.2	2.63	2.63	−0.011	−0.00090
	(0.34)	(0.30)	(142.3)	(146.8)	(0.58)	(0.57)	(0.023)	(0.017)
Panel B. Dummy interactions								
Declining	−0.32	−0.031	−323.2	−98.0	−1.94	−0.97	−0.083	−0.022
	(0.24)	(0.18)	(123.8)	(66.7)	(0.54)	(0.41)	(0.045)	(0.021)
Declining × bottom tercile	−1.12	−1.13	−341.8	−350.1	−2.10	−2.06	−0.046	−0.040
	(0.35)	(0.33)	(106.7)	(101.5)	(0.54)	(0.51)	(0.014)	(0.013)
Declining × top tercile	0.54	0.55	232.3	235.1	1.37	1.40	−0.047	−0.029
	(0.20)	(0.16)	(135.8)	(132.1)	(0.43)	(0.48)	(0.027)	(0.018)
Individual controls	✓	✓	✓	✓	✓	✓	✓	✓
Occupation & industry controls		✓		✓		✓		✓
Mean of dep. var.	23.4		6,926		38.7		0.29	
Mean of dep. var., bottom	22.3		6,001		35.6		0.27	
Observations			877,324				553,787	

Notes: Results from regressions of the indicated outcomes on the declining indicator, within-occupation earnings rank or tercile dummies (coefficients omitted from table) and their interactions are shown. Within-occupation earnings ranks are computed in 1985 and re-scaled so as to range from −1 to 1. In panel A, the main effect on the declining indicator thus applies to the individual earning the median income within her occupation, and the coefficient on the interaction gives the inter-quartile range. Individual-level controls include female, cohort, county and education dummies, as well as earnings in 1985. Occupation and industry controls include predicted lifetime income, predictors of occupational growth, occupation dummies and industry dummies. Normalised earnings are cumulative earnings divided by initial predicted earnings. The sample for columns (1)–(6) is the same as that in Table 4, and for columns (7)–(8), it is the same as that in Table 5. Robust standard errors, clustered by 1985 three-digit occupation, are given in parentheses.

A second set of robustness checks adds fixed effects for the firms that workers worked for in 1985. This specification lets us compare two workers who started out in declining and non-declining occupations, respectively, but worked at the same firm. Thus, we address the concern that declining occupations may be systematically different in terms of the quality of firms, which may differentially affect workers' future careers. Reassuringly, as Online Appendix Table OA5 shows, the findings in Tables 4 and 5 are generally robust to adding fixed effects for workers' starting firms. The effects on employment losses and occupational stability are a little smaller in magnitude, while those on earnings are a little larger. This suggests that, conditional on our other controls, differential sorting into firms does not drive our estimates.

Finally, our conclusions about earnings losses are robust to using different functional forms of earnings, as we discuss further in the next sub-section.

4.3. *Heterogeneity by within-Occupation Earnings Rank*

We now examine how employment and earnings losses from occupational decline varied by initial within-occupation earnings rank. We estimate (2) allowing the coefficient on the declining indicator to vary by earnings rank, and report the results in Table 6. Panel A shows that lower-ranked workers suffered larger employment and earnings losses than average as a result of occupational decline (columns (1)–(6)): the coefficients on the interaction of the declining indicator with earnings rank are positive and precisely estimated. Moreover, these estimates barely change when we add occupation and industry controls over individual-level controls, though the main coefficients on the declining dummy—giving the employment and earnings loss for the median worker—are affected by the inclusion of additional controls. The magnitudes implied by the interaction coefficients are meaningful and imply, for instance, that compared to the 25th percentile, the 75th-percentile worker suffered a 5% lower employment loss and a 6.5% lower earnings loss (both in terms of the overall mean).

This pattern is robust to alternative specifications that replace the linear rank measures with dummies for the bottom and top terciles. This specification also allows us to characterise losses for low-ranked workers directly. Panel B of Table 6 shows that workers at the bottom tercile of their starting occupations' earnings distributions suffered employment losses of 1.2–1.4 years (5.5%–6.5% of mean employment in the bottom tercile) and earnings losses of around 8%–11% of bottom-tercile mean earnings. Indeed, the estimates of mean losses reported in the previous sub-section mask more substantial losses for low earners (within an occupation). Our findings about earnings losses are robust to several alternative ways of measuring career earnings, as shown in Online Appendix Table OA6.[35]

The pattern for the probability of remaining in the initial occupation appears to be non-monotonic: among the workers in declining occupations, both bottom-tercile and top-tercile workers were less likely to remain in their starting occupations (panel B, columns (7)–(8)). These interaction coefficients are larger than 10% of the overall mean (although in the case of the top tercile, not precisely estimated). This hump-shaped pattern of staying probabilities (U-shaped in exiting probabilities) is intriguing from a theoretical point of view, as we discuss below.

One potential challenge in interpreting the results of Table 6 is that those with low earnings in their occupation may have differed from others along some observable dimensions, such as gender, age, or geography. To mitigate this concern, we re-estimate the regressions using workers' within-occupation rank in residualised earnings, where the residuals come from a regression of earnings on female, cohort, and county-of-residence dummies. As Online Appendix Table OA7 shows, in terms of employment and earnings losses the results are qualitatively unchanged, and the magnitude of the interaction coefficients is only slightly reduced. However, using the residual-based rank measure, there is less support for the conclusion that bottom-ranked workers were less likely to remain in the initial occupation. Online Appendix Table OA8 reports interactions using overall earnings rank instead of within-occupation earnings rank. Large losses from occupational decline for those in the lowest tercile again stand out as a consistently robust finding.[36]

We consider three further dimensions of heterogeneity. First, we examine earnings losses separately for those who remained in their initial occupation and those who did not. This purely descriptive exercise is motivated by the prediction of our baseline model in Section 1 that leavers should have lower losses than stayers. We estimate (2) with cumulative earnings as the outcome variable, and add on the right-hand side a dummy for having remained in the initial occupation, as well as its interaction with the declining dummy. Panel A of Online Appendix Table OA10 shows that among all workers, those who remained in their initial occupation had higher cumulative earnings, though in panel B we restrict the sample to those who were employed in 2013, and

[35] We consider discounted cumulative earnings, applying a 5% discount rate, discounted cumulative earnings normalised by initial earnings, the percentile rank in cumulative earnings, the log of cumulative earnings and the percentage change in earnings 1985–2013. As expected, the estimated losses in terms of discounted cumulative earnings are somewhat smaller at 1.5%−4.5% of the overall mean, depending on controls, as more weight is put on earlier years in the career.

[36] Online Appendix Table OA9 uses residualised overall earnings rank, again with similar results. Note that in the theoretical model, within-occupation and overall earnings rank and their residualised counterparts are all identical.

the finding reverses.[37] Importantly, in neither case is there evidence that those who remained in declining occupations did significantly worse than those who left a declining occupation. The same result holds when we focus on the bottom third (in terms of within-occupation earnings); see panel C. We discuss the interpretation of these results in light of the model in Section 4.6 below.

Second, while we argue that our approach delivers an upper bound on the magnitude of average losses due to occupational decline, we also explore heterogeneity related to workers in non-declining occupations. Workers who leave declining occupations may flock to similar non-declining occupations, depressing the wage in these 'control' occupations. And even in the absence of such general equilibrium effects, employing a rich set of controls may cause us to put more weight on groups of comparable occupations where there are roughly as many declining as non-declining sub-occupations. In such cases, workers may have many substitute occupations to choose from. To explore such issues, we run what we refer to as 'doughnut' specifications, namely, the same regressions as those we report in Tables 4 and 5, but excluding three-digit (SSYK96) occupations in which some, but not all five-digit occupations are declining. We indeed estimate slightly larger earnings losses than in our baseline specifications, ranging from 3%–6% of mean earnings (see Online Appendix Tables OA11 and OA12).

Finally, we explore heterogeneity by gender. As Online Appendix Table OA13 shows, occupational decline results in larger losses of employment and occupational stability for women, while men suffer larger earnings losses. Larger employment and earnings losses for those in the bottom tercile are concentrated among men, although once we use residualised earnings rank (Online Appendix Table OA14) the losses of women in the bottom tercile are roughly as large as men's.

4.4. *Unemployment, Retraining, Early Retirement and Geographic Stability*

A natural question at this stage is to what extent the loss in years of employment due to occupational decline is accounted for by increased unemployment and retraining; as discussed above, data on these last two outcomes are available for the final 22 years of our study. Table 7 reports estimates using the main specifications from Tables 4 and 6, but this time using cumulative days of unemployment (panel A) and state-sponsored retraining (panel B) as outcome variables. Columns (1)–(4) of panel A show that workers who started out in later declining occupations were only very slightly more likely to ever be unemployed, and columns (5)–(8) suggest that these workers accumulated 20−50 more unemployment days, though the estimates with more controls are imprecise. However, we again find substantial heterogeneity, with bottom-tercile workers in declining occupations spending 63 days more in unemployment, a substantial 20% of the mean.

Columns (1)–(4) of panel B suggest that occupational decline increased the risk of ever enrolling in state-sponsored retraining by 9%–27%. The estimates for cumulative days spent retraining are similarly substantial, at least in relative terms (columns (5)–(8)). Our most conservative specification including all controls suggest that the median worker spent six more days in retraining, which amounts to 21% of the mean (10 days and 29% for the bottom-tercile worker).

Our estimates for unemployment and retraining can only explain part of the estimated employment losses. For bottom-tercile workers, we conservatively estimate an employment loss of

[37] Workers classified as having remained are employed in 2013 by construction, whereas those classified as not having remained might not have been employed in 2013, and thus have zero earnings in that year, and possibly in preceding years also.

Table 7. *Occupational Decline and the Incidence of Unemployment and Retraining.*

	Ever				Cumulative days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Unemployment								
Declining	0.041	0.013	0.015	0.019	52.4	17.9	20.8	20.5
	(0.021)	(0.013)	(0.012)	(0.015)	(24.8)	(14.0)	(14.0)	(18.2)
Declining × rank			−0.036				−63.8	
			(0.012)				(21.5)	
Declining × bottom tercile				0.017				42.4
				(0.012)				(18.3)
Declining × top tercile				−0.033				−43.7
				(0.012)				(17.0)
Mean of dep. var.	0.39				262			
Mean of dep. var., bottom	0.43				317			
Panel B. Retraining								
Declining	0.035	0.012	0.013	0.015	11.4	4.73	5.04	5.81
	(0.010)	(0.0064)	(0.0063)	(0.0081)	(2.68)	(1.46)	(1.48)	(2.26)
Declining × rank			−0.027				−8.63	
			(0.0070)				(1.98)	
Declining × bottom tercile				0.014				4.38
				(0.0072)				(2.28)
Declining × top tercile				−0.022				−6.96
				(0.0064)				(2.12)
Mean of dep. var.	0.13				29			
Mean of dep. var., bottom	0.15				35			
Individual controls	✓	✓	✓	✓	✓	✓	✓	✓
Occupation & industry controls		✓	✓	✓		✓	✓	✓

Notes: Results from regressions of the indicated outcomes on the declining indicator, within-occupation earnings rank or tercile dummies (coefficients omitted from table) and their interactions are shown. Incidence of unemployment and retraining are measured during the period 1992–2013. The sample is the same as that in panel B of Table 2. See the notes to Table 6 for a description of right-hand side variables. Robust standard errors, clustered by 1985 three-digit occupation, given in in parentheses.

1.16 years.[38] Of these, unemployment and retraining account for only 22%.[39] The remaining employment loss may be accounted for by job search that is not covered by unemployment benefits, private retraining or time spent outside the labour force. Unfortunately, we lack the data to investigate this further.

There is however a group of workers for whom we can investigate the relationship between occupational decline and exit from the labour force, namely, older workers. Recall that workers in our baseline sample reached a maximum age of 64 in 2013. We now examine employment, earnings and retirement for two groups of older workers, most of whom reached the usual retirement age of 65 well before the end of our sample period.

Panel A of Online Appendix Table OA15 considers workers who were aged 37–48 in 1985. The employment losses among this group are a little larger than for our baseline sample: about eight months (four months) of a year of employment in the specification with individual (all) controls, or just under 4% (2%) of the group mean. About half of these employment losses are accounted for by a slightly younger age of retirement for those in declining occupations. The estimated earnings losses from occupational decline—about 6% (1.5%) with individual (all) controls—are similar to those of the baseline group. Finally, for this group, we also find

[38] From panel B, column (2) in Table 6 we obtain $-0.03 - 1.13 = -1.16$. To complete the calculation, we divide the unemployment and retraining coefficients by 365 to get years, multiply them by $28/22$ to account for the fact that these variables are only available during $1992-2013$, sum them and divide by 1.16.

[39] Of the mean employment loss, unemployment and retraining explain about a third and a tenth of the time, respectively.

positive and significant interactions of the declining dummy with initial occupational earnings rank, suggesting once more that those who earned least within their occupation to begin with lost more years of employment from occupational decline.

Panel B of Online Appendix Table OA15 suggests that, for an even older group, those aged 49–60 in 1985, the occupational decline that we measure had more modest costs compared to the baseline group. This likely reflects the fact that we are measuring occupational decline over a longer period, and that these older workers had little exposure to the decline.[40]

Finally, we study whether occupational decline results in geographic mobility across municipalities, commuting zones and counties. The results in Online Appendix Tables OA16 and OA17 suggest that occupational decline does not, on average, reduce geographic stability. Workers in the bottom tercile, however, are a little more likely to leave their location when their occupation declines.

4.5. *Technology-Related Occupational Decline*

Consistent with much of the literature (Goos *et al.*, 2014), we expect technological change to be a key driver of occupational decline, and especially occupational decline that is common to the United States and Sweden. Nevertheless, there could be other drivers, including changes on the supply side (changes in demographics, trade shocks or changes in government policy) and in consumer demand. Bearing this in mind, we now focus on occupations that are likely to have declined due to the introduction of labour-replacing technology, based on information from the OOH, as described in Section 2.2.[41]

We find that workers' exposure to declines in Swedish occupational employment is of very similar magnitude regardless of whether we consider all occupations classified as declining, or only those we linked to technology (Online Appendix Table OA19, panel A and Online Appendix Table OA20).[42] Moreover, technology-related occupational declines are not significantly different from other occupational declines in their implications for years of employment, cumulative earnings and the probability of remaining in the initial occupation. One way to see this is by adding an indicator for technology-linked decline to (2). We find that the coefficients on this indicator are statistically indistinguishable from zero (columns (1) and (2) in panels B–D of Online Appendix Table OA19). Alternatively, considering technology-related declines on their own, we see very similar point estimates, both for the main effect and for the interaction with earnings rank, as for the full set of declines (columns (3)–(5)).

Our second approach to investigating the consequences of technology-driven occupational decline relies on the presence of relevant labour-replacing technologies, classified using our algorithmic or manual approaches (as described in Section 2.2). Panel A of Online Appendix Table OA21 shows that both measures of technological replacement are correlated with occupational decline, although the estimates for the algorithmic measure are a little larger and (once we

[40] We verify that, for the groups of middle-aged and older workers, our declining indicator does not predict differences in prior earnings (1975 and 1980) conditional on controls; see Online Appendix Figure OA2.

[41] Some of what we classify as technology-related decline may still be influenced by other factors, and we cannot rule out that technology played a role in the remaining declining occupations.

[42] Workers starting out in 1985 in subsequently declining occupations, where we were able to identify a link to technology, were statistically indistinguishable from those in the remaining declining occupations, as seen in Online Appendix Table OA18.

include all controls) more precisely estimated.[43] As panel B shows, both measures of technological replacement are also correlated with large employment declines at the coarse three-digit level, although only the algorithmic measure survives the inclusion of the full set of controls. Panel C shows that at the individual level, both measures result in fairly moderate employment losses, with point estimates that are all below half a year of employment—similar to our main measure of occupational decline. Finally, panel D shows that the cumulative earnings losses from technological replacement are also quite similar to our main estimates: around 1%–3% (imprecisely estimated) for the algorithmic measure, and around 5%–7% (precisely estimated) for the manual measure.

4.6. *Interpreting our Findings Through the Lens of the Theoretical Model*

In our empirical analysis, we confirm that occupational decline was associated with earnings losses and higher occupational exit rates. This is consistent with our model's assumption that occupational decline was largely driven by changes in demand.

The version of the model that best fits our empirical findings is that with both differential occupational switching costs and displacement. In this case, those with lower initial within-occupation earnings rank suffer larger earnings losses as a result of occupational decline; switchers' earnings losses may be larger than those of stayers (as we find); and displacement may lead to switching probabilities that are U-shaped in initial earnings, whereby low-earning workers switch if displaced, while high-earning workers switch voluntarily.

Our empirical analysis also sheds light on the nature of the occupational switching costs in the model. In practice, we find that roughly a third of the employment years lost can be accounted for by increased unemployment, and almost 10% are due to retraining. The stronger responses to occupational decline of unemployment and retraining among lower-ranked workers further supports our interpretation of heterogeneous switching costs.

Finally, our model suggests that the effects of an adverse occupational demand shock may differ, depending on whether the shock was anticipated. Controlling for projected employment growth—thus isolating unanticipated declines—generally leads us to estimate smaller earnings losses and mobility responses. The former is consistent with our model, but the latter is not. A possible explanation may be that, conditional on predicted occupational employment growth, our declining indicator isolates a lower level of exposure to actual Swedish employment declines than in the unconditional regression, or the one only conditioning on individual characteristics.[44]

5. Conclusion

In this paper, we study the long-run employment and earnings losses that workers suffer when demand for their occupations declines. We begin by measuring anticipated and actual occupational declines in the United States, which we map into panel micro data on Swedish workers. We find that, even after controlling for key predictors of occupational decline, employment changes in declining Swedish occupations were around 20–40 log points lower than in non-declining occupations.

[43] Both measures are (conditionally) balanced on the same set of characteristics that we report in Table 3—these estimates are available on request.

[44] However, exposure declines by less than the mobility response, in relative terms. See columns (2) and (4) in Tables 1 and 4.and retirement for two groups of older workers, most of whom reached

Despite this large fall in employment, we find that over 28 years, those who in 1985 worked in declining occupations experienced earnings (employment) losses that were around 2%–5% (1%–2%) of mean cumulative earnings (employment), compared to those who initially worked in non-declining occupations. We characterise conditions under which these figures are a plausible upper bound on the magnitude of the losses due to occupational decline. The earnings losses are on the higher end of the above-mentioned range when we control only for individual covariates, and lower when we also control for anticipated occupational changes and industry and occupation characteristics. Around a third of the cumulative employment losses are accounted for by increased unemployment, and a further tenth by increased time spent in government retraining.

We find that workers in the bottom tercile of their occupations' earnings distributions suffered the largest losses (around 8%–11%). Workers in the bottom tercile also lost more years of employment and spent more time in unemployment and retraining. We find that those in declining occupations were significantly more likely to leave their starting occupations. The propensity to exit declining occupations was U-shaped in initial occupational earnings rank, with those at the bottom (and to a lesser extent at the top) more likely to leave their starting occupations.

We show that our findings are consistent with a Roy model with negative occupational demand shocks, where workers may suffer displacement, and where finding re-employment takes time. In the model, those at the bottom of a declining occupation also have low earnings capacity in other occupations, and therefore find it harder to find re-employment—whether in their own occupations or in other occupations. Hence, they lose most from occupational decline. The model also rationalises the U-shaped exit pattern that we describe above: those at the bottom of their occupations' earnings distributions are more likely to leave their occupations when they are displaced, while those at the top are more likely to leave, to avoid negative demand shocks.

Our findings suggest that the mean losses of occupational decline are lower than the losses suffered by displaced workers that have been reported in prior literature. This is likely because occupational decline is typically gradual, and can be partly managed through retirements, reduced entry into declining occupations and increased job-to-job exits to other occupations. Indeed, we document a response in terms of occupational mobility that, in terms of elasticities, is much larger than our estimated earnings losses. Gradual occupational decline may also impose fewer negative spillovers on local economies compared to large, sudden shocks, such as plant closures.

At the same time, future occupational decline could still have substantial adverse consequences for workers' outcomes, for the following three reasons. First, our paper studies occupational decline that—while unanticipated early in workers' careers—was nevertheless fairly gradual. But if, for example, machine learning improves rapidly, occupational replacement may happen faster, and may be accompanied by an overall worsening of employment opportunities (Bostrom, 2014). Second, the occupational decline that we study largely spared the most skilled occupations, but this may change with new technologies. Many professionals made sizeable investments in skills that are particularly useful in their occupations, and some may also benefit from economic rents. It is possible that, for these workers, the earnings losses from future occupational decline may be higher than those we estimate. Finally, and perhaps most importantly, our findings show that low-earning individuals are already suffering considerable (pre-tax) earnings losses, even in Sweden, where institutions are geared towards mitigating those losses and facilitating occupational transitions. Helping these workers stay productive when they face occupational decline remains an important challenge for governments.

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Additional Supporting Information may be found in the online version of this article:

Online Appendix
Replication Package

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