

Understanding the self-organization of occupational sex segregation with mobility networks

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ABSTRACT

Decades after the beginning of the gender revolution, most women and men still work in sex-typed occupations. This is a primary driver of the gender wage gap. Most research describing the patterns of occupational sex segregation focuses on supposedly innate job characteristics that match gender stereotypical abilities and preferences, such as the use of mathematical skills or social skills, on income and status differences between occupations, and on organizational job characteristics, for example, the need to work long hours. However, beyond such occupational attributes, sex segregation is hypothesized to exhibit emergent patterns that are linked to the interdependent job mobility of women and men, in particular, men selectively leaving feminizing occupations. Developing new tools inspired by statistical network research, and using representative, longitudinal data that contain detailed occupational mobility from the UK between 2000 and 2008, this replacement mechanism is analyzed. It is shown that 19–28% of observed sex segregation is linked to this emergent phenomenon in a statistical model that disentangles the various predictors of the allocation of women and men to different occupations. This makes it the most important predictor of segregation in contrast to concurrently modelled explanations based on occupational characteristics.

Data and materials availability: The BHPS data and the LFS data are available from the UK Data Service (<https://www.ukdataservice.ac.uk/>). The O*NET data is available from the O*NET homepage (<https://www.onetcenter.org/>). Software implemented in the environment R and code for data analysis are available upon request from the authors.

Introduction

While gender equality in the labor market has advanced significantly since the 1960s, women and men still tend to work in different sectors and occupations. Indeed, contemporary labor markets are commonly characterized as ‘hyper-segregated’; around 50% of employed women would need to switch occupations to achieve balanced sex compositions within occupations (Charles and Grusky, 2005; Levanon and Grusky, 2016). One important consequence of occupational sex segregation is that it is the basis of the large differences in earnings between women and men – the gender wage gap (Blau and Kahn, 2017; Charles, 2011), which is currently around approximately 15% of median income in most western economies (OECD, 2019).

Established explanations of sex segregation mostly focus on occupational characteristics and rewards. According to theories of vertical segregation, men systematically have access to higher reward and

higher status jobs (Ridgeway, 2001; Charles and Grusky, 2005; England, 2010), as discrimination against women in hiring and promotion hinders women’s access to jobs with high pay, responsibilities, and power. This can be explained by employers’ stereotypical beliefs about gender roles in society (Ridgeway, 2001), by neoclassical economic models of specialization of tasks in households (Becker, 1985), or by statistical discrimination (Bielby and Baron, 1986). Popularly known examples of vertical segregation are the metaphorical glass ceiling that restricts women from advancing to top-level positions (Gorman and Kmec, 2009) and the inverse case of the glass elevator, in which men in some female dominated occupations are advantaged in getting promotions (Williams, 2013). Next to the various forms of discrimination that sorts women into worse occupations than men, there are also essentialist mechanisms that sort women into qualitatively different occupations.

Horizontal segregation arises from women and men being assumed to differ systematically in their abilities and preferences for types of

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occupations; men work in jobs that require male-typed skills, such as mathematical ability or physical strength, while women work in jobs that need female-typed skills, such as sociability or creativity (Levanon and Grusky, 2016; Cech, 2013; Leslie et al., 2015). Sex-typed beliefs about skills of individuals come about by various socialization processes throughout the life course (e.g., Lauzen et al., 2008; Hilliard and Liben, 2010; Wood and Eagly, 2012). Horizontal sorting mechanisms work on the supply and demand side. Employers preferably hire individuals of the sex that matches the gender stereotype of an occupation. At the same time, women and men make educational and occupational choices that allow them to do tasks typically associated with their gender.

Finally, the stereotypical *division of labor* in heterosexual couples often results in women doing a majority of housework and child rearing, limiting potential employment to jobs that are compatible with family life (e.g. through part-time work; Becker, 1985; Eccles, 1994; England, 2010). This is equally based in stereotypical beliefs about gender roles but justifies sex segregation in occupations with seemingly pragmatic and necessary choices couples have to make. These three explanations (vertical, horizontal and division of labor) are widely supported by empirical studies that use representative survey data and correlate job characteristics with sex composition (Charles and Grusky, 2005; Percheski, 2008; Levanon and Grusky, 2016).

However, striking empirical regularities cannot be explained by these models. First, specializations within disciplines that are characterized by very similar income, skill requirements, and work conditions often have hugely disparate sex compositions, e.g. specialties among medical doctors or lawyers (Ku, 2011; Seron et al., 2016). While small differences in work content exist between specializations e.g. in medicine, these are minute in comparison to the similarities of these specializations that arise from similar education, labor relations and social standing, which would predict very similar sex compositions. Second, sex ratios in occupations sometimes change considerably over time, e.g. primary school teachers, pharmacists, and accountants have shifted from male- to female-dominated in recent decades (i.e. feminized; Reskin and Roos, 1990; Murphy and Oesch, 2016; Pan, 2015). These swings in sex composition do not co-occur with changes in skill profiles or entry requirements and, thus, cannot be explained by changes in occupational characteristics. Consequently, social mechanisms beyond sex-typed occupational characteristics are likely to contribute to sex segregation.

One mechanism that can explain these regularities has been described in previous work. It is suggested that men avoid and leave occupations and specializations in case the sex composition swings towards being female dominated. This is predicted by the devaluation perspective in gender studies and was named in neighboring fields a pollution theory of discrimination (Reskin and Roos, 1990; England et al., 2007b; England, 2008; Goldin, 2014). Discussions of this theory propose different potential mechanisms. On the one hand, men leaving feminizing occupations might be a result of men's psychological discomfort to work in what is perceived as a 'woman's job'. This is related to the essentialist differentiation of some tasks as female-typed and other tasks as male-typed. Men that have internalized such a differentiation might start to perceive that they are working in the 'wrong', meaning sex atypical, occupation in case the sex composition of others doing their work changes and they search for a different line of work. On the other hand, female dominated occupations tend to be devalued, that is, have lower prestige and bestow less social status on their incumbents. Further, wage penalties often occur when occupations feminize, especially when female proportion crosses thresholds of substantially more than 50% (England, 2008; Goldin, 2014; Murphy and Oesch, 2016; Pan, 2015). Thus, men might leave feminizing occupations, because they want to avoid work that has the reduced income and prestige associated with a sex-ratio leaning towards female dominated. In anticipation of decreasing wage and status, or the fear that they could be underpaid already, they move away from these occupations.

At this point we are not so much interested in why men leave

feminizing occupations, but rather, whether it can be generalized to an entire labor market that men do selectively leave them. Previous work in this area has focused on case studies of particular occupations (most prominently Reskin and Roos, 1990) or modelled replacement over larger timespans ignoring occupational characteristics (Pan, 2015). The most comparable study analyzes the effect of feminization of academic fields on male propensity to enter them (England et al., 2007a). However, none of the studies model the interdependent movement of women and men through a complete labor market. Thus, the study provides evidence whether a distinct prediction of the outlined devaluation theories is empirically observed by analyzing whether occupations that are mainly entered by women show higher rates of men leaving, controlling for occupational characteristics that govern male and female mobility.

If a relation between female inflow and male outflow is observed, a second question concerns the extent to which this produces sex segregation. How much of the observed segregation can be statistically attributed to this replacement pattern in comparison to traditional occupational characteristics used in the literature? For both questions – if replacement exists, and if yes, how important it is – longitudinal data and advanced, non-standard statistical methodology is needed.

Modelling considerations

The outlined research questions require a move to longitudinal data since the main pattern of interest is explicitly about sex-specific mobility that inherently unfolds over time. The operationalization of the research question for our purpose is: do men leave occupations beyond what is predicted by occupational characteristics and based on the sex composition of individuals entering the occupation? An intuitive approach towards this question is how the changes in female ratio in an occupation between time-points t_1 and t_2 predict the mobility decision of men in the period t_2 to t_3 . This would satisfy the requirement of temporal contiguity linking female inflow to male outflow. However, this approach does not address the main interest of the study, which is analyzing a contemporaneous outflow of women and inflow of men over the same period t_1 to t_2 . This contemporaneous relation describes an emergent phenomenon that has social basis and materializes before occupations change. Thus, the interest is not in the mediated relationship, where female inflow changes occupational characteristics (such as decreasing wages or changing work content) which leads to a male outflow. In other words, this study analyzes what happens in *feminizing* occupations, not in *feminized* occupations.

The concurrent modelling that men leave occupations that mainly are entered by women goes beyond what is possible using standard statistical methodology. Answering questions regarding emergent, contemporaneous patterns requires analyzing the movement of men through the labor market *statistically dependent* on women's movement. This inferential task violates a cornerstone of modern statistical methods: the assumption of independent observations (Snijders, 2011). Under this assumption, each individual under analysis must be unaffected by the choices of all other individuals that are concurrently analyzed. However, this is not only a technicality; it forces researchers to only include predictors in the analyses that are fully exogenous, that is, variables describing individuals and occupations. By that, individuals under analysis are socially decontextualized, as the mobility of other people cannot influence their own mobility. However, the pattern of interest in this study is the interdependent movements of women and men through the labor market, where each other's mobility is the relevant context that influences their decision.

The empirical aim to describe the system of mobility requires moving to specialized methodology that can represent such interdependency. Ignoring dependence in observations and attempting to use standard models to represent how different observations react to each other (for example a multinomial logit model) models inter-dependence while at the same time assuming independence – a clear contradiction. In practice, this leads to substantially biased parameters and, in the extreme

case, to estimated parameters that do not represent the system under analysis at all (an issue known as degeneracy in network modelling, see Lusher et al., 2013).

The current study

This study overcomes this limitation of standard approaches by developing and using statistical methods and concepts originating in network research that do not require independent observations. They are used to analyze whether, and to what extent men leave occupations when more women enter, controlling for a comprehensive set of occupational characteristics. This allows to test both, the importance of occupational characteristics – following existing research – and the prevalence of endogenous mobility patterns – extending previous research.

Conceptually, the analytical strategy attempts a comprehensive description of the patterns how women and men differ in their moves between occupations. It takes past research on sex-specific occupational choices as its starting point, modelling how occupational characteristics, such as income, skill use, or average work hours, lead to women and men ending up in different occupations. These occupational characteristics can influence mobility in multiple ways, in particular, (1) what characteristics make an occupation an attractive destination of mobility for women compared to men (pull factors), (2) what characteristics of an occupation make people leave their occupation (push factors), and (3) how this differs for women and men. Additionally, the model includes (4) between which pairs of occupation mobility is likely, based on similarity of occupational characteristics to represent that workers move to other occupations that are similar to their origin, regardless of the sex-to-job match. This results in a structural description of mobility patterns, with examples of results being “women are more likely than men to leave occupations that require regular overtime”, or “mobile men are more likely to move to occupations that require mathematical skills than mobile women”. The occupational characteristics in this analysis attempt to include those that were consistently shown to differentially influence female and male occupational choices to minimize omitted variable bias. Importantly, since this is a structural description of mobility, for the purpose of modelling it is irrelevant through what mechanisms occupational characteristics influence mobility (see theoretical discussion above), it is only important that the relevant characteristics that predict differential mobility of women and men are included in the model.

In the second step, the analytical strategy is to find out whether, additional to these occupational characteristics, there is evidence that men’s propensity to leave an occupation is related to the proportion of women entering this occupation.

The concept of a mobility network facilitates to empirically relate the mobility of different sexes to each other. Mobility networks represent the structure of occupational changes within a society. In a mobility network, nodes represent occupations, and the edges denote the number of individuals that change their occupation from the origin to the target node within a given period. Mobility networks further include self-ties (individuals that remain in their occupation). An important feature of mobility networks is that edges are characterized by attributes – in this study by the sex of mobile individuals. While mobility networks between occupations were proposed as early as the 1980s (summarized in Breiger, 1990) and have gained more attention recently (e.g., Cheng and Park, 2020), this concept has not been applied to the study of occupational segregation.

This paper uses a mobility network based on data describing occupational changes in Great Britain from 2000 to 2008 ($N = 5967$, 50.9% female). Great Britain shares important labor market characteristics with both the US and continental Europe and provides rich and high-quality data. The mobility network is enriched with harmonized information about the occupational nodes from two data sources on work conditions (e.g., income, part-time work) and on detailed skill use in the

occupations. Together, this data can provide insights into all facets of sex-specific occupational mobility that relate to *vertical*, *horizontal* and *organizational* characteristics of occupations, as well as the *interdependent mobility* of women and men through occupations.

The mobility network is analyzed with a statistical mobility networks model, a newly developed variant of an exponential family model, which applies recent advances in statistical network analysis to the study of mobility (Block et al., 2022). While exponential family models are commonly used in the analysis of occupational mobility,¹ the proposed network model enables answering new questions. It allows for the analysis of how the mobility decisions of different individuals are *inter-dependent*; in particular, whether men’s tendency to move out of occupations is *dependent* on the share of women moving in, controlling for occupational characteristics.²

The outlined, interdisciplinary network-based research design combines key advantages of classical designs from social and network science. First, as common in quantitative social science analyses the statistical approach allows the simultaneous testing of multiple competing explanations in one model. Thus, any tendency of men to leave feminizing occupations found in the analyses is *net of* modelled occupational characteristics. Second, formulating a comprehensive model of female and male occupational mobility that includes all known predictors of sex segregation enables the *quantification* of how much segregation is statistically predicted by men selectively leaving feminizing occupations using counterfactual simulations. Third, applying new concepts and methods inspired by statistical network modelling to the study of occupational mobility allows to analyze patterns in occupational mobility that result from social processes. It overcomes independence assumptions routinely made in mainstream quantitative social science studies that reduce individuals to atomistic actors.

Data

The outlined analysis uses data from the United Kingdom (UK). Three datasets are combined to obtain detailed data on occupational mobility and occupational characteristics.

Mobility data between the years 2000 and 2008 on occupational transitions comes from the British Household Panel Survey (BHPS: University of Essex, Institute for Social and Economic Research, 2010), a nationally representative, longitudinal study. The first mobility transition of all respondents of working age (25–63) that are part of the active work force is recorded in the mobility network. Individuals remaining in the same occupation for more than three consecutive observations are coded as staying in their occupation. The resulting mobility network contains 5967 (3037 female) individuals, of which 3727 (1843) are mobile. Details for data preparation of the mobility network are presented in the Methodological Appendix.

Data on the occupations in the mobility network are enriched with a comprehensive battery of 25 occupational characteristics using the British Labour Force Survey (LFS, 2009) and the O*NET database (Peterson et al., 1999). These characteristics represent current theoretical knowledge on occupational characteristics that influence sex composition (Becker, 1985; Eccles, 1994; Kaufman, 2002; Charles and

¹ The log-linear models classically used in mobility analyses are exponential family models. The relation of these models to the proposed one becomes clear when either is reformulated as a multinomial logit model, see Breen (1994), and Butts (2007).

² However, it should be highlighted that this analysis presumes no direct causal relations between individual observation in the sense of “observation X observed the actions of observations Z and Y and reacted to them”. Given that it is a nationally representative panel, it is unlikely that any pair of observations even know each other. The analysis rather describes overall patterns of occupational mobility in terms of sex composition and the sampled individuals are representative of the moves of the entire population.

Grusky, 2005; Percheski, 2008; Gorman and Kmec, 2009; Blau et al., 2010; England, 2010; Cech, 2013; Cha, 2013; Koellinger et al., 2013; Leslie et al., 2015; Levanon and Grusky, 2016; see Methodological Appendix). The LFS is a representative, quarterly survey designed specifically to provide insights into the UK labor market. It is part of the European Labour Force Survey. Data from 186,605 respondents between July 2005 and June 2006 provides information for each occupation about: average hourly income; percentage of workers in this occupation (%) working in the public sector; % working self-employed; % working full-time; % regularly working more than 40h per week; % regularly working more than 50h per week; % regularly working more than 60h per week; % regularly working any overtime; % regularly working more than 5h overtime per week; % regularly working more than 10h overtime per week; % that completed an apprenticeship; % that completed higher education; % that completed a university degree; and % that received job-related training in the previous three months.

The Occupational Information Network (O*NET) data is the most comprehensive data on skill use in detailed occupations currently available (Peterson et al., 1999). The O*NET data combines information of occupational experts and job incumbents and is constantly extended. Using scales developed previously to capture relevant dimensions of sex-typing of occupations (Levanon and Grusky, 2016), the O*NET data provides occupation wise information on the occupation specific use of strength, sociability, fine motor skills, mathematical skills, robustness, technical skills, authority, problem solving skills, creative skills and whether it is a manual occupation. Additional data of occupational status measured by the Standard International Occupational Prestige Scale (SIOPS) comes from Ganzeboom et al., (1992). The Methodological Appendix presents details for data preparation of all 25 occupational characteristics, variable choice and usability.

All data sources are harmonized to the same occupational classification, relying on so-called micro classes, modified from Jonsson et al. (2009). They represent meaningful, small groups of occupations that are well represented in the UK labor force. The final categorization scheme includes 59 occupations (for full coding schemes and cross-walks, see Methodological Appendix).

Methods

The mobility network is analyzed with a novel variant of an exponential family model that allows incorporating flexible predictors that can be based on individual and occupational characteristics, as well as emergent structures (Block et al., 2022). In its formulation it combines desirable properties of log-linear models classically used in the analysis of occupational mobility with advances from statistical network models. Compared to mainstream log-linear models, the proposed approach allows for the inclusion of parameters that represent the *inter*-dependence of observations. Thus, the probability to observe an emergent mobility system is more than the sum of independent parts. The developed methodology goes beyond what is currently possible in established statistical network methods (Butts, 2007; Lusher et al., 2013). In comparison to exponential random graph models (ERGMs), in particular, the model accommodates (i) weights on network ties without specifying a distribution of counts in dyads a priori, (ii) weighted self-ties, and (iii) attributes of edges, which represent the number of mobile and non-mobile individuals, as well as their sex, respectively, neither of which is possible in standard ERGM analyses. A full introduction to the method can be found in Block et al. (2022). One advantage of this model is that parameters that explicitly model interdependence are estimated from the data and not exogenously imposed. Thus, in case no interdependence is present, the model reduces to a standard multinomial logit model for the analysis of mobility.

Intuitively, when estimating parameters from the model these provide insights into empirical regularities in occupational mobility, for example ‘are men more likely than women to be immobile?’, ‘are mobile women more likely to move to public sector occupations than mobile

men?’, or ‘are men more likely to leave occupations that have a higher inflow of women compared to similar occupations with a lower inflow of women?’. The model provides insights about empirical patterns, e.g., the relative frequency of men to be (im)mobile compared to women, *ceteris paribus*.³

The workings of the model are presented in the short technical introduction that follows; it is extended in the Appendix. However, readers with less interest in the detailed technicalities of the model might skip the rest of the section and can interpret the model results in a first approximation as if it they came from a log-linear model with some unusual independent variables.

In line with previous approaches that focus on modelling data with dependencies between observations (Butts, 2007; Lusher et al., 2013), the probability to observe a specific mobility network $\mathbf{x}$ is given by

$$\Pr(X = \mathbf{x}) = \frac{\exp(Q(s(\mathbf{x}); \theta))}{\kappa}$$

where X is a random state, and Q is a linear predictor that depends on the sufficient statistics $s(\mathbf{x})$ of the model and a statistical parameter θ . The normalizing constant κ ensures that all probabilities sum to one (see Methodological Appendix). This is the standard formulation of exponential family models including logistic regression; however, for logistic regression it can be simplified to model individual observations. As a linear predictor, Q allows incorporating the diverse variable-based and endogenous predictors in the mobility model. In the analysis at hand it is defined as

$$\begin{aligned} Q(s(\mathbf{x}); \theta) = & \theta_1 s_{\text{loop}}(\mathbf{x}) + \theta_2 s_{\text{loop}*fem}(\mathbf{x}) + \theta_3 s_{\text{loop}*fem.in}(\mathbf{x}) + \theta_4 s_{\text{loop}*male*fem.in}(\mathbf{x}) \\ & + \sum_v \left(\theta_{v,1} s_{\text{loop}*v}(\mathbf{x}) + \theta_{v,2} s_{\text{loop}*v*fem}(\mathbf{x}) + \theta_{v,3} s_{\text{target}*v*fem}(\mathbf{x}) + \theta_{v,4} s_{v*hom}(\mathbf{x}) \right) \\ & + \sum_B \theta_{B*SB=demand}(\mathbf{x}). \end{aligned}$$

The first three statistics associated to parameters $\theta_1 - \theta_3$ represent (i) the general tendency of individuals to remain in occupations as opposed to leaving, i.e. a basic proclivity to mobility or immobility; (ii) whether this is different for women compared to men, and (iii) the general tendency to remain in occupations depending on the proportion of women moving into this occupation, respectively. Parameter θ_3 is necessary to model whether, in general, occupations that are mainly entered by women have a higher rate of out-mobility. The statistic associated to parameter θ_4 is of focal interest in this study, modelling whether men specifically leave occupations depending on the proportion of women entering. The second part of the equation contains the parameters related to occupational characteristics v , such as whether it is a manual occupation, whether it requires physical strength, or whether it is particularly well paying. For each characteristic v , four parameters $\theta_{v,1} - \theta_{v,4}$ are included that model

- the tendency of individuals to stay in an occupation higher on v , i.e. whether certain occupational characteristics to generally discourage leaving (*stickiness*, $\theta_{v,1}$);
- whether this tendency differs for women compared to men, that is, whether women are more likely than men to stay in occupations with particular characteristics v ($\theta_{v,2}$);
- if women preferentially move to occupations higher in v in case they are mobile, i.e. the tendency of women that change jobs to move to occupations with different characteristics than men’s mobility targets ($\theta_{v,3}$), there is no main effect for this parameter, since a fixed effect is included for each occupation as a target (see below);
- and, whether individuals move between occupations similar on v , that is, between jobs with similar characteristics (*homophily*, $\theta_{v,4}$).

³ Direct individual agency is a possible interpretation of the found patterns, but it is not inherent to the model.

The non-technical interpretation of these parameters is illustrated in the Results section and the Methodological Appendix. Finally, the last row of the equation contains fixed effects for all occupations B , ensuring correct representation of the column marginals of the mobility table. The model is conditional on the marginal row distribution and, consequently, needs no parameters to represent row margins (see Block et al., 2022). Full interpretation for all model parameters and the mathematical formulation of the statistics $s_{\dots}(x)$ is presented in the Methodological Appendix.

Results

Descriptively, the analyzed mobility network presented in Fig. 1 clearly shows that most women and men work in different occupations (denoted by relative node size) and switch between differing sets of occupations (edge weight). While the labor market is largely segregated, there is still a broad distribution of sex composition over occupations, and a considerable number of occupations that have fairly balanced sex ratios. Furthermore, visual inspection suggests that men are especially likely to leave occupations that women move into (node coloring). Fig. S1 gives an intuitive understanding of the overall mobility structure by showing the aggregate mobility network including labels that denote occupation titles.

This network is analyzed with the statistical network model to understand regular patterns in women's and men's mobility. A forward model selection strategy determines which of the comprehensive battery of 25 occupational characteristics introduced in the Data section and denoted v in the Methods section influences mobility (see Methodological Appendix). Fourteen characteristics are retained in the model as significantly influencing at least one of four choices (indicated by the parameters $\theta_{v,1} - \theta_{v,4}$). These 14 characteristics are average income in occupation; % working in the public sector; % working self-employed; % working full-time; % regularly working more than 40 h per week; % that completed an apprenticeship; % that completed higher education; % that received job-related training in the previous three months; strength; sociability; fine motor skills; mathematical skills; creative skills; and whether it is a manual occupation. The final model is estimated to determine whether men selectively leave occupations dependent on the proportion of women entering, conditional on the effect of these occupational characteristics. For full results see Table S3.

The results show a substantial and clear tendency of men to leave occupations when more women enter ($\theta = -2.08$, $p < 0.001$). Combined with the main parameter, this allows to calculate changes in men's probability to leave their occupation dependent on female inflow. For example, an increase of 10% in the proportion of women moving into an occupation reduces the probability of men to stay by ~12%. Men are approximately only half as likely to stay in an occupation with 75% female inflow compared to 25% female inflow, *ceteris paribus* – a substantial effect compared to other model parameters.⁴

Aside this focal parameter, the model shows occupational characteristics that are associated with women or men moving into, or staying within particular occupations (Fig. 2). Consistent with the current literature (Charles and Grusky, 2005; Percheski, 2008; Levanon and Grusky, 2016), more male-typed occupations – denoted by a decreased tendency of women to move into, or stay within these occupations – tend to require apprenticeships or higher education degrees, high rates of full-time work, and the use of physical strength. Female-typed occupations are rather in the public sector, and use fine-motor, and social skills.

For women, moving into and staying in the category of manual occupations shows opposite patterns [akin to Jacobs (1989)]. This is likely to indicate the transitory nature of manual jobs for women (e.g. in the service-sector), as opposed to male-typed manual occupations (e.g. crafts) that tend to be long-term careers. Estimates for homophily (Fig. S2) show that occupational mobility tends to be overwhelmingly between similar jobs. This can contribute to the perpetuation of sex segregation by facilitating mobility between occupations of similar sex-typed characteristics. Stickiness estimates show that multiple characteristics are related to staying long-term in the same occupation, for example being stuck in low income occupations or having reached a permanent high-skilled occupation, such as medical doctor (see Methodological Appendix).

While the estimate of the focal parameter clearly indicates that men are substantially more likely to leave occupations the higher the proportion of women that enter, it is not clear how much macro-level sex segregation in the labor market this causes. This question is answered with a counterfactual network simulation design using the initially observed data (Block, 2018), in which likely mobility networks are simulated under the condition that men (and women) pay no attention to the sex composition in their occupation when deciding to stay or leave. This means it is simulated how women and men would change jobs if their movements would only depend on occupational characteristics, reflecting the dominant paradigm in the literature. In practice, likely outcomes using the estimated model parameters are simulated, *except* that parameters θ_3 and θ_4 are artificially set to a value of zero.⁵ This mirrors conditions in which individuals are mobile identically to the full model, except that they do not pay attention to the sex composition of individuals moving to their occupation. Theoretically, this formulation of a counterfactual simulation can be translated to individual choices using the model definition, as the parameters can be interpreted as guiding individuals' multinomial choice of occupation, *given* the mobility of everybody else (see Block et al., 2022 Section 3.2). To extrapolate to longer-term consequences, the simulation is extended a further time-step into the future, resulting in an additional set of hypothetical segregation outcomes. These simulated outcomes are compared to simulated data under the full model, which provides our best representation of the empirically observed process. The metric along which the different outcomes are compared is the index of dissimilarity (D); a standard segregation measure. Definitions and details of simulation procedures are presented in the Methodological Appendix.

The results of the counterfactual simulation are presented in Fig. 3. The analysis shows that in case women and men would pay no attention to sex composition in their decision to stay in, or leave an occupation, sex segregation in the case under analysis would decrease by 19% over the modelled period and a total of 28% when simulating one period beyond the recorded data (represented by blue triangles in Fig. 3). Notably, the full model including all modelled parameters (green squares) accurately represents the empirical data (red circles) at time 2, and predicts stable levels of sex segregation at time 3. Thus, a substantial portion of sex segregation in this simulation model is caused by men leaving feminizing occupations, indicating the extent to which male and female mobility are interdependent in the analyzed data.

To further illustrate the magnitude of the effect, analogous counterfactual simulations for the fourteen occupational characteristics in the model are performed. In each case, simulated data is obtained under

⁴ This probability of men to stay in occ. with 25% female inflow relative to 75% inflow can be approximated by $\exp((-2.082 + 0.753) * (0.75 - 0.25)) \approx 0.5$; considering the usual caveats when converting exponential family parameters into relative probabilities. Analogous calculations for any differences in female inflow are possible, e.g. for a 10% increase of female inflow the relative probability of men to stay is $\exp((-2.082 + 0.753) * (0.1)) \approx 0.88$.

⁵ An alternative setup would be to re-estimate the model after excluding the parameter of interest. However, due to the high collinearity of the different statistics in the model, this results in strongly changed other parameters that are spuriously increased in size. The outcome of the simulation then tends to be confounded by the differently sized parameters, which prohibits the insight about the relative importance of the focal parameter (see also Block, 2018, and Indlekofer & Brandes, 2013 for a related discussion).

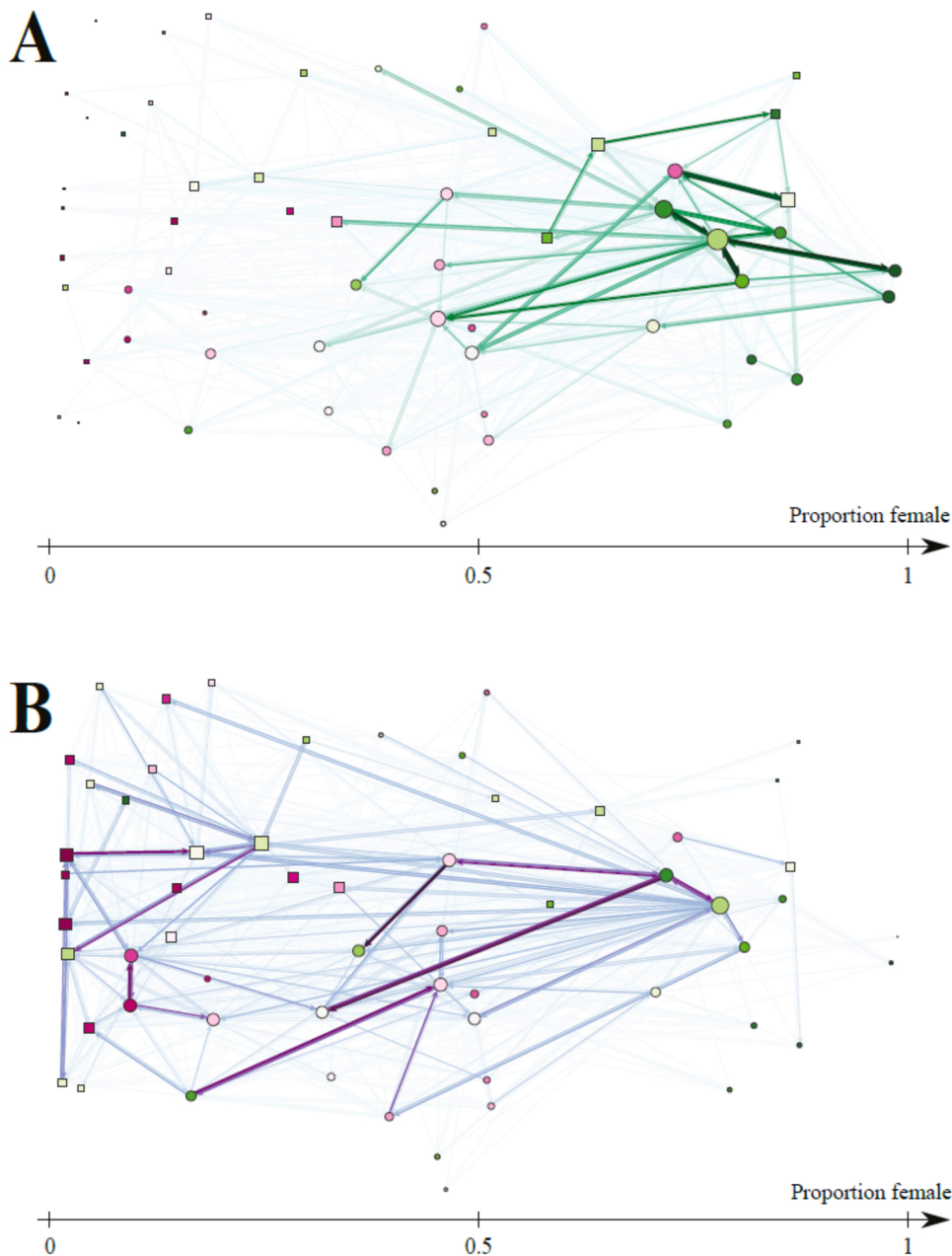


Fig. 1. : Mobility Networks omitting self-ties disaggregated by sex for (A) women and (B) men. In each network nodes represent occupations; placement on x-axis denotes relative share of females in occupation; y placement uses a stress minimization algorithm. Edge weight denotes number of transitions. Node coloring indicates relative probability of women and men to leave occupation (green: men more likely to leave, red: women more likely to leave). Squares are manual occupations, circles non-manual occupations.

the condition that women and men pay no attention to this occupational characteristic in their mobility decision. In the statistical model this is represented by parameters $\theta_{v,2} - \theta_{v,3}$ for the relevant characteristic being set to a value of zero. The use of fine-motor skills has the strongest individual effect of any variable on sex segregation. However, fine-motor skills explain only 12.6% of segregation and therefore appear less important than the replacement mechanism analyzed above. Thus, men leaving feminizing occupations is the strongest determinant of sex segregation under this research design, compared to all occupational characteristics under analysis.

Robustness analyses

The outlined results support the hypothesized mechanism that men tend to leave occupations when a higher proportion of women enter. This tendency is *net off* all occupational characteristics that are included in the model. This section reports additional robustness analyses that relate to alternative explanations that are not modelled in the main

analysis.

First, it is tested whether the statistical results are driven by few outlier occupations that swing in sex composition substantially over the analyzed period, i.e. occupations that show an unusually large outflow of men and large inflow of women given the initial composition. The descriptive statistics in Table S1 of the Methodological Appendix show that this is not the case. Swings in sex composition over the period are moderate and in the vast majority lie between -10% and $+10\%$. Only four comparatively small occupations that show more stochastic variability change sex composition to a larger extent. As the statistical method derives its power from the individuals as the unit of analyses, these small outlier occupations do not drive the results.

Second, the results might be partly driven by age-specific mobility patterns. While occupational characteristics such as income, prestige, and part-time work are included in the model, they are assumed to influence all age-groups homogeneously. However, life-cycle patterns of mobility and employment differ between women and men. The division of labor in couples intensifies in early- to mid-career, which can lead to

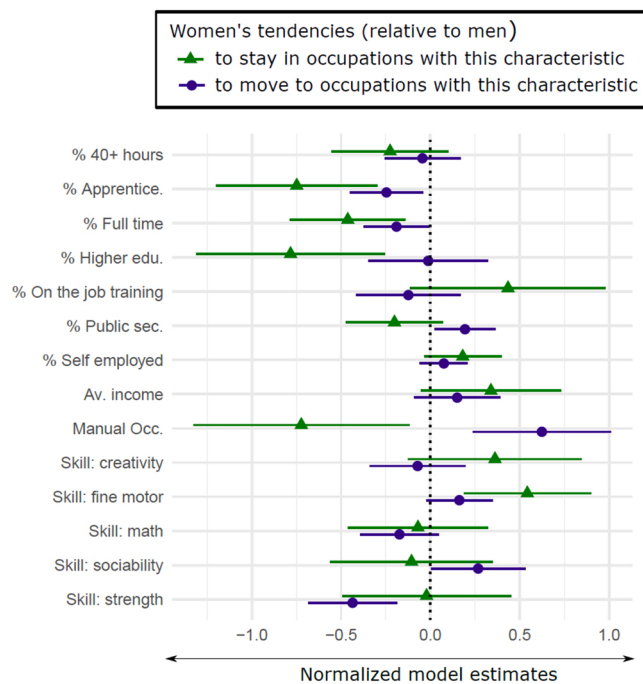


Fig. 2. : Occupational characteristics influencing mobility. Green triangles and blue circles show women's tendency (relative to men) to stay within occupations higher on the characteristic indicated by the row, and to move to such occupations in case of mobility, respectively. Estimates are normalized, i.e. the raw coefficients from the model are multiplied by the standard deviation of the underlying variable to make parameters comparable. Normalized parameter estimates indicate the effect of one s.d. in the independent variable. Error bars indicate 95% confidence intervals.

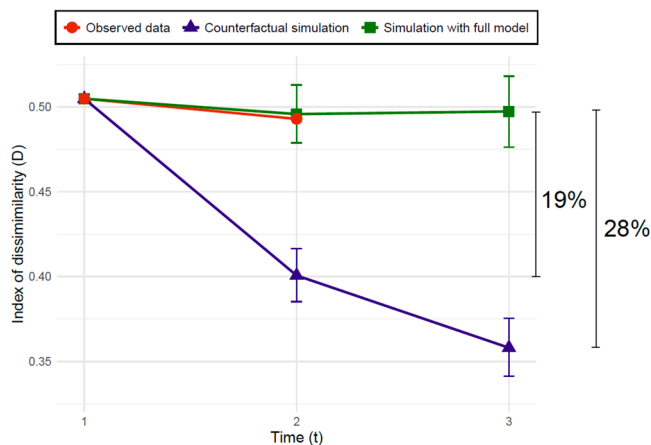


Fig. 3. : Predicted sex segregation after one and two periods for different models. Red circles: index of dissimilarity (see Methodological Appendix) in observed mobility network; green squares: data simulated using full model, error bars = 2 SD; blue triangles: counterfactual simulation data, error bars = 2 SD.

women of particular age-groups adjusting occupational choices. Similarly, employment favoritism can hinder women's progress in their career predominantly at specific ages, which can result in career adjustment at these points in the life-course. Thus, the division of labor in couples and vertical segregation can lead to occupational changes of specific age-groups. However, the model only accounts for age-homogeneous mobility patterns that relate to these mechanisms. In case the tendency of men to leave feminizing occupations is only found for specific age-groups, these age-specific phenomena require more

attention.

Additional analyses show that this is not the case. First, Fig. S4 in the Methodological Appendix shows that rates of mobility do not develop differently between women and men over the life-course. Thus, heightened rates of career adjustment at specific ages for women compared to men of the same age are not observed. Second, additional score-type analyses that model whether the replacement process is visible only in specific age-groups are performed (see Methodological Appendix). Four age groups are created, 27–35, 36–44, 45–53, and 54–63⁶ and it is tested whether any group significantly differs from the estimated age homogenous parameter in the tendency of men to leave feminizing occupations. Results show that for neither age-group results differ significantly (p-values of 0.68, 0.37, 0.17, and 0.25, respectively). Thus, the tendency of men to leave feminizing occupations is not specific to certain age-groups.

Third, a linear operationalization of female inflow into an occupation might not represent the actual process appropriately. Previous work suggests that crossing a particular threshold between 50% and 60% female share in an occupation is related to wage penalties (Murphy and Oesch, 2016). A second study suggests that men selectively move out of occupations once the female share is above a tipping point that lies between 25% and 45% (Pan, 2015). Using score-type tests (see Methodological Appendix), it is analyzed whether the initial approximation with a linear parameter represents the data appropriately, or whether further breaking points are visible. It is tested whether men are, additional to the linear effect, more likely to leave occupations once the female inflow exceeds thresholds of 20%, 25%, ..., 55%, and 60%. The p-values for these analyses range from $p = 0.89$ to $p = 0.31$. Thus, there is no indication that there are tipping points play a role beyond the linear effect of female inflow into an occupation.

Discussion and conclusion

This study uses a mobility network approach to understand the mechanisms driving occupational sex segregation. Taken together, the results suggest that sex segregation in the labor market is strongly determined by endogenous forces, mirroring segregation processes of e. g. neighborhoods, in which ethnic composition can determine residential mobility of minority and majority members (Schelling, 1971; Müller et al., 2018, see also England, 2008). Thus, the variable-based description of mobility processes dominant in current literature is insufficient and inter-individual dependencies must be taken seriously. Men leaving feminizing occupations is likely to contribute to the sex composition of detailed occupations and specializations within occupations that were previously categorized as idiosyncratic (Charles and Grusky, 2005). Furthermore, men's avoidance of work in feminizing occupations is a credible mechanism for explaining swings in sex composition of various occupations (Pan, 2015).

The goal of this study is not the description of long-term shifts in occupational sex segregation, which is driven by both, cohort replacement and work-life mobility (Blau et al., 2013). Instead, it analyses shorter-term mobility patterns that underlie not only shifts, but furthermore the persistence of sex segregation. Intra-generational occupational mobility is common, with up to 10% of workers changing occupations per year in the analyzed data.⁷ If women and men would make occupational changes independent of their sex, the labor market would desegregate rapidly, since men and women would enter the same occupations. However, sex-segregation remained consistently high in previous decades (*ibid.*) – the gender revolution has stalled in this respect (see England, 2010). Thus, in order to keep sex segregation at the

⁶ The ages 25–26 are not included in the robustness analyses, as, by construction of the data, all individuals of these ages must be mobile (see Methods and appendix), which distorts the age-specific analyses if included.

⁷ This is in line with US data reported in Jarvis and Song (2017)

observed high level mobility patterns of women and men need to differ substantially. This study shows that occupational mobility indeed differs by sex, how it differs by sex, and that female and male mobility is interdependent. The simulation analysis shows that the model can account for persistence of sex segregation over time and that the absence of sex-specific differences of mobility would lead to decreasing levels of sex segregation.

The main empirical limitation of this study lies in the representativeness of data. The analyzed case presents a period of relative employment stability before the financial crisis (2000–2008) in a country (UK) that shares similarities with economies in both, western Europe and the US. Nevertheless, at this moment we have no evidence that the found tendencies that lead to occupational sex segregation and its magnitude generalize to other periods or countries. A second potential concern is that occupational characteristics are measured at one time-point. This assumes that occupational characteristics taken from the LFS are approximately stable over the modelled period. Violation of this assumption could lead to biased parameters in case three conditions would co-occur: some occupations would (i) see most female inflow at the beginning of the mobility period, (ii) most male outflow at the end of the period, and (iii) an unobserved change in, for example, wages in between. However, further analysis of the mobility data does not indicate particular patterns of female and male mobility concentrated at the extremes of the 8-year period in any occupation, suggesting that these conditions are not met. Furthermore, given that mobility covers only an eight year-period, the assumption of stable occupational differences over the modelled period is plausible.

An interesting discussion point relates to the interpretation of the counter-factual simulations. Under the assumption that the model is “correct”, the simulations provide an idea about how macro-level patterns of segregation are influenced by different predictors of individuals’ mobility in case these are changed one-by-one. However, the assumption that only one predictor of individuals’ behavior changes while all others remain constant is unrealistic.⁸ The assumption that the model specification is a true representation of the real world is equally questionable. Consequently, the results of the simulation provide an intuition about the effect sizes of the model parameters – in particular in comparison to one another – not an expectation what would happen in the actual world, would it change in realistically achievable way. An appealing way to think about them is, consequently, as a computer-assisted thought experiment.

Irrespective of these discussion points, the findings of this study have interesting implications for public debates on gender roles in society. They question common narratives that justify prevailing sex segregation by referring to inherent differences in women’s and men’s interests and abilities in the labor market. Following these arguments, occupational sex segregation is the outcome of voluntary choices and individual freedom. Therefore, it is declared as not a matter of concern for policy makers, as discussed in Charles (2011) and Cech (2013). In contrast to these positions, this study finds that segregation is substantially produced by individuals’ active tendencies against working in mixed-gender occupations regardless of work content. Thus, sex differences in labor market positions are not purely a reflection of individual interests in types of work tasks.

Finally, if the sorting of individuals into occupations is an emergent process in which women and men react to each other’s movements, perceived occupational characteristics might be consequence, rather than a cause of sex-typing of occupations (Goldin, 2014). Qualitative evidence supports this notion. For example, typists as an occupation swung from male to female dominated; concurrently, perceived job requirements shifted from requiring (male-typed) physical stamina to (female-typed) finger dexterity (Goldin, 2014). Similarly, remuneration in occupations at least partly follows changes in sex composition

(England et al., 2007b; Murphy and Oesch, 2016). This suggests that occupational segregation is a cause, rather than a consequence of some occupational characteristics. Future research might explore in more detail how occupational status, income or perceived skill requirements change over time, to remain in line with changing sex compositions.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.socnet.2022.12.004](https://doi.org/10.1016/j.socnet.2022.12.004).

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⁸ Empirically, this is underlined by the predictors being highly correlated.

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