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JEL Classification: J23, J24, J42, J63

Keywords: monopsony, skills, Labor Market Concentration

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Monopsony, Skills, and Labor Market Concentration[1]

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Abstract

This paper extends the literature on monopsony and labor market concentration by taking a skill-based approach and estimates the causal effect of monopsony power on labor market outcomes. The prior literature has focused on industry and occupation concentration and likely overstates the degree of monopsony power, since worker skills are substitutable across different firms, occupations and industries. Exploiting linked employer-employee data that cover the universe of Norwegian workers over time, we find that our skill-based monopsony measure shows lower degrees of monopsony power than the conventional industry-and occupation-based measures. However, we also find that the gender gap in concentration is substantially larger using the skill-based measure relative to the occupation- or industry-based measures. Using mass layoffs and establishment closures as an exogenous shock to labor demand, we find that workers who experience a mass separation have substantially worse subsequent labor market outcomes when they are in more concentrated skill clusters. Our results point to the existence of employer market power in the economy that is driven by the concentration of skill demand across firms.

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1. Introduction

The extent to which employers exercise monopsony power in labor markets is a core empirical question that has wide-ranging implications for workers, firms, and labor market regulation. Because firms with monopsony power face an upward-sloping labor supply curve, market power in labor markets leads to lower wages for workers as well as lower employment relative to a competitive equilibrium. The extent and scope of monopsony power across labor markets thus has important implications for the distribution of earnings and inequality (Webber 2015). For instance, monopsony power in local labor markets for certain industries and occupation is one explanation for the findings that minimum wages and teachers' unions do not reduce (and may increase) employment (Card and Krueger 1995; Lovenheim 2009). Moreover, an emerging literature shows strong gender differences in commuting preferences, leading to a concentration of women in service intensive local labor markets close to where they live (Le Barbanchon et al. 2020; Petrongolo and Ronchi 2020). If men and women sort into local labor markets and occupations characterized by different degrees of labor concentration, it is likely that some of the persistent gender gap in labor market outcomes is driven by monopsony power. These arguments underscore the importance of understanding the extent of market power that employers exercise in order to inform optimal labor market regulation.

Accurately measuring monopsony power is critically important for public policy. For example, the US Congress has proposed giving the Department of Justice the charge to regulate the effects of prospective mergers and acquisitions on labor market concentration, similar to the way product market concentration is examined under current statutes. A key component in those proposals is the use of labor market concentration measures that are calculated within an occupation or industry. However, workers move across occupations and industries; failing to account for these outside options will make labor demand appear more concentrated than it actually is. By using measures that overstate the extent of monopsony power, regulators may impose limits on firm actions that might otherwise pose no threat to labor market competition or prevent mergers that might otherwise lead to earnings growth for workers and owners.

A large literature has used occupation- or industry-based measures of labor market concentration to estimate monopsony power. This literature has struggled to estimate the extent of monopsony power broadly in the labor market, in part due to the difficulty of grouping similar occupations together, and there has been little attention paid to workers' outside options. In this paper, we extend the literature on monopsony and labor market concentration by taking a skills-based approach to estimate the causal effect of monopsony power on labor market outcomes, with a particular focus on gender differences. Prior research examining industry, firm, or occupational concentration essentially proxies for worker type using these classifications. Such approaches are limiting because worker skills are substitutable across firms, occupations and industries. For example, an administrative assistant in one firm or industry can perform that job in another firm or industry. His skills also can translate to other occupations, such as a bookkeeper, office manager, or receptionist. Thus, we argue that the concentration of skill demand is a more relevant measure of labor market concentration than has been used in prior work. Beginning with Autor, Levy, and Murnane (2003), a large body of research has demonstrated the central importance of skills to understanding labor demand and the dynamics of earnings, wages, and employment. We are the first to apply these insights to the study of labor market concentration and monopsony.

We use Norwegian register data that allow us to link employers and employees as well as observe the local labor market in which an individual works, their background characteristics, and their occupation. We combine these data with information on skill content from O*NET. Following Autor, Murnane, and Levy (2003) and Acemoglu and Autor (2011), we consider six different skills: non-routine cognitive analytical, non-routine cognitive interpersonal, routine manual, routine cognitive, non-routine manual, physical adaptability, and non-routine interpersonal adaptability. We first standardize each skill measure, and then we perform hierarchical clustering to split occupations into 20 distinct skill groups that are characterized by different combinations of these skills. Occupations within each skill group are similar in terms of their overall skills requirements across these six categories, which we additionally validate using worker flows across occupations. We use commuting zones as our base geography, of which there are 160 in Norway. This allows us to separate areas into distinct labor markets, however we also examine whether skill demand concentration affects mobility across these commuting zones.

We calculate a Herfindahl-Hirschman Index (HHI), which is the sum of squared employment shares across establishments in each skill cluster and labor market. To identify the effect of labor market skill concentration on wages and employment, we use involuntary displacements from establishment closures and mass layoffs. A mass layoff is defined as an establishment losing at least 30 percent of its workforce in a given year. We estimate triple difference models in which we examine how outcomes change after an involuntary displacement event differentially by the HHI of a worker's skill cluster.

There are two identification assumptions we invoke, which is similar to any triple difference analysis. The first is that there are no secular trends in labor market outcomes among workers who will experience an involuntary displacement because of establishment closures or mass layoffs as a function of the skill demand concentration in his skill cluster. For example, if wages among those in a concentrated skill group were trending downward (relative to those in a less concentrated skill group) prior to an establishment closing, it would bias our wage estimates in a negative direction. We present event studies that demonstrate no evidence of such differential trends prior to an establishment closing. The second assumption is that there are no shocks that occur at the same time as an establishment closing or mass layoff that differentially affect workers in more versus less concentrated skill clusters. Put differently, the size of the shock that caused the displacement event cannot vary systematically with the concentration of skills. While difficult to test directly, we know of no reason that this would be the case and show extensive evidence that our results are robust to the most likely sources of such bias.

We first present evidence of substantial variation in skill demand concentration across and within labor markets in Norway. A variance decomposition shows that within-LLM variation in labor market concentration accounts for around 70 percent of the total variation in labor market concentration that we observe. We compare HHI concentration measures using skill clusters, occupations, and industries and show that, especially for small and mid-sized labor markets, our skill-based measure exhibits lower levels of concentration. This is an expected finding, because the skill-based measure allows for substitution across industries and occupations with similar skill requirements in a way that the industry- and occupation-based measures do not. Our large sample size and linked demographic information allows us to examine differences by gender and education as well. We show that the women tend to be in skill groups that are much more concentrated than men and that the gender gap in concentration is substantially larger using the skill-based measure relative to the occupation- or industry-based measures. There is little variation in skill concentration by worker educational attainment, however. Importantly, our results provide an additional explanation for the persistence of the gender wage gap in most industrialized nations (Blau and Kahn 2003).

The results from our triple difference analysis show that workers who experience a mass separation have worse subsequent labor market outcomes when they are in more concentrated skill clusters. We scale effects relative to a 0.10 point increase in the HHI, which is the difference between a low-concentration (<0.15) and a high-concentration (>0.25) labor market according to the *Horizontal Merger Guidelines* used by the antitrust division of the U.S. Department of Justice. A worker with a 0.1 higher HHI who experiences a mass layoff or an establishment closure has earnings that are 9,120 Krone lower after the event, which is 1.78% relative to the mean. We find positive but not statistically or economically significant effects on being out of the labor force and on employment, suggesting that the wage effects are driven predominantly by intensive rather than extensive margin responses.

Consistent with the importance of the intensive margin response, a 0.1 point HHI increase leads to a 1 percentage point increase in the likelihood of working part time after separation. We proxy for the quality of an individual's occupation by calculating the average proportion of national workers in that occupation without a high school degree and with at least a BA degree. Using these measures of occupational skill, we find strong evidence of reduced skill upgrading and increased skill downgrading in higher HHI clusters after separation. We also present evidence that skill mismatch (as defined by working in another skill cluster) decreased by 1.6 percentage points, which is approximately 4% of the mean. Hence, those in more concentrated labor markets are less likely to switch to an occupation that requires different skills after a closure or layoff. Finally, we show that workers in concentrated skill clusters are less likely to move to another labor market post-separation, although the estimates are not significant at conventional levels. Taken together, these results are consistent with skill concentration leading to more market power among employers, which reduces wages and hours on the intensive margin. These effects are driven in part by the fact that those in more concentrated industries exhibit more rigidity in their job search after separation.

The effect of monopsony power on post-separation earnings is larger for men than for women: male wages decline by 11,890 Krone (or 2.04%), while female wages are reduced by 4,812 Krone (1.13%). However, women face significantly higher levels of market concentration on average, suggesting that they may be disproportionately affected by monopsony power. The skill mismatch and mobility effects are concentrated among women. Interestingly, effects among married and non-married women are similar. The reduced cross-labor market mobility effect is concentrated among non-married women, which suggests the higher rigidity among female workers is not driven by the marriage market. We also show that the earnings effects are largest for men and women with young children, indicating that these households experience particularly high search frictions in more concentrated labor markets.

We additionally find important heterogeneity by educational attainment. The negative earnings effects of concentration following displacement grow from 0.7 percent for those with less than a high school diploma to 4 percent for those with a BA or more. Given that those with a post-secondary degree are more likely to be in occupations that use cognitive skills, this finding aligns with recent work showing that individuals in jobs characterized by high levels of non-routine, cognitive skill are more likely to encounter monopsony power (Bachmann, Demir, and Frings, 2019). Higher-educated workers are also more likely to move to a different labor market post-separation when they face a more concentrated labor market. We argue that this result is driven by these workers having access to a more national labor market.

Finally, we run horse-races between the industry HHI measure and our skill HHI measure as well as between the occupation HHI measure and our skill measure. That we have sufficient power to estimate different effects highlights that these concentration measures are substantively different. Including the industry or occupation HHI measure does not affect our results or conclusions, and the skill HHI measure we use has independent explanatory power.

We are the first to bring together the literatures on monopsony power and skill demand in labor markets. Taking a skills-based perspective allows us to substantially advance our understanding of monopsony power and labor market concentration by accounting for worker outside options, which we show is empirically important relative to measures used in prior work. Our main contribution thus is to provide a method for systematically grouping together occupations using the skill content of different jobs and to pair this new measure with a credible empirical strategy for identifying the causal effect of concentrated labor demand on workers.

The previous literature on monopsony has taken three approaches.[2] The oldest strand of research directly estimates labor supply elasticities in specific markets, such as nursing (e.g., Sullivan 1989; Matsudaira 2014; Staiger, Spetz, and Phibbs 2010) and teaching (e.g., Merrifield 1999; Falch 2010). These estimates come to differing conclusions about the size of labor supply elasticities and hence the extent of monopsony power in these markets. A second body of work comes out of the dynamic labor supply model of Manning (2003) and estimates labor supply

[2] See Manning (2020) for a review of the monopsony literature.

elasticities using separation rates (e.g., Hirsch, Schank, and Schnabel 2010; Ransom and Sims 2010; Ransom and Oaxaca 2010). These studies report more consistent labor supply elasticities on the order of 2-4, which indicates a moderate amount of market power by employers.

More recently, a number of papers have attempted to directly measure labor market concentration and then examine how concentration affects wages and employment (Azar, Marinescu, and Steinbaum 2020; Azar, et al, 2020; Azar, Berry, and Marinescu 2019; Benmelech, Bergman, and Kim 2018; Marinescu, Ouss, and Pape 2019; Qiu and Sojourner 2019; Rinz 2018; Hershbein Macaluso, and Yeh 2018). This literature universally examines concentration with respect to occupations or industries and finds that higher labor market concentration reduces wages and employment. Our paper extends this literature by embedding a direct, skill-based measure of worker's outside options to more accurately quantify the concentration of labor demand faced by workers. As we show, concentration measures based exclusively on occupation or industry overstate the extent of monopsony power because they fail to account for worker flows. Additionally, prior work on labor market concentration has used a variety of labor demand instruments that require stronger assumptions than the approach we take in this analysis.

Only one other paper of which we are aware attempts to embed outside options in the analysis of labor market concentrations. Schubert, Stansbury, and Taska (2020) use Burning Glass Technologies vacancy data and create an "outside-occupation option index" that is a leave-one-out weighted mean of local wages, where the weights are a combination of national occupation transitions and local worker shares in different occupations. The focus of their paper is on separately identifying effects of concentration (based on occupational vacancies) and of the value of the outside option on posted wages.[3] Their findings indicate that higher concentration reduces posted wages, while a higher value of the outside option leads to a higher posted wage. The result most aligned with our analysis is that concentration effects are larger in magnitude for workers who face worse outside options.

Our paper makes several contributions relative to Schubert, Stansbury, and Taska (2020). First, we employ a skill-based measure of outside options rather than a job transition based

[3] Specifically, they employ two separate instruments. They use a labor demand instrument based on the differential effects of national employer growth on local occupational demand to identify the effect of concentration of wages. To identify the effect of the outside option, they use a shift-share instrument that is composed of national wage changes in each occupation interacted with local employment shares in each occupation.

measure. We show that the skill-based occupation clusters we use correlate with job transition likelihoods, but there is independent variation in each measure. Job switching is an equilibrium outcome, while the skill demands of a given profession are less sensitive to underlying labor supply and demand forces. Hence, the skill-based measure of the outside option that we use is of independent interest. Second, Schubert, Stansbury, and Taska (2020) do not embed the notion of an outside option directly into their measure of concentration. Instead, they examine concentration and outside options separately and then estimate models with the interaction of these two forces. The wage available in a worker's outside option may, in itself, be a product of labor market power, however. An accurate measure of labor demand concentration must directly include workers' outside options, including the degree of monopsony power in those outside options, to account for the ability of workers to switch to less concentrated occupations for which they are qualified. This is what our skill-based concentration measure accomplishes, and this is the first paper in the literature to include such outside options directly in labor market concentration measures.[4] Third, we rely on mass layoffs and establishment closings that allow us to identify concentration effects under weaker assumptions. Furthermore, our ability to observe demographic information of workers permits an analysis of heterogeneous treatment effects that is not possible with vacancy data.

2. Institutional Background, Registry Data, and Variable Definitions

In this section, we provide a brief overview of employment relations in Norway. Moreover, we introduce the employer-employee data and provide a detailed description of the rich Norwegian administrative registers underlying our analysis. Finally, we carefully describe how the variables of interest are constructed.

[4] Macaluso (2017) and Caldwell and Danieli (2018) provide additional analyses of outside worker options. Macaluso (2017) develops the concept of "skill remoteness," which is designed to measure the difference between worker skills and the skills demanded in the local labor market. Using the NLSY79, she finds that more skill-remote workers experience worse labor market outcomes post-layoff. Notably, this is a different parameter from the one we estimate: skill-remoteness and labor demand concentration are conceptually and empirically distinct concepts, however our results support one another in showing the importance of local skill demand in driving post-separation outcomes. Similarly, Caldwell and Danieli (2018) estimate an "outside option index" that incorporates worker and job information (including skills) to estimate the value of each worker's outside option. They show using German data that workers with more valuable outside options experience better post-layoff outcomes. These findings align with those in Macaluso (2017) but is distinct from our examination of how the concentration of labor demand that includes outside options based on skill affects post-separation outcomes.

2.1. Institutional Background

Similar to other Nordic countries, Norway is characterized by a high degree of employment protection and generous unemployment benefits (Emerson 1987, Botero et al. 2004). When a firm decides to downsize, there is no strict rule determining the order in which workers should be laid off.[5] However, seniority is a strong norm and is institutionalized in agreements, such that firms are encouraged to lay off the less senior workers as long as the workers are otherwise identical. In practice, it is very difficult to verify the "all else equal" condition, such that this seniority rule often does not represent a binding constraint. Employment contracts require 3 months' notice of termination decisions. There is no generalized legal requirement for severance pay; however, workers may be induced to leave voluntarily through severance pay and job search assistance.

Unemployment benefits are quite generous and are available to individuals who involuntarily had their work hours reduced by at least 50 percent and had an income over a certain minimum amount ($16,500 in 2019) before becoming unemployed. The replacement rate is 62.4 percent of the previous year's pay, or 62.4 percent of the average pay over the last 3 years. The standard entitlement period during our analysis period was 104 weeks. After this period, if still unemployed, a worker may be eligible for means-tested social support, or may be eligible for disability pension and thus leave the labor force permanently.[6] Approximately 78 percent of displaced men in our sample are re-employed one year after displacement (Huttunen, Møen and Salvanes 2011).

2.2. Norwegian Register Data

Our primary data come from linked employer-employee records that cover all Norwegian residents between the ages of 16 and 74 in the years 2003-2017. The data combine information from various administrative registers, such as the education register, the family register, the tax and earnings register, and the social security register. A unique person identifier enables us to

[5] There is one important exception: there are stringent restrictions that limit the capacity of firms to dismiss sick workers ("The Norwegian Working Environment Act").
[6] Specifically, once an individual has turned 64, the time restriction on UI benefits is removed, such that the individual can keep receiving UI benefits until she reach the retirement age of 67, at which point she begins receiving public pension benefits instead (Johnson, Vaage and Willén 2019).

follow workers over time, and unique firm and establishment identifiers allow us to identify each worker's employer and to examine whether establishments are downsizing or closing down. Moreover, we have a code for the individual's municipality of residence each year. Establishment and regional labor market characteristics such as industry, size, and the rate of unemployment also are available.

Our data provide detailed earnings and employment information of each individual in the country. Labor earnings are measured as annual pre-tax labor income. The included components are regular labor income, income from self-employment, and benefits received while on sick leave, being unemployed or on parental leave.[7] We also use an alternative variable, market wage, which is pre-tax income net of government transfers. Given the generous unemployment benefits available to workers in Norway, it is interesting to examine and compare any potential labor market effects across these two measures. Employment status (employed, unemployed, and not in the labor force) is defined based on the individual's status in the labor register. Job tenure is measured in years, using the start date of the employment relationship at a given firm.

In addition to labor market characteristics, the data provide us with a broad set of demographic and socioeconomic characteristics of the individuals, including variables such as gender, age, education, marital status, and family composition. Education is measured as the normalized length of the highest attained education and comes from the education register, where each institution reports its graduates to Statistics Norway.

Table 1 presents summary statistics of key variables from our data. Labor earnings and market wage are quite similar on average, suggesting that most variation in labor earnings is driven by market wages rather than by government transfers. On average, those in our analysis sample are 46 years old, 42% are female, and 56% are married. The modal worker has a high school diploma, while almost 40% have earned a BA or a graduate degree.

2.3. Measuring Skill Concentration

The Norwegian register data contain detailed information on individuals, but they do not contain occupation-specific skill characteristics. To identify the relevant skills and tasks of each occupation, we therefore use the metrics of occupation characteristics in the 2019 edition of the

[7] This measure is used by the national government when calculating pension benefits in the universal pension system.

Occupational Information Network (O*NET) survey, which is fielded by the US Department of Labor. In the survey, workers and occupation-specific experts are asked about the knowledge, skills, abilities, and tasks associated with each occupation. To use these data, we crosswalk the Norwegian occupation classification system (STYRK) to the Standard Occupational Classification (SOC) of the O*NET database using the crosswalk constructed in Hoen (2016).[8] With this matching algorithm, we are able to match 96 percent of employees in our data to relevant SOC codes in the O*NET database.

We focus on six skill categories similar to those in Autor, Levy, and Murnane (2003) and further expanded in Acemoglu and Autor (2011): routine, manual; non-routine, physical adaptability, manual; non-routine, interpersonal adaptability; routine, cognitive; non-routine, cognitive, interpersonal; and non-routine, cognitive, analytical. Table 2 details each of the raw O*NET importance measures that enter the above composite measures. We standardize each of the raw O*NET measures shown in Table 2 with mean zero and standard deviation one and then combine them into the composite skill measures shown in the table. To account for the fact that each composite measure incorporates a different set of raw measures, we re-standardize the composite measures to have mean zero and standard deviation of one.[9]

Using these six skill measures, we perform hierarchical agglomerative clustering analysis to split all occupations in the Norwegian labor register into 20 distinct groups based on the similarity of skills across the occupations.[10] Our algorithm starts by treating each occupation as a separate cluster. It then repeatedly identifies and combines the two clusters that are closest together based on their *correlative distance,* which is one minus the Pearson correlation between two occupations. This iterative process continues until all occupations have been grouped into 20 distinct clusters. We chose 20 clusters because this is approximately the number of industrial

[8] *STYRK* is a modified version of the EU International Standard Classification of Occupations (ISCO-88(COM)), which is a modified version of the International Labor Organization's system ISCO-88. The latter can be mapped directly to CEN2000 using a crosswalk from the National Crosswalk Center, and the CEN2000 can similarly be mapped to SOC. See Hoen (2016) for a technical discussion on the algorithm used to construct this crosswalk.
[9] Note that the O*NET data are collected at the Standard Occupational Classification (SOC) code level, which is a designation that is finer than Census occupation codes. As the crosswalk from the Norwegian occupation system to the SOC codes is done using the Census occupation codes, we follow Acemoglu and Autor (2011) and create a weighted average of each skill rating in the O*NET by Census occupation code by weighting by total employment in each SOC code using the BLS Occupational Employment Statistics (OES) data for 2003-2017.
[10] When evaluating candidates for the optimum number of clusters, we use the "nbclust" package in R developed by Charrad et al. (2014).

categories, which facilitates comparisons across concentration measures.[11] We also have used a number of different validation techniques to identify the "optimal" number of clusters. While the optimal number differs somewhat across methods, all methods show that using 20 skill clusters fits the data well in the sense that 20 is either close to the optimal number of clusters or is in a flat part of the objective function that is used to find the optimal number of clusters. The details of this cluster validation analysis are available from the authors upon request.

Descriptive tabulations of demographic characteristics for each skill cluster are shown in Online Appendix Table A-1. The skill clusters differ considerably in terms of their size and composition, with the smallest cluster (4) consisting of 153 observations and the largest (1) consisting of 494,250.[12] The clusters also differ considerably in percent female, from a low of 10% for cluster 4 and a high of 90% for cluster 12. Similarly, there is much variation in the educational credentials of works in these different clusters. The large differences in the composition of workers across skill clusters underscores that occupations in different clusters are competing for different types of workers. Importantly, skill clusters regularly cross industry categories, which is one of the most important innovations in our approach.

Online Appendix Table A-2 shows labor earnings, percentage of the workforce that is part-time, and the rank for each of the six composite skills we use to construct the skill clusters. These rankings provide some insight into which skills are important in each cluster. For example, occupations in skill group 1 require high levels of non-routine skills, skill cluster 15 includes more routinized professions, and skill cluster 10 includes manual skill jobs. Some skill clusters, such as 5, require high levels of all skill, while other like cluster 17 are highly focused on one skill (non-routine, manual, physical). Part-time work and earnings vary considerably across these skill groups as well. In general, skill clusters that require more non-routine skill have higher earnings, which is consistent with prior research (Autor, Murnane, and Levy 2003).

Market concentration is calculated using the Herfindahl-Hirschman Index for each of the 20 skill clusters in each local labor market. The local labor market is defined based on

[11] If we have a significantly different amount of skill clusters than industries, part of the variation in labor market concentration across the two measures would be mechanical.

[12] Allowing for different densities and sizes of clusters is one clear advantage of hierarchical clustering over partition methods such as k-means clustering in this context. In our validation exercises, hierarchical clustering outperforms k-means on nearly every measure.

commuting distance and divides the country into 160 regions (Gundersen and Juvkvam, 2013).[13] The HHI is the sum of the squares of the labor shares of the *establishments* within the skill cluster and local labor market. The measure is proportional to the average labor share, weighted by labor share. It can range from 0 to 10,000, where 10,000 is indicative of a single monopolistic establishment in the market. Hence, the HHI measures the concentration of labor demand for a given skill grouping *across establishments* in a local labor market. According to the *Horizontal Merger Guidelines* used by the antitrust division of the US Department of Justice, an HHI score below 1,500 indicates an unconcentrated market, a score between 1,500 and 2,500 indicates a moderately concentrated market, and a score above 2,500 indicates high market concentration. To facilitate the interpretation of our results, we discuss the magnitude of our estimates relative to a 1,000 point HHI increase. This is the difference between an unconcentrated and a highly-concentrated market. When we estimate our empirical models below, we use an HHI scale of 0-1 rather than 0-10,000, and we scale our results relative to a 0.1 change in the HHI.

In addition to computing HHI based on skills, we also construct HHI measures based on industry, occupation, and education. The industry classification is based on the Standard Occupation Classification in Norway and consists of 21 aggregate industries.[14] The occupation classification is based on 2-digit occupational codes using the Standard Occupation Classification in Norway and consists of 43 aggregate occupational groups. Finally, we have calculated the HHI for each education level, where education is split into 4 groups (less than high school, high school, some college, and BA+).

2.4. Involuntary Job Displacement

Our main empirical strategy, discussed in Section 4, is to leverage involuntary job displacements caused by mass layoffs or establishment closures. We examine how subsequent labor market outcomes are affected by these displacements as a function of the local labor market concentration faced by workers. To operationalize this approach, we follow the existing job displacement literature in defining treatment and control groups (e.g., Huttunen, Møen and Salvanes, 2011). First, we define a *base year* for each worker. For the treatment group (workers

[13] Local labor markets span more than one municipality (the lowest administrative unit consisting of 435 municipalities during our analysis period), but are typically smaller than counties (the second-lowest administrative unit).
[14] See https://www.ssb.no/en/klass/klassifikasjoner/6

experiencing a mass layoff), the base year is year 0, with the displacement event taking place between year 0 and year 1. For the control group (workers not experiencing a mass layoff), we include individuals who were not displaced in those two calendar years. Hence, we compare post-base year outcomes for persons displaced in the base year to persons who are not displaced in that same year.

To ensure that the treatment and control groups are as similar as possible, we restrict our analysis to workers who have been continuously employed for at least 20 hours a week during the last five year prior to the base year. This implies that our analysis sample consists of workers highly-attached to the labor market.[15] Table 1 shows that 96.5% of those in our analysis sample are employed, and only 3.2% are not in the labor force. This high labor force participation is a reflection of focusing our analysis on a set of individuals who are initially employed.

Because of the structure of our data, an individual who experiences a displacement will appear in only one base year, while those in the control group can appear in multiple base years.[16] We follow people for 11 years in total – from 5 years before the base year to 5 years after the base year. Because we consider displacements that occur in several different years, in the analysis we redefine each base year as year 0. This enables us to stack the data and run pooled regressions using all years in event time. In doing so, we always control for the year that the displacement (or non-displacement) occurred.

The base years we use for our analysis are 2008 through 2012. We begin in 2008 as this represents the first year in which we have detailed and consistent information on occupational codes for each worker, such that we can reliably match them to the O*NET database on skills. We end in 2012, since we are interested in following workers for five years post the base year, and our register data go through 2017. Note that even if we do not have detailed information on their occupational codes prior to 2008, we do have detailed information on hours worked, employment, and earnings. As such, we are still able to follow these individuals in the five years prior to the base year.

The register data include information on all Norwegian residents aged 16-74 in the relevant year. Importantly, the data include both a person identifier and an establishment

[15] This likely implies that the estimates we obtain in our analysis represent a lower bound, as less attached workers may find it more difficult to return to work following an involuntary displacement.
[16] It is possible that workers experience more than one mass layoff in our data, but this is quite rare in practice.

identifier, so we can identify instances in which a person is working in a particular establishment in a particular year but is no longer with that establishment the following year. Furthermore, we can identify establishment closures from situations in which an establishment identifier disappears from the data and measure employment changes at establishments by simply counting how many workers are in each establishment in each year. We follow the previous literature by defining displaced workers as workers who separate from an establishment that closes down or reduces employment by 30% or more in the year that the separation takes place (See Jacobsen, Lalonde, and Sullivan 1993).[17] To ensure that our measure of mass layoffs is not driven by sporadic displacements among small firms, we restrict our sample to workers at firms that have at least 10 employees. This is consistent with the previous literature on mass layoffs and establishment closures (e.g., Huttunen, Møen, and Salvanes 2011).

3. Descriptive Evidence on Labor Market Concentration

In this section, we present descriptive evidence on our skill-based measure of labor market concentration and compare it to measures that use industry, occupation, and worker educational attainment. As we demonstrate, the skill-based measure we use contains independent variation from these other measures. In Section 5, we show evidence that the skill-based concentration measure has more empirical relevance for labor market outcomes following a mass layoff than do some of the other common concentration measures used in the literature.

Figure 1 shows average HHI by local labor market, where we have ordered local labor markets by the number of workers in each area. The size of each point represents the size of the local labor market, which is why the points get larger moving left to right along the x-axis. Panel (a) of the figure shows the skill-based HHI by LLM. There is a clear negative relationship between the size of the LLM and the amount of concentration. This is sensible, because there is greater scope for concentration in smaller markets. The largest LLM – Oslo – as well as the larger cities in Norway exhibit low levels of concentration that are under 1,500. However, for a large number of LLMs there is substantial concentration of over 2,500 and a sizable mass between 1,500 and 2,500.

The LLM concentrations shown in Panel (a) of Figure 1 are based on six skill categories.

[17] Appendix Table A-8 provide information on the percentage of workers in our sample exposed to such events during our analysis period.

Local labor market concentration measures based on each individual skill are shown in Online Appendix Figures A-1 (for non-routine skills) and A-2 (for routine skills). The skill-based labor market concentration patterns shown in Figure 1 are predominantly driven by non-routine skills, and in particular non-routine cognitive analytical, non-routine cognitive interpersonal, and non-routine interpersonal adaptability. That the non-routine skills are driving labor market concentration effects is a novel finding of our paper. This result is important because of the rising demand for such skills and the fact that these skills tend to be more concentrated in high-earning professions.

Panels (b) and (c) of Figure 1 show HHI measures calculated using occupations and industries, respectively. These measures align closely with one another, which is somewhat surprising because there are twice as many occupational categories as industry categories.[18] Moreover, these panels demonstrate that there is far more monopsony power when measuring concentration using industries and occupations than when using our skill-based measure. This is sensible, as the skill clustering is based on the idea that occupations with similar skill needs are more substitutable with one another, even if they are in different industries. While all three panels demonstrate a strong negative relationship between the concentration measure and local labor market size, at any given size the skill-based measure exhibits less concentration than does the other two measures. Hence, using industry- or occupation-based concentration measures to limit the degree of monopsony power in labor markets, which is the current antitrust practice in most industrialized economies, will overstate the degree of power that firms have. This is problematic, as it may lead regulators to impose limits on firm actions that might otherwise pose no threat to labor market competition or prevent mergers that might otherwise lead to earnings growth for workers and owners.

We argue that the skill-based HHI is appropriately smaller because of cross-occupational mobility within skill clusters. One way to validate whether occupations within skill clusters are more substitutable than those across skill clusters is to examine occupational switching (Belot, Kircher, and Muller 2019). Online Appendix Table A-3 shows the likelihood that workers who switch occupations do so within versus across skill clusters, separately by skill cluster. On

[18] There is a mechanical negative correlation between the number of categories over which the HHI is calculated and the resulting HHI. The reason is that with more categories, the share in any given category is likely to be smaller, which reduces the HHI.

average, the likelihood of job switchers moving within cluster is almost 66 percent. As a baseline for comparison, if workers switched evenly across clusters, the likelihood of a within-cluster move would be 5 percent. As the table demonstrates, the likelihood of switching within cluster is well above this baseline for each skill category. Specifically, it is above 40 percent for all but four categories, it is above 50 percent for 13 categories, it is above 60 percent for seven categories, and it is above 70 percent for three skill categories. The skill clusters with the most switchers tend to have the most within-cluster moves, which is why the weighted average is so high. Most importantly, Online Appendix Table A-3 shows that our skill clusters are informative about the types of jobs workers substitute across. The skill-based HHI measure captures this substitution behavior, which is why it exhibits less concentration than do industry- and occupation-based measures.

The final panel of Figure 1 shows the HHI index calculated using completed education level of the worker (less than high school, high school, some college, and BA+). This measure is informative because skill concentration of occupations may be picking up variation in the composition of workers. That is, what looks like concentration on the labor demand side of the market is really concentration on the labor supply side of the market. Despite the fact that there are only four education categories, this measure leads to far lower levels of concentration than do the other three shown in the figure.

To see the differences in concentration measures more easily, Figure 2 plots the difference in the HHI across measures for each LLM. As suggested by Figure 1, the skill-based HHI is systematically lower than the industry and occupation HHIs for all but the largest labor markets. Relative to the worker education based HHI, the skill-based measure demonstrates more concentration. The differences in these measures decline with the size of the workforce, which is sensible because regardless of the measure the large labor markets exhibit low levels of concentration.

The rich nature of our register data allows us to examine differences in labor market concentration by worker gender and educational attainment. Panel (a) of Figure 3 shows the patterns by worker gender. The figure clearly demonstrates that women are in more concentrated skill clusters than are men across the LLM size distribution.[19] The clusters are the same for men and women, so the differences in the figure reflect only differences in occupational sorting between men and women. The differences are large: the average HHI for men is below 2,500 in almost all labor markets, whereas women face HHIs above 2,500 in most labor markets and face HHIs above 1,500 in all but the largest labor markets. To our knowledge, this is the first evidence in the literature of this gender difference across multiple occupations, which highlights that women face much more concentrated labor markets than do men.[20] The evidence is clear that the occupations into which women sort are more concentrated in terms of their skill demand than is the case for men. We examine the implications of these difference below by estimating job separation effects separately by gender.

Panel (b) of Figure 3 shows skill-based HHI patterns separately by worker educational attainment. Here, we split workers into those with less than a high school degree, a high school degree, and more than a high school degree. While there are small differences across groups, with some evidence that more-educated workers are in more concentrated skill clusters, the cross-group differences are small. The large gender-based heterogeneity in panel (a) does not translate into education-based heterogeneity in panel (b).[21]

Figures 1-3 show that average skill-based concentration varies considerably across labor markets. However, most of the variation in skill-based HHI is within labor markets: a variance decomposition shows that 70% of the HHI variation is within, rather than between, local labor markets. Figure 4 presents this within-LLM variation directly. The points in the figure show the mean HHI, and the bars extending from each point show a standard deviation above and below the mean in that local labor market. Panel (a) demonstrates that there is an extensive amount of variation in concentration across skill clusters within a labor market. This is the variation we use directly in our empirical analysis below. Importantly, there is a large amount of variation across the LLM size distribution. Panels (b) and (c) of Figure 4 present the same information for men

[19] Online Appendix Figure A-3 shows gender-specific HHIs for each LLM using occupation (panel a) and industry (panel b) measures. As in Figure 1, the HHIs using these alternate measures are higher, but the same gender gap evident in Figure 3 is also present in Figure A-3.

[20] This finding aligns with evidence of monopsony power in teaching and nursing, two heavily female-dominated professions (Sullivan 1989; Merrifield 1999; Staiger, Spetz, and Phibbs 2010; Falch 2010; Matsudaira 2014). However, these are just two professions, which underscores the importance of examining gender differences in exposure to monopsony power more broadly in the labor market.

[21] Online Appendix Figure A-4 shows skill-based HHI patterns by educational attainment, separately for men and women.. Aligned with Figure 3, there is more concentration among women than men, but for neither group is there much difference by educational attainment.

and women, respectively. There is considerably more within-LLM variation for women than for men, which is driven by different occupational sorting patterns by gender.

Understanding the extent of skill-based labor market concentration and how it varies across labor markets is interesting in its own right, but ultimately, we are interested in estimating the implications of such concentration for labor market outcomes. The remainder of this paper focuses on this question. Figure 5 presents preliminary descriptive evidence of how different concentration measures are correlated with mean earnings in each LLM. Correlations using a skill-based measure, an occupation-based measure, and an industry-based measure of concentration are shown in panels (a) through (c), respectively. In Panel (a), there is a clear negative correlation between skill-based concentration and earnings, while in the other two panels no such relationship exists. This provides suggestive evidence that our skill-based concentration measure is better able to detect employer market power than are the industry- and occupation-based measures. The patterns in Figure 5 indicate the skill-based employer concentration negatively impacts wages. However, this is descriptive evidence, and there are many differences across LLMs that makes it challenging to interpret this cross-sectional variation as causal. We now turn to a strategy to identify the causal effect of labor market concentration on labor market outcomes to address these concerns.

4. Empirical Approach

In order to examine how skill-based labor market concentration affects earnings and labor market outcomes, we need exogenous variation in labor demand. An exogenous shift in the labor demand curve will identify the labor supply elasticity, which as discussed above is a critical measure for identifying monopsony power. To operationalize this strategy, we examine how outcomes among those who are affected by a mass layoff change relative to workers who are not affected by such a layoff as a function of the local labor market concentration a worker experiences because of where they work and the skill cluster of their pre-layoff occupation.

The thought experiment underlying our approach is to consider two observationally-similar workers in the same skill cluster who lose their jobs because of a mass layoff but who face different levels of concentration based on the local labor market in which they work. We then compare how these workers' outcomes change post-layoff relative to workers in their local labor market who were not affected by the mass layoff. To operationalize this idea, we estimate triple difference models of the following form:

$$Y_{icmntt_b} = \alpha + \delta HHI_{icmt_b} + \gamma Seperated_{it_b} + \tau Post_{itt_b} + \beta(HHI * Seperated * Post)_{icmtt_b}$$
$$+ \theta_1(HHI * Seperated)_{icmtt_b} + \theta_2(Post * Seperated)_{icmtt_b}$$
$$+ \sum_{k=1}^{3} \omega_k(\pi_c + \zeta_t + +\phi_m + \psi_n + \sum_{j=-5}^{5} \eta_j I(t - t_l = j)) + \lambda_i + \varepsilon_{icmntt_b,} \quad (1)$$

where *Y* is a labor market outcome of individual *i* in skill cluster *c*, local labor market *m*, industry *n*, in year *t* and base year panel t_b. Our full model includes skill cluster (π_c), year (ζ_t), labor market (ϕ_m), industry (ψ_n), and individual worker (λ_i) fixed effects. The model also includes controls for relative time to a forced mass separation, $I(t - t_b = j)$.[22] These relative time indicators are set to zero for those not experiencing a mass separation in the event window. We interact the skill cluster, year, labor market, industry, and relative time to forced mass separation fixed effects with educational attainment indicators (less than high school, high school diploma, and BA+, with some college the excluded category). These interactions, indexed by ω_k, account for secular variation by time, location, and type of work that can differ by worker educational attainment. Standard errors are clustered at the local labor market level throughout the analysis.

Separated is a variable equal to one if a worker has experienced a separation from a mass layoff or establishment closing in t_b, and HHI_{icmt} is the concentration measure for a worker based on her pre-separation skill cluster. Hence, *HHI* varies across skill clusters within each local labor market and year (as shown in Figure 4). Conditional on these controls, this is a triple difference model. The coefficient of interest, β, shows how outcomes change surrounding a separation relative to those who do not experience a separation as a function of the local labor market skill concentration. The variable HHI_{icmt} controls for independent effects of local labor market concentration, while the direct effects of a mass layoff are accounted for by the variable $Seperated_{it_b}$.

The coefficient β represents the causal effect of losing one's job in a more versus less concentrated skill cluster-labor market combination. The parameter is identified under the

[22] Controlling for relative time and year fixed effects also implicitly controls for base year, as base year is collinear with relative time and calendar year.

assumption that mass layoff effects in less concentrated skill cluster-LLM combinations are an accurate counterfactual for mass layoff effects in more concentrated skill cluster-LLM combinations. Because this is a triple difference model and we control directly for relative time to separation effects, we do not require that separations from establishment closings and mass layoffs are exogenous. Rather, any endogeneity in such separations needs to be similar across the *HHI* distribution. There are two main potential threats to identification. The first is that there may be secular trends in outcomes surrounding separation that differ by *HHI*. The second is that there could be unobserved shocks that correlate with the timing of separations and that differ across the *HHI* distribution within the local labor market.

To address the first concern, Figures 6-8 show event studies of job separation overall and for different HHI groups for three of our main outcomes of interest: earnings, labor force non-participation, and part-time work. These event studies show raw means relative to the year of separation, so they do not include the extensive set of fixed effects and controls in equation (1). There are two main takeaways from these figures. The first is that in no figure or panel do we observe any evidence of pre-separation relative trends. In particular, earnings in Figure 6 do not exhibit any trends prior to separation. Recall that the identifying assumption we invoke is that these trends are all the same, not necessarily that they are zero. That they are indeed zero provides additional support for our empirical approach.

The second takeaway is that adverse labor market effects are larger for higher-HHI workers. In Figure 6, log earnings drop by 0.15 log points among those with an HHI above 2,500, while the effect is about -0.06 log points among those with an HHI under 1,000. Likewise, labor force non-participation and part-time work increase by much more in the high versus low HHI occupations after a mass layoff or establishment closure. These figures provide direct evidence that our estimates are not biased by differential pre-treatment trends in outcomes and that workers in more highly-concentrated occupations are more adversely affected by labor market shocks. Our regression results reinforce these findings.

While Figures 6-8 suggest that our estimates are not biased by secular trends, they cannot speak to the existence of secular shocks. This identification assumption is not possible to test, but we highlight that such shocks are particularly unlikely in our triple difference setup. Such shocks would have to mimic the timing of mass layoffs and would have to be localized to the affected skill cluster. We view it as unlikely that such shocks exist systematically. In Section 6, we probe the sensitivity of our results to some of the most likely sources of these secular shocks. We show that our results are insensitive to controlling for the size of the labor demand shock as measured by the number of workers displaced in a given skill cluster-LLM-year as well as to allowing the size of the LLM to have an independent effect post-separation. Our estimates also are robust to controlling for the share of workers in each skill cluster, LLM, and year. Hence, our results reflect the concentration of workers in a skill cluster *across firms* in a LLM, rather than the concentration of workers in a skill cluster in a LLM. We additionally emphasize that our results are robust to including or excluding industry, local labor market, skill, and individual fixed effects as well as relative time to separation fixed effects. In the presence of secular shocks, we would not expect our results to be insensitive to these controls. Furthermore, we show in Section 6 that our results change little when we control for local labor market by year, skill cluster by year, or industry by year fixed effects. These estimates provide further support for the credibility of our empirical approach.

5. Results

5.1. Main Results

Table 3 presents estimates of β from equation (1) for labor earnings (Panel A) and market wage (Panel B). We build to the full specification across columns in order to assess the role played by various fixed effects and controls. Column (1) results show estimates that include controls for HHI and a post-separation indicator only. In column (2), we add relative time to separation and year fixed effects as well as fixed effects for local labor market, skill cluster, and industry. Column (3) shows results from the full model with individual fixed effects.

In column (1), we find an effect on labor earnings of 115,186 Norwegian Krone, which translates to $12,187.[23] This represents the separation effect of an increase from 0 to 1 in skill HHI. A more sensible way to scale the estimates is by 0.1, which represents going from a low-concentration to a high-concentration market. This is shown below the estimates in the table and indicates an effect size of 11,519 Krone, or $1,219. Relative to the mean shown in Table 1, this estimate implies that a ten percentage point increase in the HHI leads to 2.25% lower earnings post-separation. The results are relatively stable across columns. The difference in the separation

[23] We use an exchange rate of 0.105808 Krone per dollar: https://www.x-rates.com/table/?from=NOK&amount=1.

effect of a 10 percentage point increase in the HHI is 9,298 Krone, which is 1.81% relative to the mean, when we incorporate relative time to separation and year fixed effects as well as fixed effects for local labor market, skill cluster, and industry. In column (3) that includes individual fixed effects, the effect size is 9120 Krone. This represents a decline of 1.78% relative to the mean. That our results change little when we include a large battery of fixed effects that should be sensitive to secular trends and shocks supports the credibility of our empirical approach.

The estimates for market wage in Panel B align closely with those for labor earnings in Panel A. We find an effect in column (3) of -10,983 Krone, or -$1,158, which is a 2.17% decline in post-separation wages when the HHI is ten percentage points higher. The estimates in the final two columns are similar, which again supports our empirical design.

Taken together, the results in Table 3 indicate that workers in more highly concentrated skill clusters within a given labor market face a steeper labor supply curve when they lose their job because of a mass layoff or an establishment closure. Hence, firms that hire workers in more concentrated skill clusters face a steeper labor supply curve, which implies that they have more monopsony power. An important implication of this finding is that establishment closures and mass layoffs have much different impacts on subsequent wages in different labor markets. As Figure 1 demonstrates, skill-based HHIs range from close to zero for the largest labor markets to about 0.4 for the smallest. The effects of forced separation are about 9% larger in the most highly concentrated markets relative to the largest markets that exhibit little skill-based concentration.

While earnings are critical to examine in order to understand the relationship between skill concentration of labor demand and monopsony, it also is important to understand the mechanisms that drive the earnings response. In what follows, we examine different dimensions of worker responses to large involuntary separations as a function of the skill concentration in their labor market. In Table 4, we first examine labor force non-participation and employment responses. The table is laid out similarly to Table 3, and in no column do we observe much of an extensive margin response. The triple difference estimates are not statistically significant at conventional levels, and the separation effect of going from a non-concentrated to a concentrated market implies a change in labor force non-participation of 0.002 and a change in employment likelihood of 0.001.[24]

Panel (c) of Table 4 presents effects on part-time work. The post-separation effect on working part-time grows by 1 percentage point when the HHI is 10 percentage points higher. Relative to the mean of 1.6 percentage points shown in Table 1, this is a large effect. Table 4 thus shows that there is an intensive margin response, with post-separation workers in more concentrated markets more likely to work part-time, but there is no extensive margin response.

We next examine whether workers transition to different types of jobs in Table 5. We examine skill "downgrading" and "upgrading," which are defined by the educational attainment level of workers in each occupation. "Downgrading" is measured by the percent of workers in Norway in each occupation who have not earned a high school diploma, while "upgrading" is measured by the percent of workers nationally who have at least a university degree. In Panels A and B of Table 5, the point estimates are aligned with workers being more likely to skill downgrade and less likely to skill upgrade, with estimates that are both statistically significant and economically meaningful. Given the evidence that workers are much more likely to transfer to jobs within versus across skill clusters (see Appendix Table A-3), in Panel C we examine the effect on skill mismatch. Skill mismatch is defined as changing skill clusters. Surprisingly, workers are less likely to switch skill groups when they lose their jobs and face more concentrated demand for their skills: a ten percentage point increase in HHI reduces the likelihood of switching skill groups post-separation by 1.6 percentage points.

It is unexpected that higher skill concentration makes workers less likely to switch skill clusters. One mechanism underlying this finding could be changes in worker mobility. We examine whether workers move labor markets when they face a more concentrated market post-separation in Panel D of Table 5. The estimates are negative, and they are of similar magnitude to the skill mismatch findings. That skill concentration makes workers less likely to switch to occupations in another skill group and less likely to move to another labor market suggests that search frictions are higher in areas where skill demand is more concentrated. Workers who lose their jobs in more concentrated markets appear to search less broadly with respect to occupations

[24] We do not discuss mean effects for extensive margin results because our sample is comprised of those who are working prior to a separation. Marginal effects still are informative, but percent effects relative to the mean are not because of the high prevalence of labor force participation and employment in our sample. Note that our focus on a group of individuals highly attached to the labor market likely implies that the estimates we obtain represent a lower bound, as less attached workers may find it more difficult to return to work following an involuntary displacement.

and geography. The specific reasons for the higher search frictions in more concentrated markets are beyond the scope of our analysis. However, we note that recent research has demonstrated the importance of referral networks in reducing search frictions (Dustmann et al. 2016; Barwick et al. 2019). One explanation for our results is that referral networks are more concentrated when skill-based labor markets are more concentrated. Hence, more concentrated labor demand can lead workers to think less broadly about their job search.[25] Further understanding this mechanism is a promising area for future research.

5.2. Heterogeneous Treatment Effects

In this section, we further probe the data and analyze potential heterogeneous effects of monopsony power following involuntary displacement events on the labor market outcomes of individuals by gender and education.

5.2.1 Gender Differences

Figure 3 shows that there are large differences in the skill concentration faced by men and women, with women on average being in more concentrated occupations even within the same local labor market. This finding underscores the importance of examining heterogeneous treatment effects by gender in order to assess the implications of differential concentration on labor market outcomes. In Panels A and B of Table 6, we examine effects for men and women, respectively. We focus on the eight outcome variables of interest from Tables 3-5.[26] Effects on earnings are larger for men than for women. Men experience a decrease in earnings of 11,790 Krone for each 10 percentage point increase in HHI when they experience a mass layoff, while the effect for women is 4,813. Relative to the mean, these represent 2.04 and 1.13 percent reductions in earnings for men and women, respectively.

While the marginal effects are larger for men, women experience far higher skill-based HHIs on average than do men. As a result, skill-based employment concentration reduces female wages similarly to that of men. Specifically, using the average skill-based market concentration

[25] Belot, Kircher, and Muller (2019) present evidence that unemployed workers search more broadly when they are provided with information about occupations that require similar skill to their prior occupation. Their results indicate that workers search without full information and that this information asymmetry limits the set of occupations to which they apply and the geographic area in which they consider jobs. Workers may have less information about alternative jobs for which they are qualified in more concentrated markets because these alternatives are less salient.
[26] Given the similarity between labor earnings and market wage, we show only the former when examining heterogeneous treatment effects. Results for market wage are available from the authors upon request.

across LLMs faced by females (2,350) and males (1,301) based on Figure 3, we calculate that the impact of skill-based employment concentration on the involuntary displacement of the average female is 2.66 percent, and for the average male is 2.65 percent, relative to the respective means.

Extensive margin effects are small and are not statistically different from zero for both men and women, and both genders react to job losses by working part-time by the same amount when concentration is higher. Men and women do exhibit some differences in job sorting due to skill concentration surrounding an involuntary displacement. Among men, there is a half percentage point increase in skill downgrading and a decrease in skill upgrading, although only the skill downgrading estimate is significant at even the 10% level. There also is a similarly-sized (but not statistically significant) increase in the likelihood of skill mismatch and of moving labor markets. These results suggest that men are somewhat more likely to switch to lower-skill jobs that are outside of their initial skill cluster and LLM. For women, there is no change in skill upgrading or downgrading, but there are negative and statistically significant declines in skill mismatch and the likelihood of moving labor markets. Thus, the negative effects shown in Table 5 for these outcomes are driven by women.

In order to understand this result in more depth, in Online Appendix Table A-4 we show gender-specific estimates broken down by marital status. The estimates do not vary much across married and unmarried people. The exception is that married women are somewhat more likely to work part-time than are unmarried women when they face a mass separation and higher skill concentration, and the reduced likelihood of moving is driven predominantly by unmarried women. This result is again surprising, as one might expect married women to exhibit less mobility than unmarried women. We also note that the results in Tables 6 and A-4 use overall HHIs to measure skill concentration. When we instead use gender-specific HHIs in Online Appendix Table A-5, the effect on the likelihood of moving is halved and no longer is statistically significant. The other results are similar to baseline, which suggests the labor market mobility results may be sensitive to the specific way in which we measure skill concentration.

One explanation for the gender differences we document may be related to the presence and age of children in the household. In Figure 9, we show earnings effects of concentration by gender and by whether the there is a "young child" under 6 (prior to schooling age), and "old child" between 6 and 15 (of compulsory schooling age), and no child.[27] The figure demonstrates

[27] Estimates for other outcomes are available from the authors upon request.

a clear pattern of declining effects by child age and by whether there is any child in the household. Interestingly, these patterns are similar for men and women. These results suggest that the presence of any children in the household, especially young children, exacerbates search frictions when concentration is higher.

5.2.2 The Role of Education

Skill-based concentration is most prevalent among occupations that require more non-routine skill (see Online Appendix Figures A-1 and A-2), and workers with more non-routine skill tend to be more highly educated. It therefore is instructive to examine whether there are heterogeneous treatment effects by worker educational attainment. Table 7 presents the results of this analysis. There is a strong gradient in the effect of skill-based concentration on post-separation pensionable earnings by educational attainment level. Relative to the mean, a ten percentage point HHI increase induces earnings to be 0.7 percent lower among those without a high school diploma, 1.3 percent lower among those with only a high school degree, and 4.0 percent lower among those with a BA or higher. That the earnings effects are concentrated among more educated workers aligns with the types of skill that drive the HHI variation. Furthermore, these results are interesting because they highlight the interaction between worker skills and the concentration of skill demand in each local labor market.

Our main results in Table 4 shows little extensive margin effect. Table 7 suggests that this aggregate null effect masks important heterogeneity by worker education level. Non-college-educated workers increase employment when they face a more-concentrated skill-based labor market post-separation (significant at the 10% level), while there is a negative and statistically significant effect among those with a BA of about 0.7 percentage points. Highly-educated workers are also more likely to not be in the labor force. Hence, for the types of workers most likely to be working in occupations that are skill intensive in the skills that drive the HHI variation, there are modestly-sized extensive margin effects. All three education groups experience less skill upgrading and more skill downgrading due to more skill concentration post-separation, but the negative skill mismatch effects are only present for those without a college degree. Finally, those with a BA are over 1 percentage point more likely to move to a different labor market post-separation when the HHI is 10 percentage points higher. Less-skilled workers are less likely to move, which drives the overall negative effect we find. This result is sensible because higher-skilled workers face a more national labor market and tend to be more mobile (e,g., Machin, Pelkonen and Salvanes, 2012).[28]

5.3. Comparisons with Other Concentration Measures

We find strong evidence that workers who experience a mass separation have worse labor market outcomes post-separation when they are in more skill-concentrated markets. As discussed above, our skill-based HHI measure is novel, and so it is useful to compare it to more traditional measures of labor market concentration in order to understand the benefits of accounting for skill.

Table 8 presents horse-races between the skill-based HHI and the industry-based HHI (Panel A) as well as the occupation-based HHI (Panel B) measures.[29] In Panel A, the effects on labor earnings clearly load on the skill-based HHI measure: the coefficient on the HHI-post-separation treatment variable is positive and is not statistically different from zero at conventional levels. The estimate on the skill-based HHI interaction is similar to the baseline result in Table 3, and so accounting for industry HHI has little effect on the estimate. The outcome other than earnings for which there is a large concentration effect is part-time work, and for this outcome the HHI-based skill measure is clearly more relevant than the industry-based measure. Interestingly, the unexpected results that higher skill concentration reduces skill mismatch and cross labor market mobility post-separation largely disappears and loads on the industry HHI.

Panel B of Table 8 shows results from a horse race between skill- and occupation-based HHI measures. Two patterns emerge from this table. First, the estimates are similar to baseline in terms of their sign and statistical significance, however they are somewhat attenuated. Some attenuation is expected because occupations are perfectly nested within skill clusters. Hence, some portion of skill-based HHI will be captured by within-occupation concentration of employment. Second, for labor earnings and part-time work, both occupation and skill concentration matter in the same direction. It is important to emphasize that occupations are far more numerous than skill clusters, which stacks the deck against our skill-based measure in these

[28] These results are consistent with those in Lin (2020), who shows that low-skilled workers are less likely to move due to trade-induced declines in labor demand.

[29] The prior literature is split between the use of occupation and industry concentration measures. Industry is used by Benmelech, Bergman, and Kim (2018), Rinz (2018), and Hershbein Macaluso, and Yeh (2018), while occupation is used by Azar, Marinescu, and Steinbaum (2020), Azar et al. (2020), Azar, Berry, and Marinescu (2019), Marinescu, Ouss, and Pape (2019), Qiu and Sojourner (2019), and Schubert, Stansbury, and Taska (2020).

regressions. That the skill-based concentration measure has strong and statistically significant independent effects on labor earnings and part-time work even after including occupation-specific concentration in the model highlights the value of the skill-based measure. Indeed, the results in Panel B show that both occupation and skill concentration affect earnings and hours worked, which underscores the importance of accounting for both in analyses of labor market concentration.

Taken together, the results in Table 8 show that industry- and occupation-based concentration measures alone do not capture important aspects of monopsony power that affect worker earnings and other outcomes. Our skill-based concentration measure has independent explanatory power relative to these more commonly-used measures.

6. Robustness and Sensitivity Analyses

The baseline estimates in Section 4 support the theoretical predictions of monopsony power, whereby market concentration leads to economically and statistically significant negative labor market effects on the individual worker. In this section, we explore evidence on whether our results are driven by unobserved trends or shocks that are not accounted for by the controls and fixed effects in the triple difference framework outlined in Section 3. We first examine robustness to a series of additional control variables in Table 9, and then in Table 10 we explore the sensitivity of our results to adding a richer set of fixed effects into our model.

In Panel A of Table 9, we show results that control for the size of the demand shock, as measured by the number of displaced workers who are displaced in each labor market, year, and skill cluster. This robustness check addresses the concern that more concentrated markets may experience larger displacements, leading to a labor supply effect that would bias our estimates. The results are very similar to those presented in Tables 3 through 5. The magnitudes of the shocks that cause the displacement events therefore do not vary systematically with the concentration of skills in a way that biases our results.

Figure 1 shows a clear negative relationship between the size of the LLM and the amount of concentration, and thus it is possible that our main findings are driven by variation in labor market size rather than skill concentration. To explore this possibility, we include an interaction between the number of workers in a LLM-year and a post-separation indicator. These results are presented in Panel B of Table 9 and are very similar to baseline. The effect of skill concentration on post-separation labor market outcomes is unaffected by controlling for labor market size.

Panel C of Table 9 shows results from a modified version of equation (1) in which we control for the aggregate (non-firm-linked) skill-based HHI in the labor market. This is effectively the squared share of workers in each LLM, skill cluster, and base year. Conceptually, with this control we are comparing labor markets with the same skill composition but different firm shares of each skill group. The results produced by these regressions are extremely similar to our main findings and suggests our results are not driven by different skill distributions across local labor markets.

While equation (1) includes a rich set of fixed effects, it still is possible that correlated shocks at the industry, skill cluster, and local labor market level affect our estimates. To further investigate this possibility, we estimate modified versions of equation (1) in which we include LLM-by-base year, industry-by-base year, and skill cluster-by-base year, fixed effects. The results are shown in Table 10 and are similar to our baseline findings. These estimates provide additional evidence that our results are not biased by secular shocks at the LLM, industry, or skill cluster level.

We additionally show how results change when we exclude any given skill cluster from the analysis. Understanding to what extent individual skill groups drive our results has important implications for the credibility of our empirical strategy and the generalizability of our findings. Appendix Figure A-5 show the result from this exercise with respect to labor earnings and demonstrates that the effects we identify are not driven by any one particular skill cluster. Results for our other outcomes are available upon request.[30]

Finally, it is possible that skill concentration has an impact on the probability of being involuntarily displaced. This would imply that there is non-random selection into the displacement sample as a function of the concentration measure, thus biasing our results. To directly examine this concern, Appendix Table A-7 provides results obtained from estimating the effect of labor market concentration on the probability of being displaced. The estimate is neither economically nor statistically significant, suggesting that our results are unlikely to be driven by selection into the treatment sample.

[30] To ensure that individual base years are not driving our results, we also show results stratified by base year. These results are shown in Appendix Table A-6 and demonstrate that the results are similar across all base years.

7. Conclusion

In this paper, we extend the literature on monopsony and labor market concentration by taking a skill-based approach and estimate the causal effect of monopsony power on labor market outcomes. The prior research examining industry, firm, or occupational concentration is essentially proxying for worker type using these classifications. These approaches are limiting because worker skills are substitutable across different firms, occupations and industries. Thus, we argue that the concentration of skill demand is a more relevant measure of labor market concentration than what has been used in prior work. We are the first to apply these insights to the study of labor market concentration and monopsony.

We first show evidence of substantial variation in skill demand concentration across and within labor markets in Norway. We compare HHI concentration measures using skill clusters, occupations, and industries and show that our skill-based measure exhibits lower levels of concentration. In addition, we show that the women tend to be in occupations that are much more concentrated than men, and that the gender gap in concentration is substantially larger using the skill-based measure relative to the occupation- or industry-based measures. This is a novel finding of our analysis that has not been documented before. These results underscore the value of examining effects of concentration by gender: if men and women sort into local labor markets and occupations characterized by different degrees of labor market concentration, and if labor market concentration has a negative impact on an individual's labor market outcomes, this may provide an additional explanation for the persistence of the gender gap in earnings.

The results from our triple difference analysis show that workers who experience a mass separation have worse subsequent labor market outcomes when they are in more concentrated skill clusters. A worker experiencing a mass layoff or an establishment closure has earnings that are 9,120 Krone lower after the event, which is 1.78% relative to the mean. These wage effects are driven predominantly by intensive rather than extensive margin responses. In addition, we find suggestive evidence of reduced skill upgrading and increased skill downgrading in higher HHI clusters after separation. We also present evidence that skill mismatch decreased by 1.4 percentage points, which is almost 4% of the mean. Hence, those in more concentrated labor markets are less likely to switch to an occupation that requires different skills after a closure or layoff. Finally, we show that workers in concentrated skill clusters are less likely to move to another labor market post-separation, although the estimates are not significant at traditional levels. Taken together, these results are consistent with skill concentration leading to more market power among employers, which reduces wages and hours on the intensive margin. These effects are exacerbated by the fact that those in more concentrated industries exhibit more rigidity in their job search after separation.

While the marginal effects are larger for men, women experience far higher skill-based HHIs on average than do men. As a result, the skill-based employment concentration reduces female wages similarly to that of men. Finally, we run a horse race between the industry HHI measure, the occupation HHI measure, and our skill HHI measure. That we have sufficient power to estimate different effects highlights that these concentration measures are substantively different. Including the industry or occupation HHI measure does not affect our results or conclusions, and the effects on wages and part-time employment load on the skill rather than these more conventional measures.

This paper makes several contributions to the literature. First, we advance the burgeoning literature on labor market concentration by taking a skills-based approach to measuring concentration and by employing an identification strategy that can identify causal effects under weaker (or at least different) assumptions than has been used in prior work. Our analysis adds to this literature by using a skill-based measure of labor market concentration, which we argue and show empirically is a more powerful way to measure the concentration of labor demand that embeds workers outside options. Much of the prior research uses industry shares (Benmelech, Bergman, and Kim 2018, Rinz 2018, and Hershbein Macaluso, and Yeh 2018) or occupation shares (Azar, Marinescu, and Steinbaum 2020, Azar et al. 2020, Azar, Berry, and Marinescu 2019, Marinescu, Ouss, and Pape 2019, Qiu and Sojourner 2019, and Schubert, Stansbury, and Taska 2020). Workers can shift across occupations and industries, and so the extent of the demand for a given worker in a local labor market is captured more accurately by the distribution of skill demand in a local area rather than by the distribution of industry or even his occupation.

Second, we contribute to the literature on estimating the extent of monopsony. As discussed above, the existing literature on monopsony either directly estimates labor supply elasticities or estimates these elasticities using separation rates. A drawback of these studies is that they are necessarily focused on one occupation, such as teaching or nursing. The prior literature generally has struggled to estimate the extent of monopsony power more broadly in the labor market, due in part to the difficulty of grouping similar occupations together. Our approach provides a method for systematically grouping occupations based on their underlying skill requirements, which allows us to assess the extent of monopsony in local labor markets across a much broader set of occupations.

Third, our paper is the first to bring together the literature on monopsony with the growing body of research on the importance of skills in the labor market (e.g., Autor, Levy, and Murnane 2003; Peri and Sparber 2009; Acemoglu and Autor 2011; Autor and Dorn 2013; Goos, Manning, and Salomons 2014; Deming 2017). We segment the labor market according to skill content, demonstrating that employer market power operates through the concentration of skill demand. We are, to our knowledge, the first to take this approach to studying monopsony, and we show that skill-based concentration has larger effects on wages than does industry-based concentration. Our approach thus provides a new method for studying employer concentration and monopsony that is more broad than examining single occupations and is more informative than using occupation or industry-based concentration measures.

Our methodological contribution and empirical results have important policy implications, since a precise measurement of monopsony power is essential for proper regulation of the labor market. As noted above, suggestions presented to the United States Congress support giving the Department of Justice the power to regulate the effects of prospective mergers and acquisitions on labor market concentration, similar to the way product market concentration is currently being examined. An essential part of those proposals is the use of labor market concentration measures that are calculated within an occupation or industry. As our results show, these measures may overstate monopsony power by omitting workers' outside options. As a consequence, regulators may impose too strong limits on firm actions that might otherwise pose no threat to labor market competition and may even prevent mergers that might otherwise lead to earnings growth for workers and owners.

References

Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Impli- cations for Employment and Earnings." In Handbook of Labor Economics. 4: Elsevier, 1043–1171.

Ashenfelter, Orley C, Henry Farber, and Michael R Ransom. 2010. "Labor Market Monopsony." Journal of Labor Economics, 28(2): 203–210.

Autor, David H, Frank Levy, and Richard J Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." The Quarterly Journal of Economics, 118(4): 1279–1333.

Azar, Jos´e, Steven Berry, and Ioana Elena Marinescu. 2019. "Estimating Labor Market Power." Available at SSRN 3456277.

Azar, Jos´e, Ioana Marinescu, and Marshall Steinbaum. 2020a. "Labor Market Con- centration." Journal of Human Resources 1218–9914R1.

Azar, Jos´e, Ioana Marinescu, Marshall Steinbaum, and Bledi Taska. 2020b. "Concentration in US labor Markets: Evidence from Online Vacancy Data." Labour Economics, 66, p. 101886.

Barwick, Panle Jia, Yanyan Liu, Eleonora Patacchini, and Qi Wu. 2019. "Information, Mobile Communication, and Referral Effects." NBER Working Paper No. 25873.

Belot, Michele, Philipp Kircher, and Paul Muller. 2019. "Providing Advice to Job- seekers at Low Cost: An Experimental Study on Online Advice." The Review of Economic Studies, 86(4): 1411–1447.

Benmelech, Efraim, Nittai Bergman, and Hyunseob Kim. 2018. "Strong Employers and Weak Employees: How Does Employer Concentration Affect Wages?" Technical report, National Bureau of Economic Research.

Blau, Francine D., and Lawrence M. Kahn. 2003. "Understanding International Differences in the Gender Pay Gap." *Journal of Labor Economics* 21(1): 106-144.

Botero, Juan C, Simeon Djankov, Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer. 2004. "The Regulation of Labor." The Quarterly Journal of Economics, 119(4): 1339–1382.

Caldwell, Sydnee, and Oren Danieli. 2018. "Outside Options in the Labor Market." Unpublished manuscript.

Card, David, and Alan B Krueger. 1995. "Time-Series Minimum-Wage Studies: A Meta-Analysis." The American Economic Review, 85(2): 238–243.

Charrad, Malika, Nadia Ghazzali, Veronique Boiteau, and Azam Niknafs. 2014. "Package 'nbclust'." Journal of Statistical Software, 61 1–36.

David, H, and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." American Economic Review, 103(5): 1553–97.

Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." The Quarterly Journal of Economics, 132(4): 1593–1640.

Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker. 2016. "Referral-based Job Search Networks." *The Review of Economic Studies* 83(2): 514-546.

Emerson, Michael. 1987. "Labour Market Flexibility and Jobs: A Survey of Evidence from OECD Countries with Special Reference to Europe: Comments." The Fight against Unemployment: Macroeconomic Papers from the Centre for European Policy Studies, ed. by R. Lyard, and L. Calmfors 77–84.

Falch, Torberg. 2010. "The Elasticity of Labor Supply at the Establishment Level." Journal of Labor Economics, 28(2): 237–266.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polariza- tion: Routine-Biased Technological Change and Offshoring." American Economic Review, 104(8): 2509–26.

Gundersen, Frants, and Jorgen Aarhaug. 2013. "Inndelinger i Senterstruktur, Sentralitet og BA Regioner." NIBR-Rapport(2013-1. 9): .

Hershbein, Brad, Claudia Macaluso, and Chen Yeh. 2018. "Concentration in US Local Labor Markets: Evidence from Vacancy and Employment Data."Technical report, Working paper.

Hirsch, Boris, Thorsten Schank, and Claus Schnabel. 2010. "Differences in Labor Supply to Monopsonistic Firms and the Gender Pay Gap: An Empirical Analysis Using Linked Employer-Employee Data from Germany." Journal of Labor Economics, 28(2): 291–330.

Hoen, Maria Brunborg. 2016. "Occupational Crosswalk, Data and Language Requirements." Frisch Centre Working Paper 1/2016.

Huttunen, Kristiina, Jarle Møen, and Kjell G Salvanes. 2011. "How Destructive is Creative Destruction? Effects of Job Loss on Job Mobility, Withdrawal and Income." Journal of the European Economic Association, 9(5): 840–870.

Jacobsen, Louis, Robert Lalonde, and Daniel Sullivan. 1993. "Earnings Losses of Displaced Workers." American Economic Review, 83(4): 685–709.

Johnsen, Julian Vedeler, Kjell Vaage, and Alexander Willén. 2020. "Interactions in Public Policies: Spousal Responses and Program Spillovers of Welfare Reforms." NHH Discussion Paper 20/2020.

Le Barbanchon, Thomas, Roland Rathelot, and Alexandra Roulet. 2020. "Gender Differences in Job Search: Trading Off Commute Against Wage."

Lin, Gary C. 2020. "Trade Liberalization and Skill Acquisition." PhD Dissertation. Cornell University.

Lipsius, Ben. 2018. "Labor Market Concentration Does Not Explain the Falling Labor Share." Available at SSRN 3279007.

Lovenheim, Michael F. 2009. "The Effect of Teachers Unions on Education Production: Evidence from Union Election Certifications in Three Midwestern States." Journal of Labor Economics, 27(4): 525–587.

Macaluso, Claudia. 2017. "Skill Remoteness and Post-Layoff Labor Market Outcomes." Meeting Papers. No. 569. Society for Economic Dynamics.

Machin, Stephen, Kjell G Salvanes, and Panu Pelkonen. 2012. "Education and Mobility." Journal of the European Economic Association, 10(2): 417–450.

Manning, Alan. 2003. Monopsony in Motion: Imperfect Competition in Labor Markets.: Princeton University Press.

Manning, Alan. 2020. "Monopsony in Labor Markets: A Review." ILR Review, DOI: http://dx.doi.org/10.1177/0019793920922499.

Marinescu, Ioana Elena, Ivan Ouss, and Louis-Daniel Pape. 2019. "Wages, Hires, and Labor Market Concentration." Available at SSRN 3453855.

Matsudaira, Jordan D. 2014. "Monopsony in the Low-Wage Labor Market? Evidence from Minimum Nurse Staffing Regulations." Review of Economics and Statistics, 96(1): 92–102.

Merrifield, John. 1999. "Monopsony Power in the Market for Teachers: Why Teachers Should Support Market-Based Education Reform." Journal of Labor Research, 20(3): 377– 391.

Peri, Giovanni, and Chad Sparber. 2009. "Task Specialization, Immigration, and Wages." American Economic Journal: Applied Economics, 1(3): 135–69.

Petrongolo, Barbara, and Maddalena Ronchi. 2020. "Gender Gaps and the Structure of Local Labor Markets." Labour Economics, p. 101819.

Qiu, Yue, and Aaron Sojourner. 2019. "Labor-Market Concentration and Labor Com- pensation." Available at SSRN 3312197.

Ransom, Michael R, and Ronald L Oaxaca. 2010. "New Market Power Models and Sex Differences in Pay." Journal of Labor Economics, 28(2): 267–289.

Ransom, Michael R, and David P Sims. 2010. "Estimating the Firms Labor Supply Curve in a New Monopsony Framework: Schoolteachers in Missouri." Journal of Labor Economics, 28(2): 331–355.

Rinz, Kevin. 2018. "Labor Market Concentration, Earnings Inequality, and Earnings Mobility." Center for Administrative Records Research and Applications Working Paper, 10. Schubert,

Schubert, Gregor, Anna Stansbury, and Bledi Taska. 2020. "Monopsony and Outside Options." Available at SSRN.

Staiger, Douglas O, Joanne Spetz, and Ciaran S Phibbs. 2010. "Is there Monopsony in the Labor Market? Evidence from a Natural Experiment." Journal of Labor Economics 28(2): 211–236.

Sullivan, Daniel. 1989. "Monopsony Power in the Market for Nurses." The Journal of Law and Economics, 32(2, Part 2): S135–S178.

Webber, Douglas A. 2015. "Firm Market Power and the Earnings Distribution." Labour Economics, 35 123–134.

Table 1: **Summary Statistics of Analysis Variables**

Variable	Observations	Mean	Std. Dev.
Labor Earnings	7,106,235	512888.5	332712.6
Market Wage	7,139,673	505819.1	336026.9
Not in Labor Force	7,139,946	0.032	0.177
Employed	7,139,946	0.965	0.184
Part-time (more than 20 hours)	7,139,946	0.016	0.125
In different skill cluster (relative to base year)	7,139,946	0.351	0.477
In different labor market (relative to base year)	7,139,946	0.317	0.465
Age	7,139,946	46.363	10.406
Female	7,139,946	0.424	0.494
Married	7,139,946	0.559	0.496
Less than high school	7,117,737	0.139	0.345
High school	7,117,737	0.464	0.499
BA+	7,117,737	0.396	0.489
Fraction of low skill workers in occupation	7,139,946	0.157	0.157
Fraction of high skill workers in occupation	7,139,946	0.407	0.356
Base year HHI Skill	7,139,946	447.205	879.443
Base year HHI Industry	7,139,946	887.448	1177.814

Source: Authors' tabulations from Norwegian Registry Data as described in the text.

Table 2: Composition of Composite Skill Measures

Composite Skill Measure	O*NET Measures
Non-routine, cognitive, analytical	"Analyzing data/information"
	"Thinking creatively"
	"Interpreting information for others"
Non-routine, cognitive, interpersonal	"Establishing and maintaining personal relationships"
	"Guiding, directing and motivating subordinates"
	"Coaching/developing others"
Non-routine, physical adaptability, manual	"Operating vehicles, mechanized devices, or equipment"
	"Spend time using hands to handle, control or feel objects, tools or controls"
	"Manual dexterity"
	"Spatial orientation"
Non-routine, interpersonal adaptability	"Social Perceptiveness"
Routine, cognitive	"Importance of repeating the same tasks"
	"Importance of being exact or accurate"
	"Structured v. Unstructured work (reverse)"
Routine, manual	"Pace determined by speed of equipment"
	"Controlling machines and processes"
	"Spend time making repetitive motions"

Source: 2008 O*NET.

Table 3: The Effect of Involuntary Separation and Skill Concentration on Earnings

Panel A: Labor Earnings			
Independent Variable	(1)	(2)	(3)
Post-separation*Skill HHI	-115186.107***	-92980.750***	-91198.318***
	(30588.704)	(23980.556)	(24895.036)
Skill HHI	-334184.346***	43639.903***	21003.006***
	(76471.187)	(9899.286)	(7957.229)
Effect of going from a non-concentrated to a concentrated market:	-11518.611	-9298.075	-9119.832
% Effect:	-2.246	-1.813	-1.778
Relative time and year FEs:		x	x
LLM, Skill, and Industry FEs		x	x
Individual FEs			x

Panel B: Wage Earnings			
Independent Variable	(1)	(2)	(3)
Post-separation*Skill HHI	-109834.634***	-88558.275***	-88588.755***
	(34918.821)	(26854.839)	(27820.132)
Skill HHI	-333230.647***	45052.409***	23349.168***
	(77726.910)	(10012.838)	(8695.287)
Effect of going from a non-concentrated to a concentrated market:	-10983.463	-8855.828	-8858.876
% Effect:	-2.171	-1.749	-1.750
Relative time and year FEs:		x	x
LLM, Skill, and Industry FEs		x	x
Individual FEs			x

Source: Authors' estimation as described in the text. Pensionable earnings consist of pre-tax labor earnings (including self-employed earnings) plus transfers such as sick leave benefits, unemployment benets, and parental leave payments. Wage earnings include only pre-tax labor earnings (including self-employed earnings). The effect of going from a non-concentrated to a concentrated market shows the difference in the post-separation effect when the HHI changes by 0.1 (i.e., from 0.15 to 0.25). The dependent variable mean in Panel A is 512888.503 and in Panel B is 505819.110. Panel A estimates are based on 7106235 observations and Panel B on 7139673 observations. All fixed effects except for individual fixed effects are interacted with educational attainment indicators as described in the text. Standard errors are clustered at the local labor market level: * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table 4: The Effect of Involuntary Separation and Skill Concentration on Employment Outcomes

	Panel A: Not in Labor Force			Panel B: Employed		
Independent Variable	(1)	(2)	(3)	(1)	(2)	(3)
Post-separation*Skill HHI	0.020	0.014	0.014	0.008	0.015	0.015
	(0.022)	(0.019)	(0.020)	(0.028)	(0.024)	(0.025)
Skill HHI	0.004*	0.000	-0.004	0.001	-0.001	0.003
	(0.002)	(0.004)	(0.007)	(0.002)	(0.003)	(0.007)
Effect of going from a non-concentrated to a concentrated market:	0.002	0.001	0.001	0.001	0.001	0.001
Relative time and year FEs:		x	x		x	x
LLM, Skill, and Industry FEs		x	x		x	x
Individual FEs			x			x

	Panel C: Part-Time		
Independent Variable	(1)	(2)	(3)
Post-separation*Skill HHI	0.102***	0.098***	0.098***
	(0.016)	(0.015)	(0.016)
Skill HHI	0.030***	-0.003	0.002
	(0.004)	(0.002)	(0.005)
Effect of going from a non-concentrated to a concentrated market:	0.010	0.010	0.010
Relative time and year FEs:		x	x
LLM, Skill, and Industry FEs		x	x
Individual FEs			x

Source: Authors' estimation as described in the text. The effect of going from a non-concentrated to a concentrated market shows the difference in the post-separation effect when the HHI changes by 0.1 (i.e., from 0.15 to 0.25). The dependent variable mean in Panel A is 0.032, in Panel B is 0.965, and in Panel C is 0.016. Estimates in all panels are based on 7139946 observations. All fixed effects except for individual fixed effects are interacted with educational attainment indicators as described in the text. Standard errors are clustered at the local labor market level: * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table 5: The Effect of Involuntary Separation and Skill Concentration on Occupational Skill and Mobility

	Panel A: Skill Downgrading			Panel B: Skill Upgrading		
Independent Variable	(1)	(2)	(3)	(1)	(2)	(3)
Post-separation*Skill HHI	0.016	0.023*	0.023*	-0.022	-0.039***	-0.039***
	(0.015)	(0.012)	(0.012)	(0.018)	(0.013)	(0.013)
Skill HHI	-0.067*	-0.024***	-0.005	-0.147*	-0.004	0.003
	(0.040)	(0.009)	(0.004)	(0.086)	(0.007)	(0.007)
Effect of going from a non-concentrated to a concentrated market:	0.002	0.002	0.002	-0.002	-0.004	-0.004
% Effect:	1.274	1.274	1.274	-0.491	-0.980	-0.980
Relative time and year FEs:		x	x		x	x
LLM, Skill, and Industry FEs		x	x		x	x
Individual FEs			x			x

	Panel C: Skill Mismatch			Panel D: Moved Labor Markets		
Independent Variable	(1)	(2)	(3)	(1)	(2)	(3)
Post-separation*Skill HHI	-0.055	-0.160***	-0.160***	-0.011	-0.123**	-0.123**
	(0.061)	(0.046)	(0.048)	(0.057)	(0.059)	(0.061)
Skill HHI	0.016	0.020**	-0.028	0.051***	0.015	0.014
	(0.013)	(0.010)	(0.026)	(0.011)	(0.013)	(0.014)
Effect of going from a non-concentrated to a concentrated market:	-0.006	-0.016	-0.016	-0.001	-0.012	-0.012
% Effect:	-1.709	-4.571	-4.571	-0.315	-3.786	-3.786
Relative time and year FEs:		x	x		x	x
LLM, Skill, and Industry FEs		x	x		x	x
Individual FEs			x			x

Source: Authors' estimation as described in the text. The effect of going from a non-concentrated to a concentrated market shows the difference in the post-separation effect when the HHI changes by 0.1 (i.e., from 0.15 to 0.25). The dependent variable mean in Panel A is 0.157, in Panel B is 0.408, in Panel C is 0.351, and in Panel D is 0.317. All estimates are based on 7139946 observations. All fixed effects except for individual fixed effects are interacted with educational attainment indicators as described in the text.Standard errors are clustered at the local labor market level: * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table 6: Heterogeneous Treatment Effects by Gender

Panel A: Men								
	Labor Earnings	NILF	Employed	Part-time	Skill Downgrading	Skill Upgrading	Skill Mismatch	Move Labor Markets
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-separation*	-117896.876***	0.005	0.007	0.078***	0.045***	-0.054**	0.056	0.039
Skill HHI	(41935.883)	(0.030)	(0.040)	(0.016)	(0.016)	(0.024)	(0.077)	(0.074)
Concentration Effect	-11789.688	0.001	0.001	0.008	0.005	-0.005	0.006	0.004
% Effect:	-2.041	3.333	0.104	61.534	2.959	-1.393	1.724	1.250

Panel B: Women								
	Labor Earnings	NILF	Employed	Part-time	Skill Downgrading	Skill Upgrading	Skill Mismatch	Move Labor Markets
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-separation*	-48125.087***	-0.020	0.048*	0.064**	0.002	-0.040***	-0.230***	-0.137**
Skill HHI	(16750.924)	(0.024)	(0.026)	(0.028)	(0.012)	(0.010)	(0.043)	(0.054)
Concentration Effect	-4812.509	-0.002	0.005	0.006	0.000	-0.004	-0.023	-0.014
% Effect:	-1.131	5.714	0.519	30.000	0	-0.840	-6.497	-4.473

Source: Authors' estimation as described in the text. The "concentration effect" shows the difference in the post-separation effect when the HHI changes by 0.1 (i.e., from 0.15 to 0.25). All estimates include relative time to separation and year fixed effects, local labor market, skill cluster, and industry fixed effects, as well as individual fixed effects. All fixed effects except for individual fixed effects are interacted with educational attainment indicators as described in the text. Standard errors are clustered at the local labor market level: * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table 7: Heterogeneous Treatment Effects by Worker Education Level

Panel A: No High School Diploma								
Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)	Move Labor Markets (8)
Post-separation*	-29888.138	-0.058	0.099*	0.081***	0.052***	-0.041***	-0.215***	-0.181**
Skill HHI	(23100.407)	(0.049)	(0.057)	(0.029)	(0.015)	(0.015)	(0.069)	(0.076)
Concentration Effect	-2988.814	-0.006	0.010	0.008	0.005	-0.004	-0.022	-0.018
% Effect:	-0.737			38.095	1.645	-2.581	-6.377	-5.825

Panel B: High School Diploma								
Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)	Move Labor Markets (8)
Post-separation*	-62017.989***	0.001	0.032	0.104***	0.012	-0.023	-0.204***	-0.187***
Skill HHI	(23309.905)	(0.019)	(0.020)	(0.016)	(0.014)	(0.015)	(0.046)	(0.053)
Concentration Effect	-6201.80	0.000	0.003	0.010	0.001	-0.002	-0.020	-0.019
% Effect:	-1.328			58.824	0.505	-0.957	-5.764	-6.169

Panel C: BA or Higher								
Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)	Move Labor Markets (8)
Post-separation*	-242871.338***	0.090***	-0.074**	0.090***	0.035**	-0.113***	-0.02	0.115
Skill HHI	(56238.076)	(0.033)	(0.035)	(0.026)	(0.016)	(0.034)	(0.067)	(0.093)
Concentration Effect	-24287.134	0.009	-0.007	0.009	0.004	-0.011	-0.002	0.012
% Effect:	-4.026			59.231	6.780	-1.513	-0.562	3.636

Source: Authors' estimation as described in the text. The "concentration effect" shows the difference in the post-separation effect when the HHI changes by 0.1 (i.e., from 0.15 to 0.25). All estimates include relative time to separation and year fixed effects, local labor market, skill cluster, and industry fixed effects, as well as individual fixed effects. Standard errors are clustered at the local labor market level: * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table 8: Comparison of Skill-, Industry-, and Occupation-Based HHI Effects

Panel A: Skill and Industry Horse-race								
Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)	Move Labor Markets (8)
Post-separation*Skill HHI	-100780.83***	-0.025	0.042	0.085***	-0.005	0.033	0.047	-0.045
	(34554.04)	(0.022)	(0.028)	(0.018)	(0.016)	(0.021)	(0.095)	(0.078)
Post-separation*Industry HHI	2222.08	0.080***	0.011	0.028**	0.036***	-0.096***	-0.328***	-0.102*
	(6038.48)	(0.021)	(0.011)	(0.012)	(0.009)	(0.018)	(0.074)	(0.059)
Skill HHI	15316.26**	-0.005	0.005	-0.007	-0.014***	0.002	-0.009	-0.007
	(7330.04)	(0.005)	(0.005)	(0.008)	(0.004)	(0.007)	(0.022)	(0.014)
Industry HHI	-24366.90	-0.003	0.000	0.033	0.001	0.004	0.023***	0.015
	(16938.97)	(0.004)	(0.004)	(0.020)	(0.006)	(0.013)	(0.008)	(0.013)

Panel B: Skill and Occupation Horse-race								
Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)	Move Labor Markets (8)
Post-separation*Skill HHI	-41657.964**	-0.029	0.066***	0.078***	0.019	0.001	-0.108*	-0.137**
	(18358.532)	(0.018)	(0.021)	(0.014)	(0.013)	(0.019)	(0.062)	(0.059)
Post-separation*Occupation HHI	-108828.800***	0.095***	-0.113***	0.046***	0.008	-0.087***	-0.114**	0.031
	(17923.130)	(0.017)	(0.021)	(0.013)	(0.011)	(0.023)	(0.049)	(0.053)
Skill HHI	19077.679**	-0.004	0.003	0.003	-0.004	-0.000	-0.027	0.016
	(7719.937)	(0.007)	(0.007)	(0.006)	(0.004)	(0.007)	(0.026)	(0.013)
Occupation HHI	12285.640**	0.001	-0.002	-0.015*	-0.005*	0.025***	-0.013	-0.014
	(5837.345)	(0.004)	(0.004)	(0.009)	(0.003)	(0.006)	(0.012)	(0.009)

Source: Authors' estimation as described in the text. All estimates include relative time to separation and year fixed effects, local labor market, skill cluster, and industry fixed effects, as well as individual fixed effects. All fixed effects except for individual fixed effects are interacted with educational attainment indicators as described in the text. Standard errors are clustered at the local labor market level: * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table 9: Robustness Checks: Additional Controls

Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)	Move Labor Markets (8)
Panel A: Controlling for the Size of the Demand Shock								
Post-separation* Skill HHI	-91195.012***	0.014	0.015	0.098***	0.023*	-0.039***	-0.160***	-0.123**
	(24896.493)	(0.020)	(0.025)	(0.016)	(0.012)	(0.013)	(0.048)	(0.061)
Concentration Effect	-9119.501	0.001	0.002	0.010	0.002	-0.004	0.016	0.012
Panel B: Controlling for LLM Size*Post-separation								
Post-separation* Skill HHI	-72122.529**	-0.018	0.058**	0.074***	0.033***	-0.046***	-0.234***	-0.253***
	(35562.015)	(0.023)	(0.024)	(0.014)	(0.009)	(0.012)	(0.032)	(0.045)
Concentration Effect	-7217.253	-0.002	0.006	0.007	0.003	-0.005	-0.023	-0.025
Panel C: Controlling for HHI of Worker Shares in Each LLM, Skill Cluster, and Year								
Post-separation* Skill HHI	-95015.604***	0.008	0.026	0.094***	0.030***	-0.039***	-0.161***	-0.181***
	(22651.346)	(0.020)	(0.025)	(0.016)	(0.012)	(0.013)	(0.051)	(0.063)
Concentration Effect	-9501.560	0.001	0.003	0.009	0.003	-0.004	0.016	0.018

Source: Authors' estimation as described in the text. The "concentration effect" shows the difference in the post-separation effect when the HHI changes by 0.1 (i.e., from 0.15 to 0.25). All estimates include relative time to separation and year fixed effects, local labor market, skill cluster, and industry fixed effects, as well as individual fixed effects. All fixed effects except for individual fixed effects are interacted with educational attainment indicators as described in the text. In Panel (A), we control for the number of workers who were displaced in each LLM, skill cluster, and year. In Panel (B), we include an interaction with the number of workers in the LLM and a post-separation indicator. In Panel (C), we control for the squared share of workers in each LLM, skill cluster, and year. Standard errors are clustered at the local labor market level: * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

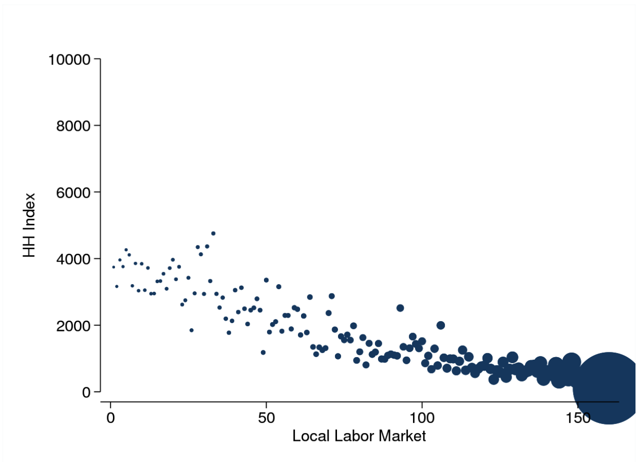
Table 10: Robustness Checks: Additional Two-way Fixed Effects

	Labor Earnings	Labor Earnings	Labor Earnings	NILF	NILF	NILF	Employed	Employed	Employed	Part-time	Part-time	Part-time
Post-separation*	-91186.028***	-91190.929***	-91200.637***	0.014	0.014	0.014	0.015	0.015	0.015	0.098***	0.098***	0.098***
Skill HHI	(24894.705)	(24896.714)	(24893.641)	(0.020)	(0.020)	(0.020)	(0.025)	(0.025)	(0.025)	(0.016)	(0.016)	(0.016)
Baseline Specification												
Base Year by LLM	x			x			x			x		
Base Year by Skill Cluster		x			x			x			x	
Base Year by Industry			x			x			x			x
	Skill Downgrading	Skill Downgrading	Skill Downgrading	Skill Upgrading	Skill Upgrading	Skill Upgrading	Skill Mismatch	Skill Mismatch	Skill Mismatch	Move Labor Markets	Move Labor Markets	Move Labor Markets
Post-separation*	0.023*	0.023*	0.023*	-0.039***	-0.039***	-0.039***	-0.160***	-0.160***	-0.160***	-0.123**	-0.123**	-0.123**
Skill HHI	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.048)	(0.048)	(0.048)	(0.061)	(0.061)	(0.061)
Baseline Specification												
Base Year by LLM	x			x			x			x		
Base Year by Skill Cluster		x			x			x			x	
Base Year by Industry			x			x			x			x

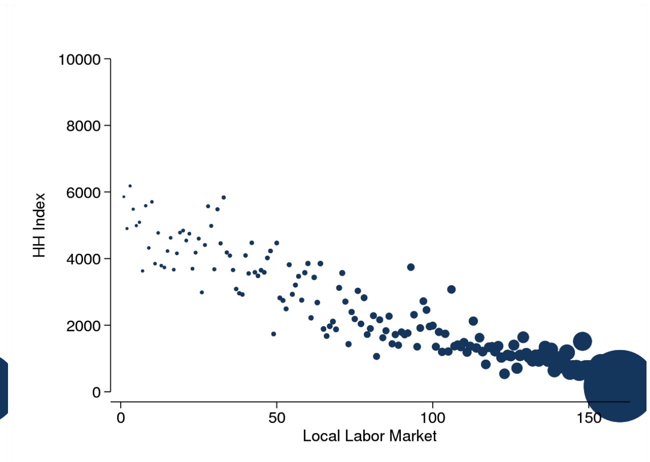
Source: Authors' estimation as described in the text. All estimates include relative time to separation and year fixed effects, local labor market, skill cluster, and industry fixed effects, as well as individual fixed effects. Standard errors are clustered at the local labor market level: * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Figure 1: Herfindahl-Hirschman Indices by Local Labor Market

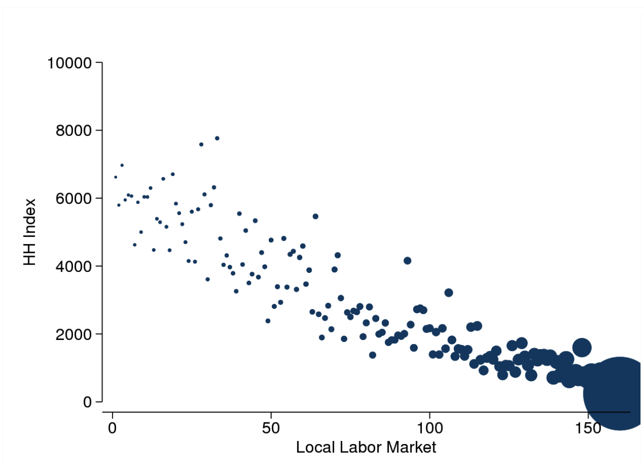
(a) Skill-based HHI



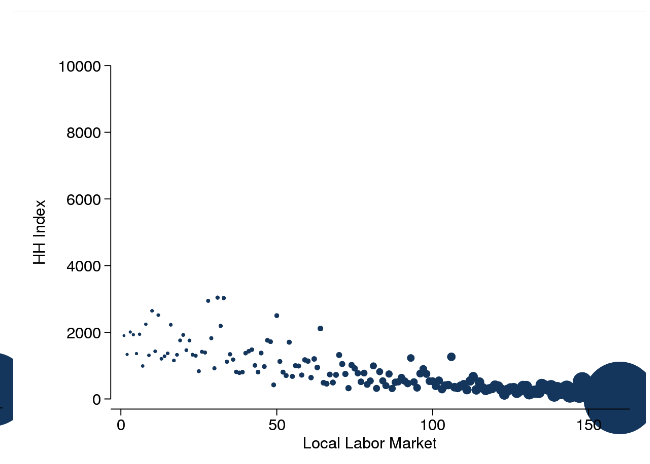
(b) Occupation-based HHI



(c) Industry-based HHI



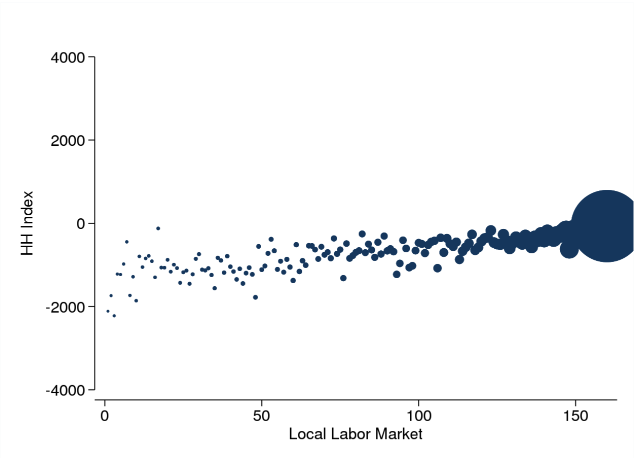
(d) Completed Education-based HHI



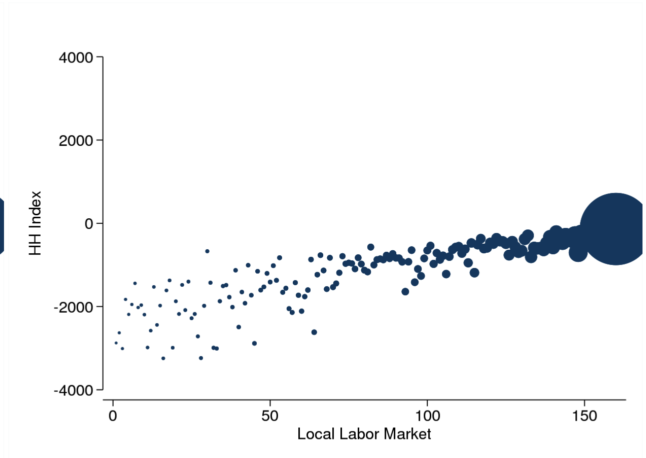
Notes: Each panel shows the Herfindahl-Hirschman Index by local labor market, calculated using different clustering measures. Each point is a local labor market, and the local labor markets are ordered by size. The size of each point represents the employed population of the local labor market. In panel (a), the HHI is calculated using 20 skill clusters as discussed in the text. In panel (b), the HHI is calculated using 43 2-digit STYRK occupation codes. In panel (c) the HHI is calculated from 21 industry groups from the Classification of Standard Occupation Classification, and in panel (d) the HHI is calculated using 4 education groups (less than HS, HS, some college, and BA+).

Figure 2: Differences in Herfindahl-Hirschman Indices Across Measures, by Local Labor Market

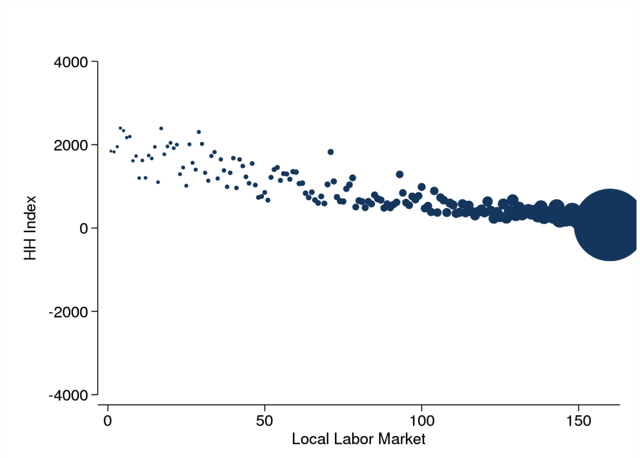
(a) Skill-based HHI - Occupation-based HHI



(b) Skill-based HHI - Industry-based HHI



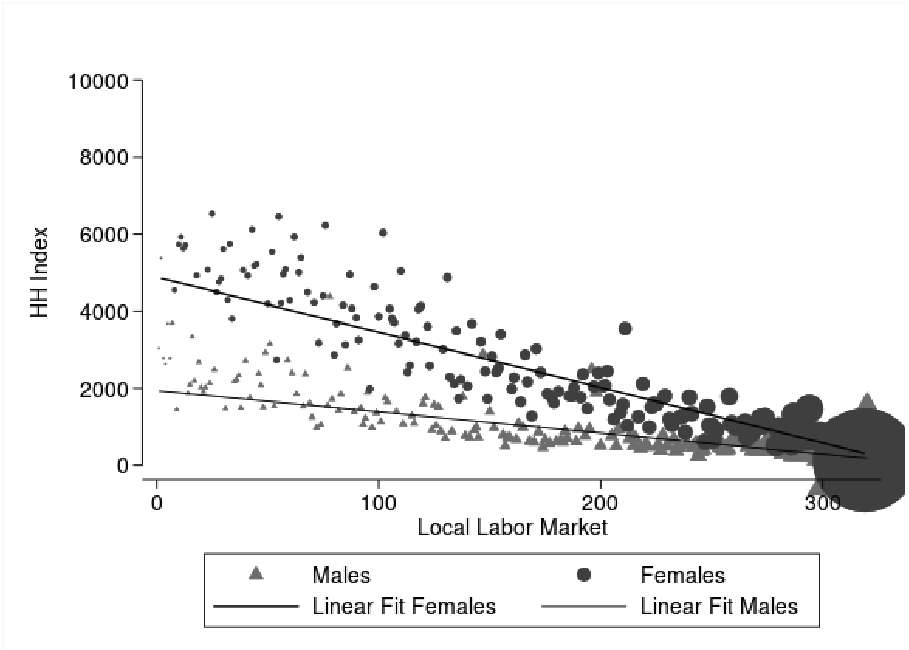
(c) Skill-based HHI - Education-based HHI



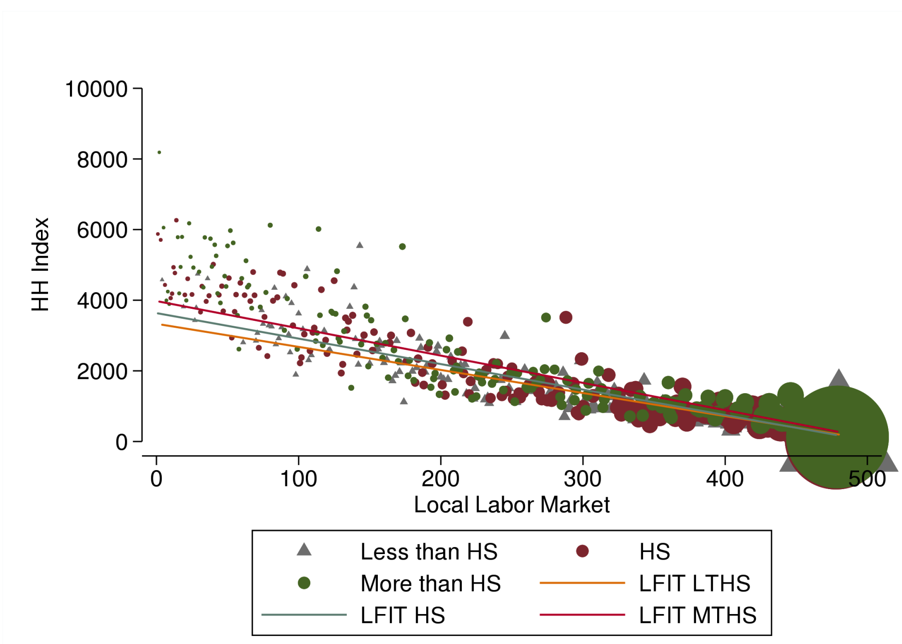
Notes: Each panel shows the difference between the HHI calculated using skills and the HHI calculated using another clustering method, by local labor market. Each point is a local labor market, and the local labor markets are ordered by size. The size of each point represents the employed population of the local labor market. The skill-based HHI is calculated using 20 skill clusters, the occupation-based HHI is calculated using 43 2-digit occupation codes, the industry-based HHI is calculated using 21 industry groups, and the education-based HHI is calculated using 4 education groups (less than HS, HS, some college, and BA+).

Figure 3: Skill-based Herfindahl-Hirschman Indices, by Local Labor Market, Gender, and Education Level

(a) Skill-based HHI by Worker Gender



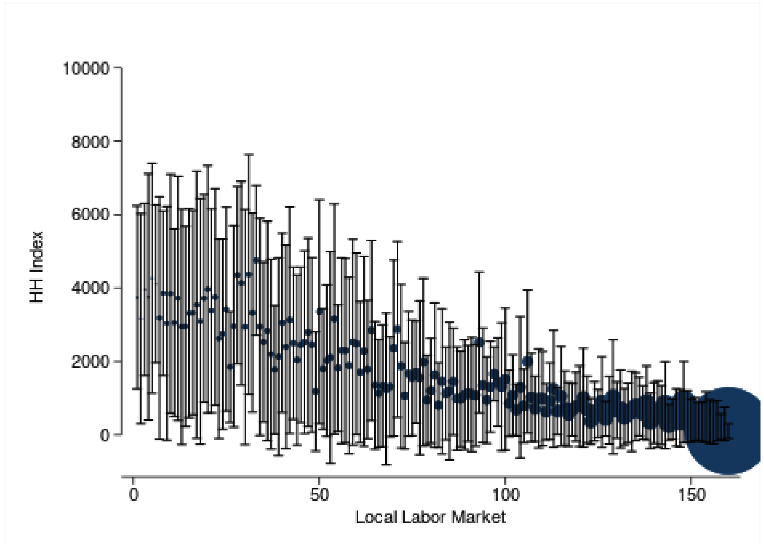
(b) Skill-based HHI by Worker Educational Attainment



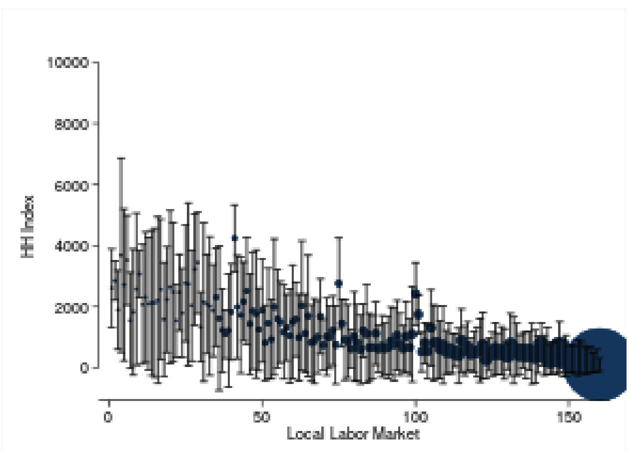
Notes: Panel (a) shows skill-based HHI for each local labor market, separately by worker gender. Each point is a gender, local labor market combination, and the local labor markets are ordered by overall size (not by gender). The size of each point represents the total employed population of the local labor market. Panel (b) shows skill-based HHI for each local labor market, separately by worker educational attainment.

Figure 4: Within-Local Labor Market Variation in Skill-based Herfindahl-Hirschman Indices

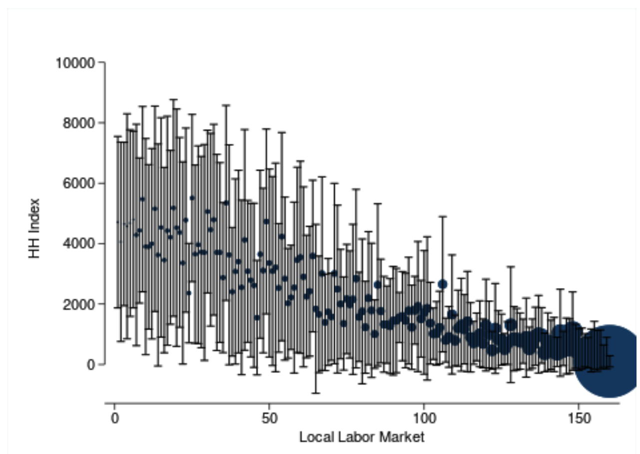
(a) Pooled



(b) Men



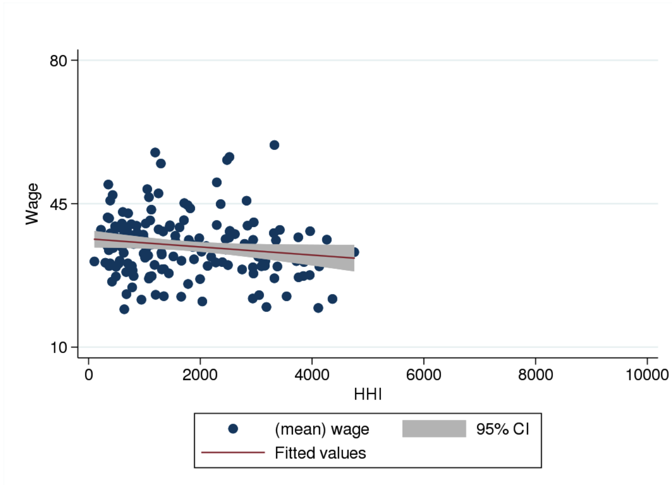
(c) Women



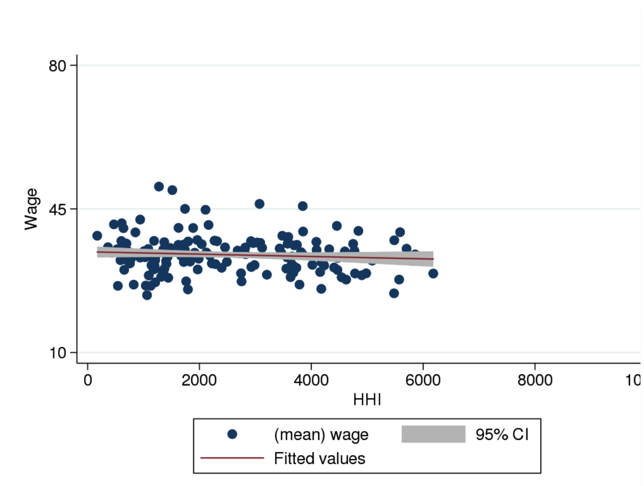
Notes: Each point shows the skill-based HHI mean in a local labor market, and the bar extending from each point shows a standard deviation above and below the mean in that local labor market. The within-LLM variation comes from different HHIs across skill clusters within the local labor market. Panel (a) shows tabulations for the pooled sample, while panels (b) and (c) show tabulations for men and women, respectively.

Figure 5: Correlations Between HHI Measures and Local Labor Market Earnings

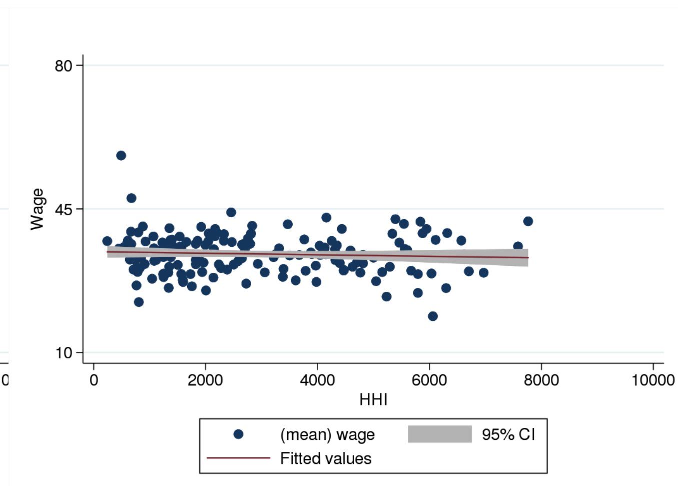
(a) Skill-based HHI



(b) Occupation



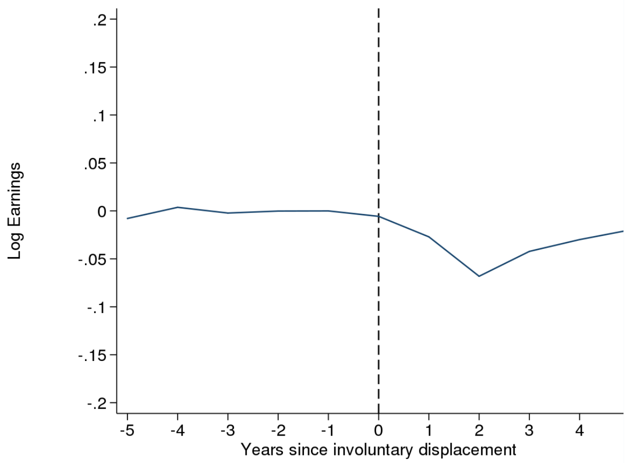
(c) Industry



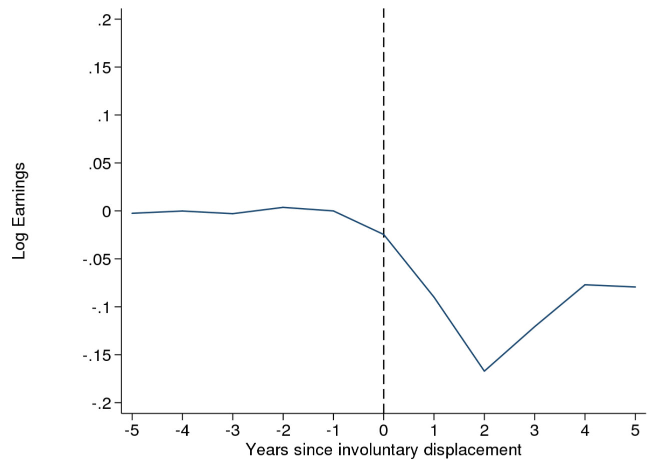
Notes: Each panel shows a scatter plot of HHI vs. mean earnings in the local labor market. The panels differ in the HHI measure used: panel (a) uses a skill-based HHI measure, panel (b) uses an occupation-based HHI measure, and panel (c) uses an industry-based HHI measure. A linear fit and 95% confidence interval is superimposed on the scatter plot.

Figure 6: Event Studies of Involuntary Displacement on Labor Earnings, Overall and by HHI

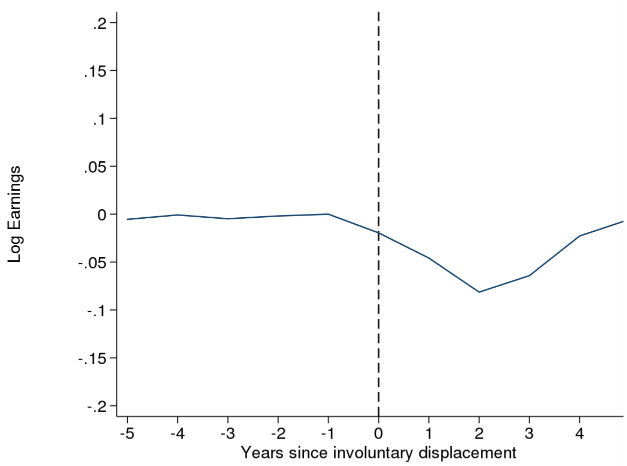
(a) Pooled



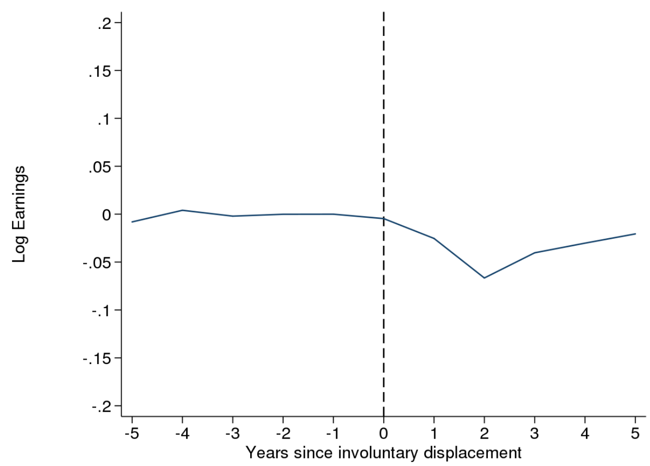
(b) High HHI (>2500)



(c) Moderate HHI (1000<HHI<2500)



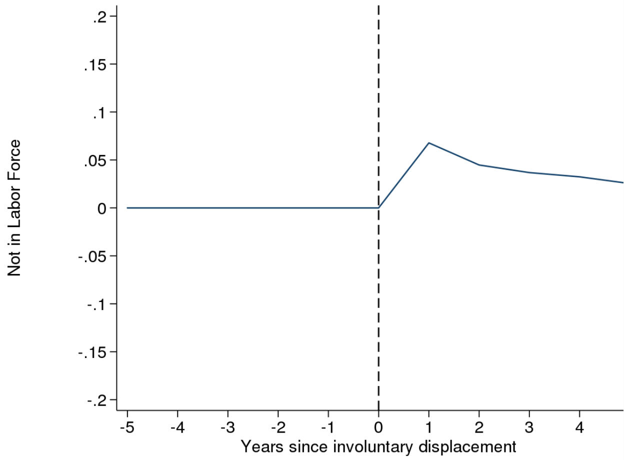
(d) Low HHI (<1000)



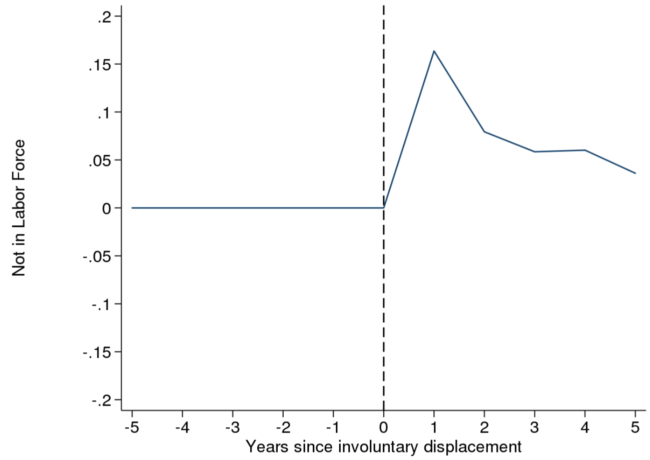
Notes: Each panel shows raw means of log earnings relative to the time of displacement. Panel (a) shows pooled estimates across all local labor markets, panel (b) shows event study plots for high HHI skill clusters, panel (c) shows event study plots for moderate HHI skill clusters, and panel (d) shows event study plots for low HHI skill clusters.

Figure 7: Event Studies of Involuntary Displacement on Labor Force Non-participation, Overall and by HHI

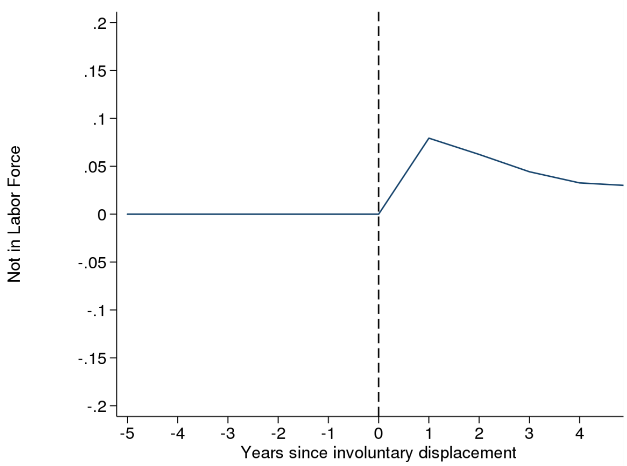
(a) Pooled



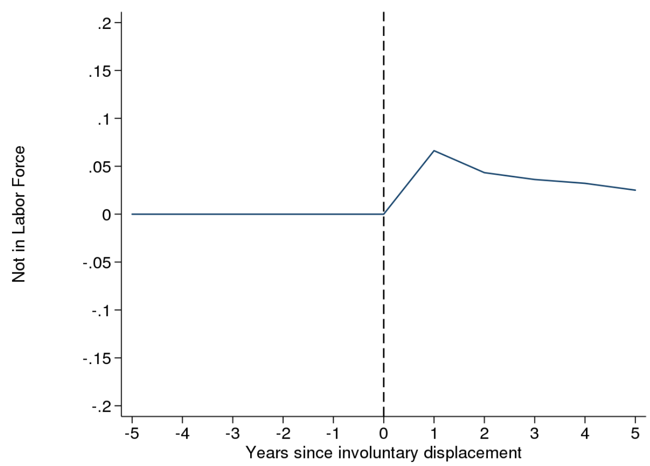
(b) High HHI (>2500)



(c) Moderate HHI (1000<HHI<2500)



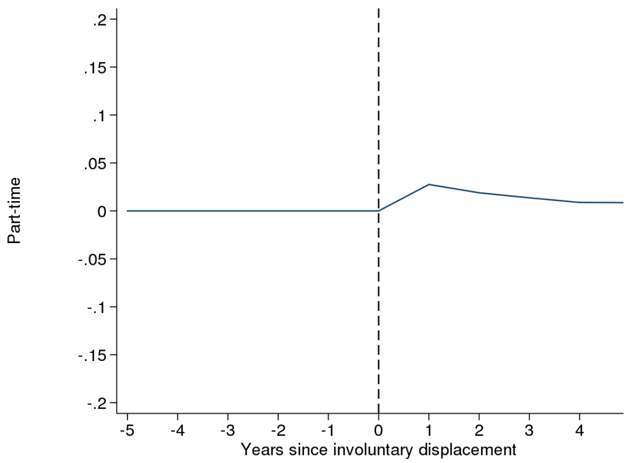
(d) Low HHI (<1000)



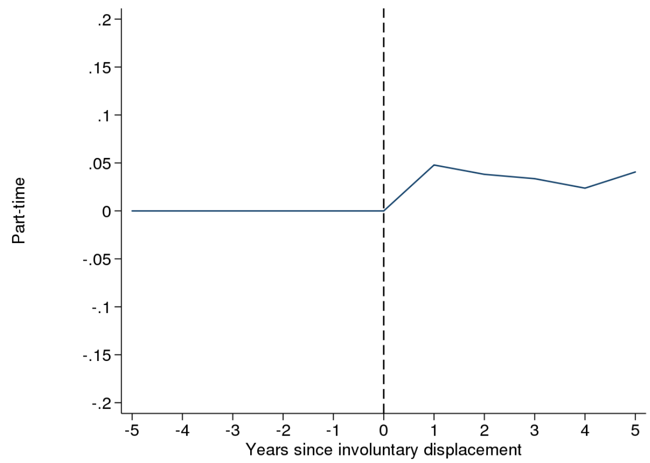
Notes: Each panel shows raw means of labor force non-participation (i.e., an indicator equal to one if the person is not in the labor force) relative to the time of displacement. Panel (a) shows pooled estimates across all local labor markets, panel (b) shows event study plots for high HHI skill clusters, panel (c) shows event study plots for moderate HHI skill clusters, and panel (d) shows event study plots for low HHI skill clusters.

Figure 8: Event Studies of Involuntary Displacement on Part-time Work, Overall and by HHI

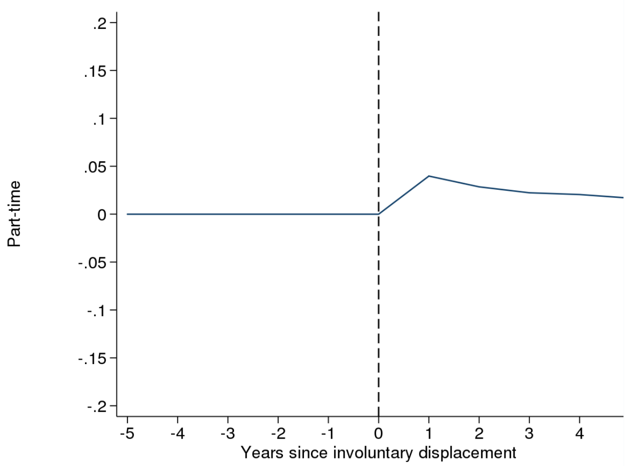
(a) Pooled



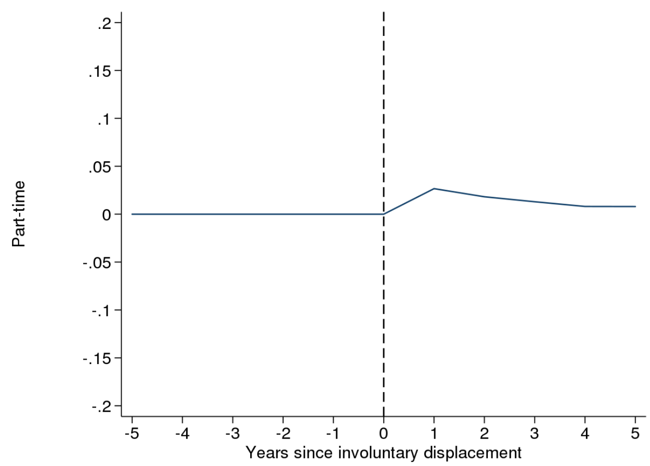
(b) High HHI (>2500)



(c) Moderate HHI (1000<HHI<2500)

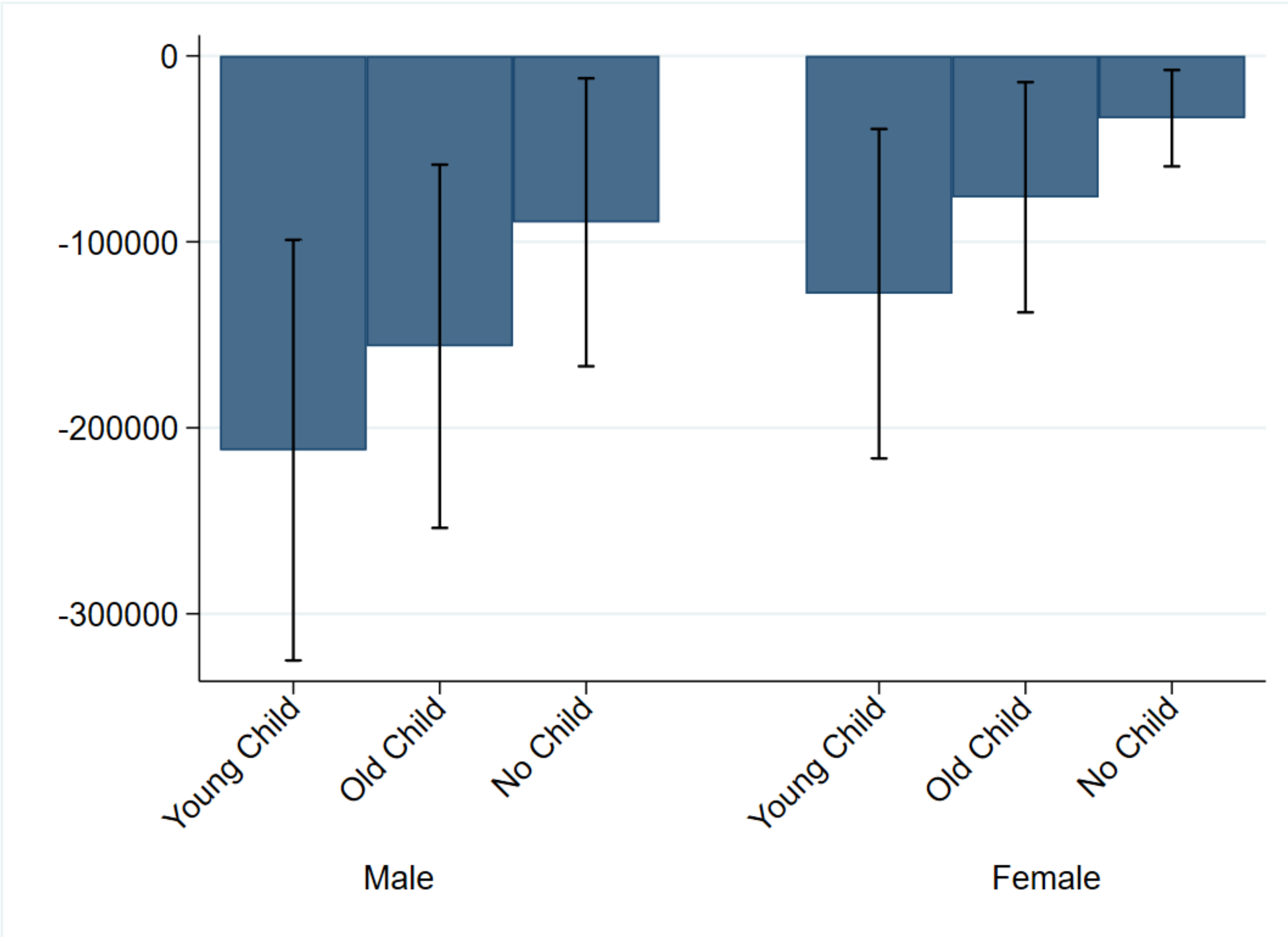


(d) Low HHI (<1000)



Notes: Each panel shows raw means of part-time work (i.e., an indicator equal to one if the person is working part time) relative to the time of displacement. Panel (a) shows pooled estimates across all local labor markets, panel (b) shows event study plots for high HHI skill clusters, panel (c) shows event study plots for moderate HHI skill clusters, and panel (d) shows event study plots for low HHI skill clusters.

Figure 9: The Effect of Skill-based Concentration on Earnings, by Family Composition and Gender



Notes: The figure shows estimates of β from equation (1) in the text, separately by gender and the age of the eldest child in the household. "Young" child refers to households whose oldest child is under 6, "old child" refers to households with children between 6 and 15, and "no child" refers to households without a child under 16 years old. Each estimate in the figure comes from a separate regression. The size of each bar represents the point estimate, while the whisker bars show the 95% confidence intervals that are calculated from standard errors clustered at the local labor market level.

Online Appendix: Not for Publication

Table A-1: Descriptive Tabulations of Demographic Characteristics by Skill Cluster

Skill Cluster	Observations	Age	Female	Less than High School	High School	BA+
1	494250	44.429	0.49	0.060	0.253	0.683
2	264858	41.813	0.51	0.051	0.317	0.629
3	1424	43.732	0.49	0.089	0.358	0.552
4	153	43.484	0.10	0.338	0.581	0.081
5	15084	42.004	0.45	0.036	0.231	0.732
6	9779	44.202	0.24	0.115	0.453	0.430
7	1944	35.958	0.36	0.222	0.726	0.039
8	86621	38.148	0.83	0.314	0.552	0.126
9	453	44.550	0.54	0.113	0.625	0.262
10	23839	44.717	0.50	0.338	0.546	0.109
11	468	48.500	0.34	0.216	0.621	0.163
12	84186	44.331	0.90	0.111	0.775	0.112
13	32431	37.037	0.72	0.306	0.501	0.183
14	71669	39.742	0.71	0.227	0.553	0.210
15	14266	34.641	0.30	0.297	0.545	0.151
16	24728	39.765	0.28	0.110	0.429	0.458
17	463265	39.398	0.15	0.329	0.609	0.053
18	15323	36.392	0.70	0.187	0.659	0.149
19	47773	39.846	0.21	0.401	0.519	0.072
20	78582	38.108	0.76	0.468	0.400	0.092

Source: Authors' tabulations as described in the text using Norwegian Registry Data.

Table A-2: Descriptive Tabulations of Outcome Variables and Skill Rankings by Skill Cluster

Skill Cluster	Obser vations	Labor Earnings	Part-time Work	Non-routine Cognitive Analytical	Non-routine Cognitive Interpersonal	Routine Cognitive	Non-routine Manual Physical	Non-routine Manual Interpersonal	Routine Manual
1	494250	511155.868	0.059	2	1	16	20	1	3
2	264858	490644.136	0.064	3	8	7	17	8	6
3	1424	383091.360	0.114	4	4	4	5	15	12
4	153	335064.784	0.059	8	9	9	7	19	13
5	15084	441628.422	0.037	1	3	6	3	6	8
6	9779	567807.921	0.051	6	2	13	2	7	14
7	1944	331013.712	0.049	13	6	18	10	14	15
8	86621	238903.701	0.241	17	5	20	12	2	2
9	453	466057.053	0.042	18	18	19	14	5	7
10	23839	359474.111	0.208	10	16	17	19	3	1
11	468	384174.135	0.154	11	11	12	9	10	5
12	84186	287583.268	0.256	15	7	11	11	4	11
13	32431 2	255468.936	0.345	12	12	5	18	9	10
14	71669	273842.644	0.149	9	15	3	15	13	19
15	14266	291770.329	0.312	16	10	1	8	11	4
16	24728	481721.080	0.042	5	20	8	16	16	9
17	463265	364119.404	0.078	14	13	10	1	20	20
18	15323	344386.184	0.076	7	14	15	4	12	18
19	47773	328510.810	0.121	19	19	2	6	17	16
20	78582	212160.429	0.367	20	17	14	13	18	17

Source: Authors' tabulations as described in the text using Norwegian Registry Data.

Table A-3: Occupational Mobility by Skill Cluster Among Those Switching Occupations

Initial Skill Cluster	Percent Moving Within Cluster	Percent Moving Across Cluster	Number of Switchers
1	77.37%	22.63%	79540
17	76.54%	23.46%	59480
2	61.75%	38.25%	45146
13	53.21%	46.79%	31140
14	25.53%	74.47%	13555
8	54.98%	45.02%	10526
20	51.13%	48.87%	6233
12	62.72%	37.28%	5410
19	45.70%	54.30%	5087
5	84.14%	15.86%	3209
16	38.44%	61.56%	3059
10	33.53%	66.47%	2338
18	54.41%	45.59%	2266
15	59.18%	40.82%	1727
6	49.94%	50.06%	1592
7	42.54%	57.46%	268
3	26.67%	73.33%	180
11	64.10%	35.90%	39
9	51.35%	48.65%	37
4	38.89%	61.11%	18
Weighted Average	65.57%	34.43%	

Source: Authors' tabulations as described in the text using Norwegian Register Data.

Table A-4: Heterogeneous Treatment Effects by Gender and Marital Status

				Panel A: Non-Married Men				
	Labor Earnings	NILF	Employed	Part-time	Skill Downgrading	Skill Upgrading	Skill Mismatch	Move Labor Markets
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-separation*	-106847.410**	-0.043	0.048	0.065***	0.038**	-0.047*	0.028	0.011
Skill HHI	(43241.822)	(0.034)	(0.046)	(0.021)	(0.017)	(0.026)	(0.089)	(0.083)
				Panel B: Married Men				
	Labor Earnings	NILF	Employed	Part-time	Skill Downgrading	Skill Upgrading	Skill Mismatch	Move Labor Markets
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-separation*	-105613.693**	0.040	-0.023	0.093***	0.050**	-0.061*	0.112	0.062
Skill HHI	(44749.717)	(0.038)	(0.047)	(0.021)	(0.020)	(0.032)	(0.079)	(0.080)
				Panel C: Non-Married Women				
	Labor Earnings	NILF	Employed	Part-time	Skill Downgrading	Skill Upgrading	Skill Mismatch	Move Labor Markets
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-separation*	-40528.284***	-0.032	0.056*	0.055**	-0.006	-0.037**	-0.241***	-0.184***
Skill HHI	(14493.305)	(0.028)	(0.030)	(0.027)	(0.017)	(0.015)	(0.044)	(0.062)
				Panel D: Married Women				
	Labor Earnings	NILF	Employed	Part-time	Skill Downgrading	Skill Upgrading	Skill Mismatch	Move Labor Markets
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-separation* -47521.340**	-43742.024*	-0.014	0.047	0.066**	0.006	-0.037***	-0.235***	-0.094*
Skill HHI (18634.480)	(22255.383)	(0.029)	(0.031)	(0.033)	(0.011)	(0.013)	(0.050)	(0.053)

Source: Authors' estimation as described in the text. The "concentration effect" shows the difference in the post-separation effect when the HHI changes by 0.1 (i.e., from 0.15 to 0.25). All estimates include relative time to separation and year fixed effects, local labor market, skill cluster, and industry fixed effects, as well as individual fixed effects. All fixed effects except for individual fixed effects are interacted with educational attainment indicators as described in the text. Standard errors are clustered at the local labor market level: * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table A-5: Heterogeneous Treatment Effects by Gender, Using Gender-Specific HHIs

Panel A: Men								
Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)	Move Labor Markets (8)
Post-separation*	-94058.783***	0.014	-0.009	0.060***	0.027*	0.000	0.071	0.042
Skill HHI	(32477.268)	(0.025)	(0.034)	(0.016)	(0.014)	(0.022)	(0.082)	(0.071)
Concentration Effect	-9405.878	0.001	-0.001	0.006	0.003	0.000	0.007	0.004

Panel B: Women								
Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)	Move Labor Markets (8)
Post-separation*	-49260.366***	-0.011	0.032	0.050**	0.001	-0.044***	-0.165***	-0.083*
Skill HHI	(15179.643)	(0.021)	(0.023)	(0.025)	(0.011)	(0.009)	(0.035)	(0.045)
Concentration Effect	-4926.037	-0.001	0.003	0.005	0.000	-0.004	-0.017	-0.008

Source: Authors' estimation as described in the text. The "concentration effect" shows the difference in the post-separation effect when the HHI changes by 0.1 (i.e., from 0.15 to 0.25). All estimates include relative time to separation and year fixed effects, local labor market, skill cluster, and industry fixed effects, as well as individual fixed effects. All fixed effects except for individual fixed effects are interacted with educational attainment indicators as described in the text. Standard errors are clustered at the local labor market level: * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table A-6: Main Effects Stratified by Base Year

Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)	Move Labor Markets (8)
Panel A: 2008								
Post-separation*Skill HHI	-116497.449***	0.054	-0.044	0.060**	0.013	-0.026	-0.148	-0.099
	(28775.972)	(0.052)	(0.060)	(0.027)	(0.026)	(0.035)	(0.106)	(0.102)
Panel B: 2009								
Post-separation*Skill HHI	-127282.051***	-0.007	0.024	0.111***	-0.008	-0.058***	-0.325***	-0.253**
	(48624.140)	(0.043)	(0.046)	(0.030)	(0.021)	(0.020)	(0.104)	(0.099)
Panel C: 2010								
Post-separation*Skill HHI	-80410.351***	0.013	0.014	0.106***	0.018	-0.047**	-0.161	-0.056
	(29558.644)	(0.031)	(0.034)	(0.020)	(0.013)	(0.021)	(0.103)	(0.124)
Panel D: 2011								
Post-separation*Skill HHI	-97160.792**	0.032	0.020	0.106***	0.059***	-0.059**	-0.172**	-0.194***
	(38331.580)	(0.038)	(0.044)	(0.023)	(0.014)	(0.024)	(0.084)	(0.073)
Panel E: 2012								
Post-separation*Skill HHI	-63828.302**	0.002	0.026	0.109***	0.020	-0.012	-0.032	-0.010
	(26092.583)	(0.026)	(0.031)	(0.027)	(0.016)	(0.014)	(0.049)	(0.041)

Source: Authors' estimation as described in the text. All estimates include relative time to separation and year fixed effects, local labor market, skill cluster, and industry fixed effects, as well as individual fixed effects. All fixed effects except for individual fixed effects are interacted with educational attainment indicators as described in the text. Standard errors are clustered at the local labor market level: * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table A-7: The Effect of Skill HHI on Involuntary Displacement

Treatment Variable	Estimate
Post-separation*Skill HHI	0.0102
	(0.0356)
Observations	649086

The sample is restricted to base years (2008-2012). The dependent variable is whether a worker experiences an involuntary displacement in the base year. We control for industry, local labor market, skill cluster, and year fixed effects. Standard errors clustered at LLM level are in parentheses.

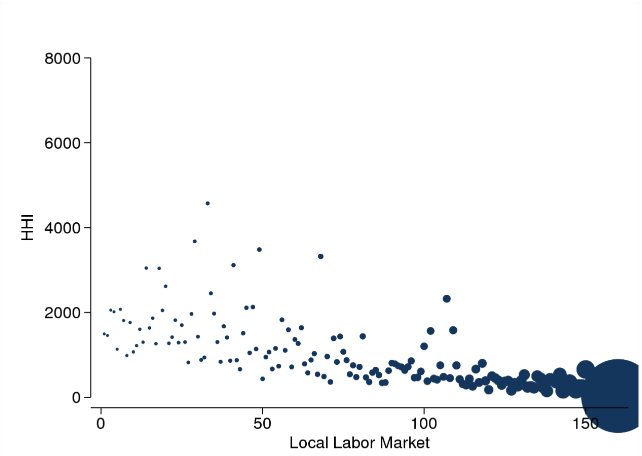
Table A-8: Percent of Analysis Sample Subject to Involuntary Displacement, 2008-2012

Category	Percent
By LLM	2.447
By Industry	2.749
By Skill Cluster	2.573
By HHI Skill	2.38
Low (HHI less than 1500)	2.667
Medium (HHI between 1500 and 2500)	2.622
High (HHI above 2500)	1.841

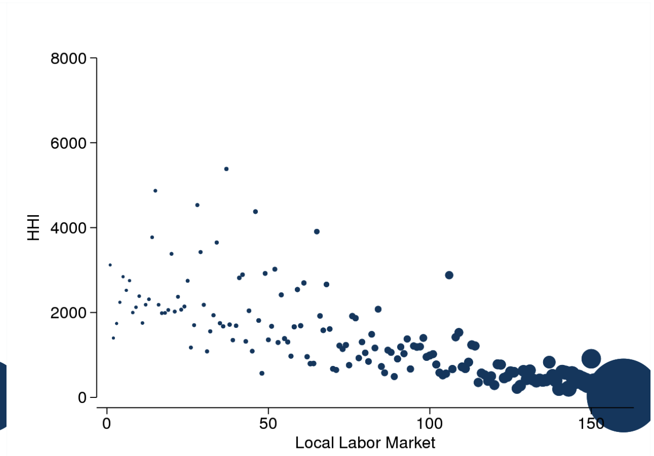
Source: Authors' tabulations as described in the text using Norwegian Registry Data.

Figure A-1: Skill-Specific Herfindahl-Hirschman Indices by Local Labor Market - Non-routine Skills

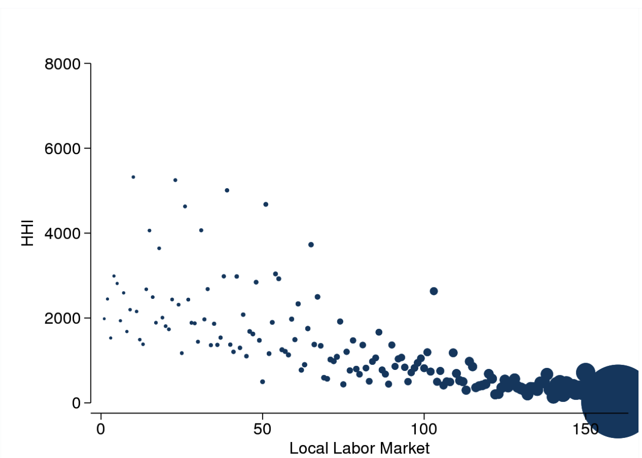
(a) Non-routine, Cognitive, Analytical



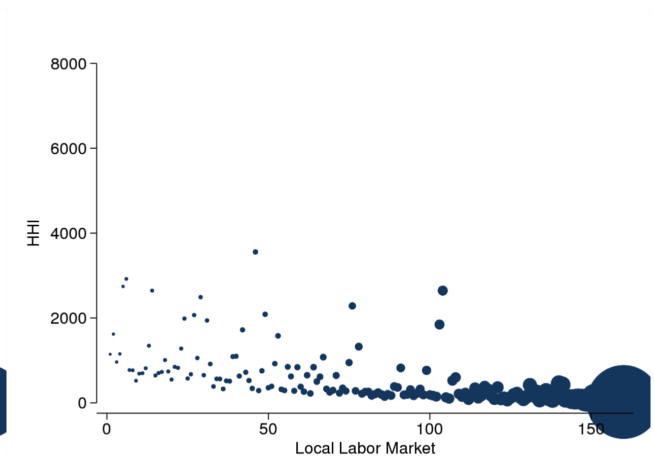
(b) Non-routine, Cognitive, Interpersonal



(c) Non-routine, Interpersonal Adaptability



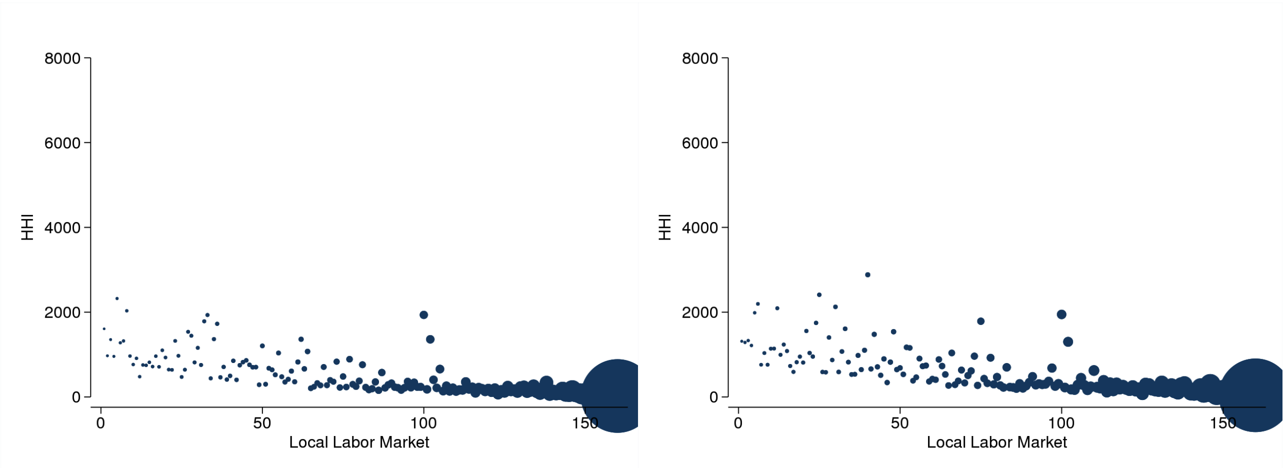
(d) Non-routine, Physical Adaptability, Manual



Notes: Each panel shows the Herfindahl-Hirschman Index by local labor market, calculated using a specific skill measure. Each point is a local labor market, and the local labor markets are ordered by size. The size of each point represents the employed population of the local labor market.

Figure A-2: Skill-Specific Herfindahl-Hirschman Indices by Local Labor Market - Routine Skills

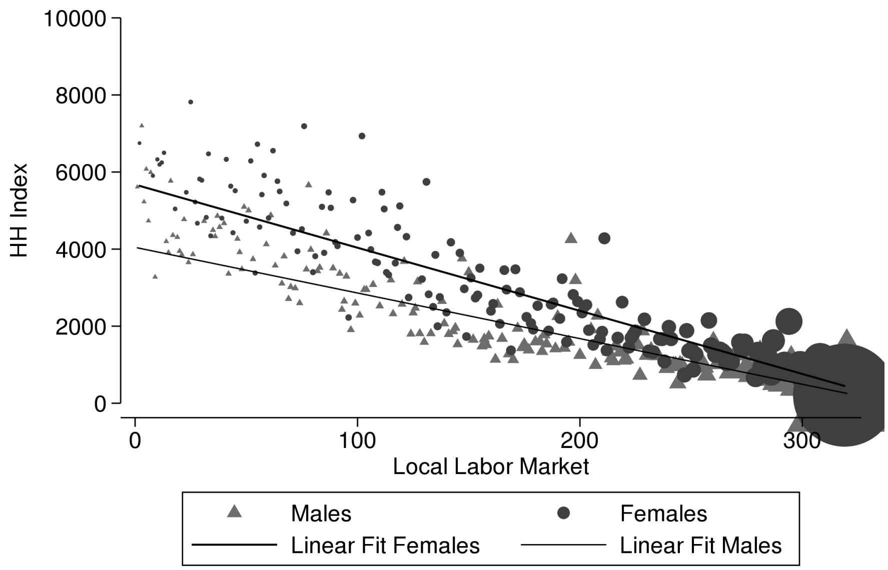
(a) Routine Cognitive **(b)** Routine Manual



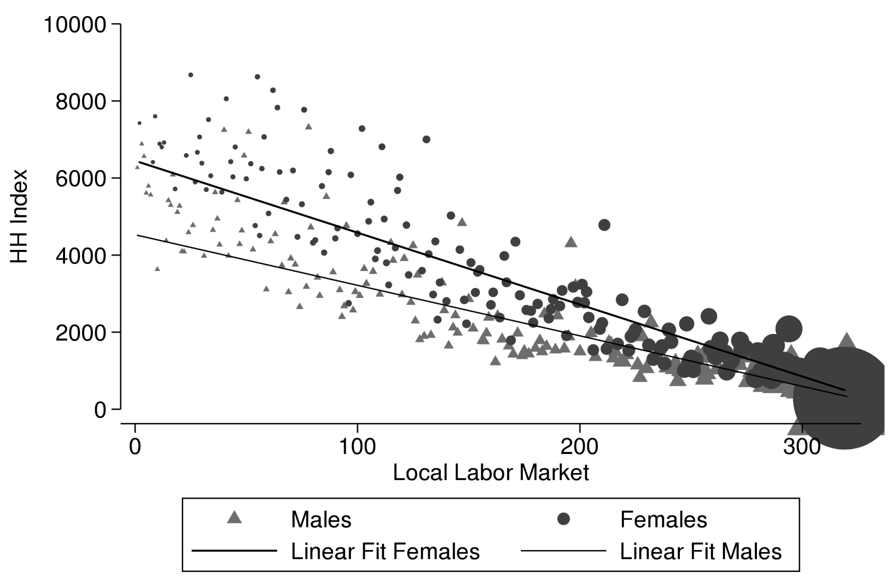
Notes: Each panel shows the Herfindahl-Hirschman Index by local labor market, calculated using a specific skill measure. Each point is a local labor market, and the local labor markets are ordered by size. The size of each point represents the employed population of the local labor market.

Figure A-3: Occupation and Industry HHI, by Local Labor Market and Worker Gender

(a) Occupation-based HHI



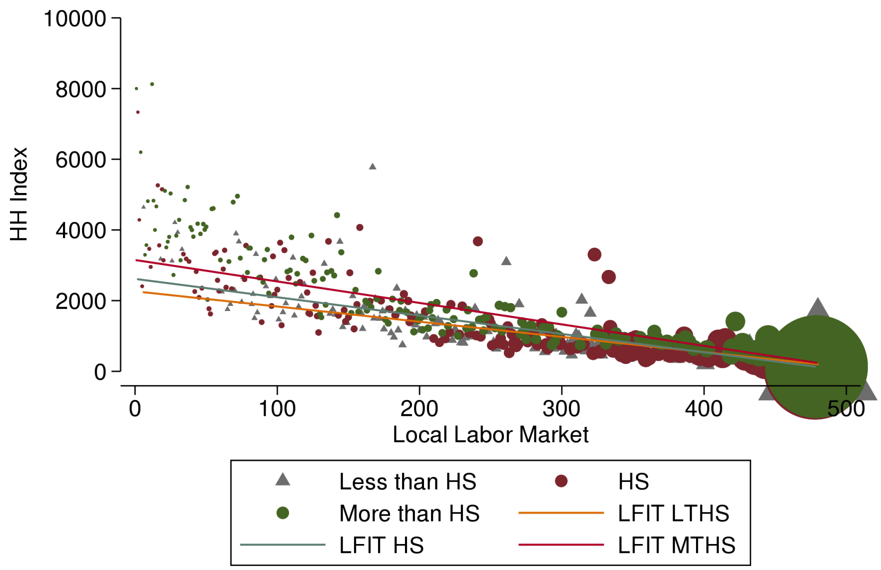
(b) Industry-based HHI



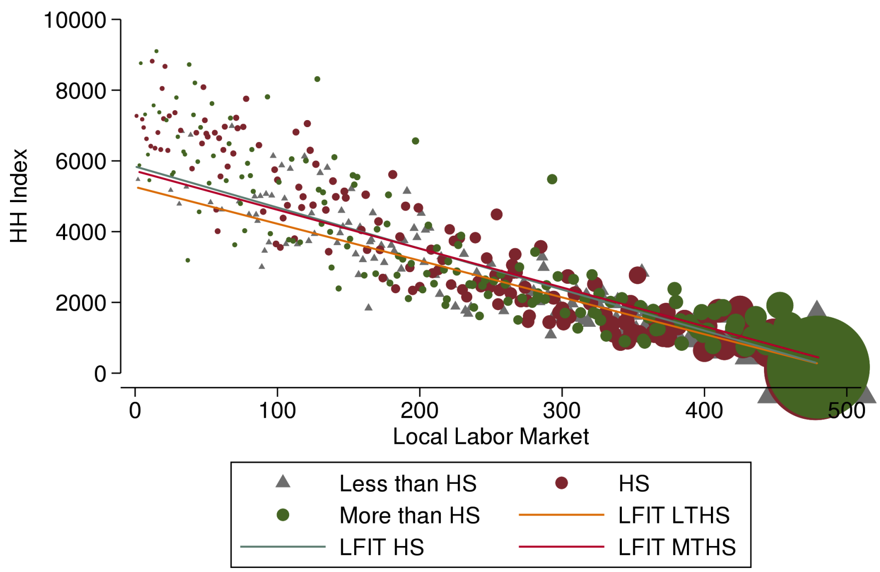
Notes: Panel (a) shows occupation-based HHI for each local labor market, separately by worker gender. Panel (b) shows industry-based HHI for each local labor market, separately by worker gender. Each point is a gender, local labor market combination, and the local labor markets are ordered by overall size (not by gender). The size of each point represents the total employed population of the local labor market.

Figure A-4: Skill-based Herfindahl-Hirschman Indices, by Educational Attainment Separately for Men and Women

(a) Men

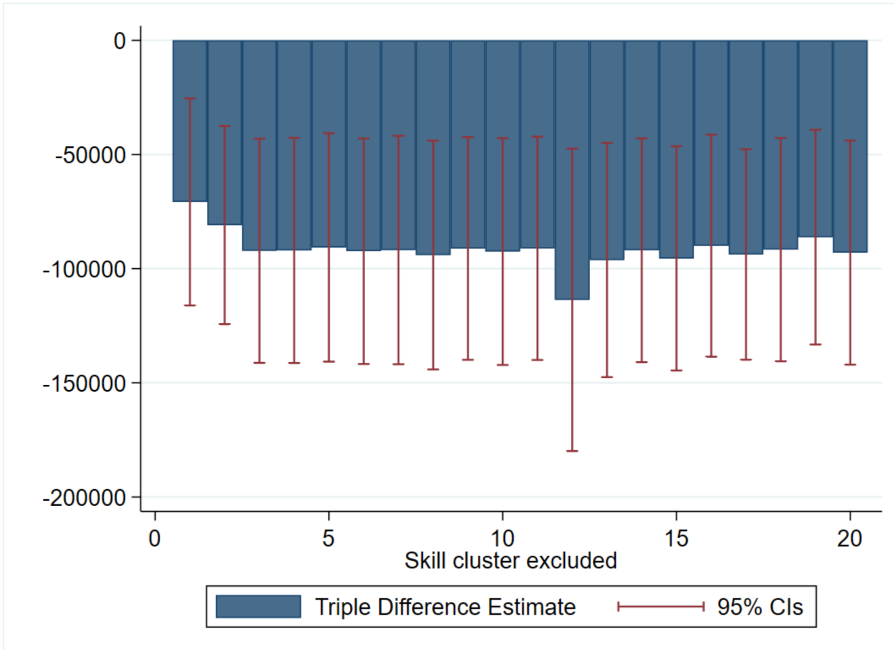


(b) Women



Notes: Panel (a) shows skill-based HHI for each local labor market among men, separately by worker educational attainment. Panel (b) shows the skill-based HHI among women by educational attainment. Each point is an attainment, local labor market combination, and the local labor markets are ordered by overall size (not by gender or educational attainment). The size of each point represents the total employed population of the local labor market.

Figure A-5: Dropping one skill cluster at a time, labor earnings



Notes: Authors' estimation as described in the text, dropping one skill cluster at a time. The lines extending from the bars show the 95 percent confidence intervals, obtained from standard errors clustered at the LLM level.