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ABSTRACT

This paper extends the literature on monopsony and labor market concentration by taking a task-based approach and estimating the causal effect of concentration in the demand for skills 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 job task-based measure shows lower degrees of concentration than the conventional industry-and occupation-based measures. We also find that the gender gap in concentration is substantially larger using this measure. Exploiting mass layoffs and establishment closures as exogenous shocks to local labor demand, we show that workers who experience a mass separation have substantially worse subsequent labor market outcomes when they are in more concentrated labor markets defined by 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, employer market power 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 implications for the distribution of earnings and inequality (Webber 2015). For instance, monopsony power in local labor markets for certain industries and occupations is one explanation for the findings that minimum wages and teachers' unions do not reduce (and may even increase) employment.[2] Moreover, an emerging literature shows strong gender differences in work preferences.[3] Men and women sorting into occupations characterized by different degrees of concentration thus could explain some of the persistent gender gap in labor market outcomes. 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 labor market concentration 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. A key component in those proposals is the use of 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. By using measures that overstate perceptions of monopsony power without adjusting regulatory thresholds, regulators may impose limits on firm actions that pose no threat to labor market competition or prevent mergers that might 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 job task-based approach to estimate the causal effect of monopsony power on labor market

[2] See, for example, Card and Krueger (1995), Lovenheim (2009), and Azar et al. (2019).
[3] See, for example, Le Barbanchon et al. (2021) and Petrongolo and Ronchi (2020).

outcomes. Prior research examining industry or occupational concentration is limited by the fact that job tasks are substitutable across occupations and industries. For example, an administrative assistant in one industry can perform that job in another industry. His task-related skills also can translate to other occupations, such as a bookkeeper, office manager, or receptionist. Thus, we argue that the concentration of demand for specific job tasks is a more relevant measure of labor market concentration than has been used in prior work.

We use rich population-wide Norwegian register data that allow us to link employers and employees as well as observe the local labor market in which an individual works, his/her background characteristics, and occupation. We combine these data with information on job task content from O*NET. Following Autor, Murnane, and Levy (2003) and Acemoglu and Autor (2011), we consider six different types of skill requirements: non-routine cognitive analytical; non-routine cognitive interpersonal; routine manual; routine cognitive; non-routine manual, physical adaptability; and non-routine interpersonal adaptability. We implement a hierarchical clustering algorithm to split occupations into 20 distinct job task groups that are characterized by different combinations of these skill requirements. Occupations within each skill requirement group are similar in terms of their task requirements across these six categories, which we additionally validate using worker flows across occupations. Conceptually, every occupational classification system aspires to group workers together. We simply take an unsupervised machine learning technique to let the data inform how this grouping should be done without having to impose any conditions other than which distance measure to use to group clusters together after they are formed. 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.

We calculate a Herfindahl-Hirschman Index (HHI), which is the sum of squared employment shares across establishments in each task cluster and labor market. To identify the effect of labor market skill requirement concentration on wages and employment, we use involuntary job 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 then estimate models in which we examine how outcomes change after an involuntary displacement event differentially by the HHI of a worker’s skill requirement cluster in the pre-event year.

The thought experiment underlying our approach is to consider workers who are separated from their jobs in labor markets that experience similar adverse demand shocks leading to the separations but differ in terms of their level of concentration. These workers then need to search for new jobs in differently-concentrated markets. The wage offers they receive will be determined by the slope of the labor supply curve they face. A concentrated market is associated with a steeper curve, which should lead to a lower post-separation wage. We approximate this thought experiment by inducing job search through mass layoffs and firm closures among individuals who are observationally similar but who are located in markets that are differentially concentrated. Involuntary job separations represent adverse local labor market shocks that causes workers to search for new jobs. The subsequent wage offers that the displaced workers receive will be lower when they face more concentrated demand.[4] Hence, larger earnings declines in more versus less concentrated labor markets and skill clusters identify monopsony power in those markets (see Appendix Figure A-7 for a conceptual visualization of our approach).

There are two identification assumptions we invoke. The first is that there are no secular trends in outcomes among workers who will experience an involuntary displacement because of establishment closures or mass layoffs as a function of the task demand concentration in his task cluster. For example, if wages among those in a concentrated job task group were trending downward (relative to those in a less concentrated group) prior to a mass layoff event, it would bias our wage estimates in a negative direction. We present event studies that show no evidence of such differential trends prior to mass layoffs. 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 task clusters. More specifically, the size of the labor demand shock that causes displacement cannot vary systematically with the concentration of job task demand. We present evidence that our results are not driven by differential exposure to mass separations by task cluster, HHI-specific earnings premia, independent effects of labor market size, or variation across labor markets in worker task concentration.

We first present evidence of substantial variation in job task requirement concentration across and within labor markets in Norway. We compare HHI concentration measures using task-based clusters, occupations, and industries and show that our task-based measure exhibits

[4] Note that our empirical method requires that the involuntary job separations represent adverse local labor market shocks that shifts the demand curve for labor down, such that the subsequent earnings effect traces out the market labor supply curve. If the layoffs just reduce labor demand at that firm but not overall in the local labor market, there should not be a differential effect by concentration. Another implication of the market-wide labor demand shift is that there should be effects on non-displaced workers. We show that this is the case as well.

lower levels of concentration. This is an expected finding, because the task-based measure allows for substitution across industries and occupations with similar task requirements in a way that the industry- and occupation-based measures do not. We further show that women tend to be in task groups that are much more concentrated than men. This difference can be explained by differential sorting of men and women into the public versus private sector. Within sector, the gender differences are small, with higher overall concentration in the public sector. There is little variation in task concentration by worker educational attainment, however.

The results from our empirical analysis show that laid off workers from such events have worse subsequent labor market outcomes when they are in more concentrated task clusters. A worker with a 0.10 higher HHI (about 1 standard deviation in our data) who experiences a mass layoff or an establishment closure has annual 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, an increase in HHI of 0.1 point 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. Our results point to 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 task cluster) decreases by 1.6 percentage points, which is approximately 4% of the mean. Taken together, these results are consistent with job task concentration leading to more market power among employers, which reduces wages and hours on the intensive margin and induces more rigidity in post-separation job search.

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%). This difference is driven almost entirely by differential effects of concentration in the public and private sector. The effect on earnings for men and women are large in the private sector and more modest in the public sector. Women are more likely to work in the public sector, which exposes them to higher concentration but mitigates the effect of concentration on labor market outcomes.

There also is substantial 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 college graduates. 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 2020).

To investigate the value of our approach relative to conventional occupation- and industry-based measures of concentration, we run horse-races between the industry HHI measure and our task-based HHI measure as well as between the occupation HHI measure and our task 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 task-based HHI measure we use has independent explanatory power. Finally, we examine how the effects of mass separation events vary across the HHI distribution for those who are not separated. Consistent with monopsony theory, we find that those at mass layoff firms who were not laid off and those in the same labor market and task cluster experience worse outcomes after a separation event.

We bring together the literatures on monopsony power and job tasks in labor markets. Taking a task-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 conventional measures used in existing work. Our main contribution is to provide a method for systematically grouping together occupations using the task 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.

2. Prior Literature and Contributions

The previous literature on monopsony has taken three approaches.[5] 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 elasticities using separation rates (e.g., Hirsch, Schank, and Schnabel 2010; Ransom and Sims

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

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.

A number of recent papers 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). That concentration in labor demand across employers can lead to monopsony power is consistent with several different types of theoretical models. Schubert, Stansbury and Taska (2021) derive the negative relationship between wages and concentration from a wage bargaining model in which employer concentration reduces the availability of feasible outside options for workers. This puts workers at a disadvantage at the negotiation table, and can result in a drop in wages. The microfoundations for the relationship that they present is strongly linked to Jarosch et al. (2019), who show that employer concentration has a negative effect on wages in a random search model with large employers. Manning and Petrongolo (2022) develop a similar relationship through a multinomial logit model of labor supply, using a labor supply model to individual firms similar to that in Card et al. (2018) and Azar, Berry and Marinescu (2019).

Prior research on labor market concentration universally examines concentration with respect to occupations or industries and finds that higher concentration reduces wages and employment. Our paper extends this literature by embedding a direct, task-based measure of workers' outside options to more accurately quantify the concentration of labor demand faced by workers. 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.

A small number of prior papers have embedded outside options into analyses of local labor markets. Manning and Petrongolo (2017) use precise data on worker and job locations to estimate the cost of distance in applications, which helps define a local labor market. They find that markets are highly local and that these local markets overlap. Our approach differs from theirs by defining outside options in terms of tasks rather than space. Nimczik (2022) defines outside options through worker flows across firms, essentially generating a network of firms for each worker. The method we employ is similar in spirit, but uses task requirements rather than observed job flows to capture the relevant labor market for workers. We also highlight that the approaches taken in Manning and Petrongolo (2017) and Nimczik (2022) are more complex and require more specific data than does our approach that is based on task requirements from a publicly-available dataset. Hence, the task-based method may be easier for policymakers and other researchers to adopt without highly-specialized data.

Only one other contemporaneous working paper of which we are aware embeds 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. 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 task-based measure of outside options rather than a job transition based measure. We show that task-based occupation clusters correlate with job transition likelihoods, but there is independent variation in each measure. Job switching is an equilibrium outcome and can reflect movements up the job ladder, while the task requirements of a given profession are less sensitive to underlying labor supply and demand forces as well as promotion issues. To speak more directly to this literature, in Section 8 we reconstruct our HHI to represent a weighted average of the skill concentration in the clusters "closest" to the worker based on national cross-cluster job transitions. The results from this exercise strongly support our empirical approach.

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 task-based concentration measure accomplishes, and this is the first paper in the literature to include such outside options directly in labor market concentration measures.[6] Third, we rely on mass layoffs and establishment closures that allow us to identify concentration effects under weaker assumptions. Our ability to observe demographic information of workers also permits an analysis of heterogeneous treatment effects that is not possible with vacancy data.

3. Institutional Background, Registry Data, and Variable Definitions

3.1. 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. However, seniority is a strong norm and is institutionalized in agreements, such that firms are encouraged to lay off otherwise similar less senior workers first. In practice, it is difficult to verify the "all else equal" condition, such that this seniority rule often does not represent a binding constraint. Employment contracts typically 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 available to individuals who involuntarily had their work hours reduced by at least 50 percent and had a sufficiently high income ($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. Approximately 78 percent of displaced men in our sample are re-employed one year after displacement (Huttunen, Møen and Salvanes 2011).

3.2. 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 population-wide administrative registers, such as the education register, the family

[6] 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. 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 both show that workers with better outside options experience better post-layoff outcomes. Notably, this is a different parameter from the one we estimate.

register, the tax and earnings register, and the social security register. A unique person identifier enables us to 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. Establishment and regional labor market characteristics such as industry, establishment size, and unemployment rate, also are available.

Our data provide location, earnings, and employment information for every individual in Norway. Labor earnings are measured as annual pre-tax labor income, which includes 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. Employment status (employed, unemployed, and not in the labor force) is defined based on the individual's status in the labor register.

The data also contain demographic and socioeconomic characteristics of 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, using the full analysis sample and time periods. 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.

3.3. Measuring Job Task Concentration

The objective underlying our approach is to construct a measure of concentration that accounts for the fact that workers can move across occupations and industries, which generates a more accurate representation of the concentration of labor market demand that a worker faces. We achieve this goal by directly embedding concentration into both the worker's currently occupation and their outside options.

The goal concentration measures in this literature is to pick up how concentrated demand is for labor, which necessitates grouping workers together. Prior research has used industry or occupation for such groupings, but we argue these are insufficient because neither really captures

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

the labor demand faced by workers. Our approach allows us to capture the concentration in demand for *job tasks*, which we argue is a more comprehensive way to aggregate workers for the purposes of measuring labor demand. That our approach does this without relying on job-to-job transitions is important, since these transitions are a direct function of the underlying labor supply and demand forces in the local area (including monopsony power).[8]

To identify the relevant tasks required of each occupation, we use the metrics of occupation characteristics in the 2019 edition of the 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).[9] 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.

In our main analysis, we focus on six categories, similar to those in Autor, Levy, and Murnane (2003) and 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 measures that enter the above composite measures. We standardize each of the raw O*NET measures to be mean zero and have a standard deviation of 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 be mean zero and have a standard deviation of one.[10]

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[8] Consider the fact that monopsonists will hire fewer workers or schedule fewer hours than in a competitive market. If, for example, there is widespread labor concentration among nurses, we may see fewer flows into nursing from other occupations such as research technicians or home health aides. We also may see more intense outflows from nursing into other occupations such as teaching, advanced medical fields, or dental assisting than would otherwise exist in a competitive market. Measuring outside options based on these flows would over- and understate monopsony power, depending on which occupation is being measured in this sector.

[9] *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.

[10] 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.

Using these six broad task measures, we perform hierarchical agglomerative clustering to split occupations into 20 distinct groups based on the similarity of required tasks in the occupations.[11] 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 along these six task dimensions. This iterative process continues until all occupations have been grouped into 20 distinct clusters. This clustering algorithm is an unsupervised machine learning algorithm in which we impose no conditions on any parameters other than which distance measure to use to group clusters together after they are initially formed. However, we have to take a stand on defining the relevant market with some sort of boundary.

We chose 20 clusters because this is approximately the number of industrial categories, which facilitates comparisons across concentration measures. We also have used a number of different validation techniques to identify the "optimal" number of clusters. While the optimal number differs slightly 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 on 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 in Appendix B. We additionally show in Section 7 that our main estimates are robust to using between 10 and 40 skill clusters.

While we center the clustering analysis on the six task categories in Acemoglu and Autor (2011), a broader set of tasks could be important for assessing market concentration. We therefore also use a data-driven principle component analysis and run the hierarchical clustering algorithm over the principal components of the O*NET rather than on our six task groups. In Appendix C, we provide evidence that the tasks we use in our main analysis generate more compact clusters and greater delineation of cluster groups than when clustering over the principal components in the O*NET database. While we favor using the task clusters based on the six groups for these reasons, we obtain similar results when using the principal components.

Descriptive tabulations of demographic characteristics for each task cluster are shown in Online Appendix Table A-1, and the five largest occupations in each cluster are shown in Appendix Table A-15. The task clusters differ considerably in terms of their size and composition, with the smallest cluster (4) consisting of 153 observations and the largest (1)

[11] We use the "nbclust" package in R (Charrad et al. 2014) to evaluate the optimum number of clusters.

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 workers in these different clusters. The large differences in the composition of workers across task clusters underscores that occupations in different clusters are competing for different types of workers. Importantly, task 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 task clusters. These rankings provide some insight into which skills are important in each cluster. For example, occupations in task group 1 require high levels of non-routine skills, cluster 15 includes more routinized professions, and cluster 10 includes manual task jobs. Some clusters, such as 5, require high levels of all tasks. Other clusters, such as 17, are highly focused on one task (non-routine, manual, physical). In general, task 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 task clusters in each local labor market. The local labor market is defined based on commuting distance and divides Norway into 160 regions (Gundersen and Juvkvam, 2013).[13] The HHI is the sum of the squares of the employment shares of the *establishments* within the skill cluster and local labor market. Specifically, the HHIs is given by

$$HHI_{cm} = \sum_{e_{cm}} \left(\frac{N_{ecm}}{N_{cm}}\right)^2 \qquad (1)$$

where e indexes establishments employing workers in task cluster c and labor market m and $\frac{N_{ecm}}{N_{cm}}$ is the share of workers in cluster c and labor market m who work in establishment e. The measure can range from 0 to 1, where 1 indicates a single monopsonist in the market. Hence, the HHI measures the concentration of labor demand for a given task grouping *across establishments* in a LLM. This effectively segments local labor markets such that the relevant market for a worker will be a combination of a local labor market and job task cluster. This also

[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.
[13] Local labor markets span more than one municipality (the lowest administrative unit consisting of 435 municipalities), but are typically smaller than counties (the second-lowest administrative unit).

means that firms will participate in multiple labor markets depending on the set of occupations they employ, and these labor markets can vary in terms of their concentration. We are the first to segment labor markets in this way, which has the benefit of using publicly-available task data and a straightforward clustering method that can be employed by policymakers and regulators.

According to the *Horizontal Merger Guidelines* used by the antitrust division of the US Department of Justice, an HHI score below 0.15 indicates an unconcentrated market, a score between 0.15 and 0.25 indicates a moderately concentrated market, and a score above 0.25 indicates highly concentrated market. To facilitate the interpretation of our results, we discuss the magnitude of our estimates relative to a 0.10 point HHI increase. This is the difference between an unconcentrated and a highly-concentrated market. This also represents a one standard deviation change in HHI in our setting (Table 1).

In addition to computing HHI based on tasks, 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+).

We note that individuals differ in their commuting propensity, and that the geographical borders of a LLM will more accurately define the search region of certain subgroups than others (e.g., Caldwell and Danielli (2022), Dodini, Loken and Willen (2022), Butikofer, Loken and Willen (2022), and Le Barbanchon, Rathelot and Roulet (2021)). If the job search area for one group is smaller than that for another, then assigning both to the same geographic area may understate the degree of concentration that one group faces. At the same time, we note that it is difficult to accurately define and measure subgroup-specific geographic search regions, and that the general convention in the literature is to use commuting zones or geographic areas.

3.4. Involuntary Job Displacement

Our main empirical strategy is to leverage involuntary job displacements caused by mass layoffs and 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 in the

[14] See https://www.ssb.no/en/klass/klassifikasjoner/6 (accessed on March 25, 2021).

pre-displacement year. Involuntary job separations represent adverse local labor market shocks to skill demand that causes workers to search for new jobs. The adverse shock shifts the market labor demand curve down, which lowers the subsequent wage offers that the displaced workers receive will receive. The more monopsony power an employer has, the less elastic is the labor supply curve, leading to larger declines in subsequent earnings.

The idea underlying our approach is illustrated in Appendix Figure A-9. Consider two firms that are hiring workers in the same task cluster but that operate in different local labor markets. Panel A represents the demand and supply of labor at a firm in a labor market with little employer market power; Panel B shows labor demand and supply at a firm in a highly-concentrated market. The only difference between the graphs in Panel A and Panel B is that the labor supply to the firm is considerably more inelastic in Panel B because labor demand is more concentrated. This is a direct implication of the firm possessing more market power. For a given level of labor demand, the firm will employ workers where the marginal cost curve intersects the labor demand curve, resulting in wage W_1. W_1 will be higher in Panel A as firms in competitive markets will be less able to extract rent from workers. Our empirical specifications always control for this possible baseline wage difference by concentration.

The job loss events we study generate an adverse labor demand shock, shifting the local market labor demand curve down. Consider a situation in which the two markets experience a similar-sized adverse demand shock. The reemployment wage should be lower irrespective of the market concentration that the worker faces. Since the labor supply curve is more inelastic in Panel B, workers should experience a stronger earnings reduction if they are subject to a layoff in such a market. This is illustrated in the figure by W_2 in Panels A and B. The wedge between the pre-displacement wage and the re-employment wage ($W_2 - W_1$) will be larger when the market exhibits more concentration. Even if a worker was in a more concentrated market before the displacement occurred, and even if the worker's pre-displacement wage was lower, the worker should still experience a larger *reduction* in re-employment wage following a job loss event.[15]

[15] The local labor demand shocks we exploit must be of sufficient size to shift the market demand curve downward without being so large that they generate macroeconomic effects. The shocks we exploit are small relative to the size of the entire local labor market (3 percent on average) and therefore are unlikely to contribute to large macroeconomic changes. However, they are large enough to affect worker wages after separation. One way to explore these assumptions is to examine the wage effects of workers who are fired for cause. These workers are not

To operationalize this approach, we follow the existing job displacement literature (e.g., Huttunen, Møen and Salvanes, 2011) and define a *base year* for each worker. For workers experiencing a mass layoff, the base year is year 0, with the displacement event taking place between year 0 and year 1. For those not experiencing a mass layoff, we include individuals who were not displaced in those two calendar years. To ensure that the displaced and non-displaced workers are similar, we follow the prior job loss literature and 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: Table 1 shows that 96.5% of those in our analysis sample are employed.

Because of the structure of our data, an individual who experiences a displacement will appear in only one base year, while non-separated workers can appear in multiple base years. 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. Similar to the existing job loss literature, 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 (Cengiz, et al. 2019).

The base years we use for our analysis are 2008 through 2012.[16] 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 job tasks. We end in 2012, since we are interested in following workers for five years after 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, including both a person identifier and an establishment identifier. We identify establishment closures when an establishment identifier disappears from the data and measure

exposed to a marketwide shift in labor demand, and there should therefore not be a difference in the effect of being fired on wages across differentially concentrated markets. We show that this is the case (Appendix Table A-11).

[16] Our base years overlap with the Great Recession. However, Norway had a very mild recession, and GDP had recovered already in 2010. In addition, our empirical approach is designed to directly account for local economic shocks that are common across skill clusters.

employment changes at establishments by 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 (Jacobsen, Lalonde, and Sullivan 1993). To ensure that our measure of mass layoffs is not driven by sporadic displacements among small firms, we follow previous research and restrict our sample to workers at firms that have at least 10 employees (e.g., Huttunen, Møen, and Salvanes 2011).

Online Appendix Table A-10 shows that on average across labor markets, 2.4% of employees in our sample experience a mass layoff. In Panel B of the table, we show the percent of workers experiencing a mass layoff by task cluster. It ranges from 0.72 (cluster 5) to 4.87 (cluster 19) percent, with most clusters between 1.5-3.0 percent. Exposure to mass layoffs is not isolated to any one or any group of task clusters.

4. Descriptive Evidence on Labor Market Concentration

In this section, we present descriptive evidence on our job task-based measure of labor market concentration and compare it to measures that use industry, occupation, and worker educational attainment. As we demonstrate, the task-based measure we use contains independent variation from these other measures. In Section 6, we show evidence that the task-based concentration measure has more empirical relevance for labor market outcomes following a mass layoff than do many of the common concentration measures used in the literature.

Figure 1 shows average HHI by local labor market, where we have ordered local labor markets by size of the employed labor force. The size of each point represents the size of the local labor market. Panel (a) of the figure shows the task-based HHI by LLM, which we calculate by taking the average HHI across all skill clusters in each LLM. These averages are calculated using individual data, so they account for differences in the size of each cluster. 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 larger cities in Norway exhibit low levels of concentration that are under 0.15. For a large number of LLMs there is substantial concentration of over 0.25 and a sizable mass between 0.15 and 0.25.

The LLM concentrations shown in Panel (a) of Figure 1 are based on six job task categories. Local labor market concentration measures based on each individual task category are shown in Online Appendix Figures A-1 (for non-routine tasks) and A-2 (for routine tasks).

The task-based labor market concentration averages shown in Figure 1 are predominantly driven by non-routine job task requirements. 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. These panels demonstrate that there is far higher concentration when using industries and occupations than when using our task-based measure. This result is expected, as the job task clustering is based on the idea that occupations with similar task requirements are more substitutable with one another. While all three panels demonstrate a strong negative relationship between the concentration measure and local labor market size, at any given size the task-based measure exhibits less concentration relative to 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 task-based HHI is appropriately smaller because of cross-occupational mobility within task clusters. One way to validate whether occupations within task clusters are more substitutable than those across task 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 task clusters, separately by cluster. On average, the likelihood of job switchers moving within cluster is almost 66 percent. As a baseline for comparison, the last column of the table shows the likelihood of switching within a task cluster if workers switch randomly across jobs in a manner that holds constant the relative size of each occupation (calculated as the percent of total employment in each task cluster). The likelihood of switching within cluster is well above this baseline for each group. Specifically, it is above 40 percent for all but four categories, it is above 50 percent for 13 categories, and it is above 60 percent for seven categories. The task 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 task clusters are informative about the types of jobs workers substitute across. The task-based HHI measure captures this substitution behavior, which is why it exhibits less concentration than do industry- and occupation-based measures.

To compare the within-task clusters mobility with the within-occupation mobility and the within-industry mobility, we analyze the extent to which individuals who switch firms remain in the same task cluster, the same occupation, and the same industry. We find that the likelihoods that firm switchers move within task cluster, occupation, and industry are 66 percent, 55 percent, and 52 percent, respectively. These results are consistent with the notion that an individual's local labor market is better defined by the task requirements of one's job rather than by one's occupation or industry.

Panel (d) of Figure 1 shows the HHI index calculated using the completed education level of the worker. This measure is informative because task 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. This measure leads to far lower levels of concentration than do the other three.

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 task-based HHI is systematically lower than the industry and occupation HHIs for all but the largest labor markets. Relative to the education based HHI, the task-based measure exhibits more concentration. The differences in these measures decline with LLM size; regardless of the measure the large labor markets exhibit low levels of concentration.

The rich nature of the Norwegian 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 gender, using HHIs that are calculated from the full sample. Hence, any differences solely reflect differences in occupational sorting between men and women. The figure clearly reveals that women are in more concentrated skill clusters than are men across the LLM size distribution.[17] The differences are large: the average HHI for men is below 0.25 in almost all labor markets, whereas women face HHIs above 0.25 in most labor markets and face HHIs above 0.15 in all but the largest labor markets.

This is the first evidence in the literature that the occupations into which women sort are more concentrated in terms of their skill demand than is the case for men. In Figure 4, we show

[17] Online Appendix Figure A-3 shows gender-specific HHIs for each LLM using occupation (Panel a) and industry (Panel b) measures. The same gender gap evident in Figure 3 is also present in Figure A-3.

that this difference largely can be explained by differential sorting by gender into the public sector. Panels (a) and (b) show that concentration is much higher in the public sector than in the private sector.[18] Panels (c) and (d) present gender differences in concentration by sector. There is virtually no gender difference in the private sector (panel c), while a smaller gender gap remains in the public sector. Hence, the higher propensity of women that work in the public sector (in 2008, 72 percent of all public sector workers in Norway were female) can largely explain their higher aggregate exposure to labor market concentration.

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. As in panel (a), HHIs are calculated using the full sample. The cross-group differences are small; the large gender-based heterogeneity in panel (a) does not translate into education-based heterogeneity in panel (b).[19]

Figures 1-4 show that average task-based concentration varies considerably across labor markets. However, a variance decomposition shows that 70% of the HHI variation is within, rather than between, local labor markets. Figure 5 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 task clusters within a labor market. This is the variation we use directly in our empirical analysis. Importantly, there is a large amount of variation across the LLM size distribution. Panels (b) and (c) of Figure 5 present the same information for men and women, respectively. There is considerably more within-LLM variation for women than for men, which is driven by occupational sorting patterns by gender.

Understanding the extent of task-based labor market concentration and how it varies across labor markets is of independent importance, 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 6 presents preliminary descriptive evidence of how different concentration measures are correlated with mean earnings in each LLM. Correlations using a

[18] This finding aligns with evidence of monopsony power in teaching and nursing, two female-dominated public sector professions (Sullivan 1989; Merrifield 1999; Staiger, Spetz, and Phibbs 2010; Falch 2010; Matsudaira 2014).
[19] Online Appendix Figure A-4 shows task-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.

task-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 task-based concentration and earnings. The correlation between the other HHI measures and earnings are weaker though still negative. This provides preliminary suggestive evidence that our task-based concentration measure is better able to detect employer market power than are the industry- and occupation-based measures. 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.

5. Empirical Approach

To examine how skill-based labor market concentration affects earnings and labor market outcomes, we need a source of exogenous variation in local market-task-level labor demand. An exogenous shift in the local labor demand curve will identify the labor supply elasticity, which is a critical measure for identifying monopsony power. The source of variation we exploit in this analysis is driven by mass layoffs and establishment closures, which we argue generate aggregate labor demand reductions in labor markets and task clusters. Using such displacement events, we examine how outcomes among workers who are affected by a mass layoff or establishment closure change as a function of the local labor market concentration that the worker experienced in the pre-layoff year.

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. Involuntary job separations represent adverse local labor market shocks to skill demand. The adverse shocks shift the local labor market demand curve down, such that the subsequent wage offers that the displaced workers receive will be lower than their pre-displacement wage offers. However, since monopsony power is reflected in a steeper (more inelastic) labor supply curve, workers will experience stronger earnings reductions in their subsequent job if they are induced to search in a more concentrated labor market. Note that our empirical method requires that the involuntary job separations represent adverse local labor market shocks that shift down the demand curve for labor, such that the subsequent earnings effect traces out the labor supply curve. If the layoffs just reduce labor demand at that firm but not overall in the local labor market, there would not be a differential effect by concentration.

The reason is that the lower earnings from concentration already should be embedded in the pre-separation earnings. In Section 7, we provide evidence consistent with this interpretation.

Our empirical test compares how workers' labor market outcomes change post-layoff as a function of their pre-separation HHI. We estimate models of the following form:

$$Y_{icmntt_b} = \alpha + \delta HHI_{icmt_b} + \gamma Separated_{it_b} + \tau Post_{itt_b} + \beta(HHI * Separated * Post)_{icmtt_b}$$
$$+ \theta_1(HHI * Separated)_{icmtt_b} + \theta_2(Post * Separated)_{icmtt_b}$$
$$+ \sum_{k=1}^{3}\{\pi_{c,k} + \zeta_{t,k} + +\phi_{m,k} + \psi_{n,k} + \sum_{j=-5}^{5}\eta_{j,k}I(t - t_l = j)\} \quad (2)$$
$$+ \lambda_i + \varepsilon_{icmntt_b,}$$

where *Y* is a labor market outcome of individual *i* in task cluster *c*, local labor market *m*, industry *n*, in year *t* and base year panel t_b. Our full model includes task cluster by education ($\pi_{c,k}$), year by education ($\zeta_{t,k}$), labor market by education ($\phi_{m,k}$), industry by education ($\psi_{n,k}$), and individual worker (λ_i) fixed effects. The addition of individual worker fixed effects allows us to control more extensively for worker heterogeneity than what has been done in most prior job loss studies. The model also includes controls for relative time to an involuntary displacement interacted with educational attainment, $I(t - t_b = j)$.[20] These relative time indicators are set to zero for those not experiencing a mass separation in the event window. Educational attainment indicators (indexed by *k*) include less than high school, high school diploma, and BA+, with some college the excluded category. Interacting the fixed effects with education accounts for secular variation by time, location, and industry that can differ by worker educational attainment. Standard errors are clustered at the local labor market level.

Separated is equal to one if a worker has experienced a separation from a mass layoff or establishment closure in t_b,[21] and HHI_{icmt} is the concentration measure for a worker in her pre-separation task cluster. Hence, *HHI* varies across task clusters within each local labor market and year. The coefficient of interest, β, shows how outcomes change surrounding a separation differentially across the HHI distribution. The variable HHI_{icmt} controls for independent effects

[20] 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.
[21] Our approach overcomes potential bias from using time-varying treatments when there are time-varying treatment effects (Goodman-Bacon 2021; De Chaisemartin and d'Haultfoeuille 2020) by using stacked panels (Cengiz et al. 2019), where unseparated workers are repeated across panels.

of local labor market concentration, while the direct effects of a mass layoff are accounted for by $Separated_{it_b}$. Notably, equation (2) differs from a traditional triple difference model because we do not control for *HHI*Post*. Adding this control would identify β by comparing separated to non-separated workers. In a setting with market power and a market-wide labor demand shock, both separated and incumbent workers should be adversely affected. Hence, the comparison between these groups should understate the extent of monopsony power. Consistent with theory, we show direct evidence below that incumbent workers at firms with mass separations and at other firms in the same LLM and skill cluster also experience more negative effects of adverse labor demand shocks when concentration is higher. Equation (2) identifies how mass layoffs affect separated workers across the HHI distribution, as these workers are likely the most impacted by these events. We use the non-separated workers to help identify the extensive set of fixed effects and controls in the model.

The coefficient β represents the causal effect of losing one's job in a more versus less concentrated task cluster-labor market combination. We now discuss two concerns that arise in interpreting β. The first is the identification assumptions underlying a causal interpretation of this parameter. The second is the conditions under which this parameter is reflective of monopsony power. We discuss each of these issues in turn.

The parameter β is identified under the assumption that mass layoff effects in less concentrated task cluster-LLM combinations are an accurate counterfactual for mass layoff effects in more concentrated task cluster-LLM combinations. Importantly, we do not require that separations from establishment closures and mass layoffs are exogenous.[22] Rather, we *only* require that any endogeneity in such separations is 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, Figure 7 plots means of earnings by relative time to displacement among displaced workers for different HHI groups. Log earnings are residualized

[22] There is strong evidence in support of the stricter assumption – that mass layoffs and establishments closures represent exogenous labor shocks – in the Norwegian setting. See, for example, Huttunen et al. (2011), Huttunen et al. (2018), and Salvanes, Willage and Willen (2022).

with respect to time relative to separation, and estimates are relative to the year prior to separation (relative time -1). These are effectively event studies that allow us to assess earnings trends prior to displacement and after displacement. Analogous figures for labor force non-participation and part-time work are presented in Online Appendix Figures A-5 and A-6. There are two main takeaways from these figures. The first is that in no figure or panel do we observe evidence of pre-separation relative trends. Recall that the identifying assumption we invoke is that these trends are all the same, not necessarily that they are zero. The fact that they are zero provides additional support for our empirical approach.

The second takeaway is that adverse effects are larger for higher-HHI workers. In Figure 7, log earnings drop by 0.35 log points among those with an HHI above 0.25, while the effect is about -0.25 log points among those with an HHI under 0.1. 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.

While the event study figures 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 setting. Such shocks would have to mimic the timing of mass layoffs and would have to be localized to the affected skill cluster. In Section 7, 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 well as to allowing the size of the LLM to have an independent effect post-separation. In addition, we demonstrate that the effect of a mass layoff or firm closure in a given task cluster and local labor market does not significantly impact the post displacement HHI in that task cluster and labor market. Our estimates also are robust to controlling for the share of workers in each task cluster, LLM, and year. Hence, our results reflect the concentration of workers in a task cluster *across firms* in a LLM, rather than the concentration of workers in a task cluster in a LLM. Our results are robust to including or excluding industry, local labor market, job task, and individual fixed effects as well as relative time to separation fixed effects. In the presence of secular shocks, our results would not be insensitive to these controls. Furthermore, we show in Section 7 that our results change little when we control for LLM by year, task cluster by year, industry by year, or task cluster by LLM fixed effects. These estimates provide further support for our empirical approach.

The second concern with the interpretation of β is whether it is reflective of monopsony power. As shown in Azar, Marinescu and Steinbaum (2019), the employment-weighted average wage markdown is given by $\frac{HHI}{\epsilon}$, where ϵ is the market-level elasticity of labor supply. Much prior work on monopsony power seeks to estimate ϵ directly while holding HHI fixed. Our approach is to exploit variation in HHI while holding ϵ fixed through the use of labor market, task cluster, industry, and individual worker fixed effects. Under the assumption that these extensive controls account for variation in the market-level elasticity of labor supply, the parameter β will identify monopsony power.

6. Results

6.1. Main Results

Table 3 presents estimates of β from equation (2) for labor earnings (Panel A) and market wage (Panel B). We build to the full specification across columns to assess the role played by various fixed effects and controls. Column (1) 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, task cluster, and industry. Column (3) shows results from the full model with individual fixed effects.

Column (1) shows an effect on labor earnings of 115,186 Norwegian Krone, which translates to $12,187.[23] This represents the separation effect of an HHI increase of 0 to 1. A more sensible way to scale the estimates is by 0.1, which represents going from a low- to a high-concentration market and also is equivalent to a one standard deviation change in HHI. The rescaled results are shown below the estimates in the table and indicate 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 effect of a 10 percentage point increase in the HHI is 9,298 Krone, which is 1.81% relative to the mean, in column (2). In our preferred model shown in column (3), the effect size is 9,120 Krone, or 1.78%. That our results change little when we include a large battery of fixed effects that should be sensitive to

[23] We use an exchange rate of 0.105808 Krone per dollar.

secular trends and shocks supports the credibility of our approach.

One notable change that occurs across columns of Table 3 is that the estimates on *Task HHI* become positive in column (2). Online Appendix Table A-4 shows that this is driven by local labor market fixed effects: more concentrated clusters tend to be located in smaller labor markets with lower earnings. In a bivariate regression, there is a clear negative relationship between earnings and HHI that corresponds to an elasticity of about -0.031. The positive estimate once we add labor market fixed effects corresponds to an elasticity of 0.004. We also emphasize that these HHI estimates are not causal. Prior research has used instruments to identify the casual effect of concentration on earnings, generally finding a negative relationship. Our approach does not require exogeneity in HHI. Rather, we examine whether adverse labor demand shocks differentially affect subsequent earnings across the pre-existing HHI distribution. That the HHI estimate becomes positive (though very small) once one accounts for market size will not cause a bias in our estimates of β.

Panel B of Table 3 presents estimates for market wage that align closely with those for labor earnings in Panel A. We find an effect in column (3) of -8,859 Krone, which is a 1.75% decline in post-separation wages when the HHI is ten percentage points higher.

Taken together, the results in Table 3 reveal that workers in more highly concentrated task clusters 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 task 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, task-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 task-based concentration.

While earnings are critical to understand the relationship between task concentration of labor demand and monopsony, it also is important to examine the mechanisms that drive the earnings response. In what follows, we analyze different dimensions of worker responses to large involuntary separations as a function of the skill concentration in their labor market. Table 4 presents estimates from the model with all controls listed in equation (2) for other labor market outcomes. Results that show the effect of adding various controls for these outcomes are presented in Online Appendix Tables A-5 and A-6. In Table 4, we first examine labor force non-participation and employment responses. The 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]

Column (3) 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. We examine skill "downgrading" (column 4) and "upgrading" (column 5), 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. 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 column (6) we examine the effect on skill mismatch.[25] Skill mismatch is defined as changing task clusters. Surprisingly, workers are less likely to switch task groups when they lose their jobs and face more concentrated demand: a ten percentage point increase in HHI reduces the likelihood of switching task groups post-separation by 1.6 percentage points. This is admittedly an unexpected finding. Workers who lose their jobs in more concentrated markets appear to face higher search frictions. One explanation for this result is that referral networks are more concentrated when task-based labor markets are more concentrated. Hence, more concentrated labor demand can lead workers to think less

[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.
[25] In prior versions of this paper we examined effects on mobility across LLMs. The results were inconclusive and not robust across specifications. These estimates are available from the authors upon request.

broadly about their job search.[26]

6.2. Heterogeneous Treatment Effects

6.2.1 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. Figure 4 presents evidence that this difference is driven by differential sorting into the private versus the public sector. These finding underscore the importance of examining heterogeneous treatment effects by gender and sector. In Panels A and B of Table 5, we examine effects for men and women, respectively. We focus on the eight outcome variables of interest from Tables 3-5.[27] 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. The results in Table 5 use overall HHIs to measure skill concentration, but results are very similar to baseline when we instead use gender-specific HHIs (Online Appendix Table A-7).

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 across LLMs faced by females (0.24) and males (0.13) 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 both for 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

[26] Recent research has demonstrated the importance of referral networks in reducing search frictions (Dustmann et al. 2016; Barwick et al. 2019). 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.

[27] 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.

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. These results suggest that men are somewhat more likely to switch to lower-skill jobs that are outside of their initial task cluster. For women, there is no change in skill upgrading or downgrading, but there is a negative and statistically significant decline in skill mismatch. Thus, the negative effects shown in Table 5 for this outcome is driven by women.

As shown in Figure 4, the gender differences in HHI exposure are driven in large part by higher representation of women in the public sector. Figure 8 shows earnings estimates by sector and by gender for each sector. The adverse effect of mass separations does not vary by HHI in the public sector. There is some evidence of a negative effect among men in the public sector, but the estimate is small and is not statistically significant. The effects are much larger in the private sector than in the public sector, with a coefficient on β of -108348.191, with no difference between men and women. These results help reconcile the finding that women are exposed to higher concentration but experience less of an adverse effect from separation in higher concentrated markets. This pattern is completely driven by differential sorting of men and women across the public and private sectors.

6.2.2 The Role of Education

There is a strong gradient in the effect of task-based concentration on post-separation earnings by educational attainment level, as shown in Table 6. 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 skill content of tasks that drive the HHI variation.

Table 6 further suggests that the aggregate null effect on the extensive margin masks important heterogeneity by worker education level. Non-college-educated workers increase employment when they face a more-concentrated task-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 intensive in the tasks 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 task concentration post-separation, but the negative skill mismatch effects are only present for those without a college degree.

6.3. Comparisons with Other Concentration Measures

We find evidence that workers who experience a mass separation have worse labor market outcomes when they are in more task-concentrated markets. Our task-based HHI measure is novel, and so it is useful to compare it to more traditional measures of concentration.

Table 7 presents horse-races between the task-based HHI and the industry-based HHI (Panel A) as well as the occupation-based HHI (Panel B) measures. In Panel A, the effects on labor earnings clearly load on the task-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 task-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 task-based HHI measure is clearly more relevant than the industry-based measure. Interestingly, the unexpected results that higher task concentration reduces skill mismatch post-separation largely disappears and loads on the industry HHI.

Panel B of Table 7 shows results from a horse-race between task- 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 job task clusters. Second, for earnings and part-time work, both occupation and task concentration matter in the same direction. That the task-based concentration measure has strong and statistically significant independent effects on earnings and part-time work after including occupation concentration in the model highlights the value of the task-based measure. Indeed, the results in Panel B show that both occupation and task concentration affect earnings and hours worked, which implies that it is important to account for both in analyses of labor market concentration.

The results in Table 8 show that industry and occupation concentration measures alone do not fully capture monopsony power that affects earnings and other outcomes. This finding is reinforced by the relatively low correlation among HHI measures: the correlation between task-and industry-based HHIs is 0.44 and between task- and occupation-based HHIs is 0.31.[28] Our skill-based concentration measure exhibits independent variation and has independent explanatory power relative to these more commonly-used measures.

6.4. Occupation-based HHI weighted by Task Similarity

In this section, we provide an alternative approach of directly incorporating job task requirements into conventional measures of occupation-based labor market concentration. We begin with traditional occupation-specific HHIs that implicitly treat each occupation as a separate market. We then generate a distance measure between that occupation and other occupations based on how similar the task requirements are in those occupations, using the six task groups described in Section 4. Next, we construct an occupation-based HHI as a weighted average of the concentration in the occupations "closest" to the worker based on the task overlap across occupations. Conceptually, this approach deviates from our baseline specification in that it treats an entire geographic region (LLM) as a single market, combining occupations by weighting by a task-based measure of closeness. The main advantage of this approach is that it more directly highlights why standard occupation-specific measures are overestimating the extent of concentration by not taking outside options into account. It does so without having to rely on job-to-job transitions, which by nature are endogenous to market conditions. We perform this exercise both with our cluster-based HHI (a weighted average of the concentration in the individual's own task cluster as well as that in all other task clusters based on the degree of skill similarity across each cluster) as well as with the more conventional occupation-based HHI (a weighted average of the concentration in the individual's own occupation as well as that in all other occupations based on the degree of task similarity across each occupation).

The interpretation of the resulting estimate differs from that in our baseline model: an HHI of 1 using this measure implies that there exists only one employer in the individual's geographic area that hires all workers, while an HHI of 1 in our baseline model simply implies that there exists only one employer in the individual's geographic area that hires individual in that specific task cluster. Table 8 shows that both the cluster-based HHI weighted by task similarity across clusters (Panel A) as well as the occupation-based HHI weighted by task similarity across occupations (Panel B) produce similar results.

[28] These correlations are constructed by calculating the HHI at the individual level using each method and then calculating the correlation coefficient between them using the individual-level data.

Alternatively, we reconstruct our HHI as a weighted average of the job task concentration in the clusters closest to the worker based on the national cross-cluster transitions displayed in Appendix Table A-3. This measure includes not only the concentration in a worker's cluster but also the concentration in the clusters that are "close" to the worker as measured by how many people from the initial cluster switch to these other clusters when they change firms. Using this HHI measure increases the magnitude the earnings effect by about 55 percent (Appendix Table A-12). While these results strongly support our empirical approach, we encourage caution when interpreting these results, as job-to-job transitions are endogenous to market conditions (including monopsony power). Taken together, the results from this section highlight that accounting for job tasks is crucial for understanding the full dynamics of employer power and its implications for workers, but the results are robust to the specific way in which this is done.

7. Alternative Explanations and Robustness Checks

The estimates presented above show that workers who are separated because of a mass separation event experience worse labor market outcomes when they are in more concentrated markets. Our preferred interpretation of this result is that it reflects monopsony power as measured by our concentration measure. This interpretation is based on the stronger assumption that the reason for larger negative labor market effects in higher HHI areas is because of monopsony power rather than other factors that are correlated with HHI. In this section, we discuss other potential explanations for our results and explore evidence on the empirical validity of these alternative explanations.

7.1. Labor Demand Shocks and the Role of Separations

Our main findings indicate that when there is a mass separation, those in more concentrated labor markets and skill clusters experience a larger decline in earnings. Our preferred explanation for this result is that the supply curve slopes upward, thus indicating monopsony power by employers. Hence, involuntary job separations represent adverse local labor market shocks that shift the demand curve for labor down. If the layoffs just reduce labor demand at that firm but not overall in the local labor market, however, we should not see a differential effect across the concentration distribution. In the situation, the lower earnings from concentration already should be embedded in the pre-separation earnings (and we have individual fixed effects).

Appendix Figure A-8 shows a histogram of the size of the local labor market demand shock induced by the mass layoff events we exploit. The average displacement event generates a

3 percent shift in the local task demand, with a standard deviation of 4 percent. These events thus trigger sizable shifts in local skill demand. Next, we estimate equation (2) focusing on individuals who are fired for cause rather than displaced due to mass layoffs and closures. The rationale underlying this exercise is that individual terminations do not induce shifts in the market-level labor demand curve. We should not see a differential effect by concentration in this case because the concentration effect on earnings already should be embedded in the pre-separation earnings. The results from this exercise are provided in Appendix Table A-11 and show that there is no differential earnings effect by market concentration. This is consistent with the notion that mass layoffs and firm closures are adverse local labor market shocks that shift the demand curve and enable us to trace out the market supply curve.

Models of monopsony predict that the marketwide reductions in labor demand on which we focus should affect both incumbent and separated workers. In Table 9, we examine how earnings of non-separated workers are affected by mass layoff events. Column (1) shows estimates of equation (2) in which we use only non-separated workers and code those at firms experiencing a mass layoff as *Separated*. The estimate indicates a negative and significant reduction in earnings of non-separated workers that is about a third of the magnitude for separated workers. In column (2), we focus on workers at firms that did not experience a mass layoff in the base year. A firm downsizing or shutting down could cause an increase in labor demand among its competitors. Alternatively, with employer market power, adverse labor demand shocks should lead to reductions in earnings of all employees. We interact *HHI* and *Post* with a measure of layoff size, which is the percent of the LLM-task HHI cluster that is separated due to a mass layoff in the base year. We include lower level interactions between layoff size and the other treatment variables as well. The estimate of -327,473 is statistically significantly different from zero at the 1% level. The mean layoff event reduces labor demand by 3 percent, which leads to an effect size at the mean of 9,824 Krone, or a 982 Krone decline in earnings from a 0.1 HHI increase. Though small, consistent with theoretical predictions those at non-layoff firms experience a decline in earnings when there are adverse labor demand shocks in the labor market and task cluster.

As discussed in Section 5, we do not estimate an explicit triple difference model because both separated and non-separated workers are affected by mass separation events. In column (3), we show the results from estimating a version of equation (2) that includes a control for

*HHI*Post*. This forces the estimated effect of separation across the HHI distribution to be relative to non-separated workers. Adding this control reduces the estimate of β, and it no longer is statistically significant. There is a negative estimate on *HHI*Post*, which is consistent with the results in columns (1) and (2) that show impacts on non-separated workers. Separated workers are more adversely affected, but the difference is not large. The results in Table 9 show that separated and non-separated workers both experience worse earnings outcomes when there are adverse local labor demand shocks, which is consistent with theoretical predictions.

7.2. Robustness Checks

In this section, we explore the robustness of our results to several factors related to the identification assumptions. One potential alternative explanation for our results is that there is a skill premium associated with being in a highly-concentrated labor market that leads to higher earnings prior to separation. We note that this explanation is unlikely, since we account directly for any HHI-specific effects by controlling for *HHI*. Furthermore, Online Appendix Table A-4 shows evidence that the correlation between HHI and earnings is small. The HHI estimates are negative without LLM fixed effects. With LLM fixed effects, there is a small positive estimate that corresponds to an elasticity of 0.004. The data are inconsistent with their being a skill premium associated with higher concentration.

Figure 9 presents earnings estimates that probe the robustness of our results to the main identification assumptions. Appendix Tables A-13 and A-14 present corresponding results for other outcomes. The first row reproduces the baseline estimate from Panel A, column (3) in Table 3. Because we are identified off of adverse demand shocks, one may be concerned that more concentrated markets experience larger displacements, leading to a labor supply effect that would bias our estimates. The second row of Figure 9 shows that our estimates are unchanged by controlling for the size of the demand shock, as measured by the number of workers who are displaced in each labor market, year, and task cluster.

Next, we include an interaction between the number of workers in a LLM-year and a post-separation indicator to account for the negative relationship between LLM size and concentration. The fourth row includes an interaction between the number of workers in a given task cluster, LLM, and base year interacted with a post-separation indicator. These estimates are similar to baseline and indicate that our results are robust to controlling for labor market size.

In the subsequent row of Figure 9, 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, task cluster, and base year. With this control, we are accounting for the composition of workers with respect to task composition in the local labor market. We next explore whether there is a nonlinear relationship between HHI and earnings by including controls for deciles of the HHI distribution. Our preferred interpretation of the results requires that there are no correlated shocks at the industry, task cluster, or local labor market level. To further investigate this assumption, we estimate modified versions of equation (2) in which we include LLM-by-base year, industry-by-base year, task cluster-by-base year, and task cluster-by-LLM fixed effects. The results from all of these robustness checks are almost identical to the baseline estimate.

We additionally show how results change when we exclude any given skill cluster from the analysis. Appendix Figure A-7 shows the result from this exercise with respect to labor earnings and demonstrates that the effects we identify are not driven by any one particular task cluster. Results for our other outcomes are available upon request.[29]

It further is possible that task 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-9 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.

Mass layoffs and establishment closures also could have an impact on the post-displacement HHI of a given skill cluster and labor market, such that the effects we identify are driven by a change in concentration at the time of the layoff. To examine this concern, we estimate the effect of displacement on post-displacement HHI at the aggregate skill cluster – LLM – base year - relative time level. We find that the average effect of a mass layoff or firm closure event on the post-displacement HHI of that task cluster and labor market is approximately -0.006, an effect that is not economically meaningful.

In addition, we explore the sensitivity of our findings to the number of task clusters used. As discussed in Appendix B, our use of 20 task clusters is consistent with a range of data-driven

[29] To ensure that individual base years are not driving our results, we show that the results are similar across base years (Appendix Table A-8).

cluster techniques. We re-estimate the cluster analysis and our empirical models using different numbers of clusters. The earnings estimates and the 95% confidence interval are shown in Figure 10 for between 6 and 40 clusters. Our results and conclusions are not sensitive to the specific number of clusters we employ once we have more than 10.

Finally, we note that high HHI could imply that more firm-specific human capital is lost in the mass layoff. A greater loss of this firm-specific human capital would lead to larger wage decreases after reemployment. We take workers in each base year and examine whether those who were separated had differential pre-separation tenure by HHI. The estimate on HHI in this regression is -0.107 (0.187): a 0.1 increase in HHI is associated with a 0.01 year reduction in pre-separation tenure, which is not statistically significant. This result suggests that those in more concentrated markets do not have more firm-specific human capital.[30]

8. Conclusion

We extend the literature on monopsony and labor market concentration by taking a task-based approach to estimate the causal effect of monopsony power on labor market outcomes. We argue that the concentration of task demand is a more relevant measure of labor market concentration than what has been used in prior work. We first show evidence of substantial variation in job task requirement concentration across and within labor markets in Norway. We compare HHI concentration measures using task clusters, occupations, and industries and show that our task-based measure exhibits lower levels of concentration. In addition, we show that women tend to be in occupations that are much more concentrated than men, which is driven by differential sorting across the public and private sectors.

The results from our main empirical analysis show that workers who experience a mass separation have worse subsequent labor market outcomes when they are in more concentrated task clusters: they have lower earnings post-separation, are more likely to work part time, and

[30] There are several additional pieces of analyses in the paper that suggest this is not the case. First, in columns (1) and (2) of Table 9, we have examined the effect of mass layoffs on non-displaced workers at firms with a mass layoff event as well as on workers in the same LLM and task cluster who were not at mass layoff firms. The results show that individuals who are not directly impacted by the job loss also experience relative reductions in earnings. This result is consistent with the theoretical predictions of the monopsony framework, and, importantly, inconsistent with our results being driven by firm-specific human capital. Second, we have explored the effect for those who are displaced not through a mass layoff or plant closure event (i.e., fired for cause). These individuals should still be influenced by any correlation between firm-specific human capital and HHI, but they do not experience any reductions in market wide labor demand. The results from this analysis are shown in Appendix Table A-10 and show evidence of a differential effect on these workers across HHI.

switch to occupations in which workers have lower average educational attainment. These results are consistent with skill concentration leading to more market power among employers, which reduces wages and hours on the intensive margin. We additionally find that marginal effects are larger for men than for women, which is driven by differences in sorting into the public versus private sector. Finally, we run a horse-race between the industry HHI measure, the occupation HHI measure, and our task HHI measure. Including the industry or occupation HHI measure does not affect our conclusions, and the effects load on the task measure.

This paper makes several contributions to the literature. First, we advance the burgeoning literature on labor market concentration by taking a task-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. Prior research uses industry shares (Benmelech, Bergman, and Kim 2018; Rinz 2018; 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; Schubert, Stansbury, and Taska 2020). Workers can shift across occupations and industries, and so the extent of the demand for a given worker is captured more accurately by the distribution of task demand in a local area rather than by industry or occupation.

Second, we contribute to the literature on estimating the extent of monopsony power. 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 task requirements, which allows us to assess the extent of monopsony in local labor markets across a much broader set of occupations. This approach can easily be adopted by regulators as a straightforward way of measuring relevant markets for workers.

Third, our paper is the first to bring together the literature on monopsony with the growing body of research on the importance of tasks 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 task content, showing that employer market power operates through the concentration of task demand. We are the first to take this approach to studying monopsony. 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 imperative for proper regulation of the labor market. Proposals 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. These measures may overstate effective market concentration by omitting workers' outside options. Without adjusting relevant regulatory thresholds, regulators may impose too strong limitations on firm actions that might otherwise pose no threat to labor market competition or may prevent mergers that might otherwise lead to earnings growth for workers and owners.

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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 task cluster (relative to base year)	7,139,946	0.351	0.477
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 Task HHI	7,139,946	0.045	0.088
Base year Industry HHI	7,139,946	0.089	0.118

Source: Authors' tabulations from Norwegian Registry Data as described in the text. All statistics are calculated using the full analysis sample and time periods.

Table 2: Composition of Composite Job Task 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 Job Task-Based Concentration on Earnings

Panel A: Labor Earnings			
Independent Variable	(1)	(2)	(3)
Task HHI*Separated*Post	-115186.107***	-92980.750***	-91198.318***
	(30588.704)	(23980.556)	(24895.036)
Task 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, Task, and Industry FEs		x	x
Individual FEs			x

Panel B: Wage Earnings			
Independent Variable	(1)	(2)	(3)
Task HHI*Separated*Post	-109834.634***	-88558.275***	-88588.755***
	(34918.821)	(26854.839)	(27820.132)
Task 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, Task, 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 benefits, 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 Job Task-based Concentration on Other Labor Market Outcomes

Independent Variable	NILF (1)	Employed (2)	Part-time (3)	Skill Downgrading (4)	Skill Upgrading (5)	Skill Mismatch (6)
Task HHI*Separated*Post	0.014	0.015	0.098***	0.023*	-0.039***	-0.160***
	(0.020)	(0.025)	(0.016)	(0.012)	(0.013)	(0.048)
Task HHI	-0.004	0.003	0.002	-0.005	0.003	-0.028
	(0.007)	(0.007)	(0.005)	(0.004)	(0.007)	(0.026)
Concentration Effect	0.001	0.001	0.010	0.002	-0.004	-0.016
% Effect:				1.274	0.980	-4.571

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, task 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 5: Heterogeneous Treatment Effects by Gender

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

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

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 6: 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)
Task HHI*Separated *Post	-29888.138	-0.058	0.099*	0.081***	0.052***	-0.041***	-0.215***
	(23100.407)	(0.049)	(0.057)	(0.029)	(0.015)	(0.015)	(0.069)
Concentration Effect	-2988.814	-0.006	0.010	0.008	0.005	-0.004	-0.022
% Effect:	-0.737			38.095	1.645	-2.581	-6.377

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)
Task HHI*Separated *Post	-62017.989***	0.001	0.032	0.104***	0.012	-0.023	-0.204***
	(23309.905)	(0.019)	(0.020)	(0.016)	(0.014)	(0.015)	(0.046)
Concentration Effect	-6201.80	0.000	0.003	0.010	0.001	-0.002	-0.020
% Effect:	-1.328			58.824	0.505	-0.957	-5.764

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)
Task HHI*Separated *Post	-242871.338***	0.090***	-0.074**	0.090***	0.035**	-0.113***	-0.02
	(56238.076)	(0.033)	(0.035)	(0.026)	(0.016)	(0.034)	(0.067)
Concentration Effect	-24287.134	0.009	-0.007	0.009	0.004	-0.011	-0.002
% Effect:	-4.026			59.231	6.780	-1.513	-0.562

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 7: 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)
Task HHI*Separated*Post	-100780.83***	-0.025	0.042	0.085***	-0.005	0.033	0.047
	(34554.04)	(0.022)	(0.028)	(0.018)	(0.016)	(0.021)	(0.095)
Industry HHI*Separated*Post	2222.08	0.080***	0.011	0.028**	0.036***	-0.096***	-0.328***
	(6038.48)	(0.021)	(0.011)	(0.012)	(0.009)	(0.018)	(0.074)
Task HHI	15316.26**	-0.005	0.005	-0.007	-0.014***	0.002	-0.009
	(7330.04)	(0.005)	(0.005)	(0.008)	(0.004)	(0.007)	(0.022)
Industry HHI	-24366.90	-0.003	0.000	0.033	0.001	0.004	0.023***
	(16938.97)	(0.004)	(0.004)	(0.020)	(0.006)	(0.013)	(0.008)

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)	(8)
Task HHI*Separated*Post	-41657.964**	-0.029	0.066***	0.078***	0.019	0.001	-0.108*	
	(18358.532)	(0.018)	(0.021)	(0.014)	(0.013)	(0.019)	(0.062)	
Occupation HHI*Separated*Post	-108828.800***	0.095***	-0.113***	0.046***	0.008	-0.087***	-0.114**	
	(17923.130)	(0.017)	(0.021)	(0.013)	(0.011)	(0.023)	(0.049)	
Task HHI	19077.679**	-0.004	0.003	0.003	-0.004	-0.000	-0.027	
	(7719.937)	(0.007)	(0.007)	(0.006)	(0.004)	(0.007)	(0.026)	
Occupation HHI	12285.640**	0.001	-0.002	-0.015*	-0.005*	0.025***	-0.013	
	(5837.345)	(0.004)	(0.004)	(0.009)	(0.003)	(0.006)	(0.012)	

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 8: Combining Occupations based on Task Similarity

Panel A: Task-based HHI weighted by task similarity across task HHI

Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)
Task HHI*Separated	-102692.428***	0.104***	-0.113***	0.093***	-0.002	-0.020	0.046
*Post	(30264.918)	(0.022)	(0.025)	(0.011)	(0.012)	(0.016)	(0.050)
Concentration Effect	-10269.243	0.010	0.010	0.010	0.000	-0.002	0.005

Panel B: Occupation-based HHI weighted by task similarity across occupation HHI

Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)
Occupation HHI	-98813.208***	0.106***	-0.112***	0.107***	-0.006	-0.031	0.034
*Separated*Post	(29125.350)	(0.022)	(0.026)	(0.017)	(0.014)	(0.020)	(0.060)
Concentration Effect	-9881.321	0.011	-0.011	0.011	-0.000	-0.003	0.003

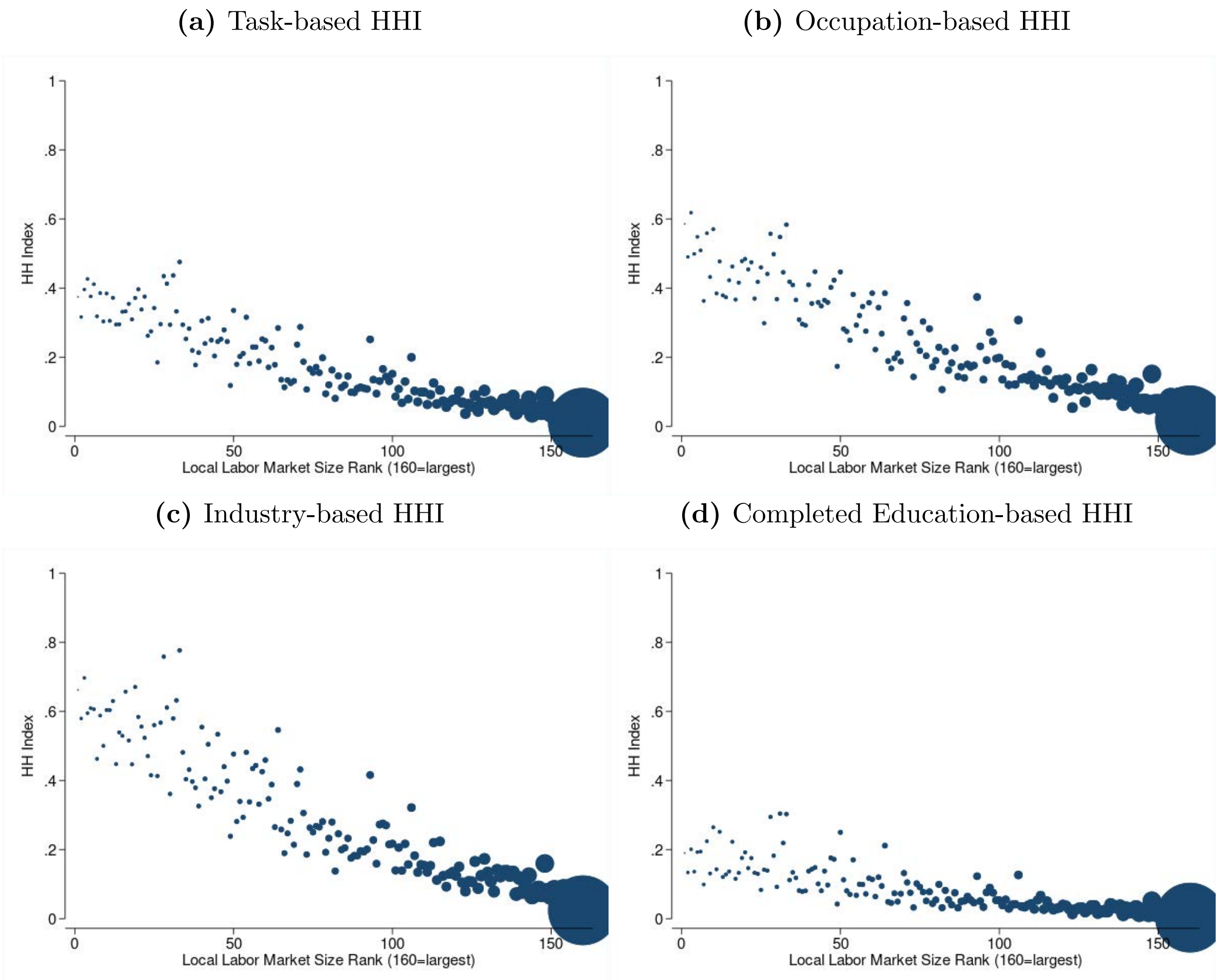
Source: Authors' estimation as described in the text. The task and occupation HHIs are weighted averages of the HHI in an individual worker's task cluster/occupation and in all other task-based clusters/occupations in the local labor market based on the correlative distance between the individual's task group/occupation and the remaining task clusters/occupations as measured by the similarity across the six task dimensions discussed in section 3. 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, task 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, task 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 9: The Effect of Involuntary Separations on Earnings of Separated vs. Non-separated Workers

Independent Variable	Non-Separated Workers at Layoff Firm (1)	Non-Separated Workers in LLM & Task Cluster at Other Firms (2)	Comparing Separated vs. Non-Separated Workers (3)
Task HHI*Separated*Post	-32022.673***		-10280.946
	(11462.074)		(13913.745)
Task HHI*Post*Layoff Size		-327473.974***	
(LLM-task cluster-base year)		(82199.566)	
Task HHI*Post			-81238.471***
			(17144.114)
Effect of going from a non-concentrated to a concentrated market:	-3202.267	-32747.397	-1028.095
% Effect:	0.624	6.369	0.200

Source: Authors' estimation as described in the text. The dependent variable in each regression is pensionable 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). Column (1) presents estimates of equation (2) using workers at firms experiencing a mass layoff who were not themselves laid off. The second column shows the effect of the total number of mass layoffs in the LLM-task cluster-base year cell on workers in firms that did not experience a mass separation. This model includes lower-level interactions between the layoff size and other treatment variables. Column (3) shows estimates of equation (2) that includes a control for HHI*post, which identifies β by comparing those who were laid off to those who were not laid off. 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) Task-based HHI

(b) Occupation-based HHI

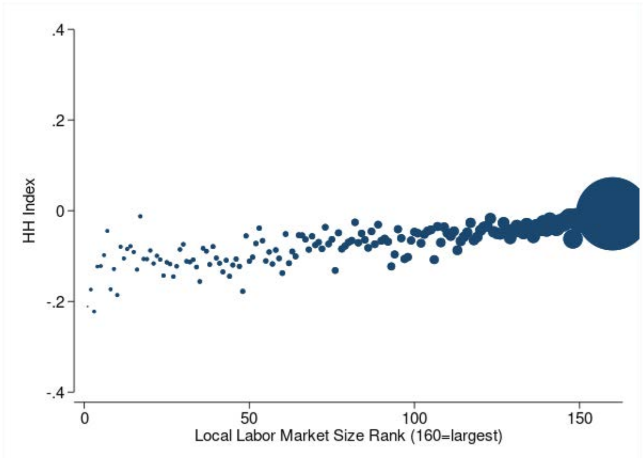
(c) Industry-based HHI

(d) Completed Education-based HHI

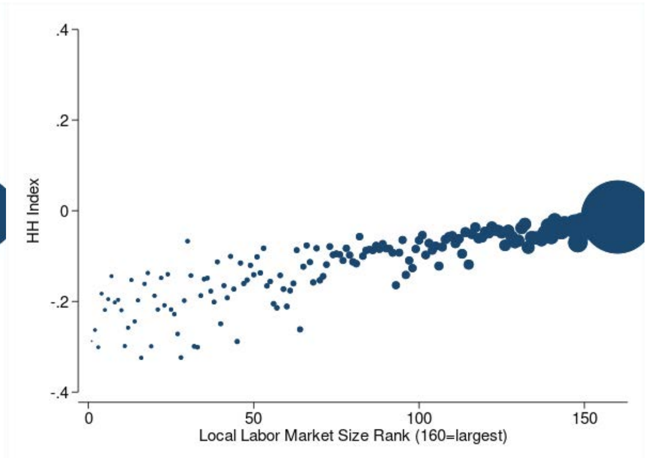
Notes: Each panel shows the Herfindahl-Hirschman Index by local labor market, calculated using different clustering measures. Each point is a local labor market, and the local labor markets are ordered by size. The size of each point represents the employed population of the local labor market. In panel (a), the HHI is calculated using 20 job task 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

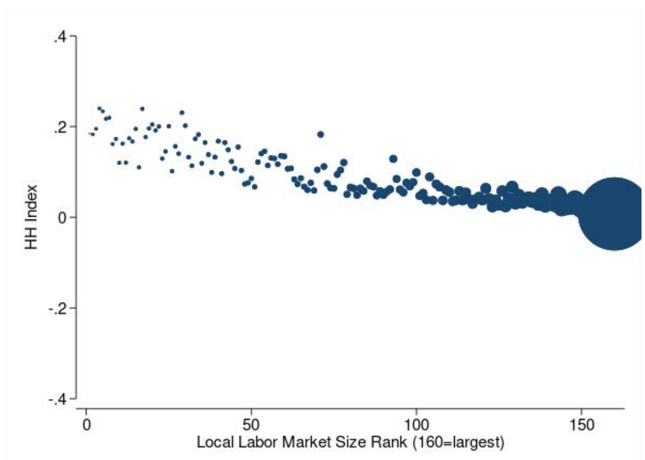
(a) Task-based HHI - Occupation-based HHI



(b) Task-based HHI - Industry-based HHI



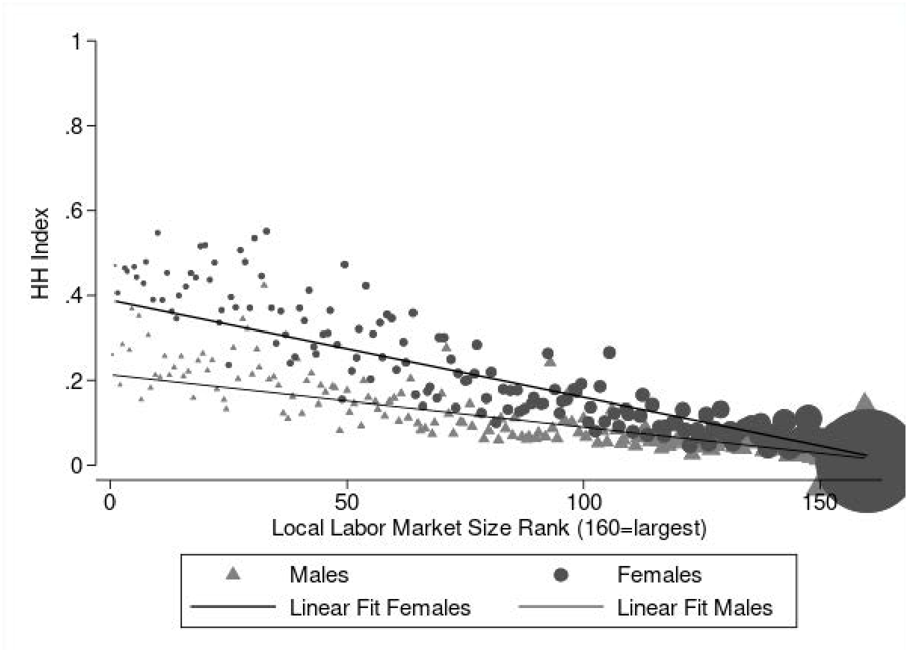
(c) Task-based HHI - Education-based HHI



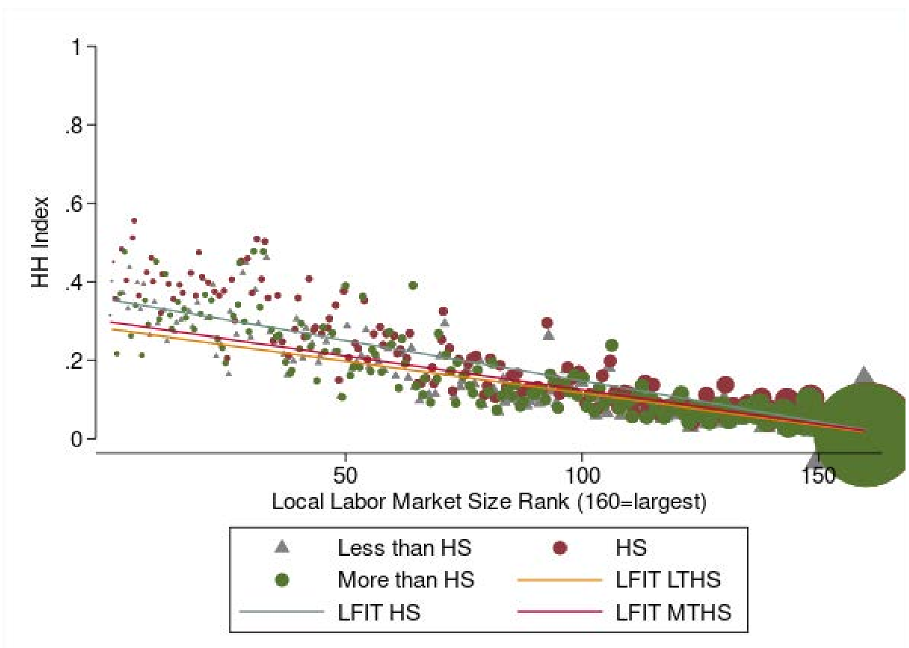
Notes: Each panel shows the difference between the HHI calculated using job tasks and the HHI calculated using another clustering method, by local labor market. Each point is a local labor market, and the local labor markets are ordered by size. The size of each point represents the employed population of the local labor market. The task-based HHI is calculated using 20 task 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) Task-based HHI by Worker Gender



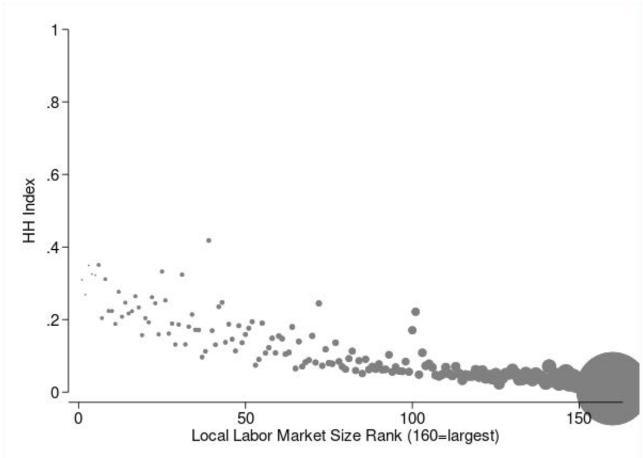
(b) Task-based HHI by Worker Educational Attainment



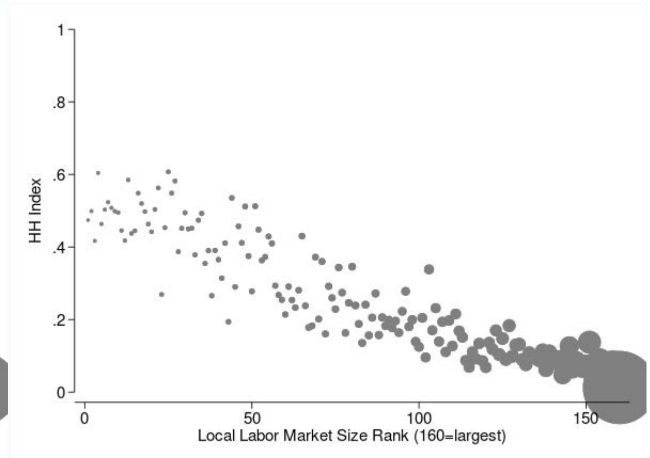
Notes: Panel (a) shows task-based HHI for each local labor market, separately by worker gender. Each point is a gender, LLM combination, and the labor markets are ordered by overall size. The size of each point represents the total employed population of the LLM. Panel (b) shows task-based HHI for each LLM, by worker educational attainment. For each subgroup, the HHI is calculated using the full sample.

Figure 4: Task-based Herfindahl-Hirschman Indices, by Local Labor Market, Sector, and Gender

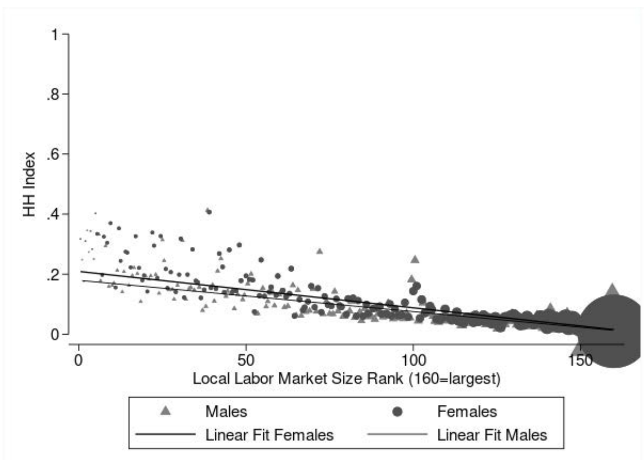
(a) Private Sector



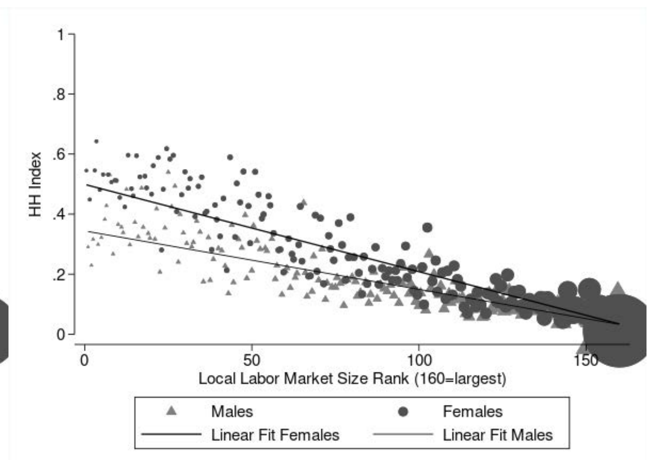
(b) Public Sector



(c) Private Sector, by Gender



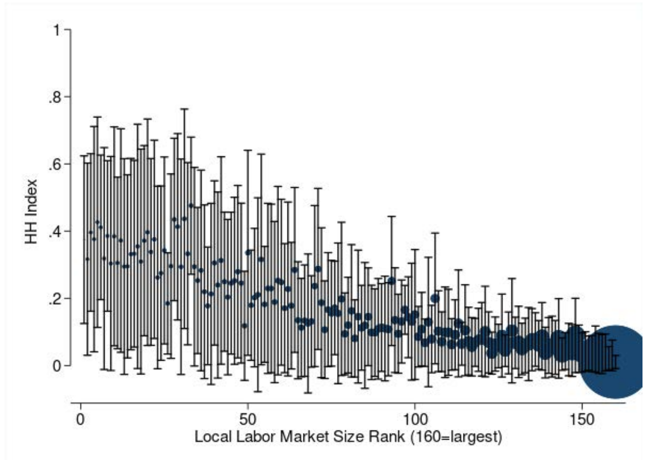
(d) Public Sector, by Gender



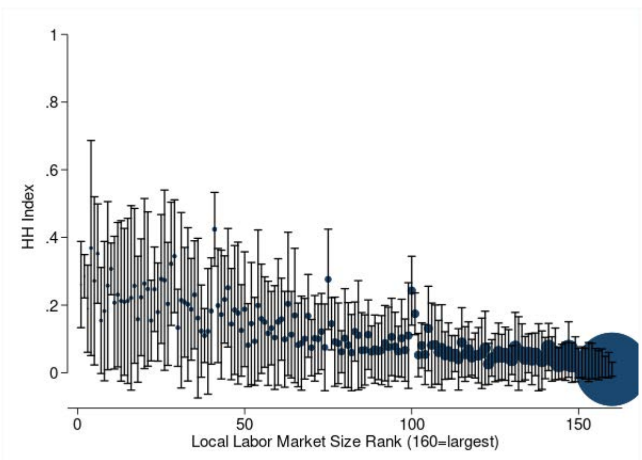
Notes: Panels (a) and (b) show task-based HHI for each local labor market, separately for private and public workers, respectively. Panels (c) and (d) show private and public task-based HHIs for each local labor market separately by gender. Each point is a sector or sector-gender, local labor market combination, and the local labor markets are ordered by overall size. The size of each point represents the total employed population of the local labor market. For each subgroup, the HHI is calculated using the full sample.

Figure 5: Within-Local Labor Market Variation in Task-based Herfindahl-Hirschman Indices

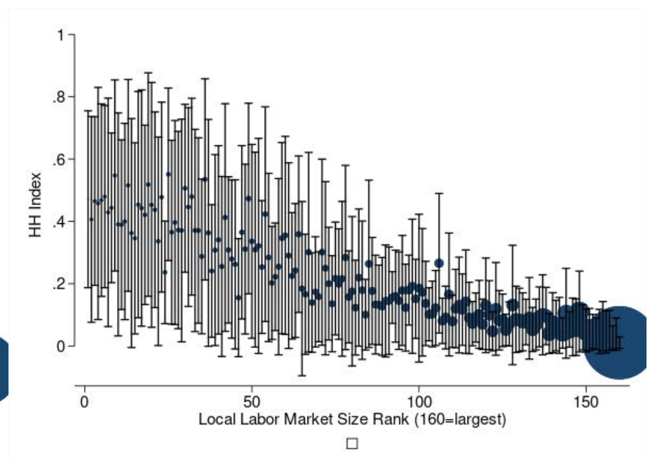
(a) Pooled



(b) Men



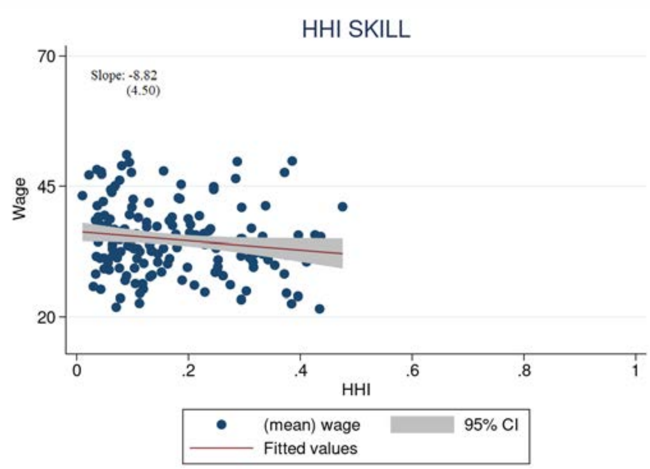
(c) Women



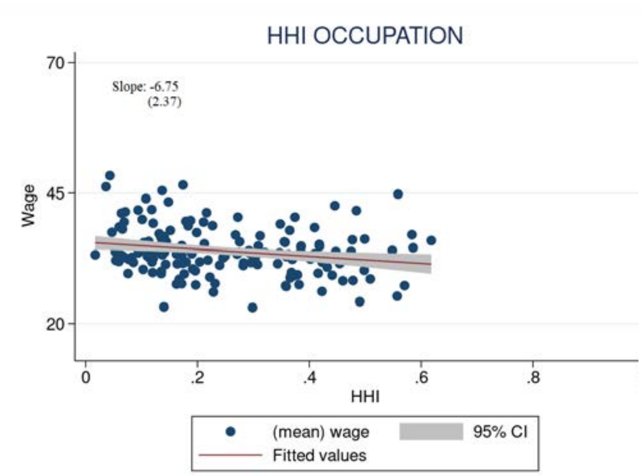
Notes: Each point shows the task-based HHI mean in a local labor market, and the bar extending from each point shows a standard deviation above and below the mean in that local labor market. The within-LLM variation comes from different HHIs across task clusters within the local labor market. Panel (a)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

Figure 6: Correlations Between HHI Measures and Local Labor Market Earnings

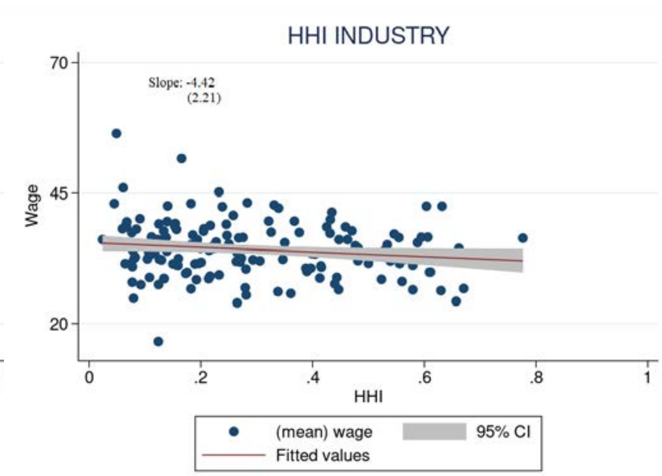
(a) Task-based HHI



(b) Occupation

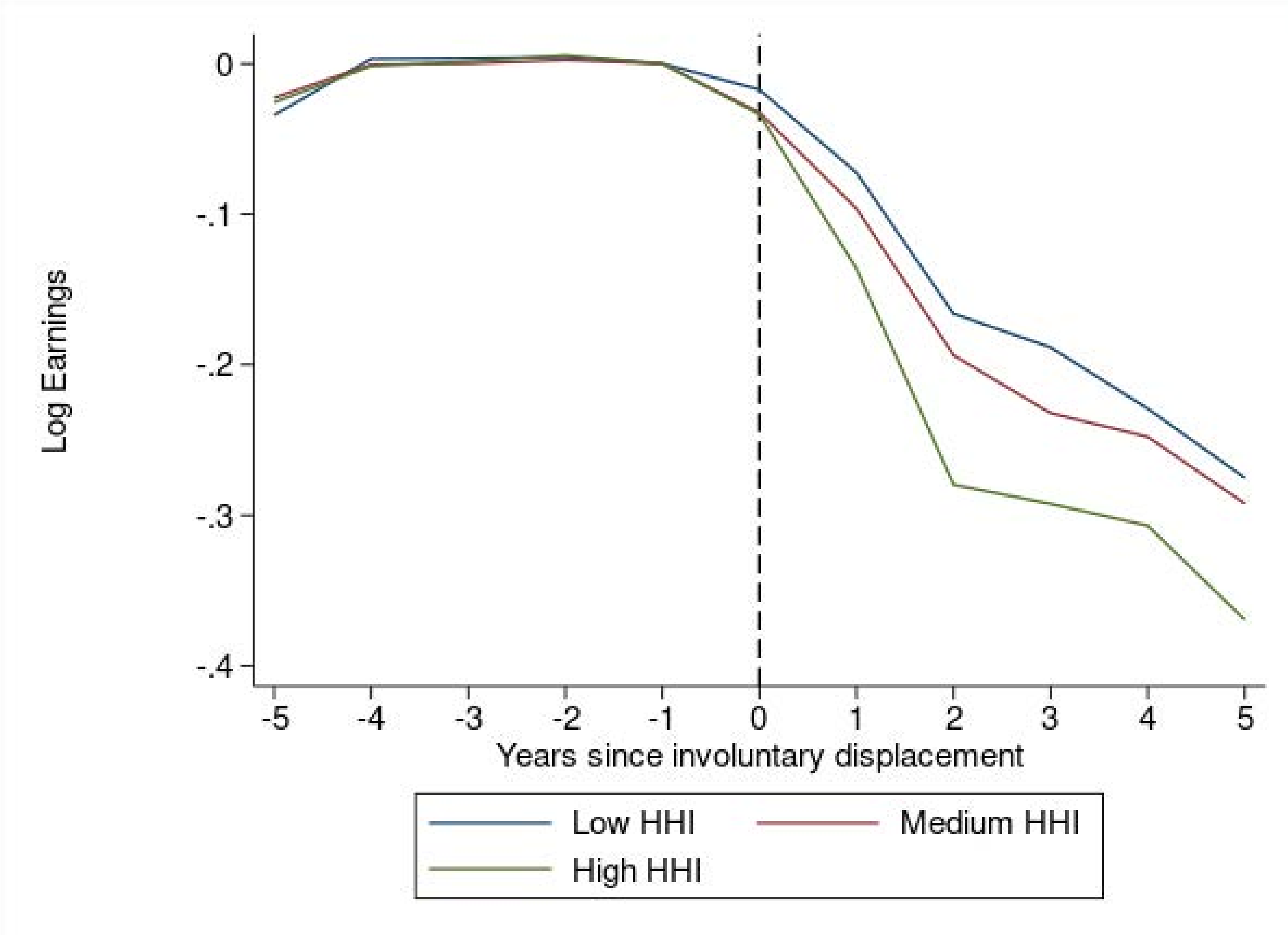


(c) Industry



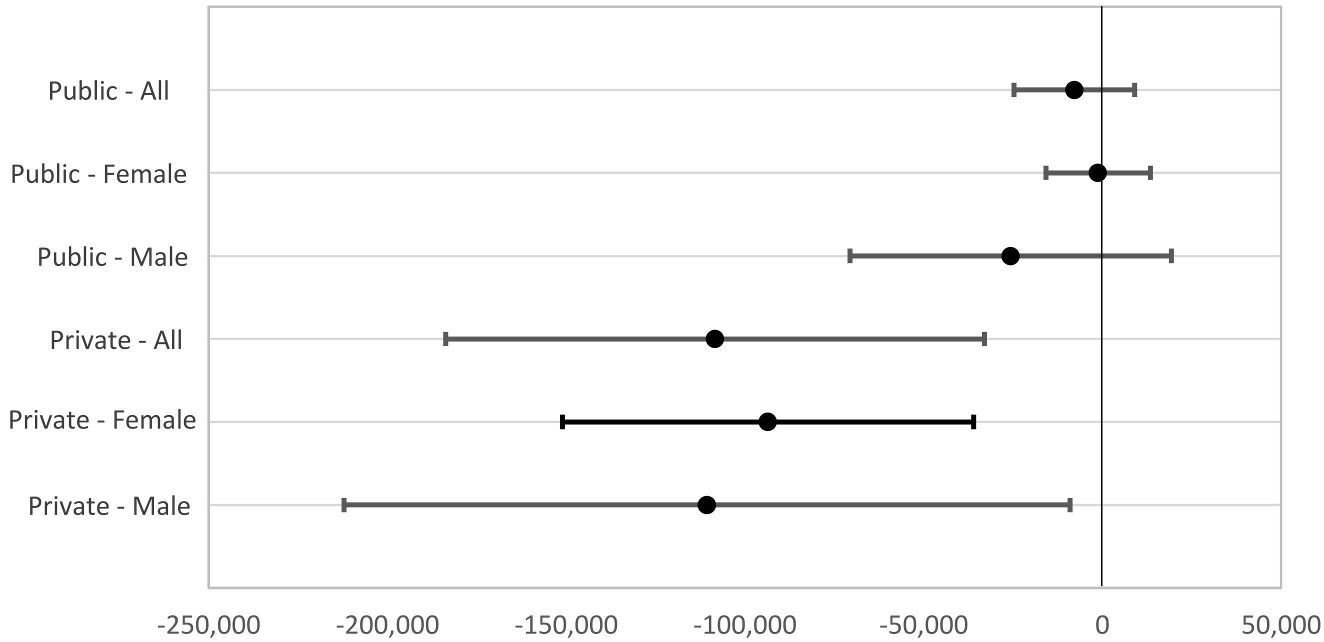
Notes: Each panel shows a scatter plot of HHI vs. mean earnings in the local labor market. The panels differ in the HHI measure used: panel (a) uses a task-based HHI measure, panel (b) uses an occupation-based HHI measure, and panel (c) uses an industry-based HHI measure. A linear fit and 95% confidence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

Figure 7: Event Studies of Involuntary Displacement on Labor Earnings, by HHI



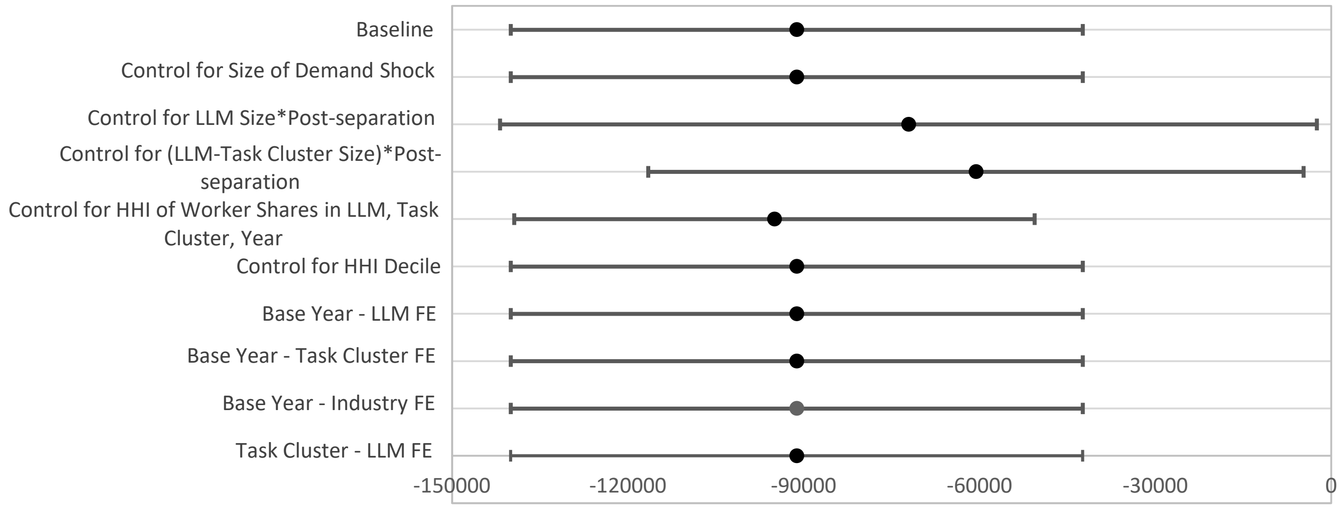
Notes: Each line shows means of labor earnings relative to the time of displacement by low (HHI<0.1), medium (0.1≤HHI≤0.25), and high (HHI>0.25) HHI levels. Earnings are residualized with respect to relative time to separation, and all estimates are relative to relative time -1.

Figure 8: The Effect of Job Task-based Concentration on Earnings, by Sector and Gender



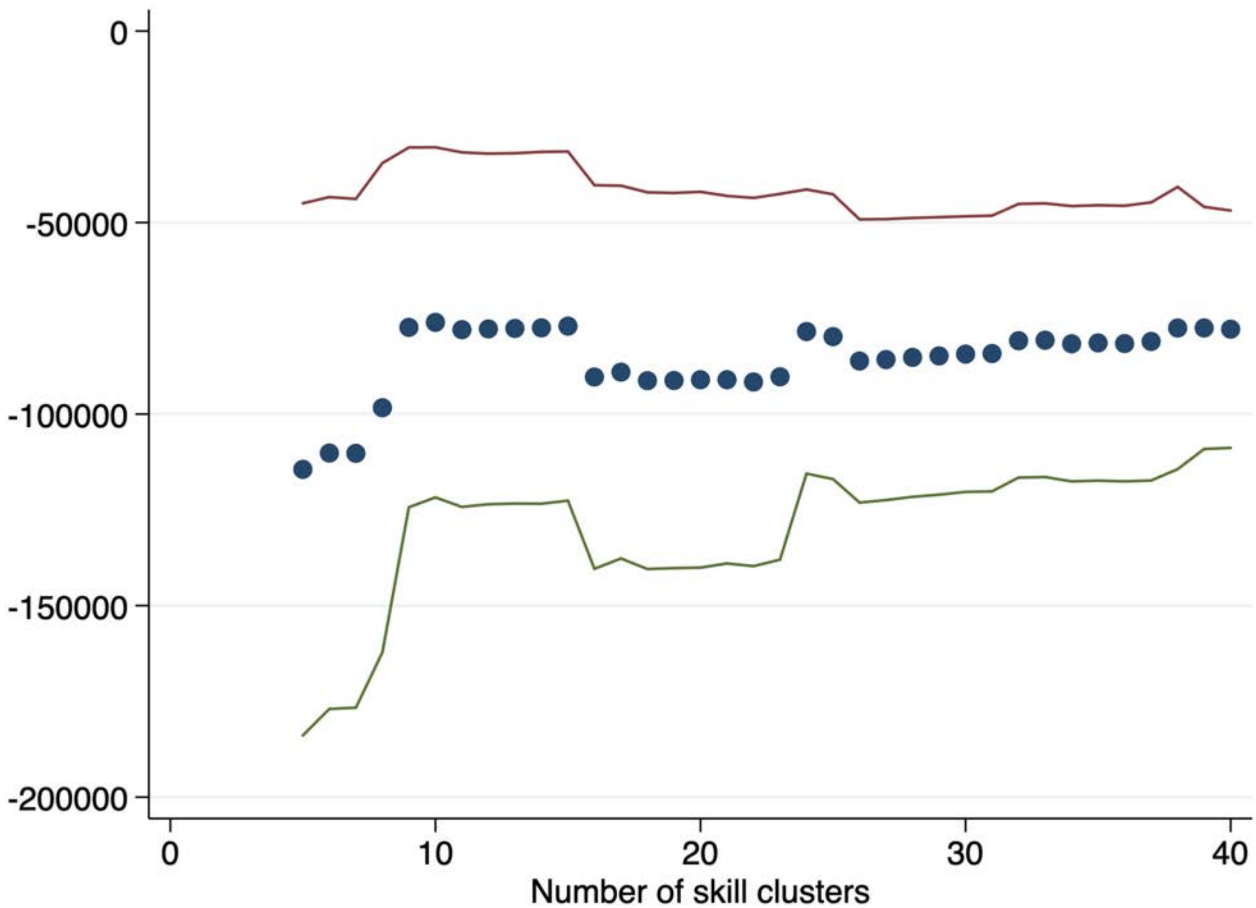
Notes: The figure shows estimates of β from equation (2) in the text by sector (public/private) and gender (male/female). The dependent variable in each regression is labor earnings, and all estimates include the full set of controls shown in equation (2). The sector is defined as the sector in which a worked is employed prior to separation or in the base year for those not separated. Each point represents the estimate of β, with the whiskers showing 95% confidence intervals that are calculated from standard errors clustered at the local labor market level.

Figure 9: The Effect of Job Task-based Concentration on Earnings – Robustness Checks



Notes: The figure shows estimates of β from equation (2) in the text, using labor earnings as the dependent variable. 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. The baseline estimate comes from column (3), Panel A of Figure 3. In the second row, we control for the number of workers who were displaced in each LLM, task cluster, and year. The third row includes an interaction with the number of workers in the LLM and a post-separation indicator. Next, we include an interaction with the number of workers in the LLM-task cluster-base year and a post-separation indicator. In the fifth row, we control for the squared share of workers in each LLM, task cluster, and year (not across firms). The sixth row show results that include controls for deciles of the HHI distribution. The final four rows control (respectively) for base year-by-LLM, base year-by-task cluster, base year-by-industry, and task cluster-LLM fixed effects. Each point represents the estimate of β, with the whiskers showing 95% confidence intervals that are calculated from standard errors clustered at the local labor market level.

Figure 10: The Effect of Skill-based Concentration on Earnings, by Different Number of Task Clusters



Notes: The figure shows the sensitivity of the β estimates from equation (2) in the text to altering the number of task clusters used in the analysis. Each estimate in the figure comes from a separate regression, sequentially adding one additional task cluster at a time, from 5 through 40. The solid lines 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 Task Cluster

Task 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 Rankings by Task Cluster

Task 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 Task Cluster Among Those Switching Occupations

Initial Task Cluster	Percent Moving Within Cluster	Percent Moving Across Cluster	Number of Switchers	Percent of Total Employment
1	77.37%	22.63%	79540	28.55%
17	76.54%	23.46%	59480	26.76%
2	61.75%	38.25%	45146	15.30%
13	53.21%	46.79%	31140	1.87%
14	25.53%	74.47%	13555	4.14%
8	54.98%	45.02%	10526	5.00%
20	51.13%	48.87%	6233	4.54%
12	62.72%	37.28%	5410	4.86%
19	45.70%	54.30%	5087	2.76%
5	84.14%	15.86%	3209	0.87%
16	38.44%	61.56%	3059	1.43%
10	33.53%	66.47%	2338	1.38%
18	54.41%	45.59%	2266	0.89%
15	59.18%	40.82%	1727	0.82%
6	49.94%	50.06%	1592	0.56%
7	42.54%	57.46%	268	0.11%
3	26.67%	73.33%	180	0.08%
11	64.10%	35.90%	39	0.03%
9	51.35%	48.65%	37	0.03%
4	38.89%	61.11%	18	0.01%
Weighted Average	65.57%	34.43%		

Source: Authors' tabulations as described in the text using Norwegian Register Data. The final column shows the percent of total employment represented by each task group, using the sample sizes from Table A-1. The estimates in the final column show what the percent moving within cluster would be if workers randomly switched jobs.

Table A-4: The Relationship Between Labor Earnings and HHI

	Dep Var.: Labor Earnings			
Independent Variable	(1)	(2)	(3)	(4)
Task HHI	-350487.47***	-163950.02***	-156407.34***	48600.91***
	(86064.16)	(53003.99)	(41402.11)	(10141.38)
Base Year and Industry FEs:		x	x	x
Task Cluster FEs:			x	x
LLM FEs:				x

Source: Authors' estimation as described in the text. Labor earnings consist of pre-tax labor earnings (including self-employed earnings) plus transfers such as sick leave benefits, unemployment benefits, and parental leave payments. Wage earnings include only pre-tax labor earnings (including self-employed earnings). The dependent variable mean is 512888.503. Column (1) shows bivariate regression estimates, column (2) adds base year and industry fixed effects, column (3) adds task cluster fixed effects, and column (4) adds local labor market 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 A-5: The Effect of Involuntary Separation and Task Concentration on Employment Outcomes

	Panel A: Not in Labor Force			Panel B: Employed		
Independent Variable	(1)	(2)	(3)	(1)	(2)	(3)
Task HHI*Separated*Post	0.020	0.014	0.014	0.008	0.015	0.015
	(0.022)	(0.019)	(0.020)	(0.028)	(0.024)	(0.025)
Task 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, Task, and Industry FEs		x	x		x	x
Individual FEs			x			x

	Panel C: Part-Time		
Independent Variable	(1)	(2)	(3)
Task HHI*Separated*Post	0.102***	0.098***	0.098***
	(0.016)	(0.015)	(0.016)
Task 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, Task, 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 A-6: The Effect of Involuntary Separation and Task Concentration on Occupational Mobility

	Panel A: Skill Downgrading			Panel B: Skill Upgrading		
Independent Variable	(1)	(2)	(3)	(1)	(2)	(3)
Task HHI*Separated*Post	0.016	0.023*	0.023*	-0.022	-0.039***	-0.039***
	(0.015)	(0.012)	(0.012)	(0.018)	(0.013)	(0.013)
Task 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, Task, and Industry FEs		x	x		x	x
Individual FEs			x			x

	Panel C: Skill Mismatch		
Independent Variable	(1)	(2)	(3)
Task HHI*Separated*Post	-0.055	-0.160***	-0.160***
	(0.061)	(0.046)	(0.048)
Task HHI	0.016	0.020**	-0.028
	(0.013)	(0.010)	(0.026)
Effect of going from a non-concentrated			
to a concentrated market:	-0.006	-0.016	-0.016
% Effect:	-1.709	-4.571	-4.571
Relative time and year FEs:		x	x
LLM, Task, 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 0.157, in Panel B is 0.408, and in Panel C is 0.351. 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 A-7: 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)
Task HHI*Separated	-94058.783***	0.014	-0.009	0.060***	0.027*	0.000	0.071
*Post	(32477.268)	(0.025)	(0.034)	(0.016)	(0.014)	(0.022)	(0.082)
Concentration Effect	-9405.878	0.001	-0.001	0.006	0.003	0.000	0.007

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

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

Source: Authors' estimation as described in the text. All estimates include relative time to separation and year fixed effects, local labor market, task 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-9: The Effect of Skill HHI on Involuntary Displacement

Treatment Variable	Estimate
Task HHI*Separated*Post	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, task cluster, and year fixed effects. Standard errors clustered at LLM level are in parentheses.

Table A-10: Percent of Analysis Sample Subject to Involuntary Displacement, 2008-2012

Panel A: By aggregate category	Percent
By LLM	2.447
By Industry	2.749
By Task Cluster	2.573
By HHI Skill	2.38
Low (HHI less than 0.15)	2.667
Medium (HHI between 0.15 and 0.25)	2.622
High (HHI above 0.25)	1.841
Panel B: By skill cluster	Percent
Skill cluster 1	2.14
Skill cluster 2	2.77
Skill cluster 3	1.64
Skill cluster 4	3.96
Skill cluster 5	0.72
Skill cluster 6	2.59
Skill cluster 7	3.41
Skill cluster 8	1.92
Skill cluster 9	2.56
Skill cluster 10	2.76
Skill cluster 11	1.79
Skill cluster 12	2.73
Skill cluster 13	2.54
Skill cluster 14	2.72
Skill cluster 15	1.71
Skill cluster 16	2.86
Skill cluster 17	3.35
Skill cluster 18	2.42
Skill cluster 19	4.87
Skill cluster 20	2.26

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

Table A-11: Effect on individuals who are fired for cause rather than displaced due to mass layoffs and closures

Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)
Task HHI*Separated	39096.825	-0.008	0.073	0.160***	0.014	-0.041	-0.121**
*Post	(42409.38)	(0.041)	(0.051)	(0.036)	(0.052)	(0.046)	(0.059)
Concentration Effect	3909.68	0.001	0.001	0.016	0.001	-0.004	-0.012

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, task 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-12: Redefining HHI to represent a weighted average of the skill concentration in the clusters closest to the worker based on the national cross-cluster transitions

Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)
Task HHI*Separated	-140893.887***	0.049	-0.014	0.155***	0.030	-0.059**	-0.227***
*Post	(37525.961)	(0.031)	(0.040)	(0.023)	(0.019)	(0.023)	(0.082)
Concentration Effect	-14089.39	0.005	-0.001	0.016	0.003	-0.006	-0.023

Source: Authors' estimation as described in the text. In this specification, the HHI has been reconstructed to represent a weighted average of the task concentration in the clusters closest to the worker based on the national cross-cluster transitions displayed in Appendix Table A3. 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, task 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-13: Robustness Checks: Additional Controls

Panel A: Controlling for the Size of the Demand Shock

Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)
Task HHI*Separated	-91195.012***	0.014	0.015	0.098***	0.023*	-0.039***	-0.160***
*Post	(24896.493)	(0.020)	(0.025)	(0.016)	(0.012)	(0.013)	(0.048)
Concentration Effect	-9119.501	0.001	0.002	0.010	0.002	-0.004	0.016

Panel B: Controlling for LLM Size*Post-separation

Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)
Post-separation*	-72122.529**	-0.018	0.058**	0.074***	0.033***	-0.046***	-0.234***
Task HHI	(35562.015)	(0.023)	(0.024)	(0.014)	(0.009)	(0.012)	(0.032)
Concentration Effect	-7217.253	-0.002	0.006	0.007	0.003	-0.005	-0.023

Panel C: Controlling for LLM,Task-cluster Size*Post-separation

Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)
Task HHI*Separated	-60611.354**	-0.021	0.063***	0.076***	0.045***	-0.075***	-0.302***
*Post	(28536.761)	(0.021)	(0.004)	(0.012)	(0.010)	(0.020)	(0.050)
Concentration Effect	-6061.135	-0.002	0.006	0.008	0.005	-0.008	0.030

Panel D: Controlling for HHI of Worker Shares in Each LLM, Task Cluster, and Year

Independent Variable	Labor Earnings (1)	NILF (2)	Employed (3)	Part-time (4)	Skill Downgrading (5)	Skill Upgrading (6)	Skill Mismatch (7)
Task HHI*Separated	-95015.604***	0.008	0.026	0.094***	0.030***	-0.039***	-0.161***
*Post	(22651.346)	(0.020)	(0.025)	(0.016)	(0.012)	(0.013)	(0.051)
Concentration Effect	-9501.560	0.001	0.003	0.009	0.003	-0.004	-0.016

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, task 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, task 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 include an interaction with the number of workers in the LLM-task cluster-base year and a post-separation indicator. In Panel (D), we control for the squared share of workers in each LLM, task 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 A-14: 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
Task HHI*Separated	-91186.028***	-91190.929***	-91200.637***	0.014	0.014	0.014	0.015	0.015	0.015	0.098***	0.098***	0.098***
*Post	(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 Task 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			
Task HHI*Separated	0.023*	0.023*	0.023*	-0.039***	-0.039***	-0.039***	-0.160***	-0.160***	-0.160***			
*Post	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.048)	(0.048)	(0.048)			
Baseline Specification												
Base Year by LLM	x			x			x					
Base Year by Task Cluster		x			x			x				
Base Year by Industry			x			x			x			

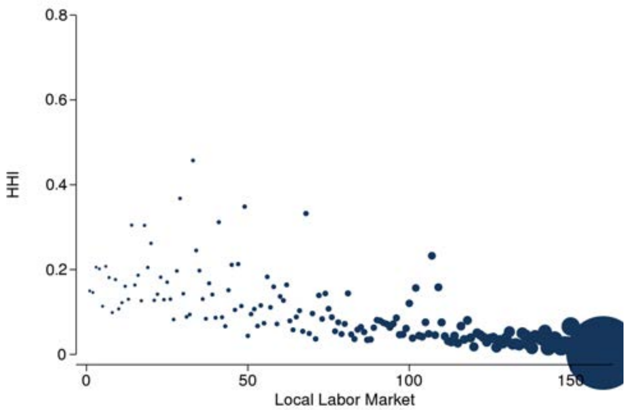
Source: Authors' estimation as described in the text. All estimates include relative time to separation and year fixed effects, local labor market, task cluster, and industry fixed effects, as well as individual fixed effects. Standard errors are clustered at the local labor market level: * indicates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

Table A-15: Top Occupations in Each Task Cluster

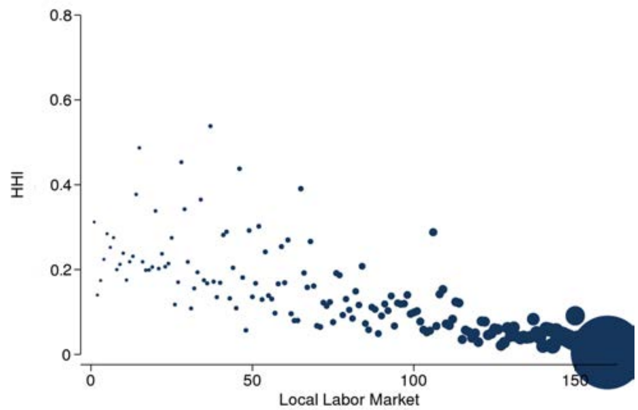
Skill Cluster	Occupation Name
1	Primary education teaching associate professionals
1	Technical and commercial sales representatives
1	Directors and chief executives
1	Other public service administrative professionals
1	Pre-primary education teaching associate professionals
2	Nurses
2	Bank associate professionals
2	Engineering technicians not elsewhere classified
2	Economists
2	Other public service administrative associate professionals
3	Cartographers and surveyors
3	Library and filing clerks
4	Blacksmiths
5	Police officers
5	Life science technicians
5	Prosecuting legal professionals
5	Fire inspectors
5	Business services agents not elsewhere classified
6	Fire-fighters
6	Other department managers not elsewhere classified
6	Dentists
6	Production and operations department managers in agriculture
6	Inspisients
7	Bakers and confectionery makers
8	Child-care workers
8	Door-to door salesmen and related workers
8	Production and operations department managers in personal care
8	Reducing treatmenthosts/- tesses and related workers
9	General managers in personal care
10	Salespersons (wholesale)
10	Home helpers
10	Trainees
11	Undertakers and crematorium workers
12	Nursing assistants and care assistants
13	Shop salespersons and other salespersons (retail)
13	Personal care and related workers not elsewhere classified
13	Secretaries
13	Administrative secretaries and related associate professionals
13	Accounting and bookkeeping clerks
14	Clerical officers
14	Pharmacy technicians
14	Telephone switchboard operators
14	Librarians
14	Tellers and other counter clerks
15	Security guards
15	Prison guards
15	Doorkeepers
16	Computer associate professionals
16	Technical illustrators
16	Laboratory assistants
16	Photographers and image and sound recording equipment operators
16	Air traffic controllers
17	Electricians
17	Carpenters and joiners
17	Heavy truck and lorry drivers
17	Caretakers
17	Cooks
18	Hairdressers
18	Safety inspectors
18	Power-production plant operators
19	Stock clerks
19	Mail carriers and sorting clerks
19	Glaziers
19	Jewellery and precious-metal workers
19	Food and beverage tasters and graders
20	Helpers and cleaners in offices and other establishments
20	Head waiters
20	Food- and related products machine operators not elsewhere classified
20	Other personal services workers not elsewhere classified
20	Domestic helpers and cleaners

Figure A-1: Task-Specific Herfindahl-Hirschman Indices by Local Labor Market - Non-routine Job Tasks

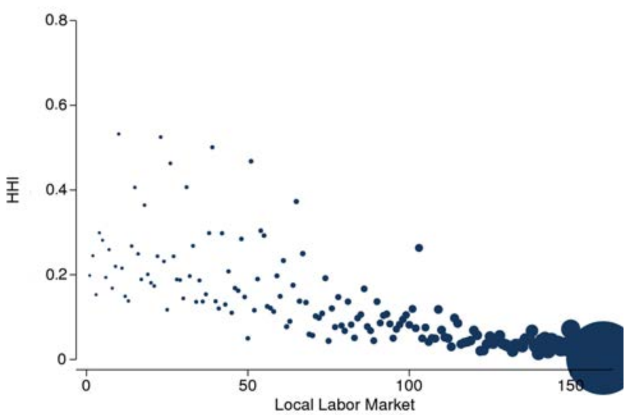
(a) Non-routine, Cognitive, Analytical



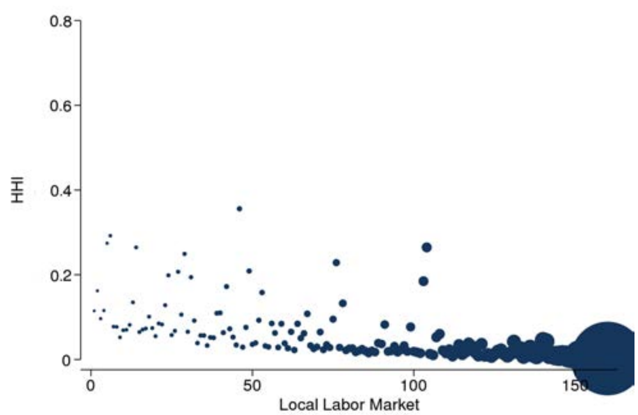
(b) Non-routine, Cognitive, Interpersonal



(c) Non-routine, Interpersonal Adaptability



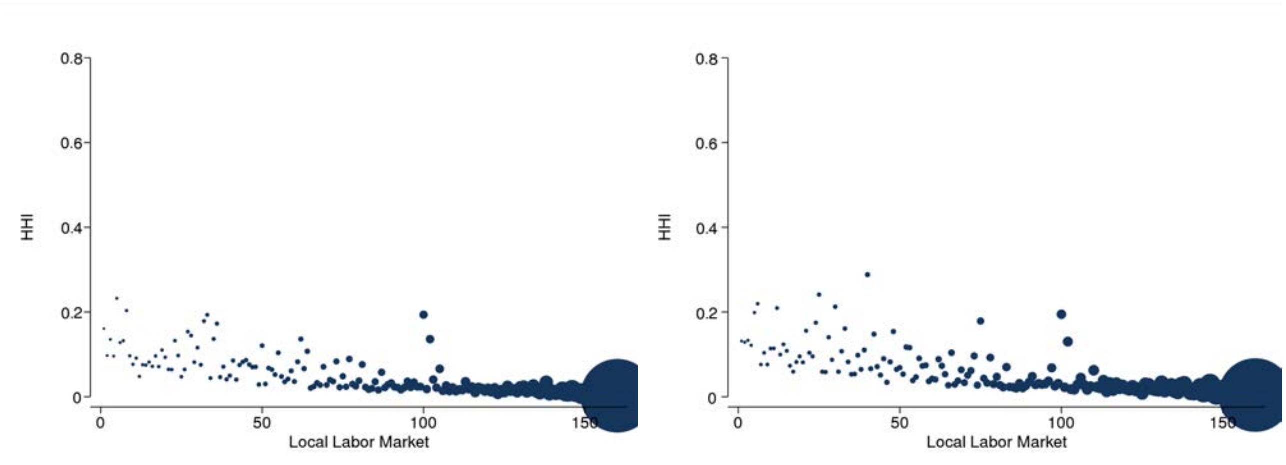
(d) Non-routine, Physical Adaptability, Manual



Notes: Each panel shows the Herfindahl-Hirschman Index by local labor market, calculated using a specific job task 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 Job Tasks

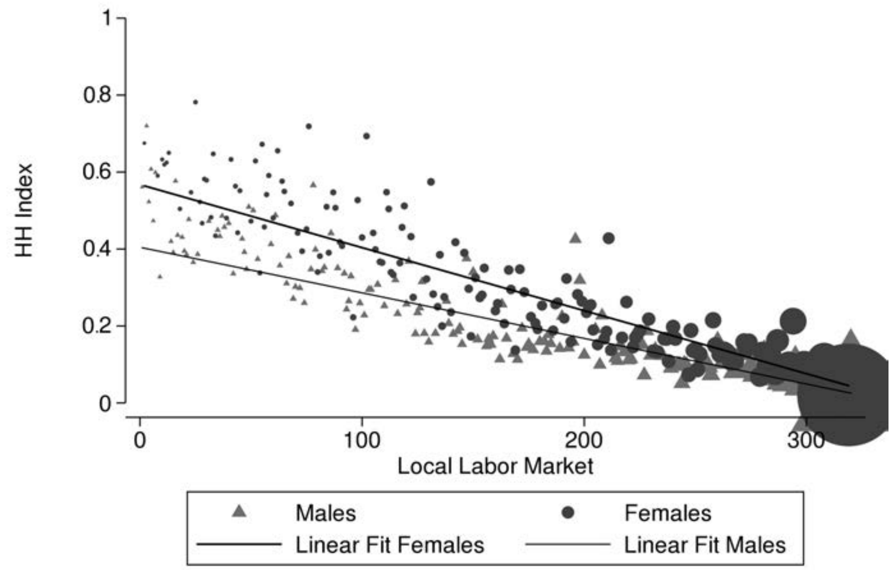
(a) Routine Cognitive **(b)** Routine Manual



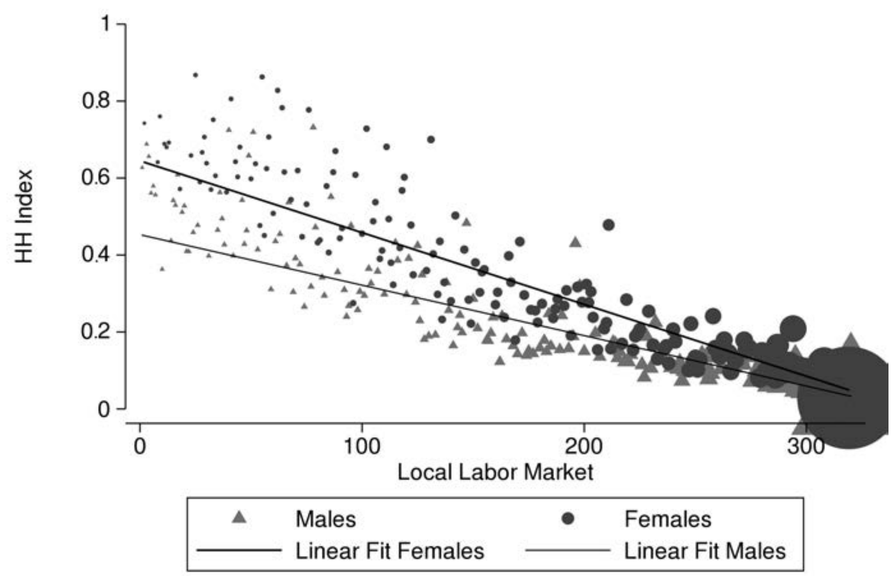
Notes: Each panel shows the Herfindahl-Hirschman Index by local labor market, calculated using a specific job task measure. Each point is a local labor market, and the local labor markets are ordered by size. The size of each point represents the employed population of the local labor market.

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

(a) Occupation-based HHI



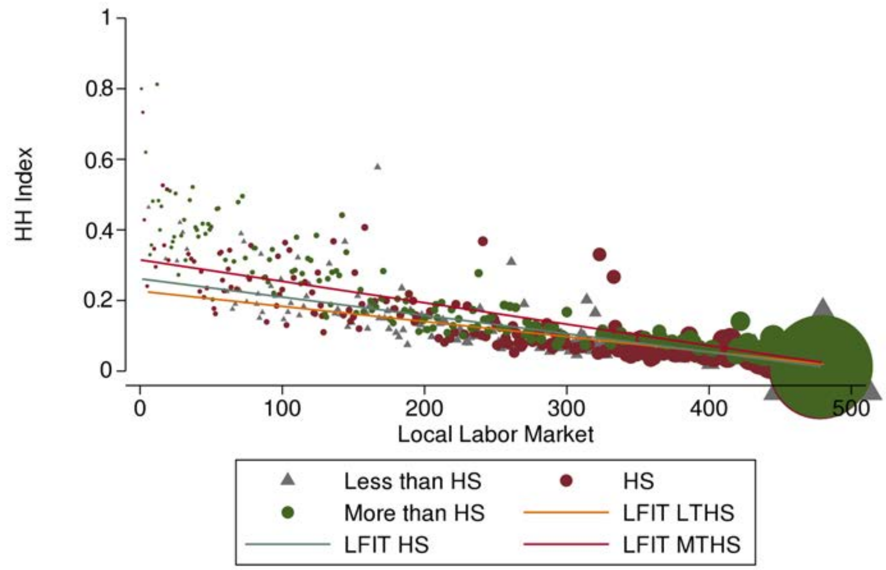
(b) Industry-based HHI



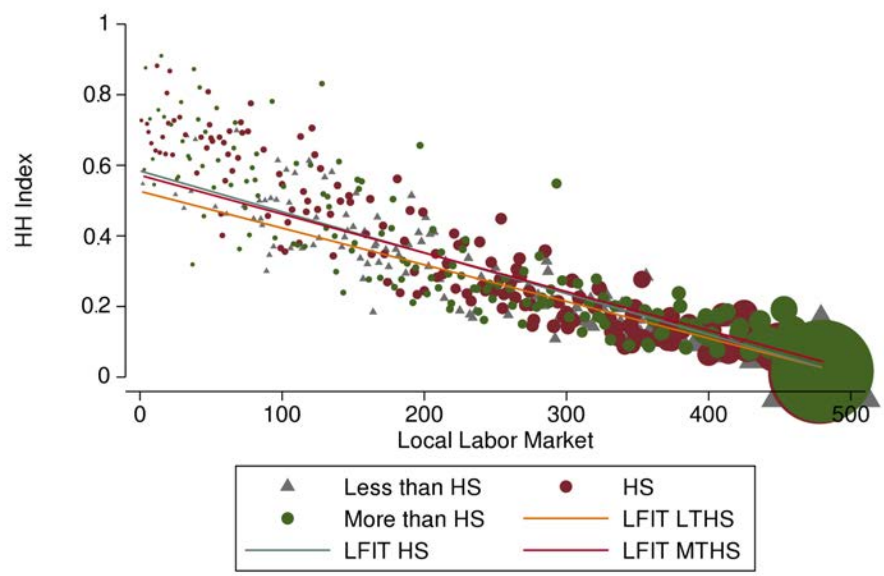
Notes: Panel (a) shows occupation-based HHI for each local labor market, separately by worker gender. Panel (b) shows industry-based HHI for each local labor market, separately by worker gender. Each point is a gender, local labor market combination, and the local labor markets are ordered by overall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

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

(a) Men

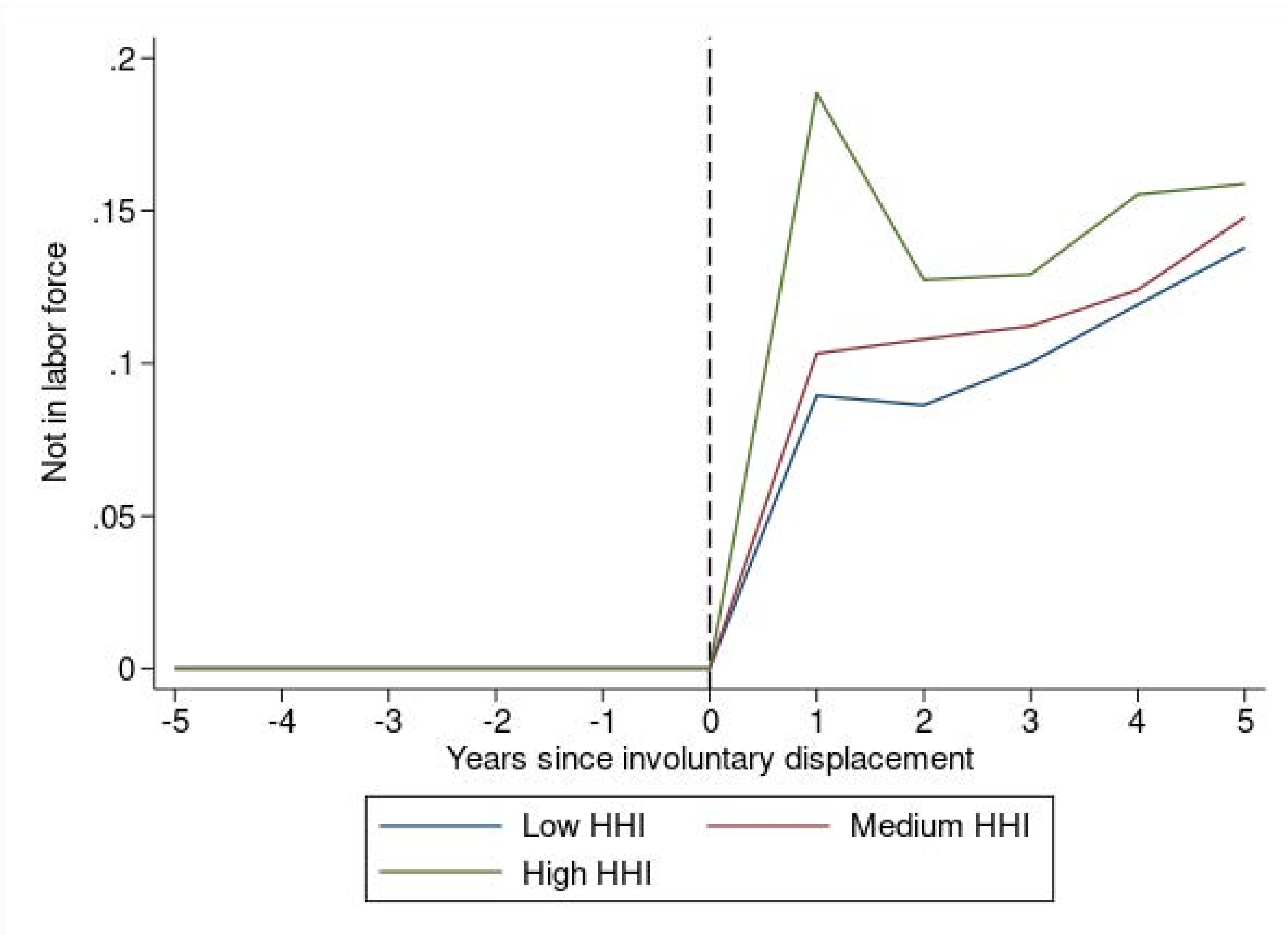


(b) Women



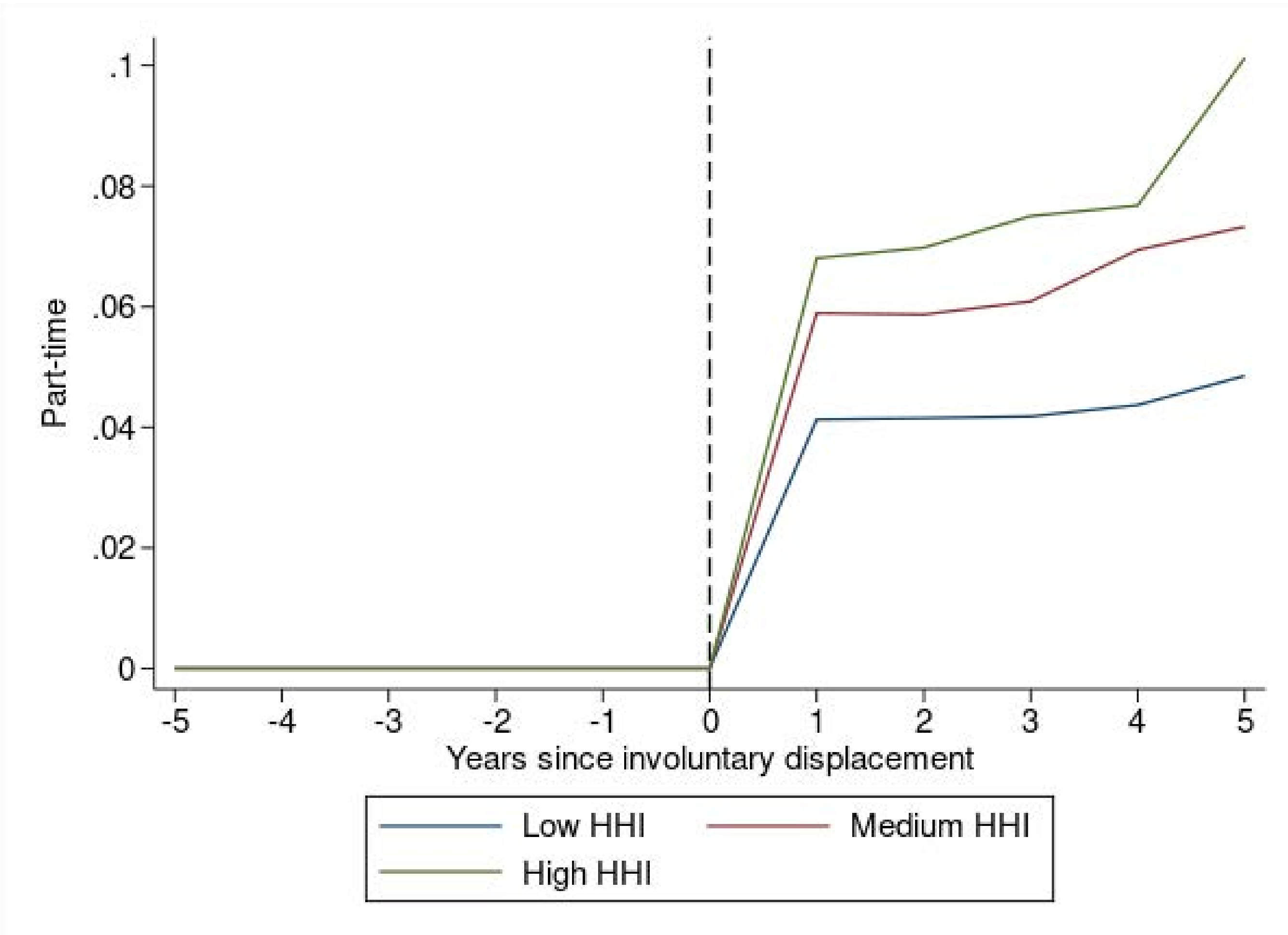
Notes: Panel (a) shows task-based HHI for each local labor market among men, separately by education. Panel (b) shows the task-based HHI among women by education. Each point is an attainment, LLM combination, and the LLMs are ordered by overall size (not by gender or educational attainment). The size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

Figure A-5: Event Studies of Involuntary Displacement on Labor Force Non-participation, by HHI



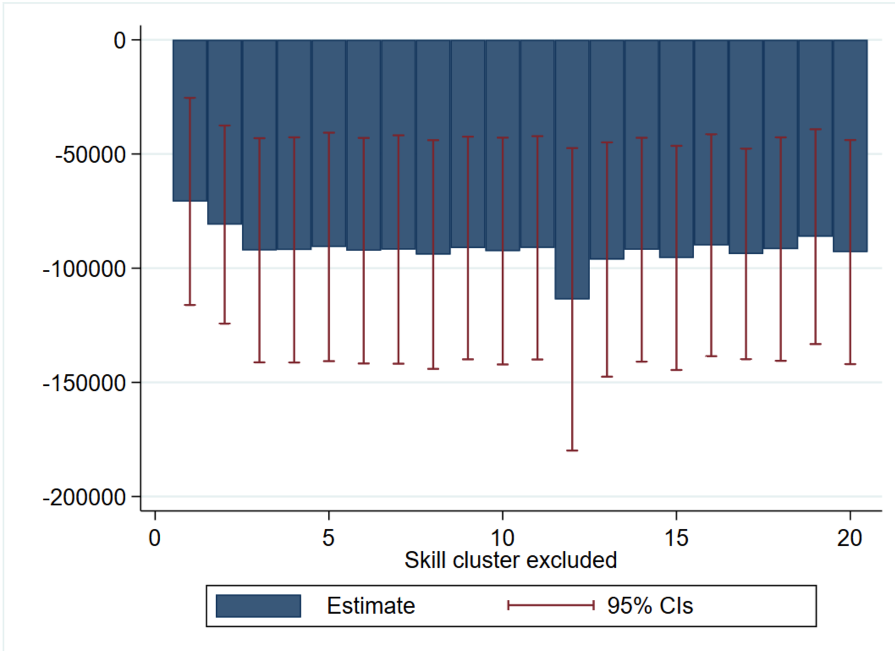
Notes: Each line shows means of labor force non-participation relative to the time of displacement by low (HHI<0.1), medium (0.1≤HHI≤0.25), and high (HHI>0.25) HHI levels. The outcome is residualized with respect to relative time to separation, and all estimates are relative to relative time -1.

Figure A-6: Event Studies of Involuntary Displacement on Labor Force Non-participation, by HHI



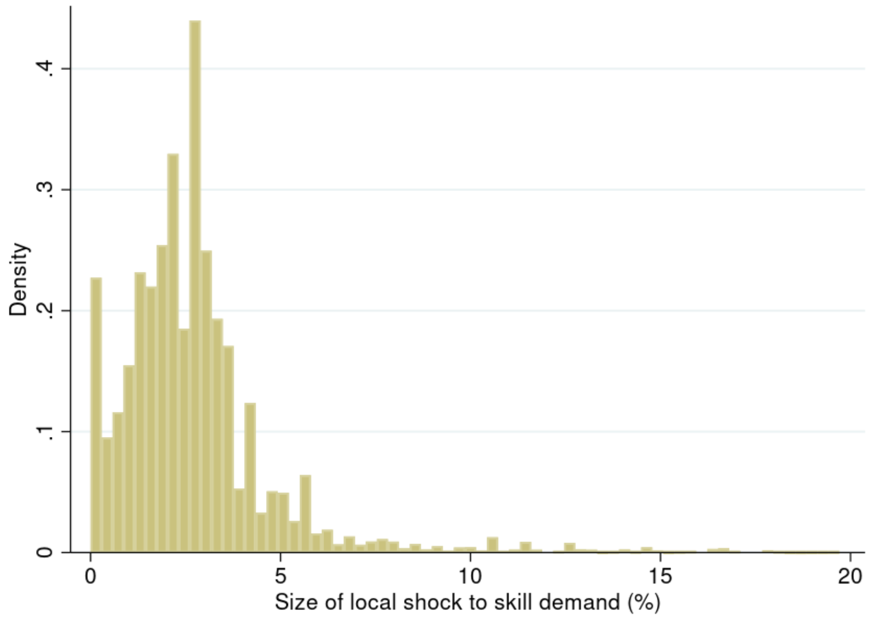
Notes: Each line shows means of working part-time relative to the time of displacement by low (HHI<0.1), medium (0.1≤HHI≤0.25), and high (HHI>0.25) HHI levels. The outcome is residualized with respect to relative time to separation, and all estimates are relative to relative time -1.

Figure A-7: Dropping one task cluster at a time, labor earnings



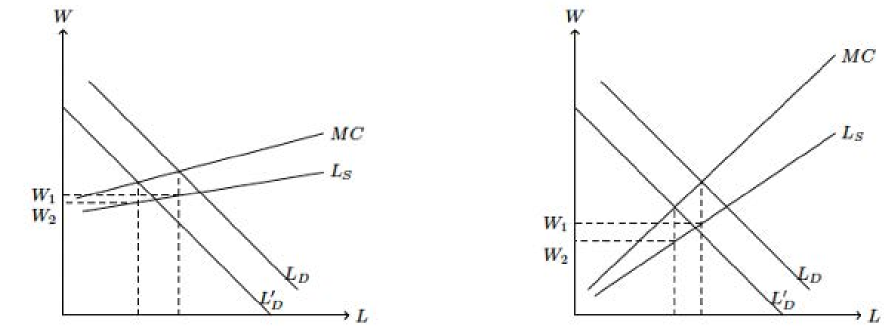
Notes: Authors' estimation as described in the text, dropping one task cluster at a time. The lines extending from the bars show the 95 percent confidence intervals, obtained from standard errors clustered at the LLM level.

Figure A-8: Histogram of the size of the adverse market demand shock generated by the mass layoff and establishment closure events



Notes: The figure shows the distribution of the size of the adverse local labor market demand shocks that are induced by the mass layoff and establishment closure events used in the analysis (i.e., the share of individuals in the skill cluster - local labor market - year cell that are being displaced). The average displacement event generates a 3 percent shift in the local skill demand, with a standard deviation of 4 percent.

Figure A-9: Visual conceptualization of the relationship between job loss and market power



Panel A: A relatively competitive market

Panel B: A relatively non-competitive market

Notes: Panel A represents the demand and supply of labor at a firm that holds relatively little monopsonistic power, while Panel B represents the demand and supply of labor at a firm that holds a substantial amount of monopsonistic power. The only difference between the graphs in Panel A and Panel B is that the labor supply to the firm is considerably more inelastic in Panel B due to outside options being prohibitively costly or unavailable. This is a direct implication of the firm possessing more monopsonistic power. For a given level of labor demand, the firm will employ workers where the marginal cost curve intersects the labor demand curve, resulting in wage W_1. By design, W_1 will be higher in Panel A as firms in competitive markets will be less able to extract rent from workers. Our empirical specifications always control for this possible baseline wage difference over concentration through the HHI_{icmt_b} term in Equation (2).

The job loss events generate an adverse labor demand shock, shifting the local labor demand curve down. This implies that the reemployment wage should be lower irrespective of the market concentration that the worker faces. However, since the labor supply curve is more inelastic in Panel B, workers should experience a stronger earnings reduction if they are subject to a layoff in such a market. This is illustrated in the figure by comparing W_2 in Panels A and B. In other words, the wedge between the pre-displacement wage and the re-employment wage ($W_2 - W_1$) in a non-competitive market will be considerably higher than the wedge between the pre-displacement wage and the re-employment wage in a more competitive market. Therefore, even if a worker was in a more concentrated market before the displacement occurred, and even if the worker's pre-displacement wage was lower, the worker should still experience a larger reduction in re-employment wage following a job loss event.

Figure B-1: Cluster Validation

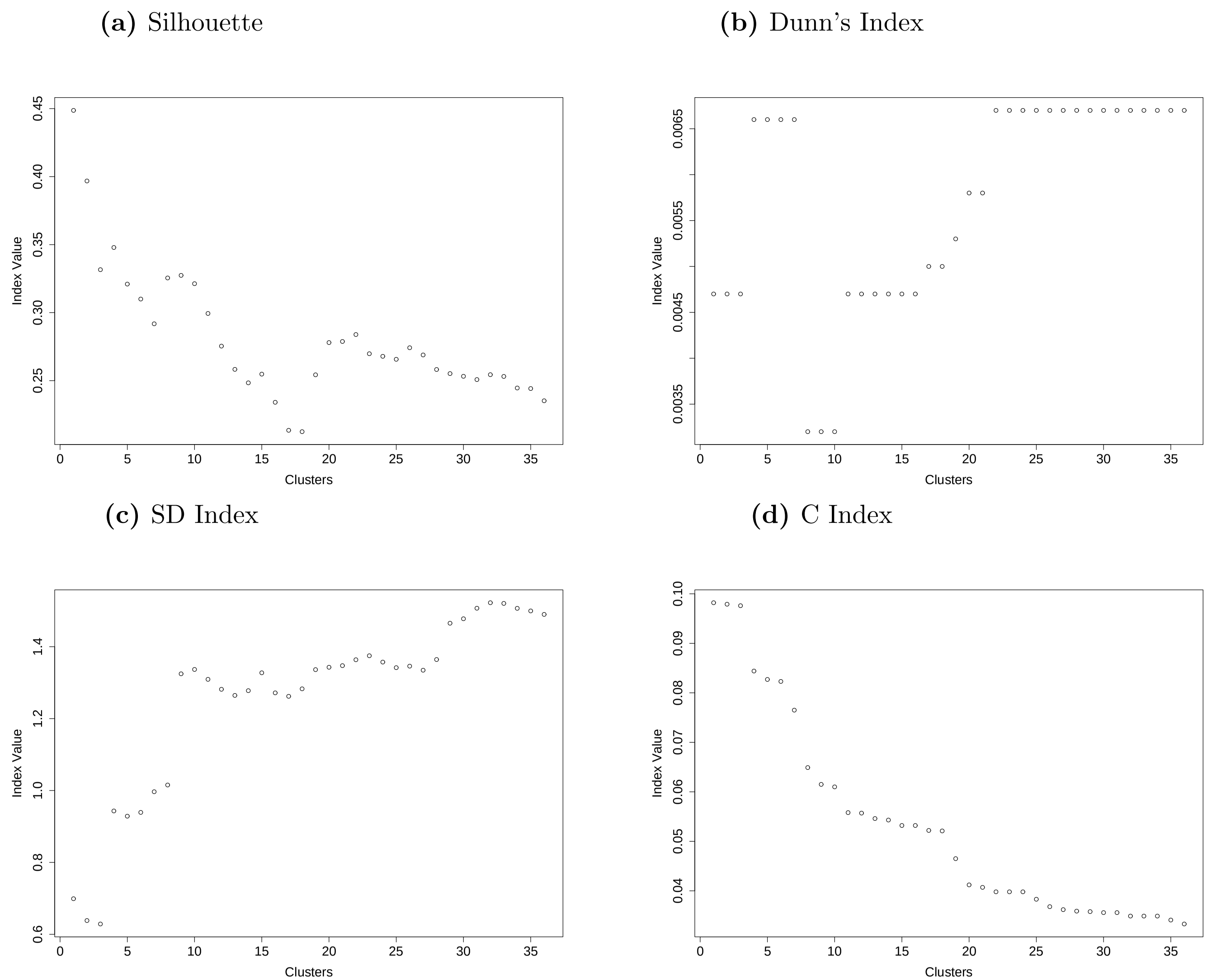
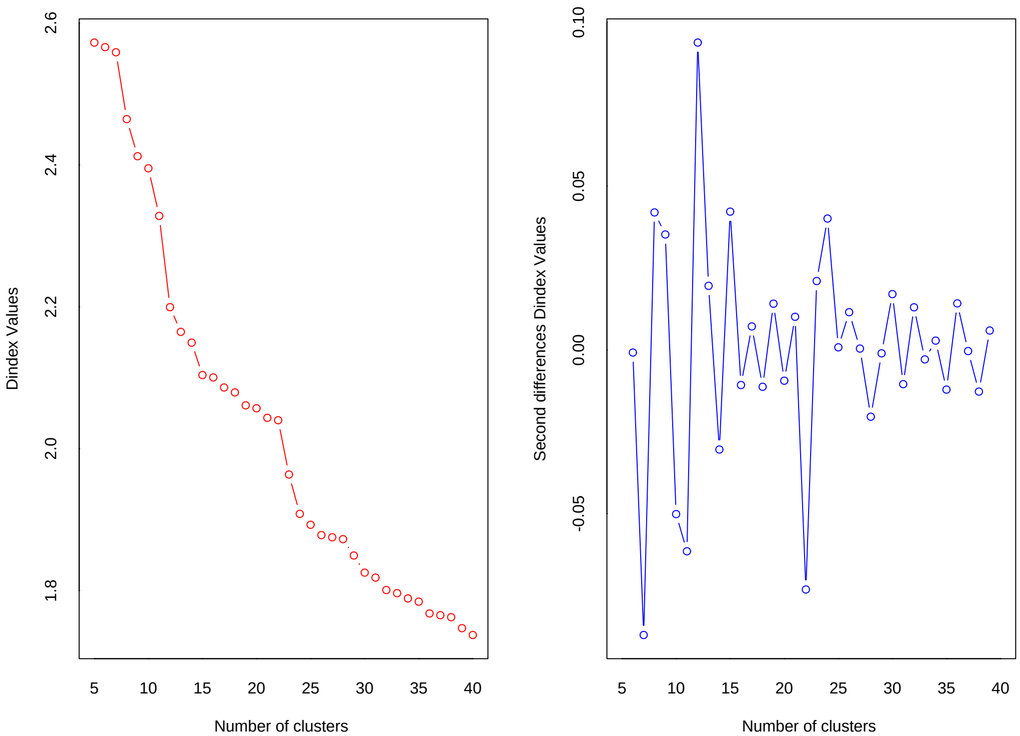


Figure B-2: Cluster Validation

(a) D Index



(b) Hubert Index

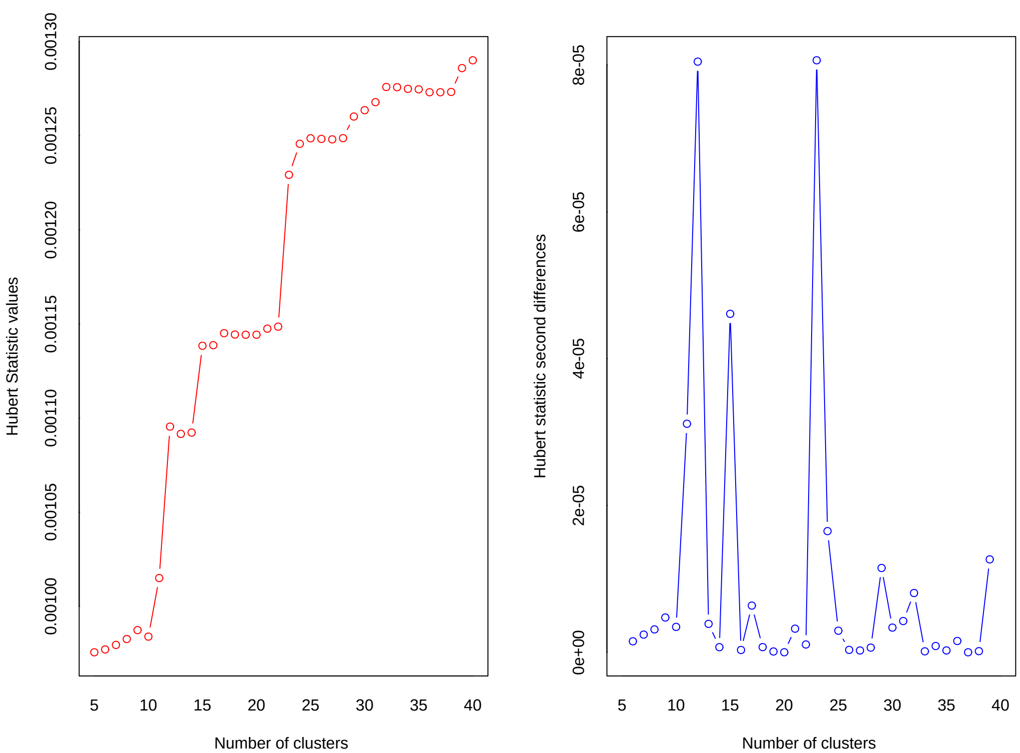
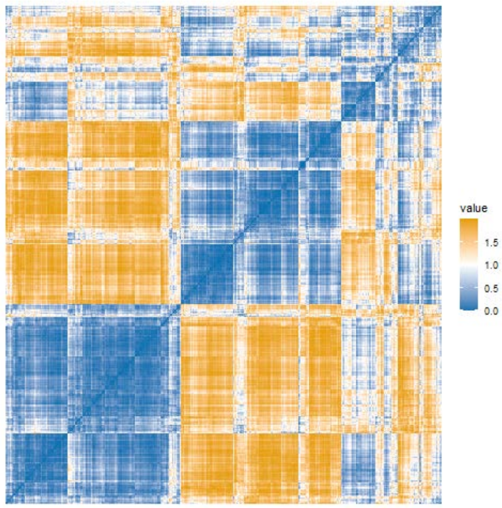


Figure C-1: Dissimilarity Measures, PCA versus Acemoglu and Autor (2011) Skills

(a) Acemoglu and Autor (2011) Dissimilarity



(b) Multiple Components Dissimilarity

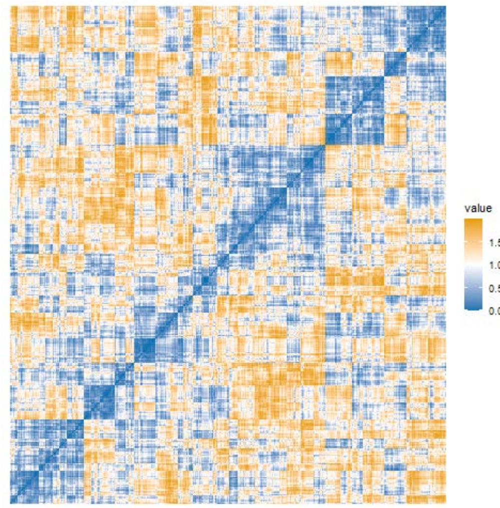


Table C-1. Main Results using a clustering algorithm based on PCA

	Income	Market Wage	NiLF	Employed	Part-time	Skill Downgrading	Skill Upgrading	Skill Mismatch
DD	-4616.124	-13519.291***	0.036***	-0.049***	0.010***	0.008***	0.007**	0.166***
	(2839.049)	(3089.073)	(0.004)	(0.005)	(0.002)	(0.001)	(0.003)	(0.014)
Base_HHItask	23402.181***	21931.491**	-0.000	-0.002	-0.009	0.003	-0.002	-0.012
	(8874.428)	(9360.522)	(0.004)	(0.005)	(0.006)	(0.004)	(0.008)	(0.022)
(DD==1)*Base_HHItask	-114439.704***	-118728.410***	0.038*	-0.016	0.086***	0.005	-0.089***	-0.215***
	(26174.154)	(29272.785)	(0.020)	(0.026)	(0.019)	(0.009)	(0.019)	(0.061)
Relative time and year FEs	x	x	x	x	x	x	x	
LLM, Task, and Industry FEs	x	x	x	x	x	x	x	
Individual FEs	x	x	x	x	x	x	x	
Outcome mean	515066.196	508046.224	0.032	0.965	0.016	0.153	0.421	0.360
Observations	7424245	7458540	7458825	7458825	7458825	7458825	7458825	7458825