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Household Joblessness in US Metropolitan Areas during the COVID19 Pandemic:

Polarization and the Role of Educational

Profiles

Thomas Biegert[1,2], Berkay Ozcan[1], and Magdalena Rossetti-Youlton[1]

Department of Social Policy
London School of Economics and
Political Science Houghton Street
London WC2A 2AE

Email: soc.pol.webteam@lse.ac.uk

Telephone: +44 (0)20 7955 6001

lse.ac.uk/social-policy

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Household Joblessness in US Metropolitan Areas during the COVID19 Pandemic: Polarization and the Role of Educational Profiles

Thomas Biegert[1,2], Berkay Özcan[1], and Magdalena Rossetti-Youlton[1]

Abstract

This study uses Current Population Survey 2016-2021 data to analyze household joblessness across metropolitan areas in the United States during the COVID19 pandemic. We first use shift-share analysis to decompose the change in household joblessness into changes in individual joblessness, household compositions, and polarization, i.e., the unequal distribution of joblessness across households. Household joblessness US metropolitan areas rises during the pandemic largely due to individual joblessness. But polarization contributes to household joblessness, indicating accumulation of employment risks in households. Second, we use metropolitan area-level fixed effects regressions to explain the large cross-labor market variance in household joblessness and polarization, focusing on the labor market make up of metropolitan areas reflected in the educational profile of the population. We measure three distinct features: educational levels, educational heterogeneity, and educational homogamy. Household joblessness is strongly correlated to educational levels. How polarization contributes to household joblessness is shaped by educational heterogeneity and homogamy.

Key words: household joblessness, COVID19, polarization; educational heterogeneity; educational homogamy

JEL: D1, I380, J210

[1] London School of Economics and Political Science, Department of Social Policy
[2] Corresponding author: t.biegert@lse.ac.uk

1. Introduction

This study analyzes household joblessness during the COVID19 pandemic in United States (US) metropolitan areas. Household joblessness is the phenomenon when no working age household member is in employment. Existing research shows that household joblessness has detrimental outcomes for all household members including children. The likelihood of poverty and material deprivation is particularly high when entire households become jobless due to one or more members losing their job (de Graaf-Zijl and Nolan 2011; Scutella and Wooden 2004; see also our discussion in our conclusion section). Furthermore, the experience of living in a household in which no parent is working detrimentally affects children's education and labor market outcomes over and above the impact of poverty (Curry, Mooi-Reci, and Wooden 2019, 2022; Ermisch, Francesconi, and Pevalin 2004; Mooi-Reci, Wooden, and Curry 2020). Thus, household joblessness has immediate adverse effects on household members, *and* it entrenches social inequalities in the long term. Given the detrimental consequences, there is surprisingly little sociological research on extent and development of household joblessness. Our first contribution is to describe whether the COVID19 economic crisis has exacerbated the issue in US metropolitan areas.

Our second contribution is to assess whether the development of household joblessness across US metropolitan areas during the pandemic results from an accumulation of disadvantages in some households. One reason for the dearth of research on household joblessness might be the assumption that individual joblessness and household joblessness move in lockstep. If we understand variance in the former, we can explain variance in the latter. However, previous work shows a decoupling between rising individual employment rates and stagnant or increasing rates of household joblessness in many advanced economies over the last several decades (Corluy and Vandenbroucke 2017; Gregg, Scutella, and Wadsworth 2008). Gregg and colleagues (Gregg et al. 2008; Gregg and Wadsworth 2001) call this process polarization, defined as the deviation in household joblessness from a counterfactual that emerges if all individuals have the same risk of joblessness, i.e., joblessness is randomly distributed across households. This trend is most visible in the rise of dual-earner households on one side and completely jobless households on the other. It emerges because households accumulate employment risks. Some have a greater share of household members with a higher likelihood to lose their job than others. Polarization implies that assessing individual labor market outcomes cannot accurately capture developments in household joblessness and thus misses an essential dimension of social inequality.

As our third contribution, we propose that educational profiles of the population can explain the stark differences in household joblessness and polarization across metropolitan areas. Existing comparative work on household joblessness during economic crises shows that sudden employment shocks not only increase household joblessness but also accelerate polarization (Biegert and Ebbinghaus 2022; Corluy and Vandenbroucke 2017). But invoking welfare regimes and typical household structures in cross-national comparisons does not yield satisfactory explanations of cross-national differences. We argue that inequality in economic outcomes such as in the likelihood of job loss in a labor market is reflected in educational levels and educational heterogeneity (Nielsen and Alderson 1997). How this translates into household joblessness depends on how education is clustered in households, which can be traced to dynamics of household formation, especially educational homogamy (Breen and Salazar 2011; Eika, Mogstad, and Zafar 2019; Schwartz 2010; Ultee, Dessens, and Jansen 1988). The educational stratification in household and labor market formation, e.g., in the shape of greater homogamy at different levels of education and educational heterogeneity, means that labor markets with different educational profiles shape household joblessness and polarization risks. Assessing differences in household joblessness and polarization across metropolitan areas with different educational profiles, our study also contributes an important dimension to the literature on spatial inequality in the USA (e.g. Chetty 2014; Jargowsky 1996; Moller, Alderson, and Nielsen 2009; VanHeuvelen and Copas 2019).

Our analysis uses quarterly data from the Current Population Survey (CPS) for 2016 to 2021 (Flood et al. 2021). Quarterly data allow us to follow the developments of the pandemic closely. We focus on metropolitan areas as local labor markets following previous research on spatial economic inequality in the USA (Abel and Deitz 2019; Doussard, Peck, and Theodore 2009; Jargowsky 1996; Milkman and Dwyer 2002; Reardon and Bischoff 2011). The analysis proceeds in two steps. First, we use shift-share analysis to decompose changes in household joblessness since before the onset of the pandemic (Biegert and Ebbinghaus 2022; Gregg et al. 2008; Gregg and Wadsworth 2001). Subsequent to describing trends in household joblessness, the decomposition enables us to assess how much of the change in household joblessness can be attributed to polarization, i.e., the unequal distribution of joblessness across households. Second, we use quarterly metropolitan area level CPS data in panel fixed-effects model to assess how the educational profiles of metropolitan area labor markets ameliorated or exacerbated household joblessness and polarization during the pandemic. Analyzing metropolitan areas provides us with a great opportunity to assess the role of educational profiles as they are relatively comparable in their underlying shared macroeconomic conditions. The analysis systematically identifies the areas in which a greater accumulation of employment risks in households causes short-term hardship and entrenched long-term disadvantage. Assessing the importance of educational profiles contributes to developing new theoretical arguments to explain growing multi-dimensional economic inequality across geographical space.

2. Background

2.1 Polarization in household joblessness because of accumulation and absorption

When people lose their jobs in economic downturns, an increase in households in which no one is working is almost unavoidable. But the extent to which individual job-loss translates to household joblessness depends on how job-loss is distributed. We use a framework proposed by Gregg and colleagues (Gregg et al. 2008; Gregg and Wadsworth 2001) that describes the unequal distribution of individual joblessness across households as polarization. Importantly, the benchmark against which they measure polarization is a random distribution of joblessness across households. The accumulation scenario comes into play when job-loss disproportionately affects households that are more likely to be thrown into household joblessness. This could be the case if many single earner households are hit or if job-loss is so concentrated that both earners in dual earner households lose their job. These households would thus accumulate joblessness while other dual earner households remain unscathed and keep both jobs. In Gregg and colleagues (Gregg et al. 2008; Gregg and Wadsworth 2001) framework, accumulation of individual joblessness in households means positive polarization (Biegert and Ebbinghaus 2022). By contrast, in the absorption scenario job-loss is concentrated so that households with only one earner keep their jobs and dual earner households lose one job but keep one household member in employment. Households would thus absorb the job-loss of single members, leading to negative polarization. In the accumulation scenario, there is a greater increase in household joblessness as compared to a random distribution of job-loss. In the absorption scenario, there is less.

The few existing explanations of why some labor markets foster household joblessness and accumulation whereas others show absorption have received only mixed empirical support. Previous research applying the polarization framework describes national trends since the 1970s and changes during the 2008 economic crisis (Biegert and Ebbinghaus 2022; Corluy and Vandenbroucke 2017; Gregg et al. 2008; Gregg and Wadsworth 2001). To explain variation in household joblessness and polarization across economies, these studies invoke typical household structures and welfare regimes. By and large, there is evidence that countries with more traditional household structures in which single breadwinners work in protected insider jobs are more negatively polarized. By contrast, countries with individualized family structures and liberal or universal welfare support show more positive polarization (Gregg et al. 2008; Gregg and Wadsworth 2001). However, there are exceptions. For instance, given its residual welfare state and prevalence of non-traditional household structures, the USA shows surprisingly low levels of polarization in the decades leading up to the 2008 economic and financial crisis (Gregg et al. 2008). Moreover, the observed secular trends do not hold in times of economic crisis. During the 2008 economic and financial crisis and thereafter, traditional male breadwinner countries in the European South showed especially large increases in polarization (Biegert and Ebbinghaus 2022; Corluy and Vandenbroucke 2017). Arguing from a micro perspective of employment risks and their clustering in households, the following section will propose that educational profiles of labor markets can help explain household joblessness and polarization.

2.2 Educational profiles of labor markets

How economic crises affect different local labor markets largely depends on their sectoral and occupational structures. To explain how shocks affect spatial inequality, we thus need to consider the distribution of jobs with different degrees of vulnerability across local labor markets. We furthermore need to understand how jobs of varying risk are clustered within households. We propose that the educational profile of the population in a local labor market provides a parsimonious way of combining considerations about labor market structures and household compositions. Our argument primarily relies on individuals, their education, and how they cluster in households. But because the educational composition of a labor market's population yields externalities, we need to look at the aggregate educational profile of a local labor market to fully understand variation in household joblessness and polarization between them. We focus on three aspects of the education profile of the population in a metro area: educational level, educational heterogeneity, and educational homogamy.

It is well-established that workers with higher educational attainment experience fewer job losses during economic downturns whereas lower education increases the likelihood of job-loss (Farber 2005, 2015; Nickell 1979). For instance, Farber (2015) finds that while there is a cyclical pattern in job loss for all educational groups in the US between 1981 and 2013, job loss rates are dramatically higher for less educated workers. Further, more educated workers find new employment more quickly after job loss, shortening unemployment spells (Farber 2015; Gesthuizen, Solga, and Künster 2011; Klein 2015; Riddell and Song 2011). Educational levels are thus important to understand varying levels of job-loss during economic downturns across labor markets. Overall educational levels are also essential for how joblessness is distributed across the labor market and households. For instance, lower educated individuals profit from living in areas with higher educational levels. Areas with high stocks of human capital deal better with economic shocks and yield positive externalities for their lower educated occupants (Glaeser and Saiz 2004; Kemeny and Osman 2018; Moretti 2004). Winters (2013), for instance, finds that human capital externalities significantly decrease their probability to become unemployed. By extension of individual joblessness, we thus expect household joblessness to rise more strongly in labor markets with lower levels of education.

Beyond educational levels, the relative position of individuals in the educational distribution of a labor market will affect their chances to lose their job in an economic downturn. The distribution of human capital among the population is the main determinant of inequality in a labor market (Mincer 1970). Studies of US labor markets show that educational heterogeneity is one central drivers of within labor market inequality in economic outcomes (Moller et al. 2009; Nielsen and Alderson 1997; VanHeuvelen and Copas 2019). During an economic downturn, greater educational inequality might lead to a concentration of job-loss among the lower educated. Educational heterogeneity thus should affect the inequality in the likelihood of individual job-loss. This might be reflected in polarization of household joblessness as well to the degree that households accumulate individual job-loss risks.

How much educational levels and heterogeneity affect household joblessness and polarization depends on how education is clustered in households. Educational clustering in households is driven by assortative mating. Highly educated couples are more likely to be dual earners in secure jobs, lower educated households are more likely to be in precarious employment or jobless. Educational homogamy thus increases the likelihood of positive polarization. The US has comparatively high levels of educational homogamy (Greenwood et al. 2014; Hryshko, Juhn, and McCue 2017; Schwartz and Mare 2005). But labor markets differ in how much they attract homogamous households. So-called superstar cities and large metropolitan areas, for instance, house significant shares of highly educated power couples because they offer them rewarding job opportunities (Costa and Kahn 2000).

We derive some guiding expectations: educational levels should be negatively correlated with household joblessness. Whether household joblessness is exacerbated by positive polarization depends on how unequally education is distributed and how it is clustered in households. When low educational levels are combined with greater educational inequality and high homogamy, we can expect higher household joblessness due to higher individual joblessness but also because higher polarization leads to disproportionate household joblessness at a given level of individual joblessness because households accumulate risks. Labor markets that combine high educational levels and low heterogeneity with lower levels of homogamy should have lower polarization, they might even show absorption.

2.2 Context: The COVID19 economic crisis in US metropolitan areas

We assess the development of household joblessness during economic downturns, the role of polarization, and the explanatory power of educational profiles of local labor markets by analyzing the COVID19 pandemic in US metropolitan areas. The COVID19 pandemic caused job-loss in the US on a scale not seen since the 2008 Great Recession. More than 9.6 million working-age individuals lost their job over the course of 2020 (Bennett 2021). The existing evidence also shows large spatial variation in the employment impacts across US labor markets (Dalton 2020; Mulligan 2022; Smith 2021).

Several specificities of the COVID19 crisis as compared to other economic downturns are worth noting. First, job loss during the pandemic was concentrated around particular occupations. For instance, areas with large hospitality sectors saw the steepest initial increases in unemployment whereas areas with higher shares in finance and insurance were less affected (Dalton 2020; Smith 2021). The

COVID19 crisis also incited the so-called “Great Resignation”. The Great Resignation refers to the massive number of workers who voluntarily left their jobs mostly for non-income reasons (Birinci and Amburgey 2022; Kuzior, Kettler, and Rąb 2022). In 2021, the monthly resignation rates across all industries in the US were the highest in the last 20 years, while the job openings were higher than the number of hires (Faccini, Melosi, and Miles 2022). How job-loss was concentrated in the occupational distribution and where it was located geographically might therefore differ from other economic downturns. Second, the US welfare state traditionally compensates for the loss of earnings with only meagre unemployment benefits. Household joblessness is therefore a particularly problematic situation. Yet, the US Government amended payments during the initial phase of the pandemic via the Coronavirus Aid, Relief, and Economic Security (CARES) Act. Still, the termination of the emergency unemployment compensation puts a significant share of the population at risk of poverty. Third, lockdown and isolation rules might have affected how households reacted to job loss as compared to previous economic downturns. For instance, there is mixed evidence that households “doubled up” during previous crises in order to cope with income loss, and, especially in the Great Recession, to cope with housing debt with the collapse of the housing market (Bitler and Hoynes 2015; Mykyta and Macartney 2011; Wiemers 2014). While changes in household composition during previous crises such as the Great Recession were more persistent, during the COVID19 pandemic, there’s evidence that headship rates decreased early in the pandemic but returned pre-pandemic levels within few months (García and Paciorek 2022).

We analyze metropolitan areas as local labor markets. Recent literature on US local labor markets prefers looking at commuting zones (e.g. Autor and Dorn 2013; VanHeuvelen and Copas 2019). Commuting zones more clearly outline local labor markets as they are constituted to represent the geographic area that clusters individuals’ work travels. For analyzing variation across local labor markets an added advantage of commuting zones is their higher case number (over 700). However, given that no dataset that allows for the creation of commuting zones offers timely data on the COVID19 pandemic, we choose to analyze the arguably next best option in metropolitan areas. There are several good reasons for analyzing metropolitan areas. First, because more than 80% of Americans live in metropolitan areas, their analysis provides an important insight into a large proportion of the US population (US Census Bureau 2022). There is a rich literature on spatial economic inequality in the US that we can connect to. Metropolitan areas in the US serve as key spatial units to study job polarization (Doussard et al. 2009; Milkman and Dwyer 2002), economic segregation and income inequality (Abel and Deitz 2019; Jargowsky 1996; Reardon and Bischoff 2011; Volscho 2007), and racial segregation (Iceland et al. 2010; Lichter, Parisi, and Taquino 2015; Massey and Denton 1988; Tienda and Fuentes 2014). This is because, second, metropolitan areas are a good approximation of local labor markets as they are made up of a large population center with dense economic activity, and adjacent communities that economically and socially interact with the center (Abel and Deitz 2019; Fowler and Jensen 2020). However, variations between metropolitan labor markets lead to significant inequalities between US cities (Mulligan, Reid, and Moore 2014). Part of the explanation for variation between metropolitan areas is that third, they have different educational profiles. A higher demand and "premium" pay in some metropolitan areas lead to the concentration of skills (Li, Wallace, and Hyde 2019; Liu and Grusky 2013). Essletzbichler (2015) finds that metropolitan areas with large shares of the top 1% are characterized by higher levels of skill polarization, higher labor force participation and lower unemployment for those with little formal education. Metropolitan areas also vary in their attractiveness to different household compositions, e.g. homogamous power couples (Costa and Kahn 2000). Processes of household formation are strongly concentrated within metropolitan areas (Liao and Özcan 2013). Finally, the COVID19 pandemic's impact was strongest in metropolitan areas. The higher early infection rates of COVID-19 in more densely populated urban areas caused severe employment losses early on. Compared to rural residents, urban adults were more often unpaid for missed hours, inability to work or to look for work (Brooks, Mueller, and Thiede 2021). These losses could have longer-term effects on persistent job reductions in metropolitan areas (Cho, Lee, and Winters 2021).

3. Current Population Survey 2016-2021[1]

3.1 Data and sample

We use repeated monthly cross-sectional data (pooled in quarters) from the Current Population Survey (CPS) 2016-2021 as provided by IPUMS (Flood et al. 2021). Our analysis proceeds in two steps. First, we conduct a shift-share decomposition of the change in household joblessness across metropolitan areas from before the pandemic to since its onset (Gregg et al. 2008; Gregg and Wadsworth 2001). The decomposition enables us to separate the contribution of polarization to changes in household joblessness from the contributions of changes in individual joblessness and changes in household size. Second, we use our measures of household joblessness and polarization at the metropolitan-area level as dependent variables in panel fixed-effects regressions to investigate their variation between metropolitan areas with different educational profiles during the pandemic.

Monthly CPS data offers large sample sizes of ~125,000 individuals in 50,000 households and a rich set of variables describing employment, socio-demographics, and family-structure status of these households. Sample sizes vary widely for metropolitan areas. Some areas have less than 10 observations in some months, whereas others consistently have many thousands. To achieve robust estimates, we pool data in quarters. Our data includes 24 quarters starting with Q1 2016 and ending in Q4 2021. We include all households with at least one working-age member (16-64). Both the shift-share analysis and the panel fixed effects analyses operate at the (aggregate) level of metropolitan areas. To ensure that we estimate all our metropolitan area level indicators robustly, we exclude metropolitan areas with less than 50 households in any quarter. That leaves us with 204 of the original 261 metropolitan areas. Aggregate level variables are constructed based on, on average, 786 working age individuals in 409 households per quarter and metropolitan area. We use survey weights included in CPS throughout to calculate aggregate level indicators. Our metropolitan area level dataset contains 4,896 cases (204 metropolitan areas over 24 quarters).

[1] Anonymized replication files can be found here: https://osf.io/6cr3n/?view_only=cd28a6eeeb5f47db88a9c9e5373e3e93

3.2 Variables

Our two main outcomes of interest are household joblessness and polarization of household joblessness. To construct our measure of *household joblessness*, we consider every individual employed (0) who indicates to be employed whether they are at work or were not at work last week but have a job or are in the armed forces. We code as non-employed (1) every other employment status - unemployed or not in the labor force, including housework, education, inability to work, early retirement, and unpaid work. We then code every household as jobless (1) if no working-age member is employed. Every household with at least one member in employment is assigned not jobless (0). We calculate the household joblessness rate at the level of metropolitan areas as the rate of working-age individuals who live in entirely jobless households.

Our measure of *polarization* captures the inequality in the distribution of joblessness across households. We follow Gregg and Wadsworth (2001) who measure polarization as the difference between the actual rate of household joblessness and a counterfactual household jobless rate. The counterfactual household joblessness rate is what would emerge if the distribution of joblessness across individuals were random, i.e., every individual had the same probability of being jobless, with

$$\widehat{w}_k = n^k \tag{1}$$

where $\widehat{w}_k$ is the counterfactual household joblessness rate for a household of k working age household members and n is the individual joblessness rate in a metropolitan area. This counterfactual household joblessness rate does not entail any inequality in the likelihood of different households being jobless. It can be calculated using the individual joblessness rate of a metropolitan area and information about household sizes as defined by the number of working-age members. A household with only one working-age member has the same counterfactual rate as the overall individual joblessness rate in a given metropolitan area at a given time. The counterfactual household joblessness rate gets lower for households with more working-age members. It is calculated as the individual joblessness rate to the power of n, with n being the number of working-age household members. On the aggregate level of metropolitan areas, the counterfactual household joblessness rate is then given by the individual joblessness rate weighted by the distribution of working-age individuals across households of different sizes with

$$\widehat{w} = \sum_{k=1}^{K} S_k \widehat{w}_k = \sum_{k=1}^{K} S_k n^k \tag{2}$$

where S_k is a weight that indicates the proportion of the population living in households of size k. A metropolitan area with a disproportional number of single households, for instance, would have a relatively higher counterfactual household joblessness rate at a given individual joblessness rate.

Polarization is the difference between this counterfactual and the actual rate of household joblessness, i.e., the proportion of working-age individuals living in households without any employment,

$$P = w - \widehat{w} = \sum_{k=1}^{K} S_k w_k - \sum_{k=1}^{K} S_k \widehat{w}_k = \sum_{k=1}^{K} S_k (w_k - n^k) \tag{3}$$

If joblessness is distributed randomly, the counterfactual and actual household joblessness rates become identical; thus, polarization becomes 0 (neutral). Negative polarization indicates that work is distributed so that fewer households are without work than predicted by random distribution. We could imagine this to be the case in contexts with strong male breadwinner models where the typical family model entails one earner with several dependents. Polarization turns positive when there are more jobless households than expected. We could imagine this in contexts with many multiple earner households on the one side and many households with no one working on the other. Positive polarization conforms to our understanding of risk accumulation in precarious jobless households while many others are more fortunate.

The information on individual and household joblessness, polarization, and household sizes are all we need for the shift-share analysis. For our metropolitan area level panel analysis, we create additional measures that capture the make-up of metropolitan area labor markets and their demographic composition.

We base the measures for our educational profiles on years of schooling of all 25 to 64 year old individuals (as transformed from detailed information on educational attainment following Jaeger (1997)). We measure *educational levels* as the average number of years of schooling in a metropolitan area-quarter. Our measure of *educational heterogeneity* is a Theil index of years of schooling. The index provides a measure of educational dividedness that takes a high value when individuals have varying numbers of years in education and a low value when most individuals have similar numbers of years in education. Finally, we measure the prevalence of *educational homogamy* as the correlation between the higher educated partner and the lower (or equally) educated partner in partner households (married and cohabiting).

We construct the other socio-demographic measures and indicators for labor market structures as shares at the metropolitan area level. Our choices follow literature on spatial income inequality in the US (Moller et al. 2009; VanHeuvelen and Copas 2019). To measure the ethnic composition of a metropolitan area, we calculate the share of Black (*% Black*), Hispanic (*% Hispanic*), and White (*% white*) population (these measures are based on the total population). We measure the share of migrants as percentage of the working age population (*% migrant*). We measure the prevalence of older people by calculating the share of individuals 65 and older of the total population (*% older*). We measure the prevalence of single households by calculating the share of households without a partner as a percentage of the total number of households (*% single*). We measure the population size of metropolitan areas as the total population in absolute numbers (*population size*). Finally, we measure distribution of the population across the center and periphery of the metropolitan area (*% living in the central city*).

To measure the economic prosperity of a metropolitan area, we use the median household income (*medianinc*) equivalized by household size (OECD equivalence scale). Income data is not available in the monthly CPS data. We calculate annual median household incomes using the CPS Annual Social and Economic Supplement (ASEC). To model labor market sectoral structures, we calculate four indicators. First, we measure the size of the government sector by the share of workers in public administration (*% gov*). We measure the size of the manufacturing sector by the share of workers in manufacturing (*% manu*). Third, we measure the size of the FIRE sector by the share of workers in finance, insurance, and real estate service jobs (*% fire*). Finally, we measure the size of the service sector as the share of workers in all other service jobs (*% service*).

4. Analytical strategy

4.1 Shift-share decomposition

Shift-share decomposition of changes in household joblessness uses data on individuals in households to assess changes in joblessness at the individual level and the household level (Gregg et al. 2008; Gregg and Wadsworth 2001). The decomposition determines which part of the change in household joblessness can be attributed to changes in individual joblessness, changes in household sizes, and changes in polarization. We want to analyze changes in household joblessness since the onset of the pandemic. We calculate changes in household joblessness and changes in the contributing factors for each quarter starting from Q2 2020. Our comparison is the average of the respectively same quarter for the years 2016 to 2019. By comparing the same quarter, we parse out seasonality effects. Using the three-year average as a benchmark helps us estimate changes that were induced by the pandemic rather than expressing a predetermined trend.

The change in household joblessness can be broken down into the change in the counterfactual household joblessness rate and the change in the actual household joblessness rate subtracting the counterfactual household joblessness rate (equation (4)).

$$\Delta w = \Delta \widehat{w} + \Delta (w - \widehat{w}) \tag{4}$$

Following from equation (3), the two terms can be calculated using information on the change in the individual joblessness rate n for households of size k weighted by the change in the share S of individuals living in households of size k and information on the change in household joblessness of households of size k (equation (5)).

$$\Delta w = \sum_{k=1}^{K} \Delta\left(S_k n^k\right) + \sum_{k=1}^{K} \Delta\left(S_k\left(w_k - n^k\right)\right) \tag{5}$$

Eventually, the decomposition breaks down over-time shifts in household joblessness into fluctuations in *individual joblessness*, structural changes in *household sizes*, and *polarization* (equation (6)).

$$\Delta w =$$

$$\sum_{k=1}^{K} \Delta S_k\left(0.5 n_t^k + 0.5 n_{t+1}^k\right) +$$

$$\sum_{k=1}^{K} \Delta n^k \big(0.5S_{k,t} + 0.5S_{k,t+1}\big) + \tag{6}$$

$$\sum_{k=1}^{K} \Delta S_k \big(0.5(w_k - n^k)_t + 0.5\big(w_k - n^k\big)_{t+1}\big) +$$

$$\sum_{k=1}^{K} \Delta(w_k - n^k)(0.5S_{k,t} + 0.5S_{k,t+1})$$

First, household joblessness changes because of structural *changes in household size* (first right-hand sum term in equation (6)). Households can pursue different strategies to buffer job loss of individuals. For instance, they might "double up", i.e., merge households, to pool resources (Bitler and Hoynes 2015; Mykyta and Macartney 2011; Wiemers 2014). Unemployment might also cause households to split up (Brand 2015; Charles and Stephens 2004). Such developments on a larger scale would affect a metropolitan area's household jobless rate. In our decomposition, we can show how much such developments contribute to the overall change in household joblessness.

Second, *change in individual employment* (second right-hand sum term in equation (6)) during the pandemic, will necessarily affect the expected probabilities of household joblessness. More individuals without a job means more households entirely without work when job loss is distributed randomly. In the shift-share analysis, we attribute the observed changes in household joblessness to changes in individual joblessness for each household size (calculated as the change in the individual joblessness rate to the power of the number of working-age members in the respective quarter). When decomposing the change in household joblessness, we thus attribute that part to the fluctuations in individual joblessness that equals the change in counterfactual household joblessness.

The third component contributing to the overall change in household joblessness is the *change in polarization*. The decomposition breaks down changes in polarization into a *between* household-type and a *within* household-type component. Between-polarization (third right-hand sum term equation (6)) changes when job loss is unequally allocated across households of different sizes. For instance, between-polarization would rise if more single households lost their jobs and become household jobless whereas couple households keep their jobs. Within-polarization (fourth right-hand sum term in equation (6)) changes when joblessness is unequally distributed among households of the same size. This might result from households facing different risks of job loss due to educational differences. In our presentation of the decomposition, we will not focus on the two components of polarization. Instead, we present figures on polarization in total, which we obtain by simply adding the two components up. We conduct the shift-share decomposition for the merged sample of all 204 US metropolitan areas and for all metropolitan areas separately.

4.2 Metropolitan area level panel fixed effects models

In our multivariate analysis, we estimate how the development of household joblessness and polarization differed between metropolitan areas with different educational profiles. Our baseline model specification is as follows:

$$Y_{it} = c_i + \beta_Q Q_{it} + \beta_E E_{it} + \beta_{QE} Q_{it} E_{it} + \beta_Z Z_{it} + \vartheta_i + \varepsilon_{it} \quad (7)$$

Where Y_{it} is the level of household joblessness or polarization in a metropolitan area i in quarter t. On the right-hand side c_i is the metropolitan area time-constant intercept. Q_{it} is an indicator of the quarter. E_{it} represents our three measures of education, i.e., levels, heterogeneity, and homogamy. $Q_{it}E_{it}$ is the interaction term of the quarter and the educational measures. We use these interactions (up to four-way) to estimate differences between the metropolitan areas in the most flexible way and to capture all combinations of education measures, which generate different "education profiles". Z_{it} represents our battery of time-varying metropolitan area level covariates. We include some as contemporaneous covariates (% Black, % Hispanic, % migrants, populations size) and some as one quarter lags to avoid overcontrol bias (% single, % older, median equivalized income, % public sector, % manufacturing, % FIRE, % other services, % living in central city) ϑ_i and ε_{it} are the time-constant and the time-varying component of the error term. We use fixed effects models to eliminate bias from time-constant unobserved heterogeneity between the metro areas (Allison 2009). The fixed-effects transformation eliminates the time-constant error term ϑ_i as well as the time-constant intercept. We cluster standard errors at the metropolitan area level.

The fixed effects model estimates coefficients for the association between deviations from the mean of metropolitan areas' household joblessness or polarization and the deviations from the mean of the right-hand side variables. We do not report the estimated regression coefficients from these specifications because our 24 time (quarter) dummies and their two-way, three-way, and up to four-ways interactions with our three key education measures generate numerous coefficients. Instead, we show and discuss the predicted values from these regressions as profile plots. The profile plots allow us to illustrate household joblessness and polarization for metropolitan areas with select combinations of education measures that describe specific education profiles, which are more or less commonly observed.

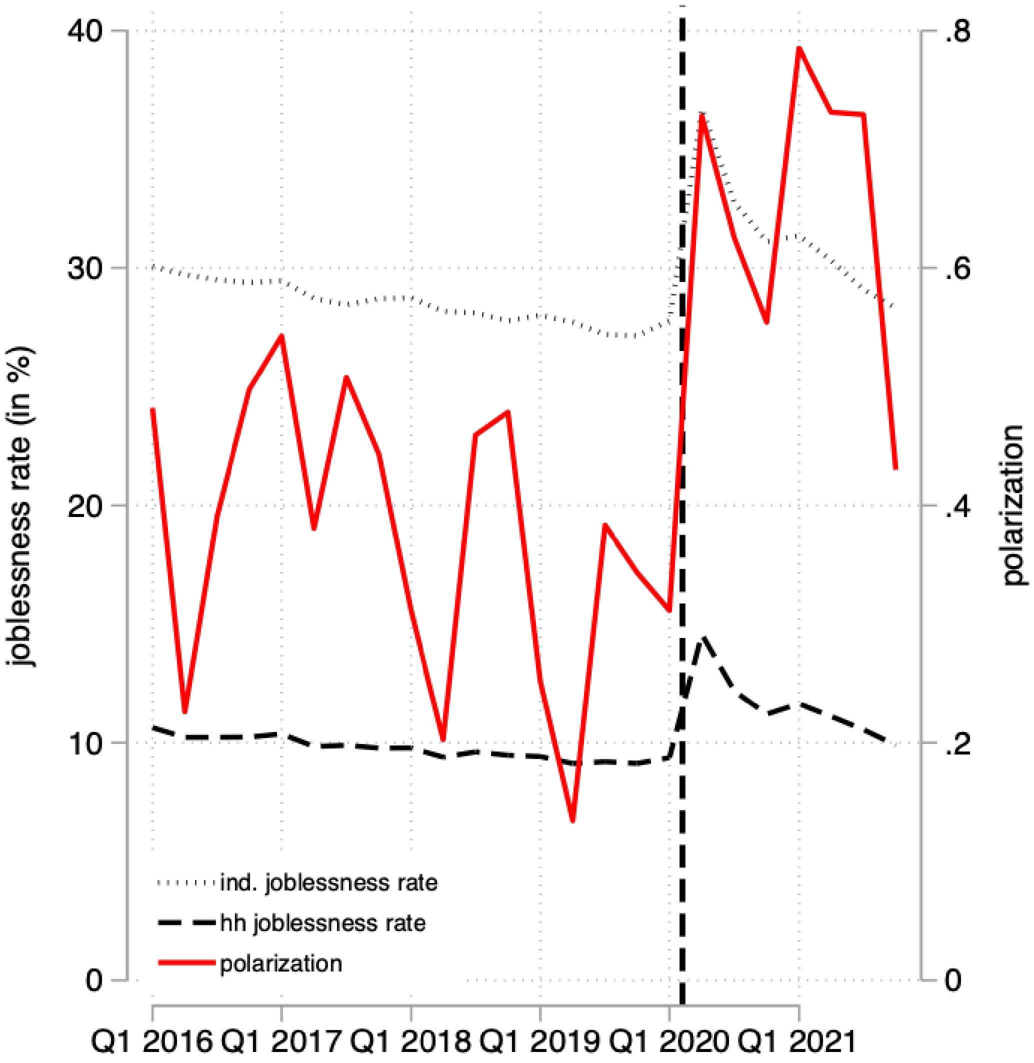
5. Results

5.1 Household joblessness and its decomposition in all US metropolitan areas combined

We first show overall trends in individual and household joblessness and polarization in all US metropolitan areas combined. Figure 1 illustrates the clear rise in joblessness both for individuals and households during the pandemic (left-hand y-axis). While the rate of household joblessness is naturally lower, an average 10% of the working-age population lives in entirely jobless households even before the pandemic hit. With the onset of the crisis, we see an uptick of about 5 percentage points. In 2021, both individual and household joblessness are trending towards pre-pandemic levels, although household joblessness plateaus slightly. That is because polarization increases, too (right-hand y-axis). Polarization hovers around 0.4% points before the pandemic but increases to 0.8% points at its pandemic peak. At this point, therefore, household joblessness is 0.8% points higher than we would expect for a random distribution of individual joblessness across households. Before and since the pandemic, polarization is always positive, thus indicating accumulation of employment risks in households.

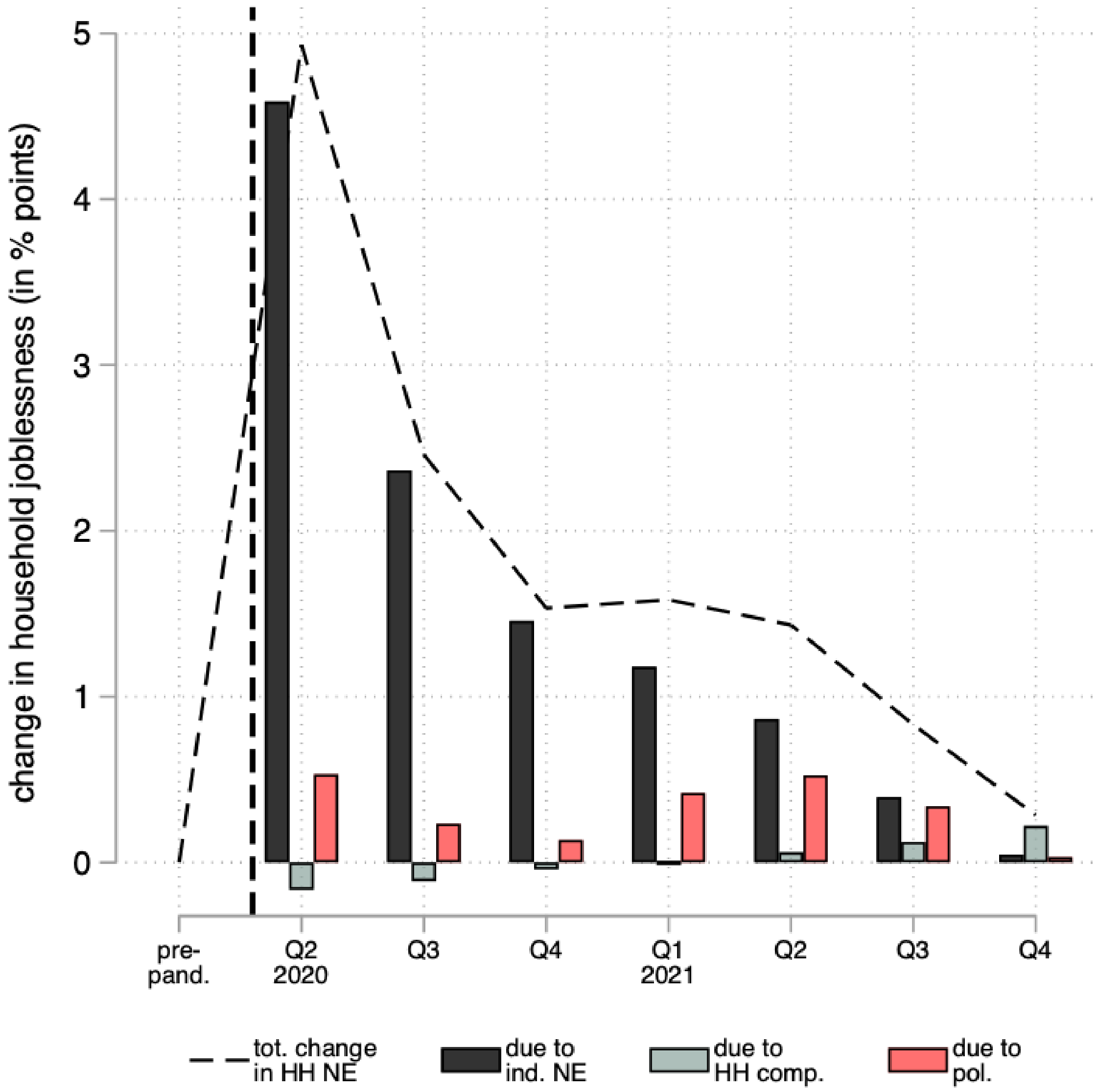
In our shift-share analysis we use the respective average quarters 2016-19 as the pre-pandemic baseline. We decompose changes relative to this baseline for each quarter from Q2 2020 until Q4 2021. Figure 2 displays the decomposition for the entire metropolitan area US. The dashed line indicates the total change in household jobless as compared to the 2016-2019 average (note that the line and bars do not show the change from quarter to quarter but always in reference to the pre-pandemic period). The bars in order from left to right represent the amount of the household jobless change for each quarter as compared to 2016-19 that is due to changes in individual joblessness, household sizes, and polarization. The three bars added together make up the total change in household joblessness compared to 2016-2019 (i.e., the dashed line). The horizontal line marks the onset of the pandemic.

Figure 1: Individual and household joblessness rates and polarization in metropolitan area US 2016-2021



Note: 'Metropolitan area US' is the population-weighted average of all 204 metropolitan areas in our sample. Left-hand y-axis indicates joblessness rate, right-hand y-axis indicates polarization. Vertical dashed line marks the onset of the pandemic before Q2 2020. Source: CPS 2016-2021, authors' own calculations.

Figure 2: Decomposition of change in household joblessness in metropolitan area US (Q2 2020-Q4 2021)



Note: Changes calculated as difference to quarter-specific average over 2016-2019. 'Metropolitan area US' represents the population-weighted average of all 204 metropolitan areas in our sample. Vertical dashed line marks the onset of the pandemic before Q2 2020. Source: CPS 2016-21, authors' own calculations.

Figure 2 shows an initial increase in household joblessness of about 5% points across metropolitan area US. This rise can be attributed to a large part to the increase in individual joblessness. Household joblessness decreases over the subsequent quarters as the contribution of individual joblessness diminishes. Household size's minimally negative contribution turns to a small positive contribution. Whereas household joblessness decreases with the lowering of individual joblessness, the contribution of polarization is increasing household joblessness by about 0.5 percentage points in most quarter until the fourth quarter of 2021.

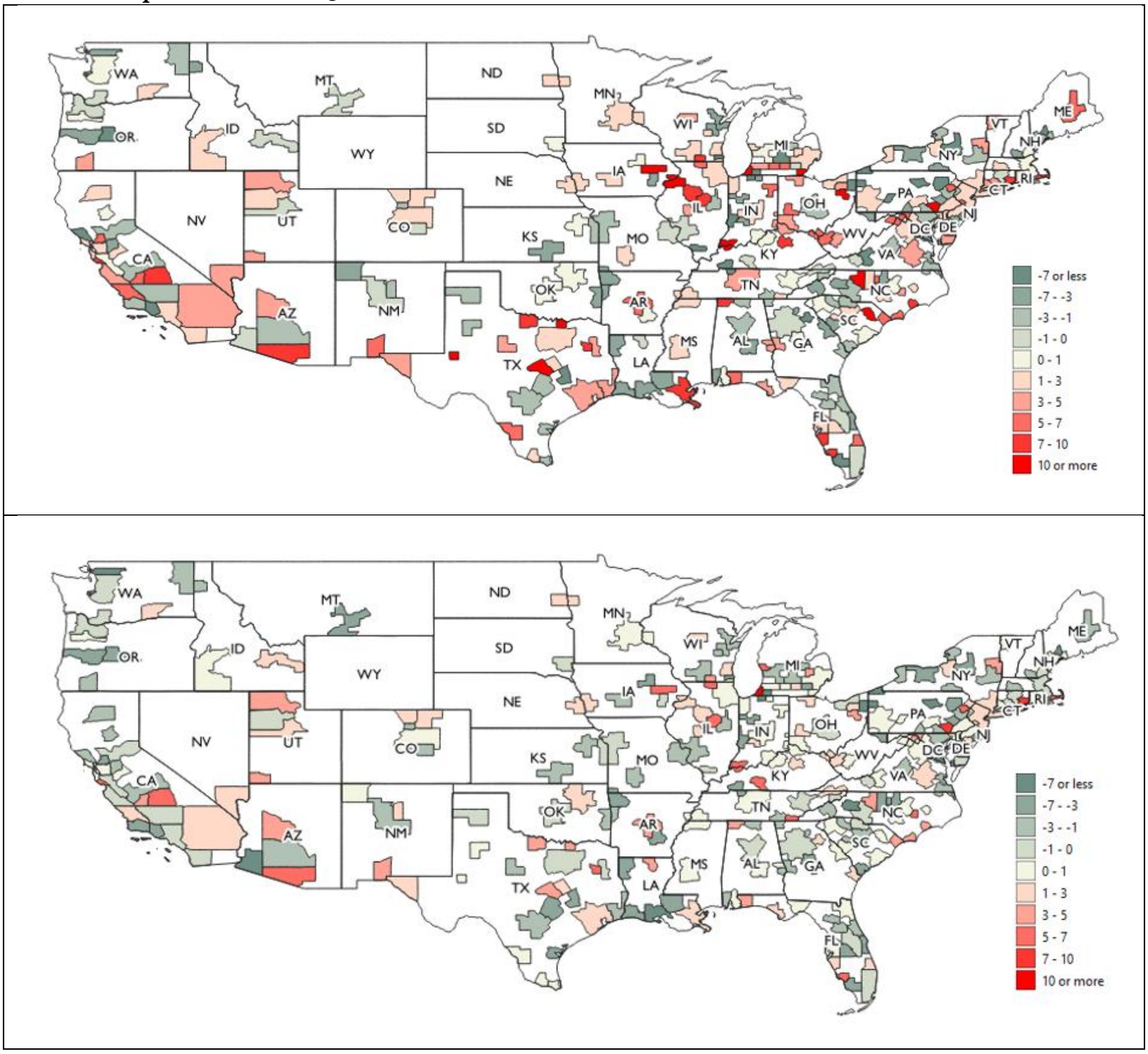
In robustness checks, we run the same decomposition for a sample that contains only households with at least one member aged 16-49. This is to test whether older households drive our findings, for instance, because they might prefer early retirement over searching for new, possibly worse jobs as implied in arguments about the "Great Resignation" (Schuster and Radpour 2022). The development of the components looks very similar for the younger subsample. Yet, while overall levels of household joblessness are lower than for the full working age sample (increase of slightly above 4% points in Q2 2020), the contribution of polarization is much larger (up to 1.8% points in Q2 2020) (see Appendix, Figure A1).

5.2 Variation across metropolitan areas

Even though the contribution of polarization is not negligible and household joblessness increases initially, looking at the US average might indicate that the issue is resolved by the end of 2021. This, however, ignores the dramatic variation in household joblessness and the contribution of polarization across metropolitan areas. Figure 2 showed that by Q1 2021 household joblessness was on average about 1.5% points higher than before the pandemic and that the average contribution of the change in polarization meant that household joblessness was 0.5% points higher than if job-loss was randomly distributed across households. Figure 3 maps the metropolitan areas in our sample and indicates the overall change in household joblessness (top panel) and the contribution of polarization to changes in household joblessness (bottom panel) for the first quarter in 2021 (as compared to the 2016-2019 average). Across metropolitan areas, the change in household joblessness ranged from -16% points to 17% points. The contribution varied between less than -13% points and more than 15% points. As a reminder, a positive contribution signifies how much larger household joblessness is than expected by a random distribution of individual joblessness. A negative contribution signifies how much smaller household joblessness is than expected.

The first thing the maps tell us is that both household joblessness and polarization varied widely across metropolitan areas. There are many areas, in which polarization reinforces the overall change. In Arizona, for example, Phoenix has low negative contribution of polarization and negative household joblessness. The neighboring Prescott Valley and Tuscon have high positive contributions to very high increases in household joblessness. Yuma, in the west, shows a strong negative contribution to moderate household joblessness. But there are also areas in which polarization contributions and overall household joblessness diverge. Several areas in Wisconsin and Minnesota, for instance, have negative polarization contributions but still increases in household joblessness. This is not unexpected because overall increases in individual joblessness can account for rising household joblessness. Yet, there are also single areas with positive polarization contributions but overall decreases in household joblessness, e.g., Provo-Orem in Utah.

Figure 3: Change in household joblessness (top) and contribution of change in polarization (bottom) across metropolitan areas in Q1 2021



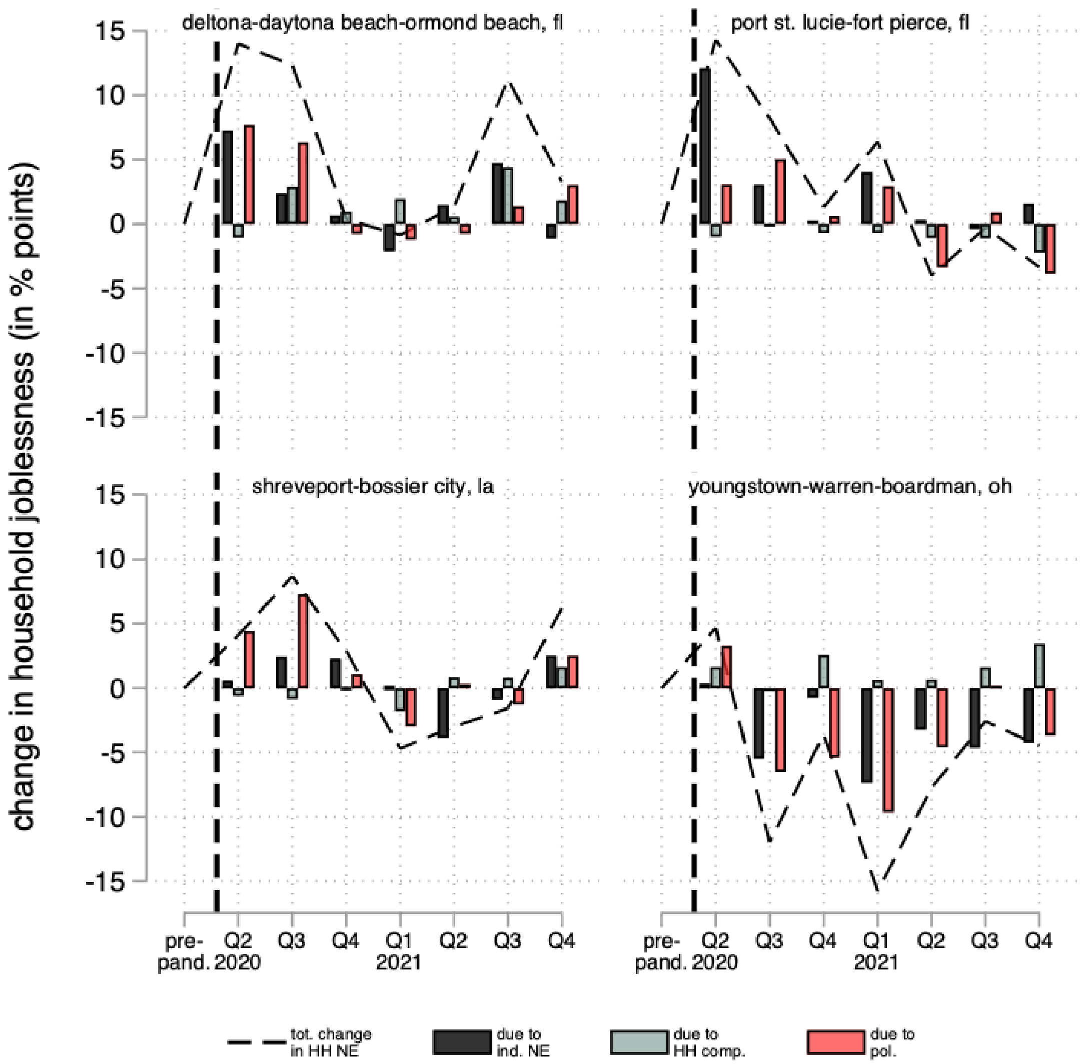
Note: Changes calculated as difference to quarter-specific average over 2016-2019. Source: CPS 2016-21, authors' own calculations.

Figures 4-7 show our shift share decomposition for selected metropolitan areas. To provide a first look at how variance might be clustered across metropolitan areas with different educational profiles, we select metropolitan areas according to their combinations of educational levels, educational heterogeneity, and educational homogamy. We choose combinations that show high or low levels of the three indicators as defined as being in the lowest third or the highest third of the distribution of the respective indicator before the pandemic (average over all quarters 2016-2019). Not all combinations are equally prevalent empirically (Figure A2 in the Appendix shows the distribution of metropolitan areas over educational profiles, plotting the correlation between educational heterogeneity and educational homogamy for three educational levels). We show the decompositions for the four largest metropolitan areas of the four combinations with the largest number of metropolitan areas.

Figure 4 shows the decomposition for the four largest areas that combine low educational levels with low heterogeneity and low homogamy. With the expectation of Youngstown, these areas show very high increases in household joblessness initially (up to 15% points) and polarization contributes relatively strongly (up to 7% points). Subsequent developments vary considerably. The contribution of polarization diminishes and turns even negative at points. Youngstown after an initial moderate rise shows a consistent decrease in household joblessness (more than -15% points) as compared to before the pandemic. About half of this decrease is due to negative polarization, i.e. absorption.

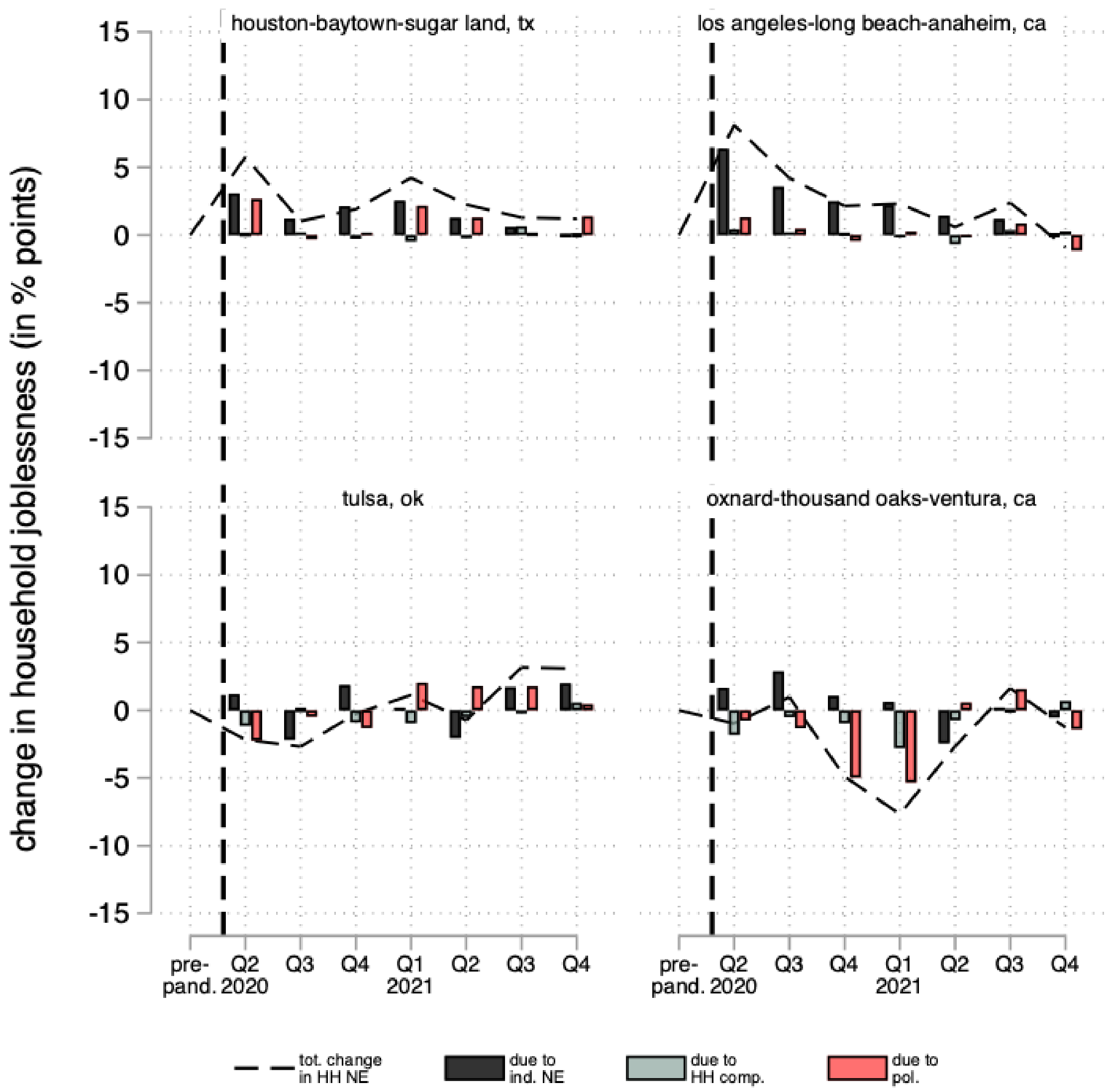
Figure 5 shows metropolitan areas that combine educational levels in the lowest third with educational heterogeneity and homogamy in the highest third. Overall changes in household joblessness are much less dramatic here (at most 7% points). Both Houston and Los Angeles show moderate contributions of polarization to household joblessness (at most around 2.5% points), which is nearing pre-pandemic levels by the end of 2021. Household joblessness decreased initially in Tulsa but is higher than before the pandemic by the end of 2021. Finally, household joblessness stayed close to pre-pandemic levels in Oxnard except for a period in late 2020/early 2021 in which negative polarization drove a relative decrease of up to -7% points.

Figure 4: Decomposition of change in household joblessness in the four largest metropolitan areas with *low educational levels, low heterogeneity, and low homogamy* (Q2 2020-Q4 2021)



Note: Changes calculated as difference to quarter-specific average over 2016-2019. Educational profiles based on pre-pandemic averages of educational variables for metropolitan areas. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-21, authors' own calculations.

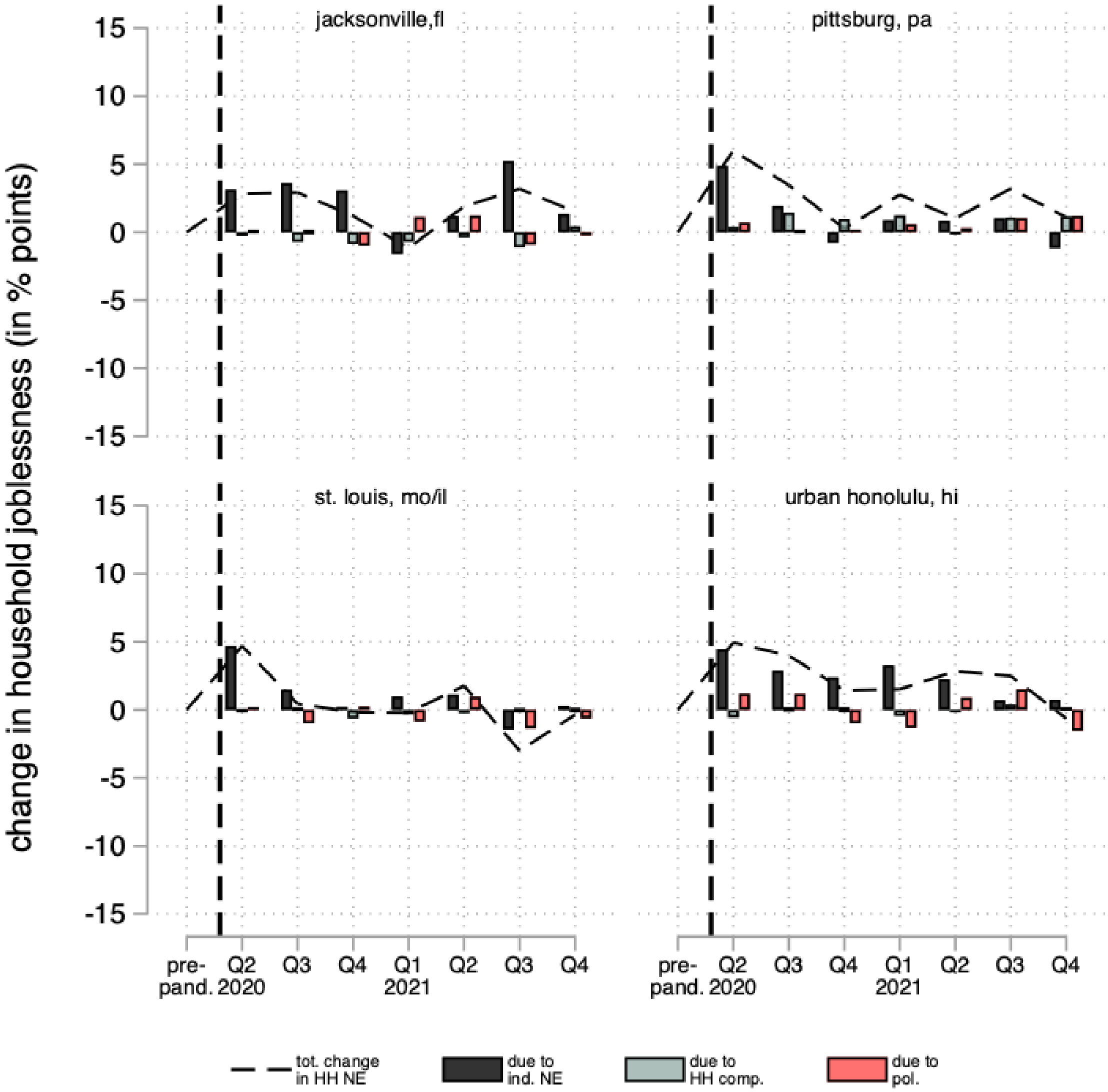
Figure 5: Decomposition of change in household joblessness in the four largest metropolitan areas with *low educational levels, high heterogeneity, and high homogamy* (Q2 2020-Q4 2021)



Note: Changes calculated as difference to quarter-specific average over 2016-2019. Educational profiles based on pre-pandemic averages of educational variables for metropolitan areas. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-21, authors' own calculations.

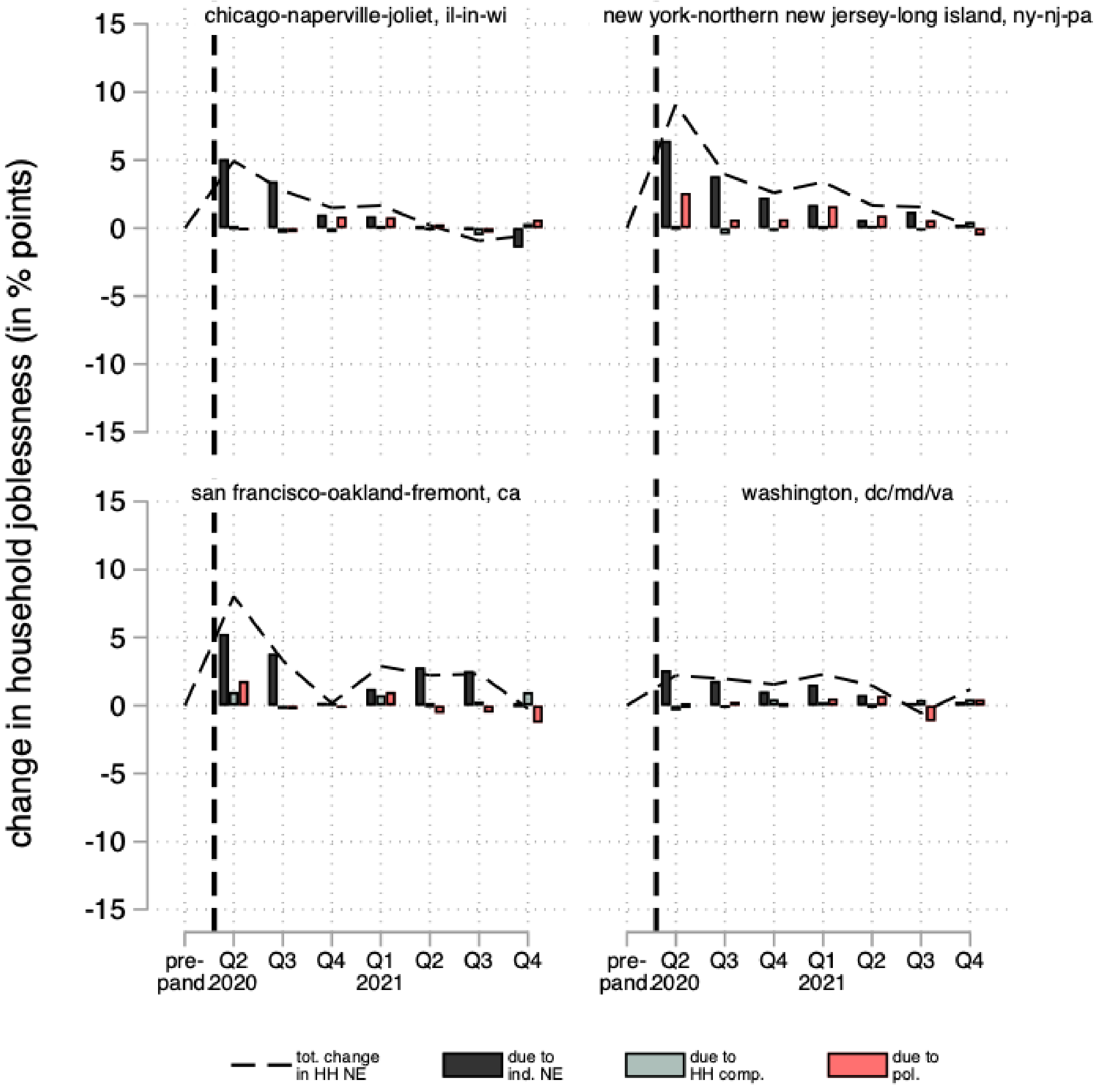
Figure 6 shows the four largest metropolitan areas with high educational levels but low heterogeneity and low homogamy. All four metropolitan areas show increases in household joblessness of up to around 5% points initially that slowly decrease and reach pre-pandemic levels by the end of our observation window, Polarization plays a moderate role, contributing up to 1% point but also contributing negatively at times in Jacksonville, St. Louis, and Urban Honolulu.

Figure 6: Decomposition of change in household joblessness in the four largest metropolitan areas with *high educational levels, low heterogeneity, and low homogamy* (Q2 2020-Q4 2021)



Note: Changes calculated as difference to quarter-specific average over 2016-2019. Educational profiles based on pre-pandemic averages of educational variables for metropolitan areas. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-21, authors' own calculations.

Figure 7: Decomposition of change in household joblessness in the four largest metropolitan areas with *high educational levels, high heterogeneity, and high homogamy* (Q2 2020-Q4 2021)



Note: Changes calculated as difference to quarter-specific average over 2016-2019. Educational profiles based on pre-pandemic averages of educational variables for metropolitan areas. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-21, authors' own calculations.

Finally, Figure 7 shows the four largest areas that combine high levels of education with high heterogeneity and high homogamy. This group of areas contains some of the largest population centers of the US. It is thus not surprising that the development of household joblessness in them resembles the national trend. In New York, where overall increases in household joblessness were the largest (around 9% points), polarization contributes notably (up to 2.5% points) while it plays a moderate role in the other areas. In all four areas, household joblessness and polarization are close to pre-pandemic levels by the end of 2021.

In the Appendix, we present an alternative set of selected metropolitan areas. The selection is based on alternative educational variables that use three levels of educational attainment to measure average educational levels, educational heterogeneity, and educational homogamy. Figures A3-A6 show the respective four largest areas for the four most frequent combinations of high and low levels of these alternative educational measures. Besides providing a look at other metropolitan areas, the findings confirm that there is great variation across metropolitan areas with different educational profiles but also within them. Using alternative educational measures also leads to different allocations of areas. For instance, some of the metropolitan areas we group as high educational level, high educational heterogeneity, and high educational homogamy in the main analysis (see Figure 7) are grouped as having high educational levels, high educational homogamy, but low educational heterogeneity when using educational attainment (see Figure A6). We prefer the measures based on years in education because attainment measures mean a loss of information.

Overall, the decompositions illustrate a large increase in household joblessness as compared to pre-pandemic levels in many metropolitan areas. By the end of 2021, household joblessness is close to pre-pandemic levels in many areas. Developments and the role of polarization varied strongly across areas. From our selected examples it is difficult to ascertain a pattern that aligns with our considerations of the moderating role of educational profiles. Especially for the first group of areas (Figure 4), the lower level of education seems to come with particularly large increases in household joblessness. Regarding the contribution of polarization, we find the most consistent contribution in areas with low levels, high heterogeneity, and high homogamy (Figure 6), but even here not all the selected examples show the same pattern. For a more systematic test of the expected moderating role of educational profiles of metropolitan areas, the following section shows the results from our panel regression models.

5.3 Fixed effects panel regressions of household joblessness and polarization

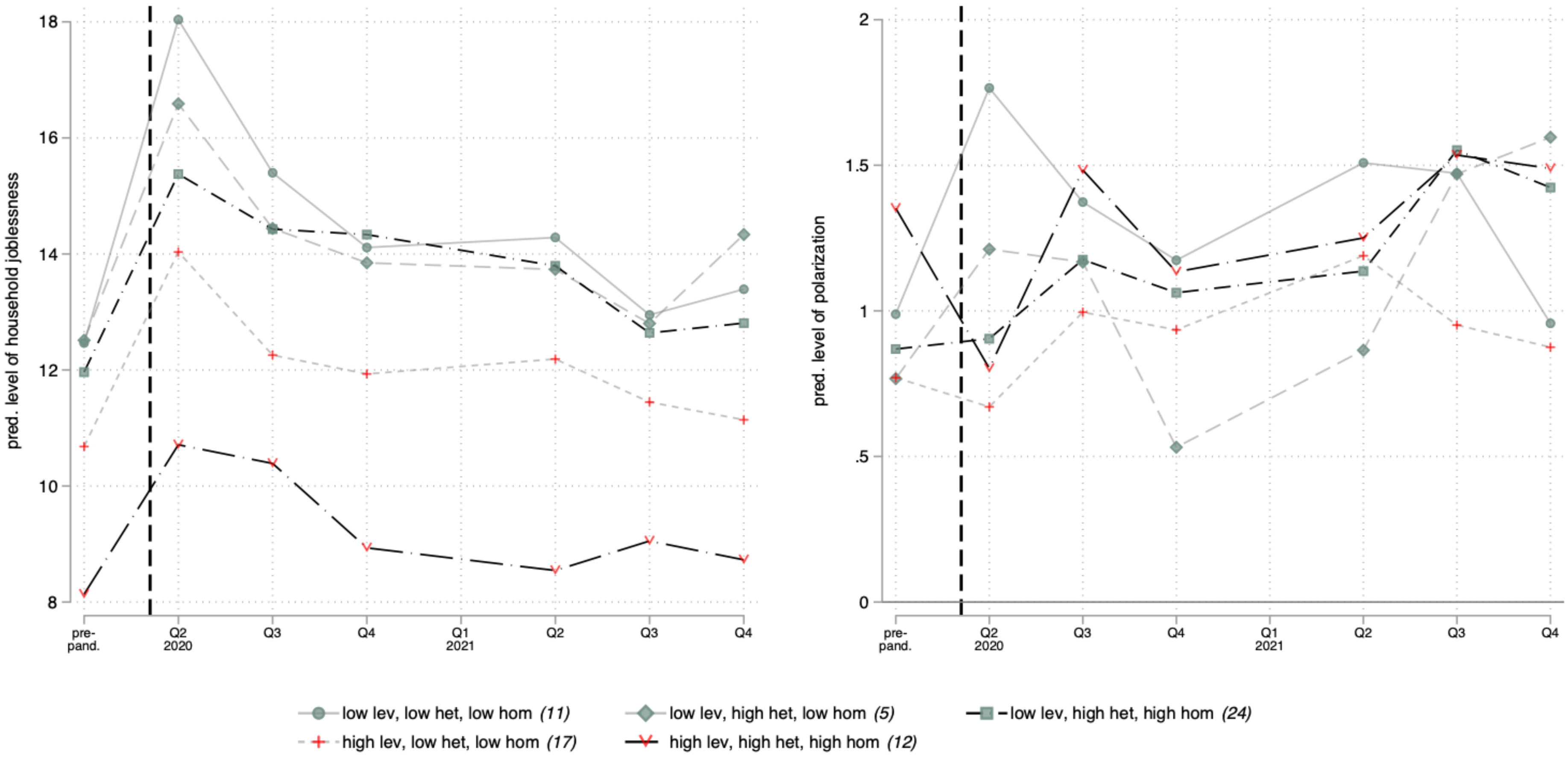
In our multivariate models, we regress the level of household joblessness and polarization on our educational profiles fully interacted with a quarter indicator and adjusting for a battery of contemporaneous and lagged covariates. In Figure 8 we display the predicted level of household joblessness (left-hand panel) and polarization (right-hand panel) for all quarters since the onset of the pandemic for metropolitan areas with different educational profiles from our model. Our models include the educational profiles as time-variant variables. For the figure, we group areas by their pre-pandemic profiles so that the displayed predictions contain a fixed set of metropolitan areas. As before, we group areas by low and high values as defined by being in the lowest or highest third of the three variables pre-pandemic. Two theoretically possible combinations do not exist empirically (low levels combined with low heterogeneity and high homogamy and high levels combined with high heterogeneity and low homogamy) and another two are evident in only few metropolitan areas: we show the results for areas with low levels, high heterogeneity and low homogamy (N=5) but omit areas with high levels combined with low heterogeneity and high homogamy (N=1).

Among the more prevalent educational profiles, metropolitan areas with low educational levels generally have higher levels of household joblessness. Areas that combine low levels with low heterogeneity and low homogamy see particularly large increase (almost 6% points) at the start of the pandemic (12 metropolitan areas representing about 2.1% of our sample). The overall lowest levels of household joblessness by a wide margin are in areas in which high educational levels are combined with high heterogeneity and high homogamy (12 metropolitan areas representing about 18.5% of our sample). But even these areas experience a notable increase initially. All areas also see household joblessness decline, many reaching close to pre-pandemic levels by the end of 2021. The exception here are the areas that combine low levels of education with high heterogeneity and high homogamy as they show a notable uptick in Q4 2021 (24 metropolitan areas representing about 10.5% of our sample).

The picture is more varied when inspecting how much polarization contributes to the increase and subsequent decline in household joblessness across areas. Given their low levels of household joblessness, polarization plays an outsize role in areas with high educational levels, high heterogeneity, and high homogamy, adding almost 1.5% points before the pandemic and closing at 1.5% points by the end of 2021. Areas with low levels, low heterogeneity, and low homogamy see a clear uptick to almost 1.8% points that remains high until Q3 2021 but returns to pre-pandemic levels of about 1% point in Q4 2021. The other three combinations see increases in polarization throughout the pandemic, albeit at different levels. Areas that combine high educational levels with low heterogeneity and low homogamy generally show the lowest levels and arrive at pre-pandemic levels by Q4 2021 (at about 0.8% points) (17 metropolitan areas representing about 7.6% of our sample). Areas that combine low levels with either high heterogeneity and low homogamy (5 metropolitan areas representing about 2.4% of our sample) or high heterogeneity and high homogamy arrive at notably higher levels of polarization in Q4 2021 as compared to before the pandemic (both at around 1.5% points whereas they started at less than 0.8% points). Thus, while educational levels seem to make the largest difference when it comes to overall household jobless, educational heterogeneity and homogamy play an important role when it comes to levels and change of polarization. On balance, there is some evidence indicating that lower heterogeneity and lower homogamy correlate with less (increase in) polarization.

Here, too, we run a number of alternative analyses to assess robustness of our findings. First, we use alternative thresholds of education our measures to represent the educational profiles of metropolitan areas is in line with our findings. Using the median to determine low and high values enables a look at all metropolitan areas (see Figure A7 in the Appendix). The overall levels and developments resemble the ones presented here but, unsurprisingly, are generally more moderate and differences between combinations are smaller. Using values in the lowest and highest quartile reduces the number of represented areas and leads to more extreme differences (see Figure A8 in the Appendix). We also test how reducing the sample to households with at least one member aged 16-49 changes our results (see Figure A9 in the Appendix). The main difference here is that polarization patterns follow more closely the development of overall household joblessness. Finally, we show how using alternative educational measures changes the results (see Figure A10 in the Appendix). As they represent different metropolitan areas, the results show some different patterns. But they confirm that household joblessness differs strongly for educational levels whereas the development of polarization is affected by heterogeneity and homogamy as well.

Figure 8: Predicted levels of household joblessness and polarization across educational profiles



Note: Predictions from panel fixed effects regressions of household joblessness and polarization on fully interacted combinations of quarter, educational level, educational heterogeneity, and educational homogamy. Models include all quarters from Q1 2016 to Q4 2021, but graphs only depict predictions from Q1 2020 onward. Predictions based on pre-pandemic averages of educational variables for metropolitan areas. "low" = lowest third in the distribution, "high" = highest third in the distribution. Represented combinations selected based on case numbers. Contemporaneous covariates: % Black, % Hispanic, % migrants, population size. Lagged covariates: % single headed HHs, % older, median equivalized income, % public sector, % manufacturing, % FIRE sector, % other services, % living in the central city. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-2021, authors own calculations.

6. Conclusions and discussion

In this paper, we set out to answer three questions. First, how did household joblessness develop in the US during the COVID19 economic crisis and how did it vary across local labor markets? Second, how much of this development and cross-labor market variation was simply due to rising numbers in individual joblessness and how much was due to the unequal distribution of job-loss across households, i.e., polarization? Third, can we explain cross-labor market variation in household joblessness and polarization with the educational profiles of these labor markets. We used monthly CPS data pooled in quarters for 204 metropolitan areas 2016-2021. To answer the first two questions, we used a shift-share decomposition that broke down changes in household joblessness since the start of the pandemic into the contribution from individual joblessness, changes in household sizes, and polarization. We found a large increase in household joblessness during the pandemic. This moved largely in step with individual joblessness but positive polarization added a non-trivial amount. Moreover, variance across metropolitan areas was large in the initial increase in household joblessness, its subsequent development, and in the contribution from polarization. We used fixed effects panel regressions on the level of metropolitan areas to answer our third question. Partly, the development of household joblessness and polarization aligned with our expectations about the educational profiles of metropolitan areas. Areas with low educational levels generally showed higher levels of household joblessness. Areas with low educational levels but high heterogeneity and homogamy saw the steadiest increase in polarization. Areas with low homogamy and heterogeneity combined with both low and high levels of education showed the lowest levels of polarization at the end of our observation period. While these findings did partly align with our expectations, metropolitan areas in with similar educational profiles showed notable differences in their development of household joblessness and polarization.

Some limitations of our study might be related to inconsistencies in our findings. First, we used CPS data and metropolitan areas because the CPS is the only available data source for analyzing household joblessness during the pandemic as it publishes new data monthly. Metropolitan areas are the spatial unit to analyze local labor markets in the CPS with sufficient case numbers, but smaller case numbers for some metropolitan areas could lead to less robust findings. While looking at metropolitan areas allowed us to extend existing research on US geographic economic inequality, we intend to explore long term trends in US household joblessness using US Census/American Community Survey data in future work. Studies analyzing commuting zones usually use US Census/American Community Survey data, meaning data case numbers per spatial unit are also notably larger (e.g. Autor and Dorn 2013; VanHeuvelen and Copas 2019). Second, because we analyzed metropolitan areas, we had to work with a very limited case number in our multivariate analysis. Our models included up to four-way interactions and a battery of covariates for which a sample of 204 metropolitan areas arguably yields not enough power. We were therefore able to cautiously describe differences in trends, but statistical tests of differences will have to be conducted in future work with larger samples. Again, analyzing commuting zones would provide a larger sample size of more than 700. Third, our focus was on the level of metropolitan areas because polarization is intuitively a macro concept and because it enabled us to consider externalities of educational measures. However, future work analyzing individual level data could help us illustrate differences between households that accumulate employment risks more clearly. Finally, analyzing household joblessness during the COVID19 pandemic might have limited generalizability because of the occupational distribution of job-loss and idiosyncratic impacts on household dynamics. Future work might test our education-based explanation for prior economic downturns as well as long-term trends.

Overall, we might look at the development of household joblessness and interpret the return to pre-pandemic levels by the end of 2021 as good news. On average, polarization levels also return to pre-pandemic levels, which are relatively low in international comparison (Biegert and Ebbinghaus 2022; Gregg et al. 2008; Gregg and Wadsworth 2001). However, it took almost two years to arrive at pre-pandemic levels, meaning that an increased number of individuals experienced the hardships connected to living in a jobless household. Also, we need to remember that pre-pandemic levels still mean that about 10% of working age adults in metropolitan areas live in households with no-one working. Moreover, both household joblessness and polarization are markedly above the national average in some metropolitan areas. Because household joblessness increased by up to 5% points nationally and by more than 15% points in some metropolitan areas, an increased share of the population lived at a higher risk of poverty. In our sample, jobless households without children showed a poverty risk of around 65% and almost 75% of jobless households with children were at risk of poverty (compared to around 15%

for employed households without children and 28% of employed households with children) (see Figure A11 in the Appendix). Notably, poverty risks of jobless households with children increased in 2021 after a brief drop in 2019-20. Thus, even though state support was generous in the first phase of the pandemic, it was cut down soon again, leaving jobless households and particularly those with children highly vulnerable to immediate adverse impacts of poverty. Experiencing household joblessness during the pandemic and after is also likely to leave household members with scars that transcend the impact of poverty (Curry et al. 2022; Ermisch et al. 2004; Mooi-Reci et al. 2020). Besides documenting the challenge of household joblessness in the US, our study provided an explanation of variation in household joblessness and polarization across labor markets that went beyond coarse models of welfare regimes and dominant family models (Biegert and Ebbinghaus 2022; Corluy and Vandenbroucke 2017; Gregg et al. 2008). Because high household joblessness implies an additional dimension of accumulated risks, further developing the education-based model might proof helpful in identifying geographic pockets of entrenched spatial economic disadvantage.

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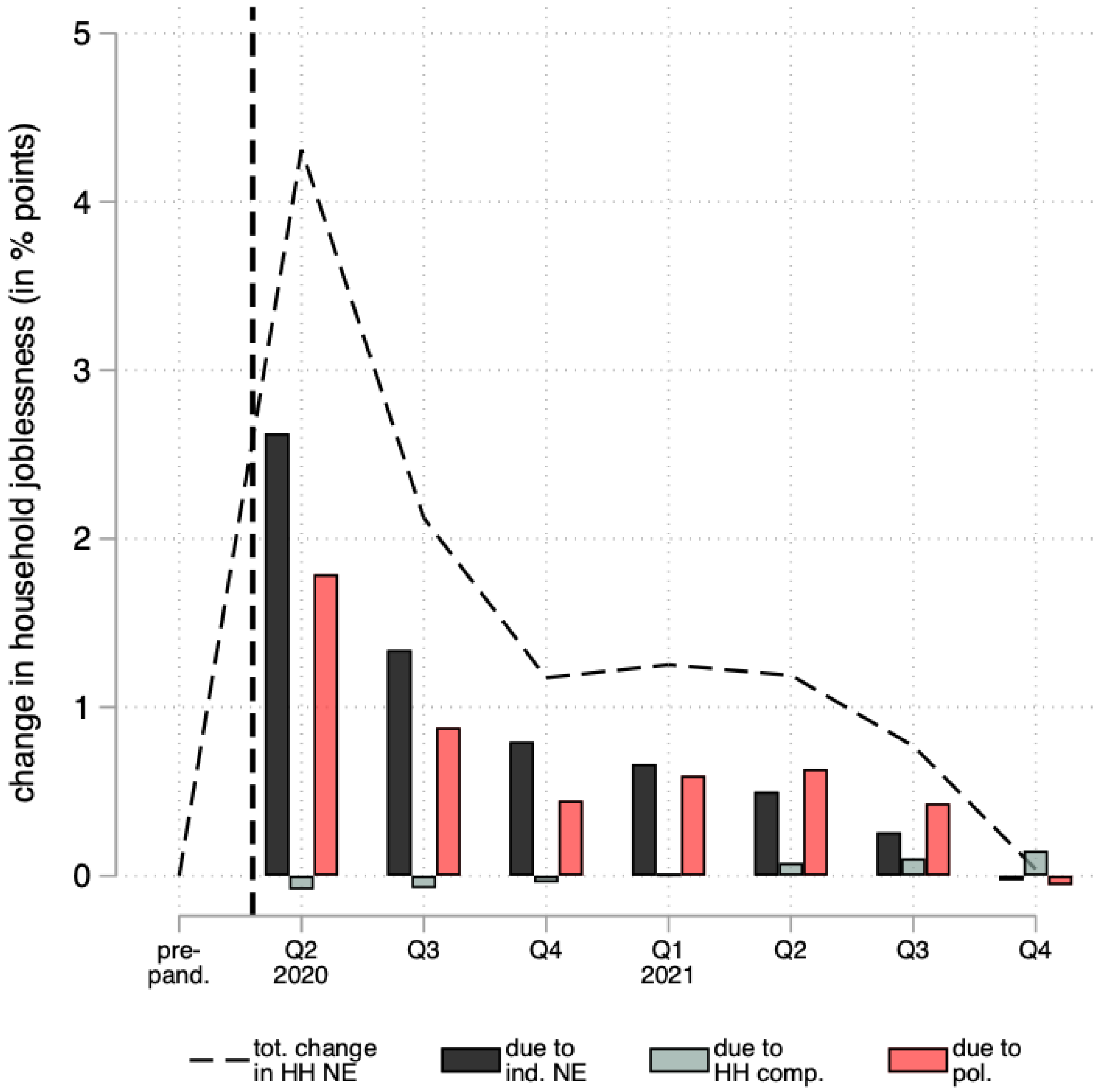
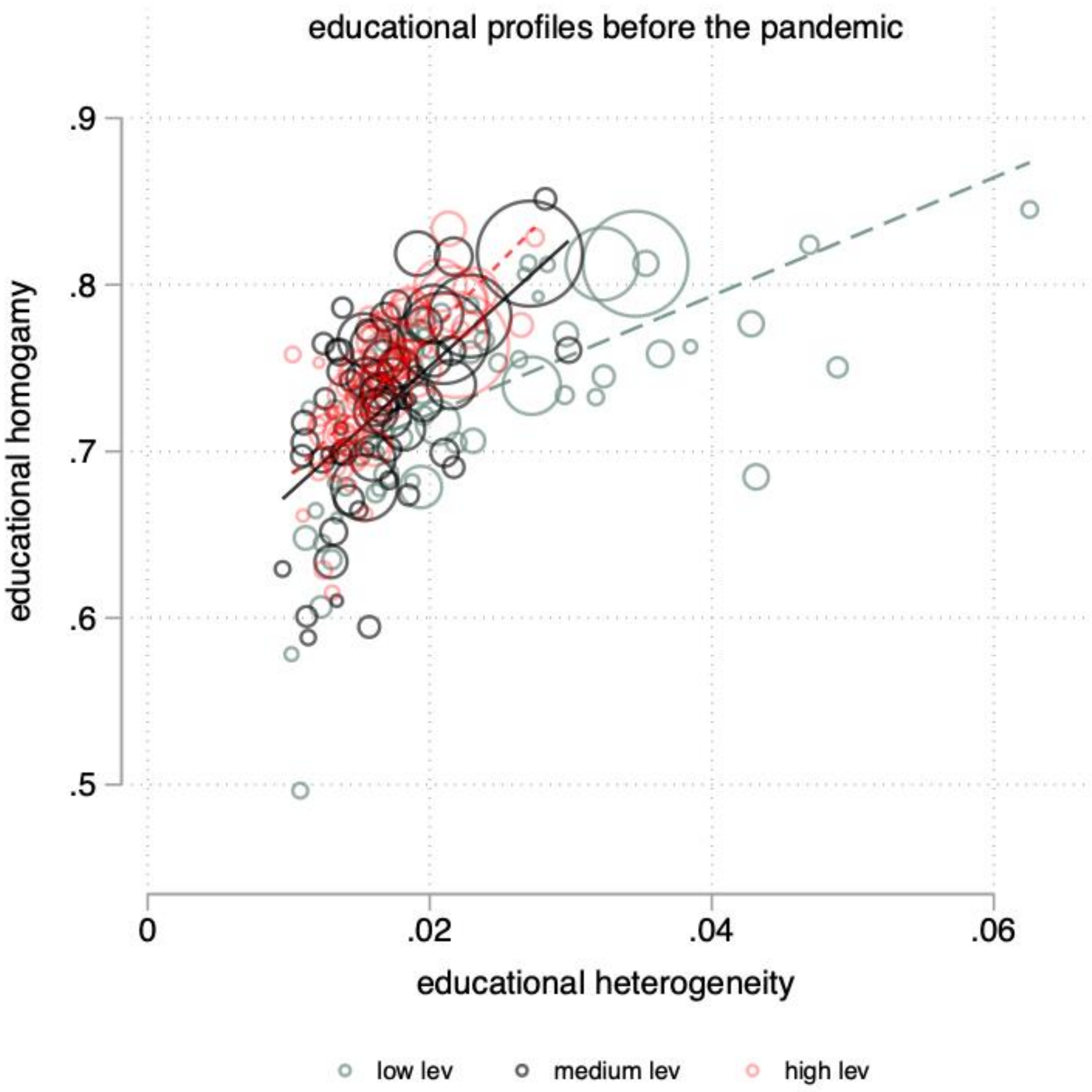
Appendix

Figure A1: Decomposition of change in household joblessness in metropolitan area US (Q2 2020-Q4 2021) for sample of households with at least one member 16-49



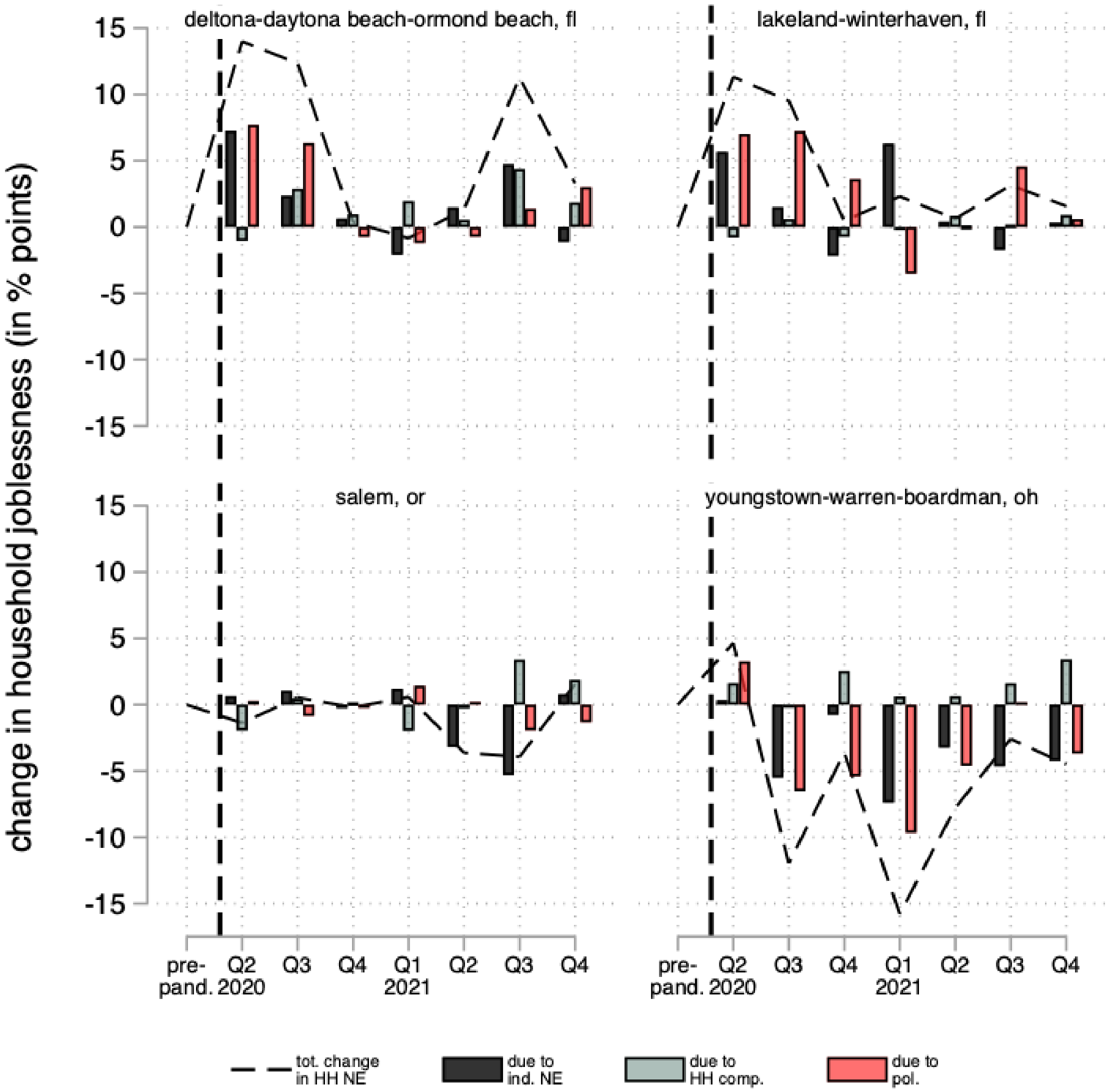
Note: Changes calculated as difference to quarter-specific average over 2016-2019. 'Metropolitan area US' represents the population-weighted average of all 204 metropolitan areas in our sample. Vertical dashed line marks the onset of the pandemic before Q2 2020. Source: CPS 2016-21, authors' own calculations.

Figure A2: Empirical distribution of educational profiles before the pandemic



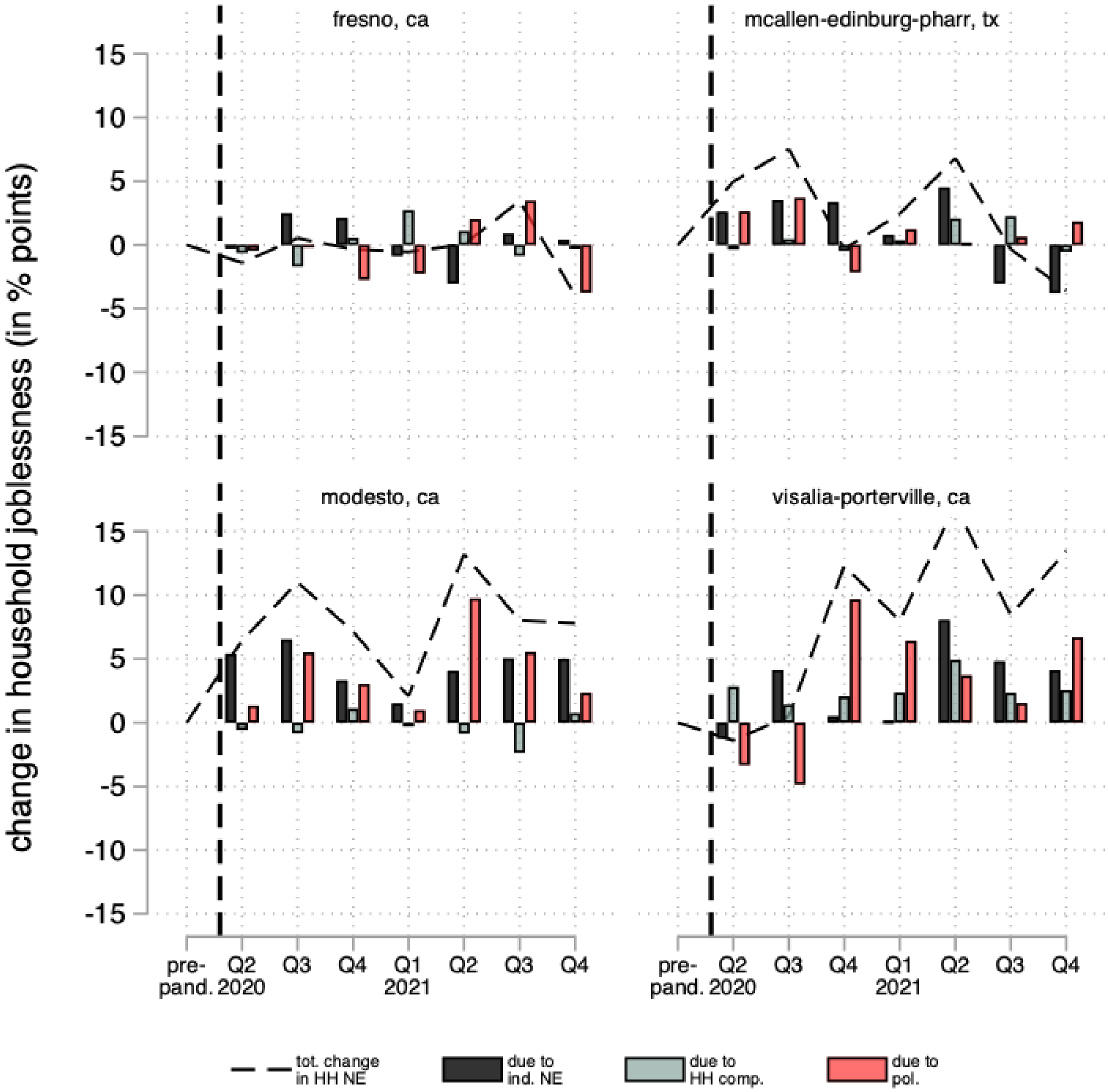
Note: Figure correlates pre-pandemic averages of educational heterogeneity and educational homogamy. Colors indicate different average educational levels. “low” = lowest third in the distribution, “medium” = middle third in the distribution, “high” = highest third in the distribution. Lines fitted for correlation between educational heterogeneity and homogamy at three levels of average education. Marker size indicates population size of metropolitan area. Source: CPS 2016-21, authors’ own calculations.

Figure A3: Decomposition of change in household joblessness in the four largest metropolitan areas with *low educational levels, low heterogeneity, and low homogamy* (Q2 2020-Q4 2021) using educational attainment variables



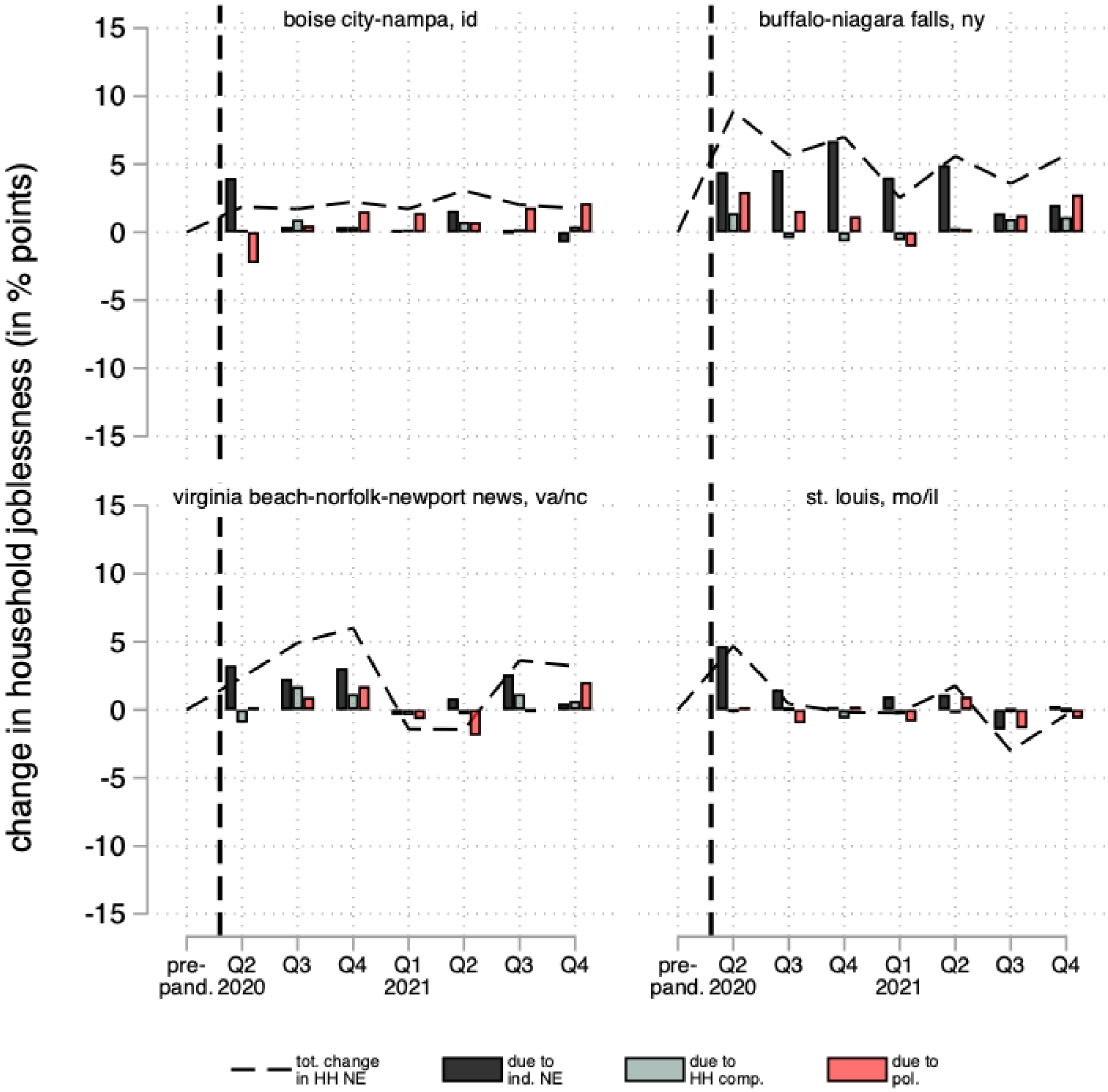
Note: Changes calculated as difference to quarter-specific average over 2016-2019. Educational profiles based on pre-pandemic averages of educational variables for metropolitan areas. Educational measures based on three levels of educational attainment (1 up to high school diploma, 2 some college, 3 college degree or more). Educational level is measure as share of individuals with some college. Educational heterogeneity is based on Theil's entropy formula as proposed by Nielsen and Alderson (1997). Educational homogamy is calculated as the share of couples (married and cohabiting) with the same educational degree as a percentage of all couples. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-21, authors' own calculations.

Figure A4: Decomposition of change in household joblessness in the four largest metropolitan areas with *low educational levels, low heterogeneity, and high homogamy* (Q2 2020-Q4 2021) using educational attainment variables



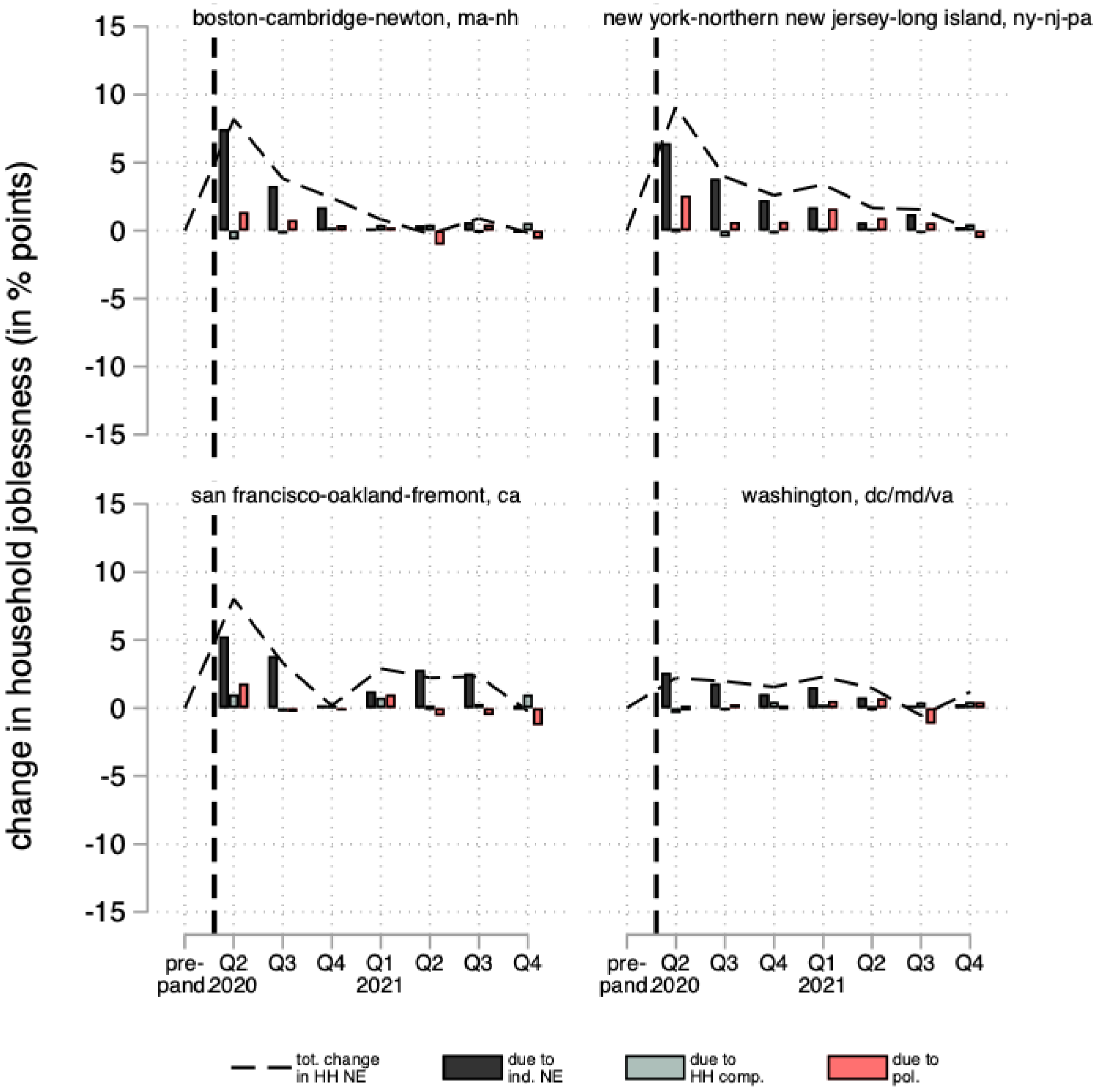
Note: Changes calculated as difference to quarter-specific average over 2016-2019. Educational profiles based on pre-pandemic averages of educational variables for metropolitan areas. Educational measures based on three levels of educational attainment (1 up to high school diploma, 2 some college, 3 college degree or more). Educational level is measure as share of individuals with some college. Educational heterogeneity is based on Theil's entropy formula as proposed by Nielsen and Alderson (1997). Educational homogamy is calculated as the share of couples (married and cohabiting) with the same educational degree as a percentage of all couples. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-21, authors' own calculations.

Figure A5: Decomposition of change in household joblessness in the four largest metropolitan areas with *high educational levels, high heterogeneity, and low homogamy* (Q2 2020-Q4 2021) using educational attainment variables



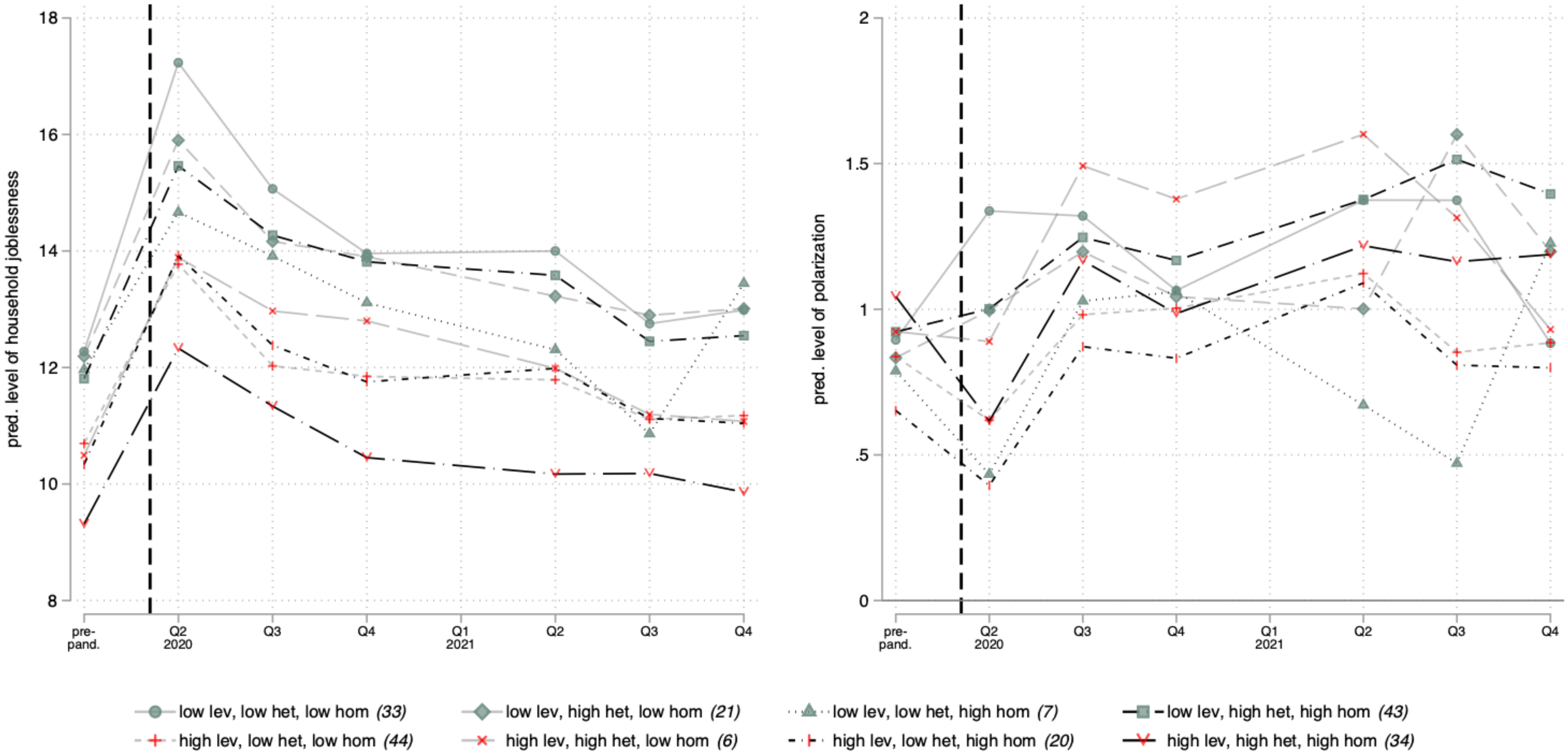
Note: Changes calculated as difference to quarter-specific average over 2016-2019. Educational profiles based on pre-pandemic averages of educational variables for metropolitan areas. Educational measures based on three levels of educational attainment (1 up to high school diploma, 2 some college, 3 college degree or more). Educational level is measure as share of individuals with some college. Educational heterogeneity is based on Theil's entropy formula as proposed by Nielsen and Alderson (1997). Educational homogamy is calculated as the share of couples (married and cohabiting) with the same educational degree as a percentage of all couples. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-21, authors' own calculations.

Figure A6: Decomposition of change in household joblessness in the four largest metropolitan areas with *high educational levels, low heterogeneity, and high homogamy* (Q2 2020-Q4 2021) using educational attainment variables



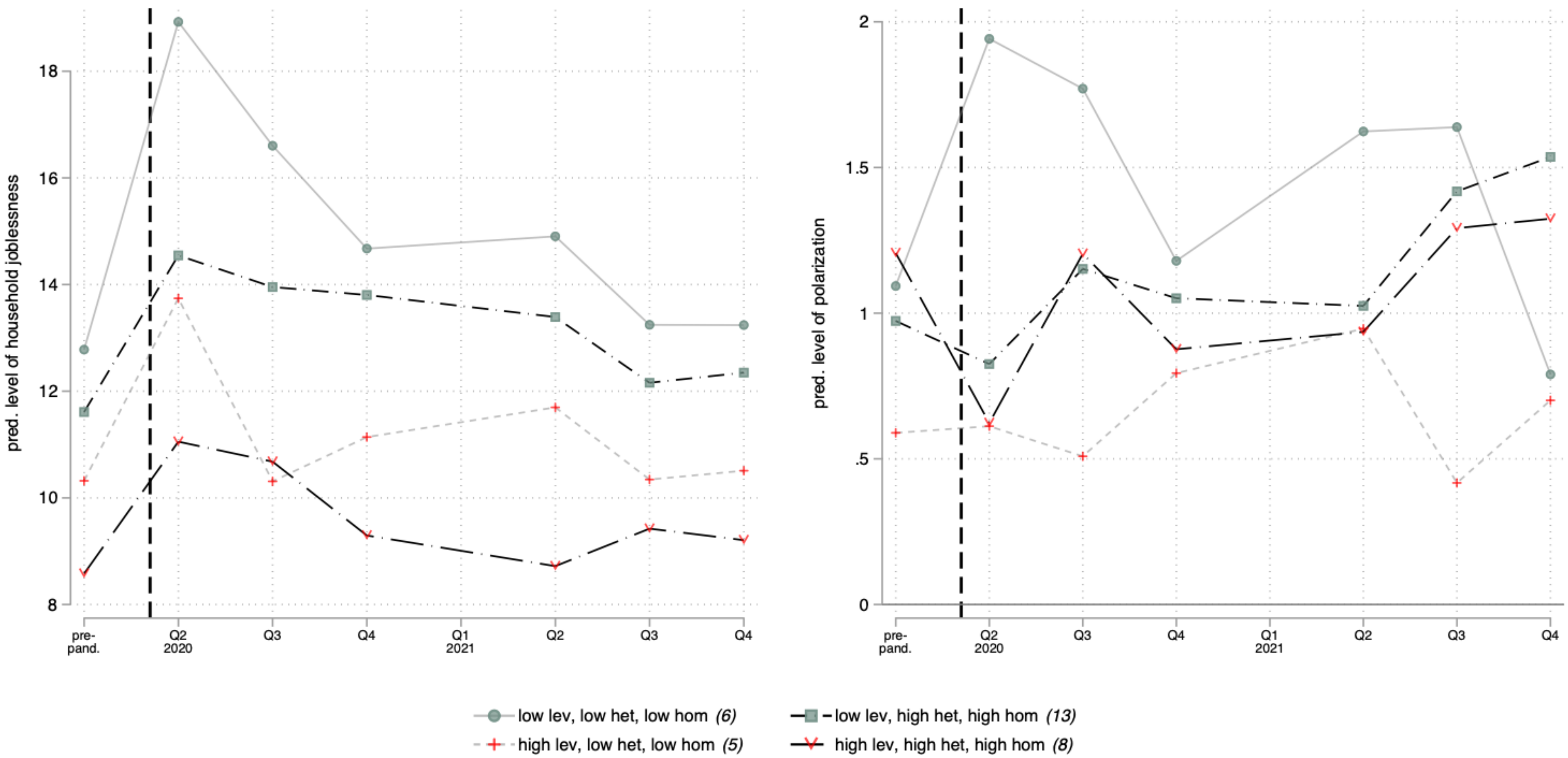
Note: Changes calculated as difference to quarter-specific average over 2016-2019. Educational profiles based on pre-pandemic averages of educational variables for metropolitan areas. Educational measures based on three levels of educational attainment (1 up to high school diploma, 2 some college, 3 college degree or more). Educational level is measure as share of individuals with some college. Educational heterogeneity is based on Theil's entropy formula as proposed by Nielsen and Alderson (1997). Educational homogamy is calculated as the share of couples (married and cohabiting) with the same educational degree as a percentage of all couples. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-21, authors' own calculations.

Figure A7: Predicted levels of household joblessness and polarization across educational profiles using *median thresholds* to indicate low and high values on educational variables



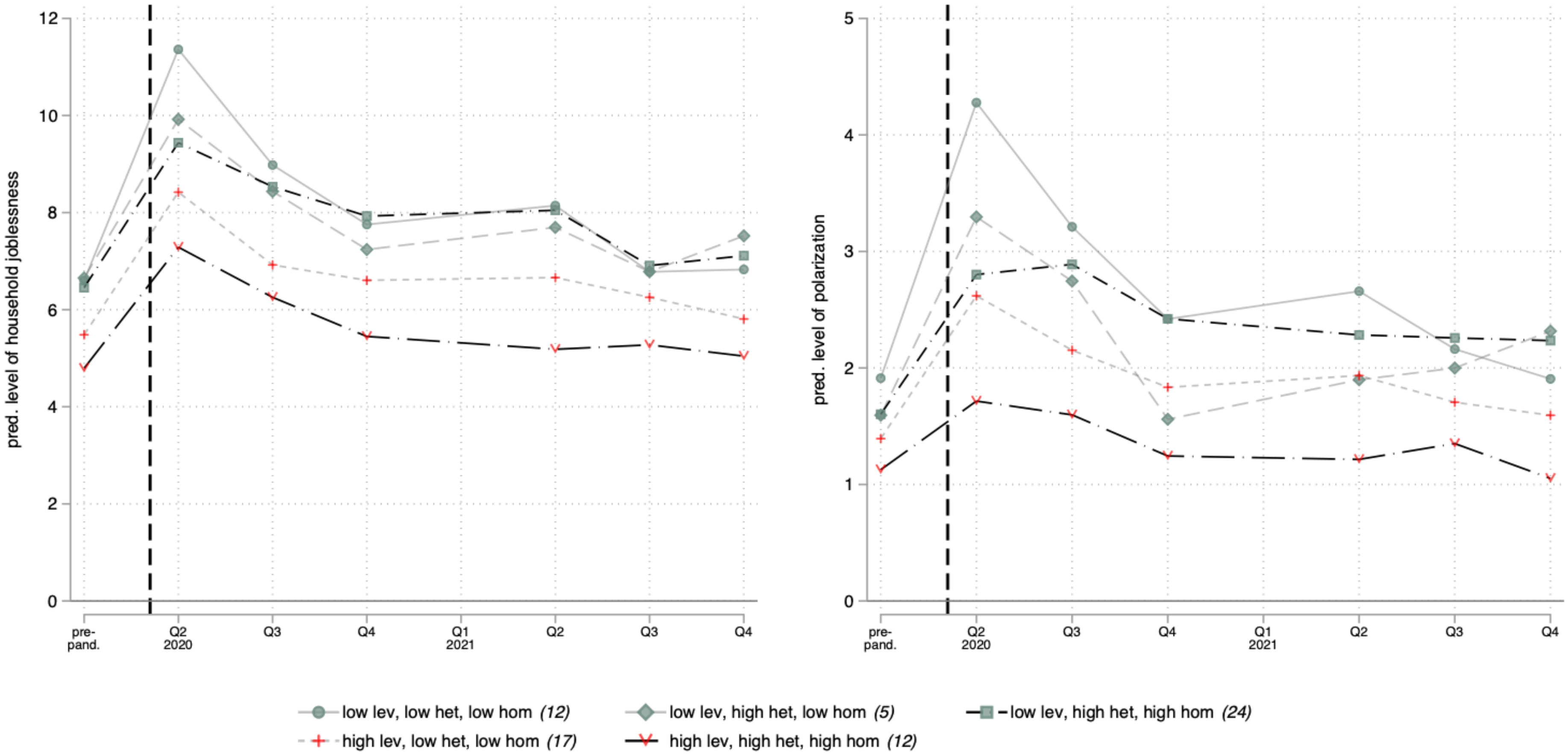
Note: Predictions from panel fixed effects regressions of household joblessness and polarization on fully interacted combinations of quarter, educational level, educational heterogeneity, and educational homogamy. Models include all quarters from Q1 2016 to Q4 2021, but graphs only depict predictions from Q1 2020 onward. Predictions based on pre-pandemic averages of educational variables for metropolitan areas. “low” = below median in the distribution, “high” = above median in the distribution. Represented combinations selected based on case numbers. Contemporaneous covariates: % Black, % Hispanic, % migrants, population size. Lagged covariates: % single headed HHs, % older, median equivalized income, % public sector, % manufacturing, % FIRE sector, % other services, % living in the central city. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-2021, authors own calculations.

Figure A8: Predicted levels of household joblessness and polarization across educational profiles using *lowest and highest quartile thresholds* to indicate low and high values on educational variables



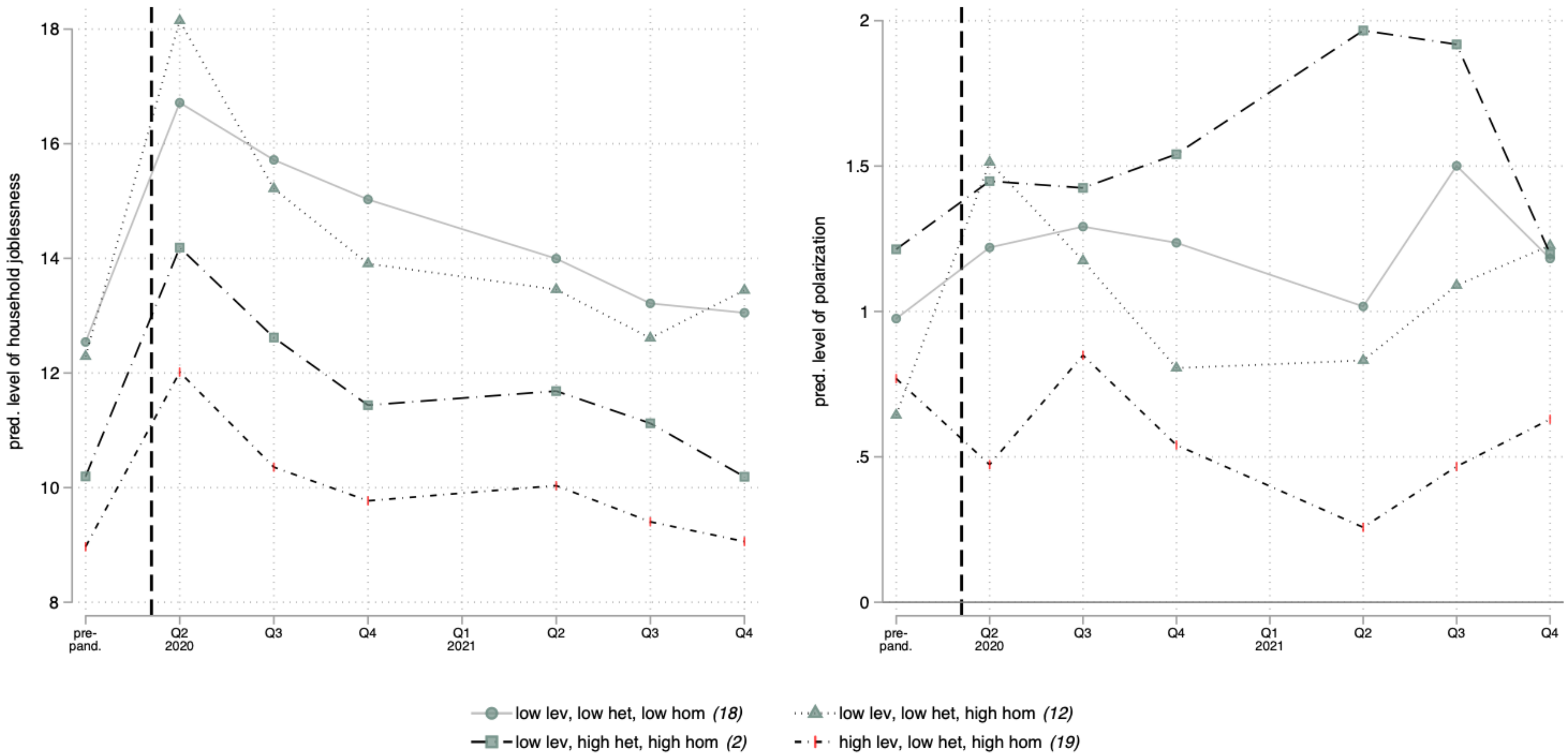
Note: Predictions from panel fixed effects regressions of household joblessness and polarization on fully interacted combinations of quarter, educational level, educational heterogeneity, and educational homogamy. Models include all quarters from Q1 2016 to Q4 2021, but graphs only depict predictions from Q1 2020 onward. Predictions based on pre-pandemic averages of educational variables for metropolitan areas. “low” = lowest quartile in the distribution, “high” = highest quartile in the distribution. Represented combinations selected based on case numbers. Contemporaneous covariates: % Black, % Hispanic, % migrants, population size. Lagged covariates: % single headed HHs, % older, median equivalized income, % public sector, % manufacturing, % FIRE sector, % other services, % living in the central city. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-2021, authors own calculations.

Figure A9: Predicted levels of household joblessness and polarization across educational profiles using sample of households with at least one member 16-49



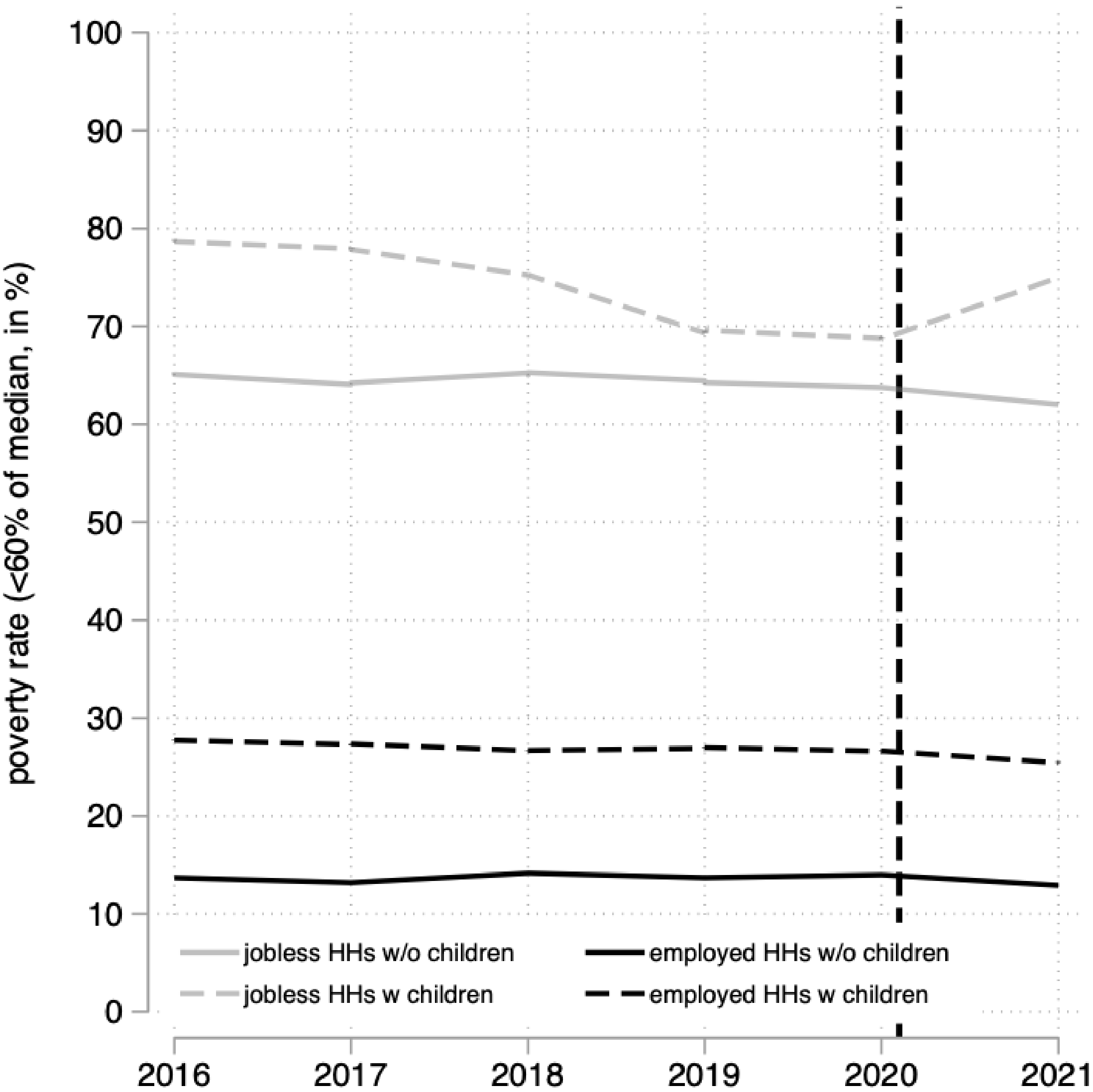
Note: Predictions from panel fixed effects regressions of household joblessness and polarization on fully interacted combinations of quarter, educational level, educational heterogeneity, and educational homogamy. Models include all quarters from Q1 2016 to Q4 2021, but graphs only depict predictions from Q1 2020 onward. Predictions based on pre-pandemic averages of educational variables for metropolitan areas. "low" = lowest third in the distribution, "high" = highest third in the distribution. Represented combinations selected based on case numbers. Contemporaneous covariates: % Black, % Hispanic, % migrants, population size. Lagged covariates: % single headed HHs, % older, median equivalized income, % public sector, % manufacturing, % FIRE sector, % other services, % living in the central city. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-2021, authors own calculations.

Figure A10: Predicted levels of household joblessness and polarization across educational profiles using educational attainment variables



Note: Predictions from panel fixed effects regressions of household joblessness and polarization on fully interacted combinations of quarter, educational level, educational heterogeneity, and educational homogamy. Educational measures based on three levels of educational attainment (1 up to high school diploma, 2 some college, 3 college degree or more). Educational level is measure as share of individuals with some college. Educational heterogeneity is based on Theil's entropy formula as proposed by Nielsen and Alderson (1997). Educational homogamy is calculated as the share of couples (married and cohabiting) with the same educational degree as a percentage of all couples. Models include all quarters from Q1 2016 to Q4 2021, but graphs only depict predictions from Q1 2020 onward. Predictions based on pre-pandemic averages of educational variables for metropolitan areas. "low" = lowest third in the distribution, "high" = highest third in the distribution. Represented combinations selected based on case numbers. Contemporaneous covariates: % Black, % Hispanic, % migrants, population size. Lagged covariates: % single headed HHs, % older, median equivalized income, % public sector, % manufacturing, % FIRE sector, % other services, % living in the central city. Vertical dashed lines mark the onset of the pandemic before Q2 2020. Source: CPS 2016-2021, authors own calculations.

Figure A11: Poverty rates for jobless households and households in employment, with and without children in metropolitan area US 2016-2021



Note: 'Metropolitan area US' is the population-weighted average of all 204 metropolitan areas in our sample. Vertical dashed line marks the onset of the pandemic before Q2 2020. Source: CPS 2016-2021, authors' own calculations.