Economic Shocks and Worker Inequality: Evidence from the Great Recession*

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Abstract

We analyze the effect of economic shocks on employment inequality in the United States during the Great Recession. A key mediating channel we explore is the extensive margin of establishment deaths, which can alter inequality if workers are matched to establishments non-randomly. In particular, workers will be disproportionately affected if they are concentrated in firms that are less able to survive adverse economic conditions. Such worker concentration is consistent with positive sorting by worker skill and firm resilience, as well as greater discrimination by more resilient firms. To distinguish between these explanations, we consider within-industry inequality effects for worker education (a proxy for skill) and for gender and race (which are more likely to indicate discrimination). Using employment data by industry, jurisdiction and worker type, we find that establishment deaths during the recession had a pronounced impact on inequality. Workers were more adversely affected by deaths if they were female, black, Hispanic, or young. The large within-industry effects for these disadvantaged groups, particularly women, imply an important role for discrimination in explaining the evolution of worker inequality during the Great Recession. More broadly, the concentration of disadvantaged workers in less resilient firms suggests that they may be more vulnerable to future downturns. *JEL* Codes: E24, J21, J31, R12, R23.

Keywords: Economic Shocks, Worker Inequality, Establishment Deaths, Employment, Industry Composition, Gap, Disparity, Decomposition

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1 Introduction

Against a backdrop of rising economic inequality, the evolution of labor market disparities between workers is a key public concern. Economists have studied worker inequality extensively, focusing on trends in factors including differential productivity by worker type (e.g., women becoming more educated, relative to men), the availability of workers (e.g., immigration, and worker transitions into and out of employment), unionization, and the mix of productive inputs (i.e., skill-biased technical change).[1] Less attention has been paid to the connection between labor market inequality by worker type (gender, race, education, etc.) and worker-firm matching.[2] Our article fills this gap by exploring a potentially important and unexplored driver of worker inequality – the resilience of firms to negative economic shocks.

We use the Great Recession, a once-in-a-generation downturn that was abrupt, deep and widespread, to uncover evidence of worker sorting by demographic group.[3] In particular, we focus on a key channel through which worker inequality can be affected by adverse economic conditions: the extensive margin of establishment deaths. In essence, if workers are matched to establishments non-randomly by type, then the type that is concentrated within firms/establishments least able to survive the downturn will experience a disproportionate share of the employment decline.[4] The degree to which workers are differentially distributed according to unobservable firm quality is revealed by the component of the worker inequality change explained by variation in establishment deaths (or, alternatively, the net change in

[1] Altonji and Blank (1999) and Katz and Autor (1999) offer excellent reviews of the relevant literature. Seminal early work includes Bound and Freeman (1992), Katz and Murphy (1992), Berman et al. (1994), Autor et al. (1998) and Card and DiNardo (2002), among others. Some notable recent additions to the literature are Autor et al. (2008) and Bayer and Charles (2018).

[2] A large literature examines how employment and earnings respond to changes in trade, government spending and defense spending (see Blau et al. 2000; Aizer 2010; Autor et al. 2013; Nakamura and Steinsson 2014; Bertrand et al. 2015; Pierce and Schott 2016, 2017; Goldsmith-Pinkham et al. 2018), though with little emphasis placed on worker inequality as an outcome of interest. An exception is Bound and Holzer (2000), which applies the methodology proposed by Bartik (1991) and developed more fully by Blanchard and Katz (1992) (see also Goldsmith-Pinkham et al. 2018 for a recent treatment of the topic) to analyze decadal patterns in inequality.

[3] Abowd et al. (1999); Card et al. (2013); Barth et al. (2016); Bonhomme et al. (2019); Song et al. (2019), and others study the contribution of such sorting to growing inequality in earnings.

[4] Research analyzing the effect of demand shocks on firm/establishment closures includes trade-oriented papers, such as Yeaple (2005) and Egger and Kreickemeier (2009), which are not concerned with inequality per se and do not address differences by race and gender. Syverson (2011) discusses a literature documenting substantial productivity differences across firms within narrowly-defined industries.

the number of establishments).

We consider two prominent hypotheses for why such concentration might arise: (1) assortative matching between worker skill and firm/establishment resilience; and (2) Beckerian, taste-based discrimination by more resilient or more well-capitalized firms. We qualitatively assess the importance of these competing explanations by comparing establishment death effects for worker education, which is a proxy for skill, with death effects for gender and race, which are more likely to be associated with discrimination.

Our analysis depends on determining the effects of the Great Recession on worker inequality. We estimate these effects by first calculating the percentage change in employment for each worker type (e.g., men and women), aggregating across all industries. We then take the difference in the changes across types belonging to the same category (e.g., gender) to obtain a measure of the change in inequality.[5] Under our formulation, the overall change in inequality is clearly expressed as the sum (across industries) of the difference in type-specific shocks by industry, weighted by the share of type-specific employment of the industry.

Having obtained a measure of the overall inequality change, we decompose it along two dimensions. First, we separate out the portion of the overall change that can be explained (predicted by) establishment deaths at the industry-jurisdiction level. Second, we adapt the well-established procedure from the literature for isolating across- and within-industry variation,[6] deriving explicit expressions for each component in terms of our notation. These components intuitively depend on type-specific shocks and employment shares at the industry level: the across component is a function of the average shock and difference in shares, while the within component is a function of the difference in shocks and average shares. While the extent to which deaths can explain across-industry patterns is interesting, we argue that focusing on the within-industry changes is particularly informative. Doing so rules out the deaths effects from being driven by a correlation between industry-specific preferences and industry vulnerability to demand shocks, bringing the two demand-side hypotheses to the fore.

[5]This measure differs somewhat from the metric commonly used in the literature: the change in a particular worker type's share of aggregate employment or earnings. Our variant is particularly conducive to analyzing demand shocks, as it reveals how each type of worker is separately affected. In the case of the standard metric, it is not apparent whether an increase in the share of total employment for a particular type is due to growth for that type or a contraction in total employment.

[6]See Freeman (1975, 1980); Katz and Murphy (1992); Berman et al. (1994); Autor et al. (1998); Dunne et al. (1996); Bernard and Jensen (1997).

We apply our empirical framework to employment data from the Census Quarterly Workforce Indicators (QWI), broken down by worker type (gender, race, education and age), geography, and industry (at the NAICS 4-digit level). These publicly available data cover the vast majority of private sector employment for virtually all counties in the United States for the years surrounding the Great Recession. Our near-universal coverage is important – we argue that, in order to identify the aggregate effect on worker inequality, it is necessary to trace out how *every* industry is impacted by a shock, rather than a subset. For our firm resilience analysis, we supplement the QWI with Statistics of U.S. Businesses (SUSB) data from the Census on the number of establishment deaths, births, expansions, and contractions by county and 4-digit NAICS.[7] We then link these establishment deaths and net establishment changes to employment shifts by industry, jurisdiction (county) and worker type. Finally, we conduct various supplemental analyses using American Community Survey (ACS) data from the United States Census. In contrast to prior literature that does not account for sampling variability when calculating across and within components, we perform inference on all components of our decomposition (across/within, as well as overall and deaths-related employment effects) using the bootstrap. This allows us to formally test whether each of the components statistically differ from each other and from zero.

We document substantial changes in employment inequality by worker type over the Great Recession. While almost all worker types lost employment, male, young and black workers (and, to a lesser degree, less-educated workers) were disproportionately affected. For example, the employment decline for men was about 7%, while the decline for women was only about 3.4%. These patterns generally persist using just the employment changes that can be predicted from establishment deaths. That is, deaths are associated with employment losses for almost all workers, but the effects are particularly large for male, young, black and low-education workers (a key exception is the deaths estimate for Hispanic workers, which is more than double the effect for black workers). Returning to gender, we estimate a deaths-only decline of 11% for men versus about 5.6% for women. Importantly, local establishment deaths (and net establishment changes) are only modestly correlated with local employment declines. There is meaningful variation in employment that is orthogonal to our deaths variable – our finding that deaths can explain a substantial fraction of the

[7] These data are not part of the standard SUSB distribution, but are available without restriction from Census for a nominal fee.

change in inequality between various worker types is not tautological.

The decomposition of these estimates into across- and within-industry components shows that the larger relative losses for both men and non-college workers were driven entirely by their unfavorable distribution across industries. Within industry, women and more-educated workers suffered larger employment losses. By contrast, the within effects for black, Hispanic and young workers have the same sign as the corresponding employment changes overall and support the claim that these groups suffered more during the downturn. The within-deaths estimates are statistically significant and, with the exception of Hispanic workers, are the same sign as the overall-within estimates. The significant within-deaths results suggest that relatively disadvantaged workers (female, black, Hispanic and young) tend to be concentrated in less resilient establishments/firms within industry. Moreover, our results are qualitatively unchanged if we use the net change in the number of establishments, rather than just deaths, to predict employment declines.

On the whole, our results are consistent with a prominent role for discrimination in driving changes in employment inequality over the Great Recession. Several interlocking pieces of evidence support this claim. First, the estimated changes by education, our only direct measure of worker skill, are smaller than the estimated changes by race. Moreover, the within-industry death effect for education has the "wrong" sign, indicating within-industry losses for more educated workers, relative to their less educated counterparts. Second, we find substantial within-industry closure effects to the detriment of women, despite women and men having fairly similar levels of education. Third, we find a gender differential in the within-industry deaths effect among both high- and low-education workers.

The remainder of the paper is organized as follows: The next section describes the data used in our analysis. In Section 3, we set out our framework for exploring changes in inequality, defining the gap in the employment growth rates of different worker types, showing how to decompose this gap into an across- and within-industry component and detailing the procedure for determining the extent to which each of the effects (across and within) is driven by establishment deaths. Section 4 then presents several empirical facts about the Great Recession. This provides context for the results from applying our framework, which we present and discuss in Section 5. Section 6 concludes.

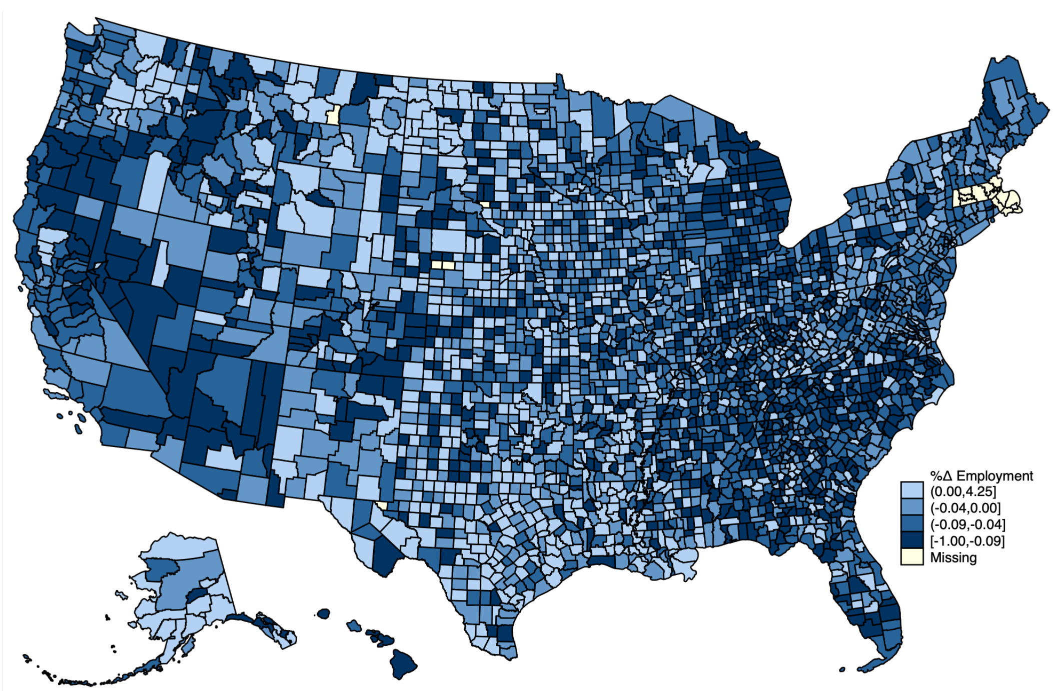
2 Data

2.1 Measure of Employment

Our measure of employment comes from the Quarterly Workforce Indicators (QWI), which is produced by the U.S. Census Bureau. It provides local labor market information (including employment) by quarter-year, jurisdiction (county), industry (4-digit NAICS), worker demographic (gender, race and ethnicity, education and age) and employer (firm) age and size. These publicly available data are aggregated from the matched employer-employee micro-level Longitudinal Employer-Household Dynamics (LEHD) dataset, which is constructed using administrative records from state unemployment insurance fillings, social security data, federal tax records and other Census data.

The QWI data cover all but one state of the United States for our period of interest (2007-2009).[8] The data also cover 95% of US private sector jobs. Figure 1 presents a map of the percent change of employment from 2007 to 2009 at the county-level, revealing the geographical variation of the measure.

Figure 1: Percent Employment Change 2007-2009 Across Counties



[8]The exception is Massachusetts, which became a part of the QWI data only in 2010.

We define each worker type from the QWI worker demographic characteristics. For gender and age, the process is straightforward: workers are either male or female, and we consider the age ranges 35 to 44, 45 to 54 and 55 to 64. For race/ethnicity comparisons, the categories "white" and "black" consist of white non-Hispanic and black non-Hispanic workers, respectively, while "Hispanic" consists of Hispanic workers of any race. For education, the category "No College" consists of workers without a high school education and those with a high school education or equivalent who did not attend college. The category "College" then includes workers with some college, an Associate's degree, a Bachelor's degree, or an advanced degree. Those for whom educational attainment is not reported are excluded from the analysis (most such workers are aged 24 or younger).

We are able to measure employment changes for each of the four worker characteristics, as well as for two gender-based interactions (gender-education and gender-age).[9] While our analysis does not differentiate between firm age or size within the QWI data, it does exploit information about the nature of employment changes by jurisdiction (as we detail next). Our employment measures do not condition on full- or part-time status. However, we draw upon the American Community Survey (ACS) to provide supplemental evidence that changes in the share of part-time workers do not drive our results (see Section 4.2).

The first column of Panels A and B in Table 1 reports descriptive statistics for the QWI data. The sample contains 3,128 jurisdictions and 312 4-digit industries. It also covers 122 million jobs, with total employment reported separately by worker type, industry and jurisdiction. We will return to Table 1 below, after first describing the other data source used in our analysis – establishment deaths.

2.2 Measure of Establishment Deaths

We measure establishment deaths and net establishment changes (births less deaths) at the county-industry level, using data from the Statistics of U.S. Businesses (SUSB). SUSB data are extracted from the Census Business Register which collects data on all known single and multi-establishment firms. These data come from several sources including the Economic Census, the Annual Survey of Manufacturers, the Current Business Surveys, and the administrative records of the Internal Revenue Service (IRS), the Social Security Administration (SSA) and the Bureau of Labor Statistics (BLS).

[9] The QWI data do not allow cross-tabulations for race.

Table 1: Descriptive Statistics

	QWI Sample	SUSB Subsample
Panel A: Industry-Jurisdiction Counts		
Industries	312	289
Jurisdictions	3128	3115
Industry-Jurisdictions	454,542	395,680
Panel B: Employment		
Total Employment	122,068,351	113,480,392
Male Employment	61,627,520	57,172,056
Female Employment	60,440,832	56,308,336
White Employment	82,757,096	77,494,744
Black Employment	14,564,350	13,263,273
Hispanic Employment	15,859,996	14,389,629
College Employment	63,675,852	58,654,204
No College Employment	40,083,372	37,245,728
55-64 Employment	16,291,822	14,856,606
45-54 Employment	28,313,954	25,992,352
35-44 Employment	28,409,986	26,280,874
Average Employment by Industry	391,245	392,666
	(792,667)	(788,487)
Average Employment by Jurisdiction	39,024	36,430
	(149,751)	(141,356)
Panel C: Establishments		
Number of Establishments		6,555,543
Net Change in Establishments		-208,829
Number of Establishment Deaths		1,495,878
Number of Establishment Births		1,287,049

Notes: The QWI sample contains labor market outcomes for the universe of industries and counties across all states (except for MA) and the time period 2007-2009. The merged QWI-SUSB data used for the analysis is a subsample of the QWI sample, since the SUSB establishment data contain a slightly smaller subset of industries and counties. The SUSB establishment count is for 2007, while the changes (net, deaths, births) are for the period 2007-2009.

For each county and 4-digit NAICS industry code, the dynamic SUSB data provide the number of establishment deaths, births, contractions, and expansions on an annual basis. These data are constructed from the Business Information Tracking Series (BITS), which longitudinally tracks each establishment in the United States across successive Business Register records.[10] Establishment deaths are defined in the SUSB data as the number of

[10]Establishments that have undergone no ownership or organizational changes are matched across years according to their Census identifier. BITS is also able to match those that do change using Employer

establishments that have positive employment in the first quarter of the initial year and zero employment in the first quarter of the subsequent year (and vice versa for births).

For our primary analysis, we merge the QWI data for 2007-08 and 2008-09 with SUSB establishment data for the corresponding years,[11] forming the "SUSB Subsample" detailed in the second column of Table 1. Comparing the two columns, the subsample used for the analysis includes over 99.6% of jurisdictions and 92.6% of industries in the QWI data,[12] accounting for 93% of total employment in the United States. The employment shares (and average earnings – see Table A.5) of each worker type are similar across samples.[13] Panel C of Table 1 reveals that there are about 6.5 million establishments in our sample, with a negative net change, reflecting a higher rate of establishment deaths than births during our period of interest (as one might expect during a deep recession).

Figure 2 shows the percent of establishment deaths by county for the period 2007-2009. A comparison of Figures 1 and 2 suggests that employment changes and establishment deaths may be correlated at the county level. This is expected – establishment deaths should be linked to employment losses during a time of low aggregate demand. However, since our method involves predicting employment changes using establishment deaths, it is important to confirm that some employment shifts (i.e., those for surviving firms) are orthogonal to establishment closures. Otherwise, the "deaths" component of our analysis would simply reflect the overall employment change. In fact, we find that the correlation between the two variables is only -0.26. Thus, we take our deaths variation as being predominantly indicative of the employment effects of firm closures rather than changes coming from surviving firms.

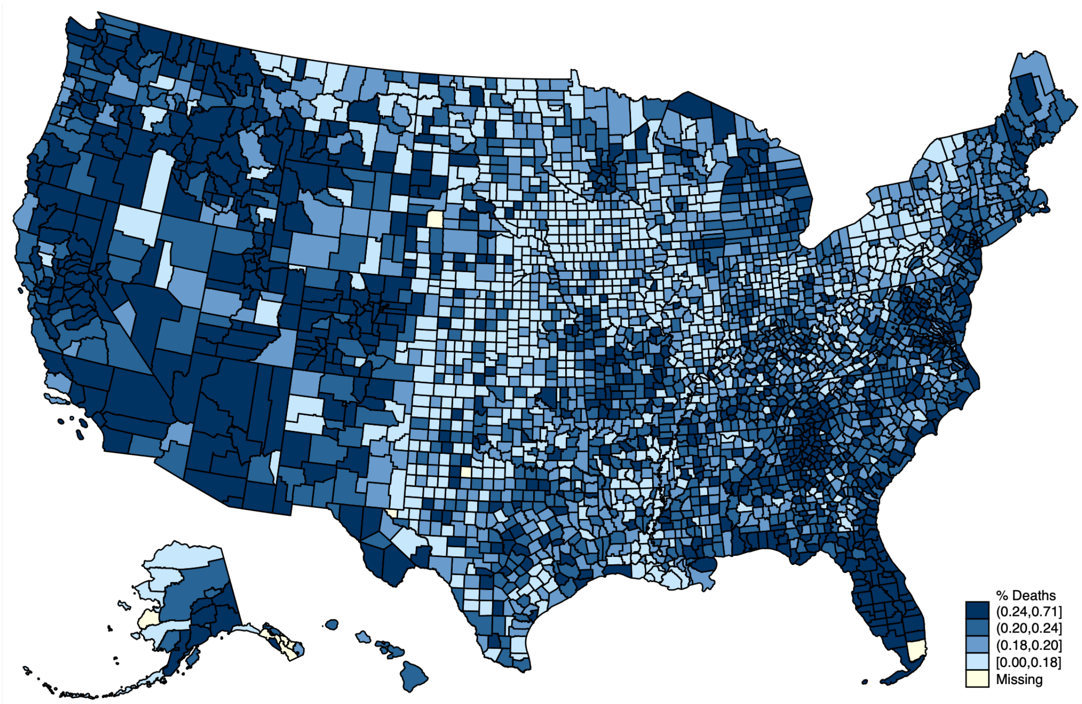
Identification Numbers, business names and addresses, and industry codes. Doing so guards against over counting of deaths or births.

[11] The 2007-08 SUSB dataset uses the 2002 NAICS classification while the 2008-09 dataset uses the 2007 classification. As the QWI uses the 2012 classification, we convert all industry categories to the 2012 definition using equivalences published by the Census, before merging the data sources. While the SUSB data contain 6-digit industry codes, we use the more aggregated 4-digit measure, to match the aggregation level of our QWI employment data.

[12] SUSB excludes some NAICS codes, including crop and animal production (NAICS 111,112), rail transportation (NAICS 482), postal service (NAICS 491), pension, health, welfare, and vacation funds (NAICS 525110, 525120, 525190), trusts, estates, and agency accounts (NAICS 525920), private households (NAICS 814), and public administration (NAICS 92).

[13] As an alternative to the SUSB data, we are also able to calculate the net change in the number of establishments using County Business Patterns (CBP) data, which is also provided by Census. The CBP reports the number of business establishments by county for each 4-digit NAICS on an annual basis, from which a change can be computed. This is in contrast to the much richer longitudinal information provided by SUSB, which separately details establishment deaths, births, contractions and expansions. Results using the level-based CBP data are very similar to those from our main SUSB-based analysis. They are available upon request.

Figure 2: Percent of Establishment Deaths from 2007-2009 Across Counties



3 Empirical Framework

In this section, we set out notation and define several measures relevant to understanding how employment gaps evolve. We first define employment gaps using actual data. Based on our framework and in the spirit of the prior literature (Katz and Murphy 1992; Berman et al. 1994; Autor et al. 1998), we then show how to identify the proportion of the change in the employment gap that arises from across- and within-industry variation. Next, we set out a procedure for determining the extent to which each of the effects (overall, across and within) is driven by either establishment deaths or the net change in the number of establishments.

3.1 Employment Gaps

Given industry $i \in \{1, \ldots, I\}$, jurisdiction $j \in \{1, \ldots, J\}$, time period $t \in \{0, 1\}$, and mutually exclusive worker types τ and τ' (e.g., men vs. women, more vs. less educated, white vs. black, etc.), let E_{ijt} represent employment at the (i, j, t) level, and let E^{τ}_{ijt} and $E^{\tau'}_{ijt}$ be type-specific analogues (so that $E_{ijt} = E^{\tau}_{ijt} + E^{\tau'}_{ijt}$). These measures can each be summed across i and j to compute the aggregate statistics $E_t \equiv \sum_i \sum_j E_{ijt}$, $E^{\tau}_t \equiv \sum_i \sum_j E^{\tau}_{ijt}$ and

$E_t^{\tau'} \equiv \sum_i \sum_j E_{ijt}^{\tau'}$ (so that $E_t = E_t^{\tau} + E_t^{\tau'}$).

We are interested in determining how employment changes for groups τ and τ' compare. Define $\theta_{ij}^{\tau} \equiv \frac{\Delta E_{ij}^{\tau}}{E_{ij0}^{\tau}} = \frac{E_{ij1}^{\tau} - E_{ij0}^{\tau}}{E_{ij0}^{\tau}}$ as the percent change in the employment at the (i, j, t) level and $\theta^{\tau} \equiv \frac{\Delta E^{\tau}}{E_0^{\tau}}$ as its aggregated counterpart (across i and j). Note that $\frac{\Delta E^{\tau}}{E_0^{\tau}} = \frac{\sum_i \sum_j \theta_{ij}^{\tau} E_{ij0}^{\tau}}{\sum_i \sum_j E_{ij0}^{\tau}}$. Thus, summing actual employment across all $i - j$ combinations yields the actual growth in employment for type τ workers θ^{τ}, through ΔE^{τ} and E_0^{τ}. Our measure of the change in the employment gap is then given by[14]

$$[\theta^{\tau} - \theta^{\tau'}] = \frac{\Delta E^{\tau}}{E_0^{\tau}} - \frac{\Delta E^{\tau'}}{E_0^{\tau'}} \tag{1}$$

3.2 Decomposition by Industry

We would like to determine how much of the overall adjustment $[\theta^{\tau} - \theta^{\tau'}]$ is due to *within-industry* and *across-industry* adjustment.[15] We define *within-industry* variation as arising from within-industry differences in type-specific growth rates: that is, $\theta_i^{\tau} \neq \theta_i^{\tau'}$ for some i. *Across-industry* variation can then be recovered from the difference between overall and within-industry adjustments.

More formally, Appendix B shows that the overall adjustment may be written as

$$\theta^{\tau} - \theta^{\tau'} = \sum_i (\tilde{\pi}_i^{\tau} \theta_i^{\tau} - \tilde{\pi}_i^{\tau'} \theta_i^{\tau'}) E_{i0}, \tag{2}$$

where $\pi_i^{\tau} \equiv \frac{E_{i0}^{\tau}}{E_{i0}}$, $E_0^{\tau} \equiv \sum_i \pi_i^{\tau} E_{i0}$ and $\tilde{\pi}_i^{\tau} \equiv \frac{\pi_i^{\tau}}{E_0^{\tau}}$. To separate this overall adjustment into within and across components, we expand the expression by subtracting and adding the average share $\tilde{\pi}_i \equiv \frac{\tilde{\pi}_i^{\tau} + \tilde{\pi}_i^{\tau'}}{2}$ on the right-hand side in the following way:

$$\theta^{\tau} - \theta^{\tau'} = \sum_i [\underbrace{\theta_i^{\tau}(\tilde{\pi}_i^{\tau} - \tilde{\pi}_i) - \theta_i^{\tau'}(\tilde{\pi}_i^{\tau'} - \tilde{\pi}_i)}_{\text{A}} + \underbrace{\tilde{\pi}_i(\theta_i^{\tau} - \theta_i^{\tau'})}_{\text{W}}] E_{i0}\,. \tag{3}$$

The under brackets label the across (A) and within (W) components in equation (3). As per our definition, within-industry adjustment can only occur if types are differentially affected

[14] An alternative measure would be $\frac{E_1^{\tau}/E_0^{\tau}}{E_1^{\tau'}/E_0^{\tau'}} = \frac{\theta^{\tau}+1}{\theta^{\tau'}+1}$, the percent change in the employment gap between worker types τ and τ'. Though informative, this recasting of the change in the employment gap does not lend itself to the across/within decomposition we pursue here.

[15] One can also adapt our decomposition procedure to accommodate *within-industry-jurisdiction* and *across-industry-jurisdiction* adjustments. To the extent that there is a quantifiable difference in particular industries by region (a collection of jurisdictions), we can redefine the industry to be the industry-region pair using a data-driven approach.

by the shock within some industries ($\theta_i^\tau \neq \theta_i^{\tau'}$ for some i). Clearly, $\sum_i \tilde{\pi}_i(\theta_i^\tau - \theta_i^{\tau'})E_{i0} = 0$ if that is not true. The across-industry component is then obtained from the residual.

We can simplify the expression for the overall adjustment and both components. Using Equation (11), Appendix B shows that the overall adjustment can be rewritten as

$$\theta^\tau - \theta^{\tau'} = \sum_i \left[\theta_i^\tau \left(\frac{E_{i0}^\tau}{E_0^\tau} \right) - \theta_i^{\tau'} \left(\frac{E_{i0}^{\tau'}}{E_0^{\tau'}} \right) \right] . \tag{4}$$

Similarly, the within-industry component simplifies to

$$[\theta^\tau - \theta^{\tau'}]_W = \sum_i (\theta_i^\tau - \theta_i^{\tau'}) \left(\frac{(E_{i0}^\tau / E_0^\tau) + (E_{i0}^{\tau'} / E_0^{\tau'})}{2} \right) . \tag{5}$$

Intuitively, the within-industry component is the sum (across industries) of the difference in the effect of the shock by type, weighted by the average share of employment in industry i. Finally, the across-industry component simplifies to

$$[\theta^\tau - \theta^{\tau'}]_A = \sum_i \left(\frac{\theta_i^\tau + \theta_i^{\tau'}}{2} \right) \left(\frac{E_{i0}^\tau}{E_0^\tau} - \frac{E_{i0}^{\tau'}}{E_0^{\tau'}} \right) . \tag{6}$$

Intuitively, the across-industry component is the sum (across industries) of the difference in industry i employment shares by type, weighted by the (unweighted) average shock in industry i.

3.3 Decomposition by Establishment Deaths and Net Deaths

We begin by showing how to use establishment death variation at the jurisdiction-industry-level to generate predicted employment changes, which we can then feed into the decomposition machinery developed in the previous section.

Our baseline approach assumes that the change in employment at the industry-jurisdiction-type level is linearly related to establishment deaths over the same period.[16] Letting D_{ij} represent the number of establishment deaths at the i-j level, we recover the change in employment explained by establishment deaths by estimating the following equation:

$$\Delta E_{ij}^\tau = \alpha_i^\tau + \beta_i^\tau D_{ij} + \epsilon_i^\tau . \tag{7}$$

We estimate equation (7) using OLS, weighting by industry-jurisdiction employment in pe-

[16]The assumption underlying this specification is that, within a 4-digit industry, the number of workers per establishment does not vary too much across establishments. If each establishment has 100 workers, say, then 4 establishment deaths should generate an employment loss of 400 workers.

riod 0. The estimated parameters of equation (7) are used as inputs to estimate the change in employment explained by establishment closure via

$$\widehat{\Delta E_i^\tau}|_D = \hat{\beta}_i^\tau \sum_j D_{ij} \, . \tag{8}$$

Finally, we estimate than change in group-τ employment due to establishment deaths as

$$\widehat{\theta}^\tau|_D = \frac{\widehat{\Delta E_i^\tau}|_D}{E_0^\tau} \, . \tag{9}$$

The predicted change stemming from deaths is

$$[\theta^\tau - \theta^{\tau'}]_D = \hat{\theta}^\tau|_D - \hat{\theta}^{\tau'}|_D \, . \tag{10}$$

It is important to note that the employment changes that we attribute to establishment deaths definitionally include employment changes from sources that are *correlated with* establishment deaths. This is a necessary assumption given our data, as we cannot directly link employment in the QWI to particular establishments. Therefore, the differences between the observed employment changes and the components explained by deaths should be interpreted as the employment changes, both across and within industries, that are orthogonal to local, industry-specific establishment deaths. As we argue in Section 2.2, much of the employment variation for surviving firms is likely to fall under this category.

Our SUSB data allows us to carry out analogous decompositions using the *net* change in the number of establishments, rather than just deaths. Letting N_{ij} be the net change in the number of i-j establishments, we simply substitute N_{ij} for D_{ij} into equations (7)-(8) above. We report these net estimates in the appendix; in practice they are qualitativey similar to the deaths estimates. This similarity is driven by the relatively high correlation between deaths and births (the other component of the net change variable) during the Great Recession.

The correlation between deaths and births highlights a limitation of our approach. Since the SUSB data also includes the number of establishment births, contractions, and expansions, a natural question is to what degree each of these components, along with deaths, can explain, separately and jointly, type-specific employment declines. However, these components are correlated enough over the Great Recession that versions of equation (7) which include all of them simultaneously present substantial evidence of multicollinearity.[17] There-

[17]Specifically, for many industries, the relevant design matrix has a condition number well above 30.

fore, we do not analyze such specifications. If we could credibly run such specifications, they would produce "conservative" estimates in the sense that the other components (contractions, births, etc.) could absorb some of the correlation between deaths and employment that actually should be (causally) attributed to deaths.

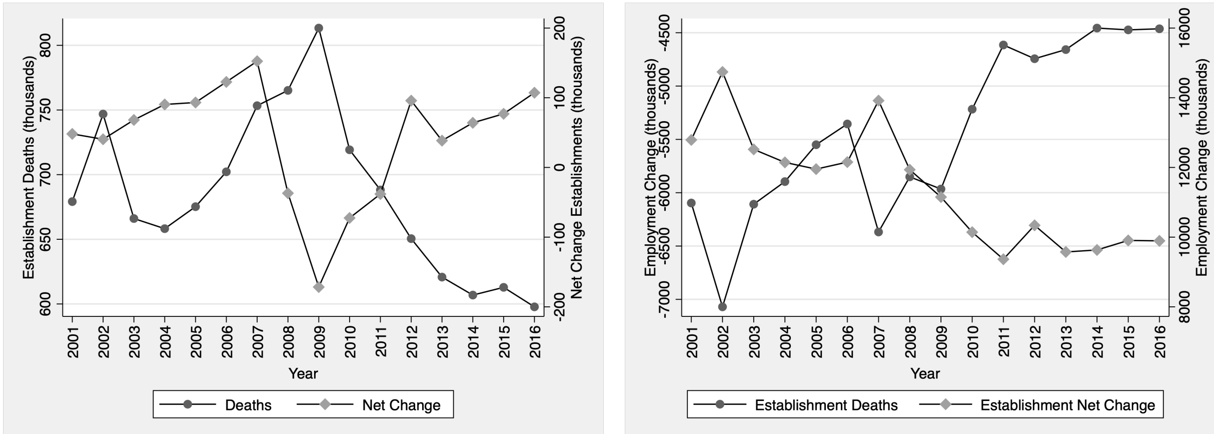
Our goal is to understand how differential sorting by worker type across firms (establishments) that are more or less likely to survive a downturn drives employment inequality. The critical distinction we make then is between establishment deaths, where *who* gets fired is not discretionary, and firm contractions, where managers presumably have some discretion. Because we cannot separately identify the contractions component, the key assumption supporting the interpretation of our results is that contractions are more important in explaining overall employment declines than in explaining the employment declines that can be predicted solely from deaths.

4 Empirical Facts about the Great Recession

Before discussing our main results decomposing employment changes during the Great Recession into across- and within-industry components, as well as components stemming from establishment deaths, we present a number of motivating facts about the period of interest. The facts are divided into five categories. First, we reveal the impact of the recession on employment and establishment deaths, relative to preceding and subsequent years. Second, we discuss the effect of the recession on part-time employment. Third, we discuss trends in the population share and labor force participation by worker type. Fourth, we document industry heterogeneity in the effect of the recession on employment, suggesting that both across- and within-industry variation might be important for understanding the effect of the downturn on relative employment outcomes. The fifth set of facts then follows naturally, presenting long-term trends in across- and within-industry components, providing context for the main estimates that follow.

4.1 Effect on Establishment Deaths and Employment

This section documents the impact of the Great Recession on establishment deaths and the net change in them (births less deaths), as well as aggregate employment. Figure 3 presents the aggregate trends from 2001 to 2016 in yearly establishment deaths and the net change,



(a) Establishment Deaths and Net Change (b) Employment Loss due to Establishment Changes

Figure 3: Trends in Establishment Deaths and Net Change (2001-2016) – SUSB Data

Notes: Panel (a) shows the evolution of establishment deaths and their net change (births-deaths) from 2001 to 2016, while Panel (b) shows the trend in employment loss due to these changes.

using the SUSB data. As shown in Panel (a) of Figure 3, establishment deaths began to increase in 2006, peaking during the height of the recession between 2008 and 2009. The net change in the number of establishment mirrors this pattern, falling substantially during the same period, which is consistent with not only an increase in establishment deaths but also a decrease in establishment births. Panel (b) depicts the employment loss linked to both establishment deaths and the net change in them over time. Both measures of establishment dynamics reveal a substantial effect of establishment deaths and net change on aggregate employment from 2007 to 2009. These trends map rather well onto the National Bureau of Economic Research (NBER) definition of the recessionary period (December 2007 to June 2009).

Figure 4 presents aggregate employment trends from 2001Q1 to 2016Q4, using the QWI data. The plotted values represent national employment as opposed to Panel (b) of Figure 3, which presents the employment change directly attributable to establishment deaths and their net change. The seasonally adjusted[18] employment trend presented in Panel (a) of Figure 4 reveals that aggregate employment decreased during the Great Recession, beginning to fall in the first quarter of 2008 and beginning to recover in the first quarter of 2010. This is very close to the NBER definition of the recession. Given that the SUSB data is only

[18]We seasonally adjust employment trends using seasonal adjustment software by the US Census Bureau, entitled "X-13-ARIMA-SEATS."

available on an annual basis, we define the Great Recession to have occurred from 2007 to 2009.

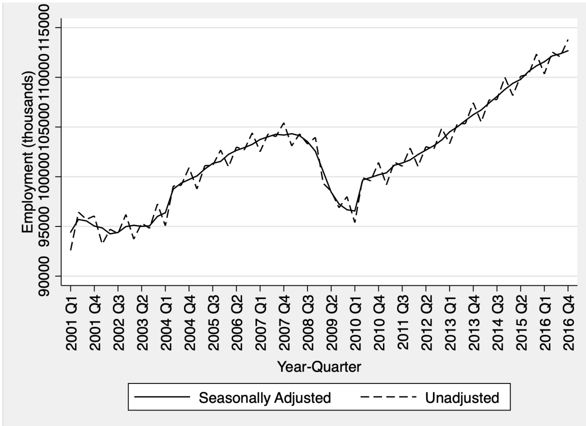
Panels (b), (c), and (d) of Figure 4 present seasonally adjusted employment trends by gender, race and education, respectively. Employment trends across worker types reveal differences in the way and the timing by which different workers were affected by the recession. For example, Panel (b) shows that males began to experience employment declines a quarter earlier (2007Q4) than the aggregate graph in Panel (a) suggests. In addition, females experienced less of an employment decline overall. Panel (c) shows that while white workers experienced a sizable decrease in employment, their recovery following the Great Recession was faster than the recovery experienced by black workers.

We provide an alternative way of visualizing employment changes over time in Appendix Figure A.1, by plotting worker type-specific percent changes in employment over time. These figures also reveal that employment losses were non-uniform across worker types. For example, employment inequality by gender was approximately stable prior to the crisis. Yet employment fell more for men than for women during the crisis and rebounded more strongly for men early in the recovery. The plots for education reveal a different pattern that indicates progressively smaller employment gains for more educated workers relative to less educated workers. This trend reverses during the recession as less educated workers experienced larger employment losses in relative terms. The pattern by race is similar to the pattern by education - black workers fared comparatively well except during the Great Recession, when they experienced larger employment declines.

4.2 Part-Time Employment

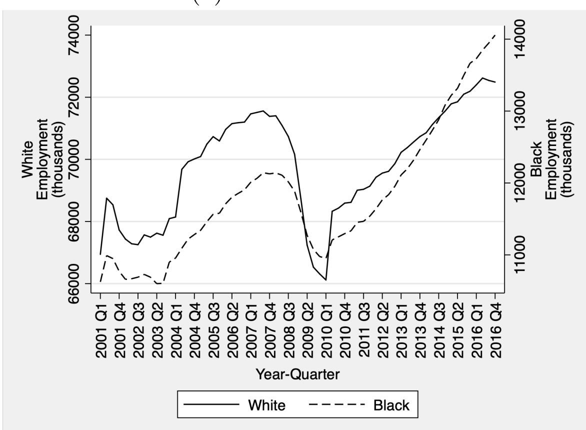
The QWI data does not distinguish between full-time and part-time employment. This complicates the interpretation of our results because the Great Recession may cause shifts on both the employed/not-employed margin and the full-time/part-time margin. Our method and data will not detect industry responses which shift workers between part-time and full-time roles. Although we cannot address this concern directly, we can nonetheless present evidence that the share of part time work is reasonably stable (1) across industries and (2) within industries over time.

We use the ACS to estimate the share of part-time and full-time workers by 4-digit industry code. Panel (a) of Figure 5 plots the mean and 95% confidence interval for the

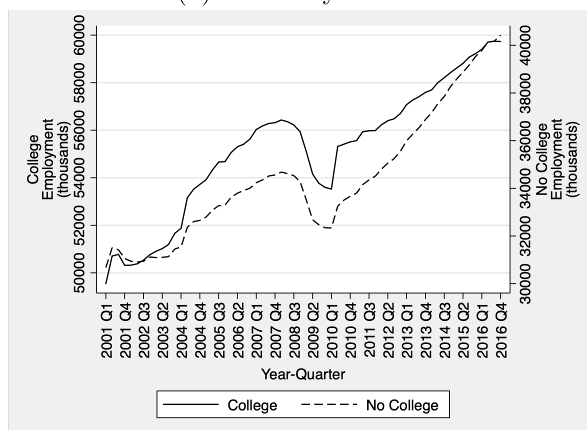


(a) Overall Trends

(b) Trends by Gender



(c) Trends by Race



(d) Trends by Education

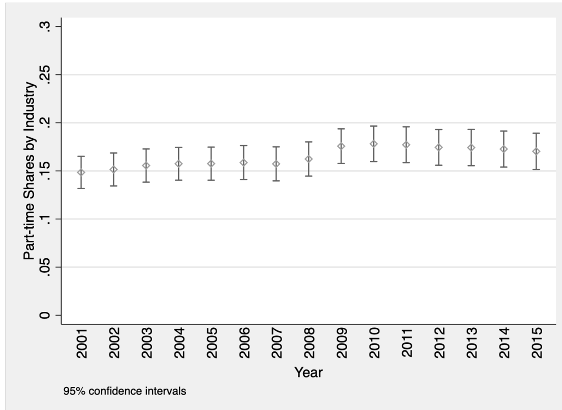
Figure 4: Aggregate Employment Trends and Employment Trends by Worker Type (2001-2016) – QWI Data

Notes: This figure shows the evolution of the observed employment from 2001 to 2016 inclusive for different worker types. Panel (a) shows quarterly trends in overall employment with and without seasonality adjustments. Panels (b), (c) and (d) show the seasonally adjusted quarterly trend of employment by gender (male versus female), race (white versus black), and education (college versus no college), respectively.

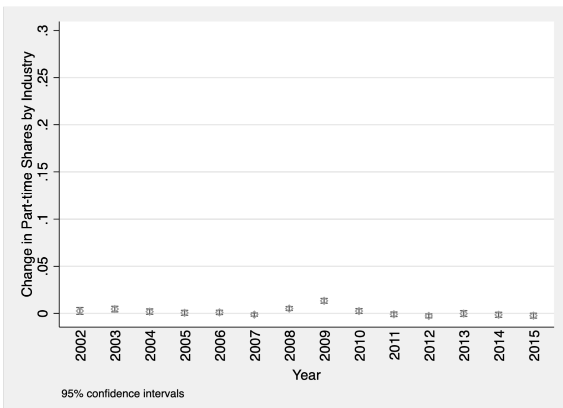
share of part time workers by industry for each ACS year (2001 to 2015). The means are around 0.15-0.18, which matches aggregate estimates from BLS quite well.[19] Moreover, the variance in this share across industries is fairly small each year, with the 95% confidence intervals generally spanning only about 0.025. The part-time share increased modestly from 0.16 to 0.18 during the recession, suggesting across-industry stability.

With respect to within-industry stability, panels (b) and (c) of Figure 5 show that the part-time shares did not change very much within industry over our sample period. In 2008 and 2009, the part time share increased for most industries, while the typical change aside

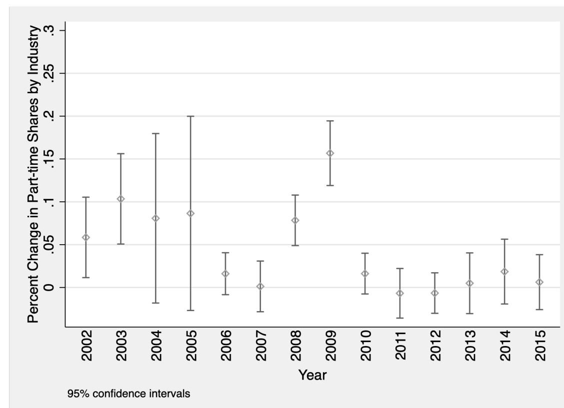
[19]Compare BLS series LNS11000000 (total labor force) to LNS12600000 (part time labor force).



(a) Across-Industry Levels



(b) Within-Industry Changes



(c) Within-Industry Percent Changes

Figure 5: Part-Time Employment Shares Across and Within Industries (2001-2015)

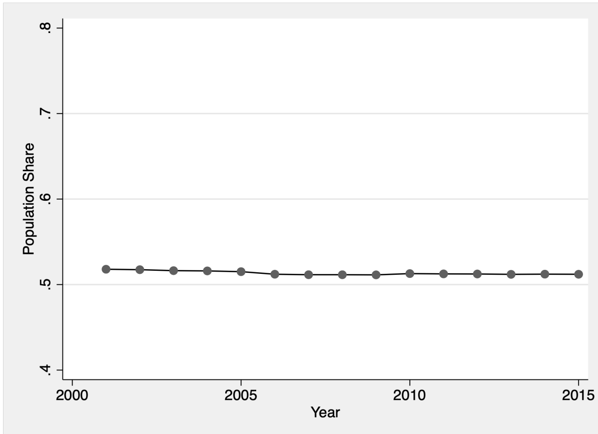
Notes: This figure shows the evolution of part-time employment shares across industries from 2001 to 2015 inclusive. In particular, panels (a), (b) and (c) show yearly variation in the level, change and percent change in part-time employment, respectively.

from these two years is around 0. However, even in 2009, the typical industry only saw its part-time share increase by about 0.015 (off a base of about 0.16). Taken together, these figures suggest that the distinction between part- and full-time is not an important source of within-industry variation.

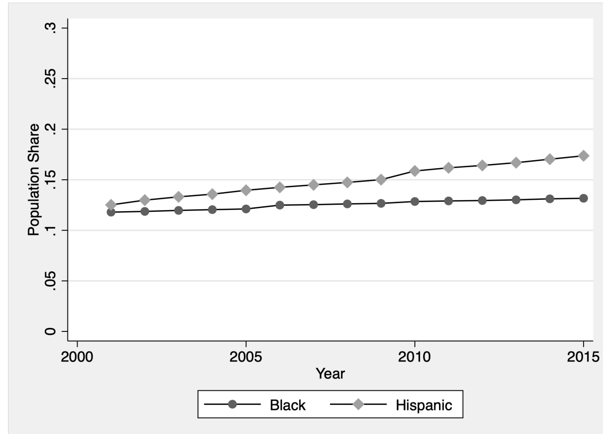
4.3 Population Share and Labor Force Participation by Type

To provide context for our results, we document trends in the population share and labor force participation by worker type surrounding the Great Recession.[20] Using supplemental

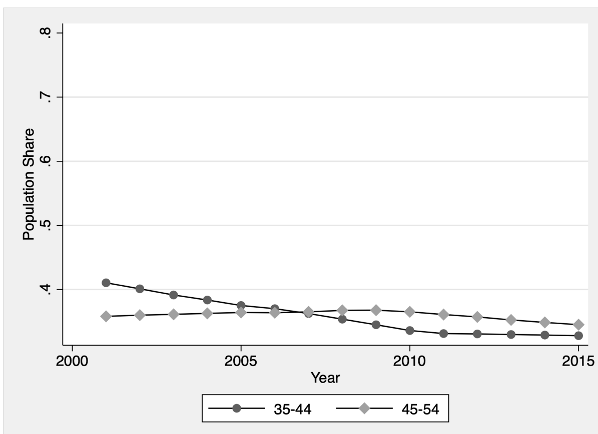
[20] We benchmark the differential employment growth rates reported in our main results against initial employment gaps that are adjusted for population share differences between worker types.



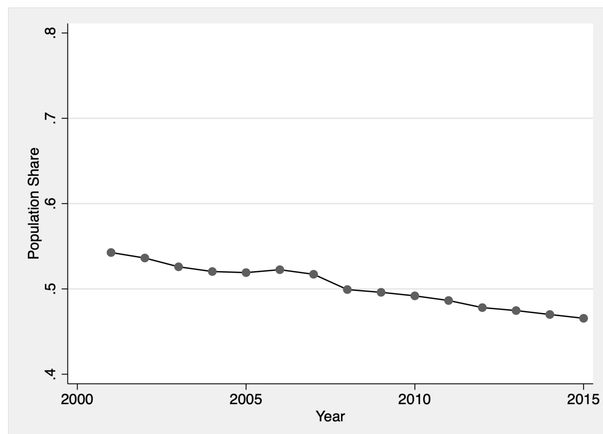
(a) Female



(b) Black and Hispanic



(c) 35-44 and 45-54



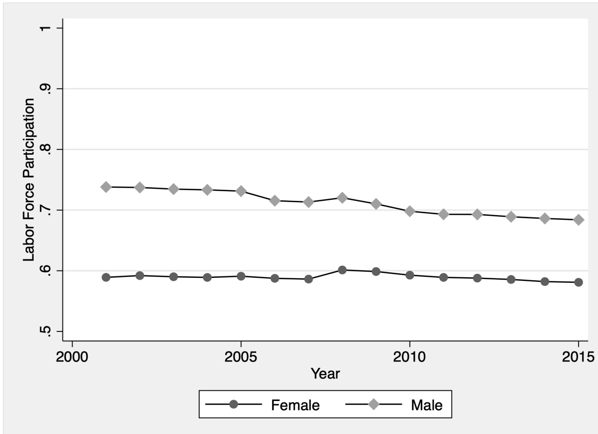
(d) No College

Figure 6: Population Share by Type (2001-2015)

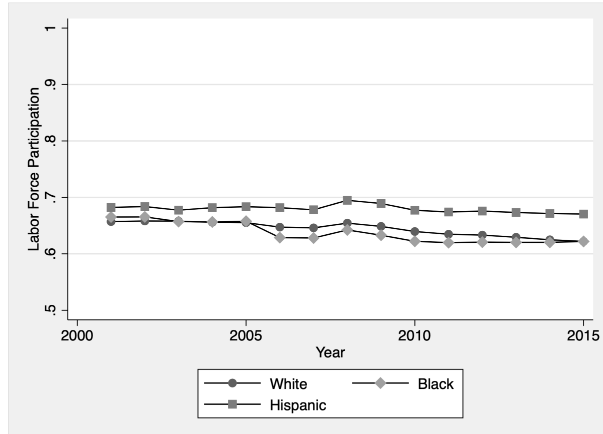
Notes: This figure shows the evolution of population share by gender, race, age and education categories from 2001 to 2015 inclusive. In particular, panel (a), (b), (c) and (d) depicts the trend for female, Black and Hispanic, age 35-44 and 45-54, and no-college educated people, respectively.

ACS data, Figure 6 plots the population share for female, black and Hispanic, age 35-44 and 45-54, and No College people over time. As one would expect, the share of females in the population is unchanged over time. The share of black and Hispanic people is rising during the 2000s, but the trend does not change during the onset of the recession. The share of people aged 45-54 rises and the share of people aged 35-44 falls. In contrast to the other categories, while the share of adults without some college education declines steadily during the 2000s, there is a discrete fall in the share during the recession in 2008. This may reflect the recession leading some potential workers to forego employment in the near term in favor of additional education.

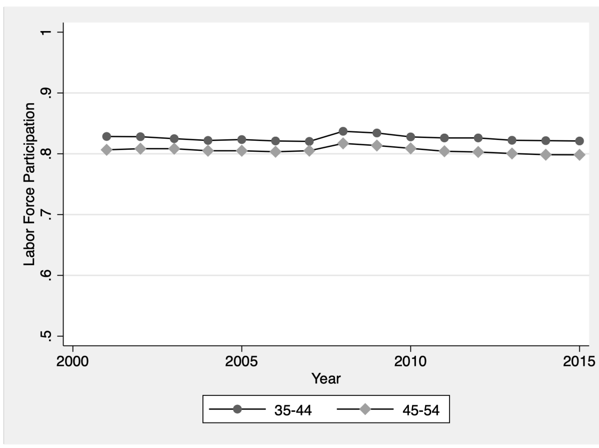
We also use the ACS data to plot the labor force participation by type in Figure 7.



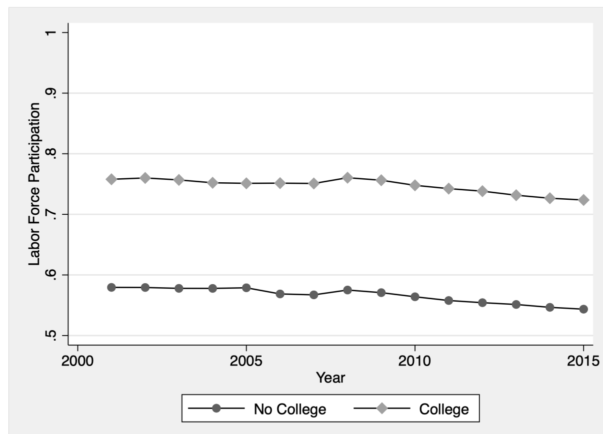
(a) Male and Female



(b) White, Black and Hispanic



(c) 35-44 and 45-54

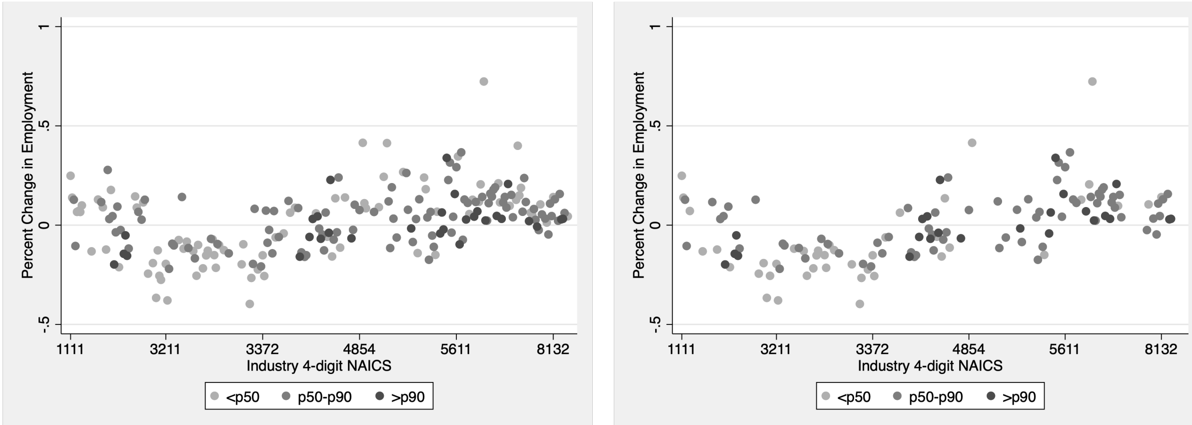


(d) College and No College

Figure 7: Labor Force Participation by Type (2001-2015)

Notes: This figure shows the evolution of labor force participation by gender, race, age and education categories from 2001 to 2015 inclusive. In particular, panel (a), (b), (c) and (d) depicts the trend for gender (male and female), race (White, Black and Hispanic), age (35-44 and 45-54), and education (college and no college), respectively.

There is a temporary uptick in the participation of all worker types during the recession, against a generally declining trend. The increase is especially pronounced for female, black, Hispanic, age 35-44 and college-educated workers. In light of the population share trends, one might expect a tailwind in terms of average employment gains for female, minority and college-educated workers. This should be kept in mind as we present our results in Section 5.



(a) No Correction (b) Holm Bonferroni

Figure 8: Percent Change in Employment by Industry (2007-2009)

Notes: This figure shows the industry-level average percent change of employment from 2007 to 2009 using the full sample. Panel (a) plots the average percent change in employment by industry that is statistically different than zero at the 10% level, while panel (b) applies the Holm-Bonferroni correction to adjust significance for multiple comparisons.

4.4 Heterogeneous Effects by Industry

This section provides evidence of heterogeneous changes in employment during the Great Recession at both the industry and worker group/industry level. This heterogeneity, coupled with the variation in worker composition by industry, implies that the "across" inequality channel is likely to be important in many cases: worker groups with a disproportionate share in industries particularly affected by the Great Recession should experience worse outcomes, all else equal, than worker groups who are concentrated in less-affected industries. This section also presents evidence that, in some industries, these shocks differentially affect worker groups, suggesting that the "within" channel may frequently be salient as well.

We first explore the change in employment from 2007 to 2009 by 4-digit industry. Despite the well-documented overall decrease in employment experienced during the Great Recession, Figure 8 suggests that several industry categories actually experienced employment increases during this time period.

We further explore heterogeneity in the changes of employment by industry and worker type in Figure A.2. Again, we observe employment increases for some industries and worker types. However, Figure A.2 shows that employment changes can vary substantially across worker types within industries. This is particularly true for race, education, and to a lesser extent, gender.

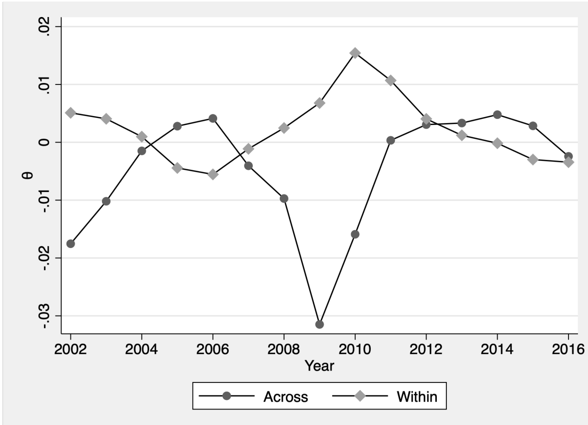
4.5 Long-Run Trends in Across and Within Components

We now use our decomposition framework (outlined in Section 3) to understand how across- and within-industry employment inequality evolved between 2001 and 2016. In particular, we want to know whether the Great Recession had a pronounced effect on the components, by assessing the extent to which there was a trend break during that time. Doing so isolates the effect of the demand-side recessionary shock from other long-run changes (e.g., prior trends and lagged effects of earlier shocks), which we assume continue to operate during the downturn. This provides suggestive evidence for the formal analysis that follows in Section 5.

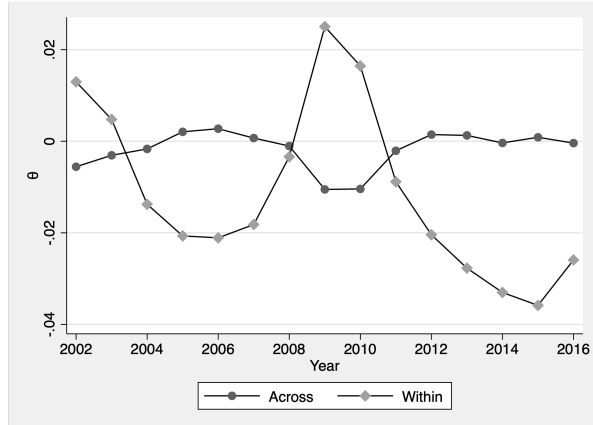
Figure 9 plots the year-over-year across and within components. Starting with gender in Panel (a), the within and across components are in opposition to each other during the Great Recession. Within industry, women experience greater employment losses and greater gains during the subsequent recovery. However, the within component is more than counteracted by the across component, as the industries hit hardest by the recession tended to have a higher concentration of men, working to the advantage of women. On balance then, men experienced relatively greater employment losses during this period (and greater gains subsequently).

As for the racial comparison between white and black workers, we see that changes in the across component generally contributes relatively little to the overall employment response to the recession – it is mainly driven by the within component. The within component is mostly negative, consistent with faster employment growth experienced by the black workers during the non-recession years, but it spikes positive during the recession. Black workers experienced much greater employment losses than white workers within industries during the downturn and had much greater employment growth at the industry level during the recovery. Interestingly, the across component does dip down slightly during the recession – the differential distribution of race groups across industries and the differential employment declines experienced by different industries on net counteracted the within-industry forces, if only partially. The patterns are similar for the white-Hispanic comparison (available upon request).

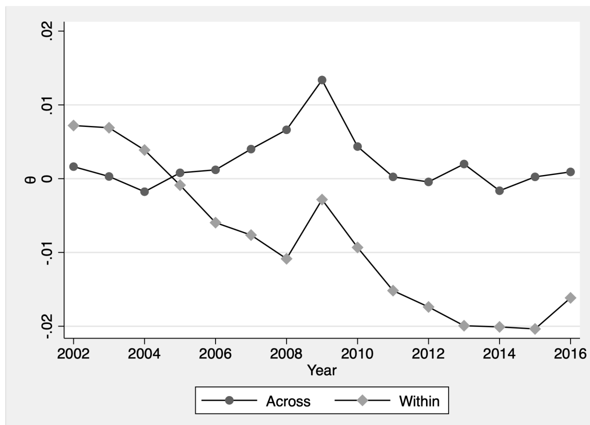
The decomposition by education follows a distinctive pattern. After 2004, the within component is consistently negative, indicating lower employment growth at the industry



(a) Gender (Male vs. Female)



(b) Race (White vs. Black)



(c) Education (College vs. No College)

Figure 9: Within and Across Component Trends by Type (2001-2016) – All Counties

Notes: This figure shows the evolution of the across and within components of the observed difference in the percent change in employment between worker types from 2001 to 2015 inclusive. Panels (a), (b), and (c) show the trend of these changes by gender, race, and education, respectively.

level for high-education workers. The across component is close to zero except during the 2005-2010 period, when it shifts positive, indicating that the industries hit hardest by the recession (with the slow down in employment growth already starting in 2005) had a relatively low share of educated workers. Of note, the within component moves from solidly negative to positive during the recession, so both forces work over this time period to advantage educated workers (in relative terms, as all groups experienced employment declines).

5 Employment Inequality and Establishment Deaths Over the Great Recession

The previous section showed that the Great Recession generated substantial increases in employment inequality and that the decomposition of these increases into across- and within-industry components differs greatly depending on the groups being compared. In this section, we report formal estimates of these effects and then assess the degree to which relative employment shifts by worker type (gender, race, education and age) over the Great Recession can be explained by establishment deaths. We carry out this analysis by implementing the various decompositions outlined in Section 3. For all results, we compute confidence intervals and p-values via the bootstrap using 1,000 draws, sampling at the jurisdiction (county) level.

We first consider the overall employment changes ("all") by worker type and the corresponding changes predicted from establishment deaths ("deaths"). Table 2 presents these results, which show how the different worker types fared over the Great Recession without adjusting for the distribution of employment across industries.

Starting with gender, while both men and women experienced substantial employment losses between 2007 and 2009, the overall decline for women was roughly half the decline for men (-0.034 versus -0.069). For both men and women, the employment losses predicted by deaths are greater than the observed losses – expansions and births counteract losses associated with deaths to some degree. Notably, the male-female difference in employment loss is larger for deaths than overall, indicating that establishment deaths are associated with differentially large employment losses for male workers.

For education, we see that, unsurprisingly, less-educated (no-college) workers suffered relatively larger employment declines than educated (college) workers (-0.043 versus -0.033). In contrast to gender, the advantaged/disadvantaged gap is not larger using employment changes predicted from deaths.

Turning to race, black workers lost modestly more employment than white workers, with a larger difference using deaths-predicted employment. Interestingly, while Hispanic workers lost about the same employment as white workers overall, they lost nearly three times as much employment due to establishment deaths (and more than twice as much as black workers lost), indicating that Hispanic workers were substantially more likely to be working

Table 2: Overall and Deaths Employment Changes, 2007-2009

	Gender			Education	
	All	Deaths		All	Deaths
θ^m	-0.069***	-0.110***	θ^c	-0.033***	-0.058***
	[-0.072,-0.066]	[-0.124,-0.085]		[-0.036,-0.031]	[-0.065,-0.043]
	(0.000)	(0.000)		(0.000)	(0.000)
θ^f	-0.034***	-0.056***	θ^n	-0.043***	-0.069***
	[-0.037,-0.032]	[-0.063,-0.040]		[-0.046,-0.039]	[-0.083,-0.042]
	(0.000)	(0.000)		(0.000)	(0.000)

	Race			Age	
	All	Deaths		All	Deaths
θ^w	-0.056***	-0.068***	θ^{54-65}	0.035***	0.015*
	[-0.058,-0.053]	[-0.083,-0.051]		[0.032,0.038]	[0.004,0.033]
	(0.000)	(0.000)		(0.000)	(0.086)
θ^b	-0.068***	-0.083***	θ^{45-54}	-0.032***	-0.042***
	[-0.072,-0.064]	[-0.095,-0.065]		[-0.035,-0.030]	[-0.049,-0.028]
	(0.000)	(0.000)		(0.000)	(0.000)
θ^h	-0.055***	-0.204***	θ^{35-44}	-0.082***	-0.108***
	[-0.059,-0.048]	[-0.227,-0.133]		[-0.084,-0.079]	[-0.122,-0.091]
	(0.000)	(0.000)		(0.000)	(0.000)

Notes: This table presents the estimates of Equation 9 for both observed changes in employment and changes in employment due to establishment deaths. Estimates are displayed for all worker characteristics: male (m), female (f), White (w), Black (b), Hispanic (h), college(c), no-college(n), and ages, 54-65, 45-54 and 35-44. 90% confidence intervals and significance are calculated using 1000 bootstrap repetitions. Confidence intervals are reported in square brackets and p-values are reported in parentheses. *** denotes significance at the 1% level.

in less resilient firms at the onset of the recession.

In terms of worker age, the estimates show clearly that older workers experienced smaller employment losses over the Great Recession. In fact, the oldest workers (age 54-65) actually gained employment overall during this period, while younger workers (age 45-54 and 35-44) both lost (-0.032 and -0.082). The predicted employment change from deaths is uniformly smaller than the overall estimates in all cases, but the slope of the age gradient is quite similar.

Worker types are not distributed evenly across industries, so some of the differential employment losses reported in Table 2 may be due to industry-level heterogeneity in the severity of the recession, not differences in how workers of different types are matched to firms within industry. Indeed, the results already presented in Figure 9 suggest that the across-industry components are likely to be important for many comparisons. The cleanest test of the hypothesis that disadvantaged workers tend to be concentrated in less resilient firms therefore is to compare the within-industry components of the overall and predicted-from-deaths employment changes.

Table 3 carries out this comparison by reporting the across- and within-industry components, using both the overall employment changes and the employment changes predicted from establishment deaths. All within- and across-industry components are statistically and economically significant. Moreover, with the exception of the within component for the white-Hispanic comparison, the all and deaths estimates always have the same sign.

As per the within-deaths estimates, our central takeaway from the table is that female, black, Hispanic, and young workers are relatively more concentrated in less resilient estab-

Table 3: Across-Within Overall and Deaths Employment Changes, 2007-2009

	Gender			Education	
	All	Deaths		All	Deaths
$[\theta^m - \theta^f]_A$	-0.045***	-0.068***	$[\theta^c - \theta^n]_A$	0.022***	0.036***
	[-0.047,-0.042]	[-0.090,-0.050]		[0.021,0.023]	[0.026,0.048]
	(0.000)	(0.000)		(0.000)	(0.000)
$[\theta^m - \theta^f]_W$	0.010***	0.013**	$[\theta^c - \theta^n]_W$	-0.012***	-0.025***
	[0.009,0.011]	[0.004,0.025]		[-0.014,-0.011]	[-0.038,-0.019]
	(0.000)	(0.038)		(0.000)	(0.000)
	Race			**Age**	
	All	Deaths		All	Deaths
$[\theta^w - \theta^b]_A$	-0.011***	-0.016***	$[\theta^{55-64} - \theta^{35-44}]_A$	0.006***	0.009***
	[-0.012,-0.009]	[-0.024,-0.010]		[0.006,0.007]	[0.006,0.013]
	(0.000)	(0.000)		(0.000)	(0.000)
$[\theta^w - \theta^b]_W$	0.023***	0.030**	$[\theta^{55-64} - \theta^{35-44}]_W$	0.110***	0.115***
	[0.020,0.026]	[0.010,0.048]		[0.109,0.112]	[0.104,0.128]
	(0.000)	(0.028)		(0.000)	(0.000)
$[\theta^w - \theta^h]_A$	0.013***	0.035***	$[\theta^{45-54} - \theta^{35-44}]_A$	0.001***	0.004***
	[0.011,0.017]	[0.020,0.054]		[0.000,0.001]	[0.002,0.006]
	(0.000)	(0.007)		(0.000)	(0.000)
$[\theta^w - \theta^h]_W$	-0.021***	0.098***	$[\theta^{45-54} - \theta^{35-44}]_W$	0.049***	0.062***
	[-0.025,-0.018]	[0.034,0.119]		[0.047,0.050]	[0.051,0.076]
	(0.000)	(0.000)		(0.000)	(0.000)

Notes: This table presents the estimates of Equations and 6 and 5 for both observed changes in employment and changes in employment due to establishment deaths. Estimates are displayed for all worker characteristics: male (m), female (f), White (w), Black (b), Hispanic (h), college(c), no-college(n), and ages, 54-65, 45-54 and 35-44. 90% confidence intervals and significance are calculated using 1000 bootstrap repetitions. Confidence intervals are reported in square brackets and p-values are reported in parentheses. *** denotes significance at the 1% level.

lishments/firms at the industry level (relative to male, white and older workers) . Notably, across-industry variation is quite prominent in explaining total employment changes for gender, race and education, with the large and often opposite sign across component tending to mask its within-industry counterpart. We now discuss each worker group comparison in greater detail.

The masking effect of the across-industry component is particularly stark in the case of gender. The across components for both all and deaths are large and negative – men were relatively concentrated within industries hit harder by the downturn. The across components are also substantially larger than their within-industry counterparts. Moreover, the within component using the deaths variation is modestly larger than the within component using all variation. This is what leads us to conclude that women tend to be concentrated in less resilient establishments within industry. Because men and women do not differ greatly in their educational attainment or their geographical distribution, these significant within-industry estimates are consistent with taste-based labor market discrimination.[21]

The decomposition results are similar for the comparison of black and white workers. The across-industry components again serve to mask the within-industry disadvantage for black workers, though only partially so. That is, black workers suffered substantially greater employment declines within-industry, but were relatively concentrated in industries that lost less overall employment. Nonetheless, the white-black across components are less important in explaining the white-black relative employment losses than they are for gender or education. The within component attributable to firm deaths is modestly larger than the overall within component, indicating a substantial role for within-industry differences in the types of establishments employing black and white workers. The sizeable within effect could be due to discrimination against black workers, but could also be explained by the large education differences between black and white workers.

We also report across- and within-industry effects for the white-Hispanic comparison. This is especially interesting, as Hispanic workers were hurt by being concentrated in less resilient firms more than any other group we analyze (recall our discussion of Table 2). Considering all sources of employment changes (i.e., deaths, births, contractions and expansions), Hispanic workers were hurt by the recession more than white workers due to their concentration in

[21]We provide support for this claim below by separately estimating effects for gender interacted with age and with education.

industries that were hit harder, but white workers were hurt more when considering only within-industry variation. However, unlike for the white-black comparison, the components using only the deaths variation reinforce each other: Hispanic workers are always more likely to be found in less resilient firms and the disparity is especially large after conditioning for differential industry shocks through the prism of within-industry variation.

The education decomposition results bolster our interpretation of the gender and race results. We find significant, positive across-industry estimates – college-educated workers were relatively concentrated in industries that were less affected by the Great Recession. However, the within-industry estimates are actually negative, corresponding to larger employment declines for such workers. While somewhat puzzling, this result may be explained by a pronounced negative age-employment-loss gradient (see Table 2) coupled with higher average educational attainment for younger workers (see Table A.4). It may also be explained by the prior trend of low-education workers experiencing employment growth at a faster rate than their high-education counterparts (see our prior discussion with respect to Figure 9(c)) – a possibility we are continuing to explore. On balance, we view the education results as being inconsistent with a story in which skill differences by race and gender are fully driving our within and within-deaths estimates. If so, taste-based discrimination is likely to play an important part in our results.

The decompositions by worker age reveal only a modest role for across-industry differences in explaining the substantially larger relative employment losses experienced by younger workers. This result is intuitive, as relatively few industries are likely to feature uneven age distributions. The within-industry deaths components tend to be a bit larger than their overall counterparts, suggesting that younger workers are concentrated in less resilient establishments.

The gender and education results in Table 3 are consistent with labor market discrimination against women at the industry level. Further evidence in favor of this point is presented in Table 4 which repeats the gender analysis separately by education (college vs. no college) and by age. These constitute the only two-dimensional breakdowns available in the QWI data.

Breaking down the within-industry gender differences by age (Panel A) reveals few clear patterns – the relative advantage for male workers is concentrated among younger workers for the overall estimates, while no such pattern exists for the deaths estimates (the point

Table 4: Within Overall and Deaths Employment Changes for Gender Across Age and Education Groups, 2007-2009

	All	Deaths
Panel A. Age Groups		
$[\theta^m - \theta^f]_{55-64}$	-0.008***	0.003
	[-0.009,-0.007]	[-0.002,0.007]
	(0.000)	(0.216)
$[\theta^m - \theta^f]_{45-54}$	0.004***	0.010*
	[0.003,0.005]	[0.006,0.021]
	(0.000)	(0.056)
$[\theta^m - \theta^f]_{35-44}$	0.014***	-0.005
	[0.013,0.016]	[-0.014,0.011]
	(0.000)	(0.462)
Panel B. Education Groups		
$[\theta^m - \theta^f]_c$	0.002***	0.003
	[0.001,0.003]	[-0.002,0.013]
	(0.000)	(0.447)
$[\theta^m - \theta^f]_n$	0.025***	0.024**
	[0.023,0.027]	[0.012,0.043]
	(0.000)	(0.027)

Notes: This table presents the estimates of Equation 5 for both observed changes in employment and changes in employment due to establishment deaths. Estimates are displayed for gender - male (m) and female (f) - across education groups - college(c) and no-college(n)- and age groups - 54-65, 45-54 and 35-44. 90% confidence intervals and significance are calculated using 1000 bootstrap repetitions. Confidence intervals are reported in square brackets and p-values are reported in parentheses. *** denotes significance at the 1% level.

estimates are non-monotonic in age, but do not differ from each other statistically). The gender differences by education (Panel B) indicate that men have an advantage within both the higher and lower education groups, although the degree of advantage is substantially larger for the No College group (an all estimate of 0.025 versus 0.002). Moreover, for deaths, only the No College estimate is statistically distinguishable from zero. The key point, however, is that women appear to be at a disadvantage relative to men within industry, even after conditioning on worker skill (education, or, to a lesser degree, age).

Finally, Tables A.1, A.2, and A.3 in the appendix repeat the analysis using the net change in the number of establishments. Overall, the resulting estimates are similar to establishment deaths estimates discussed above. In particular, Table A.2 again indicates that disadvantaged (female, black, Hispanic, and young) workers are relatively concentrated in less resilient establishments within industry. The signs of the relevant within estimates are generally the same as in Table 3, although the magnitudes tend to be somewhat smaller.

The gender results broken out by age and education, presented in Table A.3, provide yet more evidence that the within-industry disadvantage for women is not driven by skill differences. Using establishment changes, the predicted within components are uniformly significant (though modest in magnitude) for each age group, as shown in Panel A. The gender results by education (Panel B) again suggest greater relative disadvantage among less-educated workers. However, in contrast to the deaths analysis, the within-net estimates are significant for both college and no-college workers.

6 Conclusion

In this article, we considered how the Great Recession affected labor market inequality by worker gender, race, education and age. Through the lens of a familiar across/within-industry decomposition, we examined a novel driver of inequality – the differential effect of establishment deaths on employment by worker type.

Applying our approach to detailed employment data at the industry-jurisdiction-worker type level, we found that the Great Recession generated notable shifts in employment across worker demographic groups. Moreover, our decomposition of employment changes into across and within components, as well as jurisdiction-industry variation in establishment deaths, revealed that such deaths appear to be an important driver of the relatively larger employment losses suffered by disadvantaged workers during the recession. In particular, we argued that the large within-deaths components working against female, black and Hispanic workers are consistent with taste-based discrimination pushing these workers to less resilient firms within industry. At the same time, we found large differences in the degree to which across-industry differences in worker shares affected employment inequality, with men and less-educated workers particularly concentrated in industries that suffered from establishment deaths and employment declines.

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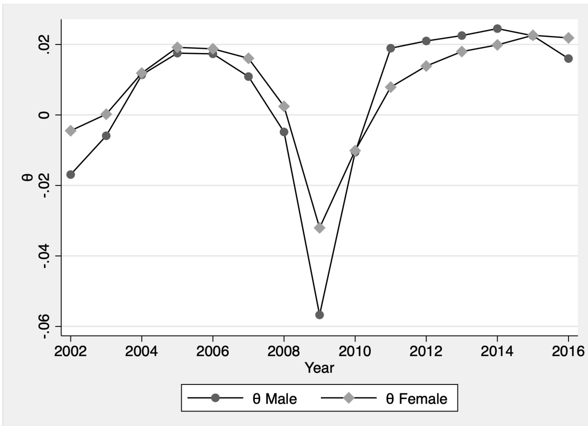
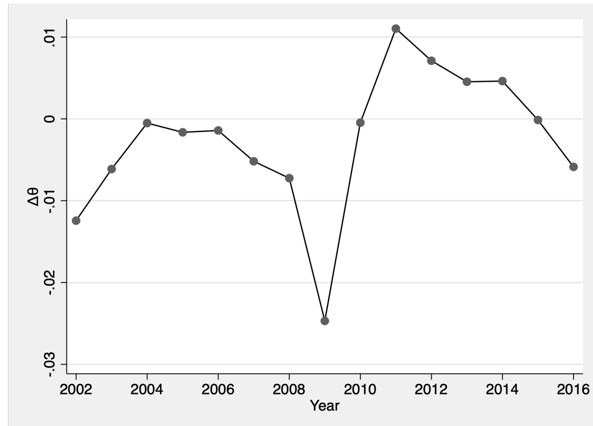
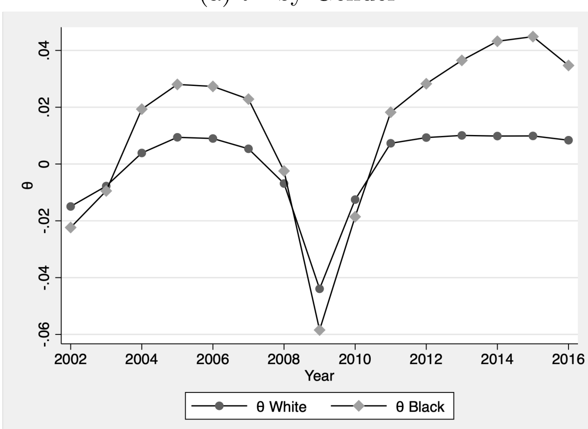
A Appendix: Additional Empirical Results



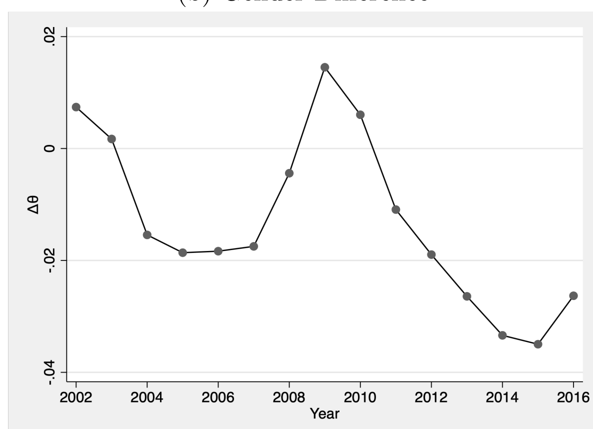
(a) θ^{τ} by Gender



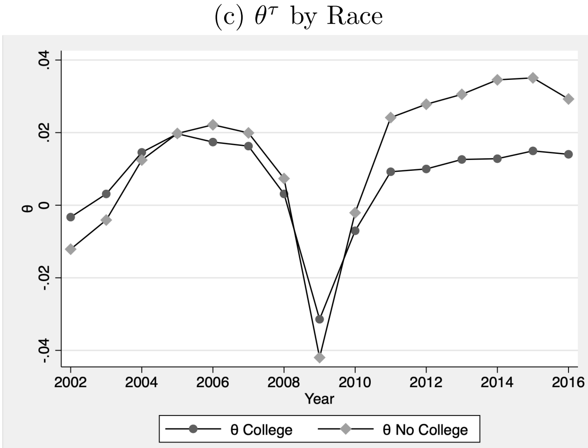
(b) Gender Difference



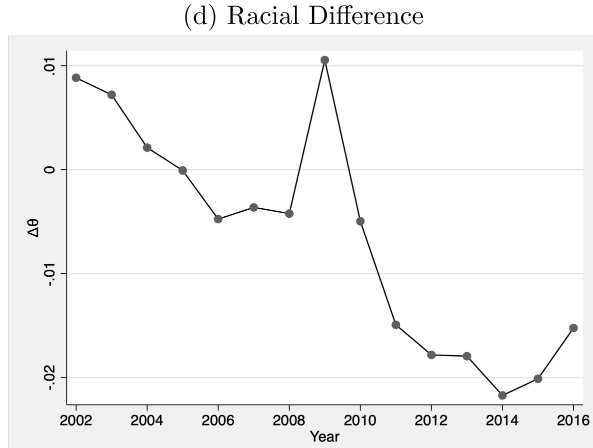
(c) θ^{τ} by Race



(d) Racial Difference



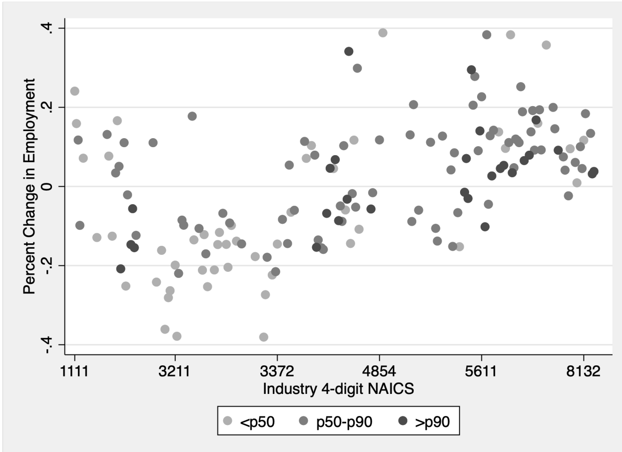
(e) θ^{τ} by Education



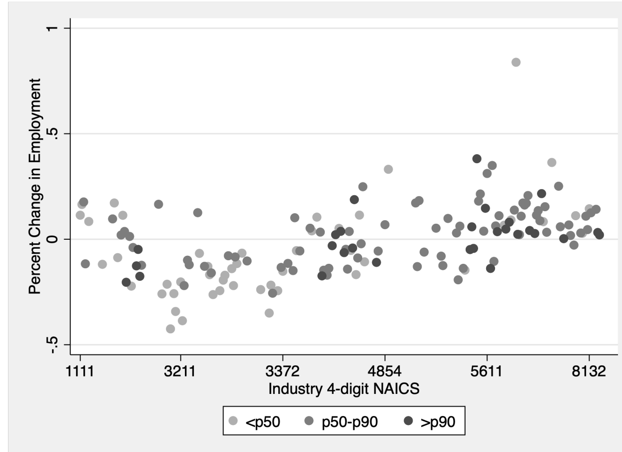
(f) Education Difference

Figure A.1: Trend of θ^{τ} by Type (2001-2015) – Full Data

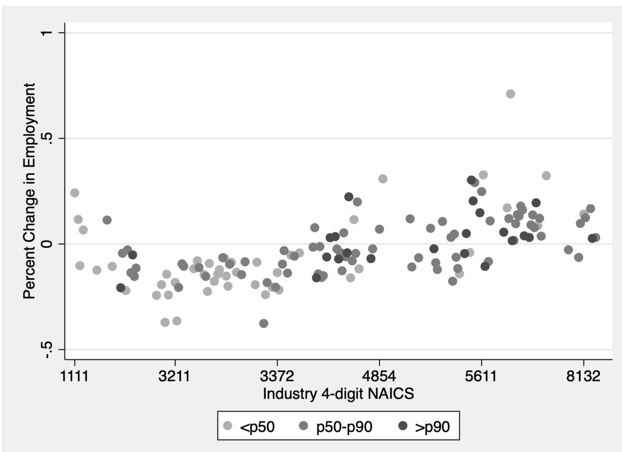
Notes: This figure shows the evolution of the observed percent change in employment from 2001 to 2015 inclusive for different worker types. Panels (a), (c), and (e) show the trend of these changes by gender (male versus female), race (white versus black), and education (college versus no college), respectively. Panels (b), (d), and (f) show the the difference between the types for gender, race, and education categories, respectively.



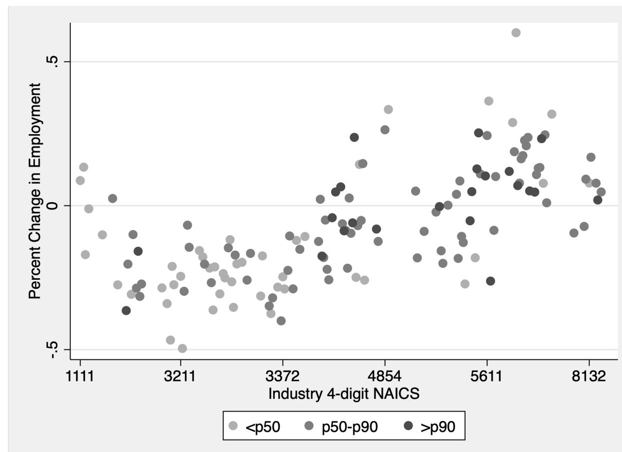
(a) Male



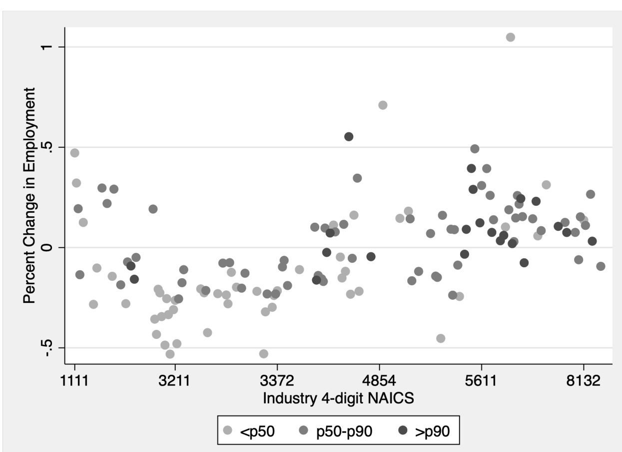
(b) Female



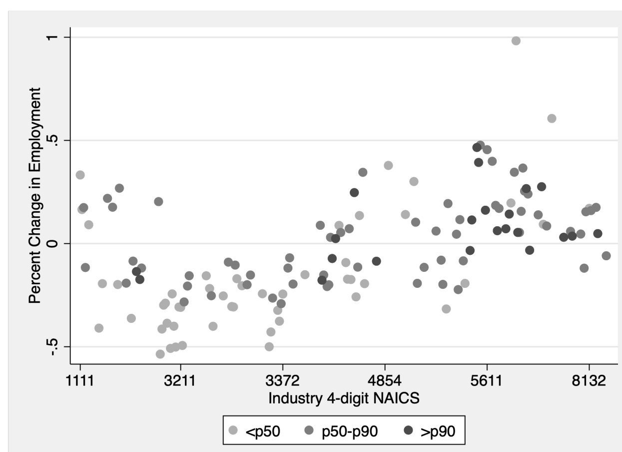
(c) White



(d) Black



(e) College



(f) No College

Figure A.2: Percent Change in Employment by Industry and Gender (2007-2009)

Notes: This figure shows the percent change of employment from 2007 to 2009 inclusive for different worker types, using the QWI sample with Holm-Bonferroni correction. Panels (a) and (b), (c) and (d), and (e) and (f) show the trend of these changes by gender (male and female), race (white and black), and education (college and no college), respectively. Plots for age show similar differences, but are omitted due to space constraints and available upon request.

Figure A.3: Earnings Across Gender and Age Groups

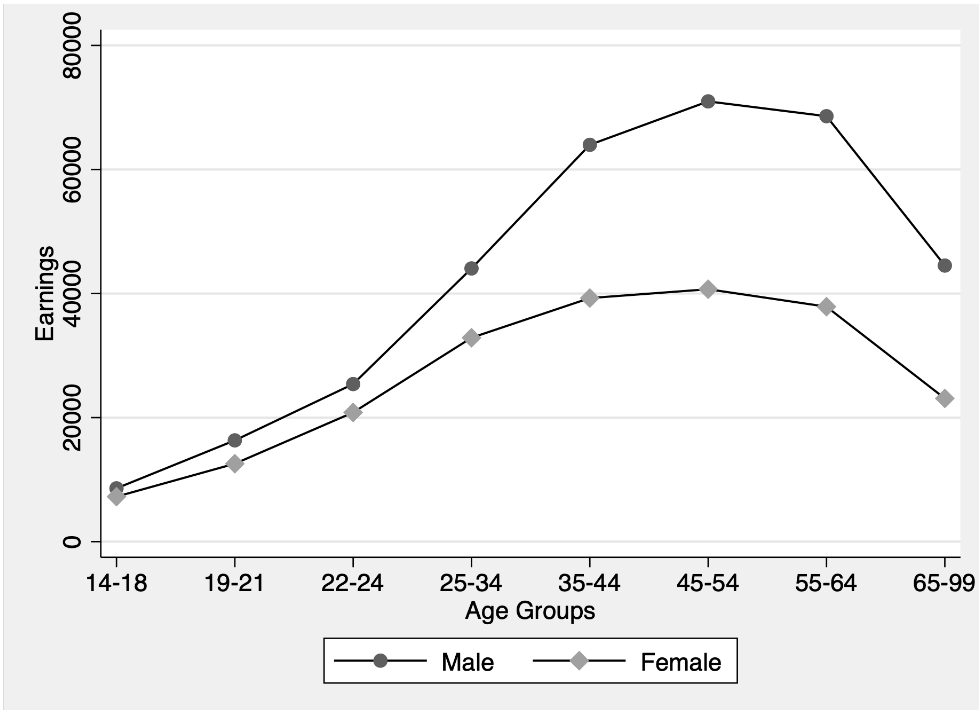


Table A.1: Overall and Net Change Employment Changes, 2007-2009

	Gender			Education	
	All	Net Change		All	Net Change
θ^m	-0.069***	-0.068***	θ^c	-0.033***	-0.037***
	[-0.072,-0.066]	[-0.078,-0.045]		[-0.036,-0.031]	[-0.043,-0.026]
	(0.000)	(0.000)		(0.000)	(0.000)
θ^f	-0.034***	-0.029***	θ^n	-0.043***	-0.049***
	[-0.037,-0.032]	[-0.035,-0.017]		[-0.046,-0.039]	[-0.058,-0.030]
	(0.000)	(0.000)		(0.000)	(0.000)
	Race			**Age**	
	All	Net Change		All	Net Change
θ^w	-0.056***	-0.037***	θ^{54-65}	0.035***	-0.011*
	[-0.058,-0.053]	[-0.044,-0.025]		[0.032,0.038]	[-0.017,-0.004]
	(0.000)	(0.000)		(0.000)	(0.086)
θ^b	-0.068***	-0.026***	θ^{45-54}	-0.032***	-0.029***
	[-0.072,-0.064]	[-0.034,-0.019]		[-0.035,-0.030]	[-0.034,-0.021]
	(0.000)	(0.000)		(0.000)	(0.000)
θ^h	-0.055***	-0.148***	θ^{35-44}	-0.082***	-0.057***
	[-0.059,-0.048]	[-0.167,-0.089]		[-0.084,-0.079]	[-0.065,-0.040]
	(0.000)	(0.000)		(0.000)	(0.000)

Notes: This table presents the estimates of Equation 9 for both observed changes in employment and changes in employment due to establishment net changes. Estimates are displayed for all worker characteristics: male (m), female (f), White (w), Black (b), Hispanic (h), college(c), no-college(n), and ages, 54-65, 45-54 and 35-44. 90% confidence intervals and significance are calculated using 1000 bootstrap repetitions. Confidence intervals are reported in square brackets and p-values are reported in parentheses. *** denotes significance at the 1% level.

Table A.2: Across-Within Overall and Net Change Employment Changes, 2007-2009

	Gender			Education	
	All	Net Change		All	Net Change
$[\theta^m - \theta^f]_A$	-0.045***	-0.054***	$[\theta^c - \theta^n]_A$	0.022***	0.019***
	[-0.047,-0.042]	[-0.064,-0.034]		[0.021,0.023]	[0.012,0.024]
	(0.000)	(0.000)		(0.000)	(0.000)
$[\theta^m - \theta^f]_W$	0.010***	0.016***	$[\theta^c - \theta^n]_W$	-0.012***	-0.007***
	[0.009,0.011]	[0.004,0.022]		[-0.014,-0.011]	[-0.011,-0.004]
	(0.000)	(0.000)		(0.000)	(0.000)

	Race			Age	
	All	Net Change		All	Net Change
$[\theta^w - \theta^b]_A$	-0.011***	-0.021***	$[\theta^{55-64} - \theta^{35-44}]_A$	0.006***	0.008***
	[-0.012,-0.009]	[-0.024,-0.016]		[0.006,0.007]	[0.005,0.010]
	(0.000)	(0.000)		(0.000)	(0.000)
$[\theta^w - \theta^b]_W$	0.023***	0.011*	$[\theta^{55-64} - \theta^{35-44}]_W$	0.110***	0.038***
	[0.020,0.026]	[0.001,0.022]		[0.109,0.112]	[0.026,0.045]
	(0.000)	(0.092)		(0.000)	(0.000)
$[\theta^w - \theta^h]_A$	0.013***	0.013**	$[\theta^{45-54} - \theta^{35-44}]_A$	0.001***	0.003***
	[0.011,0.017]	[0.005,0.024]		[0.000,0.001]	[0.002,0.004]
	(0.000)	(0.025)		(0.000)	(0.000)
$[\theta^w - \theta^h]_W$	-0.021***	0.088***	$[\theta^{45-54} - \theta^{35-44}]_W$	0.049***	0.025***
	[-0.025,-0.018]	[0.047,0.099]		[0.047,0.050]	[0.016,0.029]
	(0.000)	(0.000)		(0.000)	(0.000)

Notes: This table presents the estimates of Equations and 6 and 5 for both observed changes in employment and changes in employment due to establishment net change. Estimates are displayed for all worker characteristics: male (m), female (f), White (w), Black (b), Hispanic (h), college(c), no-college(n), and ages, 54-65, 45-54 and 35-44. 90% confidence intervals and significance are calculated using 1000 bootstrap repetitions. Confidence intervals are reported in square brackets and p-values are reported in parentheses. *** denotes significance at the 1% level.

Table A.3: Within Overall and Net Change Employment Changes for Gender Across Age and Education Groups, 2007-2009

	All	Net Change
Panel A. Age Groups		
$[\theta^m - \theta^f]_{55-64}$		
$[\theta^m - \theta^f]_{45-54}$	0.004^{***}	0.007^{*}
	[0.003,0.005]	[0.001,0.012]
	(0.000)	(0.052)
$[\theta^m - \theta^f]_{35-44}$	0.014^{***}	0.010^{*}
	[0.013,0.016]	[-0.000,0.018]
	(0.000)	(0.091)
Panel B. Education Groups		
$[\theta^m - \theta^f]_c$	0.002^{***}	0.010^{***}
	[0.001,0.003]	[0.002,0.014]
	(0.000)	(0.000)
$[\theta^m - \theta^f]_n$	0.025^{***}	0.021^{***}
	[0.023,0.027]	[0.007,0.032]
	(0.000)	(0.000)

Notes: This table presents the estimates of Equation 5 for both observed changes in employment and changes in employment due to establishment deaths. Estimates are displayed for gender - male (m) and female (f) - across education groups - college(c) and no-college(n)- and age groups - 54-65, 45-54 and 35-44. 90% confidence intervals and significance are calculated using 1000 bootstrap repetitions. Confidence intervals are reported in square brackets and p-values are reported in parentheses. *** denotes significance at the 1% level.

Table A.4: Cross Tabulation of Worker Types

		College	Male	White/Asian	Older
Education	No-College		0.483	0.679	0.512
	College		0.481	0.819	0.492
Gender	Female	0.484		0.730	0.505
	Male	0.482		0.724	0.498
Race	Black/Hispanic	0.345	0.494		0.446
	White/Asian	0.530	0.486		0.523
Age	Younger	0.527	0.499	0.698	
	Older	0.507	0.493	0.759	

Table A.5: Descriptive Statistics – Earnings

	QWI Sample	SUSB Subsample
Total Average Earnings	\$44,923	\$45,021
Male Earnings	\$55,484	\$55,902
Female Earnings	\$34,155	\$33,972
White Earnings	\$49,182	\$49,340
Black Earnings	\$31,655	\$30,949
Hispanic Earnings	\$33,135	\$32,704
College Earnings	\$59,351	\$59,988
No College Earnings	\$33,593	\$33,541
55-64 Earnings	\$53,167	\$53,838
45-54 Earnings	\$55,830	\$56,450
35-44 Earnings	\$52,147	\$52,483
Average Earnings by Industry	\$49,557	\$50,711
	(\$24,759)	(\$25,183)
Average Earnings by Jurisdiction	\$30,668	\$30,499
	(\$8,249)	(\$8,979)

Notes: The QWI sample contains labor market outcomes for the universe of industries and counties across all states (except for MA) and the time period 2007-2009. The merged QWI-SUSB data used for the analysis is a subsample of the QWI sample, since the SUSB establishment data contain a slightly smaller subset of industries and counties. The SUSB establishment count is for 2007, while the changes (net, deaths, births) are for the period 2007-2009.

B Appendix: Decomposition Derivations

$$\begin{aligned}
\theta^{\tau} - \theta^{\tau'} &\equiv \frac{\Delta E^{\tau}}{E_0^{\tau}} - \frac{\Delta E^{\tau'}}{E_0^{\tau'}} = \frac{\sum_i \Delta E_i^{\tau}}{\sum_i E_{i0}^{\tau}} - \frac{\sum_i \Delta E_i^{\tau'}}{\sum_i E_{i0}^{\tau'}} \\
&= \frac{\sum_i \theta_i^{\tau} E_{i0}^{\tau}}{\sum_i E_{i0}^{\tau}} - \frac{\sum_i \theta_i^{\tau'} E_{i0}^{\tau'}}{\sum_i E_{i0}^{\tau'}} \\
&= \frac{\sum_i \pi_i^{\tau} \theta_i^{\tau} E_{i0}}{\sum_i \pi_i^{\tau} E_{i0}} - \frac{\sum_i \pi_i^{\tau'} \theta_i^{\tau'} E_{i0}}{\sum_i \pi_i^{\tau'} E_{i0}} \\
&= \sum_i (\tilde{\pi}_i^{\tau} \theta_i^{\tau} - \tilde{\pi}_i^{\tau'} \theta_i^{\tau'}) E_{i0}\,, \qquad (11)
\end{aligned}$$

$$\begin{aligned}
\theta_W^{\tau} - \theta_W^{\tau'} &\equiv \sum_i \tilde{\pi}_i (\theta_i^{\tau} - \theta_i^{\tau'}) E_{i0} \\
&= \sum_i \left(\frac{\tilde{\pi}_i^{\tau} + \tilde{\pi}_i^{\tau}}{2} \right) (\theta_i^{\tau} - \theta_i^{\tau'}) E_{i0} \\
&= \sum_i (\theta_i^{\tau} - \theta_i^{\tau'}) \left(\frac{(E_{i0}^{\tau}/E_0^{\tau}) + (E_{i0}^{\tau'}/E_0^{\tau'})}{2} \right) . \qquad (12)
\end{aligned}$$

$$\begin{aligned}
\theta_A^{\tau} - \theta_A^{\tau'} &\equiv \sum_i [\theta_i^{\tau} (\tilde{\pi}_i^{\tau} - \tilde{\pi}_i) - \theta_i^{\tau'} (\tilde{\pi}_i^{\tau'} - \tilde{\pi}_i)] E_{i0} \\
&= \sum_i \left[\theta_i^{\tau} \left(\frac{\tilde{\pi}_i^{\tau} - \tilde{\pi}_i^{\tau'}}{2} \right) - \theta_i^{\tau'} \left(\frac{\tilde{\pi}_i^{\tau'} - \tilde{\pi}_i^{\tau}}{2} \right) \right] E_{i0} \\
&= \sum_i \left(\frac{\theta_i^{\tau} + \theta_i^{\tau'}}{2} \right) (\tilde{\pi}_i^{\tau} - \tilde{\pi}_i^{\tau'}) E_{i0} \\
&= \sum_i \left(\frac{\theta_i^{\tau} + \theta_i^{\tau'}}{2} \right) \left(\frac{E_{i0}^{\tau}}{E_0^{\tau}} - \frac{E_{i0}^{\tau'}}{E_0^{\tau'}} \right) . \qquad (13)
\end{aligned}$$