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Abstract

Racial employment segregation between large workplaces in America has grown over the last generation. We know little about how changes in patterns of employment by economic sector have contributed to this growth, though. While there are many stylized narratives about how industrial change may have affected employment segregation, there are fewer testable predictions or ways to reconcile those narratives. We argue that Theil's information statistic provides a way to compare changes within and between industries or other sub-groups in a common framework. Changes in Theil's H can be decomposed into changes in relative size, relative diversity, and relative segregation, which are precisely the mechanisms on which most stylized narratives rely. We explain permutation-test methods for summarizing changes in these factors across six major economic sectors over time. We test these methods using four decades of longitudinal data on establishment workforce composition from the Equal Employment Opportunity Commission.

Introduction

Occupational segregation by race in U.S. workplaces declined over the last generation (Stainback and Tomaskovic-Devey, 2012). At the same time, racial segregation between workplaces grew. Ferguson and Koning (2018) documented this trend and ruled out several possible drivers of it. However, they left unexplored a likely major driver, industrial change.

Silence on this makes some sense. There are *too many* theories about how "industry" could affect segregation. That is, we have stylized narratives about specific economic sectors—the decline of manufacturing, the growth of a more segregated service sector, the lack of diversity in finance—that could be accurate. Yet these narratives rarely make falsifiable predictions.

Such narratives are also partial. Diversity may have fallen in one economic sector, but that could just mean that it has risen elsewhere. Without a general framework, we cannot gauge how changes in one sector contribute to overall employment segregation. Exploring the role of a category like economic sector is impossible without a way to measure changes within those categories while also tracking each one's contribution to total segregation.

In this paper, we demonstrate how to extend Theil's (1972) mutual information statistic H to explore such categorial distinctions. This measure has gained popularity in segregation research in part because it is analytically and hierarchically decomposable (Reardon et al., 2000; Chetty et al., 2014; Ferguson and Koning, 2018) . That is, total segregation can be recursively defined as segregation between groups plus total segregation within groups. This is what you need to track sectoral changes as described above.

We show that H can also be used to test theories about industry and sector contributions to between-estabilshment segregation. Formally, a group's contribution to segregation as measured by H is the product of its size, its diversity, and its internal segregation. These are thus the mechanisms through which that contribution can change. Since most narratives about an economic sector's role in segregation involve mechanisms like growth, diversification, and internal segregation, a mechanism decomposition of secular changes to H can formalize and test those narratives' predictions.

We analyze the same longitudinal data on establishment-level workforce composition that the strongest work in this area has, annual surveys of large workplaces collected by the Equal Employment Opportunity Commission (Tomaskovic-Devey et al., 2006; Kalev et al., 2006; Cohen et al., 2009; Ferguson, 2015). A limitation of these surveys is that the EEOC used a half-dozen different industry-classification schemes in the forty-three years for which we have data. We leverage establishments that appear throughout the years in which different schemes were used, along with a brief window during which the EEOC used two coding schemes concurrently, to build the first consistent industry time series for these data.

Throughout, we focus on six economic sectors: manufacturing, services, retail, wholesaling, finance, and utilities & transportation. We use the same mapping of SIC and NAICS industries into these sectors that recent work on inequality in labor economics has used, to maximize comparability with that research (Autor et al., 2016, 2017). These are also the broad economic categories that most narratives about industry change leverage. The fractal decomposability of H allows future researchers to generate more disaggregated results without loss of comparability; indeed we include decompositions of the largest sectors by three-digit SIC industry in some of our results.

Our findings put the lie to any simple explanation of rising racial employment segregation via sectoral shifts in employment. The service sector accounts for a much greater share of total segregation today than manufacturing, which reflects services' growth and manufacturing's decline. Yet the service sector's contribution has grown faster, and manufacturing's has declined slower, than their relative size alone would predict. Manufacturing in particular has grown far more segregated internally over the last thirty years, such that it today makes little sense to discuss services as "more segregated." Meanwhile the retail sector, which today employs more people than manufacturing, looks starkly different. Retail has grown and diversified for decades, yet its internal segregation has steadily declined. There is an irony here. Researchers often characterize retail work, especially in large stores, as some of the most "low-road," precarious jobs in the today's economy (Osterman et al., 2001; Lichtenstein, 2006; Kalleberg, 2009). That they may be, yet it is only there, at the "bottom" of the labor market, that employment integration made the most progress.

Another reason that it is hard to pin rising segregation on sectoral shifts is that, in all sectors, segregation has risen between detailed industries, but not between the establishments within those industries. We use these results to argue that there are limited returns to focusing on industries and sectors as such to explain employment segrgation trends. This is because such arguments implicitly assume that the relevant changes happen at the level of the industry or the firm. Instead we suspect and theorize that our pattern of results is better interpreted by focusing on the job. Reorganizing work through external contracting has probably contributed more to rising employment segregation than the growth or shrinkage of certain types of economic activity as such (DiTomaso, 2001; Kalleberg, 2003, 2009).

This study has a large methodological component relative to its theory, so we think it is worth mapping out how we proceed. We begin by reviewing what theory there is about how industry change relates to employment segregation. Most of this consists of narratives in the study of work and employment, narratives that have rarely been tested explicitly. We discuss how to formalize some of these predictions using mechanisms like changing relative size, relative diversity, and internal segregation. We then review the properties of Theil's mutual information statistic and propose a way to decompose changes in its group components over time in terms of these mechanisms. We perform such decompositions on longitudinal employment data from 1971 to 2014, leveraging the consistent industrial classifications we developed. We revisit existing theory in light of those results, and conclude by theorizing how a different mechanism, the reorganization of existing jobs between organizations, could better explain our pattern of results. We cannot directly test this idea using these data, but we discuss how future research could explore the idea.

Industry's role in employment segregation

In their study of between-workplace segregation, Ferguson and Koning (2018) showed that, since the early 1980s, it has risen between two-digit industries and between the establishments within said industries. They offered no theory to explain that trend, though, nor did they attribute it to developments in specific economic sectors. Theories of how industrial dynamics might affect racial employment segregation can be found throughout economics and sociology, but they are rarely explicit. Consider some stylized narratives:

1. After World War Two, manufacturing provided relatively good, well-paying jobs, both skilled and unskilled. The subsequent decline of manufacturing has left extensive education as a prerequisite for many good jobs. Because educational opportunity and attainment very by race, this has affected white and non-white workers differently.

2. In most traditional industries, the wage structure was, if skewed, at least unimodal. Contemporary services, by contrast, have a bimodal wage distribution with a hollow middle. And race is predictive of which mode a worker's wages are likely to lie near.

3. For more than twenty years, a large share of the employment growth in large workplaces has occurred in retail, as big-box stores have proliferated. Retail is more geographically dispersed and local-market facing than other sectors, which imples more between-store segregation in multi-establishment firms.

4. Finance, insurance and real estate (FIRE) have ballooned as a share of GDP in recent decades. This sector is also notably less diverse, with far more white and Asian workers than the economy as a whole. The same may be said of many high-technology industries.

5. Unionization typically formalizes the conditions of work, and limits employer discretion around employment and wages. Minority workers recognized these opportunities and joined unions at high rates. The decline of unionized industries has shrunk the number of workplaces thus protected from aribtrary management.

Each of these narratives has implications for how economic changes could increase between-workplace segregation over time, and thus fit the shadows cast by explicit theories. For example, the first narrative reflects much of the work on skill-biased technological change (Autor et al., 2008; Goldin and Katz, 2010). The bimodality of the service sector is central to theories of how the rise of the "care economy" has widened inequality (Dwyer, 2013). The increasing prominence of customer-facing retail enterprises, which require more labor input, is often cited in discussions about the slowing growth of average firm productivity (Gordon, 2016). The outsize growth of FIRE industries has interested researchers and policymakers in the barriers to diversifying them (Rivera, 2012; Gee and Peck, 2017; Samila and Sorenson, 2017). Unionization's affect on employment patterns and the racial wage gap is well researched (Levy and Temin, 2010; Western and Rosenfeld, 2011; Rosenfeld and Kleykamp, 2012). Examples can be piled up. In each case, there is a way that sectoral change can be connected, through various causal paths, to patterns of employment composition and thus employment segregation. This is why we say that theories about industry and segregation abound.

These statements are each about parts of the economy, though. They are rarely clear whether changes to a single group are larger than changes to the economy as a whole. This matters because disproportionate change in a group is necessary to change its contribution to total segregation. The decline of manufacturing cannot explain increasing segregation, for example, unless manufacturing was more diverse, or less segregated, or both than other sectors, *and* if it remained so during its decline. Finance may be more white (and Asian) than other sectors, but if, say, retail is *less* white (and Asian) than other sectors, then the two sectors' growth could offset one another. Changes in one group cannot by themselves explain changes in total segregation.

As the foregoing suggests, and as we show formally, three characteristics can affect a sector's contribution to total segregation: its relative size in the economy, the relative diversity of its workforce, and the level of segregation between its own constituent industries or establishments. These characteristics are multiplicative. This means that, even within a sector, increases in one characteristic vary depending on the levels and changes in the others. We can recast the stylized industry narratives from above in terms of such mechanisms. Notice how, in so doing, we are forced to be more explicit about what is changing and what is held constant:

1. Manufacturing was more diverse and less segregated than other sectors. The decrease in its relative size has reduced its ability to offset other sectors' contributions to total segregation. *Alternatively*: The shrinking of manufacturing means that white and non-white workers who might once have gone into manufacturing now go into different sectors depending on educational attainment; this increases *between*-sector segregation, but is ambiguous as to how it affects segregation within any one sector.

2. Internal segregation in the service sector is higher than in other sectors—certainly at the industry level, possibly also at the establishment level. Because the sector has also grown, it has increased total segregation. Segregation within services does not have to increase for this to happen—the size change is sufficient—but it may have.

3. Retail grew and has higher internal segregation. This would raise total segregation even if diversity within the sector were constant.

4. Finance is less diverse relative to other sectors and has grown relative to other sectors. It accounts for a larger share of total segregation, but how this affects the total depends on its level of internal segregation, relative to other sectors. The latter is rarely discussed.

5. Unionized industries were less segregated than non-unionized ones. Their shrinkage relative to other industries would raise total segregation. Yet the size of such effects depends on the relative diversity of unionized industries, compared to the economy as a whole.

Discussing change in these terms helps show how such implicit theories might support or conflict with one another. For example, manufacturing may be more diverse and shrinking, compared to other sectors; but retail may be more diverse and growing. Are each of these facts true, and if they are, do they cancel out? The financial sector may be less diverse, but the less diverse a sector is, the lower the maximum level of internal segregation *among its own workforce* it can have.[1]

[1] Ironically, a token non-white in every firm implies low diversity in an industry, but also low internal segregation within it, as minorities are present in similar (low) levels in every firm.

Many stylized narratives focus on one of these mechanisms and theorize about the partial effect of changing it while implicitly holding everything else constant. We lack a sense of their relative importance.

To determine whether such changes have taken place, and what effect they may have had alongside others, we need a framework for measuring segregation in which we can consider such processes separately and together. Specifically, we need to compare segregation between sectors to segregation within sectors and industries, and we need to weigh the impact of changing size, diversity, and internal segregation. The decomposability of Theil's mutual-information statistic gives us a way to do this.

Method

We devote more space to explaining methods here than we would otherwise because our overall approach is new. The hierarchical decomposition of Theil's H is well-documented, so we summarize it and cite more detailed explanations. The mechanism decomposition of Theil's H is new, so we try to give an intuitive explanation of it and then offer more details in appendices. While the bootstrap is not new, its application to elements of the Theil statistic is, so we briefly review the approach and, again, give more details in appendices.

Hierarchical decomposition of Theil's mutual information statistic

We use Theil's H partly to maintain comparability with prior work. But H has other, substantive advantages that we want to underline. Here we briefly review the features and construction of the statistic; Reardon et al. (2000), Conceição and Ferreira (2000), and Reardon and Firebaugh (2002) all give more details.[2]

Theil's H is an entropy-based measure. In the context of segregation between the sub-units of a larger unit (schools in a district, housing tracts in a city, workplaces in an industry), entropy is defined by the composition of the unit. H then tells us how much information we gain, and thus how much entropy we reduce, by learning sub-unit information in addition to unit information. If there is no segregation between sub-units—if every firm in an industry is 70 percent white and 30 percent black, say—then our guess at the race of a randomly chosen worker is not improved by knowing where the worker works. If there is perfect segregation—if 70 percent of the firms are all-white and 30 percent are all-black—then knowing the specific workplace is incredibly informative. Theil's statistic formalizes this idea using Shannon (1948) entropy.

Consider a unit with J sub-units. Let ϕ_r be race r's share of the population p in the unit. The area's entropy E is then $-\sum_r \phi_r \log_R \phi_r$.[3] Similarly, for sub-unit j within J, its entropy $E_j = -\sum_r \phi_{rj} \log_R \phi_{rj}$. Let the relative size of sub-unit j be p_j/p. Then the information statistic for the unit, $H_{\langle J \rangle}$, is the size-weighted sum of the sub-units' entropy deviations from the larger unit:

[2] In segregation research, the index of dissimilarity (Duncan and Duncan, 1955) or some type of Gini coefficient (Alonso-Villar et al., 2012) has been more common than H. The index of dissimilarity has an intuitive interpretation as the share of people that would have to be moved in order to eliminate segregation, but that intuition comes at a cost. The index is not well behaved beyond the two-group case (Reardon and Firebaugh, 2002), which limits its use for studying an increasingly diverse workforce. Neither it nor the Gini coefficient can be cleanly decomposed to explore the contributions of specific sub-units or groups to total segregation. Because Theil's information statistic does not suffer from these limitations, it has been increasingly used in inequality research (Chetty et al., 2014; Rossi and Galbraith, 2016).

[3] The base of the logarithm is the number of races. Choosing the number of groups as the base of the logarithm ensures that entropy will range from 0 to 1. When $\phi_r = 0$ we define $\log_R \phi_r$ to be 0.

$$H_{\langle J \rangle} = \sum_j \frac{p_j}{p} \frac{E - E_j}{E} \tag{1}$$

We use the $\langle J \rangle$ subscript to indicate that this H has been calculated over one level, J. This is to distinguish it from H calculated over more levels, as seen next.

Decomposition of H can be done over any mutually exclusive and completely exhaustive set of hierarchical groups (Cowell, 1985). Consider the two-level case first. If our unit has G different groups, each with J_g sub-units, then we have two sources of segregation: the uneven distribution of races between the G groups, and the uneven distribution of races between the J_g sub-units within each group g. For example, the proportions of black and hispanic workers varies between the manufacturing and service sectors, but their proportions also vary between industries within those sectors. We want to account for these different distributions separately. Building on the logic above, we calculate H_g for between-group segregation. We then calculate within-group, between-sub-unit segregation for each g, which we denote H_j^g. Total segregation, which in this two-level case we would denote $H_{\langle GJ \rangle}$, is between-group segregation plus the weighted sum of within-group segregations:

$$\begin{aligned} H_{\langle GJ \rangle} &= \overbrace{\sum_g \frac{p_g}{p} \frac{E - E_g}{E}}^{\text{Between group}} + \underbrace{\sum_g \frac{p_g}{p} \frac{E_g}{E} \left(\sum_{j \in g} \frac{p_{gj}}{p_g} \frac{E_g - E_{gj}}{E_g} \right)}_{\text{Within group, between sub-unit}} \\ &= H_g + \sum_g w_g d_g h_g \\ &= H_g + \bar{H}_j^g \end{aligned} \tag{2}$$

Note that we denote any one group's contribution to total segregation as H_j^g and the weighted sum of the groups' contributions as $\bar{H}_j^g$. For convenience, we denote the relative size of a group w_g, the relative diversity of the group d_g, and the segregation between sub-units within the group h_g. It should be highlighted that h_g is just a recursive definition of H itself, calculated on observations at a lower level of aggregation. Thus this process could be repeated for sub-groups within G, and so on.

In this paper we do analyses over three levels not two, so it is worth expanding the decomposition once more. For concreteness, rather than talk about units, groups, and sub-units, we will talk about areas, sectors, and establishments. We treat sectors as nested within areas but show that we can recover sectors' total contributions across areas. Establishments are nested within sectors. This gives us three sources of segregation: the uneven distribution of races between the A areas, the uneven distribution of races between the G_a sectors within each area, and the uneven distribution of races between the J_{ag} establishments within each area-sector. Building on the logic above, we calculate H_a for between-area segregation. We then calculate within-area, between-sector segregation for each a, which we denote H_g^a. Finally we calculate within-area-sector, between-establishment segregation for each g_a, which we denote H_j^{ag}. Total segregation, which we denote $H_{\langle AGJ \rangle}$, is between-area segregation plus the weighted sum of within-area segregations, plus the weighted sum of within area-sector segregations:

$$
\begin{aligned}
H_{\langle AGJ\rangle} &= \overbrace{\sum_a \frac{p_a}{p}\frac{E-E_a}{E}}^{\text{Between area}} + \overbrace{\sum_a \frac{p_a}{p}\frac{E_a}{E}\left(\sum_g \frac{p_{ag}}{p_a}\frac{E_a-E_{ag}}{E_a}\right)}^{\text{Within area, between sector}} \\
&\quad + \overbrace{\sum_a \frac{p_a}{p}\frac{E_a}{E}\left(\sum_g \frac{p_{ag}}{p_a}\frac{E_{ag}}{E_a}\left(\sum_j \frac{p_{agj}}{p_{ag}}\frac{E_{ag}-E_{agj}}{E_{ag}}\right)\right)}^{\text{Within area-sector, between establishment}} \\
&= H_a + \sum_a w_a d_a h_a + \sum_a w_a d_a \left(\sum_g w_{ag} d_{ag} h_{ag}\right) \\
&= H_a + \bar{H}^a_g + \bar{H}^{ag}_j
\end{aligned}
\tag{3}
$$

In the within-area-sector segregation term there are two summations. The first distributes over the second one, such that a single sector's contribution, H^{ag}_j, is $\sum_a w_a d_a w_{ag} d_{ag} h_{ag}$. In other words, the contribution of a sector that is nested within areas is the relative-size- and relative-diversity-weighted sum of the sector's contribution in each area, weighted by the relative size and diversity of each area. This is how we can recover sector contributions despite the nesting of observations within different geographic areas.

Mechanism decomposition

We are interested in whether changes within and between economic sector over time can help explain changes in employment segregation. In the context of the Theil statistic, this maps to changes in the group components of $\bar{H}^g_j$. We have shown that any single group's contribution to $\bar{H}^g_j$ is $w_g d_g h_g$. Because each group's contribution H^g_j is the product of three terms, it is useful to separate its change into changes in each of those terms. We refer to this dynamic decomposition of H as a "mechanism" decomposition to distinguish it from the hierarchical, cross-sectional decomposition detailed above. As with the latter, we start with the more intuitive two-level case, then show how the math changes to accommodate three levels.

It helps to approach this with some geometric intuition. As a product of three terms, H^g_j can be drawn as a rectangular solid in $\mathcal{R}^3$ with dimensions w_g, d_g, and h_g. Adding a subscript to track time yields $H^{g1}_j = w_{g1} d_{g1} h_{g1}$. Change in these components over time is then the difference in two products:

$$
\forall g \in G : \Delta H^g_j = w_{g2} d_{g2} h_{g2} - w_{g1} d_{g1} h_{g1} \tag{4}
$$

Because $x_{g2} = x_{g1} + \Delta x$ for any $x \in \{w, d, h\}$, we can analyze ΔH^g_j into the difference in volume between two rectangular solids, as in Figure 1.[4]

The geometry of Figure 1 clarifies why change in a group's contribution to total segregation can and should have seven components. Three of these are like main effects. For example, Δwdh represents the effect of increasing the relative size of a group while leaving diversity and segregation within the group unchanged. Similarly, $w\Delta dh$ is the effect of increasing diversity within g while keeping its size and segregation between its establishments unchanged. Another three components resemble two-way interactions: thus, $\Delta w \Delta dh$ captures how changing size and changing diversity

[4]In Figure 1 we draw all changes as positive, but the math works the same if one or more are negative.

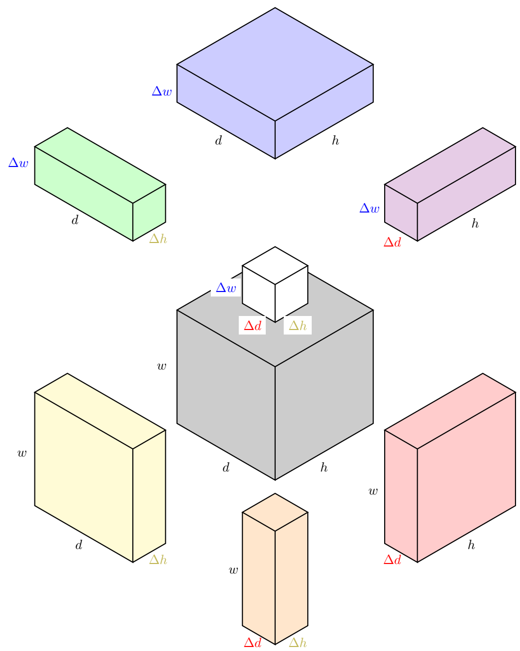

Figure 1: Analyzing ΔH_j^g into the difference of two rectangular solids. We omit g sub-scripts for clarity. The eight components form a solid whose dimensions are $w + \Delta w$, $d + \Delta d$, and $h + \Delta h$, which corresponds to H_{j2}^g. Subtracting wdh, which corresponds to H_{j1}^g, gives the between-period change, which can then be analyzed as shown.

within g tend to go hand-in-hand. Finally, $\Delta w \Delta d \Delta h$ is the "messy residual," the portion of increasing segregation that, due to simultaneous movement, cannot be assigned between these three channels. We track these subscripts to identify these components. Let $\underset{x}{\Delta} H_j^g$ be the change in H_j^g from time t to time $t+1$ that is due to change in component(s) x. Thus for example $\underset{h}{\Delta} H_j^g$ represents $wd\Delta h$, while $\underset{dh}{\Delta} H_j^g$ represents $w\Delta d \Delta h$ and so on.

Extension of this mechanism decomposition to three levels is straightforward. Let $\underset{x}{\Delta} H_j^{ag}$ be the change in H_j^{ag} from time t to time $t+1$ that is due to change in component(s) x. Consider the simplest case, where only one component, like h_{ag}, changes, and remember that $h_{ag_{t+1}} = h_{ag_t} + \Delta h_{ag}$. Then we get the following:

$$
\begin{aligned}
\underset{h}{\Delta} H_j^{ag} &= H_{j_{t+1}}^{ag} - H_{j_t}^{ag} \\
&= \sum_a w_{a_t} d_{a_t} w_{ag_t} d_{ag_t} \left(h_{ag_t} + \Delta h_{ag}\right) - \sum_a w_{a_t} d_{a_t} w_{ag_t} d_{ag_t} h_{ag_t} \\
&= \sum_a w_{a_t} d_{a_t} w_{ag_t} d_{ag_t} \Delta h_{ag} \\
&\quad + \sum_a \left(w_{a_t} d_{a_t} w_{ag_t} d_{ag_t} h_{ag_t} - w_{a_t} d_{a_t} w_{ag_t} d_{ag_t} h_{ag_t}\right) \\
&= \sum_a w_{a_t} d_{a_t} w_{ag_t} d_{ag_t} \Delta h_{ag}
\end{aligned} \tag{5}
$$

This holds for any of the components in H_j^{ag}. This means that for the three-level case, to derive the contributions of industries that are nested in areas, we can add up industry contributions within area-industries, then do a size- and diversity-weighted sum across areas. Therefore, mechanism decomposition follows the same recursively weighted summation that hierarchical decomposition does.[5]

This analysis of changes in group contributions to segregation into size, diversity, and segregation components parallels a similar discussion of the "causes" of changing segregation in Reardon et al. (2000). We have adapted our formal approach here from economic work on changes in aggregate firm producivity; see for example Foster et al. (2001). We detail those connections more explicitly, and include the full proof that these components sum to changes in total segregation, in Appendix A.

Evaluating the importance of different changes

Thus some good news: we can separate the mechanisms that, together, determine a sector's contribution to employment segregation. But the bad news is that we risk drowning in results. We look at six economic sectors; this decomposition produces seven components for each group for each time period. Even if we ignore between-sector segregation and the cross effects, a full analysis of each sector across our 40 years of data would generate more than 720 results. We can plot these as time series, but how much movement matters? Random firm turnover, and random personnel turnover within firms, would make the groups' numbers change over time even if there were no real secular trends. We need a way to separate signal from noise.

If we take a step back, our research question focuses on different sectors' roles in driving between-establishment segregation. For that question, we are not interested in whether an industry grew more or less segregated; rather, we are interested in whether it grew more or less segregated than the economy as a whole. If the changes in an industry's size, diversity, or internal segregation were on par with the national trend, then by definition they could not have affected its contribution to the total. Therefore we can use measures of statistical significance to focus on changes that differ from the pooled trend.

The difficulty inheres in defining a statistical measure. Almost none of the constituent components of H are independent of one another; nor are individual observations. This makes defining analytic standard errors for H incredibly difficult. The literature on the subject mostly consists of explanations of why earlier proposals are unworkable (Bojanowski, 2004). When one considers that one of the group weights in H_g is group g's internal segregation, which itself requires an analytic distribution of h_g, then the complexity becomes obvious.

Rather than die on the same hill, we forego the analytic approach. We determine distributions of the various sector-change components empirically, using the bootstrap (Efron and Tibshirani, 1994). We draw b repeated samples with replacement from our data and calculate the relevant statistics on those samples, in order to see non-parametrically how the variation within the observed sample influences the sensitivity of the sample statistics. More formally, if we have a data matrix F for time t and a data matrix G for time $t+1$, we can define $x = [F\ G]$ as the combined data. We then define $q(x)$ as an arbitrary function or moment of the data, such as $q(x) = H_{\langle J \rangle}(G) - H_{\langle J \rangle}(F)$ or $q(x) = w(F)d(F)[h(G) - h(F)]$. The standard error for q is then defined as follows:

$$\sigma_q = \sqrt{\frac{\sum_b \left(q(x^*) - \mu(q(x^*))\right)^2}{b-1}} \tag{6}$$

Here, the * indicates bootstrapped samples taken from x by randomly sampling with replacement from F and from G.[6]

[5] Empirically, because w, d, and h here are about the same size and smaller than one, their products are tiny. This means that we can focus on the main effects in mechanism decomposition, at least in this setting.

[6] Bootstrapped estimates of Shannon entropy are known to be biased downward (Miller, 1955). The intuition here

As with any bootstrapping procedure, you can only draw inferences about the larger population from these data if you assume they are representative. We work with the entire population of firms who have complied with the EEOC's filing requirements, so we think the assumption is sound. But we mainly want to obtain standard errors for another reason, one for which the bootstrap is extremely well suited. To wit, which changes in the industry components of the Theil are signal and which can be treated as noise stemming from the variability in the underlying data? Because the bootstrap procedure derives standard errors from that variability, it gives accurate answers to this question.

The cost of calculating bootstrapped standard errors comes in computation. Conditional on the structure of the data matrix, it can be far faster to compute the components of these decompositions using matrix algebra. A side benefit of this approach is that it requires explicit parallel calculation of several of the statistic's components, which makes decomposition along different levels simpler. We outline this approach in Appendix B.

Data

We study patterns in racial segregation between industries and workplaces using EEO-1 establishment surveys filed with the Equal Employment Opportunity Commission. Robinson et al. (2005) and Stainback and Tomaskovic-Devey (2012) have clear and detailed overviews of the scope of these data, as well as the possibilities and limitations of working with them. Here we summarize the features that are relevant for our study.

Since 1966, to monitor compliance with the Civil Rights Act, the EEOC has surveyed many types of organizations on the racial and sexual composition of their workforces. The EEO-1 surveys are completed by private-sector establishments with more than 100 employees.[7] Archival survey data are available from 1966 to the present, save for the years 1967–1970, 1974, and 1976–1977. The data series we have access to for this project stops in 2014.[8]

The EEO-1 forms originally included five race/ethnic categories: "White (not of Hispanic origin)," "Black (not of Hispanic origin)," "Hispanic," "Asian or Pacific Islander," and "American Indian or Alaskan Native." Employees can only be counted once, so this scheme implicitly treats "Hispanic" as a racial category. In 2007 the Commission altered their form, asking that employees first be classified as of "Hispanic or Latino" ethnicity or not. However, because employees can be counted only once, this scheme still treats Hispanic ancestry as exclusive with other, "racial" cat-

is that sampling with replacement allows for repeat observations, which makes it extremely likely that the sample will have lower entropy than the original. While there is still active work on developing corrections for this bias (Schürmann, 2018), general agreement seems to be that the bias affects the mean of the bootstrapped distribution, not its standard error (Darmon, 2013). Thus we use the bootstrap to simulate a distribution of the relevant statistic, calculate standard errors from that distribution, and use those standard errors to generate confidence intervals around our point statistics.

[7]The original reporting threshold was 50 employees, and Executive Order 11246 extended the reporting requirement to establishments with 25 or more employees if they had at least $50,000 of federal contract work. The Reagan Administration raised the thresholds to 100 and 50, respectively, in 1983. We exclude smaller establishments from our pre-1983 data to maximize comparability in our time series, but including them does not materially affect our results.

[8]Access to the EEO-1 reports is obtained through an Intergovernmental Personnel Act agreement between the first author and the EEOC. Data for this project were first provided in 2015. The EEOC made several changes to the EEO-1 survey in 2007. Ferguson and Koning (2018, appendix) discuss the impact of those changes on data comparability across years. We follow their lead and omit both the 2007 data and the 2007 cohort of entering establishments when doing any calculations on later years. In 2007, the EEOC also began collecting data on firms whose size is below the reporting threshold. We omit these smaller firms because their participation is voluntary and thus likely non-representative.

egories. This is, frankly, convenient for us, but we recognize the real-world problems with treating Hispanic ancestry as a racial classification. The 2007 redesign also made changes to the "Asian or Pacific Islander" and "American Indian or Alaskan Native" categories. These groups are very small in most establishments, so we combine them into an "Other" category when calculating segregation. This means that the 2007 redesign does not affect consistency in our data series.[9]

One reason why the EEOC insists on single classifications for every worker is because the meat of the EEO-1 survey is a matrix of race/sex/occupation cells, with counts of employees in each. These surveys are collected at the establishment, not the firm, level, but the EEOC also records parent-firm information where appropriate. The survey's occupational categories are broad ("Supervisory," "Skilled Operators," etc.) and have not been substantially revised since the late 1960s. By contrast, the EEOC also records the industry of each establishment, and the Commission has periodically updated the industry-classificaton scheme it uses, when the Department of Commerce issues new guidelines. In the data available to us, for example, the EEOC variously used the 1967, 1972, and 1987 editions of the Standard Industrial Classification system, as well as the 1997, 2002, 2007, and 2012 editions of the North American Industry Classification System. Both of these coding systems involve lexicographic levels of granularity. The most consistently recorded levels are three-digit SIC codes and six-digit NAICS codes. We standardized the industry in all of our records to three-digit SIC codes using the 1987 edition. We are fortunate, first, that many establishments show up in our data before and after such coding changes, which helps us generate probability weights for classifying the establishments that do not; and second, that the EEOC recorded *both* SIC87 and NAICS97 data from 1999 through 2005, as they switched over to the new system. This greatly increases our confidence in our crosswalks for what is, at root, a series of many-to-many matches. Details of how we standardized the industry classifications in our data are in Appendix C.[10]

Results

In Figure 2, we plot segregation between and within economic sectors over time. The left panel of Figure 2 shows H_g^a, segregation between sectors within counties, weighted and summed across counties; and the right panel shows $\bar{H}_g^a$, segregation within county-sectors, weighted and summed across sectors and then across counties. We have drawn the two panels so that the scale of the y-axes is the same though their intercepts differ; this simplifies comparing the magnitudes of changes over time. In general, racial segregation is greater within sectors than between them.

Figure 2 shows that there has been some growth in segregation between economic sectors since its low point around 1990. However, the growth in segregation between the establishments within sectors has been much greater. By 2010, within-sector segregation had reached levels comparable to the early 1970s, when our data series begins. Literally all change had been reversed.

The trends shown in Figure 2 are important for ruling out one line of inquiry. By itself, the generation-long shift from a manufacturing to a service economy cannot account for the rise in between-workplace racial segregation. We say this because the distribution of racial groups across the high-level sectors has changed relatively little. Let us be clear: this does not imply that the distribution of racial employment across broad economic sectors in the United States is equal, or optimal. It just implies that it has been stable.

[9] Beginning in 2007, the EEOC also allowed workers to identify as "Two or More Races"—again, exclusively with other classifications. Through 2014, fewer than 3 percent of workers had opted for this classification.

[10] The 1983 decision to exclude smaller establishments affects the industry composition of some larger multi-establishment firms, becuase some of their smaller branches were not recorded afterward. This causes large jumps in several series between 1982 and 1983. Because we have reason to think that these changes reflect reclassification rather than real movement, we exclude 1983 from our time series.

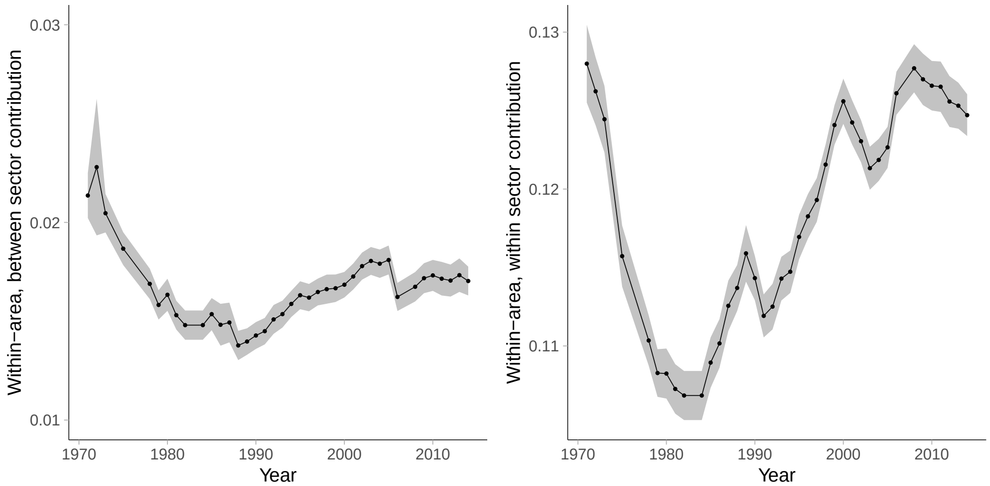

Figure 2: Segregation by race between versus within economic sectors. The sectors used here are Manufacturing, Services, Retail, Wholesale, Finance, and Utilities. See the text for discussion of the excluded years. The levels on the y-axes differ but the scale is the same, so absolute changes are the same vertical size. Far more of the increase in racial employment segregation has happened within than between broad economic sectors.

We can split $\bar{H}_g^a$ from the right panel of Figure 2 into the additive components from each sector. We do this in Figure 3. What should be immediately apparent from Figure 3 is that the overall contribution to between-establishment segregation from the service sector *has* grown over the last 40 years. Manufacturing has similarly declined. The retail sector's contribution has grown somewhat, while the smaller wholesale, finance, and utilities & transportation sectors have been almost flat.

It is tempting to conclude from Figure 3 that the rise in segregation comes from the rise of the service sector, case closed. The problem with doing so is that the trends in Figure 3 confound several processes. Today the service sector contributes more to total segregation, but it is also bigger. If services and manufacturing had had the same levels of diversity or internal segregation then their changing relative sizes would not change $\bar{H}_g^a$. To understand where the growth in the right-hand panel of Figure 2 comes from, we have to decompose the changes in Figure 3 into relative size, relative diversity, and internal segregation.

Figure 4 plots the changes in sector contributions due solely to changing sector size. These trends resemble those in Figure 3, but the differences are worth noting. The service sector nearly tripled in size during these years, but its contribution to segregation "only" doubled. The manufacturing sector's contribution shrank by two thirds, but its relative size fell by nearly three fourths. If relative size were all that mattered here, we would expect the service sector to contribute more to segregation today than it does, and the manufacturing sector to contribute less. The gap in the retail sector is more extreme than in services: it nearly doubled in relative size while its contribution only grew by about 50 percent.[11]

Part of the gap has to do with services' declining relative diversity, seen in Figure 5. In the early 1970s the service sector had a much greater share of minority employment, as was consistent with the historical tendency for the dominant group to monopolize relatively good, secure, high-paying jobs in manufacturing (Milkman, 1985; Nelson, 2001; Lichtenstein, 2002; Rosenfeld and Kleykamp,

[11]The three other sectors make smaller contributions and show less change over time. To simplify our presentation, we omit them from later figures. Decompositions for all sectors can be found in Appendix D.

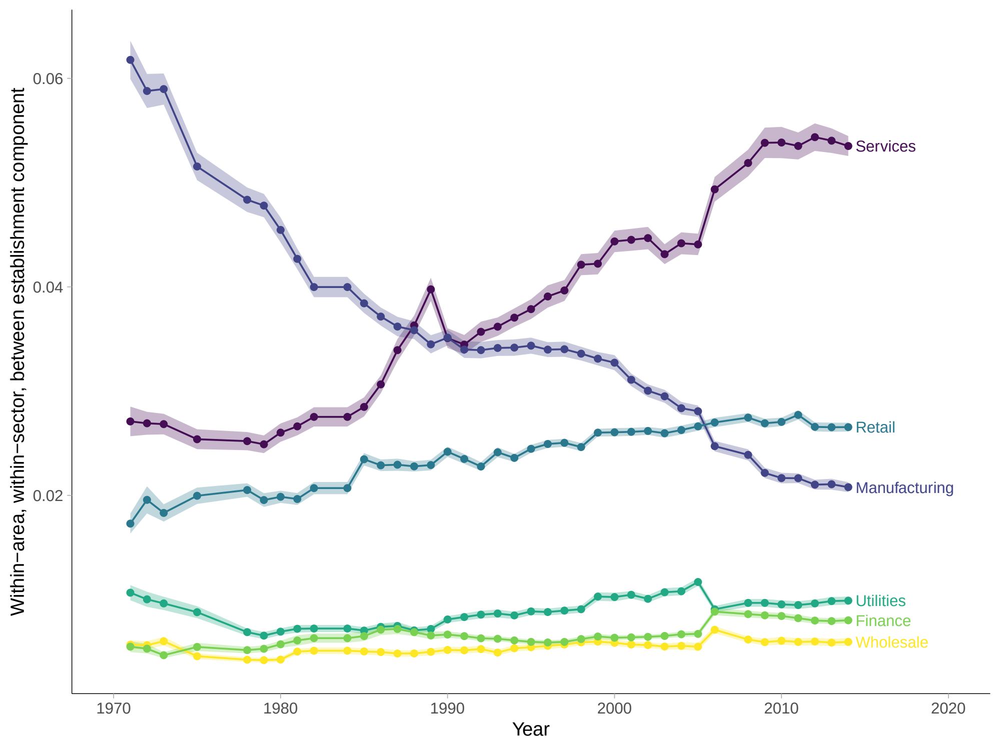

Figure 3: Sectoral contributions to racial employment segregation. These six sectors sum to the within-sector series in figure 2.

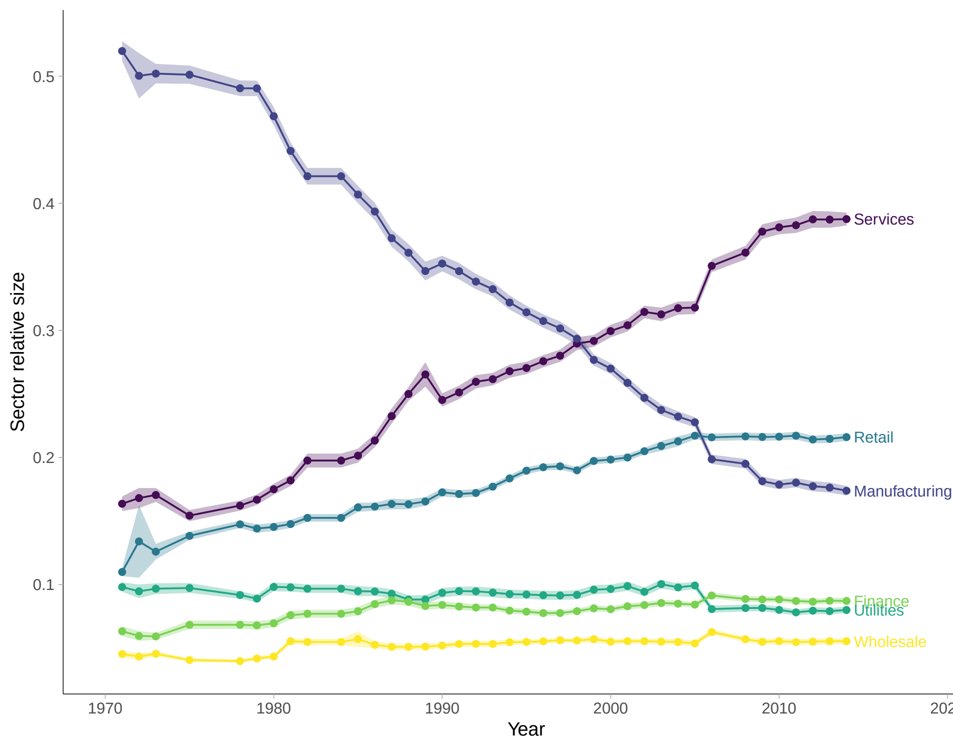

Figure 4: $\underset{w}{\Delta} H^g_j$: Relative-size component of sectors' contributions to racial employment segregation.

2012). As discussed earlier, a sector's potential to contribute to total segregation increases as its relative diversity increases. As minority workers moved into manufacturing jobs through the 1970s and 1980s, the two sectors rapidly converged on this measure. More generally, the relative diversity of different economic sectors has converged over the last four decades—which make sense given the stable decline in *between*-sector segregation shown in the left-hand panel of Figure 2. Yes, services and manufacturing have swapped relative sizes, but their converging relative diversity have pulled their contributions closer together.

To note this, though, is to sharpen the contrast with the retail sector. Figure 5 shows that retail has grown far *more* relatively diverse, even as it has grown. At least in large workplaces, minority employment in retail was comparatively rare in the early 1970s. In many customer-facing businesses, employers historically cited taste-based discrimination by their own customers as a reason to hire staff that looked like their clientele (Becker, 1957). This has obviously changed in recent decades. Yet because the retail sector was also growing in size, its rise in relative diversity should have increased its contribution to segregation even more. For its contribution to have grown more slowly than its size, as in fact happened, internal segregation within the retail sector must have fallen steadily.

Figure 6 shows that this is precisely what happened. At the start of the period, retail had by far the greatest segregation between its workplaces. This actually dovetails with its low relative diversity: most large retailers were heavily staffed by whites to serve a largely white clientele, while a minority hired minorities to serve minorities. Its internal segregation then declines more or less steadily for four decades.[12] By comparison, both services and manufacturing reversed course on

[12] We think that some of the jump in retail's internal segregation in the late 1980s is a residual artifact from our

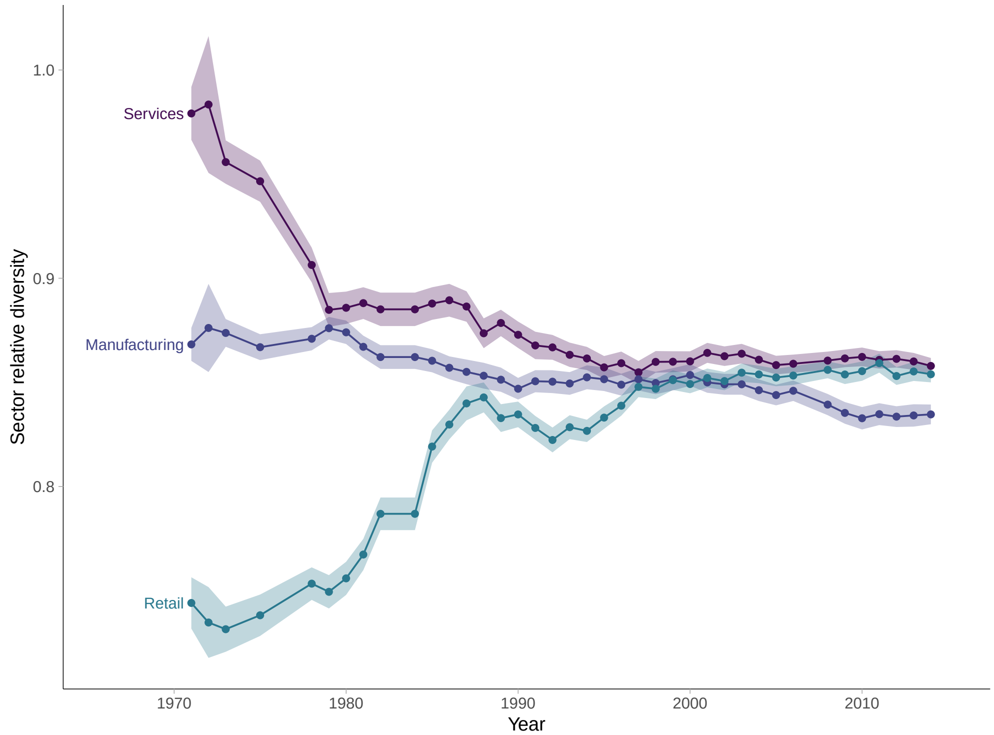

Figure 5: $\underset{d}{\Delta} H_j^g$: Relative-diversity component of sectors' contributions to racial employment segregation.

their internal segregation in the late 1980s. Manufacturing saw the most extreme reversal, in that by the turn of the twenty-first century, between-workplace segregation in manufacturing was back to levels last seen in the early 1970s. The level in services was actually higher, though it also began from a higher base. Figure 6 suggests that the narrative of a more-segregated service sector was developed in the 1970s and 1980s, when that was in fact the case. The growth of between-establishment segregation cannot simply be blamed on the growth of the service sector, though, because at least in terms of internal segregation, it and manufacturing have converged.

Before going further, it is worth revisiting the narratives of how industrial change has affected workplace segregation that we introduced earlier. First, the role of the financial sector in increasing segregation we can set aside. The industry lacks diversity, to be sure, but it simply is not large enough in terms of total employment for changes within it to have mattered much. Also, and ironically, the demographic problem of finance is not one of segregation between firms. Total diversity is so relatively low in the sector that the potential for segregation is also weak.

Was manufacturing more diverse and less segregated than other sectors? The answer must be "sort of." While manufacturing was more diverse on average than retail through the 1980s, it was consistently less so than the service sector. And in terms of internal segregation, manufacturing's exemplar status was a passing phenomenon. Throughout the 1990s, segregation between workplaces grew faster in the manufacturing sector than anywhere else. Why this might be so we have to leave

harmonizing different industrial-classification schemes. The same goes for the steep rise-and-fall in services in the same period. By the later versions of the SIC, there were a rising share of enterprises in industries like contracting and e-commerce that were harder to allocate cleanly between services and retail; this is part of what motivated the redesign and deployment of the NAICS. The useful counter-example is manufacturing, which faced less ambiguity and shows little discontinuous change in these years.

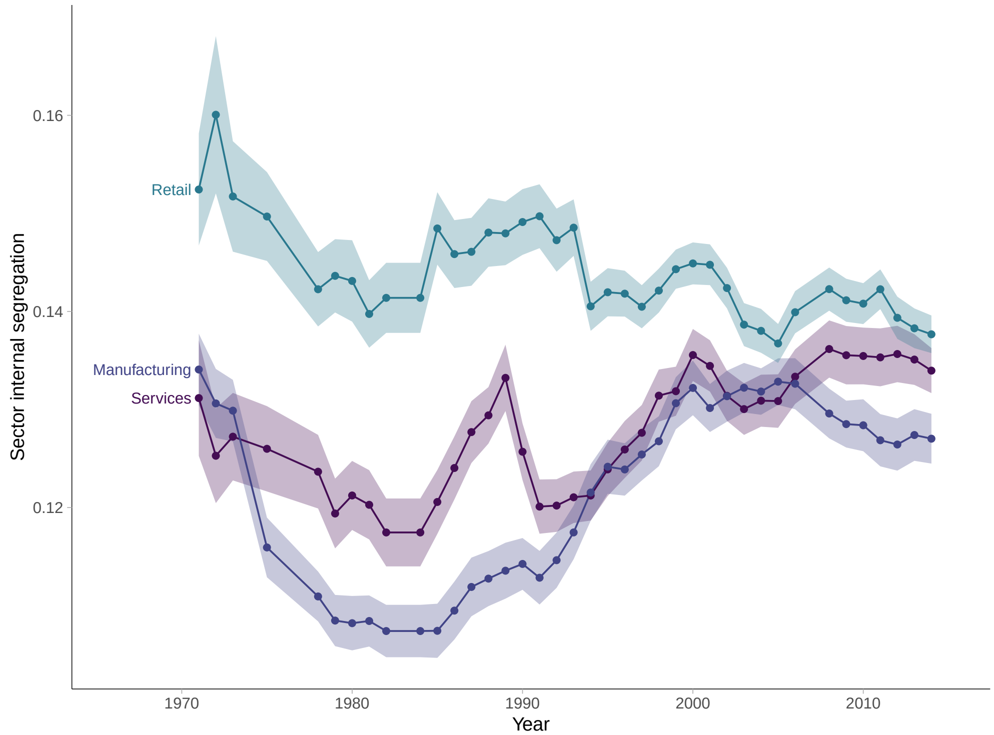

Figure 6: $\underset{h}{\Delta} H_j^g$: Internal-segregation component of sectors' contributions to racial employment segregation.

for future research, but it is worth remembering that this reversal in trends in the sector aligns for example with the decline of industrial unions in manufacturing. Since the industrial unions are often credited with integrating many mass-manufacturing industries in the first place (Levy, 1994; Halpern, 1997; Nelson, 2001; Lichtenstein, 2002), the possibility of these trends' being related is worth exploring further.

By contrast, the growth of the service sector does seem to have boosted overall between-workplace segregation in the U.S. economy. It is not that the sector got "worse" over this period—if anything, its declining *relative* diversity moderated the size of its contribution—but because the sector made only brief and transitory progress on internal integration during the period, its growth has dragged the total figure upward.

The strongest contrast here relative to expectations lies in the retail sector. Historically, retail was one of the most segregated parts of the U.S. economy. In addition, diversity was low, as white employees were favored in many large establishments to cater to a largely white clientele. In fact, the retail sector was the most common example cited in early studies of taste-based discrimination. Researchers contested Becker's (1957) hypothesis that competition would tend to drive firms that discriminated in the labor market out of business, noting that discriminatory employers would face no product-market penalty if their customers shared their prejudices (Pager, 2016).

The path of the retail sector has looked quite different, though. The sector more than doubled in size since the early 1970s while also growing far more diverse. Yet large retailers integrated throughout this period. Given the tendency of dominant social groups to preserve favored positions in the division of labor for their members (Weeden, 2001), this pattern was perhaps to be expected. The retail sector is often flagged for having some of the worst jobs and the most blatantly "low-road" employers in the U.S. economy (Osterman et al., 2001; Lichtenstein, 2006). But the relative undesirability of retail jobs may have also made them less attractive to preserve for the dominant group. There has, in essence, been room at the bottom.

In short, many of the common narratives about how industrial change has affected U.S. employment segregation are, at best, half true. Indeed the single biggest problem with concentrating on economic sectors as explanatory variables is that they mask variation within these sectors.

To see what this means in practice, consider Figure 7. Here we decompose the service, manufacturing, and retail sectors' contributions to employment segregation, seen in Figure 3, into two parts: segregation between *industries* in the sector, and segregation between *establishments* within sector-industries. This is the same type of hierarchical decomposition as shown in Figure 2, done one level lower in the hierarchy. Figure 7 casts the rising within-sector segregation seen in Figure 6 in a very different light. Essentially *all* the increase in within-sector segregation in these three largest parts of the economy has taken place between three-digit industries. Furthermore, between-industry sorting has happened in services as much as in manufacturing—and even in retail, where it is less visible in the aggregate contribution because within-industry retail segregation has fallen so much more.

We want to highlight the puzzle in this pattern of results. The different economic sectors have largely converged in their relative diversity *and* their internal segregation over the last 40 years. That convergence in diversity largely explains why there has been little growth in segregation *between* sectors, as shown in Figure 2. Instead, segregation has risen within economic sectors—not within industries but rather between them. Furthermore, that between-industry growth has happened in *all* major economic sectors. This means that the demographic composition of the sectors' workforces have come to resemble one another, and the establishments in various industries have become more integrated, even as racial employment has been increasingly stratified across different industries, irrespective of economic sector.

What we hope we have shown, in other words, is that we *cannot* explain the growth of between-workplace racial employment segregation in terms of broad sectoral shifts in the U.S. economy. Instead there seems to be a process happening one level farther down, yet in common across parts of the economy.

Discussion and Conclusion

What might such a process be? We think that the corporate restructuring that researchers documented throughout the 1990s and 2000s needs re-examining. The basic issue is whether the appropriate unit of analysis for understanding these trends is the *firm* or the *job*.

Ferguson and Koning (2018) noted that outsourcing could increase segregation between workplaces while lowering segregation within them. We think that outsourcing as typically construed, the replacement of workers on a firm's payroll with contract workers employed by an external firm, is not widespread enough a practice to explain this rise. Mostly this is because outsourcing so defined was largely an epiphenomenon of the transition away from the bureaucratically controlled internal labor markets of the twentieth-century firm (Cappelli, 1999; Jacoby, 1999; Cappelli, 2001). Younger firms never had certain types of employees to outsource, instead contracting for services from their birth (Sturgeon, 2002). Yet the practice of external contracting, of which outsourcing is one example, could explain far more of these shifts.

Our thinking is as follows. The initial integration of many workplaces in the wake of the Civil Rights movement brought with it occupational stratification by race. Given the existing pyramidal structures of most firms' internal labor markets, black and Hispanic employees were hired at the traditional ports of entry, placing them on the bottom of many career ladders (Doeringer and Piore,

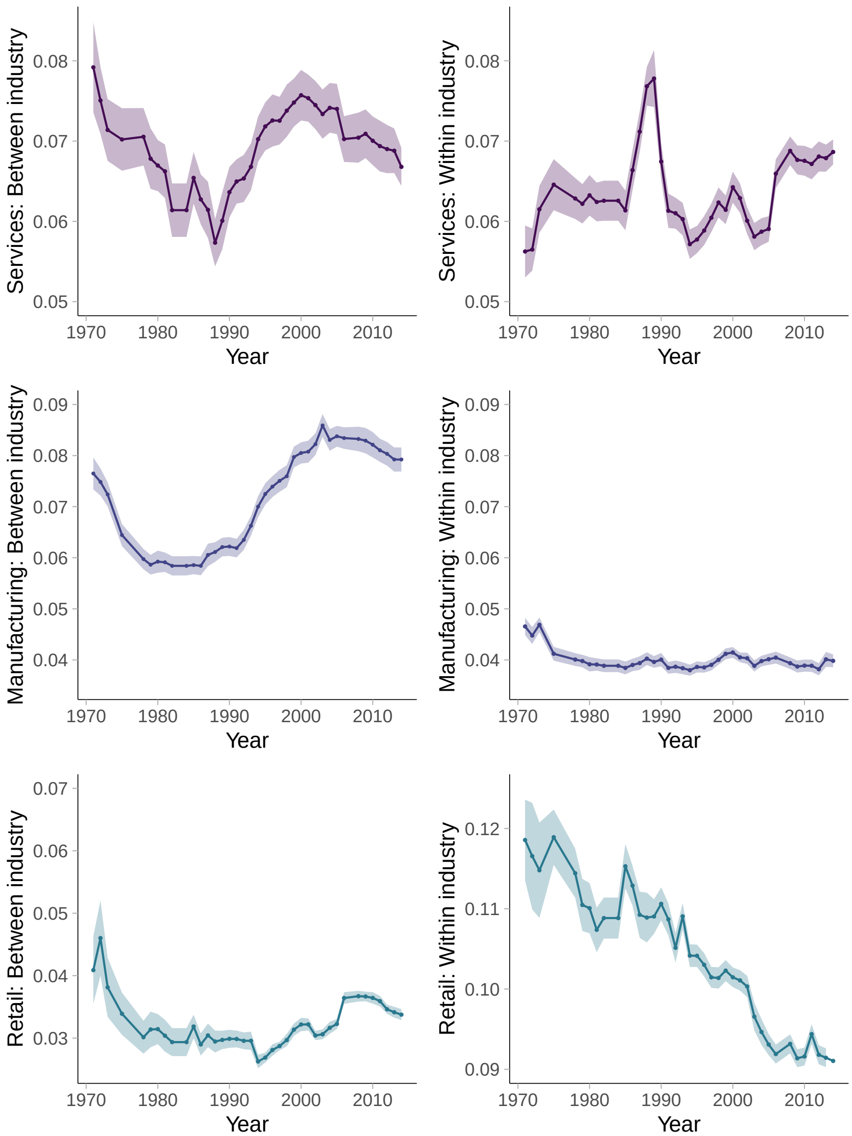

Figure 7: Within- and between-industry components of sectors' contributions to racial employment segregation.

1971; Osterman and Burton, 2004). Minority workers were often allocated to more peripheral jobs within those organizations, jobs with lower pay and employment security, and fewer benefits. It was the clustering of newer, minority employees into peripheral and subordinate positions that drew scholarly attention to patterns of occupational segregation as the 1970s and 1980s progressed (O'Reilly et al., 1989; Dobbin et al., 1993; Baron et al., 2007).

In the 1980s and 1990s, the modal structure of the large firm began to change. In line with the rise of the shareholder value movement, the conception of the large firm shifted from an internal labor market to a nexus of contracts (Davis et al., 1994). Strategic thinking about the nature of the firm changed accordingly: academics and consultants encouraged firms to identify their core activities, those that directly created value for it and/or were a source of competitive advantage, and to protect those activities while contracting for other business services (Conner and Prahalad, 1996; Nickerson and Zenger, 2004). Accordingly, by the 2000s organizational researchers were writing about the proliferation of precarious jobs (Kalleberg, 2009). Those positions in the division of labor had once been part of larger internal labor markets, and thus had their work norms shaped by the normative expectations of those labor markets, but now tended to be concentrated within firms of their own and served the residual core jobs of the older internal labor markets on a contract basis (Nickerson and Zenger, 2008).

It is not difficult to tie these trends together. If firms tended to be racially stratified by occupation, and if the decline of internal labor markets and the rise of external contracting has tended to regroup firms by occupational specialization, then it follows that occupational specialization could increase racial segregation between firms while lowering it (by lowering occupational and racial diversity) within them.

It is important for this study to consider what this would imply at the sector and industry level. At the firm level, we know that a non-trivial number of firms have been reclassified from manufacturing to services precisely because they have spun off most of their physical manufacture, retaining their industrial design, research & development, and other services (Bernard et al., 2016). Such reclassification is far more common at the job level, where workers performing the same tasks now show up in the service rather than the manufacturing sector. Professional and business services outsourcing could account for as much as 36 percent of the "growth" in service employment and 25 percent of the "fall" in manufacturing (Berlingieri, 2013). Though the economic sectors we use here are still canonical in most government data-collection, policymakers are aware of the slippage between production processes that were historically thought of as firm-bounded and today's actual organizational arrangements:

> Definitional issues have made it more challenging to assess the state of the manufacturing sector. Lines between manufacturing and other economic sectors are increasingly blurred. Many workers in fields such as industrial design and information technology perform work closely tied to manufacturing, *but are usually counted as employees in other sectors unless their workplace is within a manufacturing facility.* Temporary workers in factories typically are employed by third parties and *not treated as manufacturing workers in goernment data.* Further, technology, apparel, and footwear firms that design and market manufactured goods but contract out production to separately owned factories are not considered to be manufacturers, even though *many of their activities may be identical to those performed in manufacturing firms* (Congressional Research Service, 2019, emphasis added).

The puzzle we described in the last section is based on a fallacy of aggregation. If industrial shifts involve the the differential birth and death of firms, holding those firms' internal divisions of labor constant, then it is very hard to explain rising segregation between but not within industries, across economic sectors. If we instead let industrial shifts involve moving jobs between existing (or similar) firms in different industries, then the explanation becomes relatively simple. As long as we assume some racial segregation between types of jobs, then job specialization within establishments will increase racial segregation between establishments.[13]

Unfortunately, the occupational information within the EEO-1 surveys is quite coarse, which makes testing this idea difficult with just these data. However, if it were possible to link EEOC data to other government sources, such as the Bureau of Labor Statistics's establishment surveys that gather detailed job information, then the idea could be tested directly. If and when the U.S. government chose to gather linked employer-employee data, studying this would be easier still.

The broader point raised by this data issue matters for more than just research on employment segregation. Many of our stylized facts about work in America have at their core assumptions about the division of labor in different industries. As Barley and Kunda (2001) recognized almost twenty years ago, those assumptions are woefully out of date. They can lead us astray whenever we reason using macro-level constructs, such as sector or industry, that depend on them.

A Appendix: Decomposition of mechanisms of changes to the Theil statistic over time

We identified three approaches that prior work has used to decompose changes in a statistic like the Theil into, for lack of a better term, "mechanism" components. The most directly related one, in the sense that it studies the behavior of a Theil statistic used to measure segregation, was taken by Reardon et al. (2000) in their analysis of changing patterns of school segregation. As we do, the authors studied changes in sub-unit contributions to total segregation, where sub-unit contributions were a product of a size component, a relative diversity component, and an internal segregation component. Reardon *et al.* presented average values of the changes in each component across the geographic divisions of interest. The authors themselves noted that this was an approximation, though a good one:

> Because the average of a product does not, in general, equal the product of the averages, the average changes in the three factors do not multiply to equal the average change in the component. Nonetheless, the figures... indicate the relative directions and magnitudes of changes in the three factors; this information is sufficient for our purposes (p. 361).

Because Reardon et al. (2000) studied change between just two time periods, their mean-value approximation was indeed quite close. Here, where we have changes over many time periods, this approach runs into difficulties. A time series built by chaining together such approximations suffers from error propagation and quickly becomes unreliable.

A second approach was taken by Conceição et al. (2001), also involving the Theil statistic, but with reference to income inequality rather than segregation. The authors take the implicit derivative of the Theil statistic with respect to time. This allows them, via the law of total derivatives, to analyze changes in income inequality between groups over time into an income effect and a population effect. This approach works well for income inequality, because the distributions

[13] This line of reasoning is not inconsistent with work showing declines in occupational segregation within establishments (e.g., Stainback and Tomaskovic-Devey (2012)). The index of dissimilarity used in most such work is margin-dependent and thus able to conflate declines in establishment diversity with declines in within-establishment segregation.

of dollars and individuals across groups (such as quintiles of the income distribution) are cleanly separable. Theil statistics for income inequality also have only two terms (relative size and internal segregation) rather than three (there is no equivalent of our relative-diversity component), so the various partial derivatives are functions of a single variable. Finally, the authors analyze monthly data over a long time period. While in theory the effects of a change in one variable depend on the level of the other variable, at the frequency with which their observations are measured the moves in the latter can largely be ignored. Unfortunately, none of these conditions hold in our case. We have three variables not two, which means that even in theory the effects of changing one variable depend more on levels of the others. Worse, because size, diversity, and internal segregation are all changed by moving people between sub-units, empirically the mechanisms are more sensitive to one another. Finally, we measure changes annually not monthly, which reduces the plausibility that one of our variables can change while the others stay nearly constant. For practical studies of segregation over time, the implicit-differentiation approach does not yield accurate results.

The third approach we found was not developed with the Theil statistic in mind, but has the most potential for adaptation. This is the method for decomposing changes in aggregate firm productivity into two parts: changes in the size of firms (holding productivity constant) and changes in fundamental firm productivity (holding firm size constant). We draw most on the technique set out by Foster et al. (2001), hereafter FHK; Murao (2017) reviews this and other techniques. The advantage of the FHK approach is that it focuses on discrete rather than instantaneous changes in time. This means it embraces the "covariance" of different components of the measure explicitly, rather than implicitly assuming they can be ignored as in Conceição et al. (2001). At the same time, because the FHK approach involves a complete decomposition, it is amenable to more accurate comparisons over time than the mean-value summaries in Reardon et al. (2000).

A.1 The FHK approach

FHK developed a method to partial changes in aggregate firm productivity into changes in firms' relative size w and changes in their fundamental productivity ϕ. Let aggregate productivity be a size-weighted sum of i units' productivities at time t:

$$\Phi_t = \sum_i w_{it}\phi_{it} \tag{1}$$

where $\sum_i w_{it} = 1$ for all t. Notice the parallel to H_t as described in this paper, which is also a weighted sum. The change in aggregate productivity $\Delta\Phi = \Phi_2 - \Phi_1$. FHK decompose $\Delta\Phi$ into five components:

$$\Delta\Phi = \Delta_{within} + \Delta_{between} + \Delta_{across} + \Delta_{enter} - \Delta_{exit} \tag{2}$$

The first three of these components are calculated over the survivors; the latter over the entrants and exiters, respectively.

$$
\begin{aligned}
\Delta_{(W)ithin} &= \sum_{survivors} w_1(\phi_2 - \phi_1) \\
\Delta_{(B)etween} &= \sum_{survivors} (w_2 - w_1)(\phi_1 - \Phi_1) \\
\Delta_{(C)ross} &= \sum_{survivors} (w_2 - w_1)(\phi_2 - \phi_1) \\
\Delta_{e(N)ter} &= \sum_{entrants} w_2(\phi_2 - \Phi_1) \\
\Delta_{e(X)it} &= \sum_{exits} w_1(\phi_1 - \Phi_1)
\end{aligned}
\tag{3}
$$

Algebraically, the survivor components can be rearranged into the firms' period-2 deviations from the period-1 average productivity, weighted by their period-2 size, *net of* their period-1 deviations from period-1 average productivity, weighted by their period-1 size:

$$
\begin{array}{llllllllll}
\Delta_W & = & \sum w_1(\phi_2 - \phi_1) & = & w_1\phi_2 & -w_1\phi_1 & & & & \\
\Delta_B & = & \sum (w_2 - w_1)(\phi_1 - \Phi_1) & = & & -w_1\phi_1 & +w_2\phi_1 & -w_2\Phi_1 & +w_1\Phi_1 & \\
\Delta_C & = & \sum (w_2 - w_1)(\phi_2 - \phi_1) & = & -w_1\phi_2 & +w_1\phi_1 & -w_2\phi_1 & & & w_2\phi_2 \\
\hline
Total & = & & & & -w_1\phi_1 & & -w_2\Phi_1 & +w_1\Phi_1 & +w_2\phi_2 \\
 & = & \sum (w_2(\phi_2 - \Phi_1) + w_1(\Phi_1 - \phi_1)) & & & & & & &
\end{array}
\tag{4}
$$

The FHK decomposition lets one completely separate the effects of changes in firms across time periods from the effects of changes to the population of firms across time periods. For example, if entrants and exits happened to have identical size and productivity, their effects would cancel each other out. Alternatively, if there were no changes in surviving firms, all the change in aggregate productivity would come from differences between entrants and exits. However, the FHK decomposition does not further decompose the *relative* effects of entrants and exits—it does not show whether entrants are more productive than exits because they are larger or because they are more fundamentally productive, for example.

A.2 Adapting FHK decomposition to the Theil statistic

Like FHK's Φ, the group contributions to Theil's H are weighted sums, but they have three terms instead of two:

$$
\bar{H}^g_{jt} = \sum_g w_{gt} d_{gt} h_{gt} \tag{5}
$$

where w_{gt} is group g's size, d_{gt} its relative entropy, and h_{gt} its internal segregation. Where the FHK decomposition requires three components for survivors—essentially, two main effects and an interaction—a full decomposition of the three-termed H^g_{jt} requires seven components for survivors. These map to three main effects, three two-way interactions, and one three-way interaction, as discussed in the main text.

On the other hand, a decomposition of H can ignore entry and exit. This would obviously be wrong at the *firm* level, where turnover is a major part of any changes, but it makes sense at the *sector* level, where we assume the number of sectors is constant between time periods.[14] In this case, we want the seven "survivor" terms to sum completely to $\Delta H_j^g = H_{j2}^g - H_{j1}^g = w_{g2}d_{g2}h_{g2} = w_{g1}d_{g1}h_{g1}$. We define the following components:

$$\underset{w}{\Delta} H_j^g = (w_2 - w_1)d_1h_1 \tag{6a}$$

$$\underset{d}{\Delta} H_j^g = w_1(d_2 - d_1)h_1 \tag{6b}$$

$$\underset{h}{\Delta} H_j^g = w_1d_1(h_2 - h_1) \tag{6c}$$

$$\underset{dh}{\Delta} H_j^g = w_1(d_2 - d_1)(h_2 - h_1) \tag{6d}$$

$$\underset{wh}{\Delta} H_j^g = (w_2 - w_1)d_1(h_2 - h_1) \tag{6e}$$

$$\underset{wd}{\Delta} H_j^g = (w_2 - w_1)(d_2 - d_1)h_1 \tag{6f}$$

$$\underset{wdh}{\Delta} H_j^g = (w_2 - w_1)(d_2 - d_1)(h_2 - h_1) \tag{6g}$$

What do these components reflect? $\underset{h}{\Delta}$ is the isolated effect of segregation between sub-units in the group—the sorting of people between sub-units while holding the size and composition of the group constant. Similarly, $\underset{d}{\Delta}$ and $\underset{w}{\Delta}$ are the isolated effects of changing group size and composition while holding the other terms constant. Then there are the two-way terms: $\underset{dh}{\Delta}$ for example tracks if and how sub-unit segregation and group diversity increase together. Finally, $\underset{wdh}{\Delta}$ is the "messy residual," the portion of changing inequality that cannot be apportioned to specific factors because of co-movement.

To confirm this decomposition, consider the following sum of the expanded terms:

$$\begin{array}{cclllllll}
\underset{h}{\Delta} & = & -w_1d_1h_1 & +w_1d_1h_2 & & & & & & \\
\underset{d}{\Delta} & = & -w_1d_1h_1 & & +w_1d_2h_1 & & & & & \\
\underset{w}{\Delta} & = & -w_1d_1h_1 & & & & +w_2d_1h_1 & & & \\
\underset{dh}{\Delta} & = & w_1d_1h_1 & -w_1d_1h_2 & -w_1d_2h_1 & +w_1d_2h_2 & & & & \\
\underset{wd}{\Delta} & = & w_1d_1h_1 & & -w_1d_2h_1 & & -w_2d_1h_1 & & +w_2d_2h_1 & \\
\underset{wh}{\Delta} & = & w_1d_1h_1 & -w_1d_1h_2 & & & -w_2d_1h_1 & +w_2d_1h_2 & & \\
\underset{wdh}{\Delta} & = & -w_1d_1h_1 & +w_1d_1h_2 & +w_1d_2h_1 & -w_1d_2h_2 & +w_2d_1h_1 & -w_2d_1h_2 & -w_2d_2h_1 & +w_2d_2h_2 \\
\hline
Total & = & -w_1d_1h_1 & & & & & & & +w_2d_2h_2
\end{array} \tag{7}$$

In short, the seven decomposition terms sum to the total change in H_j^g.

Thus far we have discussed changes in a Theil statistic with two levels, which is closest analytically to the FHK approach. In the main text though we first decompose the Theil statistic by labor-market areas, so as not to confound differences in the broad geographic distribution of workers with segregation between types of economic activity that may themselves vary by location. Thus we need a way to aggregate a mechanism decomposition by area-industries into one by industries.

[14]For similar reasons, an FHK decomposition done at higher levels of aggregation with constant groups can also ignore entry and exit. For recent work on adjusting changes in H for entry and exit of groups, see Elbers (2019).

Just as H may be hierarchically decomposed, so too can the mechanism decomposition of H. Consider $H_{\langle AG \rangle}$, segregation defined as between areas plus within areas, between industries. Per the above,

$$H_g^a = \sum_a \frac{p_a}{p} \frac{E_a}{E} \left(\sum_g \frac{p_{ag}}{p_a} \frac{E_a - E_{ag}}{E_a} \right) = \sum_a w_a d_a h_a \tag{8}$$

where h_a is the internal segregation in area a. Therefore

$$\Delta H_g^a = \sum_a w_{a2} d_{a2} h_{a2} - \sum_a w_{a1} d_{a1} h_{a1} \tag{9}$$

In our case, we want to know how much total segregation has changed because of changing patterns of segregation in and between industries. This means that we are interested in $\underset{h}{\Delta} H_g^a$, the portion of changes due to changing industry segregation while holding changes in area populations and diversity constant. In other words, we want $w_a d_a \Delta h_a$. For now, let $w_{a2} d_{a2} = w_{a1} d_{a1} = k_a$ because the first two terms are held constant; then we can write

$$\underset{h}{\Delta} H_g^a = \sum_a k_a h_{a2} - \sum_a k_a h_{a1} = \sum_a k_a \Delta h_a \tag{10}$$

We can rewrite h_a. In equation 8, it captures segregation between sectors within areas, but we can add segregation between establishments within sectors:

$$\begin{aligned} h_a &= \sum_a \frac{p_a}{p} \frac{E_a}{E} \left(\sum_g \frac{p_{ag}}{p_a} \frac{E_a - E_{ag}}{E_a} \right) + \sum_a \frac{p_a}{p} \frac{E_a}{E} \left(\sum_g \frac{p_{ag}}{p_a} \frac{E_{ag}}{E_a} \left(\sum_j \frac{p_{agj}}{p_{ag}} \frac{E_{ag} - E_{agj}}{E_a g} \right) \right) \\ &= \sum_a w_a d_a h_a + \sum_a w_a d_a \left(\sum_g w_{ag} d_{ag} h_{ag} \right) \end{aligned} \tag{11}$$

Between-sector segregation will be the same for each sector and thus will cancel out. And again we can hold relative size and diversity constant. Then focusing on the right-hand side of equation 11 to calculate changes yields

$$\begin{aligned} \Delta h_a &= \overbrace{\sum_a w_a d_a \left(h_{a2} - h_{a1} \right)}^{\text{Cancels}} + \sum_a w_a d_a \left(\sum_g w_{ag} d_{ag} \left(h_{ag2} - h_{ag1} \right) \right) \\ &= \sum_a k_a \left(\sum_g k_{ag} \left(h_{ag2} - h_{ag1} \right) \right) \\ &= \sum_a k_a \left(\sum_g k_{ag} \Delta h_{ag} \right) \end{aligned} \tag{12}$$

Therefore, to calculate mechanism changes for industries that are nested within geographic areas, we can mechanistically decompose each area-industry segregation between two time periods, weight the results by the area's first-period relative size and diversity, and then sum across areas for each industry.

B Appendix: Computing mechanism decompositions of the Theil statistic

B.1 Design considerations

We do not define standard errors for the Theil statistic analytically, because there is no agreed procedure for doing so (Bojanowski, 2004). Instead we bootstrap probability distributions for the components of the statistic, and calculate standard errors from those distributions. The Bootstrap requires calculating each relevant statistic many hundreds or thousands of times, which in turn impels fast computation.

For anyone used to programming in a statistical language like Stata or R, the "natural" way to calculate the Theil is to create its weights and entropy measures as new variables in a data matrix, and then to create its weighted sums using a series of collapses, using Stata's `bysort` or R's `dplyr` commands. This works but requires computational overhead, for example for `dplyr` to execute base R code, which in turn performs matrix manipulations. We are able to speed up calculation considerably by implementing the statistics as a series of transformations to a raw matrix. This leverages routines that are pre-compiled in C. In some cases, this increases computation speed by more than a factor of 500.

In the past it was common for sociologists to publish algorithms or other approaches to computation (e.g., Wang and Wong (1987); Frank and Yasumoto (1998)), but the practice fell by the wayside as computing power increased and standardized packages spread. Today, as Moore's Law plateaus while the size of datasets continues to grow, it seems it might become useful to do so again—particularly since such methodological appendices can now be stored online. Therefore we lay out approach here.

Our goal is to generate probability distributions for year-on-year changes, but for any year t we only need that year's data to calculate Theil components. Assume N establishments that are members of a set of G mutually-exclusive and completely exhaustive industries. These industries are themselves present within A areas. For any year, we define the design matrix $\mathbf{Q}$ that has the area a, industry g, establishment n, and a set of vectors $\mathbf{R}$ with counts of r different races:

$$\begin{bmatrix} 011 & 1 & aaa & 10 & 9 & 30 & 2 \\ 011 & 1 & aab & 4 & 4 & 4 & 4 \\ 011 & 2 & bbb & 30 & 19 & 0 & 3 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 999 & 6 & zzz & 12 & 17 & 22 & 19 \end{bmatrix} \tag{13}$$

We also specify several operators (matrices) that we will use repeatedly to calculate statistics:

- **The j-operator**: For any $n \times k$ matrix $\mathbf{A}$, the matrix $\mathbf{Aj}$ is defined as post-multiplication by a $k \times 1$ vector of 1s. Thus $\mathbf{Aj}$ produces a column vector with the row totals of $\mathbf{A}$.

- **The i-operator**: For any $n \times k$ matrix $\mathbf{A}$, the matrix $\mathbf{iA}$ is defined as pre-multiplication by a $1 \times n$ vector of 1s. Thus $\mathbf{iA}$ produces a row vector with the column totals of $\mathbf{A}$.

- **The S-operator**: For any $n \times k$ matrix $\mathbf{A}$ with a vector $\mathbf{s}$ that defines groups $g \in G$ of observations, $\mathbf{s_g}$ is a $n \times 1$ vector whose ith element equals 1 if $a_{i,s} = g$ and equals 0 otherwise. In turn, $\mathbf{S_g}$ is a $n \times G$ matrix, where G is the number of groups. The vector $\mathbf{s}$ can be a unique vector in $\mathbf{A}$ or it can be a vector with unique values for each tuple of values across multiple vectors.

- **The Hadamard product**: For any matrices $\mathbf{A}$ and $\mathbf{B}$ of equal size, the Hadamard product $\mathbf{A} \odot \mathbf{B}$ is a binary operator whose (i, j)th element is $a_{i,j} \cdot b_{i,j}$. Thus the Hadamard operator $\odot$ performs element-wise matrix multiplication.

- **The Hadamard quotient**: For any matrices $\mathbf{A}$ and $\mathbf{B}$ of equal size, the Hadamard quotient $\mathbf{A} \oslash \mathbf{B}$ is a binary operator whose (i, j)th element is $a_{i,j}/b_{i,j}$. Thus the Hadamard operator $\oslash$ performs element-wise matrix division.

- **The $\triangle$-operator**: For any $n \times k$ matrix $\mathbf{A}$, the matrix $\mathbf{A}^{\triangle}$ is an $n \times k$ matrix whose (i, j)th element is $\log_R(a_{i,j})$. For any element of $\mathbf{A}$ that equals 0, the corresponding element of $\mathbf{A}^{\triangle}$ is defined as 0.[15]

B.2 The two-level case

B.2.1 Generating w_g and w_{gj}

Presume that we focus on establishments nested within areas, and ignore areas. Recall that $w_g = p_g/p$ and $w_{gj} = p_{gj}/p_g$. Because $\mathbf{R}$ has each establishment's racial counts as row elements, $\mathbf{Rj}$ is the vector holding p_{gj}, the total size of each establishment.

To calculate p_g, that is, to generate total size for the industries rather than for the establishments, apply the S-operator. For example, $\mathbf{S_g}(\mathbf{S_g}'\mathbf{Rj})$ yields an $N \times 1$ vector with each establishment's relevant industry total. We can then calculate w_{gj} with the Hadamard quotient:

$$\overset{N\times 1}{w_{gj}} = \overset{N\times r}{\mathbf{R}} \underset{r\times 1}{\mathbf{j}} \oslash \overset{N\times G}{\mathbf{S_g}} \left(\underset{G\times N}{\mathbf{S_g}'} \overset{N\times r}{\mathbf{R}} \underset{r\times 1}{\mathbf{j}} \right) \tag{14}$$

The parentheses indicating order of operations are very important here. $\mathbf{SS}'$ produces an $N \times N$ matrix. When, as here, $N \gg 100{,}000$, this matrix can easily comprise tens of billions of elements. Thus it is important to post-multiply $\mathbf{S}'$ by successive terms before pre-multiplying it by $\mathbf{S}$.

Calculating p works similarly, except that we do not need to segment the summation by industry. Instead we can use the i-operator to sum across all observations, and thus calculate the denominator of w_g. The numerator meanwhile is the denominator from w_{gj}:

$$\overset{N\times 1}{w_{g}} = \overset{N\times G}{\mathbf{S_g}} \left(\underset{G\times N}{\mathbf{S_g}'} \overset{N\times r}{\mathbf{R}} \underset{r\times 1}{\mathbf{j}} \right) \oslash \overset{N\times 1}{\mathbf{i}'} \left(\underset{1\times N}{\mathbf{i}} \overset{N\times r}{\mathbf{R}} \underset{r\times 1}{\mathbf{j}} \right) \tag{15}$$

Suffice to say that all equations in the rest of this appendix produce conformable matrices.

B.2.2 Generating E

For any establishment j, $E_{gj} = -\sum_r \phi_r \ln \phi_r$, where ϕ_r is race r's share of j's total population. We can generate $\mathbf{\Phi_{gj}}$, which expresses $\mathbf{R}$ as shares of a total rather than counts:

$$\mathbf{\Phi_{gj}} = \mathbf{R} \oslash \mathbf{Rjj}' \tag{16}$$

Then we can calculate a vector of E_{gj}s as $-1 \times (\mathbf{\Phi_{gj}} \odot \mathbf{\Phi_{gj}^{\triangle}})\mathbf{j}$.

To calculate E_g we use the S-operator again:

$$\mathbf{\Phi_g} = \mathbf{S_g}(\mathbf{S_g'R}) \oslash \mathbf{S_g}(\mathbf{S_g'Rj})\mathbf{j}' \rightarrow E_g = -1 \times (\mathbf{\Phi_g} \odot \mathbf{\Phi_g^{\triangle}})\mathbf{j} \tag{17}$$

[15] We chose a $\triangle$ to represent taking logarithms because the notation for powers, roots, and logarithms is a dumpster fire. We draw inspiration for notation here from the Triangle of Power (`https://www.youtube.com/watch?v=sULa9Lc4pck`), which deserves wider recognition.

B.2.3 Generating h_g

The h terms are undefined at the establishment level, so there is only the internal segregation within industries to calculate. This is just the segregation between establishments in an industry, and all of the components for this calculation have already been defined:

$$h_g = \mathbf{S_g}(\mathbf{S_g}'(w_{gj} \odot ((E_g - E_{gj}) \oslash E_g))) \tag{18}$$

B.3 The three-level case

For this example, we consider establishments nested within area-industries, which are nested within areas.

B.3.1 Generating w_a, w_{ag} and w_{agj}

The populations and weights for a three-level are calculated in the same was as in the two-level case, with one additional layer:

$$\begin{aligned} p_{agj} &= \mathbf{Rj} \\ p_{ag} &= \mathbf{S_{ag}}(\mathbf{S'_{ag}}\mathbf{Rj}) \\ p_a &= \mathbf{S_a}(\mathbf{S'_a}\mathbf{Rj}) \\ p &= \mathbf{i}'(\mathbf{iRj}) \end{aligned} \tag{19}$$

$$\begin{aligned} w_{agj} &= p_{agj} \oslash p_{ag} \\ w_{ag} &= p_{ag} \oslash p_a \\ w_a &= p_a \oslash p \end{aligned} \tag{20}$$

B.3.2 Generating E and d

Measures of entropy at different levels also works similarly to the two-level case:

$$\begin{aligned} \mathbf{\Phi_{agj}} &= \mathbf{R} \oslash \mathbf{Rjj}' \\ \mathbf{\Phi_{ag}} &= \mathbf{S_{ag}}(\mathbf{S'_{ag}}\mathbf{R} \oslash (\mathbf{S_{ag}}(\mathbf{S'_{ag}}\mathbf{Rjj}'))) \\ \mathbf{\Phi_a} &= \mathbf{S_a}(\mathbf{S'_a}\mathbf{R} \oslash (\mathbf{S_a}(\mathbf{S'_a}\mathbf{Rjj}'))) \\ \mathbf{\Phi} &= \mathbf{i}'(\mathbf{iR} \oslash (\mathbf{i}'(\mathbf{iRjj}'))) \end{aligned} \tag{21}$$

Likewise,

$$\begin{aligned} E_{agj} &= -1 \times (\mathbf{\Phi_{agj}} \odot \mathbf{\Phi^{\triangle}_{agj}})\mathbf{j} \\ E_{ag} &= -1 \times (\mathbf{\Phi_{ag}} \odot \mathbf{\Phi^{\triangle}_{ag}})\mathbf{j} \\ E_a &= -1 \times (\mathbf{\Phi_a} \odot \mathbf{\Phi^{\triangle}_a})\mathbf{j} \\ E &= -1 \times (\mathbf{\Phi} \odot \mathbf{\Phi}^{\triangle})\mathbf{j} \end{aligned} \tag{22}$$

In cases of three or more levels, all aggregations above the lowest require a weight for relative entropy:

$$
\begin{aligned}
d_{agj} &= E_{agj} \oslash E_{ag} (\text{Not used}) \\
d_{ag} &= E_{ag} \oslash E_a \\
d_a &= E_a \oslash E
\end{aligned} \tag{23}
$$

Generating h_{ag}, h_a, and h_g

As in the two-level case, h is not defined at the lowest level of the decomposition. We also do not have to generate h_a. In a hierarchical structure where establishments are nested into area-industries that are nested into areas, h_a gives the between-area component of segregation. To get individual industry contributions, instead of moving from h_{ag} to h_a, we should move from h_{ag} to h_g. We will do this by summing area-industries *by* industry *across* areas, weighting each component of the sum by its area's relative size and diversity. We nonetheless show the calculation of h_a here for completeness' sake.

$$
\begin{aligned}
h_{agj} &= w_{agj} \odot ((E_{ag} - E_{agj}) \oslash E_{ag}) \\
h_{ag} &= \mathbf{S_{ag}}(\mathbf{S'_{ag}} h_{agj}) \\
h_a &= \mathbf{S_a}(\mathbf{S'_a}(w_{ag} d_{ag} h_{ag})) \\
h_g &= \mathbf{S_g}(\mathbf{S'_g}(w_a d_a w_{ag} d_{ag} h_{agj}))
\end{aligned} \tag{24}
$$

Notice that the calculation of h_g here has the same structure as seen in equation 5 in the main text.

We implement these operations in R. In addition to paying careful attention to order of operations, we have found that it is important for performance to implement the data structures, particularly the **S**-operators, as sparse matrices. We have made code for this procedure public.

Bootstrapping standard errors

C Appendix: Constructing a consistent industry time-series

Between 1971 and 2014, the EEOC used seven different industry classification schemes: three editions of the Standard Industrial Classification (SIC) system and four of the North American Industry Classification System (NAICS). Building consistent time series across each switch entails many-to-many matching, because the schemes are never strict sub- or supersets of one another. To do our main analyses, we mapped all observations to the 1987 SIC edition (hereafter, we refer to this as SIC87, and others similarly). In this appendix, we explain the choices we made and the procedure we followed to do so.

C.1 1987 SIC to 1997 NAICS

The most formidable switch is from SIC87 to NAICS97. While updating editions of the SIC or NAICS might entail reclassifying some establishments, moving between the SIC and the NAICS requires reclassifying all of them. The Bureau of Labor Statistics (BLS), which publishes these schemes, offers some guidance. For the switch between SIC87 and NAICS97, the BLS publishes concordance files.[16] These show crosswalks between 4-digit SIC industries and 5-digit NAICS ones.

[16] `https://www.census.gov/eos/www/naics/concordances/concordances.html`

The difficulty in working with these files stems from the many-to-many problem. If one SIC87 code was partitioned among several NAICS97 codes, we do not know which NAICS97 code to give an establishment that had the original SIC87 one. Because all or part of several SIC87 industries might have been given a single NAICS97 code, we also cannot work backward. In some cases, such as when detailing changes between NAICS editions, the BLS publishes employment weights for these partitions. Those weights have some use, as we discuss below, but they are based on the entire economy rather than the population of large establishments that we have here. The noise thus introduced in using them might be small for edition changes, which only affect a small percentage of firms. Using them for the main SIC/NAICS shift though produces substantial measurement error. If we use the BLS's unaltered weights, we see large jumps in employment across economic sectors between 1998 and 1999, which is when the classification changes.

Fortunately for us, the EEOC began recording industry data in the NAICS97 scheme in 1999, but also continued to record SIC87 information through 2006. This means there are many organizations with their industry recorded in both systems. These seven years are our Rosetta Stone: based on the frequencies of reclassifications within the observed data, we can build a transition matrix for probabilistically classifying other establishments.

Presume there are 100 establishments in SIC97 industry 24211 in the 1999–2006 data. Of these, 90 also list SIC87 industry 352, 6 industry 353 and 4 industry 348. For the post-2006 observations of these establishments, we carry forward these SIC87 industries. For establishments that appear after 2006, we generate a unique random variable x for each. We then assign them to a SIC87 industry based on their recorded NAICS97 industry and the observed concordance probabilities:

$$
\begin{aligned}
\text{NAICS}_{1997} = 24211 \wedge x \in [0, .9) &\mapsto \text{SIC}_{1987} = 352 \\
\text{NAICS}_{1997} = 24211 \wedge x \in [.9, .96) &\mapsto \text{SIC}_{1987} = 353 \\
\text{NAICS}_{1997} = 24211 \wedge x \in [.96, 1] &\mapsto \text{SIC}_{1987} = 348
\end{aligned}
$$

For simplicity, here we assumed that all the 1999–2006 establishments are the same size, and that their NAICS97 industry does not change between 1999 and 2006. When implementing this idea, we weight establishments by average employment size to generate the transition probabilities, and use the modal NAICS97 industry for each establishment to minimize classification errors from coding errors.

This procedure relies on two assumptions that we think are reasonable. In using the observed concordance frequencies of the 1999–2006 observations to update industries for establishments that entered the data after 2006, we assume that the latter resemble the former, at least within industries. That is to say, the establishments that were present in industry 24211 in 2007 but *not* in 2006 were "spread around" in the industry in proportions equal to those in the data a year earlier, and thus would have been mapped with similar frequencies into the SIC87. We do not think that a change in the EEOC's recording methods has any direct effect on firm survival, nor that there was any big event in the economy that correlated with that change, and thus have no reason to think that the entering firms are systematically different *in terms of the SIC classification scheme* from the older ones. That said, this assumption becomes stronger the farther forward in time one goes. It has to: if there were no latent changes within the firms in an industry, there would be no need to update the classification scheme. Fortunately, most of the edition updates to the NAICS happen at the three- or four-digit level, so the noise introduced by this procedure should grow relatively slowly. Furthermore, this problem is not unique to our approach. Anyone using the canonical weights from the BLS faces the same type of potential classification error.

A second assumption is that an establishment's probability of being mapped into a specific industry upon reclassification depends only on the industry-wide probabilities, and in particular is orthogonal to the racial employment composition of that establishment. This assumption may well be violated. To the extent that it is, our mapping procedure will shuffle establishments among what in reality are more segregated industries, and thus bias downward our calculation of between-industry segregation.

C.2 NAICS 1997 to NAICS 2002, and beyond

Every five years since 1997, the BLS has published a new edition of the NAICS. The EEOC used NAICS97 through 2007, NAICS07 from 2008 to 2011, and NAICS12 from 2012 to 2014. To map these later years to SIC87, we first map observations to NAICS97, using the BLS's published concordance files to derive transition probabilities. We worry less about classification error from relying on these pre-assigned weights. The changes between NAICS editions are fewer, and usually at more fine-grained industry levels, than the SIC87/NAICS97 switch. Our main analyses focus on three-digit SIC industries, which best correspond to three-digit NAICS industries, and both of these schemes are hierarchical. Thus moving an establishment between five-digit NAICS industries within the same three-digit NAICS will have no implications for our mapping.

C.3 SIC 1967 to SIC 1972

The EEOC used the SIC67 at least through 1975.[17] The BLS published a technical report detailing changes between SIC67 and SIC72 (Goldstein, 1972), but that report includes no weights. We therefore use an approach similar to what we used for the SIC87/NAICS97 transition, working backward rather than forward in time. We start with the subset of firms present both in the 1975 and the 1978 data and note their classifications under the two schemes. We remove rare reclassifications (affecting fewer than 1 percent of the establishments in any given three-digit industry) and then generate transition probabilities. We use these to assign SIC72 industries to establishments that exit the data before 1978.

This procedure makes the same assumptions as we made when moving from SIC87 to NAICS97: that there is no direct or spurious relationship between the EEOC's administrative decision to change classification schemes and the composition or vital rates of establishments in any particular industries. We think it is worth making. We also think that this is a more accurate procedure than using a transition matrix based on the unweighted concordances in the BLS's documentation.

C.4 SIC 1972 to SIC 1987

The EEOC adopted the SIC87 in 1990. The BLS published concordances with weights for the SIC72/SIC87 transition (Bureau of Labor Statistics, 1991), but we are less willing to rely on these weights than we are on the ones for different NAICS editions. The gap between SIC72 and SIC87 is three times longer than any of the NAICS editions, for starters, and while the concordance report includes weights, it mixes together entries for different levels of the SIC. We typically only have three-digit SIC recorded, so if for example the BLS publishes information at the four-digit level, we would need weights for their weights, which we do not have. We therefore follow the same procedure as in the SIC67/SIC72 transition: generate transition probabilities based on establishments that existed through the 1989/1990 changeover, then use those probabilities to reclassify establishments that exited the data before 1990.

[17] We do not have data for 1976 or 1977. The 1975 EEO-1 files use SIC67, the 1978 files SIC72.

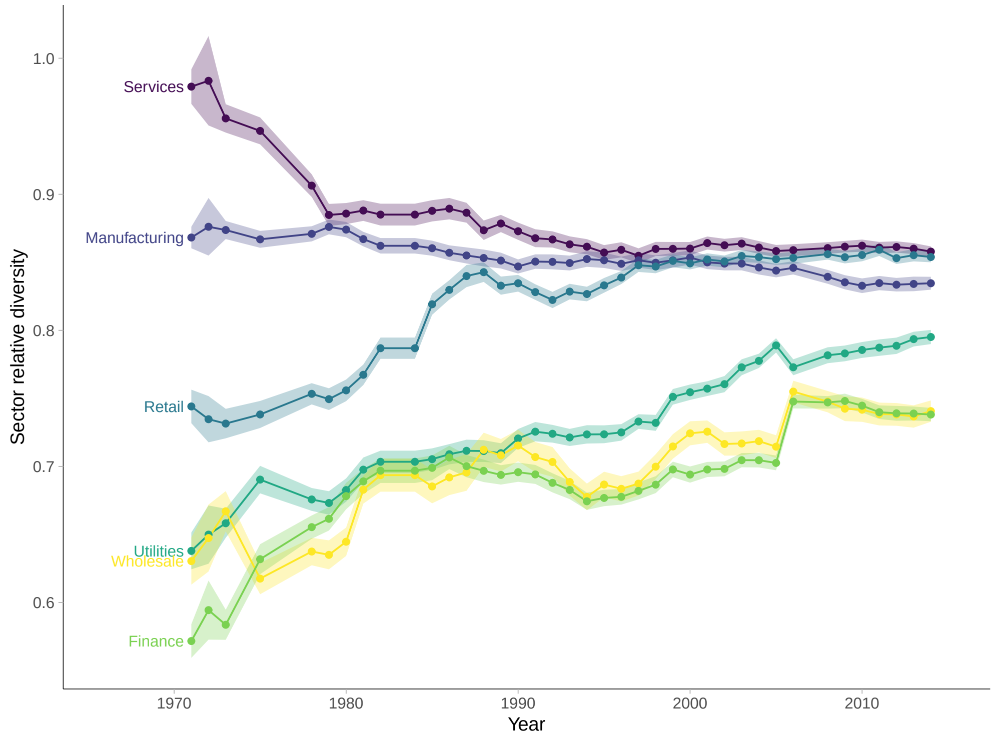

Figure D1: $\underset{d}{\Delta} H_j^g$: Relative-diversity component of sectors' contributions to racial employment segregation.

C.5 The combined procedure

Our workflow for industries thus proceeds as follows:

- Remap NAICS12 to NAICS07
- Remap NAICS07 to NAICS97
- Remap NACIS97 to SICS87
- Remap SIC67 to SIC72
- Remap SIC72 to SIC87

Because these mappings are probabilistic, each remapping can introduce error in a reclassified industry. The number of establishments affected by each of these remappings is a small portion of the total, though. Furthermore, this process lets us leverage the information provided by establishments that persist through these reclassifications. We have made our code for this procedure public, for others who would like to build similar industry time-series for the EEOC's data. Note that running the code requires a copy of the EEOC's EEO-1 data files.

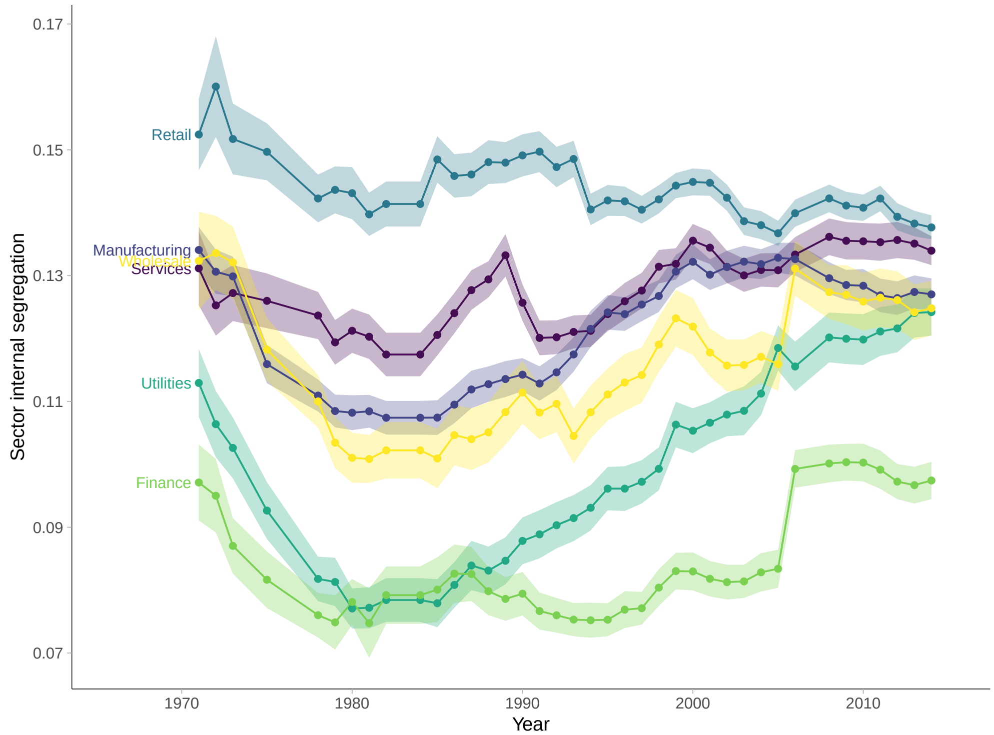

Figure D2: $\underset{h}{\Delta} H_j^g$: Internal-segregation component of sectors' contributions to racial employment segregation.

D Appendix: Mechanism decompositions for all economic sectors

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