The joint effect of ethnicity and gender on occupational segregation. An approach based on the Mutual Information Index

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Guinea-Martin’s work was supported by the Economic and Social Research Council (UK) [grant number RES-163-27-003] and the National Program for Research of the Spanish government [grant numbers CSO2008-03222 and CSO2011-30179-C02-02]. Mora’s work was supported by the National Program for Research of the Spanish government [grant number ECO2009-11165]. Ruiz-Castillo’s work was supported by the National Program for Research of the Spanish government [grant number SEJ2007-67436].
Abstract

This article studies the effects of gender and ethnicity on occupational segregation. Traditionally, the two sources of segregation have been studied separately. In contrast, we measure their joint effect by applying a multigroup segregation index—the Mutual Information or $M$ index—to the product of the two genders and seven ethnic groups distinguished in our census data for England and Wales in 2001. We exploit $M$’s strong group decomposability property to pose the following two questions: (i) How much does each source contribute to occupational segregation, controlling for the effect of the other? (ii) Is there an interaction effect? The main findings are the following two. First, we confirm the greater importance of gender over ethnicity as a source of segregation. Second, there is a small, “dwindling” interaction effect between the two sources of segregation: ethnicity slightlyweakens the segregativepower of gender, and vice versa.

*Keywords:* Britain, disadvantage, ethnicity, gender, intersectionality, Mutual Information Index, occupations, segregation
Since the 1970s, feminist researchers have widened the scope of their interest in gender to encompass a variety of sources of inequality. The seminal works of Beal (1969) and Epstein (1973) introduced the idea that ethnicity and gender combine as sources of disadvantage for ethnic minority women. In this article we study occupational segregation, one feature of the labor market that many authors claim contributes to disadvantages for women and minorities (see, for example, Blau, Brinton, and Grusky 2006, and Kaufman 2010). All writers on this topic have concluded that gender is a greater source of occupational segregation than ethnicity (see, *inter alia*, Albelda 1986; Blackwell 2003; King 1995; Mintz and Krymkowski 2011; Reskin and Cassirer 1996; Tomaskovic-Devey 1993; Wright and Ellis 2000). However, one of the tenets of the so-called “theories of intersectionality,” the idea that these two exemplars of ascribed status intertwine in producing inequality (Browne and Misra 2003; King 1988; McCall 2001), has received much less attention in applied research. We translate this interest to the study of occupations by asking the following question: do the segregative effects of ethnicity and gender interact in the ways proposed by intersectional theories? More generally, given the scenarios discussed in the literature we ask whether the combined impact of ethnicity and gender on segregation is greater than, equal to, or smaller than the sum of their individual effects.

The traditional approach to the effects of gender and ethnicity on occupational segregation separately measures segregation by gender, on the one hand, and segregation by ethnic group, on the other. We claim, in contrast, that the problem requires that segregation by gender and ethnic group be jointly, or simultaneously, addressed. We will show how, in this more general framework, it is possible to accomplish the two tasks at hand: (i) the analysis of each source of segregation separately, controlling for the effect of the other source of segregation, and (ii)
the study of the different ways in which the two sources may interact. As we have at least two ethnic groups and two genders, for a total of four or more categories, we require a multigroup segregation index that overcomes the limitations of traditional dichotomous indicators such as the well–known Dissimilarity Index originally proposed by Duncan and Duncan (1955).

Moreover, as we must isolate the two sources of segregation from each other, it is essential that the segregation index be additively decomposable for any partition of the population into sub–groups. Fortunately, the Mutual Information Index, $M$, is a multigroup segregation index that satisfies the Strong Group Decomposability property ($SGD$ hereafter). Indeed, Frankel and Volij (2011) have recently shown that the $M$ index is the only segregation index that satisfies various acceptable ordinal properties and, in addition, is strongly group decomposable. Therefore, we can only conduct our analysis using the $M$ index.

To exemplify the usefulness of our approach, we draw on the 2001 Census of England and Wales, countries that are among the most ethnically heterogeneous in Europe. Additionally, we check the sensitivity of our results to two compositional effects that could be driving them. First, a critic could note that the fact that women represent a greater share of the labor force than ethnic minorities biases our measurement. Likewise, some authors argue that the outcomes of ethnic minorities in the labor market are associated with their relative weight in the population (see, for example, Clark and Drinkwater 2002; Catanzarite 2003; Durlauf 2004; Jacobs and Blair-Loy 1996; Tienda and Lii 1987). Therefore, we explore the sensitivity of our results to the ethnic composition of Local Authority Districts, the smallest geographical area for which information on ethnicity is available in standard Census output.

Second, it is reasonable to think that at least some of the segregation that we attribute to
ethnicity and gender is really due to differences in the stock of education and potential work experience accrued by women, men, and ethnic groups (for a similar concern, see, among others, Carmichael and Woods 2000; Clark and Drinkwater 2007; Jacobs and Blair-Loy 1996; Reskin and Cassirer 1996). To address this objection, we control for differences in the age profile and educational attainment of the working population.

The remainder of this paper is organized into four sections. In the first section, we briefly review the literature on gender, ethnicity, and occupational segregation. We discuss the traditional approach to the study of gender and ethnic occupational segregation. We then present three scenarios of interaction between gender and ethnicity, where both sources of segregation play roles. Next, we introduce our empirical strategy based on the $M$ index, and afterwards, provide an illustration with British data. Finally, in the last section, we summarize our argument.

**Traditional Notions: Ethnic Segregation and Gender Segregation**

By segregation we refer to the tendency of members of different groupings (women and men; white and ethnic minority individuals) to be distributed unevenly across organizational units. This is the so-called “evenness” dimension of segregation (Massey and Denton 1988; Reardon and Firebaugh 2002). When the organizational units are workers’ occupations, most authors focus exclusively on the notion of occupational segregation by gender for two reasons, one methodological and the other substantive. Methodologically, sociological analyses have been constrained by dichotomous indexes. In the study of women and men, the Dissimilarity Index ($DI$ hereafter),
the Gini, and the Karmel–MacLachlan indexes, are natural alternatives (see Flückiger and Silber 1999 for a review). However, such indexes are not ideal tools when there are more than two groups, as is often the case in ethnic studies. The reason is that, for instance, Asian people are not only more or less segregated from, say, Black people but also from all other ethnic groups (for a similar concern, see, among others, Alonso-Villar, Del Rio, and Grdin 2012).

Nevertheless, the main reason for privileging gender over ethnicity in the study of segregation is substantive: in modern society, gender is “the most basic divide” (Epstein 2007) along which inequality arises. Gender–based differences draw their legitimacy from essentialist beliefs and stereotypes, such as the idea that women are biologically better equipped for caring, nurturing, and servicing tasks than men (Ridgeway 2006). In contrast, the application of essentialist beliefs to ethnic distinctions is taboo, at least in Western societies. Except for overtly racist and marginal groups, the opinion that certain ethnicities are better suited for performing some tasks is not normatively accepted (Jacobs and Blair-Loy 1996). Still, ethnic prejudices appear to influence recruitment, job allocation, and promotion (Carmichael and Woods 2000; Castilla 2008; Catanzarite 2003; Moss and Tilly 2001; Reskin, McBrier, and Kmec 1999) through a variety of forms that range from employers’ explicit (Becker 1971) or implicit (Bertrand, Chugh, and Mullainathan 2005) preferences for one ethnic group over another to statistical discrimination (Phelps 1972). However, in the aggregate, there are differences in ethnic and gender stereotyping and in the population weight of women and minorities. Many occupations employ women or men almost exclusively (e.g., nurses, drivers). But very few occupations, if any, are dominated by a single ethnic minority (Cohn 1999; Jacobs and Blair-Loy 1996). In short, in spite of the rise of gender egalitarianism since the 1960s, gender essentialism, as Charles and Grusky (2004) calls it,
reigns supreme.

If this is the case, then why worry about ethnicity at all when studying occupational segregation? Because the few studies that consider the ethnic affiliations of workers conclude that it shapes their occupational distribution to a noticeable degree (for two recent contributions in this vein, see Åslund and Skans 2010, and Kaufman 2010). In the case of Great Britain, the very ethnic makeup of the country is closely related to the recent evolution of the British labor market. At the end of the Second World War, significant numbers of overseas workers joined British industry and the public sector. For example, the nascent National Health Service recruited sizable numbers of Black and Asian women (Batnitzky and McDowell 2011), while England's textile, clothing and steel industries attracted migrants from the Caribbean and South Asia (Cross 1992; Owen and Green 1992; Phizacklea and Wolkowitz 1995). Some of these original migrants still worked in those occupations at the time of the 2001 Census. In addition, many of their offspring who grew up in Great Britain were already in the labor market at that date (Clark and Drinkwater 2007). Certainly, the labor supply of migrants' descendants is not necessarily tied to the occupational niches in which their forebears found work—particularly if these niches were not very attractive or advantageous (Waldinger and Feliciano 2004) or were in economic sectors that have declined over the years (Allen and Massey 1988; Cross 1992; Crouch 1999). Nevertheless, many observers have concluded that there are substantial differences in economic performance between people with immigrant origins and the rest of the labor force (Berthoud 2000; Clark and Drinkwater 2007; Fernández 2010; Heath and Yu 2005). For example, ethnic minority entrepreneurs concentrate in the retail, catering, and transport sectors (Parker 2004) but are underrepresented in professional and intermediate non-manual occupations (Carmichael and Woods 2000).
Some authors have, in a single study, examined occupational segregation by gender, on the one hand, and occupational segregation by ethnic group, on the other (Abbott and Tyler 1995; Albelda 1986; Alonso-Villar et al. 2012; Blackwell and Guinea-Martin 2005; Blackwell 2003; Jacobs 1989; King 1995, 2009; Mintz and Krymkowski 2011; Reskin and Padavic 1999; Tomaskovic-Devey 1993; Wright and Ellis 2000). These studies measure the effects of one source of segregation on people’s distribution across occupations, and only afterwards do they gauge the effects of the other dimension. If they use dichotomous indices such as the DI or the Gini index, analysts restrict the ethnic contrasts to pairwise comparisons between (i) Whites and the most prominent minority group, which is usually Black people in the US (Cohn 1999; King 1995, 2009; Tomaskovic-Devey 1993); (ii) White people and non-white people (Albelda 1986; Xu and Leffler 1992); (iii) White people and each ethnic minority separately (Hegewisch et al. 2010); or, finally, (iv) between all ethnic–gender pairs that can be formed (Reskin and Cassirer 1996; Wright and Ellis 2000). Studies conducted using the traditional notions of segregation have unanimously concluded that the level of occupational segregation is larger by gender than by ethnicity. They also tell us, for example, that White people are more segregated by gender than Chinese people in Great Britain (Blackwell 2003) or that there is more ethnic segregation among men than among women (see, *inter alia*, Alonso-Villar et al. 2012).

However, under the widespread procedure of using dichotomous indexes to calculate gender segregation for each ethnic group, and ethnic segregation for each gender, there is no methodologically sound way of integrating these separate indexes to produce meaningful measurements of gender segregation, controlling for ethnicity, and of ethnic segregation, controlling for gender. Moreover, we are unaware of any measurement of the impact on segregation of both statuses.
together, enabling a comparison of their relative importance directly and unambiguously. We address the substantive nature of this problem in the next section, where we describe three alternative scenarios for the joint effect of ethnicity and gender on segregation.

The Joint Effect of Ethnicity and Gender on Segregation

In ethnically heterogeneous societies, both ethnicity and gender are arguably part and parcel of our collection of “master statuses” (Becker 1963; Hughes 1945): the categories to which we are ascribed by virtue of our genitals, skin color, language and cultural heritage (Jacobs and Blair-Loy 1996). To a large extent these are circumstances outside individuals’ control. Nevertheless, upon visual and auditive perception of these features, everyone is classified almost immediately as adept or inept in certain tasks and as free of, or subject to, certain norms, duties and expectations. Everyone—including, certainly, employers and employees—knows this, if only unwittingly (Chugh 2004). People carry a wealth of social knowledge triggered by the physical cues of their phenotype.

We all belong to one gender and one ethnic group at the same time (Reskin 1993) and are easily perceived as members of these groups in the labor market. Hence, the traditional approach, which appraises each dimension separately, makes sense only if workers’ ascribed characteristics have an additive relationship. Ethnicity puts minority women at a disadvantage. Simultaneously, but independent of ethnic discrimination, these women also suffer the consequences of sexism. Abbott and Tyler (1995) and Blackwell (2003) find evidence of this segregation pattern in Britain.

Few authors, however, argue on theoretical grounds in favor of the additivity of the effect of
ethnicity and gender. In particular, social scientists advocating an intersectional perspective (see, *inter alia*, Bradley and Healy 2008; Misra 2012) aim to prove that ethnicity and gender “are not independent analytic categories that can simply be added together” and “have separate (…) influences” (Browne and Misra 2003:487,494). Instead, they seek “evidence to demonstrate that race and gender intersect in the labor market” (ibid.:487). This second scenario corresponds to what King (1988) calls the “multiple jeopardy hypothesis”: the general outcome of being oppressed on various accounts exceeds the sum of the outcomes of being disadvantaged on each dimension separately. With regard to occupational segregation, the evidence most often offered in favor of the intersection of ethnicity and gender is the crowding of ethnic minority women into the most menial, least desirable activities, while white women perform skilled and administrative tasks (Nakano Glenn 1985; King 1995; Phizacklea and Wolkowitz 1995).

Surprisingly, most contributions to the debate on the compound effect of ethnicity and gender are based on qualitative evidence or on qualitative interpretations of cross-tabulations of ethnicity, gender and broad occupational titles (see, for example, Abbott and Tyler 1995; King 1995) and sets of pairwise indexes (Blackwell 2003; King 1995). To our knowledge, only Reskin and Cassirer (1996) and Wright and Ellis (2000) explicitly debate the question in statistical terms.

If both forms of ascribed status are the source of at least some non-negligible segregation in the workplace and if they interact in the sense proposed in the intersectional tradition, then when we separately estimate one of the two types, e.g., the segregative effect of people’s gender status, as if they had no ethnic ascription, we report a potentially inflated measure of gender segregation. The quantity that we obtain includes the part of segregation that arises from the interaction between gender and ethnicity through, for example, racialized and gendered job queues (Lieberson
and Waters 1988; Reskin and Roos 1990). Consequently, the resulting index will overestimate the contribution that being a woman or a man has on people's occupational distribution (see Reskin and Cassirer 1996:241 on the same idea).

Apart from their contribution to the previous point, Reskin and Cassirer (1996) note that “the social processes that produce sex segregation typically relegate women and men to different occupations, thereby preempting or at least minimizing the segregative effect of race” (ibid.:237). In other words, gender and ethnicity interact, but not in the way envisaged by intersectional theorists: rather than multiplying their repercussions, gender, the status that by itself seems to segregate workers the most, softens the impact of ethnicity—which, to begin with, is a lesser dimension in terms of its segregation potential. More generally, we propose a third scenario in which each of the two ascribed characteristics concentrates workers in a sub-set of occupations, and the effect of the second characteristic is curtailed to some extent. This final possibility reflects an interaction that diminishes the effect on segregation of each status. We refer to it, in short, as the “dwindling interaction” between ethnicity and gender. In this third scenario, the traditional measurements of gender segregation underestimate the net contributions of both gender and ethnic status to the segregative process.

**An Approach Based on the Mutual Information Index**

The starting point of our empirical strategy is simple. People belong to one of two genders and, in our data, one of seven ethnic groups: White, Indian, Pakistani, Bangladeshi, Black Caribbean, Black African, and Chinese (see Data section). Hence, the segregation that we mea-
sure stems from the uneven distribution of $2 \times 7 = 14$ groupings across occupations. To avoid the need to constantly repeat “ethnic and gender,” we also refer to this notion as “total” or “overall” segregation. To conduct an analysis that combines ethnic and gender categories, we must employ a multigroup index of segregation.

We must also employ an index of segregation that satisfies the property of Strong Group Decomposability (SGD) defined by Frankel and Volij (2011). The reasons are twofold. First, an index that satisfies SGD allows us to identify the proportion of occupational segregation by ethnicity and gender that can be attributed exclusively to either ethnicity or gender (Mora and Ruiz-Castillo 2011). Second, once we can compute the proportion of segregation attributable to each source, controlling for the other, we can study whether the sum of these two quantities is greater than, equal to, or smaller than total segregation. In the first case, gender and ethnicity interact in a multiplicative way; in the second case, they do not interact; and in the third case, they interact in a dwindling way.

As indicated in the Introduction, Frankel and Volij (2011) have shown that the $M$ index is the only segregation index that, in addition to possessing other desirable properties, satisfies the SGD property. Therefore, the remainder of this Section is devoted to a brief presentation of the $M$ index and its properties relevant to this study. However, before we do so, we must define the entropy of a distribution (see Hamming 1991 for an overview).

Consider a variable $X$ which takes a value $q$ with probability $p_q$. In Information Theory, $\log \left( \frac{1}{p_q} \right)$ captures the amount of information, or “surprise,” experienced when we observe $q$: if $q$ is unlikely, then $p_q$ is small; consequently, the information that $q$ carries, defined as $\log \left( \frac{1}{p_q} \right)$, is large. To illustrate, consider the distribution of British workers by ethnicity (see the last column

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of Table 1 below). An overwhelming 94.5 percent of this population is White. Therefore, if we sampled one person in the working population and she happened to be White, we would not be very surprised. In more technical terms, the information gained would be small: \( \log \left( \frac{1}{0.945} \right) = 0.06 \), to be precise. If we sampled an Indian person, a less likely event, the amount of information obtained is \( \log \left( \frac{1}{0.021} \right) = 3.86 \), or \( \frac{3.86}{0.06} = 64 \) times larger than in the case of a white person.

The entropy of the distribution of \( p_q \) is the expected value of the information attained with the variable \( X \): \( E(P) = \sum p_q \log \left( \frac{1}{p_q} \right) \), where \( P = \{p_q\} \) denotes the probability distribution of \( X \).

In our example, \( E(P) = 0.30 \).

Let \( P_{occ} \) and \( P_{occ|e,g} \) be the unconditional and conditional distribution of occupations, respectively. Suppose we sample a worker randomly. The entropy of \( P_{occ} \), \( E(P_{occ}) \), is defined as the expected information obtained from learning the worker’s occupation. If we were also informed about the worker’s ethnicity and gender, the expected information from learning the worker’s occupation would now be measured by the entropy of the distribution conditional on ethnicity and gender, \( E \left( P_{occ|e,g} \right) \). The \( M \) index of total or overall segregation, denoted by \( M^* \), is the average increase in the information we have about the worker’s occupation that comes from learning her or his ethnicity and gender:

\[
M^* = \sum_{e,g} w_{e,g} \left[ E \left( P_{occ} \right) - E \left( P_{occ|e,g} \right) \right]
\]

where \( w_{e,g} \) is the demographic weight of workers of ethnic group \( e \) and gender \( g \). If all groups are equally distributed across occupations, then \( M^* \) attains its minimum at 0. Conversely, \( M^* \) reaches its maximum if groups do not mix together in occupations and all groups have identical
demographic weights. This quantity is equal to the smaller value of either the logarithm of the number of groups or the logarithm of the number of occupations.\footnote{\textsuperscript{7}}

**Strong Group Decomposability: A crucial property**

The SGD property states that for any partition of the population into subgroups, $M^*$ equals the sum of the segregation between subgroups and a weighted average of within-subgroup segregation levels, where the weights are the population shares of each subgroup. We can study the segregation induced by a given source, e.g., gender, in two ways. In the first case we have the “between-term” denoted by $M^g$, which is called thus because it gauges the segregation that arises from distinguishing between women and men in the overall population. This term is equivalent to traditional measurements of gender segregation.

In the second case, the $M$ index of gender segregation within an ethnic group $e$, $M^g(e)$, captures the average increase in information that arises from learning the worker’s gender, given that the ethnicity is $e$, with $e = 1, \ldots, E$. The weighted average of these indexes, $\sum_e p_e M^g(e)$, is the “within-term” in the decomposition of $M^*$, which is called thus because it measures the central tendency of gender segregation within an ethnic group. Similarly, we can study segregation between ethnic groups in the population, $M^e$, and also within gender groups, $M^e(g)$. The corresponding within-term is $\sum_g p_g M^e(g)$.

As the $M$ index fulfills the SGD property, the overall index $M^*$ defined in equation (1) satisfies the following two decompositions:\footnote{\textsuperscript{8}}

$$M^* = M^g + \sum_g p_g M^e(g) = M^e + \sum_e p_e M^g(e). \quad (2)$$
The first equality in equation (2) states that $M^*$ can be decomposed into segregation by gender, $M^g$, and ethnicity’s contribution to segregation after controlling for gender, $\sum_g p_g M^e(g)$. Alternatively, $M^*$ can be decomposed into occupational segregation by ethnic group, $M^e$, and the effect that gender has on segregation once ethnicity is controlled for, $\sum_e p_e M^g(e)$.

Equation (2) is important because it quantifies how much of ethnic and gender segregation is exclusively due to either ethnicity or gender. More precisely, the within–terms answer the following question: how much of the overall segregation would disappear if gender (in the case of $\sum_e p_e M^g(e)$) or ethnicity (in the case of $\sum_g p_g M^e(g)$) played no role in the segregative process? Hence, each within–term singles out the contribution to overall segregation that can be attributed to one dimension on its own, once we control for the other (Mora and Ruiz-Castillo 2011). As these contributions do not contain the segregation that arises from the interaction between ethnicity and gender, the within–terms can be considered the “marginal” effects of either ethnicity or gender on overall segregation.9

**The three scenarios for the joint effect of ethnicity and gender and a single analytical framework**

The decomposition in equation (2) is ancillary to the identification of the interaction between ethnicity and gender. It provides a single analytical framework for evaluating which of the three scenarios concerning the joint effect of ethnicity and gender holds true in a given time and place. Simple arithmetical manipulation of equation (2) identifies the putative intersection of ethnicity and gender, denoted by $I$, as follows:
\[
I = M^* - \left( \sum_g p_g M^e(g) + \sum_e p_e M^g(e) \right).
\]

Alternatively, we can interpret \( I \) as the portion of the segregation jointly induced by ethnicity and gender that cannot be attributed uniquely to either of these two factors—and that, consequently, arises from their interaction:

\[
I = M^e - \sum_g p_g M^e(g) = M^g - \sum_e p_e M^g(e).
\]

The value of \( I \) in equations (3) or (4) indicates which of the three scenarios pertains in a given instance. When \( I = 0 \), the sum of the exclusive contributions of ethnicity and gender to segregation, \( \sum_g p_g M^e(g) \) and \( \sum_e p_e M^g(e) \), add up to their joint effect, \( M^* \). In this case, such contributions are equal to the traditional measures of ethnic segregation, \( M^e \), and gender segregation, \( M^g \). This is the additive scenario, in which ethnicity and gender do not interact in producing segregation.

When \( I > 0 \), there is a part of \( M^* \) that cannot be attributed to either factor in isolation. This part results from the interaction of gender and ethnicity in the multiplicative scenario. In this case, traditional measures overestimate the amount of segregation induced by each status: \( M^e > \sum_g p_g M^e(g) \) and \( M^g > \sum_e p_e M^g(e) \).

When \( I < 0 \), ethnicity and gender interact in the sense that their combination produces less segregation than we would observe if we simply added together the net segregative effects of each status. Through their joint effect, the marginal contributions of ethnicity and gender taper off. This is the dwindling scenario, in which traditional measures underestimate the portion of
segregation that each status begets: \( M^e < \sum_g p_g M^e(g) \) and \( M^g < \sum_e p_e M^g(e) \).

**Robustness checks**

To this point, we have argued that traditional indexes measure the strength of the association between one variable, normally gender or ethnicity, and occupation. As an alternative, we have proposed an approach in which a multigroup index of segregation jointly applies to both dimensions. We now wish to consider two possible objections to our research design. These objections concern the so-called “compositional effects.”

In the first place, we know that minorities are not distributed evenly and randomly across a given geographical area (Jacobs and Blair-Loy 1996). In Great Britain, for example, they cluster in certain areas, mostly urban, as a result of labor demands at certain points in history (Clark and Drinkwater 2002; Cross 1992). To assess the sensitivity of our results to the percentage of the population that belongs to a minority, we have created two “sub–countries” in our data. One is composed of the geographical areas in which minorities concentrate. In the other areas, minorities represent only a negligible proportion of the overall population. (We present the details in the Data section.) If our measures are robust to the ethnic composition of the areas, the amount of ethnic segregation, its joint effect with gender, and the intersection of ethnicity and gender, should be roughly equal, independently of the ethnic mix of the area.

Second, we should bear in mind that economists’ main supply–side explanation of differences between women and men in occupational outcomes relies on the notion of human capital, i.e., the acquired stock of competences to work and produce economic value. The nub of the theory is that people accrue education and work experience as a result of investment decisions that affect
their future earnings and occupations (Ben-Porath 1967). Consequently, observed occupational segregation must be associated, at least partly, with group differences in levels of human capital. Hence, as a robustness check on our findings, we evaluate to what extent ethnic and gender differences in human capital characteristics account for occupational segregation. How do we expect segregation levels and the intersection of ethnicity and gender to vary, once we control for the human capital characteristics of the working population? From the literature, we can think of two possible outcomes. The first responds to the meritocratic ideal and the second to the specialization of population subgroups in certain types of occupations. We review each in turn.

One of the main findings regarding the link between human capital and gender segregation indicates that many women with college degrees and continuous work histories are employed in male and integrated occupations, thereby decreasing the overall level of segregation (Cotter, Hermans, and Vanneman 2004; Hakim 2004). In the case of ethnicity, the role of human capital is less clear-cut because it depends, to some extent, on where it was acquired. Customarily, employers in migrants’ countries of destination either do not recognize or somewhat devalue the education achieved in migrants’ countries of origin, particularly if the language is different (Heath and Yu 2005; Platt 2005). However, for ethnic minority people who earned their educational credentials in the country where they work, the consequences of human capital should be similar, in principle, to the outcomes observed among women and men: the higher the education level achieved, the greater the potential for making inroads into jobs with meritocratic points of entry. In summary, if achieved status and merit buffer some of the discrimination brought about by ascribed status (Carmichael and Woods 2000; Mintz and Krymkowski 2011; Reskin et al. 1999), we should observe that segregation jointly induced by ethnicity and gender, as well as any multiplica-
tive interaction between these two dimensions, diminishes once we control for human capital.

The alternative outcome concerns specialization: at any level of human capital, women pursue distinctive occupational careers (Jarman, Blackburn, and Racko, 2012; Shauman, 2006). For example, in Scandinavian countries, where many women have tertiary education, women follow feminized career ladders in the public sector (Hansen 1997; Mandel 2012). Likewise, highly qualified members of certain minorities tend to avoid the “ethnic penalty” (Heath, McMahon, and Roberts 2000) that they might endure in the broader labor market by carving out occupational niches in which they achieve a certain critical mass (Lieberson 1988) or serve a co–ethnic clientele (Aldrich et al. 1985). In Great Britain, Indian and Black African men have Medical practitioners and Software analysts among their most common occupations and, together with the Chinese, often work in professional and business services (Blackwell and Guinea-Martin 2005; Clark and Drinkwater 2009; Modood and Berthoud 1997; Pang and Lau 1998).

The specialization story is likely most often referenced in the cases of workers in the lowest echelons of human capital formation. Women without tertiary education who join the labor market intermittently are often employed in female, “working class” occupations or in service occupations with flexible schedules (Cotter et al. 2004; Hakim 2004), while minorities with few qualifications concentrate in the least desirable occupations. For example, South Asian women in the North of England have traditionally worked as sewers in the textile and clothing industry (many at home) and South Asian men in taxi driving (Blackwell and Guinea-Martin 2005; Clark and Drinkwater 2009; Green, Owen, and Wilson 2005; Modood and Berthoud 1997; Phizacklea and Wolkowitz 1995). In the US, Catanzarite (2000) has found that recent immigrant Latinos, who have a limited stock of human capital (Wright and Ellis 2000), concentrate in “brown–collar”
occupations in the agriculture, construction, manufacturing, and low-level service sectors. In summary, the specialization argument posits that women and minorities with high and low levels of human capital concentrate heavily in subsets of occupations, thereby increasing the overall level of segregation. If this is the case, then we should observe that segregation increases once we control for human capital. Moreover, the findings should attest to the existence of a multiplicative interaction between ethnicity and gender.

To our knowledge, no contribution to the literature would lead us to expect any particular pattern in the way in which the dwindling interaction between ethnicity and gender, if any, might behave, once we account for the human capital characteristics of women and men and of each ethnic group. Under this scenario, such control will simply help us assess the robustness of the findings to the possible confounding effect of human capital.

To assess the sensitivity of our results to human capital characteristics, we exploit the information available in the Census related to educational achievement and age, which together can be considered proxies of education and potential work experience. First, we classify workers into occupations and $H$ human capital proxy categories. We denote by $M^{**}$ the $M$ index of segregation by ethnicity and gender in terms of human capital and occupational categories. We can decompose $M^{**}$ as follows:

$$M^{**} = M_{HC} + M_{occ(HC)}$$  \hspace{1cm} (5)$$

where $M_{HC}$ is a between-term that captures the segregation induced by human capital levels and is of little interest for our purposes. $M_{occ(HC)}$ averages the ethnic and gender segregation that...
exists for each level of human capital. In particular,

\[ M_{doc(HC)} = \sum_h p_h M(h). \]  

(6)

Each of these terms \( M(h) \) can itself be decomposed, as in equation (2), so that, for each human capital level, we can identify the interaction term using an expression such as equation (3). Hence, the decomposability properties of the \( M \) index ensure that our notion of overall segregation and the identification of the interaction term can also be implemented after controlling for human capital categories.

**An Empirical Illustration**

We illustrate our approach using aggregated individual–level data from the 2001 Census of England and Wales. First we describe the data and the variables used. We then present and discuss our results.

**Data**

British society is one of the most diverse in Europe. Even so, people from the six major ethnic minorities in Britain (Indian, Black Caribbean, Pakistani, Black African, Chinese and Bangladeshi) represent only 5.5 percent of the working population. To contextualize the ethnic heterogeneity of the British labor force, recall that—according to the US Census Bureau—in 2000, 26.3 percent of workers in the US did not place themselves in the "white alone, not Hispanic or Latino" category. Given the scant demographic importance of minorities in Britain, Census data—with its
almost universal coverage and fully coded occupational questions—constitute the only dataset that is sufficiently large and representative to analyze occupational segregation by ethnicity and gender.

However, as noted above, minorities are unequally distributed throughout Britain (Clark and Drinkwater 2002). Local Authority Districts (LADs) are the lowest level of geographical information in our data. On average, each LAD has a population of around 140,000 individuals (Clark and Drinkwater 2010). Casting a broad net, we define areas where five percent or more of the population declare themselves to be members of an ethnic minority as ethnically heterogeneous areas—“Mixed” for short. This figure rounds off the 5.5 percent of the ethnic minority people in the overall British labor force. Additionally, it divides the country neatly by grouping together all metropolitan areas in the Mixed group: from Portsmouth, with a 5 percent ethnic minority population, to Newham, a borough of East London where 60 percent of the population belongs to an ethnic minority. In total there are 113 Mixed LADs.  Below the five percent benchmark, there are 408 LADs, which we call Non–mixed areas.

Tables 1 and 2 provide basic descriptive statistics of the dataset. Minority workers concentrate in Mixed areas: 86.5 percent of them, but only 37.6 percent of white workers, are found there. Women and men are similarly distributed, both across and within Mixed and Non–mixed areas. On average, 11.9 percent of workers in Mixed areas belong to a minority, in contrast to the 1.2 percent in Non–mixed areas.

We use the 2000 Standard Occupational Classification, which has 81 categories at the three–digit level (Office for National Statistics 2000). This is the most detailed classification available in British Census data when used in conjunction with variables such as ethnicity. Many researchers
Table 1: Ethnic Groups by Type of Area

<table>
<thead>
<tr>
<th></th>
<th>Non–mixed areas</th>
<th></th>
<th>Mixed areas</th>
<th></th>
<th>Total</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Counts</td>
<td>%</td>
<td>Counts</td>
<td>%</td>
<td>Counts</td>
<td>%</td>
</tr>
<tr>
<td>White</td>
<td>13,097,854</td>
<td>98.8</td>
<td>7,878,540</td>
<td>88.1</td>
<td>20,976,394</td>
<td>94.5</td>
</tr>
<tr>
<td>Indian</td>
<td>59,562</td>
<td>0.4</td>
<td>497,449</td>
<td>4.6</td>
<td>457,011</td>
<td>2.1</td>
</tr>
<tr>
<td>Black Caribbean</td>
<td>25,237</td>
<td>0.2</td>
<td>222,308</td>
<td>2.5</td>
<td>247,545</td>
<td>1.1</td>
</tr>
<tr>
<td>Pakistani</td>
<td>21,004</td>
<td>0.2</td>
<td>158,078</td>
<td>1.8</td>
<td>179,082</td>
<td>0.8</td>
</tr>
<tr>
<td>Black African</td>
<td>16,129</td>
<td>0.1</td>
<td>158,073</td>
<td>1.8</td>
<td>174,202</td>
<td>0.8</td>
</tr>
<tr>
<td>Chinese</td>
<td>32,800</td>
<td>0.2</td>
<td>63,209</td>
<td>0.7</td>
<td>96,009</td>
<td>0.4</td>
</tr>
<tr>
<td>Bangladeshi</td>
<td>10,577</td>
<td>0.1</td>
<td>50,786</td>
<td>0.6</td>
<td>61,363</td>
<td>0.3</td>
</tr>
<tr>
<td>Total</td>
<td>13,261,163</td>
<td>100</td>
<td>8,938,443</td>
<td>100</td>
<td>22,201,606</td>
<td>100</td>
</tr>
</tbody>
</table>

Notes:
Only people aged 16 to 64 and in paid work are included.

Table 2: Joint Distribution of Ethnicity and Gender by Type of Area

<table>
<thead>
<tr>
<th></th>
<th>Non–mixed areas</th>
<th></th>
<th>Mixed Areas</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Men</td>
<td>Women</td>
<td>Total</td>
<td>Men</td>
<td>Women</td>
</tr>
<tr>
<td>White People</td>
<td>53.6</td>
<td>45.2</td>
<td>98.8</td>
<td>47.4</td>
<td>40.8</td>
</tr>
<tr>
<td>Minorities</td>
<td>0.7</td>
<td>0.5</td>
<td>1.2</td>
<td>6.5</td>
<td>5.3</td>
</tr>
<tr>
<td>Total</td>
<td>54.3</td>
<td>45.7</td>
<td>100</td>
<td>53.9</td>
<td>46.1</td>
</tr>
<tr>
<td>Count</td>
<td>7,200,521</td>
<td>6,062,642</td>
<td>13,263,163</td>
<td>4,818,695</td>
<td>4,119,748</td>
</tr>
</tbody>
</table>

Notes:
Only people aged 16 to 64 and in paid work are included.

have noted that the more occupations existing in a classification, the higher the measure of segregation. Baron and Bielby (1980) have argued that the numerous jobs that official classifications subsume under the same occupational title are segregated by gender and, possibly, ethnicity. From this perspective, segregation indexes that use occupational–level information systematically under–report the degree of segregation (Reskin 1993).

Nonetheless, comparisons of segregation levels measured at different degrees of occupational detail report that most segregation is visible at a surprisingly high level of aggregation (Herranz et al. 2005; Charles and Grusky 2004). The reason is that a limited set of cleavages in the workplace...
determines much of the sorting of women and men across occupations: the manual divide, the cliff separating managerial and professional occupations from the rest, and the split into full–time and part–time jobs (Charles and Grusky 2004; Fagan and Rubery 1996), principally. For this reason, we deem the level of occupational aggregation that we employ acceptable for measuring segregation in the British labor market. If we had a more detailed classification, surely the levels of segregation we report would be higher, but we doubt that the patterns would change. Moreover, as Åslund and Skans (2009), Carrington and Troske (1997) and Winship (1977) note, analyzing extremely detailed units has the disadvantage of boosting the random variation that exists in the allocation of individuals across occupations.

We derive a proxy for human capital by combining six age groups (for ages 16 to 19, 20 to 29, 30 to 39, 40 to 49, 50 to 59 and 60 to 64), and three levels of educational attainment (without academic or professional qualifications, with secondary or professional qualifications, and with tertiary qualifications). The resulting 18 categories tap into the different work experiences and educational attainments of women and men in each ethnic group (see Clark and Drinkwater 2009, for a similar operationalization of human capital). Ethnic minorities have a younger age structure and higher levels of educational qualifications (a point that Leslie et al. 1998, and Clark and Drinkwater 2007, have noted already). For example, the percentage of people aged between 20 and 29 years is around 28 percent for minorities and only 19 percent for White people. A larger percentage of ethnic minorities under 40 have more tertiary education than do White peoples, with the only exceptions being Caribbean men and Bangladeshi people. In summary, White people have an older age profile and lower levels of education among the youngest age group. Hence, overall, the potential for having accrued work experience is greater among white
workers than among minorities.

**Results and discussion**

In Table 3, we report, separately, the $M$ indexes based on the traditional notions of occupational segregation by ethnicity, $M^e$, and by gender, $M^g$. The value for ethnic segregation, 1.4, is very small. To appreciate this, the possible maximum value that ethnic segregation can reach is 194.6 (the natural logarithm of 7 times 100). In addition, of a maximum of 69.3 (the natural logarithm of 2 times 100), gender segregation stands at 20.1.\(^{13}\)

However, we cannot bluntly collate measures of gender segregation with measures of ethnic segregation because they are scaled differently. The standard practice is to normalize both. Most authors juxtapose normalized values of the $DI$ index ranging from 0 to 100. In our case, we would conclude that gender induces $\frac{21.7}{69.3} \times 100 = 29.05$ percent of the maximum it could reach, while ethnicity originates a meager $\frac{1.4}{194.6} \times 100 = 0.71$ percent of its maximum. However, as discussed above, to directly compare the role of gender segregation and ethnic segregation, we must apply the $SGD$ property of the $M$ index shown in equation (2), to the partition of the population into 14 subgroups (2 genders times 7 ethnic groups). The relevant information is in column 3 of Table 3.

By definition, the segregation that ethnicity and gender jointly induced, measured by $M^*$, cannot be less than either ethnic or gender segregation measured separately, by $M^e$ or $M^g$, as equation (2) shows. $M^*$ stands at 21.7, while $M^e$ and $M^g$ are 1.4 and 20.1, respectively. However, in relative terms, this value of $M^*$ represents only $\frac{21.7}{204} = 8.22$ percent of the maximum level of segregation that ethnicity and gender could generate together. The reason, of course, is that
the low segregative effect of ethnicity compensates for the greater impact of gender and that the

denominator is much larger than before: the logarithm of $2 \times 7 = 14$ ethnic–gender groupings,

which is approximately $1.146$.

One advantage of this methodological framework is that we can provide a meaningful answer
to the basic question: How does ethnic segregation compare with gender segregation? If there
were no segregation by gender within ethnic groups, i.e., if $\sum_e p_e M^g(e) = 0$, then overall segre-
gation, $M^*$ in equation (2), would decrease by $\frac{20.3}{21.7} \times 100 = 93.6$ percent. In contrast, if there were
no ethnic segregation within genders, i.e., if $\sum_g p_g M^e(g) = 0$, then $M^*$ would only decrease by
$\frac{1.6}{21.7} \times 100 = 7.2$ percent. Though these numbers merely confirm the well–known fact that the
segregative force of gender overpowers that of ethnicity, it is worth appreciating that the $M$ index
allows us to demonstrate that fact in such a parsimonious and rigorous manner. Traditionally,
researchers would produce dichotomous indexes for pairs of comparisons ranging from the sim-
plest instance, in which there are only 2 ethnicities and 2 genders, to the 52 ethnic–race–gender

Table 3: Measurements of Occupational Segregation

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.4</td>
<td>20.1</td>
<td>21.7</td>
<td>1.6</td>
<td>20.3</td>
<td>-0.17</td>
</tr>
</tbody>
</table>

Notes:
(1) By Ethnic Group
(2) By Gender
(3) Jointly By Ethnic Group and Gender
(4) By Ethnic Group within Gender
(5) By Gender within Ethnic Group
(6) Putative Interaction between Ethnicity and Gender

Only people aged 16 to 64 and in paid work are included.
groupings studied by Reskin and Cassirer (1996). In the first case, there is a manageable set of \(\binom{4}{2} = 6\) pairs. However, in the second situation, the output, \(\binom{52}{2} = 1,326\) pairs, is so unwieldy that analysts face “a complexity that does not lend itself to easy summarization” (ibid.:234).

For comparative purposes, we could calculate \(\binom{14}{2} = 91\) local \(M\) indexes, one for each pair of our 14 ethnic–gender groupings. Nevertheless, sensu stricto, we cannot set side–by–side pairwise indexes of, say, gender segregation in a given ethnic group with the indexes of ethnic segregation for each gender because they do not lie along a common scale of ethnic and gender segregation. Moreover, using traditional indexes in our comparison would be very limited because, under the latter approach, local indexes—of ethnic segregation for each gender and of gender segregation for each ethnicity—cannot be added together, nor can the exclusive contribution of each variable to segregation be isolated. As explained above in the presentation of the \(M\) index, these two latter measurements are the auxiliary terms needed to identify interactions between ethnicity and gender, as well as their additive effects on segregation. This question is at the core of our inquiry. We turn our attention to it in the next subsection.

**How do gender and ethnicity interact?**

To determine how ethnicity and gender combine as sources of occupational segregation, we can compute intersection \(I\) using equation (3), i.e., we subtract from \(M^*\) the net inputs of each variable. The result is \(-0.17\) (column 6 in Table 3).14 Therefore, we conclude that the action of one dimension somehow diminishes the segregative potential of the other. Thus, the joint effect of ethnicity and gender on segregation produces a dwindling interaction between the two dimensions. Reskin’s and Cassirer’s (1996) intuition is borne out by our identification strategy.
Still, we must recognize that the interaction is small. It represents a scant $\frac{0.17 \times 100}{21.7} = 0.78\%$ percent of the segregation that ethnicity and gender together produce. We can examine the issue from two perspectives. First, let us focus on ethnic segregation once we control for gender (column 4 in Table 3). In this case, the index is 1.6. When we do not exert this control and simply measure ethnic segregation in terms of $M^e$, the figure is similar, though slightly lower: 1.4 (column 1 in Table 3). In other words, the added information that we gain by knowing someone’s gender does not significantly alter the occupational distribution predicted on the basis of ethnicity.

Second, let us turn to gender. Because interactions are commutative and because we already know that ethnic segregation does not vary once we control for gender, after controlling for ethnicity, gender segregation should remain roughly equal to what it was on its own. The comparison between columns 5 and 2 of Table 3 confirms this presumption. The level of gender segregation increases somewhat, from its value of $M^g = 20.1$ to 20.3 when we control for ethnicity. In brief, conditioning on ethnicity hardly influences the distribution of women and men across occupations. Gender induces more occupational segregation than ethnicity does, and each factor reduces, very slightly, the impact of the other on segregation. Altogether, however, each ascribed characteristic segregates workers independently of the segregation induced, simultaneously, by the other dimension.

This conclusion may surprise theorists of intersectionality.15 Therefore, it is fair to ask whether it is also surprising in the context of the literature on ethnic and gender occupational segregation in Great Britain. This corpus is small and recent because official statistics have included data on ethnicity only since the 1980s. In particular, three studies have posed the question of whether
ethnicity interacts with gender multiplicatively, such that the two statuses reinforce each other in creating segregation for ethnic minority women. To address this multiplicative conjecture, the three studies have relied on contingency tables showing the occupational distributions of women and men of various ethnic groups. However, the authors differ in the number of ethnicities considered, the data used, and the degree of detail employed in their occupational classifications. King (1995) analyzes the 1989 Labour Force Survey (LFS), the British equivalent of the US Current Population Survey, and concentrates on the contrast between the White and Black categories. In contrast, Abbott and Tyler (1995) and Blackwell (2003) draw on the 1991 Census data, which was the first Census to ask for ethnic information. Moreover, Abbott, Tyler and Blackwell include in their tables all of the ethnic groups that we use in this article.

These researchers draw very different conclusions. King argues for the intersection of ethnicity and gender in the manner to which we alluded in the literature review section: “Black women are even more concentrated in ‘women’s jobs’ than are white women” (1995:26). Abbott and Tyler, conversely, cannot “confirm any tendency for non–white women to be segregated uniformly in the ‘lower’ employment grades” (Abbott and Tyler 1995:339). For her part, Blackwell finds that Other Asian, Black African, and Chinese people are more likely to be in the most advantageous occupations than White people. On these grounds, she concludes that “ethnicity and gender do not combine to create double disadvantage for minority women in the labor market” (Blackwell 2003:713).

Surely, to a certain extent, these disparate conclusions are due to the different data used and to the relatively small sample size of the LFS in comparison to the Census. Arguably, another reason for the discrepancy lies in King’s merging of the Black African and Black Caribbean cate-

Artículo disponible en la web de la U. Carlos III y bajo revisión. Por favor, no lo publiquen en las actas del congreso.
categories into a single “Black” group. As Blackwell notes, Black people of African origins are more successful in terms of occupational attainment than Black people from the Caribbean. Nevertheless, none of these authors employ a systematic method of identifying the joint effect of ethnicity and gender. They rely on contingency tables of workers’ distribution across major occupational titles by ethnicity and gender. In addition, Blackwell (2003) and Blackwell and Guinea-Martin (2005) make pairwise comparisons using the Gini index. In contrast, the method that we propose offers a single metric by which we can conclude, unambiguously, that the dependence between ethnic and gender segregation is minimal.

Sensitivity of the results to compositional effects

The $M$ index is not “margin free”: it is sensitive to the shares of each ethnic–gender group in the population and to the overall occupational mix. Intuitively, if the proportion of minority workers varied, our initial uncertainty about a worker’s ethnicity would change. Furthermore, after learning her or his occupation, our ethnic uncertainty would also adjust to the new proportion. As Frankel and Volij (2011:10) state, this fact makes the index “unsuitable for judging whether different (...) groups are becoming more similarly distributed” across different organizational units over time.

Our research covers one year only. Nevertheless, the violation of the margin free property could entail that our conclusions regarding intersectionality are driven by the ethnic composition of the population. Is the observed, but tiny, dwindling effect an outcome of the small proportion of minorities in Britain? We explore the consequences for our results of measuring ethnic and gender segregation in Mixed areas, where the average percentage of minority workers (11.9) is
almost ten times larger than the average percentage in Non–mixed areas (1.2). Perhaps unsurprisingly, according to the $M^*$ index, there is more ethnic segregation and a stronger interaction between ethnicity and gender in areas of the country with sizable ethnic minorities. However, though 88.1 percent of the working population in the Mixed areas is white, overall segregation would decrease by a non–negligible $\frac{2.8}{20.8} = 13.5$ percent if ethnicity played no role in the segregative process (see columns 3 and 4 of Panel 1, Table 4). Moreover, in column 4 of Table 4, Panel 1, the net contribution of ethnicity is $\frac{2.8}{0.7} \times 100 = 4.1$ times larger than in Non–mixed areas; and, finally, in the column 6, the magnitude of the dwindling interaction is $\frac{0.28}{0.05} = 5.9$ times larger.

We conclude that a) the ethnic composition of Local Authority Areas influences our measurements to some extent but that b) it does not alter the main finding: ethnicity and gender interact slightly in a dwindling way; on the whole, they bring about segregative processes that are independent of each other.

The second robustness check involves controlling for a proxy of human capital. Earlier in the article, we discussed the literature and summarized its expectations in the form of two arguments. One vision posits that workers are not segregated on account of their ethnicity and gender but because they have different degrees of work experience due to their age and educational qualifications. Leaving aside the possibility of age discrimination and the fact that investment in education, to a large extent, reflects class differences (Breen and Jonsson 2005), this picture comes close to the meritocratic ideal: an occupation for everyone in accordance with one’s own merits. If this interpretation is correct, then ethnic and gender segregation should disappear or, at least, shrink drastically once differences in age and educational attainment are controlled for. Moreover, under these circumstances, there should be no interaction whatsoever between ethnicity
Table 4: Measurements of Segregation by Human Capital and Area

**Mutual Information Indexes: England and Wales, Census Data, 2001.**

<table>
<thead>
<tr>
<th></th>
<th>Panel 1: Without controlling for human capital</th>
<th>Panel 2: Controlling for human capital</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Non–mixed areas</td>
<td>0.6</td>
<td>21.7</td>
</tr>
<tr>
<td>Mixed areas</td>
<td>2.5</td>
<td>18.0</td>
</tr>
</tbody>
</table>

Notes:
1. By Ethnic Group
2. By Gender
3. Jointly By Ethnic Group and Gender
4. By Ethnic Group within Gender
5. By Gender within Ethnic Group
6. Putative Interaction between Ethnicity and Gender

Only people aged 16 to 64 and in paid work are included.
and gender.

Alternatively, each ethnic–cum–gender population subgroup may specialize occupationally at any given level of human capital: members of each of these subgroups with minimal qualifications concentrate in a set of low–level, low–paying occupations with little prestige, while the members who obtain educational credentials concentrate in certain occupations at the top end of the classification. In any case, the outcome in terms of segregation would be that there is a multiplicative interaction between ethnicity and gender—the women and men of each ethnic group are located in different occupational niches—and such interaction, together with overall segregation, rises once we compare people of like age and education.

What is the verdict? When we control for human capital, ethnic and gender segregation increases somewhat by \( \frac{23.5 - 22.4}{23.5} \times 100 = 4.7 \) percent in Non–mixed areas and by \( \frac{22.6 - 20.8}{22.6} \times 100 = 8.0 \) percent in Mixed areas (column 3 in Table 4). These results bear out the specialization interpretation to a certain degree: women and minorities follow relatively differentiated occupational careers at each level of human capital, and our measurement is sensitive to the compositional effect that is unveiled once we compare people of similar age and educational level with each other rather than with the whole population. This finding echoes the well–known fact that in spite of the trend towards gender equalization in education starting in the 1960s (Jacobs 1989), segregation persists over time at remarkably stable levels. It is reasonable to expect that better proxies for work experience and education (such as actual years employed and field of study; see Charles and Bradley 2002; England 2010; Shauman 2006) will accentuate the effects of occupational specialization among women and minorities.16

However, the interaction remains “dwindling” rather than multiplicative, and the change is
minimal (column 6 of Table 4). Hence, our major conclusion with regard to the joint effect of ethnicity and gender is robust to this sensitivity check: even given the occupational specialization that controlling for human capital reveals, each ascribed characteristic slightly lessens the impact of the other characteristic on segregation. On the whole each status prompts independent segregative processes.

Conclusions

Fifteen years ago, Leffler and Xu (1996:71) wrote that “although everyone can be characterized in terms of both a sex and a race, relatively little research explores the effects of the two factors simultaneously on people’s work fates.” Likewise, Reskin and co–authors have called for further research on “the joint effects of race and sex” (Reskin et al. 1999:335) and for ‘race’ to be defined beyond the Black/white dichotomy (Reskin and Padavic 1999). In light of the increasing ethnic diversity of Western labor markets and their enduring gender inequalities, any sociologist would agree with such a research agenda. What stopped us then?

In the matter of occupational segregation, it turns out that the limits lay in the comforts of our old methodological tool: the DI index. There is no doubt that this index has contributed much to social research since its introduction in 1955. However, it is striking that fifty years later, when quantitative articles routinely employ far more sophisticated models than in the 1950s, most segregation research still relies on a dichotomous measure that restricts comparisons to men vs. women, white vs. Black, and white vs. Nonwhite, among others. However, ethnic and gender categories are not mutually exclusive. People belong to one gender and to one ethnic group at the
same time. Moreover, in any given setting, there are typically more than two ethnic groups. In fact, there are seven in our data.

The first contribution of this article has been to tailor the $M$ index to address Leffer’s, Re-skin’s, Xu’s and many others’ calls for the joint study of ethnicity and gender in relation to occupational segregation. We exploit the fact that the $M$ index can be applied to analyze any partition of the population into as many groups as dictated by the researcher’s goals (which, in our case, are $2 \times 7 = 14$ ethnic–cum–gender categories). Updating the sociologists’ toolkit in this manner, we have compared, rigorously, the relative importance of ethnicity and gender to occupational segregation. We have substantiated the claim that most ethnic and gender segregation would disappear if the share of women and men in each occupation were equal to their proportion in the overall working population. Nevertheless, ethnicity contributes up to 13.5 per cent of all segregation in Mixed areas, where minorities concentrate. In settings where ethnic groups have similar demographic weights, and/or where the segregative force of ethnicity is heightened (through, for example, exacerbated discrimination, an upsurge of occupational specialization among minorities, or blunt racial apartheid), the gap in the relative importance of ethnicity and gender may narrow.

However, the main purpose of a methodological framework that isolates the exclusive contribution of each status to segregation, net of any effects due to the other dimension, lies elsewhere; namely, in the identification of how the two statuses interact. We have found that there is a small “dwindling” interactive effect: ethnicity weakens the segregative power of gender, and vice versa. But the curtailment is minimal. By and large, the effects of ethnicity and gender on segregation are independent of each other. Minority women suffer segregation on account of both their eth-
nicity and their gender, but the consequences of belonging to both statuses overlap almost not at all. In King's terms (1988), altogether there is double, but not multiple, jeopardy in being an ethnic minority woman. Such an identification strategy relies on $M$’s Strong Group Decomposability property.

Finally, we have conducted two robustness analyses. First, by splitting the population into two areas defined by proportions of ethnic minorities, we have assessed to what extent our main result is driven by the low presence of minorities in Britain. Second, we have explored the sensitivity of our results to controlling for age and educational levels. In the first place, unsurprisingly, we have corroborated that, as measured by the $M$ index, there is more ethnic segregation in ethnically mixed areas than in ethnically homogeneous ones. In the second place, our results support the specialization rendering of the human capital theory to a certain extent: women, men and ethnic groups are slightly more segregated from people of like educational levels and work experience than from the overall working population because each subgroup specializes occupationally. However, although each of these two compositional effects adds richness to the segregation story, they do not alter our fundamental finding: the dwindling, but tiny, interaction between ethnicity and gender.
Notes

1 UK Census data is Crown Copyright. We use the term “gender” throughout the article, rather than “sex” because the occupational segregation of women and men is a macro result of the social construction of gender—a process that is entrenched in institutions such as the labor market (West and Zimmerman 1987). Furthermore, we use the term “ethnicity” in lieu of “race” for two reasons. First, in the Census the respondent is asked about the ethnicity with which she identifies. Second, we reflect the widespread usage of the term “ethnicity” in British English, where “race” is viewed as potentially linked with “essentially racist theories” (Bradley and Healy 2008:4). When we quote other authors we respect the terms they use. Finally, for brevity we use feminine pronouns as shorthand for both women and men.

2 Following the usual convention, we use the term Great Britain as shorthand for England and Wales, and British for English and Welsh. Scotland’s 2001 Census is an independent statistical operation conducted by the General Register Office for Scotland, a part of the devolved Scottish Administration, and we do not use these data in this article.

3 There are gender categories other than women and men, as gender studies and queer theory evidence. Notwithstanding, these alternative gender groups are not recorded in the British census.

4 It could be argued that this set also includes the major age groups that we successively occupy during the life cycle: childhood, teenage years, young adulthood, adulthood, seniority (Collins 2000). This is another argument for checking the robustness of our results with a proxy for work
experience that includes age among its component parts, as we argue later in the article.

This is also the case of people who could, in principle, claim many ethnic identities. For example, in the British Census contains various mixed options that we do not consider in this article for reasons discussed in the Data section.

One normalized version of the $M$ index, known as Theil's $H$ index, satisfies a weaker decomposability property than $SGD$ (Frankel and Volij 2011; Reardon and Firebaugh 2002). However, Mora and Ruiz-Castillo (2011) have demonstrated the shortcomings of the $H$ index and the weaker decomposability property that it satisfies.

See Frankel and Volij (2011) for a motivating example of this requirement.

See Mora and Ruiz-Castillo (2011) for the proof of this result in the case with only two groups and Frankel and Volij (2011) for the multigroup case.

See also Puyenbroeck et al. (2012) for an alternative decomposition in the analysis of the interaction of education levels and occupations in gender segregation.

We created an aggregated data extract from the mainframe dataset with the 100 percent, individual-level, Census data. The extract, which only includes the variables and the population subgroups we analyze, is held by the UK Office for National Statistics, to which applications for access should be directed.

White includes people who define themselves as white British or Irish. We study them and the six minorities mentioned because they are the major and most stable sources of ethnic self-
identification of people in Great Britain. Together, these seven ethnicities comprise 98 per cent of the British population (Clark and Drinkwater 2009). We do not consider people who declare themselves to belong to a mixed, or “Other,” ethnic category because, in the aggregate, such forms of self-identity are subject to great variability over time (Simpson and Akinwale 2007).

12 See Lupton and Power (2004) for the full list of LADs by percentage of ethnic minorities. See also Clark and Drinkwater (2002) for a discussion of the economic consequences of minority concentration in relatively deprived areas. These economists use the five percent figure as one of their basic benchmarks. Nonetheless, it is obvious that this number is not set in stone. Instead, it should be argued case by case, depending on the overall representativeness of the subpopulation of interest. For example, in her study of recent immigrant Latinos, Catanzarite (2003) uses a one percent criterion in her classification of metropolitan areas.

13 For clarity, we report the indexes multiplied by 100 and rounded to the first decimal point. Additionally, we report the results obtained with seven significant digits. For example, the value 20.1 for gender segregation found in Table 3 is the result of rounding 0.2013721x100.

14 Again, we report the rounded results of calculations with seven significant digits. Hence, we calculate \[0.2168989 - (0.0155268 + 0.2030584)\]x100 = -0.17

15 Nevertheless, we should recall that our measurements are rooted in quantitative, hypothesis-testing research. Consequently, we do not and cannot say anything about the painful, subjective experiences that ensue from the double burden of racism and sexism that minority women experience in their everyday lives (Browne and Misra 2003; McCall 2005).
Moreover, as we noted above, the place where people were educated is a factor that may influence occupational outcomes (Heath and Yu 2005; Platt 2005). Unfortunately, Census data have limited information on fields of study and none at all on the countries where people obtained their education.
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