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ARTICLE

A Two-Path Theory of Context Effects: Pseudoenvironments and Social Cohesion

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Abstract
Social cohesion suffers when people *perceive* that they live among others who differ from them, even if such people *live* in homogeneous neighborhoods. This article shows that (1) two individuals who live in equally diverse local contexts may not perceive the same amount of diversity in that context, nor think of the boundaries of their local community in the same way; and (2) when comparing two individuals who live in equally diverse local contexts, the one who *thinks* they live with more minorities tends, on average, to see lower social cohesion and less collective efficacy among their neighbors. These descriptive results align with a causal framework that distinguishes the objective environment from that of the subjective context. Revealing that perceptions of social reality matter above and beyond the experience of objective context adds evidence to a theory of context effects that involves perceptions as well as experience.

Keywords: Context effects; ethnic diversity; social cohesion; perceptions; intergroup attitudes

An environment can change the behavior or attitudes of a person via two complementary yet different processes: (1) via exposure to a physical, objective milieu that requires no understanding on the part of the person to have its causal effect (for example, new precinct boundaries change vote turnout, regardless of whether residents know anything about the new lines [Amos et al. 2017; Hayes and McKee 2009, 2011]), and (2) via the creation of a mental image or map of the environment in the mind of the person before an attitude or behavior (like fear or discrimination) can be produced. This could explain why administratively recorded demographic change heralds conflict and segregation in some places but not in others (Cho and Baer 2011; Van der Meer and Tolsma 2014; Portes and Vickstrom 2011), and why some researchers find that people who live in diverse objective environments tend to display less social capital and social trust than people who live in homogeneous environments (Alesina and La Ferrara 2000; Dinesen and Sønderskov 2015; Putnam 2007; Stolle et al. 2008) while other scholars find no such relationship (Abascal and Baldassarri 2015; Gijsberts et al. 2012; Savelkoul et al. 2015).

The two causal mechanisms could be operating separately: in some places, objective diversity might prevent social cohesion and public goods provision, and in other places perceptions of this diversity are at odds with the objective context and thus mute the effects assessed using objective data such as that from the Census (Dinesen et al. 2020; Habyarimana et al. 2007). We propose that the mechanism by which diversity may reduce social cohesion depends on individual perceptions as well as Census measures of diversity in a place. Efforts to measure contextual effects tend to show that people's definitions of relevant environments vary, and even when they see a map of local Census units, few report exactly what the Census has measured (Koopmans and Schaeffer 2016; Lameris et al. 2018; C Wong et al. 2012). This misfit between what people see and where they live justifies the present study, in which we establish that perceptions can operate independently of objective context in predicting social cohesion.

Furthermore, the effects of perceptions compound. Why might *perceived* diversity matter for social cohesion? Our theoretical account builds on the idea of conditional co-operation. If people *believe* they do not share preferences, norms, or values with their diverse neighbors, perceptions of diversity can diminish norms of reciprocity, civic engagement, co-operation, and the sharing of social goods without any change in objective diversity.[1] If an individual thinks '*They* will not work to benefit *Us*; why should I contribute to a common good and let *Them* free-ride?', this mechanism linking perceptions and cohesion should operate across people living in the same places: differences in tax compliance or feelings of trust between two people living in the same city or block can be explained by differences in perceptions of diversity, even as they cannot be explained by differences in geography.

The idea that environmental or contextual effects operate via perceptions is not new. Lippmann (1922) explains how people react as much, if not more, to 'pseudoenvironments' as to real environments. Yet, the study of 'context effects' has largely focused on the objective pathway, even while many of the mechanisms implied by the theories involve subjective responses like fear, inspired by feelings of 'power threat' (Blalock 1967). The administrative data-based approach has been sensible because measuring pseudoenvironments has been very difficult, and disentangling the subjective from the objective environment even more challenging. This paper builds on previous work about perceptions and their effects on intergroup attitudes (Chan et al. 2023; Herda 2010; Hipp and Wickes 2016; Lameris et al. 2018; Semyonov et al. 2004), and it uses a research design that enables us to hold constant objective context within pairs of survey respondents so as to isolate differences in social cohesion arising from perceptions. This attempt to separate the perceptions-to-social-cohesion link from the experience-to-social-cohesion link does not follow common social science research design practices: we are not trying to estimate a causal effect or test a hypothesis about causal differences; we are not holding constant objective context because we imagine that perceptions are exogenous to either objective context or the background characteristics of people.[2] Rather, we use some of the tools of causal inference – such as non-bipartite pair matching – to *describe* the partial correlations between perceptions and outcomes where objective contexts have been held constant. As we will explain below and should be clear from the preceding paragraphs, experience of a place and its mental representation are bound together, neither is exogenous of each other, and we do not claim to have broken causal links in this paper. Instead, we create a careful research design that clarifies *one way* by which place matters for social cohesion. We explain more below.

To learn whether the two-path theory of contextual effects explains individual attitudes, we need to (1) measure the mental images that people construct of the groups in a given place as well as the boundaries that people imagine around their personally relevant places using maps and (2) describe the association between pseudoenvironments and outcomes in ways that are isolated from the effects of objective environments. We know that perceptions and understandings of locales lead people to choose to arrive at, stay in, and leave places. So, simple comparisons of people who perceive their locales differently will not merely tell us about the impact of

[1]And, once one sees that a norm is being violated, one is more likely to start ignoring other norms (Keizer et al. 2008).

[2]In this article, we do not provide a study of predictors of perceptions (Herda 2010, 2013). While demographic and socio-economic factors are related – much like for other measures of knowledge – we also know other psychological factors are at work (Guay et al. 2025; Landy et al. 2018; Wong 2007).

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pseudoenvironments, but also about the impact of objective environments. And, of course, we cannot compare the same person with herself after changing perceptions in her mind.

We tackle the first challenge by using measurement tools developed by Wong et al. (2018) for capturing the mental images individuals create of their surroundings: we ask people to draw their 'local community' on a map as a way to measure the *boundaries* of a geographic pseudoenvironment. We use these hand-drawn maps to determine the relationship between ethnic diversity and social cohesion, free from the concerns raised by the Modifiable Areal Unit Problem (Bhat and Guo 2004). We then ask respondents to report on how they see the characteristics of the people in that community (that is, measure the *content* of those pseudoenvironments); the boundaries and content together are our solution for measuring perceived context. This use of maps builds on the work on mental mapping pioneered by Lynch (1973) that has continued across the social sciences (Coulton et al. 2001; Grannis 1998; McCartan et al. 2024; Wong et al. 2012).

We confront the challenge of isolating the perceptions-to-outcome relationship from the effect of objective context by finding pairs of survey respondents who are identical (or nearly so) in the objective context of their neighborhoods and making comparisons of social cohesion only within those pairs. In our descriptive analysis, we are not isolating perceptions from their causes; we only isolate them from their objective context. We allow perceptions to be caused by many factors, and we engage below with some alternative explanations for our descriptive results. We present four different research designs with ever more closely matched respondents: all show the same results. Our results show that perceptions can differ greatly within pairs – even for people living in places that are virtually the same in terms of objective ethnic diversity – and that these differences in perceptions predict attitudes about the perceived social cohesion of places.[3]

Data and Measures: The Mapping Local Communities Canada Study

We use online survey responses from 7,811 English-speaking Canadians who answered the Mapping Local Communities Canada Study (MLCC) in April–July 2012. A non-partisan electoral education initiative sponsored by the Canadian Broadcasting Corporation called Vote Compass provided the sampling frame (see Appendix for more details). The respondents in our convenience sample were better educated, wealthier, more likely to be informed about politics, and more comfortable using technology than the average Canadian. Our aim is to provide a focused assessment of the relationship between perceptions of place and attitudes about social cohesion, and our results are likely conservative given that misperceptions would be greater for the Canadian population as a whole; better educated, wealthier, and more politically informed survey respondents are likely to differ less from one another in regard to their perceptions than survey respondents representing all of English-speaking Canadian society (Delli Carpini and Keeter 1996; Nadeau et al. 1993).

Canada suits our study because of its immigrant history, rapidity of demographic change, and ethnic heterogeneity across the nation. 'Visible minorities', the Canadian Census term for non-white and non-Aboriginal Canadians, grew from less than 1 per cent of the population in 1971 to about 16 per cent in the 2006 Census. The effect of this diversity is noticeable in its biggest cities. For example, by the 2016 Census, visible minorities made up more than one in five Canadians and both Toronto and Vancouver were majority–minority. Furthermore, Canada has an official policy of multiculturalism, and diversity is a salient political issue (Bouchard 2008). Because we care about theories of threat posed by minorities and social cohesion in the context of ethnic diversity, our main analyses in this article focus on majority group members (non-visible minorities and non-Aboriginals).

[3]Furthermore, we show below that misperceptions are not proxy measures for ethnocentrism; we find no evidence that misperceptions are simply moderating the effect of prejudice on social cohesion, for example.

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Outcomes: Social Cohesion and Collective Efficacy

Respondents were asked to agree or disagree (strongly or not) with the following three statements about the people in the local community they drew:

1. People around here are willing to help others in their community.
2. People in this community generally don't get along with each other.
3. People in this community do not share the same values.

We created an additive index of the three items (coded in the same direction) for a *Social Cohesion Index*.

Respondents were also asked how likely or unlikely (very or not) the following scenarios would be, given the people in their self-defined local community:

1. If some children were painting graffiti on a local building or house, how likely is it that people in your community would do something about it?
2. Suppose that because of budget cuts the library closest to your home was going to be closed down by the city. How likely is it that community residents would organize to try to do something to keep the library open?

We created an additive *Collective Efficacy Index* from these two items, which represent an action-oriented aspect of social cohesion.[4]

These indices capture what respondents think *others* believe or would do under certain circumstances. These measures fit well with the literature on conditional co-operation, which emphasizes that individuals rely on their predictions of how others will behave to decide their own actions.

What Do the Census and People See?

Measures of objective context

For our objective-context measures, we use data from the 2006 Canadian Census for levels of visible minority population and used both the 2006 and the 2016 Canadian Census to create a measure of change in visible minority population.[5] We created an index of the percentage of visible minorities for Census dissemination areas (DAs); they are the smallest Census unit for which all information is disseminated.[6] We followed the Statistics Canada definition of 'visible minority' (which includes 'persons who are non-Caucasian in race or non-white in colour and who do not report being Aboriginal').[7] In 2006, 50 per cent of Canada's roughly 55,000 DAs contained less than 6 per cent visible minorities.[8]

[4]Sampson et al. (1997) use this concept of Collective Efficacy in explaining disparate outcomes of otherwise similarly poor neighborhoods in Chicago.

[5]We originally had intended to use both 2011 and 2006 Census data to look at contemporaneous diversity and changes in diversity. However, in 2011, the long-form of the Census – which is where Canadians are asked about their ethnicity and race – became voluntary in the newly renamed National Household Survey (Thompson 2010). The response rate dropped 25 percentage points. The Census summaries for small geographic units (such as dissemination areas) were made particularly imprecise and/or are missing given this change in the Census (Grant 2015; Sheikh 2013).

[6]The MLCC contains 6,369 DAs.

[7]See Appendix for Census question wording.

[8]As a point of comparison, in Canada overall, visible minorities made up 16 per cent of the population.

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Measures of subjective context

To create a measure of personally relevant places that operationalizes context as pseudoenvironments, respondents see an online map centered on the postal code where they live and then draw their 'local community'. (For details about the map-drawing measure – including its validity and reliability – see Wong et al. (2018).) Figure 1 shows an example of fifty such maps drawn by people living in the Greater Toronto Area (GTA) overlaid on each other and on a Google Map of the GTA. Each map was unique.

After respondents drew their 'local community' on the map, they answered a battery of questions about their perceptions of the relative size of ethnic/racial groups captured in their drawing: 'Just your best guess – what percentage of the population in your local community is . . . ' The list of groups included the following: black, Canadian Aboriginal, white, Chinese, Latin American, South Asian (East Indian, Pakistani, Sri Lankan, etc.), and Other Asian (Korean, Japanese, Filipino, etc.). The percentage perceived visible minority in a context was an index adding together responses following the government's definition of 'visible minority'.[9]

We also showed respondents, at random with equal probability, a map of one of six administrative geographic areas highlighted, centered on their address or postal code: the area ranged from the respondent's smallest Census unit (DA) to Canada as a whole. Respondents were told the name of the administrative unit the map represented, and were shown its boundaries overlaid on a Google Map. They then were given the same battery of questions about the demographic make-up of this fixed geography. We use both perceptions of their own hand-drawn map and perceptions of fixed Census neighborhoods (DAs) as our measures of perceptions in this

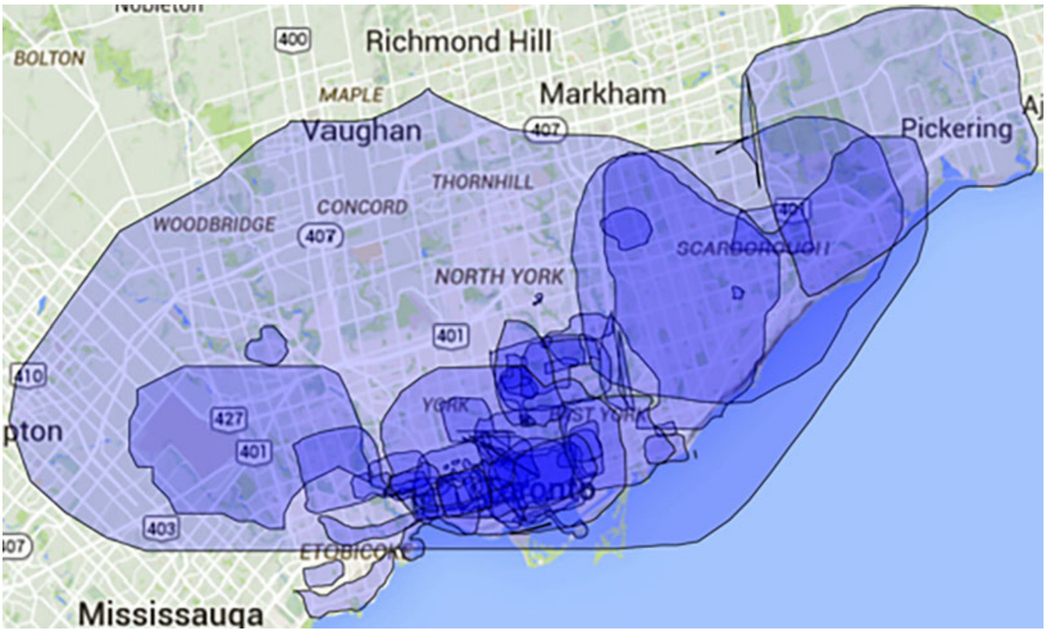

Figure 1. A random sample of fifty 'local community' maps drawn by residents of Toronto in the MLCC.

[9]Because people routinely overestimate the size of minority groups for a range of reasons, the index often exceeded 100 per cent (Hipp and Wickes 2016; Landy et al. 2018; Wong 2007; Wong et al. 2018). The question format used an interactive slider, so any response between 0 and 100 was possible for each group. We consider Census numbers as objective, but recognize that respondents may be thinking about a demographic composition that is not residence-based (Hamel and Wilcox-Archuleta 2022). Nevertheless, we do not expect that the responses will be as accurate as any numbers reported by the Census (Moore and Reeves 2020; Velez and Wong 2017).

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paper. Since more than one respondent might have been shown the same fixed Census neighborhood, this will allow us (in Appendices C.2, C.3, and C.4) to show that the effects of differences in perceptions are not driven by differences in maps drawn.

The respondents overestimate the percentages of visible minorities in all their contexts: the median response was 28 per cent visible minority for those viewing a map of their DA, while the median Census measurement for these 'neighborhoods' was 7 per cent; the median perception of proportion of visible minorities in their hand-drawn 'local community' was also 29 per cent, while our median estimate of the proportion of visible minorities in the boundaries of their maps using Census data was 10 per cent (weighting all DAs touching the hand-drawn map equally in their contribution to objective context within the subjective boundaries) or 8 per cent (weighting each DA in proportion to the land area it accounted for within the hand-drawn map).[10] These overestimates are consistent with previous research (see Guay et al. (2025) for a recent example).

Design: Isolating Perceptions from Objective Context

Our research design uses 3,772 respondents living in 3,098 DAs and creates pairs of people with different perceptions, living in very similar (or even identical) DAs in terms of proportion of visible minorities, the amount of change in the proportion of visible minorities between 2016 and 2006 as measured by the Census, and within the 2006 Canadian Census categories for urban versus rural.[11] Because DAs do not vary much in total population – most contain between 400 and 700 people by design – our matched respondents live in environments with very similar total populations.[12]

This paired research design removed differences between people due to objective context without trying to hold constant any other covariates. Without pairing, we would have compared white people living in areas with no visible minorities to white people living in places with nearly 100 per cent visible minorities. In the design we present here, 99 per cent of the pairs differed by less than 0.036 percentage points in proportion of visible minority, the maximum difference in percent of visible minority within a pair was less than 0.04 percentage points, and 70 per cent of the matches were identical in regard to objective context. Also, no two people within a pair differed by more than 3 percentage points in change in visible minority population between 2006 and 2016, with 50 per cent of pairs differing by less than 0.8 percentage points of change.

Within pairs, holding nearly constant the objective characteristics of where people live, do people still differ in their perceptions of their surroundings? Our primary research design requires that each pair differ in perceptions – after all, a difference in social-cohesion attitudes between two people who differ in perceptions is undefined if those two people do not in fact differ in perceptions, and those pairs would drop from the analysis. To answer the preliminary question of whether two people living in the same objective context are likely to differ in their perceptions, we recreated the matched design described above without any requirements on the amount of

[10]Measuring the objective context of a geographic object with subjective boundaries using data from the Canadian Census is difficult since the hand-drawn boundaries rarely follow DA boundaries. Since objective context of the subjective boundaries is not the central focus of this paper, we provide only two approximations: one simply averages the proportion of visible minorities as measured by the Canadian Census in each DA that overlaps in any way with the given set of polygons drawn by the survey respondent, and the other calculates the proportion of the area in the hand-drawn map that overlaps with each DA and weights the DA contributions to the estimated visible minority proportion in the map by this contribution.

[11]This approach of creating pairs of units who are similar in regard to a measure that has more than two categories (or is continuous in our case) is called optimal non-bipartite matching (Lu et al. 2001; Lu et al. 2011; Rosenbaum 2009). We used the Canadian Census 2006 definitions for 'urban' as a Census Subdivision (CSD) having a population of at least 1,000 and a population density of at least 400. See the appendix for more information about the design and matches.

[12]See Appendix F for more details about the design. The non-bipartite matching algorithm that we used (Zubizarreta et al. 2023) allowed us to specify that all pairs must differ in perceptions. Pairs that do not differ in perceptions provide no statistical power for the subsequent analyses that compare the person who perceives more visible minorities to the person who perceives fewer visible minorities within the pair.

difference in perceptions. If objective context is a good proxy for perceptions, we should expect nearly no variation within pairs in perceptions.[13] The pairs in this unrestricted perceptions design (where people were matched on the same objective-context numbers as the main design but with no mention of perceptions) were successfully matched on objective context: 80 per cent of the pairs were identical in proportion of visible minority, with the largest difference being less than 1 percentage point, and 90 per cent of the pairs differed by less than 2 percentage points in change in visible minority between 2016 and 2006. Yet, the majority of pairs differed in perceptions: only 45 out of 1,638 pairs (roughly 3 per cent) had two people with the same perceptions, the mean difference in perceptions is 21 percentage points, and 50 per cent differed by between 7 and 30 percentage points.

Returning to our main design, which requires non-zero differences in perceptions in the same way that an experiment would require both treated and control units within a pair, we can report that those pairs differ in perceptions on average by 25 percentage points, with a minimum difference of 0.01 percentage points by construction, and 50 per cent of the differences fall between 7 and 33 percentage points. That is, differences in perceptions between people living in the same kinds of context are the norm in this study.

This design and the versions described below hold objective context (nearly) constant so that we may assess the differences in social cohesion attributable to perceptions isolated from objective context. The description of our design also reveals that perceptions differ within a pair even when the objective context is the same (whether by construction or without restriction on perception differences within a pair). The Appendix contains the results of four other designs, including a design that compares people who live in exactly the same DA who are asked to evaluate the visible minority proportion of that DA: even those people differ in their perceptions of diversity of their DA. Notice that this approach to research design allows us to describe the relationship between perceptions and outcomes while partialling out the influence of objective context in a non-parametric manner. This relationship is exactly as would be implied by the two-path theory, and we show it below. We are not estimating the causal effect of perceptions of diversity on perceptions of social cohesion under a selection on observable assumptions (after all, we are only matching on one or two covariates); rather, we are describing how perceptions of diversity relate to perceptions of social cohesion after holding constant objective context. If objective context and perceptions stand in for one another, the two-path theory is not useful. If perceptions vary within pairs, and those within-pair differences in perception are systematically related to within-pair differences in social cohesion, we will have discovered that context matters via the path of perceptions. Notice also that we are not exploring the interaction of perceptions and objective context in this paper: many other papers have established that objective context has a relationship with outcomes such as social cohesion. By adding perceptions, we help explain why those relationships have varied – some of them arise from the operation of direct experience with the context and others, our evidence suggests below, should arise from the operation of perceptions.

Analysis: How Do Pseudoenvironments Influence Social Cohesion?

Our empirical strategy in this paper comes in two general stages. In the first stage (which we called 'Design' in the previous section), we created pairs of survey respondents who live in objectively similar places in regard to ethnic homogeneity in their home Census DAs. The second stage (which we call 'Analysis') describes how people who perceive more ethnic diversity than their

[13]We focus first on respondents' self-defined communities because these are the most salient and personally relevant geographic contexts. Nevertheless, we also use respondents' perceptions of their objective DAs as an alternative measure of subjective context. We discuss those results in the next section and appendix. They do not differ substantively from the results we present here.

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paired respondent also differ with regard to their responses to survey questions about social cohesion and collective efficacy.

If we could have implanted two different perceptions in the mind of a person and compared their responses to the outcome questions, we would not have needed to create pairs in order to isolate perceptions from objective context: we would have had a single person living in an identical place with two different perceptions of that place. Alternatively, if we had been able to randomly assign perceptions to the minds of many people, we could also have isolated the two mechanisms of the bundle of drivers that we are calling 'perceptions' and the bundle of drivers that we call objective context as they influence the outcomes. These two idealized designs suffer from problems of feasibility and, more importantly, connection to the theory. The effect of being told to perceive one's environment in a particular way is different from the effect of the natural perceptions that are generated from experience upon facing a survey question. That said, the paired designs that we created should allow us to isolate the way perceptions of place matter for the outcome in a way that is separate from the way objective context matters: if the person who perceives more diversity in their environment within the pair tends to be the person who also reports less social cohesion, then we can claim that this difference is not due to differences within pairs arising from differences in the objective context. Our analysis of the data makes exactly such calculations, and Appendix C shows a total of five different paired designs demonstrating that the substantive results hold regardless of the details of how we create the pairs.

How do we do this analysis? The simplest analysis would subtract outcome values within pairs and regress those differences on within-pair differences in perception.[14] The analyses that generate the results that we present here build on and extend this pair-differences approach because (1) common calculations of standard errors using this approach will tend to produce overly small standard errors that do not account for the fact that people are clustered in dissemination areas such that two or more people might share a DA even if they are spread across different pairs,[15] and (2) we would like to reduce the influence of any small within-pair objective-context differences left over from the design stage.[16] Multilevel models allow us to describe the relationship between within-pair differences while calculating standard errors that account for cross-pair clustering by DA and removing any remaining average linear relationship between pair-members in objective context. We use that modeling strategy for the results presented here. The disadvantage of the multilevel model is that it requires an assumption about the probability process generating the outcomes (a likelihood function), which would not be necessary were we to pursue the simpler but perhaps overly optimistic approach of fixed effects. To address these trade-offs, Appendix D shows that the simple, fixed effects approach and two multilevel modeling based approaches (one fully Bayesian and the likelihood based approach presented here) all give substantively the same answers, and nearly the same answers numerically.[17]

Equations (1) and (2) show the multilevel model describing how mean social cohesion (μ) for respondents $i = 1, \ldots, n$ in pairs matched on objective context $s = 1, \ldots, S$ and dissemination areas $d = 1, \ldots, D$ varies as a function of perceptions and remaining objective-context differences within pairs. The outcome and two random effects are modeled as arising from three different normal distributions in the creation of the likelihood function that we use for estimation and

[14]This approach is also known as a 'fixed effects' approach.

[15]Roughly 2,533 respondents are the only survey respondents in their DA, but about 543 share a dissemination area with one or two other respondents, and twenty-two share their dissemination area with more than two other survey respondents. Since pairs can only contain two respondents, two people from the same dissemination area might be paired with two other people from two different DAs or two people from the same other DA.

[16]We follow Rubin and Thomas (2000) in combining a stratified research design with covariance adjustment. To make the case for the two-path theory of context effects, we aim only to isolate subjective from objective differences, not subjective from all other observed differences between people.

[17]We explain more about the 'pair fixed effects' or 'pair differenced' approach and how it relates to the multilevel model and the fully Bayesian multilevel model in Appendix D.

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statistical inference.[18] If we had only written $\mu_{is} = \alpha_s + \beta_1 \text{perceptions}_{is}$ we would have the equivalent of a fixed effects or within-pair model where β_1 is the relationship between within-pair perceptions differences and the within-pair differences in social cohesion.[19] The random effect term α_d models the dissemination area clustering across pairs, and the term $\beta_2 \text{objective}_{id}$ adjusts the calculation of β_1 for any remaining linear relationship between perceptions and objective contexts within pairs: although most pairs are nearly identical in objective context, we would like to ensure that if there is any overall relationship such that the higher perceiver tends to live in the more diverse place than the lower perceiver within the pair, we remove that relationship.

$$\begin{aligned} y_{isd} &\sim N(\mu_{isd}, \sigma_{isd}) \\ \alpha_s &\sim N(\gamma_{s,0}, \sigma_s) \\ \alpha_d &\sim N(\gamma_{d,0}, \sigma_d) \end{aligned} \tag{1}$$

$$\mu_{isd} = \underbrace{\alpha_d}_{\text{DA random effect}} + \underbrace{\alpha_s}_{\text{Pair random effect}} + \underbrace{\beta_1 \text{perceptions}_{is}}_{\text{Effect of perception differences}} + \underbrace{\beta_2 \text{objective}_{id}}_{\text{Remaining objective DA diffs}} \tag{2}$$

Since we have two random effects that are not nested, we present profile confidence intervals below rather than Wald intervals. The Wald interval uses the second-derivative of the log-likelihood function evaluated at its maximum as an estimator of a standard error and uses a normal approximation and assumption of symmetry of the likelihood function around the maximum to create confidence intervals. However, when the likelihood surface is complicated (such as when we have two random effects), the Wald approach can yield inaccurate estimates of standard errors. The profiling approach calculates an interval of possible parameter estimates around the maximum of the likelihood function for a given parameter instead of calculating a standard error and then relying on assumptions about symmetry and normality to calculate an interval. Pinheiro and Bates (2000) and Raudenbush and Bryk (2002) suggest the use of profile-based intervals for complex multilevel models, and we follow their advice below.

Results

Figure 2 shows the relationship between perceiving more minorities and responses to the social cohesion and collective efficacy scales. For two respondents who live in almost identical contexts, the one who perceives more minorities in her local community is more likely to think people who live in that community do not share the same values, do not get along, and would not help each other.

The coefficient from the model for social cohesion is −0.065 – representing the average difference in social-cohesion score between a person perceiving no visible minorities in their local community (0 per cent) and a person who perceives that 100 per cent of their local community is a visible minority. We present such an unrealistic coefficient both to connect it with the model itself and to the multiple auxiliary analyses that we present later in the paper. For now, however, let us put this estimate in perspective. Few pairs differ by 100 percentage points in perceptions: 50 per cent differ by 16 percentage points or less and 90 per cent of pairs differ by less than 54 percentage points. Given a typical difference in perceptions within pairs, for example, of 20 percentage points, our results predict a difference of $-0.065 * 0.20 \approx -0.013$ on the social-cohesion scale. Is this a large difference in regard to the outcome? Pairs differ in social cohesion by about 0.17 and community efficacy by about 0.13 (the median differences) on 0 to 1 coded scales. So, a roughly

[18]Appendix D shows R code for this model as well as a fully Bayesian model with t-distributions for priors as well as the fixed effects model.

[19]We follow Smith (1997) in the idea that one can use random effects in lieu of fixed effects in the analysis of a stratified observational study.

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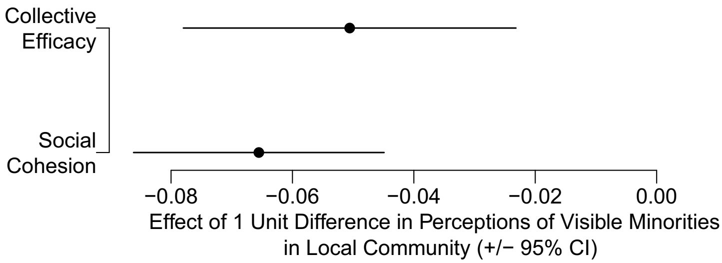

Figure 2. The influence of perceptions of visible minorities on social cohesion and community efficacy holding constant objective context. Points show the average difference in perceptions of visible minorities in the hand-drawn 'local community' on outcomes (listed on the y-axis) conditional on objective-context matched pairs (3,772 pairs, 3,098 DAs) and using the model shown in eq. (2). The segments show 95 per cent profile-likelihood confidence intervals (D Bates et al. 2015).

median difference in perceptions would be associated with about a tenth of a median difference in social cohesion or community efficacy: a moderate effect if we are thinking about typical differences in surveys. We could also say that an extreme difference in perceptions within pairs would lead to a moderate difference in the outcomes within pairs (0.065 being close to 1/2 of the median difference within pairs in the outcomes). Another way to see this relationship is in standardized scales. The standard deviation of pairwise differences in perceptions is 0.20 and the standard deviations of social cohesion and community efficacy are 0.13 and 0.17 respectively. So, the effect of 1 sd difference in perceptions is about $-.1 = -0.065 \times \left(\frac{.20}{.13}\right)$ standard deviations on the social-cohesion scale or about $-.08 = -0.065 \times \left(\frac{.20}{.17}\right)$ standard deviations on the community efficacy scale. These are all moderate to low effect sizes estimated relatively precisely by our research design.

Another description of the relationship between perceptions and social cohesion within pairs is simply the proportion of pairs in which the person who reports perceiving more diversity is also the person with the lower social-cohesion score. In this case, 56 per cent of pairs have this pattern versus 44 per cent of pairs either tied in social cohesion or where the person perceiving more diversity has the higher social-cohesion score. For collective efficacy, the numbers are similar: 59 per cent of pairs have the higher diversity perceiver with the lower collective efficacy score.

These results help explain why diversity diminishes support for social goods provision: senses of reciprocity and shared preferences are weaker when majority group members believe they live among more outgroup members, even if they actually live among relatively few outgroup members according to the Census. The social cohesion and collective efficacy indices capture attitudes about what respondents think *other* people in their community would do.

Alternative Designs

We created four additional designs that we summarize here. We describe each and present results in the appendix: all findings tell the same story, regardless of the design used.

Matching on similar DAs, perceiving one's DA

In the analyses presented above, we compare people who drew different community maps and thus reported different perceptions of different objects, even if they lived in nearly equally diverse DAs. Using only those respondents who reported on the perceptions of their own DA, we follow the same design: creating pairs that minimize differences in the percent visible minority as measured by the Census for the respondents' DAs, within 3 percentage points of change in percent visible minority between 2006 and 2016, and within urban v. rural classification.

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Matching on the exact same DA, perceiving one's community

It is possible that matching someone from a dissemination area in Vancouver and a person living in an equally diverse dissemination area in Toronto is not a good comparison; the cities have distinctive histories and demographic compositions, even if the DAs are relatively similar in size and are both embedded within large cosmopolitan cities. Therefore, we replicated our analyses, matching only individuals who lived in exactly the same DA; we looked at the influence of perceptions of their self-drawn communities.

Matching on the exact same DA, perceiving one's DA

We replicated the analyses, matching only individuals who lived in exactly the same DA, and looking at the impact of perceptions of those DAs. There are only roughly a dozen such pairs in the dataset.

Diversity indices for both matching and perceptions

Living in a community where a single outgroup forms a majority could be different from living in a community where no single group is the numerical majority, but where the numbers of multiple different visible minorities add up to more than 50 per cent. By focusing on the percentage of visible minorities in aggregated form, we may be comparing apples and oranges; this is especially true if attitudes and behavior are driven by perceptions that one's ingroup is outnumbered by a unified outgroup. Therefore, we repeat our analyses, this time using a diversity index (the Herfindahl–Hirschman index) for both the matching algorithm and for the perception measure. In other words, we match individuals whose dissemination areas are similar in ethnic fractionalization and compare the effects of perceiving greater fractionalization (using respondents' perceptions of the size of each group instead of Census numbers in the formula). Scholars have argued that diversity or fractionalization indices can often hide a great deal of heterogeneity across cases (Fearon 2003; Posner 2004) and so we require slightly tighter comparisons on change in visible minority population (2.5 percentage points) and also use the same exact matching on urban v. rural.

All four alternative designs produce similar results: regardless of how we create pairs of people so that they live in comparable objective environments, the individual within each pair who perceives greater ethnic heterogeneity reports less social cohesion and collective efficacy.

Alternative Explanations

One might wonder whether antecedent conditions uncorrelated with objective context could explain both perceptions and social cohesion. Thus, our results would be explained not by differences in perceptions within pairs, but differences in ethnocentrism or socio-economic status that are uncorrelated with the ethnic diversity of a place, for example. We address this topic briefly to assuage worries about alternative explanations based on prejudice and socio-economic status.[20]

Could Ethnocentrism Drive Our Results?

What if prejudice explains our description of differences more than perceptions? For example, prejudiced individuals may react more strongly to outgroup members and thus perceive more of

[20]For example, if the higher perceivers differ from lower perceivers within pairs systematically in ethnocentrism, *and* ethnocentrism strongly predicts social cohesion, then our interpretation of the impact of differences within pairs in subjective context might be confounded with differences in ethnocentrism. A general challenge to studying effects of perceived contextual characteristics is that there may be variables affecting both perceptions and outcomes.

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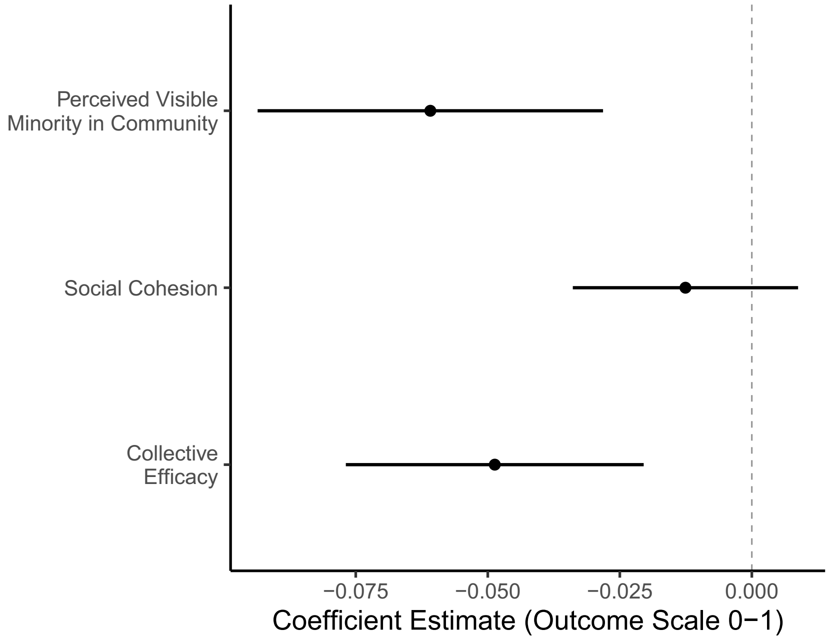

Figure 3. Does ethnocentrism predict both perceptions and social cohesion? Within pairs, greater ethnocentrism is associated with *lower* perceived ethnic diversity, social cohesion, and collective efficacy. Pairs matched on Census-based per cent visible minority in the respondents' DA, Census Subdivision (CSD) urbanicity, and change in per cent visible minority in the DA between 2006 and 2016 as described above.

them (Nadeau et al. 1993). In other words, more prejudiced white individuals living in nearly identically diverse neighborhoods may *both* perceive more visible minorities living near them *and* be more likely to believe their neighbors do not share their values. In that case, while (mis) perceptions may be part of the story, the real engine driving the relationship would be the underlying ethnocentrism that exists as a stable personality trait unaffected by objective context (since this is held constant) or subjective perceptions. Since it is beyond the scope of this paper to explore the influence of all of the ways that people form perceptions – including their stereotypes, direct experience, or education – we engage with the question about ethnocentrism briefly here to show that, in fact, the results are not explainable by ethnocentrism.

If ethnocentrism drives our results, we should see a positive relationship between perceptions and expressions of prejudice. To assess this possibility we created a racial resentment measure from three items in the survey, and using the pairs from our first design we examined whether individuals who were more prejudiced within pairs were more likely to perceive more visible minorities in their local communities.[21] Figure 3 shows the opposite: the person within each pair who expresses more racial resentment on average is also likely to see *fewer minorities* in her community than her counterpart. As expected from past research, the figure also shows that more racial resentment is related to (slightly) lower levels of social cohesion and (appreciably) lower collective efficacy. It is clear that differences in ethnocentrism are not the same as differences in perceptions; nor do they act the same way in regard to our outcomes.[22]

[21]See the Appendix for question wordings for the items in the index.

[22]As previous research has shown (Guay et al. 2025; Wong 2007), misperceptions (particularly overestimates of minority groups and underestimates of whites) occur for all groups, not just whites. This provides further evidence that ethnocentrism is not a likely confounding variable.

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What About Socio-economic Status?

Even if pre-existing ethnocentrism is not related to overestimates of visible minorities within the local community maps drawn, could within-pair differences in socio-economic status (SES) drive our findings? We know that education and income influence people's residential choices, affect people's perceptions, and can prompt differential reactions to the environments in which they live (Clark 2009; Herda 2010). But, an alternative explanation could be that perceptions are so strongly related to SES as to be empirically indistinguishable. This explanation would say that, since the person within the pair who perceives more visible minorities would have to be the person with lower education and/or income (Delli Carpini and Keeter 1996), our findings might merely tell us that people with less education perceive less social cohesion in their environments (relative to people living in more or less the same environments but who have higher SES).

To assess this version of the socio-economic alternative explanation, we asked whether the higher perceiver within pairs tended to be the person with lower education and/or lower income. We recoded the education variable to indicate a college degree or more, contrasted with anyone with less than a college degree. Using our first design, we compare the education levels of the respondents within each of our pairs. We find that 52 per cent of the pairs have identical education levels (in those pairs which differ in perceptions but are constant in education, differences in education cannot be a part of the differences in social cohesion associated with differences in perceptions, just as differences in objective context cannot be part of that relationship); in 23 per cent of the remaining matches, the individual with more education perceived more visible minorities in her community, and in 25 per cent, the individual with less education perceived more visible minorities in her community. We find a similar pattern when it comes to income (coded in 12 categories): 11 per cent of pairs are identical on income, in 43 per cent of pairs the person with the higher income perceived more visible minorities, and in 45 per cent of pairs the person with lower income perceived more visible minorities. In other words, the relationship between socio-economic status and perceptions within those pairs is very weak. Socio-economic status does not determine which member of a pair *matched on objective context* perceives more or fewer visible minorities in their community, and in most of the pairs, education cannot play a role in the relationship because both members of the pair have the same education level. Thus, while socio-economic status surely predicts perceptions in the same way it predicts political knowledge, it does not do so strongly enough within pairs to be a credible alternative explanation for our findings.

Conclusion

There are two kinds of context effects: one kind (objective) does not depend on an individual perceiving and/or understanding the character of the context (for example, the effects of voter registration laws or particulate pollution); another kind, which we call 'pseudoenvironments' following Lippmann (1922), does not have effects on attitudes and behaviors unless it is perceived and evaluated. We add to the broad literature on context effects with evidence in favor of this two-path theory by (1) showing how people living in nearly identical objective environments can have different pseudoenvironments, and (2) that these pseudoenvironments relate to social cohesion – such that greater perceived diversity is related to lower social cohesion – even when the objective environment is held nearly exactly constant.[23]

What about self-selection? The research design of this paper does not require random selection of neighborhoods by people (or random assignment of people to neighborhoods), let alone random assignment of perceptions to minds. People do not choose where to live at random; both racial and economic segregation are pronounced across Canada. Similarly, it is safe to assume that

[23]Given that our sample has a higher socio-economic status than that of Canada as a whole – and SES has been shown to be negatively related to ethnocentrism and positively related to knowledge – we expect that our findings are conservative relative to what would be found for a representative sample.

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more and less racist individuals have different considerations about what makes a neighborhood 'good' or not. People choose where they live, and our research design does not require us to make any claims about the exogeneity of the objective context or perceptions thereof. Matching individuals on the demographic make-up of their choice of residence allows us to isolate the relationship of pseudoenvironments and outcomes from the impact of objective environments, thereby clarifying a theoretically relevant descriptive relationship that would have been otherwise clouded. We have shown that these results do not reflect pre-existing differences in ethnocentrism or socio-economic differences. Furthermore, although it is not essential to our primary contribution, we note that our findings here show that self-selection does not entirely determine perceptions.

A skeptical reader might raise reverse causality as a possible alternative explanation for our results.[24] In other words, believing that one's neighbors do not share one's values or would not help one another could lead to perceiving more outgroup members in their community. Given that we have matched individuals on objective context, this explanation or rationalization likely would be driven by ethnocentrism and negative stereotypes of outgroup members. However, as we have just shown, while ethnocentrism can lead to lower levels of social cohesion and collective efficacy, it leads to perceptions of *fewer* outgroup members in their community, not more.

Our findings are enlightening, particularly as we think of answers to the question posed by Portes and Vickstrom (2011, 475): 'What is the fuss really about?' Respondents who see more diversity around them expect that others in their community will be less likely to share the same values, help each other, or mobilize to benefit the community. This descriptive result lets us build on the literature on 'conditional co-operation', which suggests that different mechanisms – including norms and reciprocity – may explain the existence of greater civic-minded behavior than would be expected from theories of self-interest (Frey and Torgler 2007). Answers to our survey questions suggest both mechanisms are at work, but that *perceptions* play a key role.[25] Outgroups may indeed have different norms about altruism, but even if they do not, *beliefs* that outgroups differ in norms still affect political judgments. In other words, people who perceive more outgroup members in their communities are more likely to perceive that these outgroup members do not share their values and practices that promote prosocial behavior.[26] These misperceptions can, in turn, diminish the possibilities for intergroup co-operation.

Why should we care about perceptions and pseudoenvironments beyond their role in theories of intergroup relations and the social, political, and economic consequences of diversity? Public policy can, in principle, change pseudoenvironments more easily than objective contexts. Housing cannot be assigned to individuals in liberal democracies (except for among special populations, like refugees, people dependent on certain restricted government programs, and incoming college students living in university-controlled dorms [Chetty et al. 2015; Edin et al. 2003; West et al. 2009]). However, our results here suggest we can try to improve intergroup relations and/or access some of the benefits of social cohesion in general by changing perceptions of where people live, particularly about geographies in which they have a vested interest, like their communities. It is, of course, not an easy task to change people's attitudes (Gladwell 1995; Hopkins et al. 2019; Kuklinski et al. 2000;

[24]We have been explicit that we are not making causal claims. Nevertheless, we note that reviewers have repeatedly stressed to us that scholars of subjective context must be aware of the potential for a range of methodological problems, including reverse causality, confounding variables, and measurement bias.

[25]If objective context is not simply a proxy for subjective context, one may wonder how the former is still related to social cohesion. One possibility is that greater demographic heterogeneity could mean political attention and resources are focused on visible minorities (the outgroup). This reduction in attention to one's ingroup can lead white people to feel that people around them do not care about the community any longer, even if their perceptions are about changing policies and not changing demographics.

[26]Krysan et al. (2008) found that by simply manipulating the race of a few individuals shown in a video clip about a neighborhood, they could significantly change white respondents' judgments about the quality of that neighborhood, its housing values and property upkeep, its safety, and the quality of its schools.

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Lawrence and Sides 2014), but it is more feasible than convincing ordinary citizens to give up autonomy over their residential choices.[27] Taking into account subjective contexts has implications for how policy makers think about diversity's effects on the provision of social goods, and on tipping points, segregation, and white flight. From a scientific perspective, we can apply what we know about information processing more broadly to our understanding of geography and intergroup relations: pseudoenvironments enhance the relevance of psychology for the study of political geography.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S0007123425101099.

Data availability statement. Replication data for this article can be found in Harvard Dataverse at: https://doi.org/10.7910/DVN/R6ABJ2.

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Ethical standards. The research meets all ethical guidelines, including adherence to the legal requirements of the study country.

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Appendix 1. Question wording of the Census Race Question

Our measure of objective context used the 2006 Canadian Census reports of responses to the following two questions:

> (1) Mark more than one or specify, if applicable. This information is collected in accordance with the Employment Equity Act and its Regulations and Guidelines to support programs that promote equal opportunity for everyone to share in the social, cultural, and economic life of Canada. (1) Is this person an Aboriginal person, that is, First Nations (North American Indian), Metis or Inuk (Inuit)?
>
> (2) Is this person: White, South Asian (e.g., East Indian, Pakistani, Sri Lankan, etc.), Chinese, Black, Filipino, Latin American, Arab, Southeast Asian (e.g., Vietnamese, Cambodian, Malaysian, Laotian, etc.), West Asian (e.g., Iranian, Afghan, etc.), Korean, Japanese, Other (specify)?

Appendix 2. Measures of Subjective Context

We considered multiple ways to measure people's perceptions of the numbers of visible minorities around them. Version 1 simply adds up all responses for the VM groups. Version 2 runs from 0 to 1, where 0 represents 0 percent and 1 represents all responses that added up to 100 percent or more. Version 3 recalculates responses such that a respondents' answers for all groups totaled 100 percent; in other words, a respondent who said her community was 50 percent Latin American, 50 percent Black, and 50 percent White would have a VM score of 67 percent. We chose to use Version 1 in the analyses presented. Version 2 makes the display of information easier and down-weights outliers, but it throws away information distinguishing respondents whose estimates total 110 percent and 500 percent, for example. Version 3 helps address the issue of innumeracy — and the problem that many ordinary citizens do not realize that percentages should total 100 — but it makes the assumption that the ethnic/racial groups listed are mutually exclusive and that they are the only ones that count.

Appendix 3. Design Details

The MLCC Study involved roughly 7800 English speaking Canadians spread across all the provinces of Canada. We worked to isolate comparisons based on perceptions of the percent visible minority (VM) in local areas from Census measurements of percent VM in local areas in two main ways: (1) by matching people into pairs based on the percent VM in the Canadian Census dissemination area (DA) measured in 2006, the change in percent VM in the DA between 2006 and 2016, and census defined urbanicity of the municipality (the CSD) and (2) by restricting comparisons to people who lived in the same DA.[28]

We originally had intended to use both 2011 and 2006 census data to look at contemporaneous and changes in diversity. However, in 2011, the long-form of the Census — which is where Canadians are asked about their ethnicity and race — became voluntary in the newly renamed National Household Survey (Thompson 2010). The response rate dropped 25 percentage points. The Census summaries for small geographic units (such as dissemination areas) were made particularly imprecise and/or are missing given this change in the Census (Grant 2015; Sheikh 2013). Since the survey occurred in 2012, we hope that by matching on change between 2006 and 2016, we can capture some of the difference in visible minority population between that measured in 2006 and what would have been measured in 2011 if the visible minority items had been used universally.

[28] This document can be rebuilt from the unix command line using R and LaTeX and the GNU Make system by downloading the reproduction archive (insert link upon publication). at http://github.com/bowers-illinois-edu/wong_bjps_2025.

Appendix 3.1 Matching on Visible Minority in the DA, Perceptions of Own Local Community.

This design compared perceptions of context with subjective boundaries within pairs matched on objective context. That is, the "effect of perceptions" in this design was defined as a comparison of perceptions of the ethnic composition of the local community maps drawn by the respondents. Before matching in this design, we excluded the roughly 1425 respondents who did not draw a map or report on their perception of visible minorities in their map. The pair-creation process yielded 3772 respondents in 1886 pairs representing 3098 DAs.

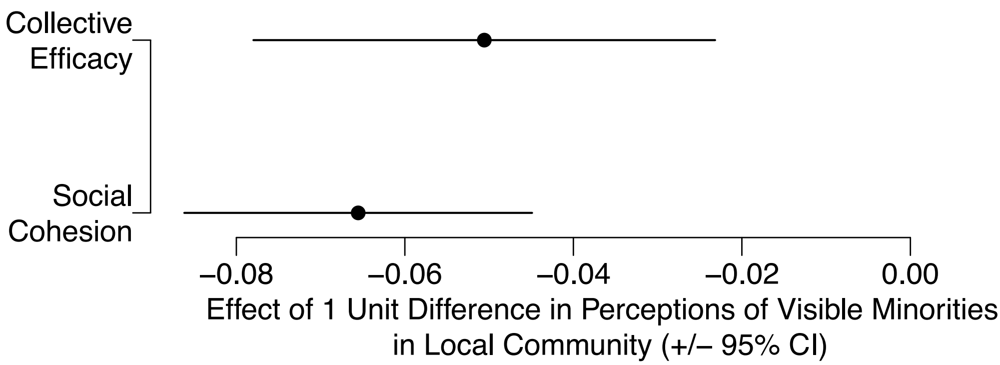

Figure 2. Average differences in outcome between the person perceiving more and the person perceiving fewer visible minorities in their own hand-drawn maps within pairs matched on % VM in DA, change in % VM 2006–2016 in the DA, and urban-vs-rural classification of the CSD. Estimates (black dots) from multilevel models with crossed random effects for dissemination area and matched pair. Approximate confidence intervals (horizontal lines) from a profiled likelihood approach (D Bates et al 2015).

Appendix 3.2 Matching on Visible Minority in the DA, Perceptions of Own DA.

This design assessed the influence of perceptions by comparing reported percent visible minorities by respondents who were shown their Census DA as a polygon overlaid on a Google map. Since we randomly assigned roughly 1/6 of the sample to be exposed to and report on their DA (and other sixths to see and report on other census geographies), and because we excluded respondents who did not answer the perceptions question, this design used roughly 448 respondents out of a possible 650, with 443 DAs represented.

The matches again are homogeneous in objective context: 20 percent of the matches differ by less than .001 on their DA level diversity; the median difference in percentage visible minority between matches is 0.01 percent; 90 percent of matches have a difference of less than 1 percentage points, and the maximum is 1.6 percentage points. When it comes to population size of the DA, the median difference is 182 people, 90% of pairs differ by less than 1122 and the maximum difference is 11,429.

The analysis show us the same pattern of results as before: those who perceive a more diverse dissemination area within their pair tend also to be those reporting diminished perceptions of social capital and collective efficacy.

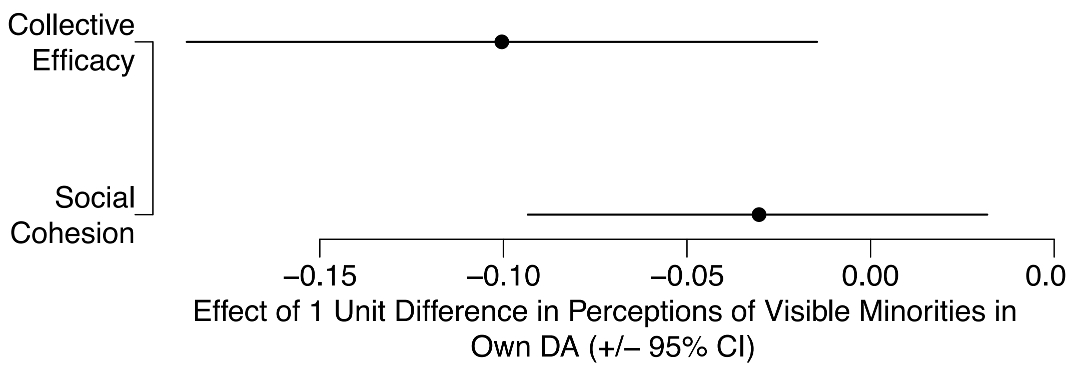

Figure 3. Average differences in outcome between the person perceiving more and the person perceiving fewer visible minorities in their own census DA within pairs matched on % VM in DA, change in % VM 2006–2016, and urban-vs-rural classification of the CSD from multilevel models with crossed random effects for dissemination area and matched pair. Approximate confidence intervals (horizontal lines) from a profiled likelihood approach (D Bates et al 2015).

Appendix 3.3 Exact matching on DA, Perceptions of own Local Community

This design assessed the effect of pseudoenvironments by comparing perceptions of their own local communities by people who lived in the same DA. The MLCC study had about 1894 respondents who shared a DA with at least one other respondent and who had valid perceptions-of-their-own-maps data spread across 838 DAs. While there were 674 DAs containing only 2 respondents, there were 131 DAs containing 3 respondents, and 33 containing between 4 and 9 respondents. Because we only compare people living in the same DA without further pairing, we no longer have clustering by DA, so the results that we present below come from linear regressions with fixed effects for DA.

Even when we match respondents who live in the same DA our overall story is unchanged. Among individuals who live in exactly the same dissemination area, those who see a more diverse community perceives lower social capital and collective efficacy in their own hand-drawn local community than the people in the same DA who perceive relatively less diversity in their local communities.

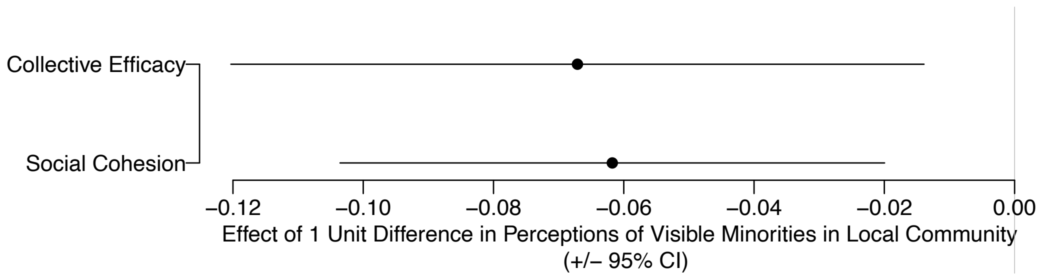

Figure 4. Average differences in outcome between the person(s) perceiving more and the person(s) perceiving fewer visible minorities in their own hand-drawn map within groups (mostly pairs) living in the same dissemination area. Linear regression models with fixed effects for DA and HC2 robust standard errors.

Appendix 3.4 Exact matching on DA, Perceptions of DA

This design assessed the effect of subjective context by comparing perceptions of the census DA between people living in the same DA. That is, in this design we have people living in the same census location and evaluating the same census object. The MLCC study included 20 people with these characteristics in 10 DAs who had valid outcome answers as well as valid answers about the proportion visible minority of their Canadian Census DA polygon. Just by chance, each of these DAs contained exactly 2 people. The plots below show the mean differences in outcomes between the high and low perceiving person and the intervals containing 75% of these differences for the 10 DAs.

Even though there is a great deal of noise, the coefficients have the same sign as in the previous analyses showing a negative relationship between perceptions of diversity and social cohesion and collective efficacy.

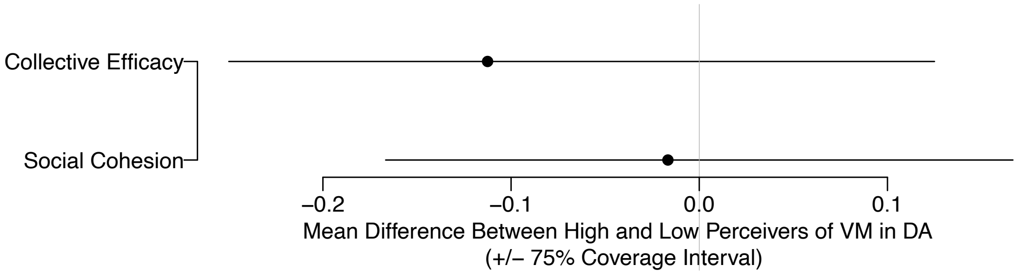

Figure 5. Average differences in outcome between the person perceiving more and the person perceiving fewer visible minorities in the dissemination areas in which both people live. Intervals show the range of the central 75% of the paired differences. Dots show the means of the paired differences.

Appendix 3.5 Matching on Fractionalization Score of DA, Fractionalization Score of Perceptions of Own Local Community

This design assessed the effect of subjective context by comparing fractionalization scores created from perceptions of people's own local communities. We created the scores as the sum of the squared proportions of the different racial and ethnic minorities measured at the DA level by the Census using proportions of the following census categories: "Black,""Chinese,""Latin American,""South Asian," and "Other Asian." This score is often know as the Herfindahl-Hirschman index Rhoades 1993.

The matches were created by pairing people living in DAs with very similiar fractionalization scores within the Census urban-vs-rural classification and requiring that pairs differ by less than 2.5 percentage points in change in visible minority population between 2006 and 2016. These restrictions left us with 4330 respondents matched into pairs representing 3599 DAs. The half of pairs in the final design were identical in the fractionalization score and the maximum difference in this score (which runs from 0 to .33) was .00009.

What is the effect of perceiving greater fractionalization on attitudes about social capital? The results are similar to those we found earlier: the individual within each pair who sees greater heterogeneity reports less social capital and collective efficacy.

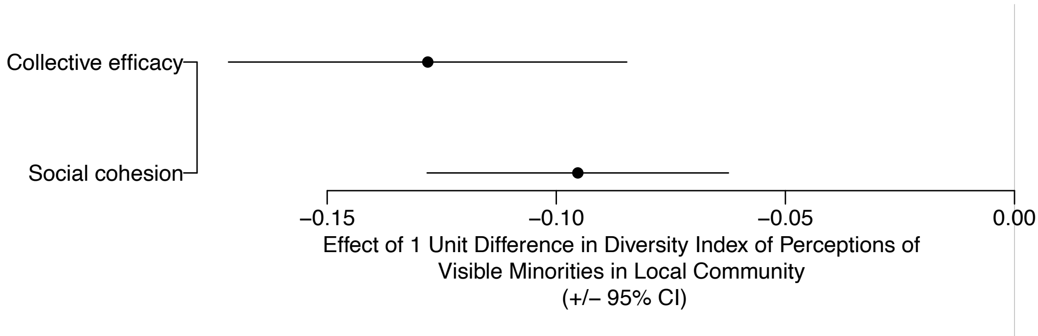

Figure 6. Average differences in outcome between the person perceiving more and the person perceiving fewer visible minorities in the dissemination areas in which both people live. Estimates from multilevel models with crossed random effects for dissemination area and matched pair and covariance adjustment for proportion visible minority in the DA as of 2006. Approximate confidence intervals (horizontal lines) from a profiled likelihood approach (D Bates et al 2015).

Appendix 4. Analysis details: Crossed Random Effects versus Fixed Effects

The paired designs presented in the main body of the text and in the preceding sections of the appendix lead to analyses which summarize the relationship between pair-wise differences in perceptions and pair-wise differences in social cohesion and collective efficacy. We used multi-level modeling strategy to further remove remaining relationships between objective and subjective context within pairs and to calculate standard errors and confidence intervals accounting for clustering by DA. Here we discuss our reasoning for choosing one empirical strategy out of several and also compare the results between them. The reader will notice that the substantive results and statistical significance decisions remain the same across all of the approaches. We focus our explorations here on the design with the most units, the design that we discuss in the main body of the text in Figure 2. And we focus on the social cohesion outcome. The point of this appendix is to illustrate that different approaches to calculating standard errors and estimates do not change the story.

Figure 7 shows the raw relationship between pair-differences in perceptions and pait-differences in the social cohesion index. Across three different scatterplot smoothers (OLS, an outlier robust linear smoother, and an outlier robust local non-linear smoother), we see that as the difference in perceptions increases (such that one member of the pair perceives a more heterogeneous community than the other) the difference in social cohesion becomes more negative: the person perceiving a more diverse community tends more and more to be the person responding with lower values to the social cohesion scale. This figure suggests that a straight line is a reasonable summary of relationship and that the slope of this line is not driven by a few overly influential points.

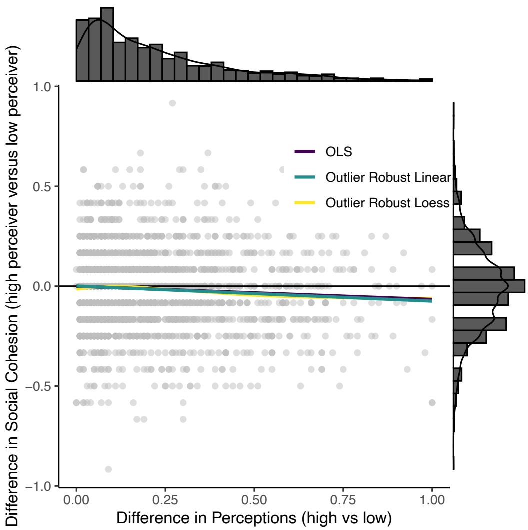

Figure 7. Difference in social cohesion between the higher and lower perceiver within pairs by difference in perceptions between the higher and lower perceiver. The relationship summarized by OLS (blue line), an outlier robust linear fit (Koller and Stahel 2011), and an outlier robust local smoother (loess, span=.5, degree=2). This plot excludes pairs where both people report the same perception.

The analyses presented in the main body of the text and in the preceding section improve on the simple smoother shown above in two ways.

First, in all of the designs other than the design with people living in exactly the same DAs shown in Appendix 3.4, members of pairs are not exactly identical in terms of objective context even if the matching process made them extremely similar. Since we are trying to isolate the effects of perceptions from the effects of objective context, and following the advice of Rubin and Thomas (2000), we adjust our estimates for any remaining linear relationship between objective context and perceptions and between objective context and the outcome. This is what Rubin and Thomas (2000) call "covariance adjustment" and is often referred to as "controlling for" in political science. This strategy is implemented below in Table 2 in the column labeled "FE" for "fixed effects" and the row labeled "estimate" contains values calculated using R code like the following.[29]

```
library(dplyr)
library(estimatr)

## Make a data set for analysis dropping unmatched people and
## pairs with identical perceptions (subj_rank==.5)
analysisdat <- maindata %>%
  filter(!is.na(pairidx)) %>%
  group_by(pairidx) %>%
  mutate(
    subj_rank = rank(community_perception) - 1,
    social_cohesion_rank = rank(social_cohesion) - 1,
    community_efficacy_rank = rank(community_efficacy) - 1
  ) %>%
  filter(subj_rank != .5) %>%
```

[29] Regressing pair-differences on pair-differences yields the same estimates as regressing individual level outcomes on individual level perceptions with fixed effects for pair. Since fixed effects models are common in political science, we label this model the "fixed effects" model rather than the "pair-differenced" model.

```
  droplevels() %>%
  ungroup()

fe_est <- lm_robust(social_cohesion ~ community_perception +
    objective_pct_vm_DA,
  fixed.effects = ~pairidx, data = analysisdat
)
```

Second, we improve the calculation of confidence intervals by using a multi-level model. The fixed effects approach assumes that the observations are independent across pairs when we know that they are not. The analogy in what we are calling the fixed-effects approach is to that of a randomized experiment where first the units are placed into pairs, and then one person in each pair is selected to have the higher of the two existing perception values. The standard error in that design describes the variability we would expect in our estimates from one hypothetical within-pair randomization to another one, where each pair is independent of each other and randomization occurs only within pairs.[30]

In this design, although each person only appears in one pair, multiple pairs can share the same value of objective context. In fact, although roughly 2533 respondents are the only survey respondents in their DA, about 543 share a dissemination area with 1 or 2 other respondents, and 22 share their dissemination area with more than 2 other survey respondents. Since pairs can only contain 2 respondents, two people from the same dissemination area might be paired with two other people from two different DAs or two people from the same other DA. Since we have two kind of groups — pairs and census dissemination areas (DAs) — and since those groups are not nested and the DA groups vary in size, we worried that the fixed effects design-based standard error from `lm_robust()` would be overly liberal because it assumed an unrealistic independence across pairs.

Because this dependence is not a part of the design itself that we have created, but arises from the fact that we want to adjust for objective context, we depart from the standard practice of design-based statistical inference in pair-matched randomized experiments (Gerber and Green 2012) and non-randomized studies like ours (PR Rosenbaum 2020) in this paper although we show those results in the “FE" columns in Table 2. Another tradition in the analysis of paired experiments and observational studies uses probability models to describe the outcome and relationships between predictors using a likelihood function such that we imagine that the values of the social cohesion index (and/or community efficacy index) arise from some underlying stochastic process and also that parameters of this model have their own generating processes that can reflect dependencies across units. This approach, often known as the model-based approach, also allows us to make a model in which the responses to the social cohesion index vary systematically by both pair and by the dissemination area. This approach, known as a multi-level model or random-effects model, has been proposed for use in matched studies (Smith 1997) and as a part of a Bayesian analysis of such designs in general (Gelman et al 2013).

We present the multilevel model here in equation 3 for respondents $i = 1, \dots, n$, matched pairs $s = 1, \dots, S$ and dissemination areas $d = 1, \dots, D$. We write out the likelihood version below (but using some Bayesian style notation to connect with the fully Bayesian model).

[30]See Gerber and Green (2012), Chapter 3 for an introduction to this perspective on design-based standard errors in block or pair-randomized experiments. The `lm_robust()` function by default calculates those design-based standard errors (Blair et al 2024).

$$
\begin{aligned}
y_{isd} &\sim N(\mu_{isd}, \sigma_{isd}) \\
\mu_{isd} &= \alpha_s + \alpha_d + \beta_1 \text{perceptions}_{is} + \beta_2 \text{objective}_{id} \\
\alpha_s &\sim N(\gamma_{s,0}, \sigma_s) \\
\alpha_d &\sim N(\gamma_{d,0}, \sigma_d)
\end{aligned}
\tag{2}
$$

Equation 4 shows that the fully Bayesian version of the model is nearly the same as the likelihood based model, but with different prior distributions for the intercepts (using t-distributions and half-t distributions (t^+) which are restricted to positive values rather than Normal distributions to downweight extreme points), and with the addition of prior distributions for other model parameters. This is the default prior distribution used by the `brms` package.

$$
\begin{aligned}
y_{isd} &\sim N(\mu_{isd}, \sigma_{isd}) \\
\mu_{isd} &= \alpha_s + \alpha_d + \beta_{1,isd} \text{perceptions}_{is} + \beta_{2,isd} \text{objective}_{id} \\
\alpha_s &\sim t(\gamma_{s,0}, 0, 2.5) \\
\alpha_d &\sim t(\gamma_{d,0}, 0, 2.5) \\
\beta_{1,isd} &\sim U(-\infty, \infty) \\
\beta_{2,isd} &\sim U(-\infty, \infty) \\
\gamma_{s,0} &\sim t^+(3, .5, 2.5) \\
\gamma_{d,0} &\sim t^+(3, .5, 2.5) \\
\sigma_{isd} &\sim t^+(3, 0, 2.5)
\end{aligned}
\tag{3}
$$

Table 2 contains results from our use of `brms` (Bürkner 2017) for the fully Bayesian model and `lme4` (D Bates et al 2015) for the likelihood based version with R using code like the following:

```
library(lme4)
library(brms)

## Likelihood Models with crossed random effects
## da_id is dissemination area census id

lmer_social_cohesion <- lmer(
  social_cohesion ~ community_perception + objective_pct_vm_DA +
      (1 | pairidx) + (1 | da_id),
  data = analysisdat
)

## Bayesian model with two random intercepts
## with student_t(3,0,2.5) default priors.
## Slopes have flat priors.
## The brm function uses the Stan language for MCMC sampling.

blmer_social_cohesion <- brm(
  social_cohesion ~ community_perception + objective_pct_vm_DA +
      (1 | pairidx) + (1 | da_id),
  data = analysisdat,
```

```
  chains = 4, iter = 2000, cores = 4,
  control = list(adapt_delta = 0.99, max_treedepth = 20)
)
```

Table 2 shows the results used in Figure 2, in the columns labeled “MLM" and compares them to an alternative method that only accounts for the paired-design using fixed effects (the columns labeled “FE") as well as to the fully Bayesian model, in the columns labeled “Bayes MLM." The entries labeled "standard error" and "95% CI" show estimates of uncertainty for these calculations. The standard errors and confidence intervals for the FE columns are those that would be used in a large pair-randomized experiment (Gerber and Green 2012) and are the defaults from the `lm_robust()` command in R and are often known as the "HC2" robust standard errors. They do not take into account dependence across pairs within DA, but they do not rely on any assumptions about the data generating process of the outcome (i.e., there is no Normality assumption in regards the outcome that is required for these confidence intervals to be valid). The multilevel model columns do involve assumptions about the data generating processes (as shown in the preceding equations), however these assumptions allow us to directly represent dependence across pairs by DA. The confidence intervals for the MLM columns use the profiled-likelihood approach recommended over the Wald-style intervals by (D Bates et al 2015), (Raudenbush and Bryk 2002), and (Pinheiro and DM Bates 2000) for models with complex random effects like ours. The confidence intervals for the Bayes MLM columns are the boundaries of the 95% highest posterior density regions for the posterior distributions implied by the model and arising from MCMC sampling using the `brms()` function to interface with the `stan` Bayesian computation system. Standard errors for the fully Bayesian model are the standard deviations of the posterior distribution. Each approach has its own weaknesses and strengths, but the point estimates in Table 2 shows that none differ in their substantive interpretation.

Table 2. Comparison of results from multilevel models (MLM and Bayes MLM) (with random effects for both dissemination area and matched pair) and Fixed Effects models (FE) (with fixed-effects for matched pair and HC2 standard errors (Gerber and Green 2012)). The Bayesian MLMs use the default priors of the `brm` command from the `brms` package for R: students t priors

	Social Cohesion			Collective Efficacy		
	MLM	Bayes MLM	FE	MLM	Bayes MLM	FE
Estimate	-0.0655	-0.0653	-0.0660	-0.0506	-0.0506	-0.0333
Standard Error	0.0105	0.0102	0.0166	0.0140	0.0140	0.0214
95% CI Low	-0.0862	-0.0854	-0.0986	-0.0780	-0.0773	-0.0753
95% CI High	-0.0449	-0.0458	-0.0335	-0.0232	-0.0241	0.0087

Intuition about likelihood profile confidence intervals A confidence interval for the effect of perceptions on social cohesion should contain a range of values for this effect that are plausible and exclude those values that are implausible. While many social scientists are used to calculating a confidence interval as an unbiased estimate plus-or-minus roughly 2 times the standard error of that estimate, the intuition about plausible values and the everyday use of confidence intervals can help us calculate those intervals via another route: via hypothesis tests. First, recall that if the 95% confidence interval contains 0, we know that the p-value for the test of the hypothesis of no effects is larger than $p = .05$. That is, social scientists commonly use confidence intervals as hypothesis tests. This use of confidence intervals is perfectly correct because, in fact, a 95% confidence interval is a collection of hypotheses that would not be rejected at $\alpha = .05$ using a given test statistic. This fact means that when, say, the standard error of an estimator is difficult to calculate and/or the plausible range is not necessarily plausibly symmetric around the estimate, one can generate a confidence interval using a series of hypothesis tests.

The profile confidence interval arises from this logic and helps solve problems that arise when the Hessian matrix for the log-likelihood function is numerically unstable and/or difficult to calculate. These kinds of difficulties arise from likelihood functions containing many parameters (such as likelihood functions that arise from multilevel models with many random effects.) The idea is to use the Likelihood Ratio (LR) hypothesis test — which tests the hypothesis that a given change to a model improved its overall fit — and to search for the range of values for the parameter that do not significantly improve the model fit over that of the maximum itself (which is the value of the estimate reported as "Estimate" in the table.)

Appendix 5. Discussion: Alternative Explanations: What about personality?

One alternative explanation that we consider is that people's personalities are an important factor in determining where they live, what they see in the maps in their heads, and their attitudes about where they live. Unfortunately, we do not have measures of personality in our survey. However, we hope in this case that previous research on the Big 5 can help us assess this concern, at least to a certain extent. Does personality affect residential choices? Jokela et al (2015) show that openness to experience is most strongly related to living in a city center where there is greater ethnic diversity (and also higher population density, housing prices, and crime rates). Extraversion is also related to living in urban areas; in contrast, living in more suburban neighborhoods is correlated with agreeableness and conscientiousness.

Who has greater political knowledge (and by implication, will more accurately perceive their contexts)? Mondak and Halperin (2008) show that the more knowledgeable people are individuals who are more open, less conscientious, less extroverted, and possibly more neurotic.

When it comes to attitudes about immigration, Gallego and Pardos-Prado (2014) find that agreeableness has the strongest relationship to positive attitudes about immigrants' impact on a society. Openness to experiences has a weak positive relationship to such attitudes, and this may largely be driven by the fact that more educated individuals are more open and also more tolerant about immigration. Extraversion has no effect, and neuroticism and conscientiousness are only weakly related to beliefs that there are too many immigrants, that they do not help a neighborhood, and that they should not be entitled to the same benefits as natives.

So, it is possible that in our matches, the respondent who scores higher on openness to experience perceives fewer visible minorities in her local community, (weakly) sees immigrants in a positive light, and also has lower political trust (Mondak and Halperin 2008); however, both types of respondents are likely to live in similar types of areas, since openness is associated with living in the city center. The respondent in a match who is more conscientious will perceive more minorities, and (weakly) perceive immigrants have a negative impact, but again the pair likely live in similar areas, since the more conscientious tend to live in the suburbs with fewer minorities. Finally, agreeableness, which has the strongest predictive power of immigration attitudes, has no relationship with political knowledge.

More research is obviously needed, but at this point, we do not think there is enough evidence to dispel our conclusion that pseudoenvironments matter for attitudes about social capital above and beyond objective environments.[31]

Appendix 5.1 Racial Resentment Question Wording

Respondents were asked to agree or disagree with the following statements:

1. Irish, Italian, Jews and many other minorities overcame prejudice and worked their way up. Other minorities should do the same without any special favors.

[31] It should be noted that the studies we cite here are not based on the same population that we use in our study although we think that the relationships driven by personality should not differ greatly across these studies: the residential choice study was based on a self-selected sample in the Greater London metropolitan area between 2009 and 2011; the knowledge study was based on surveys in select cities and counties in the US in 1998, 2004, and 2005; and the immigration attitudes study was based on a representative national panel study of the Netherlands in 2007 and 2008.

2. It's really a matter of some people not trying hard enough; if racial and ethnic minorities would only try harder they could be just as well off as whites.
3. Government officials usually pay less attention to a request or complaint from someone who is a racial or ethnic minority than from someone who is white.

Appendix 6. Diagnostics about the paired design

Figure 8 plots the respondents by their objective and subjective context, connecting the individuals in each pair with a line segment. Figure 8 shows that respondents' views of who lives around them — particularly the proportion of ethnic outgroup members — vary within pairs of people living in nearly the same kinds of objective contexts. The length of the lines from left to right shows that the respondent who perceives greater diversity could be more or less accurate than her match; similarly, both respondents could be quite inaccurate. The fact that the lines are all relatively flat illustrates the similarity in objective diversity within pairs (a sign that our design compares like with like); the lengths of the lines tell us that perceptions of these matches differ (a sign that perceptions are not a simple proxy for objective context). The fact that most of the points are below the 45 degree line tells us that the white respondents in the MLCC tended to report more visible minorities in their hand-drawn local communities than were measured by the Canadian Census in their DAs.

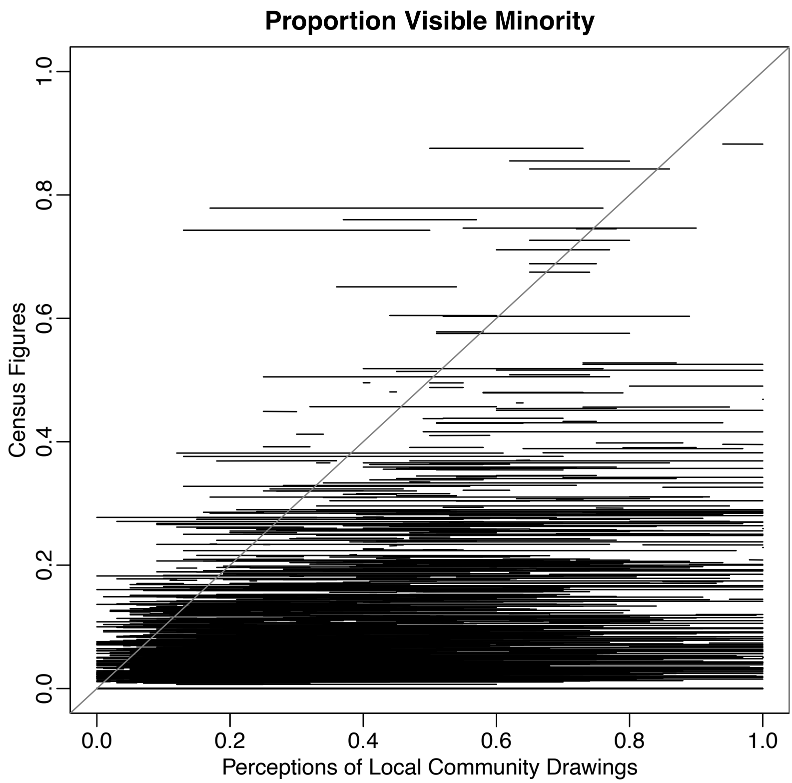

Figure 8. The Objective and Subjective Context of the Matched Pairs. The y-axis is the percentage of visible minorities in the Census DAs. The x-axis is the perception of the percentage of visible minorities in respondents' "local communities."

Appendix 7. Affirmation of Compliance with the APSA Principles and Guidance in Human Subjects Research

This research involved an online survey sent to people who had used the Canadian Broadcasting Corporation-sponsored Vote Compass tool: a non-partisan electoral education initiative that invited citizens to answer twenty policy questions to place themselves in a policy space relative to the major political parties (which had also completed the survey). Over 1 million Canadians visited the Vote Compass website surrounding the May 2011 federal election. We contacted all of the 80,000 or so respondents who agreed to be contacted for future studies and about 10 percent agreed to take our survey. The survey consent process and instrument and plans for protecting the personal information of the survey respondents were reviewed by the Institutional Review Board of the university of the investigators: they were not appreciably different from those used in online surveys in general.