The Content and Correlates of Subjective Local Contexts

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Abstract

The study of the role of local context in shaping individual behavior and attitudes has received renewed attention in recent years, but is greatly challenged by problems of measurement. Recent research suggests that subjective local contexts, i.e. individuals' own perceptions of their local context, bear only minimal resemblance to the administrative units typically used. However, little is known about what subjective local contexts do correspond to, if anything. We provide new evidence on subjective local contexts, exploiting a unique opportunity to link survey respondents' map drawings to geocoded population data from public registries. This allows us to characterize the content of subjective local contexts with previously unseen precision. Three findings stand out. First, respondents demonstrate substantial ethnic and economic biases, evaluating areas with higher levels of ethnic diversity and unemployment more negatively. Second, respondents on average perceive characteristics of subjective contexts with high accuracy. Third, perceptions and evaluations of subjective contexts differ very little according to respondent political orientation. The results indicate that individuals' perceptions of their local context are generally accurate and relatively unaffected by political orientation.

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1 Introduction

Modern mass societies are, to varying extents, spatially segregated by various individual characteristics, including racial/ethnic background and economic resources. As a consequence, the everyday experiences of citizens depend not only on their own characteristics, but also on the characteristics of their local contexts. Scholars of social and political behavior have debated the extent to which contexts affect behavior and attitudes (Agnew, 1996; King, 1996), but more recent studies provide ample evidence of the effects of context (e.g., Chetty et al., 2016; Enos, 2015; Hopkins, 2010; Sharkey, 2010). However, observational studies of context effects typically suffer from the challenge that for a given individual, reliable measures of the characteristics of his or her context are not readily available. Instead, scholars typically settle for measures available at the level of administrative units such as countries, states, counties, zip codes, or census tracts. Yet there is no guarantee that such measures correspond to the context individuals actually experience.

Recent work has sought to remedy this shortcoming in various ways. Using an innovative approach based on freehand drawing on local maps, Wong et al. (2012) show that *subjective contexts*, i.e. individuals' own perceptions of their social context, correspond only minimally to the administrative unit which they reside. However, due to data constraints this approach still requires relying on administrative units when characterizing the content of subjective contexts. In another approach, Dinesen and Sonderskov (2015) use data from public registries to precisely characterize contexts defined by concentric circles varying in size. Although this approach allows for precisely characterizing context content, the circular shape of the context is a purely theoretical construct which may not correspond to individuals' subjectively experienced contexts. In sum, though both of these approaches improve on previous work, they do so by improving the measurement of either context shape or content.

In this article, building on this work, we present and evaluate an approach which combines these two advantages. In a nationally representative sample of Danish citizens, we ask respondents to draw their subjective contexts, as well as other spatial constructs, in an on-line map-drawing module. We then link these drawings with spatial data in public registries, allowing us to characterize the content of these drawings with previously unseen precision. In the following, we first present the design of the survey and then some key results from preliminary analyses of the data.

2 Method

Here, we present an overview of the survey, which utilizes a map-drawing task to identify respondents' subjective context.

2.1 Survey design

In June 2016, we sent out postal survey invitations to 13,000 Danish citizens ages 18-75, whose names and addresses were drawn from public registries.[1] Within this group, 10,000 invitees were drawn from a simple random sample of all Danish citizens in the target group. 3,000 were drawn from one specific neighborhood in northeastern Copenhagen for the purpose of retrieving a subsample of respondents from the same area. In this article, we treat the entire group of invitees as one. Each postal invitation contained a link to a webpage with a unique access code. In addition to encouraging invitees to participate in the study, the invitation also offered incentives in the form of gifts offered to five respondents selected at random.

Of those invited, 2,623 respondents completed the survey, yielding a response rate of 20.7 percent (AAPOR3). An additional 718 respondents started the survey but broke it off, most of them during the map-drawing tasks at the beginning of the survey, suggesting that the considerable portion of the survey dedicated to map-drawing (cf. below) came at the cost of some respondent attrition.

The collected survey data were subsequently enriched with reliable and up-to-date public registry data by Statistics Denmark and the merged data made available (in encrypted form) via remote servers. This setup allows us to retrieve detailed information such as country of origin, level of education, income, labor market status, and moving history on not only the survey respondents, but also—and more importantly for our aims related to studying the role of context—every individual residing within the subjective contexts drawn in the survey.

2.2 Measuring subjective contexts

One of the key empirical questions addressed in this paper is the extent to which individuals think in meaningful ways about their immediate spatial surroundings. In order to examine this, we ask – following the work of Wong et al. (2012) – respondents to draw subjective contexts using an online map-drawing module in which they describe contexts by drawing polygons on top of an embedded Google Maps map.

[1]The upper age bound was chosen to minimize the number of respondents technically unable to navigate the web-based survey.

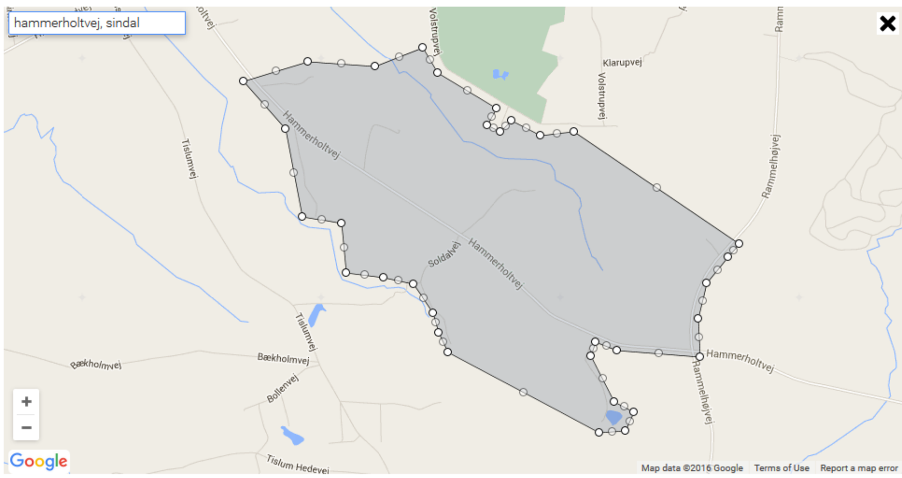
However, even assuming that respondents can think intuitively about subjective contexts, they may not be familiar with the concept of subjective contexts or the map-drawing module. (Though it may be familiar to some respondents: some real estate websites, such as Zillow.com, use a similar module to identify where visitors to the website want to search for housing). We took two steps to familiarize respondents with the map-drawing portion of the survey. First, we showed respondents three hypothetical examples of subjective contexts, telling them that "to illustrate the idea, we will first show you three examples of how three different people perceive their primary neighborhood." The examples, which consist of hypothetical subjective contexts from an urban, a rural, and a suburban area respectively, are shown in Figure 1.

The example contexts were designed to be relatively small and very precise with respect to physical features of the landscape. We designed the examples this way in order to signal to respondents to think of context in local terms corresponding to their actual experiences of their spatial surroundings as opposed to more abstract allegiances to region or country. The precision of the examples also served to encourage respondents to invest effort in drawing the contexts accurately, allowing us to fully exploit the precision of the data in public registries, which locates individuals spatially at the level of individual households.

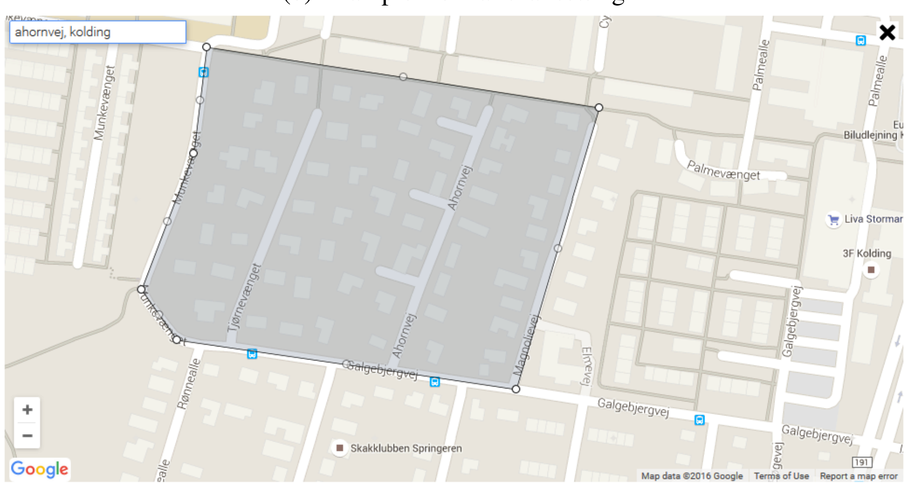
The other step we took consisted a practice map-drawing task to which respondents were assigned before coming to the actual map-drawing portion of the survey. In the practice map-drawing task, we asked respondents to reproduce the last of the three examples, the subjective context from a suburban setting (panel c in Figure 1), deliberately designed in a geometrically simplified shape which should be relatively easy to reproduce. On the screen following the examples, we asked respondents to use the search field in the top left corner of the map to find the street and city shown and draw a polygon identical to the one shown. In addition to giving respondents some practice with the map-drawing module, the task also allows us to screen for inattentive, satisficing respondents by excluding those who fail to draw a polygon resembling the example. However, in the results presented below, we have not yet excluded these cases.

First of all, we ask respondents to draw their *subjective context*, described as what respondents "perceive as [their] primary neighborhood", referring to the three examples described above. This question is deliberately open-ended, phrased to elicit respondents' intuitions about which part of their surroundings they perceive to be their neighborhood, building directly on the approach pioneered in Wong et al. (2012). Second, we ask respondents to draw a *good area*, defined as an area they would recommend to a hypothetical newcomer to the area. Third, we correspondingly ask respondents to draw a *bad area* based on the same hypothetical. Comparing and contrasting characteristics of good and bad areas allows us to assess what matters for how areas are evaluated as we describe below. Fourth, we ask respondents to draw their *area of exposure*, defined as the

(a) Example from an urban setting



(b) Example from a rural setting



(c) Example from a suburban setting

Figure 1: Examples of subjective contexts shown to respondents.

Table 1: Question wordings in the map-drawing task

Label	Instruction
Subjective context	*Please draw the area you perceive as your primary neighborhood. You can use the search function to find where you live. For example, you can search for the street you live on followed by your zip code.*
Good area	*Most people would rather live some places than others. Imagine someone you know who is not familiar with your neighborhood, asking you about different areas close to where you live. Which area would you highlight as an especially good place to live? The area can be the area where you live, but it can also be another area nearby.*
Bad area	*Again imagine someone you know who is not familiar with your neighborhood, asking you about different areas close to where you live. What would you highlight as a not so good place to live? As before, the area can be the area where you live, but it can also be another area nearby.*
Area of exposure	*In the last map, we will ask you to draw the area around your residence where you come and go regularly. The area can be the same as your neighborhood, but can also be larger or smaller. For example, the area can consist of areas nearby where you have errands or just spend time.*

"the area around [their] residence where [they] come and go regularly". Though self-reported measures are potentially subject to bias, we include this measure to gauge where respondents experience actual exposure to everyday neighborhood life.

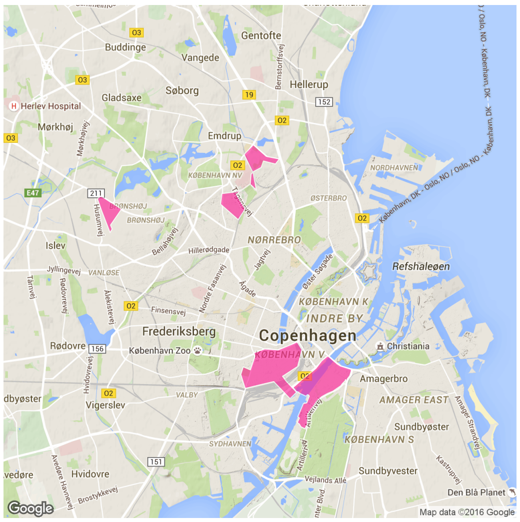
Cursory inspection of the maps drawn by respondents suggest that conditional on completing the task, they drew all four contexts fairly meticulously. Specifically, almost all of the contexts drawn closely track major and minor roads on the map, indicating that respondents invested real effort in drawing each context. Figure 2 shows examples of contexts drawn by respondents, showing one of each type of context included in the survey for four respondents residing in Copenhagen.

As indicated in Figure 2, the contexts drawn by respondents are as a general rule relatively small. Figure 3 shows the full distribution of context sizes with respect to area and population.

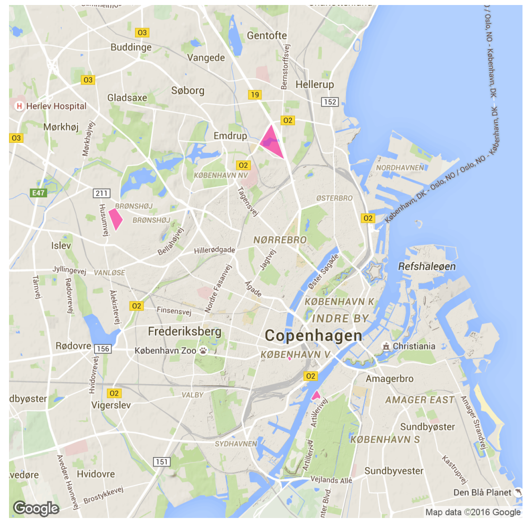
Both measures are strongly right-skewed in that a small number of respondents have drawn very large contexts. The typical context, however, is relatively small. The median context contains 479 people and is 90,000 m^2 large, roughly equivalent to a circle with a 169 meter radius. The small average size of contexts suggests that the examples were reasonably successful in prompting respondents to think about subjective contexts in local terms.

2.3 Estimating context characteristics

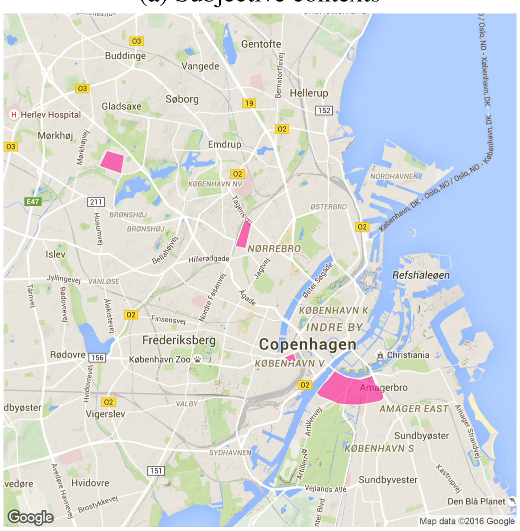
In the analyses to follow, we compare characteristics of various contexts and how they relate to individual differences between respondents. We focus on two specific characteristics: *ethnic*



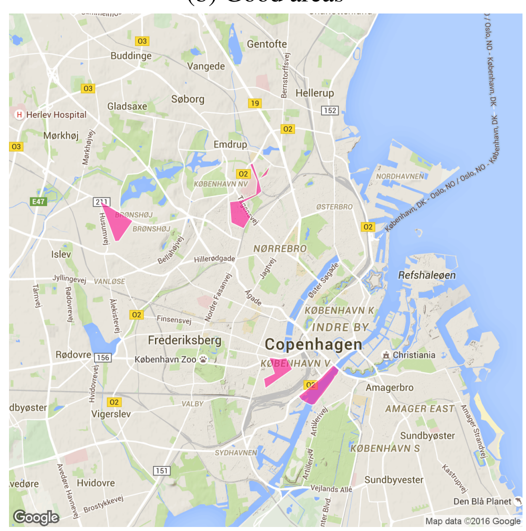
(a) Subjective contexts



(b) Good areas



(c) Bad areas



(d) Areas of exposure

Figure 2: Examples of each type of subjective context for four select respondents residing in Copenhagen.

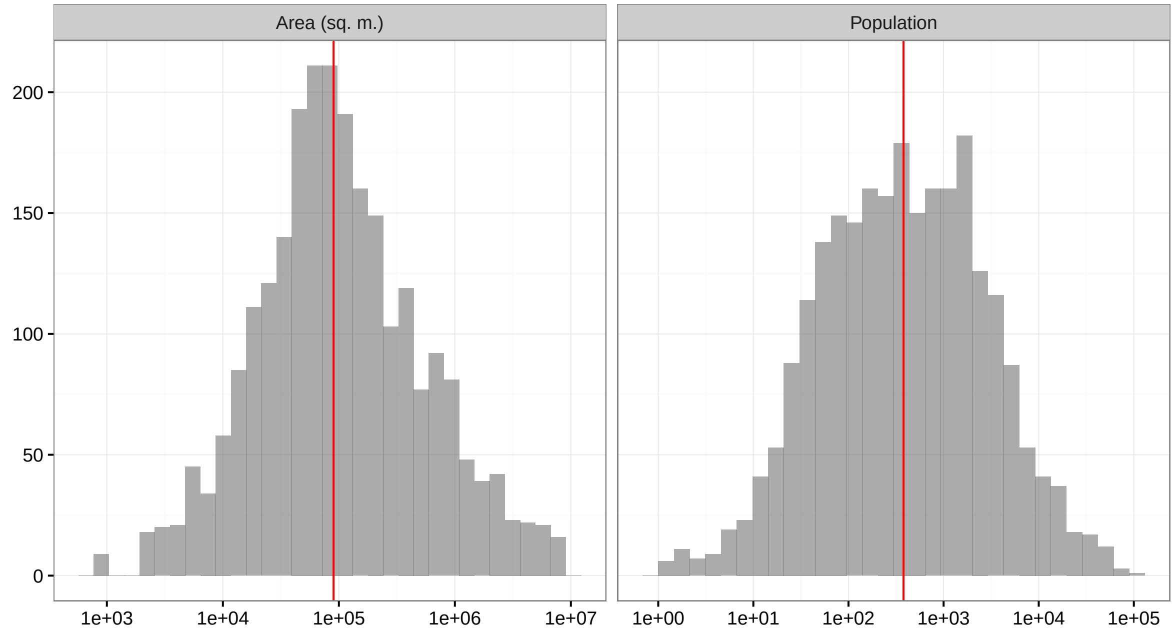


Figure 3: Distribution of sizes of subjective contexts, measured by area (left panel) and population (right panel). X-axes are logged. The red vertical lines mark the median size (respectively 90,000 m^2 and 479 individuals). 90,000 m^2 corresponds to approximately 0.035 mi^2. Means are respectively 412,447 m^2 and 787 individuals.

diversity, measured as the context share of non-western immigrants and descendants, and *unemployment rate*, measured as the context share of individuals classified as unemployed in public registries. The advantage of focusing on these two characteristics is twofold. First, we ask respondents directly about their perceptions of each of these characteristics, allowing us to compare their perception directly with the true value. Second, we ask respondents about their political attitudes toward each topic (i.e., immigration and unemployment benefits), allowing us to test whether perceptions vary by respondent political orientation.

One important challenge in measuring the characteristics of contexts is that subjective contexts vary considerably in size. This represents a special problem for very small subjective contexts, which may contain only very few households and where averaged measures of context characteristics will accordingly have very high variance. For example, a very small subjective context containing just five individuals, two of whom are immigrants, will be assigned a level of ethnic diversity of 40 percent. If one of the immigrants were not included – perhaps by chance – the level would drop to 25 percent, resulting in large variance in the estimated level of ethnic diversity.

In order to get more stable measures of characteristics of very small contexts, we use a partial-pooling approach similar to the one presented in Park et al. (2004). In short, instead of directly calculating ethnic diversity or the unemployment rate in each subjective context (i.e., a no-pooling approach), we estimate an intercept-only multilevel model with individuals grouped in subjective contexts and assign the group-level prediction as the estimated value of each subjective context. For small subjective contexts, this approach results in 'shrinkage', pulling estimated values toward the global mean, in turn reducing the influence of outlier measures based on very few individuals. For larger contexts, the partial-pooling estimates converge to the no-pooling estimates.

3 Results

We structure the presentation around three themes: *preferences for context* (Section 3.1), *perceptual accuracy* (Section 3.2), and lastly *individual differences in perceptions* (Section 3.3). For each theme, we present results for respectively ethnic diversity and unemployment rate. Since respondents are encouraged to draw areas close to where they live, respondents' contexts will have different baseline levels of ethnic diversity and economic conditions. In order to level out these differences and focus on the the choices respondents make given their broader context, we subtract the average level in the respondent's municipality from each distribution. Hence, the distributions are centered around zero, representing contexts typical for the respondent's municipality.

3.1 Preferences for context

Figures 4 and 5 show the distribution of each characteristic in each of the four types of context elicited in the survey.

Since respondents are encouraged to draw contexts close to where they live, the characteristics of their local surroundings will to some extent constrain the content of the contexts they draw. To focus the comparison on the choices respondents make conditional on their surroundings, the Figures 4 and 5 show each distribution minus the average level of the characteristic in the respondent's municipality. Hence, the distributions are centered around zero, reflecting that most respondents draw contexts with ethnic diversity and unemployment levels typical of where they live.

Nevertheless, there are clear differences between the four types of context. While subjective context (upper left) and area of exposure (lower right) are concentrated around the local average (indicated by the vertical line), good and bad areas are visibly concentrated respectively below and above the average. In other words, respondents tend to identify good (bad) areas in their local

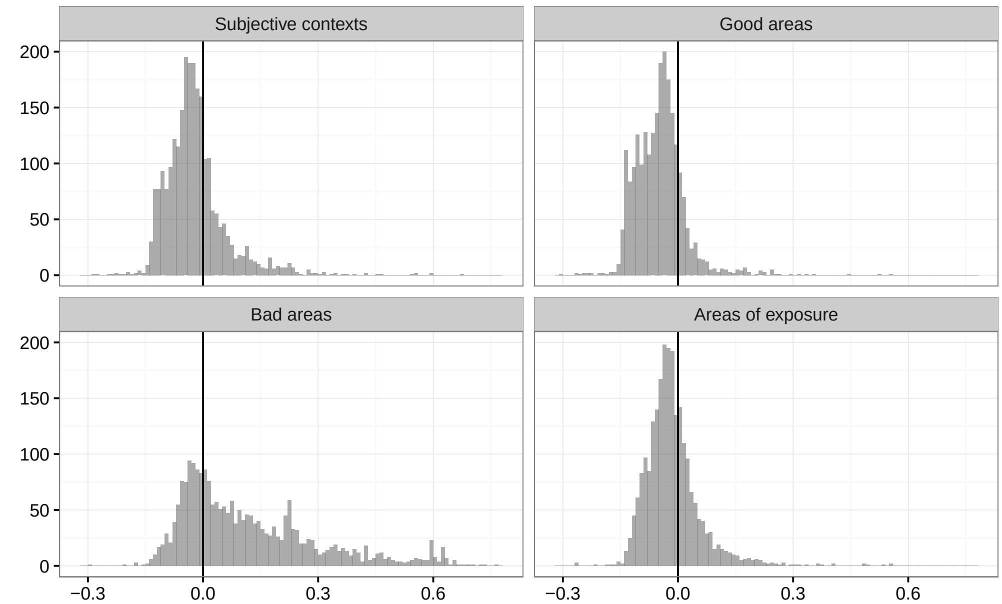


Figure 4: Distribution of ethnic diversity (share of non-western immigrants and descendants) in each of the four types of context elicited in the survey. To account for local conditions, the x-asis shows the level of ethnic diversity in each type of context minus the average ethnic diversity in the respondents' municipality.

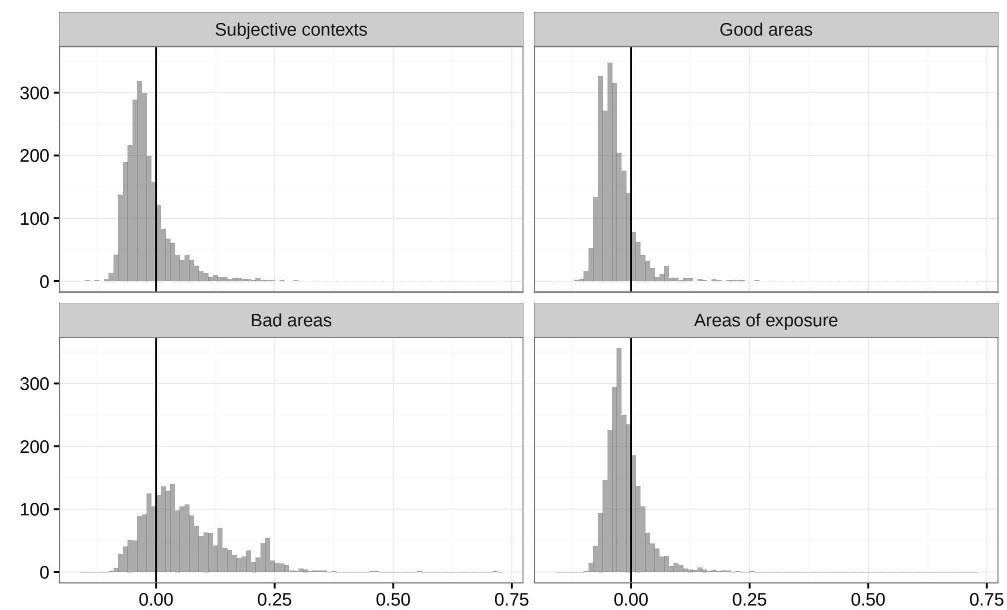
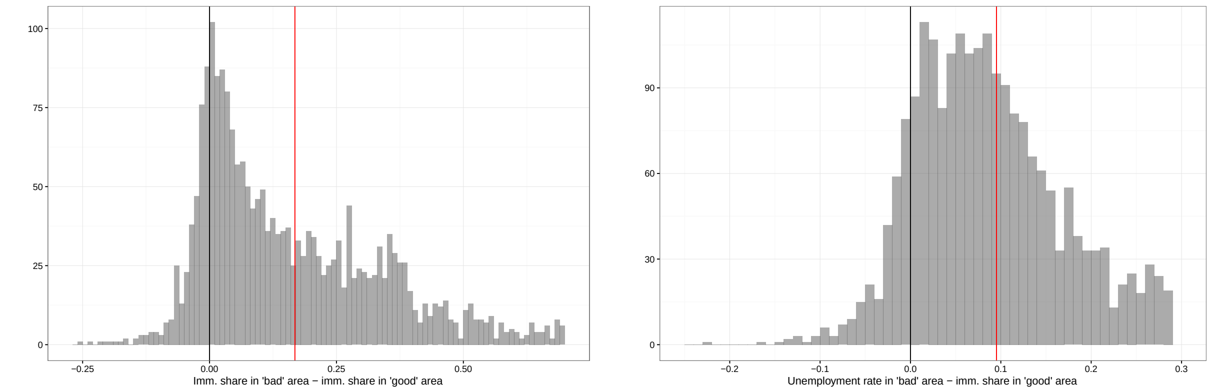


Figure 5: Distribution of unemployment rate in each of the four types of context elicited in the survey. To account for local conditions, the x-asis shows the unemployment rate in each type of context minus the unemployment rate in the respondents' municipality.

context with low (high) ethnic diversity and unemployment. The trend is particularly pronounced



(a) Share of non-western imm.s and descendants

(b) Unemployment rates

Figure 6: How 'good' and 'bad' areas differ by ethnic diversity and economic status. The figure shows the distribution of differences between 'good' and 'bad' areas with respect to share of non-western immigrants and descendants (left panel) and unemployment rate (right panel). The black lines represent no difference. The red lines represent the mean difference. Compared to 'good' areas, 'bad' areas have on average 16 percentage points higher ethnic diversity and 9 percentage points higher unemployment rates.

for areas identified by respondents as bad.

Figure 6 presents this result in a more direct way, showing the distribution of the difference between bad and good areas for each characteristic.

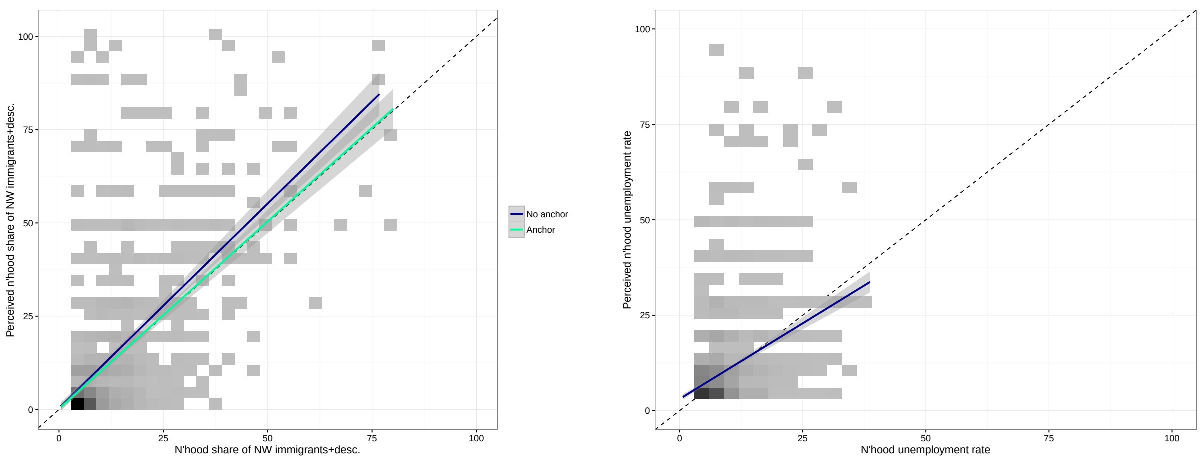
Distribution of differences in share of non-western immigrants and descendants between good and bad areas. The black line represents no difference. The red line represents the actual average difference, 9.6 percentage points.

As shown, the distributions are right-skewed such that for the majority of respondents, bad areas are characterized by higher ethnic diversity and higher unemployment relative to good areas. On average, bad areas have ethnic diversity levels 16 percentage points higher and unemployment rates 9 percentage points higher. Note, however, that this characterization does not adjust for other differences between types of neighborhood, such as average income or age of housing stock.

3.2 Perceptual accuracy

Immediately after the map drawing tasks, we asked respondents about their best guess at the level of various characteristics of their subjective local context. Here, we compare their guesses with the true values of those characteristics as a way of assessing how accurately individuals perceive their local context.

Figure 7 plots perceptions of ethnic diversity and unemployment rate against the true value in each subjective context. As shown, perceptions track the true value closely on average, although there is considerable variation in individual respondents' perceptions.



(a) Share of non-western imm.s and descendants

(b) Unemployment rates

Figure 7: How accurately individuals perceive characteristics of local contexts. The figure plots respondents' estimates of the characteristics of their subjective contexts, respectively ethnic diversity (left panel) and unemployment rate (right panel). The two lines in the left panel plot represent the experimental conditions with and without the informational anchor about the national level of ethnic diversity. For privacy reasons, the scatter plot is shown in pixelated form. The dotted diagonal line corresponds to perfect accuracy. The blue line is an OLS best fit.

In order to ensure that respondents' estimates were not merely driven by innumeracy, we included an informational 'anchor' in the question, noting what the national average of the characteristic is. For example, for ethnic diversity, the question notes that "in Denmark as a whole the level is 9 out of 100, but the level in your neighborhood can be higher or lower". In order to ensure that this informational anchor is not driving the results, we randomized the presence of the anchor in the question about local ethnic diversity. As shown in the left panel of Figure 7, the slopes and intercepts for the lines with and without the anchor are virtually identical. Hence, there is no indication that the finding of high perceptual accuracy on average is driven by the presence of information about the national average.

As an additional piece of evidence in favor of this interpretation, consider Table 2, which shows results from a test of perceptual accuracy in regression form.

The dependent variable in Table 2 is the respondents' own estimate of the ethnic diversity (models 1-3) or unemployment rate (models 4-5) in the respondents' subjective local context. The key coefficient of interest is the actual level of each characteristic, shown in rows 1 and 5. If respondents perceived contexts with perfect accuracy on average, the coefficients would be 1.

As shown, the coefficients imply nearly perfect perceptual accuracy on average. It is notable, however, that perceptual accuracy is slightly lower for unemployment compared to ethnic diversity. We revisit this pattern in the conclusion section.

Table 2: Predictors of perceived characteristics of subjective contexts

	Perceived context ED			Perceived context UR	
	(1)	(2)	(3)	(4)	(5)
Subjective context ED	0.940***	0.940***	0.941***		
	(0.033)	(0.033)	(0.033)		
Anti-imm.	−0.584	−0.582	−0.143		1.277
	(1.324)	(1.466)	(1.978)		(1.213)
Anti-imm. × Num. anchor			−0.702		
			(2.521)		
Num. anchor			−0.771		
			(1.505)		
Subjective context UR				0.770***	0.761***
				(0.047)	(0.047)
Econ. conservatism		−0.352	−0.354	−0.581	−1.102
		(1.496)	(1.495)	(1.125)	(1.244)
Age	−0.076***	−0.076***	−0.076***	0.037**	0.040**
	(0.020)	(0.021)	(0.021)	(0.017)	(0.017)
Gender (m)	0.118	0.107	0.111	0.421	0.291
	(0.558)	(0.563)	(0.563)	(0.465)	(0.467)
Education (yrs)	−0.461***	−0.468***	−0.467***	−0.221**	−0.199**
	(0.116)	(0.117)	(0.117)	(0.096)	(0.097)
Income (100k DKK)	0.092	0.101	0.103	−0.259**	−0.261**
	(0.157)	(0.158)	(0.158)	(0.131)	(0.131)
Constant	14.618***	14.777***	15.087***	7.796***	7.006***
	(2.077)	(2.109)	(2.216)	(1.693)	(1.763)
N	2,374	2,366	2,366	2,400	2,366
Muni. FE	✓	✓	✓	✓	✓
R^2	0.395	0.395	0.396	0.176	0.176
Adjusted R^2	0.368	0.368	0.368	0.140	0.139

*p < .1; **p < .05; ***p < .01

In addition to actual levels, perceptions of local characteristics may also be associated with respondents' own political orientation. For example, following the theory of group threat, respondents who perceive higher levels of local ethnic diversity should respond react with more anti-immigration attitudes (e.g., Quillian, 1995; McLaren, 2003). The arrow of causation could also run in the opposite direction, such that individuals with anti-immigration attitude through a process of motivated reasoning conclude that local levels of ethnic group threat are high (Kunda, 1990; Taber and Lodge, 2006). Both of these theories predict a positive association between anti-immigration attitudes and perceptions of local levels of ethnic diversity.

To test for this association, we calculated two indices of respondent ideological orientation, each composed of items directly connected to the relevant features of local contexts. One, here labelled *anti-immigration*, measures respondent attitudes toward immigration. The other, labelled *economic conservatism*, measures respondent attitudes to redistribution and the government's role in reducing inequality. The items used in each index are presented in Table 6 in the appendix. Both indices have high reliability (Cronbach's $\alpha = .84$ and .77 respectively). The two attitude indices are only moderately strongly correlated ($r = .41$). Given the sample size, multicollinearity is thus not likely to be a concern, so we include the two indices simultaneously in some model specifications.

As shown in Table 2, contrary to the theories outlined above, there is no significant relationship between respondent attitudes and perceptions of context characteristics net of actual levels. In fact, the point estimates imply that individuals with more anti-immigration attitudes tend to (relatively speaking) *underestimate* local ethnic diversity, although the association is not statistically significant. Similarly, economically conservative individuals tend to perceive lower rather than higher levels of local unemployment, although again the association is not statistically significant. We also interact the dummy for the randomized informational anchor about national ethnic diversity with the the anti-immigration attitude index, once again finding no significant effect. Altogether, the results suggest that not only are perceptions fairly accurate in average, they are also broadly shared across the ideological spectrum.

In Table 3, we present the same result in an alternative way, showing how individual-level variables correlate with *misperception*, i.e. the difference between perceived and actual levels of local characteristics.

Table 3 reiterates the point from above, namely that political attitudes are not systematically associated with higher or lower levels of misperceptions of local conditions. The only reasonably robust pattern across dependent variables and model specifications is that higher level of education is associated with less misperception. This may reflect that more highly educated individuals possess more information about local conditions, or more prosaically that they are more familiar

Table 3: Predictors of misperception of subjective contexts

	Misperception of ED			Misperception of UR	
	(1)	(2)	(3)	(4)	(5)
Anti-imm.	−0.564	−0.641	−0.292		1.072
	(1.325)	(1.466)	(1.977)		(1.219)
Anti-imm. × Num. anchor			−0.530		
			(2.521)		
Num. anchor			−0.877		
			(1.505)		
Econ. conservatism		−0.166	−0.169	0.073	−0.325
		(1.493)	(1.492)	(1.123)	(1.242)
Age	−0.075***	−0.075***	−0.075***	0.041**	0.045***
	(0.020)	(0.021)	(0.021)	(0.017)	(0.017)
Gender (m)	0.107	0.088	0.092	0.319	0.184
	(0.558)	(0.563)	(0.563)	(0.466)	(0.469)
Education (yrs)	−0.451***	−0.458***	−0.457***	−0.171*	−0.148
	(0.116)	(0.117)	(0.117)	(0.096)	(0.097)
Income (100k DKK)	0.121	0.127	0.128	−0.212	−0.213
	(0.156)	(0.158)	(0.158)	(0.132)	(0.131)
Constant	13.484***	13.614***	13.982***	4.869***	4.031**
	(1.983)	(2.011)	(2.130)	(1.592)	(1.672)
N	2,374	2,366	2,366	2,400	2,366
Muni. FE	✓	✓	✓	✓	✓
R^2	0.075	0.075	0.077	0.064	0.067
Adjusted R^2	0.035	0.034	0.035	0.024	0.025

*p < .1; **p < .05; ***p < .01

with expressing numerical quantities.

3.3 Individual differences in context perceptions

Given the subjective nature of the mapping tasks, a natural question is whether the subjective contexts respondents define differ according to respondents' political orientation. For example, the pattern identified above whereby 'bad' areas tend to be higher in ethnic diversity and unemployment might plausibly vary according to respondent ideology. Specifically, we might expect that individuals with strong anti-immigration attitudes are more prone to defining areas in terms of their ethnic composition, and similarly for economically conservative individuals and areas' economic status.

Table 4 presents models predicting ethnic diversity in three context measures, namely the difference in ethnic diversity between bad and good areas, the subjective context, and the area of exposure. Table 5 presents the same analysis except with unemployment rate as the contextual characteristic and an economic ideology measure based on an index of economic policy attitudes as the attitudinal independent variable.

Table 4: Predictors of ethnic diversity in various subjective contexts

	Good/bad diff.	Subj. context	Area of exposure
	(1)	(2)	(3)
Anti-imm.	0.040	0.010	0.001
	(0.022)	(0.009)	(0.008)
Econ. conservatism	-0.014	-0.031^{**}	-0.027^{**}
	(0.022)	(0.010)	(0.008)
Age	-0.001^{*}	-0.0002	-0.0001
	(0.0003)	(0.0001)	(0.0001)
Gender (m)	0.006	0.003	0.002
	(0.008)	(0.004)	(0.003)
Education (yrs)	0.003	-0.002^{*}	-0.001
	(0.002)	(0.001)	(0.001)
Income (100k DKK)	0.003	-0.004^{***}	-0.003^{**}
	(0.002)	(0.001)	(0.001)
Constant	0.208^{***}	0.195^{***}	0.178^{***}
	(0.029)	(0.013)	(0.011)
N	2,086	2,366	2,255
Muni. FE	✓	✓	✓
R^2	0.199	0.229	0.235
Adjusted R^2	0.159	0.195	0.200

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

As was the case for perceptual accuracy, anti-immigration attitudes is not statistically significantly correlated with ethnic diversity in any of the three context measures, and only with

Table 5: Predictors of unemployment rate in various subjective contexts

	Good/bad diff.	Subj. context	Area of exposure
	(1)	(2)	(3)
Anti-imm.	0.027^{**}	0.009	0.002
	(0.011)	(0.005)	(0.004)
Econ. conservatism	0.007	0.033^{***}	0.017^{***}
	(0.011)	(0.006)	(0.005)
Age	-0.001^{***}	-0.0002^{***}	-0.0001^{*}
	(0.0002)	(0.0001)	(0.0001)
Gender (m)	0.006	0.004^{**}	-0.001
	(0.004)	(0.002)	(0.002)
Education (yrs)	0.002^{**}	-0.002^{***}	-0.001^{***}
	(0.001)	(0.0004)	(0.0004)
Income (100k DKK)	0.001	-0.002^{***}	-0.001^{***}
	(0.001)	(0.001)	(0.0005)
Constant	0.058^{***}	0.092^{***}	0.084^{***}
	(0.017)	(0.009)	(0.007)
N	2,086	2,366	2,254
Muni. FE	✓	✓	✓
R^2	0.121	0.122	0.164
Adjusted R^2	0.077	0.083	0.126

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

unemployment rate in the good/bad difference measure, suggesting context perceptions do not depend on respondent political orientation. The results with respect to economic conservatism are not quite as consistent, with economic conservatism being associated with lower levels of ethnic diversity and higher levels of unemployment in subjective context and area of exposure.

In sum, there is no consistent pattern in the types of contexts respondents draw depending on their political attitudes. In the Section A.2 in the appendix, however, we report a related finding with a clearer pattern. After drawing the 'good' and 'bad' area maps, we asked respondents if they had found it easy to think of a good or bad area. In Section A.2, we show that individuals with more anti-immigration attitudes are significantly more likely to have found it easy to think of a bad area. The finding suggests that the local presence of ethnic outgroups may be more mentally salient to respondents with more anti-immigration attitudes. However, the results in this section suggest that though more pro-immigration individuals may be less immediately inclined to think of a bad area, the area they eventually draw is no less likely to contain high levels of ethnic diversity.

4 Conclusion

For researchers studying the role of local contexts in shaping individuals' attitudes and behavior, the challenge of properly measuring context is ubiquitous. Recent studies of context have improved on standard approaches in one of two ways. Some have improved the how the shape of local contexts are measured by probing how individuals subjectively perceive their local context. Others have improved how the content of local contexts are measured by relying on high-precision registry data. In this paper, we present and evaluate an approach that combines the advantages of these two approaches.

The main findings are structured in three sections. In Section 3.1, we examine the average content of various types of context. When asked to identify 'bad' vs. 'good' areas, respondents consistently identify areas with high ethnic diversity and high unemployment as bad. In Section 3.2, we test the accuracy with which individuals perceive characteristics of local contexts. We find that although estimates have high variance, perceptual accuracy is on average quite high. Furthermore, although there are theoretical reasons to expect perceptions to be associated with respondents' political attitudes, we find no evidence of such an association. Lastly, in Section 3.3 we test whether respondents' political attitudes are associated with the content of subjective contexts. Although some attitudes are significantly associated with some content characteristics, the overall pattern suggests no clear link between political attitudes and the content of subjective context.

Two trends in these results deserve additional comment. First of all, although as reported in Section 3.2 perceptual accuracy is high on average, the association between actual and perceived levels is notably weaker for unemployment compared to ethnic diversity. There could be any number of reasons for this difference, but one plausible explanation could be that the ethnic background of a neighborhood's inhabitants is more immediately visible than their labor market status. We might accordingly speculate that individuals are more likely to rely on experiential sources of information on issues for which local context characteristics are more immediately visible. This heterogeneity across different characteristics of contexts is an interesting avenue for future research.

Second, the inconsistency of the findings in Section 3.3 stand in contrast to the clarity of the pattern found in Section 3.1: viewed jointly, the findings suggest that individuals hold strong views about what characterizes good vs. bad areas on average – i.e., high levels of ethnic diversity and unemployment – and that these views cut across ideological divisions. Considering that particularly immigration is a highly polarizing political issue at the national level, this extent of cross-ideological agreement is striking. It suggests that political polarization may be less prevalent for more local, experientially grounded issues. This link between the geographical scale of political issues and their degree of ideological polarization is another important topic for future research.

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A Appendix

A.1 Question wording for attitude indices

Table 6: Question wordings in the map-drawing task

Index	Items	Scale
Anti-immigration	*Would you say it is generally bad or good for Denmark's economy that people come to live here from non-western countries?*	0-10
	Would you say that Denmark's cultural life is generally undermined or enriched by people coming to live here from non-western countries?	0-10
	Would you say that crime problems are made worse or better by people coming to live here from non-western countries?	0-10
Economic conservatism	*Many unemployed people do not actually want a job*	1-5
	Income differences in Denmark are too large (rev.)	1-5
	The government should take measures to reduce income differences (rev.)	1-5
	Government should spend less on benefits for poor people	1-5

A.2 Ease of identifying bad areas and political attitudes

Table 7 shows models predicting whether respondents find it easy to think of a bad area nearby.

Table 7: Predictors of ease of thinking of bad area nearby (logit)

	Easy to think of bad area		
	(1)	(2)	(3)
Anti-imm.	1.028***		0.889***
	(0.208)		(0.230)
Econ. conservatism		0.723***	0.331
		(0.214)	(0.238)
Age	0.002	0.006**	0.003
	(0.003)	(0.003)	(0.003)
Gender (m)	0.115	0.131	0.103
	(0.089)	(0.088)	(0.089)
Education (yrs)	0.028	0.016	0.027
	(0.019)	(0.018)	(0.019)
Income (100k DKK)	0.062*	0.048	0.055*
	(0.033)	(0.032)	(0.033)
Area ED	−0.692**	−0.372	−0.754**
	(0.314)	(0.297)	(0.319)
N	2,374	2,400	2,366
Log Likelihood	−1,526.612	−1,548.457	−1,519.953
AIC	3,065.225	3,108.914	3,053.907

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Area ethnic diversity (measured as the ethnic diversity of a circle drawn around the respondents' subjective context) is positively associated, such that respondents living among higher numbers of non-western immigrants and descendants find it easier to think of a bad area nearby.

But even conditional on contexts, individuals who are more anti-immigration find it easier to think of a bad area nearby. This finding ties neatly into the literature on political conservatism and negativity bias (e.g., Oxley et al., 2008; Hibbing et al., 2014).