Consumption Peer Effects and Utility Needs in India

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September 2021

Abstract

We construct a peer effects model where mean expenditures of consumers in one's peer group affect utility through perceived consumption needs. We provide a novel method for obtaining identification in social interactions models like ours, using ordinary survey data, where very few members of each peer group are observed. We implement the model using standard household-level consumer expenditure survey microdata from India. We find that each additional rupee spent by one's peers increases perceived needs, and thereby reduces one's utility, by the equivalent of a 0.25 rupee decrease in one's own expenditures. These peer costs may be larger for richer households, meaning transfers from rich to poor could improve even inequality-neutral social welfare, by reducing peer consumption externalities. We show welfare gains of billions of dollars per year might be possible by replacing government transfers of private goods to households with providing public goods or services, to reduce peer effects.

We thank Chris Muris and Niharika Singh for comments on this work. We also thank seminar participants

by governments all over the world. As a result, we cannot make use of network information or variation in peer group sizes (as in Lee 2007) to obtain identification.

We estimate our model using consumption survey data from India.[1] Our groups are de-

tion for identification, but we cannot. Examples of such network information include the use of exogenous variation in group composition or size (e.g., Lee 2007; Carrell, Fullerton and West 2009; and Duflo, Dupas and Kremer 2011), or the use of detailed network structure like intransitive triads, where data on friends of friends provides instruments for identifica-

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identifies comparable structural parameters obtained from utility-derived demand functions via revealed preference.

A number of papers relate consumption choices to peer consumption levels, although these analyses are essentially nonstructural (Chao and Schor 1998, Boneva 2013, de Giorgi, Frederiksen and Pistaferri, 2016). All these papers suggest that the magnitudes of peer effects in consumption choices are large. In our notation, these papers use empirical approaches analogous to regressing q_i on x_i and $\overline{q}_g$. However, establishing how much consumption q_i changes when peer consumption $\overline{q}_g$ changes does not answer the welfare question of how $\overline{q}_g$ affects utility, and hence how much one would need to increase x_i to compensate for the loss of utility from an increase in $\overline{q}_g$. Answering this type of welfare question requires linking expenditures to utility, which is what our structural model does.

2.1 The Utility-Derived Demand Model

Our model is that each consumer, indexed by i, is a member of a peer group, indexed by g. Note that g should have a subscript i, denoting the particular group that contains consumer i, but we drop this subscript to avoid notational clutter. Let q_i be the vector of (continuous) quantities of goods that consumer i consumes. Utility is given by $U_i = U(q_i \quad f_i)$, where U_i is the attained utility level of consumer i, U is a utility function (ignoring taste heterogeneity for now), and f_i

One can equivalently represent preferences using an indirect utility function, defined as the maximum utility attainable with a given budget x_i when facing prices p. Gorman (1976) shows[6] that for any regular utility function in this form, there exists a corresponding indirect utility function V such that

$$U_i = V\left(p, x_i - p'f(z_i, \overline{q}_g)\right). \tag{2}$$

Indirect utility functions of this form can be shown to have many desirable properties for welfare calculations.[7] Blackorby and Donaldson (1994) and Donaldson and Pendakur (2006) show that the function f (without $\overline{q}_g$) is uniquely identified up to location from consumer demand functions. We show later that we can also uniquely identify how f depends on $\overline{q}_g$.

Luttmer (2005) regresses a self-reported measure of happiness on z_i, y_i, and $\tilde{y}_g$ (where for Luttmer, y_i is the income of consumer i, and $\tilde{y}_g$ is the observed within-group average income). We can interpret his regression as a simplified and linearized version of equation (2), where self-reported happiness is assumed to proxy for U_i, income y_i replaces x_i, and all the effects of $\overline{q}_g$ are subsumed by $\tilde{y}_g$. Table 1 (column 3) in Luttmer (2005) gives endogeneity-corrected estimates of the coefficients of $\tilde{y}_g$ and y_i of -0.296 and 0.361, respectively. The negative ratio of these is 0.82, meaning that a 100 dollar increase in group-average income has the same effect on reported happiness as an 82 dollar reduction in own-income. We later estimate an object that has a comparable interpretation to this relative coefficient. But instead of assuming that U_i equals an observed happiness measure that can be compared across individuals and regressed on covariates, we let U_i be unobserved. We instead derive demand equations from equation (2), and then recover the implied peer effects on utility.

The demand functions that result from maximizing our utility function can be obtained by applying Roy's (1947) identity to the indirect utility function of equation (2). These demand functions have the form $q_i = h(p, x - p'f_i) + f_i$, where $f_i = f(z_i,$

where v_g is a J

we assume

$$V(p;x) = \quad (x \quad R(p))^{1} \; B(p) \quad D(p) \tag{6}$$

for some di erentiable functions R, B and D geographically. In the Appendix we derive results at this added level of generality, including t subscripts for time and price regimes.

As is standard in the estimation of continuous demand systems, we only need to estimate the model for goods $j = 1; :::; J \quad 1$. The parameters for the last good J are then obtained from the adding up identity that $q_{Ji} = \quad x_i \; x$

tion, ε_{gi} is given by

$$\varepsilon_{gi} = \left(\bar{y}_g^2 - \hat{y}_g^2\right) a^2 d + 2\left(\bar{y}_g - \hat{y}_g\right) x_i abd + \left(\bar{y}_g - \hat{y}_g\right) a. \tag{14}$$

Inspection of equations (13) and (14) shows many of the obstacles to identifying and estimating the model parameters a, b, and d. First, with either fixed or random effects, v_g could be correlated with $\hat{y}_g$. Second, since n_g does not go to infinity, if $\hat{y}_g$ contains y_i then $\hat{y}_g$ will correlate with u_i. Third, again because n_g is fixed, ε_{gi} doesn't vanish asymptotically, and is by construction correlated with functions of $\hat{y}_g$ and x_i. We can think of $\bar{y}$

instrument for by

using GMM with instruments r_{gii^0}, and then recovering the parameters a, b, and d from the estimated coe cients. By construction, the errors in this model are correlated across the pairs of individuals within each group, so we must cluster standard errors at the group level to obtain proper inference.

Theorem 1 in Appendix A.2 describes these results formally, including extending this model to allow for vector x_i

However, we repeat this construction for every individual i' (other than i) in the group, and use the GMM estimator to combine the resulting moments over all individuals i' in g, thereby once again exploiting all of the information in the group. With this replacement, equation (19) becomes

$$y_i = \hat{y}_{g,-ii'} y_{i'} a^2 d + (a + 2x_i abd)\hat{y}_{g,-ii'} + \left(x_i b + x_i^2 b^2 d\right) + v_g + u_i + \tilde{e}_{gii'};$$

where by construction the error $\tilde{e}_{gii'}$ has the form

$$\tilde{e}_{gii'} = \left(\bar{y}_g^2 - \hat{y}_{g,-ii'} y_{i'}\right) a^2 d + (a + 2x_i abd)\left(\bar{y}_g - \hat{y}_{g,-ii'}\right)$$

In Appendix A.4 we show that $E(\tilde{e}_{gii'} | x_i; r_g) = -da^2 Var(v_g)$ and so equals a constant. Our constructions in estimating the group mean eliminates correlation of the error $\tilde{e}_{gii'}$ with x_i. But $\tilde{e}_{gii'}$ still does not have conditional mean zero, because both $\hat{y}_{g,-ii'}$ and $y_{i'}$ contain v_g, so the mean of the product of $\hat{y}_{g,-ii'}$ and $y_{i'}$ includes the variance of v_g.

It follows from these derivations that

$$E\left[y_i - \hat{y}_{g,-ii'} y_{i'} a^2 d - (a + 2x_i abd)\hat{y}_{g,-ii'} - \left(x_i b + x_i^2 b^2 d\right) - v_0 \mid x_i; r_g\right] = 0; \tag{20}$$

where $v_0 = E(v_g) - da^2 Var(v_g)$ is a constant to be estimated along with the other parameters, and r_g are the same group level instruments we defined earlier. Letting r_{gi} be functions of x_i and r_g (such as x_i, r_g, x_i^2, and x_i

Appendix A.4 provides the formal proof of identification and associated GMM estimation for the random effects generic model as discussed above (and for the extension to multiple equations), and Appendix A.6 proves that this identification and estimation extends to our full utility-derived demand model with random effects.

4 Empirical Results

4.1 Data

For our main empirical analysis, we use household consumption data from the 61st round of the National Sample Survey (NSS) of India, which was conducted from July 2004 to June 2005. This survey contains information on household demographics and spending for a representative sample of the country.

To define appropriate peer groups, we exploit a property of multi-stage sampling, which is a standard feature of the NSS and other consumption surveys. To cut down on surveying costs, consumers are sampled from small geographic areas like villages and neighborhoods. These areas are particularly small and relevant in urban areas, where they're constructed to be compact and bounded by well-defined, clear-cut natural boundaries whenever possible, and so generally correspond to recognizable neighborhoods (NSS, 2019). Households in the same neighborhood are likely to be similar to each other in observable and unobservable ways because of assortative geographic selection, and are likely to be in at least indirect contact. This makes them appropriate candidates for defining our groups, and crucially are available as a byproduct of the sampling design in many consumption surveys.

We restrict our attention to urban households, where the geographic sampling areas are particularly small. Each sub-block, the smallest geographic unit available in the data, has a population of roughly 150 to 400 households. In each sub-block in our data, up to 10 households are sampled. We call this level of geography the neighbourhood. To reflect the fact that much social activity is within religion and caste groups, we interact the neighborhoods with indicators of religion (Hindu or not) and caste (NSS scheduled caste/tribe or not). We refer to these groups defined by neighborhood, religion, and caste as neighborhood-subcastes, and use them as the peer groups in our analysis.[14]

Our sample includes all urban households in groups where we observe at least three households, the minimum required for our method of identification and estimation. To avoid expenditure outliers, we include only households that are between the 1st and 99th percentiles

[14] The NSS contains information on whether the household is in a scheduled caste or tribe, but not the exact subcaste. However, since subcastes are typically geographically concentrated, we expect that the neighborhood-religion-scheduled caste groups will mostly capture subcastes as well.

of household expenditure in each state. We also restrict our sample to households with 12 or fewer members, whose head is aged 20 or more. Together, these restrictions drop roughly 4% of the sample.

Table 1 shows summary statistics for our sample. The number of observed households in each group averages around 5 (with a range from 3 to 10), which is a small share of the several hundred households that comprise each group in the population. These small within group samples illustrate the importance of showing identi cation and consistent estimation without assuming that many of the members of each group are observed.

For our main sample, we have a total of 4,599 distinct groups, and 24,757 distinct house-

Our fixed-effects approach involves substituting the leave-two-out within-group sample average quantity $\hat{q}_{gj;-ii'}$ for the within-group mean $\bar{q}_{gj}$, and differencing across people within groups. Thus, we substitute $\hat{q}_{gj;-ii'}$ for $\bar{q}_{gj}$ in the definition of X_i (eq. (10)) to create $\tilde{X}_i$ as

$$\tilde{X}_i = x_i - R_{11}p_{1g} - R_{22}p_{2g} - (A_{11}\hat{q}_{g1;-ii'} + C_1'z_i)\,p_{1g} - (A_{22}\hat{q}_{g2;-ii'} + C_2'z_i)\,p_{2g},$$

and substitute $\hat{q}_{gj;-ii'}$ for $\bar{q}_{gj}$ and $\tilde{X}_i$ for X_i in the demand equation (11). Then, we difference the demand equation across individuals within groups to generate a moment condition analogous to (18):

$$E[(p_{1g}q_{1i} - p_{1g}q_{1i'} - (\tilde{X}_i^2 - \tilde{X}_{i'}^2)e^{(b_1 \ln p_{1g} + (1-b_1)\ln p_{2g})}d_1 - (\tilde{X}_i - \tilde{X}_{i'})b_1 + C_1'p_{1g}(z_i - z_{i'}))r_{gii'}] = 0. \quad (22)$$

Notice that, as in the generic model, many group-varying terms, including $A_{11}p_{1g}\bar{q}_{g1}$, drop out as a result of this differencing. Further, since $\tilde{X}_i - \tilde{X}_{i'} = x_i - x_{i'} - C_1'(z_i - z_{i'})\,p_{1g} - C_2'(z_i - z_{i'})\,p_{2g}$, such variables are present only in the quadratic term $\tilde{X}_i^2 - \tilde{X}_{i'}^2$ via interactions between group-average quantities $\bar{q}_{g1}$ and other elements of $\tilde{X}_i$ (e.g., x_i). The formal derivation of these moments for GMM estimation is given in Appendix A.5.

Our random-effects approach, derived in Appendix A.6, involves substituting the within-group sample average quantity and another group member's quantity for the within-group means. We use the above definition of $\tilde{X}_i$

Let $\tilde{z}_i$ and $\tilde{z}_g$ be, respectively, the individually-varying and group-level subvectors of z_i. In our baseline model, $\tilde{z}_i$ includes all covariates; however, when we consider additional heterogeneity in peer effects, we will additionally include group-level covariates in $\tilde{z}_g$. Letting denote element-wise multiplication, our complete instrument list for the fixed-effects model is:

$$r_{gii^0} = \ x_i^2 \quad x_{i^0}^2 \ ; (x_i \quad x_{i^0}) \ (1; p_g \ q_g; p_g \ \tilde{z}_g) ; p_g \ (\tilde{z}_i \quad \tilde{z}_{i^0}) \ (1; p_g \ q_g) ; x_i p_g \ (\tilde{z}_i \quad \tilde{z}_{i^0}) :$$

Our instrument list for the random-effects model is:

$$r_{gi} = (1; p_g; p_g \ q_g; p_g \ z_i) ; x_i \ (1; p_g; x_{it} ; p_g \ q_g; p_t \ z_{ig}) ; p_g \ p_g:$$

The last term provides instruments for v_0 in equation (20).

Our primary focus is on the peer effects given by elements of the matrix A. We start with the simplest and most interpretable version of this structural model, where $A = aI_J$ is a diagonal matrix with the scalar a replicated in each element of the main diagonal. In this specification, an increase in the group-average food quantity of increases needs for food by a , and an increase in the group-average non-food quantity of increases needs for non-food nondurables by the same a . Also, having A be diagonal means that group-average food quantities have no effect on needs for non-food nondurables (and vice versa). We relax these restrictions later.

In this restricted version of the model, the welfare implications of peer effects simplify. Needs are given by $f_i = A\overline{q}_g + Cz_i$ and group-average expenditure is given by $\overline{x}_g = p^0\overline{q}_g$, so when $A = aI_J$, the cost of needs, p^0f_i, simplifies to $p^0f_i = a\overline{x}_g + p^0Cz_i$. Consequently, the scalar a equals the increase in the rupee cost of needs, p^0f_i, of a one rupee increase in group-average expenditure $\overline{x}_g$.

4.4 Baseline Estimates and Alternative Group Sizes

Table 2 gives estimates of the scalar a. In our baseline model, groups are defined by neighborhood-subcastes, that is, a group is people who live in the same neighborhood, are of the same religion (either Hindu or not), and are of the same caste status (either scheduled caste or not). For comparison, we also consider two larger group sizes: people who live in the same neighborhood regardless of religion and caste, and people who live in the same district regardless of religion and caste.

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of our instrument vector. This dimension reduction is needed for feasibility of our GMM estimator, because q_g is multiplied by the demographic controls to generate the final instrument vector.

Note that neighborhoods have populations of roughly 150 to 400 households, of which at most 10 are observed in our sample. Districts are much larger than neighborhoods, with populations of roughly 500,000 to 3,000,000 households. In our data, we observe 5.4 households from the average neighborhood-subcaste, while with the larger group definitions we average 6.9 and 53.1 observed households per group, respectively.

We report results for two samples. The upper half of Table 2 (Panel A) uses all the data available for each of the three group definitions, and so ends up with somewhat different samples for each. Panel B holds the sample constant across the group definitions, using only the observations from our baseline model (the smallest group definition).

Table 2 reports both random effects (RE) and fixed effects (FE) estimates of the scalar a, for all three group sizes. Columns (1) to (3) give RE, Columns (4) to (6) give FE, and columns (7) to (9) give the difference RE minus FE.

A key implementation question is how to define our groups. If we define them at too large a level, we should expect the estimated peer effects to be biased towards zero, because our estimate of group consumption $\bar{c}_{gj;-ii'}$ will be mismeasured by including consumption from non-peers. We should similarly expect the significance level of the estimates to fall if the defined groups are too large. In contrast, if we define our groups at too small a level, the estimator will likely be consistent but inefficient, because although we are grouping only households that do indeed have peer effects on each other, in each group we will be leaving out some informative peers who were placed in another group.

For both RE and FE, we find that the larger group sizes have estimates that are closer to zero and have lower t statistics than our baseline, suggesting that our baseline groups, while quite small, are the most appropriate size (the largest group size FE estimate actually flips sign to negative, but is not statistically significant). We therefore focus our remaining analyses on the baseline neighborhood-subcaste group definition, reported in columns (3) and (6), and the difference between them in column (9).[18]

As expected, the RE estimates have far lower standard errors than the FE estimates, because they are based on much stronger assumptions, and do not lose information from differencing. The RE point estimate of 0.606 in column (3) also turns out to be much larger than the FE estimate of 0.266 in column (6), and we reject equality of the coefficients (column (9)).

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Random effects imposes strong restrictions on unobserved heterogeneity that may not be valid, and that fixed effects do not impose, potentially biasing the RE estimates. In particular, our estimated positive difference between RE and FE estimates is consistent with group-level preferences for food consumption v_{gj} being correlated with group expenditure levels, causing upward bias in the RE peer effects estimates. This is easiest to see in a simplified version of equation (13). Suppose that the true model was linear (so $d = 0$), and we instrumented for $\hat{y}_g$ only with other-period group consumption $\hat{x}_{g;-t}$. Then, positive correlation between group expenditure and group tastes (conditional on x_i) would result in upwards bias in the estimated peer effects for normal goods like food.

In applications like ours where RE has much lower variance than FW (as indicated by standard errors) and is likely to be biased, to reduce mean squared errors it is common to employ shrinkage estimators. These are constructed as weighted averages of RE and FE estimates, trading off the bias of RE with the higher variance of FE (a recent example is Armstrong, Kolesar, and Plagborg-Møller 2020). We report both the RE and FE estimates in our remaining empirical analyses, so one may implement such shrinkage if desired. However, for simplicity in our later policy discussions, we will focus on the smaller FE coefficients

4.5 Measurement Error in Group Means

The neighborhood-subcaste groups in our baseline analysis each have between 3 and 10 observed households, out of an average of around 200 households in the population. This suggests that the group mean measurement errors $\hat{q}_{gj} \quad \bar{q}_{gj}$ are likely to be substantial. Much would be consistent in the absence of measurement error, we can form a Hausman test to compare the estimators, and the uncorrected estimators are rejected.

The direction and size of bias is di erent for the FE estimator. Here, at all three group sizes, the uncorrected estimates are about twice as large as the corrected, suggesting a signi cant impact of nonlinearity and di erencing on the size and direction of bias in the FE models. As with the RE models, the uncorrected FE estimates have smaller standard errors than the corrected estimates, and Hausman tests reject the uncorrected estimates. We conclude that our corrections for measurement errors due to small within group sample sizes are empirically justi ed and important.

4.6 Alternative Speci cations and Robustness Checks

4.6.1 Peer e ects by demographic groups

In Tables 2 and 3, the peer e ect parameter a indicator, defined to equal to 1 if the household head has at least high school education and zero otherwise. Here the FE and RE models disagree, with the FE model showing the more educated households having larger peer effects, while the RE model shows the opposite.

Particularly when focusing on the FE estimates, our estimated peer effects are larger for higher socio{economic status groups. A possible explanation is that the poorest households in India are close enough to subsistence that it is more costly to engage in status competitions. This is similar to Akay and Martinsson's (2011) finding for very poor Ethiopians.

4.6.2 Cross Group Peer Effects

Our baseline estimates allow only for within-group consumption peer effects. However, conceptually, it is possible that needs could depend on consumption levels of other \nearby" peer groups. Our baseline grouping structure is neighbourhood-subcaste, so that in a given neighbourhood, there could be several groups defined by varying religion and caste. In this subsection, we consider the possibility that peer effects may be relevant between groups, and that, in particular, needs may be \upward-looking" or aspirational, in the sense that perceived needs are affected by the consumption behaviour of our betters in the social hierarchy. We operationalize this by focusing on a subset of 564 groups that are low-caste

4.6.3 Peer E ects with Alternative Speci cations of the A Matrix

Next, Table 6 considers what happens when we relax the restriction that A opposite signs and greatly increased standard errors, and even more extreme estimates in column (4) where all four elements of A have impossibly large magnitudes and varying signs. These are all common hallmarks of substantial positive multicollinearity.

We should expect that the multicollinearity issues among the $p_j \bar{q}_{kg}$ terms would be much more severe in the FE model, and not just because it is based on a weaker set of assumptions. The identification of A in the FE estimator comes only from interaction terms between each $p_j \bar{q}_{kg}$ and the budget x_i. This is due to the fact that the level terms for each $p_j \bar{q}_{kg}$ get differenced away. In contrast, the identifying variation for A in the RE estimator comes from both the level terms $p_j \bar{q}_{kg}$ and their interactions with x_i.

We take from these results that the multicollinearity of group-average expenditures is too severe in our data to get trustworthy estimates of variation in the elements of A in our preferred fixed effect specification, however, our baseline restriction $A = aI_J$ appears to be reasonable and adequate.

4.6.4 A Three Goods Model

All the models presented so far have been demand systems with $J = 2$ goods (food and non-food). When $J = 2$, we only need to estimate a single demand equation (since the other is determined by the restriction that consumers exhaust their budget). However, our theorems show identification of peer effect parameters in demand systems where J is any number of goods. In Table 7, we present estimates of a $J = 3$ equation demand model, having two equations we need to estimate. The 3 goods are taken to be food, fuel and other nondurable goods. The former non-food category is now divided into fuel and other, so total expenditures x_i for each household remains the same as before.

We report estimates for the RE and FE models, with an unrestricted diagonal A matrix in columns (1) and (3) of Table 7, and with the restriction that $A = aI_J$ in columns (2) and (4). As before, groups are defined at the neighborhood-subcaste level.

In the RE models, a in column (2) and the varying diagonal elements of A in column (1) are all significant and larger than before, ranging from 0.740 to 0.938. Since adding more goods should not increase the magnitude of the overall peer effects, we take this as additional evidence that the restrictions imposed by the RE model may not hold, and are likely inducing an upward bias. We also perform a Hausman test of the RE model against two goods baseline model. We take this as additional evidence in favor of the FE model with $A = aI_J$.

4.6.5 Alternative Classifications of Goods

Previous research on peer effects in consumption has emphasized the possibility that such

Note that "visible" is dominated by food (because food-at-home and food-out together make up the single-largest expenditure component, and all food expenditures are classified as visible expenditures), whereas "luxury" and "visible luxury" are dominated by food-out. For the FE models, the point-estimates for "visible" are (not surprisingly) similar to our baseline based on food. Models based on "luxury" or "visible luxury" give point-estimates of a that are larger than those for "visible". The most precisely estimated of these FE models is that which contrasts visible to invisible expenditures. Here, the point-estimate of a is 0:418, with an estimated standard error of 0:115. This is roughly one standard error above our baseline estimate of 0:266.

We draw three conclusions from these alternative specifications of the classification of goods. First, the demand system we choose to estimate does make a difference when it comes to the magnitude of the estimated peer effect. Second, even with these quite different classifications of goods, we find large and statistically significant peer effects for all of them. Third, given the large estimated standard errors for FE models, the general picture we obtain is similar between the baseline specification and these alternatives. Overall, our baseline FE model appears to give a conservative significant estimate of peer effects at a = 0:266.

4.7 Are Peer Expenditures Really Negative Externalities?

Our findings suggest that higher peer expenditures makes consumers behave, at the margin, as if they were poorer. We take this to mean that, in a welfare sense, they feel poorer. While peer expenditures may in theory have both positive and negative effects, our quintiles. Since the same granular geographic identifiers are not available in the WVS, we define groups using the intersection of state and religion, and identify average expenditure for each group using the NSS data.

Interpreting ordinal self-reported well-being as a crude measure of utility, we regress this self-reported well-being on one's own income bin and on the average expenditure in one's group. The results are reported in Table A2 in the Appendix. We find that the resulting coefficient estimates have signs that are consistent with our theory: higher income increases self reported well being, but higher group expenditure decreases it. A 1,000 rupee increase in peer group expenditure (relative to a mean of 5,554, with standard deviation of 2,580) decreases self reported well being by 15% of a standard deviation, which is in line with the welfare effects we found using our structural model.[23] As we discuss in Appendix B.2, these effects of peer expenditure are similar throughout the distribution of own income, consistent with our linear index structure for peer effects.

5 Implications for Tax and Transfers Policy

Our finding that perceived needs rise with peer group average consumption has significant implications for policies regarding redistribution, transfer systems, public goods provision, and economic growth. In this section we provide some crude, back of the envelope calculations that illustrate the rough magnitudes that our estimated peer effects have on policy questions.

Our model is one where consumption has negative externalities on one's peers. Boskin and Shoshenski (1978) consider optimal redistribution policies in models with general consumption externalities. They show that distortions due to negative externalities from consumption onto utility can generally be corrected by optimal taxation. In particular, their results imply that negative consumption externalities make the marginal cost of public funds lower than it would otherwise be. Here we apply the same logic to our estimated consumption peer effects, and in particular show how large free lunch gains may be possible.

A potentially peculiar attribute of our model is that it could be social welfare improving

[23] In principle, one could use self reported well being data to estimate a, the effect of peer expenditure in money-metric terms. There are three issues with this approach. First, self reported well being is generally crudely measured and may not be interpersonally comparable. Second, few if any existing datasets record both consumption and self reported well being. Third, this approach (as well as that of other papers in the literature, such as Luttmer (2005), that apply this approach) relies on a random-effects assumption that expenditures are uncorrelated with other determinants of self reported well being. A key advantage of our utility-derived demand model is that the FE approach allows identification even when group preferences are correlated with group expenditures. Given these issues, we take the self reported well being results here

to transfer income from someone with poor peers to someone else of equal income who has rich peers. This is not a specific feature of our model; similar implications can arise as long as peer spending negatively affects individual utility. As a practical matter, we rule out such transfers, by only considering tax and transfer programs that are based on personal income rather than peer group membership. Many of our conclusions then follow from the observation that the demographics that determine peer group membership (e.g., education and neighborhoods) strongly correlate with income. So, e.g., transfers from high to low income households will on average transfer resources from higher socio-economic status groups to lower status groups.

As discussed in Section 2, the sum (over households) of income minus the sum of spending on needs (as we define them) is a valid money-metric social welfare index. This means that if needs go down, all else equal, social welfare goes up. Consider the money metric costs in lost utility of, say, an across-the-board tax increase. This tax increase lowers average expenditures by households, which in turn lowers perceived needs, thereby offsetting some of the utility that was lost by having to pay the tax.

For simplicity, round our conservative baseline estimate of $a = 0.266$ to $1/4$. Suppose you experience a 4 rupee tax increase, and for simplicity let your marginal propensity to consume be 100%. If your peers also have their taxes increase by the same amount, then your loss in utility will only be equivalent to that of a 3 rupee tax increase. The reason is that although your net income, and therefore expenditure, will have dropped by 4 rupees, so will have that of your peers. Consequently, your needs will have dropped by $1/4 \times 4 = 1$ rupee, so that your net loss in money-metric utility is only 3 rupees.

However, to fully evaluate the effect of this tax increase, we must also consider potential peer effects in how the government uses the additional tax revenue. If the money is transferred to other groups of consumers who also have peer effect spillovers of $a = 1/4$, then the welfare gains from reduced expenditures on needs by the taxed consumers will be offset by the welfare losses associated with increased perceived needs by the recipients of those transfers.

There are two ways we can reduce or eliminate these offsetting welfare losses, thereby exploiting the potential free lunch associated with the reduced perceived needs from taxing peers. One way is to transfer the tax revenues to individuals in groups that have smaller peer effects, and the other could be to spend the tax revenue on public goods or government services.

We found some evidence that the size of the peer effects may be smaller for poorer and less educated groups than for other consumers. If so, then transfers from higher income to lower income individuals will lead to an overall increase in social welfare, by reducing the total negative consumption externalities of peer e ects. This is true even with an inequality-neutral

more rupees (say, because of a tax cut) is the same as the increase in utility you would get from spending only 100 26 = 74 more rupees if no one else in your peer group increased their spending.

These results can at least partly explain the Easterlin (1974) paradox, in that income growth over time, which increases people's consumption budgets, results in lower utility growth than is implied by standard demand models that ignore peer e ects.

These results also suggest that income or consumption taxes can have far lower negative e ects on consumer welfare than are implied by standard models. This is because a tax that reduces my expenditures by 100 rupees will, if applied to everyone in my peer group, have the same e ect on my utility as a tax of only 74 rupees that ignores the peer e ects. This implies that about a fourth of the money people might get back from an across the board tax cut doesn't increase utility, but instead is spent on increased perceived needs due to peer e ects. The larger these peer e ects are, the smaller are the welfare gains associated with tax cuts or mean income growth. We show this is particularly true to the extent that taxes are used to provide public goods or government services (that are less likely to induce peer e ects themselves) rather than transfers.

We provide some calculations showing that the magnitudes of these peer e ects on social welfare calculations, which are ignored by standard models of government tax and spending policies, can be very large. For example, we nd potential welfare gains of hundreds of billions of rupees could be available in just a single existing government transfer program in India. We nd similarly that the welfare gains in transfers from richer to poorer households (and more generally from progressive vs at taxes) may be much larger than previously thought, to the extent that poorer households do indeed have smaller peer e ects than richer households.

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7 Tables

Table 1: Summary statistics for consumption data

Table 2: Estimated peer e ects by group de nition

	RE			FE			Di erence		
	District (1)	Neighborhood (2)	Neighbor-hood-caste (3)	District (4)	Neighborhood (5)	Neighbor-hood-caste (6)	District (7)	Neighborhood (8)	Neighbor-hood-caste (9)
Panel A: All data									
A (group consumption)	0.334	0.558	0.606	-0.228	0.088	0.266	0.562	0.470	0.341
	(0.044)	(0.036)	(0.036)	(0.138)	(0.121)	(0.119)	(0.131)	(0.115)	(0.114)
J overid stat	14138.36	1264.97	653.76	22426.79	2130.89	1305.88			
p-value	0.000	0.000	0.000	0.000	0.000	0.000			
N pairs	3,761,688	195,282	128,640	3,761,688	195,282	128,640	3,761,688	195,282	128,640
N households	30,184	29,462	24,757	30,184	29,462	24,757	30,184	29,462	24,757
N groups	568	4,282	4,599	568	4,282	4,599	568	4,282	4,599
Average group size	53.14	6.88	5.38	53.14	6.88	5.38	53.14	6.88	5.38

Table 3: Estimated peer e ects by measurement error correction

	RE			FE		
	District	Neighborhood	Neighbor-hood-caste	District	Neighborhood	Neighbor-hood-caste
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Naive (no correction)						
A (group consumption)	0.143	0.038	0.054	0.470	0.559	0.529
	(0.031)	(0.017)	(0.016)	(0.215)	(0.089)	(0.090)
J overid stat	11354.53	1340.51	1013.93	17386.44	1651.41	1300.67
p-value	0.000	0.000	0.000	0.000	0.000	0.000
N pairs	2,564,578	150,184	128,640	2,564,578	150,184	128,640
N households	24,757	24,757	24,757	24,757	24,757	24,757
N peer groups	564	3,941	4,599	564	3,941	4,599
Average group size	43.90	6.28	5.38	43.90	6.28	5.38

Panel B: BaselineE68 66150,1868 66150,18.1d [t757

Table 4: Peer e ects by demographic group

	RE				FE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.606	0.606	0.600	0.694	0.266	0.255	0.078	0.145
	(0.036)	(0.035)	(0.057)	(0.041)	(0.119)	(0.121)	(0.125)	(0.143)
Scheduled non-Hindu		0.168				0.130		
		(0.066)				(0.237)		
Scheduled Hindu		0.247				-0.285		
		(0.087)				(0.330)		
Non-scheduled non-Hindu		0.179				-0.075		
		(0.055)				(0.153)		
Owns land			0.031				0.446	
			(0.054)				(0.136)	
High school or greater				-0.186				0.454
				(0.057)				(0.163)
p-value heterogeneity		0.00	0.56	0.00		0.68	0.00	0.01

Table 5: Peer e ects of own-group and out-group spending

	RE		FE	
	(1) Own-group	(2) Upper caste	(3) Own-group	(4) Upper caste
A (group consumption)	0.802	0.052	0.445	0.011
	(0.070)	(0.039)	(0.138)	(0.302)
Number of pairs	8,962	8,962	8,962	8,962
Number of groups	564	564	564	564

Dependent variable is household food spending. Individual controls include household size, age, marital status and amount of land owned. All models include price controls. Analysis Own85.998(o)27m0eest5.9tedn85.99trn0 1 -m0eestc85.998(mo)9890Itwned..rice con-6Tidual3trols. Analys385.998(consls)-414.con

Table 6: Peer effects by A matrix specification

	RE			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
A (group food on food consumption)	0.411	0.639	0.606	9.741	2.228	0.266
	(0.171)	(0.036)	(0.036)	(2.066)	(0.382)	(0.119)
A (group non-food on non-food consumption)	0.452	0.572	0.606	5.400	-0.911	0.266
	(0.171)	(0.034)	(0.036)	(1.577)	(0.276)	(0.119)
A (group food on own non-food consumption)	-0.397			-7.695		
	(0.275)			(1.828)		
A (group non-food on own food consumption)	-0.095			-6.383		
	(0.102)			(1.860)		
p-value equality	0.896	0.001		0.000	0.000	
p-value diagonal	0.002			0.000		
N pairs	128,640	128,640	128,640	128,640	128,640	128,640
N households	24,757	24,757	24,757	24,757	24,757	24,757
N peer groups	4,599	4,599	4,599	4,599	4,599	4,599

Selected estimates for structural demand model, Controls include household size, age, marital status, land owned, ration card indicator, education, religion, and group size. Standard errors clustered at the district level. $p < 0.05$, $p < 0.01$

Table 7: Estimated peer e ects in a three-good demand system

	RE		FE	
	(1)	(2)	(3)	(4)
A (group food on food consumption)	0.848	0.932	2.393	0.296
	(0.023)	(0.014)	(0.426)	(0.100)
A (group fuel on own fuel consumption)	0.938	0.932	2.820	0.296
	(0.018)	(0.014)	(0.913)	(0.100)
A (group other on own other consumption)	0.740	0.932	-1.387	0.296
	(0.023)	(0.014)	(0.334)	(0.100)
Hausman H			42.151	41.701
p-value			0.00	0.00
p-value equality	0.000		0.000	
N pairs	128,640	128,640	128,640	128,640

Table 8: Peer e ects in spending, by consumption categorizations

	RE			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
	Lux	Visible	Vis. lux	Lux	Visible	Vis. lux
A (group consumption)	0.546	0.401	0.581	0.758	0.418	0.654
	(0.079)	(0.084)	(0.132)	(0.207)	(0.115)	(0.132)
Number of pairs	128,974	128,974	128,974	128,974	128,974	128,974

Appendix for Consumption Peer Effects and Utility Needs in India

Arthur Lewbel, Samuel Norris, Krishna Pendakur, and Xi Qu

Appendix A: Derivations

A.1 Peer Effects as a Game

The interactions of peer group members may be interpreted as a game. We assume that group members have utility functions that depend on peers only through the true mean of the peer group's outcomes. More precisely, what we are assuming is that there is an underlying distribution of the (infinite) population of potential group members. Everyone who is actually in the group in the real world population is a draw from this underlying potential population. Each individual in the group knows the true mean of this distribution that individuals are drawn from, and bases their behavior on that true mean. This model implies that the individual's own choice has zero effect on the group mean[1].

If group members observe each other's private information and make decisions simultaneously (corresponding to a complete information game), then we assume that each individual's actual behavior will only depend on others through the group mean. Estimation of complete games typically depends on having data on all members of each observed group. An

A.2 Generic Model Identification and Estimation With Fixed Effects

Let y_i denote an outcome and x_i denote a K vector of regressors x_{ki} for an individual i. Let $i \in g$ denote that the individual i belongs to group g. For each group g; assume we observe $n_g = \sum_{i \in g} 1$ individuals, where n_g is a small fixed number which does not go to infinity. Let $\bar{y}_g = E(y_i \mid i \in g)$, $\bar{y}_{g;ii^0} = \sum_{l \in g; l \neq i; i^0}$ fects

=

We assume that the number of groups G

Taking the within group expected value of this expression gives

$$\bar{y}_g = \bar{y}_g^2 d a^2 + a(2db'\bar{x}_g + 1)\,\bar{y}_g + db'\overline{xx'_g}b + b'\bar{x}_g + v_g. \tag{A3}$$

so the equilibrium value of $\bar{y}_g$ must satisfy this equation for the model to be coherent. If $a = 0$, then we get $\bar{y}_g = db'\overline{xx'_g}b + b'\bar{x}_g + v_g$ which exists and is unique. If $a \neq 0$, meaning that peer effects are present, then equation (A3) is a quadratic with roots

$$\bar{y}_g = \frac{1 - a(2b'\bar{x}_g d + 1) \pm \sqrt{[1 - a(2b'\bar{x}_g d + 1)]^2 - 4a^2 d[db'\overline{xx'_g}b + b'\bar{x}_g + v_g]}}{2a^2 d}. \tag{A4}$$

Note that regardless of whether $a = 0$ or not, $\bar{y}_g$ is always a function of $\bar{x}_g$, $\overline{xx'_g}$, and v_g. If the inequality in Assumption A2 is satisfied the this yields a quadratic in $\bar{y}_g$, which, if $a \neq 0$, has real solutions and having a solution means that an equilibrium exists. If a does equal zero, then the model will trivially have an equilibrium (and be identified) because in that case there aren't any peer effects. We do not take a stand on which root of equation (A4) is chosen by consumers, we just make the following assumption.

Assumption A3: Individuals within each group agree on an equilibrium selection rule.

The equilibrium of $\bar{y}_g$ therefore exists under Assumption A2 and is unique under Assumption A3.

For identification, we need to remove the fixed effect from equation (A1), which we do by subtracting off another individual in the same group. For each $i, i' \in g$, consider pairwise difference

$$\begin{aligned} y_i - y_{i'} &= 2ad\bar{y}_g b'(x_i - x_{i'}) + db'(x_i x_i' - x_{i'} x_{i'}')b + b'(x_i - x_{i'}) + u_i - u_{i'} \\ &= 2ad y_{g;ii'} b'(x_i - x_{i'}) + db'(x_i x_i' - x_{i'} x_{i'}')b + b'(x_i - x_{i'}) + u_i - u_{i'} - 2ad\varepsilon_{yg;ii'} b'(x_i - x_{i'}); \end{aligned} \tag{A5}$$

where the second equality is obtained by replacing $\bar{y}_g$ on the right hand side with $y_{g;ii'} - \varepsilon_{yg;ii'}$. In addition to removing the fixed effects v_g, the pairwise difference also removed the linear term $a\bar{y}_g$, and the squared term $da^2\bar{y}_g^2$. The second equality in equation (A5) shows that $y_i - y_{i'}$ is linear in observable functions of data, plus a composite error term $u_i - u_{i'} - 2ad\varepsilon_{yg;ii'} b'(x_i - x_{i'})$ that contains both $\varepsilon_{yg;ii'}$ and $u_i - u_{i'}$. By Assumption A1,

$u_i - u_{i'}$ is conditionally mean independent of x_i and $x_{i'}$. It can also be shown that

$$\varepsilon_{yg,ii'} = \hat{y}_{g,ii'} - \overline{y}_g = \frac{1}{n_g - 2} \sum_{l \in g, l \neq i,i'} \left[2ad\overline{y}_g b'(x_l - \overline{x}_g) + db'(x_l x_l' - \overline{xx'}_g)b + b'(x_l - \overline{x}_g) + u_l \right]$$

$$= 2ad\overline{y}_g b'\varepsilon_{xg,ii'} + b'\varepsilon_{xxg,ii'}bd + b'\varepsilon_{xg,ii'} + \hat{u}_{g,ii'};$$

where

$$\varepsilon_{xg,ii'} = \frac{1}{n_g - 2} \sum_{l \in g, l \neq i,i'} (x_l - \overline{x}_g); \quad \varepsilon_{xxg,ii'} = \frac{1}{n_g - 2} \sum_{l \in g, l \neq i,i'} \left(x_l x_l' - \overline{xx'}_g \right):$$

Substituting this expression into equation (A5) gives an expression for $y_i - y_{i'}$ that is linear in $\hat{y}_{g,ii'}(x_i - x_{i'})$, $(x_i x_i' - x_{i'} x_{i'}')$, $(x_i - x_{i'})$, and a composite error term.

In addition to the conditionally mean independent errors $u_i - u_{i'}$ and $\hat{u}_{g,ii'}$, the components of this composite error term include $\varepsilon_{xg,ii'}$ and $\varepsilon_{xxg,ii'}$, which are measurement errors in group level mean regressors. If we assumed that the number of individuals in each group went to infinity, then these epsilon errors would asymptotically shrink to zero, and the the resulting identification and estimation would be simple. In our case, these errors do not go to zero, but one might still consider estimation based on instrumental variables. This will be possible with further assumptions on the data.

In the next assumption we allow for the possibility of observing group level variables r_g that may serve as instruments for $\hat{y}_{g,ii'}$. Such instruments may not be necessary, but if such instruments are available (as they will be in our later empirical application), they can help both in weakening sufficient conditions for identification and for later improving estimation efficiency.

Assumption A4: Let r_g be a vector (possibly empty) of observed group level instruments that are independent of each u_i. Assume $E(x_i$

$i \in g) = 0$ and $E(\varepsilon_{ix}\varepsilon_{ix}' \mid \overline{x}_g, r_g$ for $i \in g) = E(\varepsilon_{ix}\varepsilon_{ix}' \mid i \in g)$. To see this, we have

$$
\begin{aligned}
E(x_i x_i' - \overline{xx'}_g \mid i \in g, \overline{x}_g, r_g) &= E[(\varepsilon_{ix} + \overline{x}_g)(\varepsilon_{ix} + \overline{x}_g)' \mid i \in g, \overline{x}_g, r_g] - \overline{xx'}_g \\
&= E(\varepsilon_{ix}\varepsilon_{ix}' \mid i \in g, \overline{x}_g, r_g) + E(x_i \mid i \in g) E(x
\end{aligned}
$$

Equation (A7) is linear in these L variables and so could be estimated by GMM. This linearity also means they can be aggregated up to the group level as follows. Define

$$\Psi_g = \{(i,i') \mid i \text{ and } i' \text{ are observed}, i \in g, i' \in g, i \neq i'\}.$$

So Ψ_g is the set of all observed pairs of individuals i and i' in the group g. For $\ell \in \{1, 2k, 3k, 4kk' \mid k, k' = 1, ..., K\}$, define vectors

$$Y_{\ell g} = \frac{\sum_{(i,i') \in \Psi_g} L_{\ell gii'} r_{gii'}}{\sum_{(i,i') \in \Psi_g} 1}.$$

Then averaging equation (A7) over all $(i,i') \in \Psi_g$ gives the unconditional group level moment vector

$$E\left(Y_{1g} - \sum_{k=1}^{K} b_k Y_{2kg} - 2ad \sum_{k=1}^{K} b_k Y_{3kg} - d \sum_{k=1}^{K} \sum_{k'=1}^{K} b_k b_{k'} Y_{4kk'g}\right) = 0. \tag{A8}$$

Suppose the instrumental vector $r_{gii'}$ is q dimensional. Denote the $q \times (K^2 + 2K)$ matrix $Y_g = (Y_{21g}, ..., Y_{2Kg}, Y_{31g}, ..., Y_{3Kg}, Y_{411g}, \cdots, Y_{4KKg})$. The following assumption ensures that we can identify the coefficients in this equation.

Assumption A5: $E(Y_g')E(Y_g)$ is nonsingular.

Theorem 1: Given Assumptions A1-A5, the coefficients a, b, d are identified from

$$(b', 2adb', db_1 b', \cdots, db_K b')' = \left(E(Y_g')E(Y_g)\right)$$

$$\arg\min\left[\frac{1}{G}\sum_{g=1}^{G}\left(Y_{1g}-\sum_{k=1}^{K}b_kY_{2kg}-2ad\sum_{k=1}^{K}b_kY_{3kg}-d\sum_{k=1}^{K}\sum_{k'=1}^{K}b_kb_{k'}Y_{4kk'g}\right)\right]'\widehat{\Omega}\left[\frac{1}{G}\sum_{g=1}^{G}\left(Y_{1g}-\sum_{k=1}^{K}b_kY_{2kg}-2ad\sum_{k=1}^{K}b_kY_{3kg}-d\sum_{k=1}^{K}\sum_{k'=1}^{K}b_kb_{k'}Y_{4kk'g}\right)\right] \quad (A9)$$

for some positive definite moment weighting matrix $\widehat{\Omega}$. In equation (A9), each group g corresponds to a single observation, the number of observations within each group is assumed to be fixed, and recall we have assumed the number of groups G goes to infinity. Since this equation has removed the V_g terms, there is no remaining correlation across the group level errors, and therefore standard cross section GMM inference will apply. Also, with the number of observed individuals within each group held fixed, there is no loss in rates of convergence by aggregating up to the group level in this way.

One could alternatively apply GMM to equation (A7), where the unit of observation would then be each pair (i, i') in each group. However, when doing inference one would then need to use clustered standard errors, treating each group g as a cluster, to account for the correlation that would, by construction, exist among the observations within each group. In this case,

$$\left(\hat{a}, \hat{b}_1, \ldots, \hat{b}_K, \hat{d}\right)=\arg\min\left(\frac{\sum_{g=1}^{G}\sum_{(i,i')\in 2_g} m_{gii'}}{\sum_{g=1}^{G}\sum_{(i,i')\in 2_g} 1}\right)'\widehat{\Omega}\left(\frac{\sum_{g=1}^{G}\sum_{(i,i')\in 2_g} m_{gii'}}{\sum_{g=1}^{G}\sum_{(i,i')\in 2_g} 1}\right); \quad (A10)$$

where

$$m_{gii'}=\left(L_{1gii'}-\sum_{k=1}^{K}b_kL_{2kgii'}-2ad\sum_{k=1}^{K}b_kL_{3kgii'}-d\sum_{k=1}^{K}\sum_{k'=1}^{K}b_kb_{k'}L_{4kk'gii'}\right)r_{gii'}.$$

The remaining13.31i6euhe

of our survey. For example, we might let x_g include $x_{gt} = \sum_{s \neq t} \sum_{i \in g_s} x_i = \sum_{s \neq t} \sum_{i \in g_s} 1$ where s indicates the period and t

From

$$y_{ji} = d_j(\bar{y}_g'a_j)^2 + 2\bar{y}_g'a_j d_j x_i'b_j + b_j'x_i x_i'b_j d_j + \bar{y}_g'a_j + x_i'b_j + v_{jg} + u_{ji};$$

we have the equilibrium

$$\bar{y}_{jg} = d_j(\bar{y}_g'a_j)^2 + 2d_j\bar{y}_g'a_j\bar{x}_g'b_j + b_j'\overline{xx'}_g b_j d_j + \bar{y}_g'a_j + \bar{x}_g'b_j + v_{jg}$$

and the leave-two-out group average

$$\tilde{y}_{jg;-ii'} = d_j(\bar{y}_g'a_j)^2 + 2d_j\bar{y}_g'a_j\tilde{x}_{g;-ii'}'b_j + b_j'\widetilde{xx'}_{g;-ii'}b_j d_j + \bar{y}_g'a_j + \tilde{x}_{g;-ii'}'b_j + v_{jg} + \tilde{u}_{jg;-ii'}.$$

Therefore, the measurement error is

$$\varepsilon_{yjg;-ii'} = \tilde{y}_{jg;-ii'} - \bar{y}_{jg} = 2d_j\bar{y}_g'a_j\varepsilon_{xg;-ii'}'b_j + b_j'\varepsilon_{xxg;-ii'}b_j d_j + \varepsilon_{xg;-ii'}'b_j + \tilde{u}_{jg;-ii'}.$$

Using the same analysis as in Appendix A.2,

$$\begin{aligned} y_{ji} - y_{ji'} = {} & 2d_j\tilde{y}_{g;-ii'}'a_j(x_i - x_{i'})'b_j + d_j b_j'(x_i x_i' - x_{i'}x_{i'}')b_j + (x_i - x_{i'})'b_j + u_{ji} - u_{ji'} \\ & - 2d_j\varepsilon_{yg;-ii'}'a_j(x_i - x_{i'})'b_j. \end{aligned}$$

Therefore, for $j = 1,\ldots,J$, we have the moment condition

$$E\left[\left(y_{ji} - y_{ji'} - (x_i - x_{i'})'b_j - 2d_j\tilde{y}_{g;-ii0}'a_j(x_i - x_{i'})'b_j - d_j b_j'(x_i x_i' - x_{i'}x_{i'}')b_j\right)\middle| r_{gii'}\right] = 0.$$

Denote

$$L_{1jgii'} = (y_{ji} - y_{ji'}), L_{2kgii'} = (x_{ki} - x_{ki'}), L_{3jkgii'} = \tilde{y}_{jg;-ii'}(x_{ki} - x_{ki'}), L_{4kk'gii'} = x_{ki}x_{k'i} - x_{ki'}x_{k'i'}.$$

For $\ell \in \{1j, 2k, 3jk, 4kk' \mid j = 1,\ldots,J; k,k' = 1,\ldots,K\}$, define vectors

$$Y_{\ell g} = \frac{\sum_{(i,i')\in\mathcal{P}_g} L_{\ell gii'} r_{gii'}}{\sum_{(i,i')\in\mathcal{P}_g} 1}$$

and the identification comes from the group level unconditional moment equation

$$E\left(Y_{1jg} - \sum_{k=1}^{K} b_{jk}Y_{2kg} - 2d_j\sum_{j'=1}^{J}\sum_{k=1}^{K} a_{jj'}b_{jk}Y_{3j'kg} - d_j\sum_{k=1}^{K}\sum_{k'=1}^{K} b_{jk}b_{jk'}Y_{4kk'g}\right) = 0;$$

where b_{jk} is the kth element of b_j and $a_{jj'}$ is the j'th element of a_j:

Let the $q(K^2+2K)$ matrix $Y_g = (Y_{21g};\ldots Y_{2Kg};Y_{311g};Y_{312g};\ldots Y_{3JKg};Y_{411g};\quad;Y_{4KKg})$

where

$$m_{gii'} = \begin{pmatrix} L_{11gii'} r_{gii'} \\ \vdots \\ L_{1Jgii'} r_{gii'} \end{pmatrix} \quad \left(\sum_{B} \right.$$

where

$$\ddot{e}_{gii^0} = \bar{y}_g^2 \quad \dot{y}_{g;ii^0} y_{i^0} \quad a^2 d + a(1 + 2b^0 x_i d) \quad \bar{y}_g \quad \dot{y}_{g;ii^0}$$
$$= ("_{yg;ii^0} + "_{y;i^0}) \bar{y}_g a^2 d \quad "_{yg;ii^0} "_{y;i^0} a^2 d \quad a(1 + 2b^0 x_i d) "_{yg;ii^0}:$$

Formally, we make the following assumptions.

Assumption A6: For any individual l, v_g is independent of $(x_l; \bar{x}_g; \overline{xx_g^0})$, the error term u_l, and measurement errors $"_{xl}$ and $"_{xxl}$.

Assumption A7: For each individual l in group g, conditional on $(\bar{x}_g; \overline{xx_g^0})$ the measurement errors $"_{xl}$ and $"_{xxl}$ are independent across individuals and have zero means.

Assumption A8: For each group g, v_g is independent across groups with $E(v_g jx; \bar{x}_g; \overline{xx_g^0}) =$ and we have the conditional homoskedasticity that $Var(v_g jx; \bar{x}_g; \overline{xx_g^0}) = {}^2$.

Let $v_0 = \; da \; {}^2 \; {}^2$. It follows from Assumptions A6-A8 that, for any $l \neq i$, $E(\bar{y}_g "_{yl} jx_i; \bar{x}_g; \overline{xx_g^0}) =$ 0 and $E("_{yl} x_i jx_i; \bar{x}_g; \overline{xx_g^0}) = 0$. Hence, $E(\ddot{e}_{gii^0} jx_i; \bar{x}_g; \overline{xx_g^0}) = \; da \; {}^2 E("_{yg;ii^0} "_{y;i^0} jx_i; \bar{x}_g; \overline{xx_g^0}) =$ $da \; {}^2 Var(v_g)$ and

$$E(v_g + u_i + \ddot{e}_{gii^0} j \bar{x}_g; \overline{xx_g^0}; x_i) = \quad da^2 \; {}^2 = v_0: \tag{A15}$$

By construction $v_g + u_i + \ddot{e}_{gii^0}$ is also independent of r_g. Given this, equation (20) then follows from equations (A14) and (A15).

A.5 Identi cation and Estimation of the Demand System With Fixed E ects

Here we outline how the parameters of the demand system are identi ed. This is followed by the formal proof of identi cation, based on the corresponding moments we construct for estimation. As with the gef2(As)-pTd 94(the)podelequations2.994ef2(As23.003(g3c84Tj 0 g Tj 0 g Tj
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We show identi cation of the parameters of the demand system (8) in two steps. The rst step identi es some of the model parameters by closely following the identi cation strategy of our simpler generic model, holding prices xed. The second step then identi es the remaining parameters based on varying prices. We summarize these steps here, then provide formal assumptions and proof of the identi cation in the next section.

For the rst step, consider data just from a single time period and region, so there is no price variation and p can be treated as a vector of constants.

We distinguish between elements of z that vary at the individual versus group level, writing C as $C = \tilde{C} : D$ for submatrices $\tilde{C}$ and D, and replacing Cz_i in Equation 9 with $Cz_i = \tilde{C}\tilde{z}_i + D\tilde{z}_g$, where $\tilde{z}_i$ is the vector of characteristics that vary across individuals in a group and $\tilde{z}_g$ are group level characteristics.

Let $= A^0 p$, $= p^{1=2} Rp^{1=2}$, $e = \tilde{C}^0 p$, $= D^0 p$, $= b=p$, $Cz_i = \tilde{C}\tilde{z}_i + D\tilde{z}_g$, $r_j = r_{jj} + 2 \sum_{k>j} r_{jk} p_j^{1=2} p_k^{1=2}$, and $m = e^{b^0 \ln p} d=p$ with constraints of $b^0 1 = 1$ and $d^0 1 = 0$. Then equation (8) reduces to the system of Engel curves

$$q_i = x_i \quad {}^0\overline{q}_g \quad e^0\tilde{z}_i \quad {}^0\tilde{z}_g \;{}^2 m + x_i \quad {}^0\overline{q}_g \quad e^0\tilde{z}_i \quad {}^0\tilde{z}_g \qquad \text{(A16)}$$
$$+ r + A\overline{q}_g + \tilde{C}\tilde{z}_i + D\tilde{z}_g + v_g + u_i;$$

This has a very similar structure to the generic multiple equation system of equations (A11), and we proceed similarly.

De ne $\tilde{v}_g = {}^0\overline{q}_g + \; + {}^0\tilde{z}_g \;{}^2 m \quad {}^0\overline{q}_g + \; + {}^0\tilde{z}_g \quad + r + A\overline{q}_g + D\tilde{z}_g + v_g$. Then equation (A16) can be rewritten more simply as

$$q_i = (x_i \quad e^0\tilde{z}_i)^2 m \quad 2(x_i \quad e^0\tilde{z}_i) \quad {}^0\overline{q}_g + \; + {}^0\tilde{z}_g \; m + (x_i \quad e^0\tilde{z}_i) \; + \tilde{C}\tilde{z}_i + \tilde{v}_g + u_i; \quad \text{(A17)}$$

Here the xed e ect v_g has been replaced by a new xed e ect $\tilde{v}_g$. As in the generic xed e ects model, we begin by taking the di erence $q_{ji} \quad q_{ji^0}$ for each good $j \; 2 \; f1; :::; J \; g$ and each pair of individuals i and i^0 in group g. This pairwise di erencing of equation (A17) gives, for each good j,

$$q_{ji} \quad q_{ji^0} = (x_i \quad e^0\tilde{z}_i)^2 \quad (x_{i^0} \quad e^0\tilde{z}_{i^0})^2 \; m_j + e_j^0(\tilde{z}_i \quad \tilde{z}_{i^0})$$
$$+ \;_j \quad 2m_j \quad {}^0\overline{q}_g + \; + {}^0\tilde{z}_g \; [(x_i \quad e^0\tilde{z}_i) \quad (x_i \quad e^{\;m}$$ the1o[355 T]g23[0]eg2T5f 4.Tj /T:

between $\tilde{q}_{g;ii'}$ and $\bar{q}_g$.

Define group level instruments r_g as in the generic model. In particular, r_g can include $\tilde{z}_g$, group averages of x_i and of z_i, using data from individuals i that are sampled in other time periods than the one currently being used for Engel curve identification. Define a vector of instruments $r_{gii'}$ that contains the elements r_g, $x_i; \tilde{z}_i; x_{i'}; \tilde{z}_{i'}$, and squares and cross products of these elements. We then, analogous to the generic model, obtain unconditional moments

$$0 = E\{[(q_{ji} - q_{ji'}) - (x_i - e'\tilde{z}_i)^2 - (x_{i'} - e'\tilde{z}_{i'})^2 \; m_j - e_j'(\tilde{z}_i - \tilde{z}_{i'}) \\ - (\cdot_j - 2m_j(\cdot'\tilde{q}_{g;ii'} + \cdot + \cdot'\tilde{z}_g))((x_i - e'\tilde{z}_i) - (x_{i'} - e'\tilde{z}_{i'}))]r_{gii'}\}. \qquad (A18)$$

Combining common terms, we have

$$0 = E\{[(q_{ji} - q_{ji'}) - (x_i^2 - x_{i'}^2)m_j + 2(x_i\tilde{z}_i - x_{i'}\tilde{z}_{i'})'e\,m_j - e'(\tilde{z}_i\tilde{z}_i' - \tilde{z}_{i'}\tilde{z}_{i'}')e\,m_j \\ - e_j' - (\cdot_j - 2m_j\,\cdot)e'(\tilde{z}_i - \tilde{z}_{i'}) - (\cdot_j - 2m_j\,\cdot)(x_i - x_{i'}) \\ + 2m_j(\cdot'\tilde{q}$$

large enough T, that is, $T \quad 1 + \frac{J(J+1)}{2(J\ \ 1)}$, we get more equations than unknowns, allowing R and b

0. With similar arguments in the generic model, Assumption B4 suffices to ensure that

$$E(\varepsilon_{qg;ii'}[(x_i - x_{i'}); (\tilde{z}_i - \tilde{z}_{i'})']' | x_i; x_{i'}; z_i; z_{i'}; r_g) = E(\varepsilon_{qg;ii'} | r_g)\,[(x_i - x_{i'}); (z_i - z_{i'})']' = 0.$$

Then we have the moment condition

$$0 = E\{[q_i - q_{i'} + 2m(\gamma'\eta_{g;ii'} + \alpha'\tilde{z}_g)[(x_i - x_{i'}) - e'(\tilde{z}_i - \tilde{z}_{i'})] - (x_i^2 - x_{i'}^2)m \quad \text{(A22)}$$
$$- e'(\tilde{z}_i\tilde{z}_i' - \tilde{z}_{i'}\tilde{z}_{i'}')em + 2me'(\tilde{z}_i x_i - \tilde{z}_{i'}x_{i'}) - \beta(x_i - x_{i'}) + (\beta e' - C)(\tilde{z}_i - \tilde{z}_{i'})]|x_i; x_{i'}; z_i; z_{i'}; r_g\}$$

for the Engel curves, where $\beta = -2m\delta$, and so

$$E\Big\{q_i - q_{i'} + 2e^{b'\ln p_t}\frac{d}{p_t}(p_t'A\eta_{gt;ii'} + p_t'D\tilde{z}_g)[(x_i - x_{i'}) - p_t'C(\tilde{z}_i - \tilde{z}_{i'})] - e^{b'\ln p_t}\frac{d}{p_t}$$
$$[(x_i^2 - x_{i'}^2) + p_t'C(\tilde{z}_i\tilde{z}_i' - \tilde{z}_{i'}\tilde{z}_{i'}')C'p_t - 2p_t'C(z_i x_i - z_{i'}x_{i'})] - \Big(\frac{b}{p_t} - 2e^{b'\ln p_t}\frac{d}{p_t}p_t^{1/2'}Rp_t^{1/2}\Big)$$
$$(x_i - x_{i'}) + [(\frac{b}{p_t} - 2e^{b'\ln p_t}\frac{d}{p_t}p_t^{1/2'}Rp_t^{1/2})C'p_t - C](\tilde{z}_i - \tilde{z}_{i'})|x_i; x_{i'}; z_i; z_{i'}; r_g\Big\} = 0.$$

(A23)

for the full demand system.

We define the instrument vector $r_{gii'}$ to be linear and quadratic functions of r_g, $(x_i; z_i')'$, and $(x_{i'}; z_{i'}')'$. Denote

$$L_{1jgii'} = (q_{ji} - q_{ji'}), \; L_{2jgii'} = \eta_{jg;ii'}(x_i - x_{i'}), \; L_{3jkgii'} = \eta_{jgt;ii'}(\tilde{z}_{ki} - \tilde{z}_{ki'}),$$
$$L_{4k_2gii'} = \tilde{z}_{k_2g}(x_i - x_{i'}); \; L_{5kk_2gii'} = \tilde{z}_{k_2g}(\tilde{z}_{ki} - \tilde{z}_{ki'}); \; L_{6gii'} = x_i^2 - x_{i'}^2; \quad \text{(A24)}$$
$$L_{7kk'gii'} = \tilde{z}_{ki}\tilde{z}_{k'i} - \tilde{z}_{ki'}\tilde{z}_{k'i'}, \; L_{8kgii'} = \tilde{z}_{ki}x_i - \tilde{z}_{ki'}x_{i'}, \; L_{9gii'} = x_i - x_{i'}; \; L_{10kgii'} = \tilde{z}_{ki} - \tilde{z}_{ki'};$$

For $\ell \in \{1j; 2j; 3jk; 4k_2; 5kk_2; 6; 7kk'; 8k; 9; 10k \,|\, j = 1; ...; J; k; k' = 1; ...; K; k_2 = 1; ...; K_2\}$, define vectors

$$Q_{\ell g} = \frac{\sum_{(i;i')\in\Omega_g} L_{\ell gii'} r_{gii'}}{\sum_{(i;i')\in\Omega_g} 1}.$$

Then for each good j, the identification is based on

$$E\Big(Q_{1jg} + 2m_j\sum_{j'=1}^{J}\gamma_{jj'}Q_{2j'g} - 2m_j\sum_{j'=1}^{J}\sum_{k=1}^{K}\gamma_{jj'}e_kQ_{3j'kg} + 2m_j\sum_{k_2=1}^{K_2}\alpha_{k_2}Q_{4k_2g} - 2m_j\sum_{k=1}^{K}\sum_{k_2=1}^{K_2}e_k\alpha_{k_2}Q_{5kk_2g}$$
$$- m_jQ_{6g} - m_j\sum_{k=1}^{K}\sum_{k'=1}^{K}e_ke_{k'}Q_{7gkk'} + 2m_j\sum_{k=1}^{K}e_kQ_{8kg} - \beta_jQ_{9g} + \sum_{k=1}^{K}(\beta_je_k - c_{jk})Q_{10kg}\Big) = 0;$$

where e_k is the kth element of $e = \tilde{C}^0 p$, $_{k_2}$ is the k_2th element of $= D^0 p$, and e_{jk} is the $(j;k)$th element of $\tilde{C}$.

Assumption B5: $E \; Q_g^0 \; E(Q_g)$ is nonsingular, where

$$Q_g = (Q_{21g};\ldots;Q_{2Jg};Q_{311g};\ldots;Q_{3JKg};Q_{41g};\ldots;Q_{4K_2g};Q_{511g};\ldots;Q_{5KK_2g};$$
$$Q_{6g};Q_{711g};\ldots;Q_{7KKg};Q_{81g};\ldots;Q_{8Kg};Q_{9g};Q_{101g};\ldots;Q_{10Kg}):$$

Under Assumption B5, we can identify

$$(2m_j \; ^0;2m_j \; _1e^0;\ldots;2m_j \; _Je^0; \; 2m_j \; ^0;2m_j \; _1e^0;\ldots;2m_j \; _{K_2}e^0;m_j;m_je_1e^0;\ldots;m_je_Ke^0;$$
$$2m_je^0; \; _j;c_j^0 \; _je^0)^0 = E \; Q_g^0 \; E(Q_g)^{1} \; E \; Q_g^0 \; E(Q_{1jg})$$

for each $j = 1;\ldots;J \; 1$. From this, $;\;;\; e, \tilde{C};\; m$, and $= \; 2m$ are identified. To identify the full demand system, let p_t denote the vector of prices in a single price regime t. Let

$$P = (p_1;\ldots;p_T)^0 \text{ and } = (\,^0_1;\ldots;\,^0_T)^0$$

with the $(J \; 1) \; [J \; 1 + J(J+1)=2]$ matrix

$$_t = \begin{pmatrix} 1 \\ T_1 \end{pmatrix}$$

matrix $P = (p_1; :::; p_T)^0$ and the $(J \quad 1)T \quad [J \quad 1 + J(J+1)=2]$ matrix both have full column rank.

Given Assumption B6, A and D are identi ed by

$$A = (P^0 P)^{1} P^0 ({}_1; :::; {}_T)^0 \text{ and } D = (P^0 P)^{1} P^0 ($$ 978 c809Tj /T1I_2 -4.936d (1))Tj /T1_3 11.95- 22.762 0 Td

The GMM estimator, using group level clustered standard errors, is then

$$\left(\hat{A}_1^0;\ldots;\hat{A}_J^0;\hat{b}_1;\ldots;\hat{b}_{J-1};\hat{d}_1;\ldots;\hat{d}_{J-1};\hat{e}_1^0;\ldots;\hat{e}_J^0;\hat{D}_1^0;\ldots;\hat{D}_J^0;r_{11};\ldots;r_{JJ};r_{12};\ldots;r_{J-1,J}\right)^0$$

$$= \arg\min \left(\frac{\sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{(i,i^0)\in 2_{gt}} m_{gtii^0}}{\sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{(i,i^0)\in 2_{gt}} 1} \right)^0 \hat{W} \left(\frac{\sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{(i,i^0)\in 2_{gt}} m_{gtii^0}}{\sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{(i,i^0)\in 2_{gt}} 1} \right);$$

where the expression of $m_{gtii^0} = (m^0_{1gtii^0};\ldots;m^0_{J-1;gtii^0})$ is

$$m_{jgtii^0} = [(q_{ji} - q_{ji^0}) - (x_i - e_t^0 z_i)^2 - (x_{i^0} - e_t^0 z_{i^0})^2 - m_{jt} - m \quad ()$$

because

$$E\ \overline{q}_{gt}[(x_i \quad x_{i^0}) \quad {}^0_{gt}(z_i \quad z_{i^0})](x b_{gt;ii^0} \quad \overline{x}_{gt})\ j\ \overline{x}_{gt}; \overline{x\,x^0}_{gt}; v_{gt}; \overline{w}_{gt}; "_{wgt}; x_{it}; x_{i^0t} = 0;$$

and

$$E\ [(x_i \quad x_{i^0})](x b_{gT;ii^0} \quad \overline{x}_{gt})^0\ j\ \overline{w}_{gt}; "_{wgt}; x_{it}; x_{i^0t} = 0;$$

$$E\ [(x_i \quad x_{i^0})](x^d x^0{}_{gt;ii^0} \quad \overline{x\,x^0}_{gt})^0\ j\ \overline{w}_{gt}; "_{wgt}; x_{it}; x_{i^0t} = 0;$$

where $x = (x; z^0)^0$. It follows that $x^d x^0{}_{gt}; x b_{gt}\, x b^0_{gt}; x b_{gt}$ is a valid instrument for $q_{gt;ii^0}$.

The full set of proposed instruments is therefore $e_{gii^0} = r_g \quad (x_i \quad x_{i^0}; x_i x_i^0 \quad x_{i^0} x_{i^0}^0)$, where

$$r_g = \quad x^d x^0{}_{gt}; x b_{gt}\, x b^0_{gt}; x b_{gt}; x_i + x_{i^0}; x_i^2 + x_{i^0}^2; x_i^{1=2} + x_{i^0}^{1=2} \quad ;$$

for the Engel curve system, and $r_{gtii^0} = r_{gt} \quad (x_i \quad x_{i^0}; x_i x_i^0 \quad x_{i^0} x_{i^0}^0)$, where

$$r_{gt} = p_t^0 \quad x^d x^0{}_{gt}; x b_{gt}\, x b^0_{gt}; x b_{gt}; x_i + x_{i^0}; x_i^2 + x_{i^0}^2; x_i^{1=2} + x_{i^0}^{1=2} \quad :$$

for the full demand system.

A.6 Identi cation and Estimation of the Demand System with Random E ects

The Engel curve model with random e ects is

$$\begin{aligned} q_i = {} & x_i^2 m + (e^0 z_i z_i^0 e)\, m \quad 2m e^0 z_i x_i + m \quad {}^0\overline{q}_g + {}^0 z_g + {}^2 \\ & 2m \quad {}^0\overline{q}_g + {}^0 z_g + \quad (x_i \quad e^0 z_i) \\ & + \quad x_i \quad {}^0\overline{q}_g \quad e^0 z_i \quad {}^0 z_g \quad + r + A\,\overline{q}_g + C z_i + D z_g + v_g + u_i, \end{aligned}$$

Therefore,

$$\begin{aligned} "_{qi^0} = q_{i^0} \quad \overline{q}_g = {} & "_{x^2 i^0} m + {}^{0\prime}{}_{zzi^0}\ m \quad 2m\ {}^{0\prime}{}_{zxi^0}\ 2m \quad {}^0\overline{q}_g + {}^0 z_g + \quad ("_{xi^0} \quad e^{0\prime}{}_{zi^0}) \\ & + \quad "_{xi^0} + (C \quad e^0)"_{zi^0} + v_g \quad + u_{i^0}; \end{aligned}$$

$$\begin{aligned} "_{qg;ii^0} = b_{q g;ii^0} \quad \overline{q}_g = {} & "_{x^2 g;ii^0} m + {}^{0\prime}{}_{zzg;ii^0}\ m \quad 2m\ {}^{0\prime}{}_{zxg;ii^0}\ 2m \quad {}^0\overline{q}_g + {}^0 z_g + \\ & ("_{xg;ii^0} \quad {}^{0\prime}{}_{zg;ii^0}) + \quad "_{xg;ii^0} + (C \quad e^0)"_{zg;ii^0} + v_g \quad + b u_{g;ii^0}: \end{aligned}$$

By rewriting

Denote

$$L_{1jgi} = q_{ji},\; L_{2jj'gi} = \frac{1}{n_g - 1}\sum_{i' \in g; i' \neq i} q_{jg;ii'} q_{j'i'};\; L_{3gi} = x_i^2,\; L_{4kk'gi} = z_{ki} z_{k'i};\; L_{5k_2k_2'gi} = z_{k_2g} z_{k_2'g};$$

$$L_{6kgi} = z_{ki} x_i;\quad L_{7k_2gi} = z_{k_2g} x_i;\quad L_{8jgi} = q_{jg;-i}\, x_i,\quad L_{9jkgi} = q_{jg;-i}\, z_{ki},\; L_{10jk_2gi} = q_{jg;-i}\, z_{k_2g},$$

$$L_{11kk_2gi} = z_{ki} z_{k_2g},\; L_{12jgi} = q_{jg;-i},\; L_{13gi} = x_i,\; L_{14kgi} = z_{ki},\; L_{15k_2gi} = z_{k_2g};\; L_{16gi} = 1.$$

For $\ell \in \{1j;\ 2jj';3;4kk';5k_2k_2';6k;7k_2;8j;\ 9jk;\ 10jk_2;11kk_2;12j;13;14k;15k_2;16 \mid j;j' = 1;\dots;J;k;k' = 1;\dots;K;k_2;k_2' = 1;\dots;K_2\}$; define group level vectors

$$H_{\ell g} = \frac{1}{n_g - 1}\sum_{i \in g} L_{\ell gi}\, r_{gi}.$$

Then for each good j, the identification is based on

$$E\left(H_{1jg} \quad m_j \sum_{j=1}^{J} \sum^{J}\right.$$

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for each $j = 1;:::;J \quad 1$. From this, e; , ; m, $= \quad 2m$, A_j, e_j, D_j; and $m_j \quad ^2$ $_j \quad + r_j + v_{j0}$ for $j = 1;:::;J \quad 1$ are all identi ed. Then, $A_J = \quad \sum_{j=1}^{J \, 1} A_j p_j \quad =p_J$, $e_J = (e \quad \sum_{j=1}^{J \, 1} e_j p_j)=p_J$, and $D_J = (\quad \sum_{j=1}^{J \, 1} D_j p_j)=p_J$ are identi ed. Here without price variation, we can identify A and D. This is di erent from the xed e ects model because the key term for identifying A is $A\bar{q}_g$, which is di erenced out in xed e ects model, and only $\hat{e}$ can be identi ed from the cross product of $\bar{q}_g$ and $(x_i; z_i)$. Furthermore, to identify the structural parameters b, d; and R, we need the rank condition in Assumption B6(2).

With our data spanning multiple time regimes t, we estimate the full demand system model simultaneously over all values of t, instead of as Engel curves separately in each t as above. To do so, in the above moments we replace the Engel curve coe cients , e, , , r_j, and m with their corresponding full demand system expressions, i.e., $= A^0 p$, $= p^{1=2} Rp^{1=2}$, etc, and add t subscripts wherever relevant. The resulting GMM estimator based on these moments (and estimated using group level clustered standard errors), is then

$$(\hat{A}_1^0; :::; \hat{A}_J^0; \hat{b}_1; :::; \hat{b}_{J\,1}; \hat{d}_1; :::; \hat{d}_{J\,1}; \hat{e}_1^0; :::\hat{e}_J^0; ; \hat{D}_1^0; :::\hat{D}_J^0; \hat{R}_{11}; :::\hat{R}_{JJ}; \hat{R}_{12}; :::; \hat{R}_{J\,1J};$$
$$\hat{b}, \; b_{v;11}; :::; b_{v;JJ}; b_{v;12}; :::; b_{v;J\,1;J};)^0$$
$$= \arg\min \quad \left(\frac{\sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{i2 \, gt} m_{gti}}{\sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{i2 \, gt} 1} \right)^0 b \quad \left(\frac{\sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{i2 \, gt} m_{gti}}{\sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{i2 \, gt} 1} \right);$$

where the expression of $m_{gti} = (m_{1gti}^0; :::; m_{J\,1;gti}^0)$ is

$$m_{jgti} = f q_{ji} \quad m_{jt} \quad {}_t^0 \mathbf{q}_{gt;\,ii\,0} \quad {}_t^0 q_{i0} \quad m_{jt}(x_i \quad e_t^0 z_i)^2 \quad m_{jt}(\, {}_t^0 z_{gt} + \quad _t)^2$$
$$+ [(2m_{jt}(x_i \quad e_t^0 z_i \quad {}_t^0 z_{gt} \quad _t) + \quad _{jt}) \quad {}_t^0 \quad A_j^0] \mathbf{q}_{gt;\,ii\,0} + 2m_{jt}(\, {}_t^0 z_g + \quad _t)(x_i \quad e_t^0 z_i)$$
$$_{jt}(x_i \quad _t \quad e_t^0 z_i \quad {}_t^0 z_{gt}) \quad r_{jt} \quad e_j^0 z_i \quad D_j^0 z_g \quad v_{jt\,0} g r_{gti}$$

with

$$m_{jt} = e^{b \, {}^0 \ln p_t} \frac{d_j}{p_{jt}}; \quad _t = A^0 p_t, \; e_t = \hat{e}^0 p_t; \quad _t = D^0 p_t; \quad _t = p_t^{1=2} Rp_t^{1=2};$$
$$_{jt} = \frac{b_j}{p_{jt}} \; 2m \; _{jt} p_t^{1=2} Rp_t^{1=2}, \quad _{jt} = \frac{b_j}{p_{jt}}; \; r_{jt} = R_{jj} + 2 \sum_{k>j} R_{jk} \quad \sqrt{p_{kt}=p_{jt}};$$
$$v_{jt\,0} = \quad _{jt} \quad e^{b \, {}^0 \ln p_t} \frac{d_j}{p_{jt}} \sum_{j_1=1}^{J} \sum_{j_2=1}^{J} \sum_{j=1}^{J} \sum_{j^0=1}^{J} A_{j_1 j} p_{j_1 t} A_{j_2 j^0} p_{j_2 t} \quad _{vt;jj\,0}:$$

Note that $v_{jt\,0}$ are constants for each value of j and t, that must be estimated along with the other parameters. In our data T is large (since prices vary both by time and district). To reduce the number of required parameters and thereby increase e ciency, assume that

$= E(v_{gt})$ and $_v = Var(v_{gt})$ do not vary by t. Then we can replace v_{jt0} with

$$v_{jt0} = \quad _j$$

surveyed sample n, not the true sample N. We then get the decomposition:

$\bar{y}$

where ε_i is given by

$$\begin{aligned}\varepsilon_i &= \left(\bar{y}_{iN}^2 - \hat{y}_{in}^2\right) a^2 d + 2\left(\bar{y}_{iN} - \hat{y}_{in}\right) x_i abd + \left(\bar{y}_{iN} - \hat{y}_{in}\right) a \\ &= -\left(\frac{1}{n_i}\sum_{j \in n_i} W_{ij} u_j - \left(1 - \frac{n_i}{N_i}\right)\eta_{iN}\right)\left[\left(2\bar{y}_{iN} + \left(1 - \frac{n_i}{N_i}\right)\eta_{iN} - \frac{1}{n_i}\sum_{j \in n_i} W_{ij} u_j\right)a^2 d + 2 x_i abd + a\right] \qquad (A.26)\end{aligned}$$

As before, this ε_i does not have zero conditional mean due to the quadratic term.

Since we no longer have groups, we cannot look at all pairs of observations within a group. Instead, we can randomly split i's observed friends into two subsets $n_i = n_i^{(1)} + n_i^{(2)}$ and construct the sample mean from each subset

$$\hat{y}_{in}^{(1)} = \frac{1}{n_i^{(1)}}\sum_{j \in n_i^{(1)}} W_{ij} y_j \text{ and } \hat{y}_{in}^{(2)} = \frac{1}{n_i^{(2)}}\sum_{j \in n_i^{(2)}} W_{ij} y_j :$$

Then,

$$\begin{aligned}\hat{y}_{in}^{(1)} &= \bar{y}_{iN} + \left(1 - \frac{n_i^{(1)}}{N_i}\right)\eta_{iN}^{(1)} - \frac{1}{n_i^{(1)}}\sum_{j \in n_i^{(1)}} W_{ij} u_j ; \\ \hat{y}_{in}^{(2)} &= \bar{y}_{iN} + \left(1 - \frac{n_i^{(2)}}{N_i}\right)\eta_{iN}^{(2)} - \frac{1}{n_i^{(2)}}\sum_{j \in n_i^{(2)}}\end{aligned}$$

where

$$
\begin{aligned}
\tilde{e}_i &= \bar{y}_{iN}^2 - \hat{y}_{in}^{(1)}\hat{y}_{in}^{(2)} - a^2 d + 2\bar{y}_{iN} - \hat{y}_{in}^{(1)} - \hat{y}_{in}^{(2)}\, x_i abd + \bar{y}_{iN} - \hat{y}_{in}\, a \\
&= a^2 d \left(\frac{1}{n_i^{(1)} n_i^{(2)}} \sum_{j \in n_i^{(1)}} W_{ij} u_j \sum_{j \in n_i^{(2)}} W_{ij} u_j + \left(1 - \frac{n_i^{(1)}}{N_i}\right) \epsilon_{iN}^{(1)} \left(1 - \frac{n_i^{(2)}}{N_i}\right) \epsilon_{iN}^{(2)} \right) \\
&\quad + a^2 d \left(\left(1 - \frac{n_i^{(1)}}{N_i}\right) \epsilon_{iN}^{(1)} \frac{1}{n_i^{(2)}} \sum_{j \in n_i^{(2)}} W_{ij} u_j + \left(1 - \frac{n_i^{(2)}}{N_i}\right) \epsilon_{iN}^{(2)} \frac{1}{n_i^{(1)}} \sum_{j \in n_i^{(1)}} W_{ij} u_j \right) \\
&\quad + d \left(\frac{1}{n_i^{(1)}} \sum_{j \in n_i^{(1)}} W_{ij} u_j + \frac{1}{n_i^{(2)}} \sum_{j \in n_i^{(2)}} W_{ij} u_j - \left(1 - \frac{n_i^{(1)}}{N_i}\right) \epsilon_{iN}^{(1)} - \left(1 - \frac{n_i^{(2)}}{N_i}\right) \epsilon_{iN}^{(2)} \right) (x_i ab + a^2 \bar{y}_{iN}) \\
&\quad + \left(\frac{1}{n_i} \sum_{j \in n} W_{ij} u_j - \left(1 - \frac{n_i}{N_i}\right) \epsilon_{iN} \right) a
\end{aligned}
$$

We can then show that,

$$E(u_i + \tilde{e}_i \mid x_i; x_j) = 0, \tag{A28}$$

where x_j are from those of i's observed friends. With these moments, we can now construct instruments as before for GMM estimation.

Appendix B: Preliminary Data Analyses

B.1 Generic Model Estimates

In other, non-demand settings, the generic peer effects model of Section 3 may be more appropriate than the structural demand model. We implemented this model in Section 4.2, but in this section describe the results in more detail.

As in the presentation in (12), y_i is expenditures on food, $\bar{y}_g$ is the true group-mean expenditure on food, $\hat{y}_g$ is the observed sample average, and x_i is total expenditures.

We provide estimates using random-effects unconditional moments (21) and fixed-effects unconditional moments (18). Define $\bar{x}_{g,-t}$ to be the group-average expenditure in other time periods. Fixed-effects instruments $r_{gii'}$ are: $\bar{x}_{g,-t}$; $(x_i - x_{ii'})$; $(x_i - x_{ii'})\bar{x}_{g,-t}$; $(x_i^2 - x_{ii'}^2)$; $(z_i - z_k)$; $(z_i - z_k)\bar{x}_{g,-t}$; z_g; $z_g(x_i - x_{i'})$; 1. Random-effects instruments r_{gi} are: $\bar{x}_{g,-t}$; x_i; $x_i\bar{x}_{g,-t}$; x_i^2; z_i; 1. These instruments are constructed to mirror the sources of identification in the FE and RE cases, respectively. Resulting GMM estimates of the parameters are given in Table A3.

In the RE model, higher levels of peer food expenditure work in the same direction as own expenditure; in effect making the household behave (in a demand sense) as if it was richer when peer expenditures rise. Since this is not sustainable in equilibrium, it is reassuring that in the FE specification, higher peer expenditure makes households reduce their demand for food.

This difference between the models is a natural consequence of the group-level unobservable taste for an expenditure category $\mathbf{y}_g$ being correlated with expenditure in that category. Unsurprisingly, the Hausman tests decisively reject the RE specification.

However, the peer effects in the FE specification are very large. Variation in peer expenditure has over twice the effect of own expenditure on demand behavior (see the estimates of a/b), but we cannot reject equivalence of the two effects given the imprecision of the peer effect estimates. This is a potential consequence of excluding group-average non-food spending from the right hand side. We take this as a reason to focus on the structural estimates, which restrict behavior (including price responses) in a way consistent with economic theory.

In both models, the estimated values of b is positive, and d is negative. As a result, food budget shares are declining with expenditure, consistent with Engel's Law..

B.2 Subjective well-being and peer consumption

Our generic model estimates above are consistent with a theory in which increased peer consumption decreases the utility one gets from consuming a given level of food, as suggested by our theoretical model of needs. However, the generic model only reveals the effect of peer consumption on one's own consumption, not on one's utility. For example, it is possible that the success of my peers makes me happy rather than envious. Or peer consumption could increase the utility I obtain from my own consumption, e.g., my own telephone becomes more useful when my friends also have telephones. In short, our needs model implies that peer expenditures induce negative rather than positive consumption externalities.

To directly check the sign of these peer spillover effects on utility, we would like to estimate the correlation between utility and peer expenditures, conditioning on one's own expenditure level. While we cannot directly observe utility, here we make use of a proxy, which is a reported ordinal measure of life satisfaction.

Table A1 summarizes the 4^{th} (2001), 5^{th} (2006), and 6^{th} (2014) waves of the World Values Survey. In each year the surveyor asks the question, "All things considered, how satisfied are you with your life as a whole these days?" Answers are on a 5-point ordinal scale in the 5^{th} wave, so we collapse all waves to a 5-point scale.

Neither wave of the survey reports actual income or consumption expenditures. What this survey does report is position on a ten-point income distribution. The exact cutpoints are undocumented, so we collapse the scale to five points for interpretability and use dummies for the income groupings directly in our analysis.

For this analysis we define groups by religion (Hindu vs non-Hindu) and state of residence (20 states and state groupings). These are much larger, more coarsely defined groups than we use for all of our other analyses. This is for two reasons: first, we do not observe caste or geographic indicators smaller than states; and second, larger groups are needed here because the WVS sample size is much smaller than the NSS and we have no asymptotic theory to deal with small group sizes in this part of the analysis.

Table A2 presents estimates of well-being as a function of both own total expenditures and group total expenditures, specified as

$$U_i = \sum_{s=2}^{5} \beta_g 1[I_i = s] + \gamma \bar{x}_{gt} + X_{igt}\delta + \alpha_g + \tau_t + \varepsilon_{igt}, \quad \text{(A29)}$$

where U_i is the z-normalized well-being indicator, $1[g_i = s]$ is an indicator for individual i belonging to income group s, $\bar{x}_{gt}$ is imputed group expenditures, X_{igt} is vector of individual level controls, α_g is a group level fixed effect (groups are defined within states, so this effectively includes a state fixed effect as well), and τ_t is a year fixed effect. Identification of γ comes from group-level changes in expenditure between rounds, and corresponds to the change in self-reported utility as group income is rising versus falling, holding own income constant. We also repeat this analysis using an ordered logit specification.

Results in the second column of Table A2 imply that satisfaction is increasing over the entire range of individual expenditures, but that a 1000 rupee increase in peer expenditure $\bar{x}_{gt}$ decreases satisfaction by 0.15 standard deviations. Other specifications in Table A2 give similar results. The signs of these effects are consistent with our model of peer expenditures as negative consumption externalities. The magnitudes are also relative large (average peer expenditure is 5,554, with a standard deviation of 2,580), consistent with our structural results.

Since well-being is reported on an ordinal scale, to check the robustness of these results, we estimate the same regression as an ordered logit (see columns 4 and 5 of Table A2). The results are qualitatively the same, suggesting that our results are not being determined by the normalizations implicit in z-scoring the satisfaction responses. We conclude that welfare is indeed increasing in household expenditure and decreasing in peer expenditure.

Finally, we include an interaction term (the product of peer expenditures and the individual being in the top two income groups) in the regression in columns 3 and 6, and find its coefficient to be insignificantly different from zero, which is consistent with our linear index modeling assumption.

Table A1: Subjective well-being summary statistics

	Mean	SD	Min	Max
Income group 2 (=1)	.4	.49	0	1
Income group 3 (=1)	.21	.4	0	1
Income group 4 (=1)	.087	.28	0	1
Income group 5 (=1)	.041	.2	0	1
Group expenditure (1000 rupees)	5.6	2.6	2.8	18
Age	.34	.12	.15	.77
Sex	1.4	.49	1	2
Household size	.32	.19	0	.9
Married (=1)	.84	.36	0	1
Primary education (=1)	.095	.29	0	1
Secondary education (=1)	.13	.34	0	1
Observations	5,084			

Life satisfaction variable from World Values Survey. Participants were asked \All things considered, how satis ed are you with your life as a whole these days?"and asked to point to a position on a ladder. Coded as 1-5 in 2001 and 2006, and 1-10 in 2014. We collapsed to a 1-5 scale in 2014. Group income measured in thousands of Rs/month.

Table A2: Satisfaction on household and peer income

	OLS (SDs)			Ordered logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Income group 2 (=1)	0.14	0.12	0.12	0.33	0.30	0.30
	(0.06)	(0.06)	(0.06)	(0.11)	(0.12)	(0.12)
Income group 3 (=1)	0.36	0.33	0.33	0.80	0.74	0.75
	(0.07)	(0.08)	(0.08)	(0.15)	(0.15)	(0.15)
Income group 4 (=1)	0.40	0.39	0.21	0.95	0.93	0.47
	(0.10)	(0.10)	(0.19)	(0.23)	(0.23)	(0.42)
Income group 5 (=1)	0.52	0.51	0.33	1.19	1.17	0.71
	(0.17)	(0.17)	(0.19)	(0.42)	(0.40)	(0.45)
Group expenditure (1000 rupees)	-0.15	-0.15	-0.16	-0.35	-0.34	-0.37
	(0.07)	(0.07)	(0.07)	(0.17)	(0.18)	(0.18)
Group expend X top 2 quintiles			0.03			0.07
			(0.03)			(0.06)
Controls	No	Yes	Yes	No	Yes	Yes
Observations	5,084	5,084	5,084	5,084	5,084	5,084

Dependent variable as noted in column header, in SD. Subjective well being data from World Values Survey, imputated group income from NSS. Peer groups de ned as intersection of state and religion (Hindu and non-Hindu). Controls include household size, age, sex, marital status and education. All columns include year xed e ects. Standard errors in parentheses and clustered at the group level. p < 0:10, p < 0:05, p < 0:01.

Table A3: Food spending as a function of group spending, generic model estimates

	RE		FE	
	(1)	(2)	(3)	(4)
a (peer mean expenditure)	0.142	0.131	-1.024	-1.077
	(0.047)	(0.046)	(0.428)	(0.442)
b (own expenditure	0.413	0.415	0.462	0.456
	(0.011)	(0.011)	(0.019)	(0.018)
d (curvature)	-0.181	-0.182	-0.099	-0.067
	(0.010)	(0.010)	(0.017)	(0.012)
a=b	-0.344	-0.315	2.214	2.361
	(0.118)	(0.115)	(0.928)	(0.975)