Exploring the link between the income distribution and visible spending: evidence from from South Africa

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Abstract

There is an ongoing debate about how changes in the income distribution may influence the household spending on visible spending (see, e.g., Hopkins and Kornienko, 2004, 2009). Using South African household spending data, we empirically examine how the share of group members who posses a similar income level to a given household is related to its spending on visible goods, such as jewelry and clothes. Our results suggest that an increase in this 'local income share' is positively associated with household spending on visible goods which are used to signal status. This result suggests that, while increases in mean group income are associated with a reduction in visible spending, a reduction in income inequality is associated with increases in visible spending. Ergo, policies that promote greater income equality may in fact be also fostering spending on status signalling. At the same time, this effect appears to be nonlinear such that when the local income share is large, additional increases in the local income share appear to have only a small or no effect on visible goods spending.

Keywords: Conspicuous consumption, Status, Income distribution

JEL classification: D12, D83, J15, O12

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1 Introduction

Recent years have witnessed a great deal of theoretical and empirical progress being made in studying the economic implications of conspicuous consumption (Frank, 1985; **?**; Becker, Murphy and Wening, 2005; Grinblatt et al., 2008; Heffetz, 2011). Household spending on visible goods such as jewellry, automobiles and clothes are thought are thought to reflect an underlying desire of individuals to demonstrate their wealth and accumulate social status. Recent empirical studies have uncovered evidence that certain economic features of social groups *do* indeed shape conspicuous spending patterns in such settings: spending on visible goods among US and South African households is negatively correlated with the mean income of the social group (Charles et al., 2009; Kaus, 2013). Specifically, both studies found that, *ceteris paribus*, individuals who belong to a social group that possesses a relatively high average income tend to spend relatively less on visible goods compared to others who belong to a social group with a low average income.

If average social group income does affect the demand for visible goods, this begs the question of whether higher moments of the income distribution may also influence household spending on visible goods. Does greater income inequality within a group enhance or diminish the demand for visible goods among its members? This straightforward question turns out to be surprisingly tricky to answer theoretically (see, e.g., Hopkins and Kornienko, 2004, 2009). Several argue that the relationship is negative since greater income inequality decreases the household's incentive to signal their socioeconomic position as it reduces the number of peers who possess a similar income level (Frank, 1985; Robson, 1992; Hopkins and Kornienko, 2009). Ergo, greater income equality actually fosters higher spending on visible goods. Others posit that more inequality can actually lead to an increase in spending on visible goods, if the status function is cardinal (Bilancini and Boncinelli, 2008, 2012). This issue is particular pertinent given that conspicuous consumption is thought to inhibit the accumulation of household savings among low income households in developing economies (Moav and Neeman, 2012), as well as the ongoing debate about proposals to tax conspicuous spending (Frank, 1985; Robson, 1992; Hopkins and Kornienko, 2009).

This paper devises a new empirical approach to study the relationship between the income distribution and the demand for visible goods. To date, the existing empirical work undertaken on this issue has used traditional group level measures of income inequality, such as the Gini coefficient and the coefficient of variation, to explore how income inequality affects spending for visible goods (Charles et al., 2009; Brown et al., 2011). These have found that the income distribution has a relatively small effect on visible spending. However, if visible spending really is a function of the number of peers who possess a similar income level, such an approach fails to take into account the fact that changes in the income distribution will have heterogenous effects on the demand for visible goods across different regions of the income distribution. An increase in income inequality can lead to some households experiencing an increase in the number of peers with similar incomes, while other households located in other income regions experience a fall. As such, if visible spending increases with a rise in the number of peers who possess a similar income level, then one would predict that spending on visible goods would increase among households in tail regions, but fall in regions close to the mean.

To properly disentangle how changes in the income distribution affect spending on visible goods, we develop a new alternative household level variable to directly track how many other household possess a similar income level to a given individual household. This allows us to directly examine the popular claim that it is the number of peers who possess a similar income level which determines how the income distribution affects visible spending (Frank, 1985; Robson, 1992; Hopkins and Kornienko, 2009). We define 'local income share' as the share of peers in the social group that possess the same level of income (within a range of five per cent) to a given household. We then proceed to explore how this share influences household spending on visible goods. Moreover, we discern how this effect may differ in the tail regions of the social group income distribution by exploring how the influence of local income share on visible spending varies across income and local income share levels. We compare these results to those obtained from using a global measure.

Our results show that this local income share has a positive and significant effect on conspicuous consumption and performs much better than group level measure of income inequality (Brown et al., 2011). Moreover, we also find that changes local income share have a relatively stronger effect on conspicuous consumption in the tail regions of the social group income distribution and a relatively less significant effect around the mean group income. This suggest that the effect of the local income share on visible spending is nonlinear and lends some support to the argument that increasing income equality may, under certain circumstances, lead to no changes in household spending on visible goods. In this regard, our paper sheds new light on the relationship between the social group income distribution and conspicuous spending patterns.

Finally, we also examine the extent to which the basked of goods used for signalling status is itself dependent on the household income level. To date, studies have assumed that the basket of visible goods, composed of jewelry, clothing, footwear and automobiles, is fixed across all income levels (Charles et al., 2009; Brown et al., 2011). But what if relatively poor household use a different basket of goods relative to rich people to signal wealth? We examine how each particular visible good is sensitive to changes in the income distribution, and how this relationship itself varies at different levels of household income. The results are striking in that they indicate that range of goods used to signal status tends to expand as household income rises. At low income levels, we observe that most of these visible goods are in fact not responsive to changes in the social group income distribution. This could reflect the fact that they are mainly used for non-signaling purposes. At higher income levels, however, household spending on a wider range of visible goods becomes responsive to changes in the dispersion of social group income. These findings contribute to a better understanding of how growing affluence can lead to positional concerns becoming more prominent in spending decisions related to a growing range of goods and services (Frank, 1999; Besharov, 2002; Solnick and Hemenway, 2005).

This paper is structured as follows. Section 2 reviews the various different conjectures about how the income distribution of social groups affects conspicuous spending. Section 3 discusses the new empirical approach taken to study the relationship between visible spending and the income distribution and discusses the data. Section 4 reports results for how both the overall group income distribution and the local income share affects visible spending. Section 5 presents examines how the effects of changes in the income distribution on visible spending varies across different types of visible goods and income levels. Section 6 concludes.

2 Background

The desire of individuals to demonstrate their wealth has been the subject of a long-standing theoretical debate (see e.g., Frank, 1985; Becker, Murphy and Wening, 2005; Arrow and Dasgupta, 2009; Frijters and Leigh, 2008; Heffetz, 2011). However, it is only recently that empirical research has started to make a substantial contribution to this debate. These contribution have started to shed light on important issues such as the extent to which different goods and services are visible to peers (Solnick and Hemenway, 2005), how the visibility of good affects income elasticities (Heffetz, 2011), how geographical proximity plays a role in visible spending (Grinblatt et al., 2008), as well as how household spending on visible goods is affected by business cycles (Kamakura and Du, 2012).

The income distribution has always featured prominently in this debate as many, including Veblen (1899), Kuznets (1943) and Brady and Friedman (1947), posit that an important determinant of consumption and savings choices is the individual's desire to signal their wealth represents (Hynes, 1998). Recent empirical studies have uncovered evidence that certain economic features of social groups *do* indeed shape conspicuous spending patterns in such settings: spending on visible goods among US and South African households is negatively correlated with the mean income of the social group (Charles et al., 2009; Kaus, 2013). Specifically, both studies found that individuals who belong to a social group that possesses a relatively high average income tend to spend relatively less on visible goods compared to others who belong to a social group with a low average income. Elsewhere, using US panel data Maurer and Meier (2009) find evidence for a strong and predictable co-movement between household consumption expenditure within peer groups over time. These results about the significance of mean group income beg the question whether higher moments of the income distribution also play a role in determining household visible spending.

Yet identifying how exactly changes in the group income distribution affect visible spending turns out to be surprisingly tricky to answer from a theoretical perspective (see, e.g., Hopkins and Kornienko, 2004, 2009). On the one hand, rank-based models posit that the relationship is negative since greater income inequality decreases the household's incentive to signal their socioeconomic position as it reduces the number of peers who possess a similar income level (Frank, 1985; Robson, 1992; Hopkins and Kornienko, 2009). Assuming the utility received from their social status is ordinal and people only care about their group rank, the basic intuition is that the greater are the number of peers who possess a similar income level to a households, the greater is the household's desire to differentiate itself from these peers via conspicuous consumption. As shown by Hopkins and Kornienko (2004), if there are relatively few other peers who possess a similar income, then the prospective status payoff (i.e. the marginal increase in rank) from engaging in conspicuous consumption is relatively low. Ergo, greater income inequality actually reduces spending on visible goods by reducing the number of peers who possess a similar income level, thereby reducing the payoff from spending on visible goods. This logic suggests that visible spending is greater in societies where income inequality is low.

Other scholars posit that if the status function is cardinal, under certain conditions, more inequality can actually lead to an increase in spending on visible goods (Bilancini and Boncinelli, 2008, 2012). If individuals care not only about their rank, but how much further ahead they are from their peers in the status distribution, then the differences between the benefits of being a high status individual (relative to a low status individual) can be magnified as income inequality increases. greater income inequality leads to more spending on visible goods, as households have a greater incentive to increase their status. A similar scenario is discussed by Merzyn (2006), who argues that in the presence of heterogenous preferences and heterogenous wealth levels, greater income equality heightens uncertainty about the household's motivation to consume visible goods (discussed further in Section 5).[1]

Empirical studies seeking to verify these conjectures must necessarily make certain assumptions about i) what goods are used to signal status, ii) what other uses visible goods have, iii) the extent to which households do correctly infer income from spending on visible goods (Charles et al., 2009). In terms of capturing the effect of the income distribution, previous studies have used a number of different group-level measures to capture the changes in the per capita household income distribution in the natural village, including: the Gini index, the skewness statistic, the kurtosis statistic and interaction term between skewness and kurtosis (Charles et al., 2009; Brown et al., 2011). In particular, Brown et al. (2011) have found some evidence for a positive correlation between the dispersion of income and conspicuous spending in rural Chinese villages. While the Gini coefficient appears to have no significant effect on spending on visible goods - in their case funeral and wedding expenses - they do find that this spending increases among the poorest 25 per cent of households when the kurtosis of per capita income distribution rises.[2] However, in spite of finding some evidence that the income distribution affects conspicuous spending among the richest 25 per cent of household, the authors conclude that the rank-based model of status conspicuous consumption is only useful for describing the poorest segment of society, while the behavior of high income groups may be guided by other motives (Brown et al., 2011, p. 146).

There are three potential drawbacks to using these group-level measures to examine how changes in the income distribution affect visible spending. First, they do not directly address the main conjectures (described above) that revolve around the notion that household spending on visible goods is a function of how many peers are observed to possess a similar income level. Although this number is related to the income distribution of the group, it is not exactly the same thing. To illustrate, consider a mean-preserving redistribution of income that increases the dispersion of income, as illustrated in Figure 1 by a change from Y to Y'. This income redistribution leads to a reduction in the density of households in dense regions (from A to B, e.g., close to the mean), but an increase in the density of households in regions close to the tails of the distribution from (e.g., from C to D). As such, if visible spending increases with a rise in the number of peers who possess a similar income level, then one would predict that spending on visible goods would increase among households in tail regions, but a fall in regions close to the mean. Such nuances would not be captured by regressing global measures of income inequality on visible spending. As there are many different possible redistributions through which the overall income inequality increases, there is no *a priori* reason to assume that all of these redistributions would affect the number of peers within a particular region in the same way.

FIGURE 1 ABOUT HERE

[1] Still others argue that the relationship depends on whether the shape of the Engel Curve for visible goods is concave or convex (Charles et al., 2009). In and accompanying paper (Chai and Kaus , 2012), we explore the link between Engel curves and visible spending in the South African data.

[2] An interaction term combining the effects of kurtosis and skewness was also found to be significant for increasing conspicuous spending among the bottom 25 per cent as well the top 25 per cent.

Secondly, in terms of how the income distribution tends to evolve as economies grow, studies have found that income inequality typically rises in an asymmetric fashion through which the skewness of the distribution increases: a small segment of individuals become (very) wealthy, while the income of other remains relatively stable (Chotikapanich et al., 2012). This is the case in the US data studied by Charles et al. please use tex code: Charles et al. (2009, see Figure 2, p. 444), as well as in most (but not all) of the social group income distributions featured in the South African data (see Table 1). Here it is worth pointing out that an growing income inequality does not necessarily imply that there will be an increase in the number of peers with similar incomes to any given household within the tail region. This is because as more households enter this region, the tail may expand in such a way that it covers a larger income range. As a result, the tail region may grow to cover a larger range of income such that the number of peers who possess a similar income level at any point within the tail may remain constant even when the number of households within the tail grows. This again highlights the inadequacy of using group-level measures of income inequality to verify rank-based models of visible spending.

Thirdly, concerning the use of group-level measures of the income distribution is the use of measures of skewness and kurtosis as proxies for changes in the dispersion of income (Brown et al., 2011). These third and fourth order moments do not precisely capture the same effect as the second order moment. In particular, unlike the second order, both skewness and kurtosis are non-dimensional in nature in that their values purely describe the shape of the distribution (Press et al., 1992). This means that for these values to be meaningful, it is important to take into account *their* standard deviation which implies making assumption about the shape of the underlying distribution for the value and, rather critically, on the tail of this distribution.[3] In particular, Kurtosis depends on such a high moment that its the standard deviation is very large Press et al. (1992, p. 607). As an alternative to using group level measures of income inequality, we now develop a more direct, household-level variable to study how the social group income distribution affects visible spending.

3 Empirical approach and Data

The data is from the South African Income and Expenditure Survey (IES) conducted in 1995, 2000, and 2005. It covers a representative sample of South African households and consists of 29,582 households in 1995, 26,263 in 2000, and 21,144 in 2005, respectively. In terms of constructing the dataset, two issues have to be confronted. Firstly, the structure of the IES 2005 series differs from preceding surveys (Yu, 2008). As a result, the 1995 and 2000 income and expenditure items were recategorized according to the the UN Statistics Division's Classification of Individual Consumption According to Purpose (COICOP). Furthermore, the 2005 values of income, *housing and utilities* as well as total expenditure had to corrected for the values of imputed rent to ensure that they are consistent with IES samples. Although the change of methods from recall to diary method may also diminish comparability, von Fintel (2007) finds no systematic change in estimating income elasticities of aggregated product categories that can be attributed to the change in this methodology. A second issue is that there exists some doubt about whether the IES

[3] measures of skewness and kurtosis tend to have very large standard deviations, which is problematic given that the sample size in (Brown et al., 2011) ranges between 129 to 346 (see Table 5–7C).

of 2000 is representative of the SA population (Burger et al., 2004; van der Berg et al., 2008). Due to migration between the 1996 census and the collection of IES data for 2000, the survey is known to over-represent the black population while under-representing the white population (Özler, 2007). To account for possible shortcomings, the 2000 sample was reweighted to match it up with the corresponding population shares reported in the 2001 census, as suggested by Özler (2007).

Visible spending is defined as the sum of all household expenditures spent on personal care, clothing and footwear, jewelry, and cars (Charles et al., 2009; Kaus, 2013). A recent study by Heffetz (2011) confirmed that these goods are considered to be highly visible among US households.[4] The 'social group' is defined by social affiliation at the provincial level. This method follows previous studies which also define social groups by region and race (Charles et al., 2009; Kaus, 2013). This approach is also justified in the South African case as much evidence suggests that race is an important factor in a range of social interactions such as the labour market, the education system and the housing market (Moodley and Adam, 2000). Descriptive statistics about the social group income derived by this method can be found in Table 1.

TABLE 1 ABOUT HERE

We proceed by regressing log household spending on visible goods Vis_i on social group dummies which indicate whether a household Black Bl_i or Coloured Col_i, the log of a household's permanent income $pInc_i$, a vector of demographic indicators Dem_i as well as a vector of year dummies Yr_i. These include a dummies for education, the first for whether the head of the household has more than ten years education and the second for whether this includes a university degree. Dem_i includes area type, age, age squared, and family size.

$$ln(Vis_i) = \beta_0 + \beta_1 Bl_i + \beta_2 Col_i + \gamma ln(pInc_i) + \delta \mathbf{Dem_i} + \epsilon \mathbf{Yr_i} + \varepsilon_\mathbf{i}. \quad (1)$$

Results are reported in Table 2. The log-log formulation of the regression equation allows us to interpret the coefficient γ as the (permanent) income elasticity of visible consumption expenditure. Note that permanent income, measured by total expenditure, needs to be instrumented with to alleviate endogeneity and measurement error problems.[5] in specification (2) we examine whether observed differences in conspicuous consumption between social groups can be accounted for by differences in group income levels, as suggested by Charles et al. (2009). We do so by entering the average social group income ($Inc^{\mu}_{k,t}$), which renders the social group indicators insignificant. Specifications (3) and (4) introduce 'global' measures of income dispersion, including the coefficient of variation, $Inc^{v}_{k,t}$, in (3); and the Gini coefficient $Inc^{\gamma}_{k,t}$ in (4). Specifications (5) and (6) introduce the former variables alongside $Inc^{\mu}_{k,t}$.

To measure local income share, we count the number of households within a bandwidth b of income that are located in the same reference group k that denotes households found in a particular province, social group unit and time period (e.g. Black population in Western Cape province surveyed in 1995, see Table 1). We define the variable $LS_{k,t}$ as this number divided by the total number of households in k. This variable reports what percentage of the social group is located within b. Note that this implies that for

[4]See Kaus (2013) for a discussion on the visible consumption item composition.

[5]Tests of the statistical validity of different sets of instruments showed that a specification with the log of current income to be the best suited as a single instrument for permanent income.

some given increase in $LS_{k,t}$, a greater number of peers need to enter b in larger social groups than in smaller groups. This is consistent with the key concept of reference-dependence that has emerged in behavioral economics Tversky and Kahneman (1991); Kahneman and Varey (1991): changes observed by individuals tend to be interpreted by individuals relative to a reference level. In the case of observing changes in the number of peers who possess a similar income level, we posit that the reference point would be the size of the social group. Thus individuals in small groups are much more likely to notice one additional peer entering b relative to a those who are part of large social groups. In terms of selecting an appropriate b, we choose to count all households that are within a five per cent income range of the household.

The choice of b is illustrated in Figure 2, which depicts the number of peers within the 5 per cent bandwidth for each particular income level. The left hand side figure depicts the kernel density distribution of household income of the Black population in 1995 within the Western Cape province. The right hand side figure displays a scatter plot of the corresponding local income share variable. Comparing the two shows that the use a five per cent range for b generates a $LS_{k,t}$ that accurately reflects the social group income distribution depicted on the left hand side. Both the kernel density and the local density variable have a similar shape in that they possess right skewed distribution and approximately the same mean. Larger values of b yield a less accurate reflection of the actual income distribution. Consequently, we judge the 5 per cent value to be a satisfactory value for b.

The effect of $LS_{k,t}$ on visible spending is evaluated in specifications (1) and (2) in Tables 3 and 4. In specification (3) we proceed to examine whether the effect of local income share on visible spending differs across relatively rich and poor households within the social group. Following the partition approach (Yip and Tsang, 2007), we include a dummy intercept term for below mean income households ($DummyLOW$) and two interaction terms: $LS_{k,t}$*HIGH for above mean income households and $LS_{k,t}{*}LOW$ for below mean income households.

As an alternative strategy to examine the potentially nonlinear effects of $LS_{k,t}$ on visible spending, in specification (4) we partition the population according to whether the household is located in either a relatively sparse ($LS_{k,t}{*}SPARSE$) or relatively dense income region ($LS_{k,t}{*}DENSE$). In creating this dummy variable, we have to choose a cut off point for $LS_{k,t}$ that distinguishes between a relatively sparse income region from a relatively dense income region. We call this value c and select a cut off point where $LS_{k,t} \leq 2\%$ of k. Note that whether or not a income region with a given number of households is dense or sparse depends on the overall size of the social group. In large groups, an income region with 100 households could be classed as sparse, whereas this could be classed as dense if the total number of members belonging to the social group is small. This logic is again consistent with the notion of reference dependence Tversky and Kahneman (1991); Kahneman and Varey (1991).

Figure 3 illustrates how the number of sparse income regions vary by the cut off point c used to define a sparse region. Each figure depicts a scatter plot of the nominal local income share variable of the Black population in 1995 within the Western Cape province. As the cutoff point increases, the more households are allocated to relatively sparse neighborhood (highlighted in red). To properly capture the left *and* the right tail of the distribution, whilst simultaneously excluding households in the central region of the distribution, the two per cent cut off appears to strike an appropriate balance (middle left hand side figure).[6] Lastly, we proceed with combining interaction terms defined in specification (3) and (4) to partition the population into four groups across both above and below mean group income households, as well as sparse and dense regions of the income distribution in specification (6).

FIGURE 2 AND 3 ABOUT HERE

4 Results

Adopting group level measures of income inequality (results in Table 2) suggest that changes in the social group income distribution have a negative influence on visible spending. The Gini coefficient $Inc^{\gamma}_{k,t}$ in (4) is negatively and significantly correlated with visible spending at the $\alpha = 1\%$ level of significance. The negative and significant finding for $Inc^{\gamma}_{k,t}$ is consistent with Charles et al. (2009) findings for White Americans and the findings of Brown et al. (2011) for the poorest 25% in rural China. To check whether this significance of $Inc^{\gamma}_{k,t}$ may be capturing the effect of change in the mean social group income, specifications (5) and (6) includes ($Inc^{\mu}_{k,t}$) alongside these variable. However, we also note that the coefficient of variation, $Inc^{v}_{k,t}$, in (3) does not appear to be significantly correlated to visible spending. These results provide a useful benchmark to compare with the results for local income share which we now turn to.

TABLE 2 ABOUT HERE

Results for local income share are reported in Table 3 and 4, where Table 3 uses the Gini coefficient ($Inc^{\gamma}_{k,t}$) as a group level control variable, while Table 4 uses the coefficient of variation ($Inc^{v}_{k,t}$). Specification (1) in these tables shows how $LS_{k,t}$ is positively correlated with visible spending, which is significant at the $\alpha = 0.1\%$ level. Consistent with results for group level measure reported in Table 2, the positive sign supports the notion that household spending on visible goods increases as the number of peers with a similar income level increases. Comparing results in specification (1) to specification (5) and (6) in Table 2, we observe that including $LS_{k,t}$ has reduced the magnitude and significance of $Inc^{\gamma}_{k,t}$ and $Inc^{v}_{k,t}$. This was to be expected given that both of these variables convey information about the dispersion of income, although there is a low correlation between $LS_{k,t}$ and both $Inc^{\gamma}_{k,t}$ (-0.0506) and $Inc^{v}_{k,t}$ (-0.0157).[7] These results suggest that $LS_{k,t}$ has an effect on visible spending that is not captured by either $Inc^{\gamma}_{k,t}$ and $Inc^{v}_{k,t}$, which is also reflected in an increase in the goodness of fit of the model (rising from 0.4962 in (6) of Table 2 to 0.4972 in (1) of Table 3).

Specification (2) indicates that the effect of $LS_{k,t}$ is nonlinear. In particular, the derivative of visible spending with respect to changes in $LS_{k,t}$ needs to be evaluated by $d(vis_i)/d(LS_{k,t}) = (-58.08 * LS_{k,t} + 5.363)e^{LS_{k,t}*(2.309-29.04*LS_{k,t})}$. The effect of $LS_{k,t}$ is thus positive, but the size of the effect diminishes as $LS_{k,t}$ increases. This suggests that as the local income share grows, additional increases to its level do not appear to be positively correlated with visible spending. Moreover for $LS_{k,t}$ values larger than 0.0932, the effect turns negative. This concerns, however, only a small number of observations (less than 3%). This could be interpreted as some evidence for the notion that the status

[6] The following section reports on robustness checks that further validate this choice (see Figure 4).

[7] This low correlation is chiefly because $LS_{k,t}$ is defined at household level, while $Inc^{\gamma}_{k,t}$ and $Inc^{v}_{k,t}$ are defined at the k group level.

function is cardinal, although this appears to hold in very densely populated regions of the income distribution (Bilancini and Boncinelli, 2008).

TABLE 3 and 4 ABOUT HERE

Results from (3) indicate that visible spending among above average income households is positively correlated with $LS_{k,t}$. Compared to specification (1), the size of the parameter estimate for $LS_{k,t}$*HIGH is much larger than the parameter estimate of $LS_{k,t}$. However, these differences may be due the right hand tail of the income distribution is much larger than the left hand tail (see Figure 3). Since we know that the effect $LS_{k,t}$ on visible spending is nonlinear and diminishes when the local income share is large, the parameter estimate for $LS_{k,t}$*HIGH may simply reflect the fact that the average local income share value is relatively low among rich household and relatively high among poor households. As such, these results alone do not disentangle the effect of being relatively wealthy from the effect associated with being located in a relatively sparse income interval.

A chief question is how the effect of $LS_{k,t}$ on visible spending relates to the underlying level of $LS_{k,t}$. Results from (4) show that the effect of a change in local income share on visible spending is very strong in relatively sparse intervals of the income distribution, but weak among relatively dense intervals of the income distribution, as reflected in the significant and large value of $LS_{k,t}{*}SPARSE$. This is consistent with the results found in (2) and provides further evidence that $LS_{k,t}$ appears to have a strong effect on visible spending when the local income share is is less than or equal to two per cent of k.

Figure 4 sheds greater detail on this aspect by depicting how the effect of $LS_{k,t}$ on visible consumption (vertical axis) differs across sparse (line with square markers) and relatively dense income intervals (line with diamond markers) as both b and the cutoff value for defining a sparse income region c is altered (horizontal axis). The dotted lines represent the 95% confidence interval for the parameter estimate of $LS_{k,t}$ on visible consumption in relatively sparse regions. In specification (4), a sparse income region is defined as one in which $LS_{k,t} = 2\%$ and $b = 5\%$ (third bin from the left in the top right hand figure).

This Figure 4 reveals three things. Firstly, in terms of selecting an appropriate value for c, the figures show that the higher is c, the smaller is the effect of $LS_{k,t}$ on visible consumption in sparse income intervals. This is entirely to be expected as increasing c implies a greater of observations in from the relatively dense mean region of the income distribution are captured by the dummy for sparse income intervals (see Figure 3). Also note that at low cut off values, the confidence intervals are very large as there are only a small number of observations are located in the sparse region. As such, a choice of $c = 2\%$ strikes an adequate balance between having an sample size that is not too small (which delivers wide confidence intervals) and not too large.

Secondly, this downward trend is again consistent with previous evidence that $LS_{k,t}$ has a nonlinear, concave effect on visible spending. As the level of $LS_{k,t}$ increases, the effect of $LS_{k,t}$ on visible spending declines. Regardless of the chosen level of b this effect is also consistently larger in sparse income regions relative to dense income regions: the mean effect of $LS_{k,t}$ on visible spending in dense regions is close to zero or even negative, irrespective of chosen value for b or c. Taken together, this provide more evidence that it is only in sparse income regions that $LS_{k,t}$ is positively correlated with visible spending.

Finally, concerning income bandwidth b, each quadrant shows a figure that uses a different b. The figure in the top left hand side uses a small income bandwidth of 2.5% of household income while the figure on the bottom right hand side uses a relatively large bandwidth of 10% of income. Differences across the quadrants reveal evidence that the household's visible spending decisions are only affected by changes in the local income share that occur within a income bandwidth of 5%. Changes density that occur outside the income bandwidth at 7.5% and 10% appear to be less influential since parameter estimates of $LS_{k,t}$ on visible spending are relatively lower when b is increased (see bottom left and right hand figures). On the other hand, when $b \leq 5\%$, the effect of $LS_{k,t}$ on visible spending is relatively larger. This represents some interesting evidence about precisely how local changes $LS_{k,t}$ have to be in order for these changes to have an effect on visible spending patterns.

The results from (5) in Table 3 and 4 indicate that the effect of local income share on visible spending is consistently positive and significant across both relatively poor (left-hand tail region) and rich households (right-hand tail region). This contrasts strongly with specification (3) where a significant positive effect was found for relatively wealthy households, but not for relatively poor households. The positive and significant effects in (3) can thus be explained by a large overlap between $LS_{k,t}$ values of the relative affluent and those in the sparsely populated regions of the income intervals. These results also indicate that within dense regions of the income interval, the effect of $LS_{k,t}$ is consistently small and hardly significant among both relatively wealthy or poor households. This finding confirms the observation by (Brown et al., 2011) that changes in the income distribution have little influence on visible spending by households located in the relatively dense regions of the income distribution. Moreover, the different results across sparse and dense regions of the income distribution are consistent with the findings of nonlinearity of $LS_{k,t}$ in specification (2). In contrast to sparse regions where rising $LS_{k,t}$ is positively correlated with visible spending, in dense income regions - where $LS_{k,t}$ is high - marginal increases in $LS_{k,t}$ appear to have no significant or even a negative effect on visible spending.

5 Differences across visible goods

Our results suggest that changes in the income distribution have a relatively weak effect on visible spending among low income households. In contrast, Brown et al. (2011) found that spending on visible goods by the poorest segment of society responds strongly to the dispersion of income. One possible explanation for our result is that there are few low income households situated in income intervals that possess a relatively small number of social group peers. Given that the effect of a change on income distribution on conspicuous spending is particulary strong in relatively sparse income neighbourhoods, this could explain why visible spending among low income households do not appear to respond to changes in the income distribution.

A second possible explanation for this result could be that the manner in which households actually use visible goods and services is itself dependent on their income level. Visible goods are typically composed of automobiles, clothing and footwear, as well as jewelery (Charles et al., 2009; Kaus, 2013). Many of these can be used for purposes other than status signalling. While there is little doubt that they are highly visible to others (as recently verified by Heffetz (2011), there is a subtle yet important difference between consuming visible goods and actually using them to signal status Merzyn (2006). In particular, its possible that affluent households are more likely to use visible goods to signal status, while low income household are more likely to use them to satisfy other, more basic needs (Scitovsky, 1976; Frank, 1999; Witt, 2001).

For example, an automobile can be used for transport and can be used to signal wealth. However, most households use cars only for transport since those cars which can also signal wealth typically attract a premium. Thus the possibility that low income households use a relatively limited number of visible goods may therefore account for why the income distribution has an insignificant effect on the aggregated level of visible spending among low income households in specification (3) of 3 and 4. On the other hand, more affluent consumers also use a wider range of goods to signal their wealth. There are countless other examples of how goods can be modified in order for them to be used to signal wealth. Witt gives the example generic pens are normally used for writing, but can be modified to signal status via ornamental decoration and the use of expensive(Witt, 2001). Another good example is the 5,000 Viking-Frontgate Professional barbecue grill mentioned by Frank (1999): a cooking device that appears to possess an excessive amount of features and qualities which is designed to impress guests. This also suggests that the range of goods being used to signal status will increase as household income rises.

For this exercise we focus on the visible spending pattern of the black population, which represents the largest group in South Africa. We do so as it is the only social group in which within-group tests confirmed that mean group income had a negative impact on visible spending (Kaus 2012, p. 69). We therefore run specification (3) from Table 3 separately for the black population and for each subcategory of visible goods, which includes *clothing*, *footwear*, *automobiles* and *jewelry*.

The results are shown in Table 5. They confirm that the range of goods and services used for status signalling tends to grow as household rises. In relation to low income households, only *jewelry* appears to have a significant negative correlation (at the $\alpha = 0.5$ level) with the dispersion of social group income among the four types of visible goods. This suggests that *jewelery* is indeed being used to signal status among low income households, while other goods, including *automobiles*, *clothing* and *footwear*, are being primarily used for non-signaling purposes. In contrast, among high income households, all four categories have a negative and significant correlation with the dispersion of income, which suggests they are all used for the purposes of status signalling by high income households. In this sense, the results support the view that the footprint of status signalling on household spending patterns tends to grow as income rises, resulting in more observable goods being used by households to signal status.

6 Discussion and conclusions

This paper has developed a new household level approach to studying how changes in the income distribution affect household spending on visible goods. Our results underline how the local income share variable provides a better empirical approach to studying the relationship between social group income distribution and household spending on visible goods. In particular it allows scholars to properly disentangle how visible spending tends to change across relatively dense and sparse regions of the income distribution. An important feature of our results is that we find evidence that, irrespective of their income level, households tend to respond to a change in local income share in the same way: increases in the local income share are associated with increases in spending on visible goods. This casts doubt on the idea that rank-based model of status conspicuous consumption is only useful for describing the "poorest segment" of society (Brown et al., 2011, p. 146). Rather, it suggest that such models are highly relevant for understanding the consumption patterns of all households.

Another important result is that the influence of local income share on visible spending appears to be nonlinear. Large increases in visible spending are only observable when the local income share is relatively small. Among households who are located in relatively dense regions of the income distribution, where the local income share is large, changes in local income share appear to have a relatively smaller effect on visible spending. This result provides some consolation to those who entertain the possibility that there may exist conditions in which low income inequality may be compatible with low spending on visible goods (Bilancini and Boncinelli, 2012). It is also worth noting the implications of this nonlinear effect for understanding how economic growth affects visible spending. Typically economic growth fosters increases in income inequality by enabling a small segment of individuals become (very) wealthy, while the income of other remains relatively stable (Chotikapanich et al., 2012). Our results suggest that such change in the income distribution would have a twofold impact on visible spending. On the one hand, in dense income neighbourhoods, this would lead to a small decline in visible spending among the households whose income has remained stable, since the share of peers in the group who possess similar incomes has declined. On the other hand, households in relatively sparse income regions may experience a relatively large increases in visible spending, if the local income share in these regions has increased due to new wealthy individuals being moving into their income interval. This prospect suggest that it is far from clear that increasing income inequality will lead to an overall reduction in visible spending among a group. Much depends on the precise nature in which changes in the incomes distribution affect the local income shares across different income neighbourhoods.

In the context of the post-apartheid South Africa, we note there a limitation of our study is that it did not consider how changes in the income distribution of other social groups to which households do not belong affect visible spending. Nevertheless, our results suggest that although there has been a decline in geographical segregation between differnet social groups (Christopher, 2001), a predominant share of spending on visible goods still appears to be mainly orientated towards signalling wealth towards fellow group members, as evidenced by the significant impact that local income share has on visible spending. A question for future research is whether this situation will change as segregation between groups continues to decline, and how this would effect spending on visible low income households.

Finally, an important issue for policymakers is to understand the extent to which positional concerns vary across different spending categories (Solnick and Hemenway, 2005; Besharov, 2002). Here most studies have conducted survey work to examine which categories are perceived to be the most visible among households (Solnick and Hemenway, 2005; Charles et al., 2009; Heffetz, 2011). These have yielded relatively robust results, in that spending on jewelry, automobiles and housing are consistently found to be viewed by respondents as the most visible type of household spending activity. Yet a somewhat neglected dimension has been the question of whether the *range* of visible goods that are actually used to signal status may depend on household income. In this regard, our findings show that for the largest social group in the sample, Black South Africans, *jewelry* appears to be the only visible good that is used by low income households to signal status. In contrast, among high income households, the expenditure categories of *cloth-*

ing, *footwear*, *automobiles*, as well as *jewelry* all appear to be used for status signaling as they are correlated to the distribution of social group income. In terms of policy implications, this suggests that any tax of on status-signalling activities (Frank, 1999) can not simply impose a tax on a fixed set of visible goods without taking into account how this set is conditional on the household income level. This is particularly important for understanding the substitution effects that result from a tax on status-related spending.

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Tables and Figures

Table 1: Income distribution by social group, province and year

	Black			Coloured			White		
	1995	2000	2005	1995	2000	2005	1995	2000	2005
Province 1									
Mean	32,729	26,349	30,400	49,805	47,918	51,395	147,165	146,419	192,179
SD	26,441	24,088	22,871	43,178	47,026	51,855	136,600	138,250	21,2239
Min	353.20	0	0	3602.65	0	0	7629.14	0	1399.73
Max	188,609	203,520	141,735	270,198	276,480	303,883	1,058,525	729,600	1,913,720
Kurtosis	4.55	13.88	6.43	7.20	7.90	8.08	13.10	5.93	22.23
Skewness	2.11	2.73	1.70	1.85	2.10	2.17	2.60	1.65	3.51
Median	24,849	19,507	24,807	36,026	31,642	33,107	113,642	107,238	129,118
Obs.	525	575	484	1,578	1,473	1,357	1,017	393	505
Province 2									
Mean	25,781	19,024	25,826	39,182	35,561	48,395	144,265	130,238	143,887
SD	29,425	24,075	31,895	38,471	43,422	54,007	150,017	107,392	128,442
Min	0	0	10	2,119	0	918	848	0	753
Max	212,652	161,879	205,527	216,774	294,646	336,476	1,010,155	538,240	707,177
Kurtosis	12.11	11.97	11.71	7.00	15.49	9.69	10.81	5.02	7.13
Skewness	2.81	2.82	2.81	1.93	3.17	2.33	2.52	1.41	1.86
Median	16,530	9,927	14,625	25,107	20,314	28,232	97,211	94,348	111,309
Obs.	3,945	2,892	2,234	622	264	271	536	194	235
Province 3									
Mean	20,222	23,279	26,681	29,132	28,643	37,628	118,314	157,165	152,355
SD	18,933	26,104	29,714	27,145	34,780	46,974	116,566	170,789	132,463
Min	706	0	0	2,331	0	0	5,298	0	49.63
Max	103,693	181,760	185,638	178,013	193,920	305,225	863,053	1,024,000	583,561
Kurtosis	8.09	12.74	10.40	8.84	8.67	11.74	13.48	11.48	4.10
Skewness	2.13	2.73	2.54	2.19	2.37	2.76	2.74	2.69	1.25
Median	13,637	13,609	16,723	20,267	15,360	19,992	86,534	111,309	106,882
Obs.	393	474	759	614	603	756	373	187	168
Province 4									
Mean	21,451	20,553	29,893	23,399	36,653	48,926	106,351	134,024	160,872
SD	23,331	23,218	35,377	22,025	52,606	59,511	86,831	157,271	158,188
Min	0	0	0	3,108	3,840	786	2,525	0	7,214
Max	153,641	177,037	209,435	121,854	267,882	265,617	535,099	1,275,520	849,357
Kurtosis	9.34	14.27	9.63	8.32	12.13	5.82	6.79	21.63	7.52
Skewness	2.35	2.93	2.51	2.15	2.92	1.83	1.69	3.65	1.97
Median	12,857	12,791	16,967	16,742	16,589	20,060	84,768	93,440	119,645
Obs.	2,267	1,989	1,428	198	39	95	589	199	189
Province 5									
Mean	36,429	21,119	24,360	69,648	53,954	60,460	159,609	146,533	195,856
SD	33,018	22,830	26,069	56,989	47,738	62,577	161,426	119,583	174,105
Min	0	0	0	8,477	2,304	503	0	1,605	168
Max	205,563	161,280	180,966	339,073	194,514	332,675	1,245,362	768,000	918,191
Kurtosis	8.25	12.53	11.98	7.21	4.68	9.64	17.68	7.44	7.55
Skewness	2.10	2.78	2.73	1.79	1.50	2.34	3.29	1.75	1.97
Median	25,430	13,670	15,890	53,969	40,832	42,650	125,210	115,200	153,258
Obs.	3,437	3,654	4,172	192	37	51	625	251	154
Province 6									
Mean	32,753	25,668	29,437	45,434	43,830	33,614	161,482	119,135	160,103
SD	36,836	26,451	34,041	41,482	45,773	32,085	238,247	109,173	135,002
Min	0	0	0	4,945	0	2,212	3,857	0	4,299
Max	233,070	192,000	204,198	190,012	161,480	156,427	2,609,913	697,600	630,291
Kurtosis	9.41	10.22	9.07	4.41	3.84	6.30	44.67	12.01	5.15
Skewness	2.37	2.37	2.37	1.42	1.36	1.81	5.40	2.48	1.59
Median	19,073	16,896	16,966	28,821	24,064	22,044	105,960	98,304	120,424
Obs.	1,897	2,473	1,351	118	38	52	337	172	112
Province 7									
Mean	54,926	32,686	44,299	86,689	60,281	145,346	177,866	162,569	230,073
SD	50,223	33,420	49,538	64,666	64,356	160,736	143,335	145,843	226,921
Min	2,296	0	0	4,662	0	3,216	3,758	0	334
Max	307,285	230,400	306,666	328,300	360,832	588,497	974,834	988,160	1,452,604
Kurtosis	7.03	11.60	9.45	4.05	9.37	3.93	9.53	7.62	8.94
Skewness	1.88	2.62	2.36	1.18	2.39	1.43	2.17	1.77	2.17
Median	38,135	23,040	27,366	72,376	39,014	77,601	146,449	122,880	162,930
Obs.	1,686	3,141	1,935	250	143	48	1,052	481	402
Province 8									
Mean	30,410	24,828	29,752	63,656	40,312	29,770	135,927	120,581	203,050
SD	24,910	26,090	34,762	44,594	36,489	38,089	104,587	108,834	169,671
Min	2,296	0	0	8,265	2,227	2,837	7,883	0	10,512
Max	154,702	187,649	274,019	166,887	154,061	156,703	646,357.6	1,017,472	813,093
Kurtosis	7.13	12.47	14.47	2.32	5.71	1	6.11	5.28	4.84
Skewness	1.84	2.78	2.98	0.73	1.72	0	1.58	1.21	1.37
Median	23,837	16,000	18,550.71	49,801	27,648	29,770	110,676	101,747	140,047
Obs.	1,844	2,075	1,540	56	23	2	378	95	98
Province 9									
Mean	41,964	23,427	25,777	76,779	11,469	37,776	164,174	159,769	143,576
SD	52,122	31,694	30,109	60,256	3,285	36,100	159,548	154,549	107,997
Min	0	0	0	7,064	7,680	9,305	3,179	0	22,002
Max	363,463	217,600	211,358	199,576	13,517	100,251	1,147,947	858,880	609,599
Kurtosis	11.19	14.02	12.19	2.39	1.5	2.95	17.83	8.36	8.33
Skewness	2.64	3.12	2.81	0.72	-0.70	1.26	3.32	2.11	2.06
Median	21,282	12,288	15,576	65,918	13,210	23,927	124,327	113,600	105,591
Obs.	2,310	2,870	1,809	14	3	5	184	86	63

Notes: All amount are reported in 2005 South African Rand. Due to limited sample size, Asians, Indians and other minorities have been excluded.

Table 2: The effect of social group income dispersion on visible spending

Variables	Specifications					
	(1)	(2)	(3)	(4)	(5)	(6)
Social group variables						
Black	0.56***	0.09	0.57***	0.59***	0.09	0.12
	(0.04)	(0.09)	(0.04)	(0.04)	(0.09)	(0.09)
Coloured	0.37***	0.04	0.38***	0.39***	0.03	0.05
	(0.04)	(0.07)	(0.04)	(0.04)	(0.07)	(0.07)
Moments of the income distribution						
$Inc^{\mu}_{k,t}$		-0.30***			-0.32***	-0.30***
		(0.05)			(0.05)	(0.05)
$Inc^{\upsilon}_{k,t}$			-0.05		-0.16*	
			(0.08)		(0.08)	
$Inc^{\gamma}_{k,t}$				-0.75**		-0.76**
				(0.28)		(0.28)
Household controls						
Household income	1.32***	1.34***	1.32***	1.32***	1.34***	1.34***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Year1995	-0.21***	-0.19***	-0.22***	-0.24***	-0.21***	-0.21***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Year2000	0.24***	0.18***	0.24***	0.23***	0.17***	0.17***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age^2	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Family size (various dummies)	(+)***	(+)***	(+)***	(+)***	(+)***	(+)***
Area type (urban)	-0.01	0.03	-0.01	-0.02	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Education>10 years	-0.08**	-0.08**	-0.08**	-0.07**	-0.08**	-0.08**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Education (university degree)	-0.10*	-0.11*	-0.10*	-0.09+	-0.10*	-0.10*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Constant	-5.41***	-2.04***	-5.34***	-5.02***	-1.67**	-1.65**
	(0.22)	(0.59)	(0.24)	(0.27)	(0.64)	(0.63)
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2 (centered)	0.4951	0.4958	0.4951	0.4954	0.4960	0.4962
Obs.	72163	72163	72163	72163	72163	72163

Notes: The regressions use the full sample described in Table 1 in Kaus (2013). Robust standard errors, clustered at PSU level, are indicated in parentheses. *** (**, *) Significant at the 0.1% (1%, 5%) level.

Table 3: The effect of local and global (Gini coefficient) density on visible spending

Variables	Specifications				
	(1)	(2)	(3)	(4)	(5)
Social group variables					
Black	0.138	0.119	0.139	0.099	0.111
	(0.0870)	(0.0871)	(0.0879)	(0.0872)	(0.0874)
Coloured	0.0678	0.0559	0.0758	0.0360	0.0505
	(0.0649)	(0.0650)	(0.0663)	(0.0650)	(0.0654)
Moments of the income distribution					
$Inc^{\mu}_{k,t}$	-0.287***	-0.294***	-0.543***	-0.290***	-0.423***
	(0.0508)	(0.0509)	(0.0696)	(0.0517)	(0.0711)
$Inc^{\gamma}_{k,t}$	-0.683*	-0.642*	-0.314	-0.713*	-0.557
	(0.281)	(0.282)	(0.293)	(0.284)	(0.296)
$LS_{k,t}$	2.309***	5.363***			
	(0.344)	(0.943)			
$LS^2_{k,t}$		-29.04**			
		(8.965)			
Interaction effects - partitioning approach					
$LS_{k,t}$ * LOW			-0.583		
			(0.467)		
$LS_{k,t}$ * HIGH			9.353***		
			(1.899)		
$LS_{k,t}$ * SPARSE				10.95***	
				(3.033)	
$LS_{k,t}$ * DENSE				-0.403	
				(0.412)	
$LS_{k,t}$ * HIGH * SPARSE					10.87***
					(2.973)
$LS_{k,t}$ * LOW * SPARSE					13.89***
					(4.060)
$LS_{k,t}$ * LOW * DENSE					-1.070*
					(0.437)
$LS_{k,t}$ * HIGH * DENSE					1.776
					(2.299)
Household controls					
Household Income	1.330***	1.316***	1.616***	1.286***	1.448***
	(0.0214)	(0.0215)	(0.0547)	(0.0220)	(0.0608)
Year1995	-0.219***	-0.216***	-0.197***	-0.221***	-0.209***
	(0.0278)	(0.0278)	(0.0280)	(0.0278)	(0.0281)
Year2000	0.168***	0.167***	0.182***	0.161***	0.172***
	(0.0210)	(0.0209)	(0.0218)	(0.0208)	(0.0215)
Age	-0.0259***	-0.0254***	-0.0252***	-0.0245***	-0.0241***
	(0.00238)	(0.00238)	(0.00242)	(0.00238)	(0.00239)
Age^2	0.00014***	0.00014***	0.00014***	0.00013***	0.00013***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Family size (various dummies)	(+)***	(+)***	(+)***	(+)***	(+)***
Area type (urban)	0.0298	0.0345	0.00289	0.0388*	0.0254
	(0.0195)	(0.0194)	(0.0195)	(0.0208)	(0.0208)
Education>10 years	-0.0630*	-0.0479	-0.110***	-0.0200	-0.0499
	(0.0264)	(0.0266)	(0.0296)	(0.0273)	(0.0314)
Education (university degree)	-0.0665	-0.0367	-0.146**	0.0161	-0.0380
	(0.0475)	(0.0480)	(0.0518)	(0.0478)	(0.0534)
Constant	-1.869**	-1.741**	-2.556***	-1.264*	-1.449*
	(0.624)	(0.625)	(0.639)	(0.628)	(0.634)
Dummy LOW			0.641***		
			(0.100)		
Dummy SPARSE				-0.310***	-0.274*
				(0.0419)	(0.113)
Dummy HIGH					-0.281***
					(0.0516)
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	72136	72136	72136	72136	72136
R^2 (centered)	0.4972	0.4983	0.4855	0.4994	0.4959

Notes: The regressions use the full sample described in Kaus (2013). Robust standard errors, clustered at PSU level, are indicated in parentheses. *** (**, *) Significant at the 0.1% (1%, 5%) level.

Table 4: The effect of local and global (coefficient of variation) density on visible spending

Variables	Specifications				
	(1)	(2)	(3)	(4)	(5)
Social group variables					
Black	0.111	0.0931	0.128	0.0712	0.0904
	(0.0887)	(0.0888)	(0.0896)	(0.0888)	(0.0891)
Coloured	0.0436	0.0337	0.0676	0.0115	0.0335
	(0.0665)	(0.0665)	(0.0680)	(0.0664)	(0.0671)
Moments of the income distribution					
$Inc^{\mu}_{k,t}$	-0.301***	-0.306***	-0.548***	-0.304***	-0.437***
	(0.0523)	(0.0523)	(0.0693)	(0.0530)	(0.0705)
$Inc^{\upsilon}_{k,t}$	-0.150	-0.131	-0.0235	-0.144	-0.0921
	(0.0822)	(0.0826)	(0.0871)	(0.0833)	(0.0875)
$LS_{k,t}$	2.350***	5.408***			
	(0.343)	(0.949)			
$LS^2_{k,t}$		-29.06**			
		(9.053)			
Interaction effects - partitioning approach					
$LS_{k,t}$ * LOW			-0.590		
			(0.469)		
$LS_{k,t}$ * HIGH			9.539***		
			(1.916)		
$LS_{k,t}$ * SPARSE				10.85***	
				(3.030)	
$LS_{k,t}$ * DENSE				-0.343	
				(0.412)	
$LS_{k,t}$ * HIGH * SPARSE					10.85**
					(3.302)
$LS_{k,t}$ * LOW * SPARSE					13.87***
					(4.060)
$LS_{k,t}$ * LOW * DENSE					-1.046*
					(0.439)
$LS_{k,t}$ * HIGH * DENSE					2.055
					(2.312)
Household controls					
Household Income	1.332***	1.318***	1.620***	1.289***	1.455***
	(0.0214)	(0.0215)	(0.0548)	(0.0219)	(0.0606)
Year1995	-0.212***	-0.208***	-0.189***	-0.213***	-0.200***
	(0.0275)	(0.0275)	(0.0277)	(0.0275)	(0.0278)
Year2000	0.169***	0.168***	0.184***	0.162***	0.174***
	(0.0211)	(0.0210)	(0.0219)	(0.0209)	(0.0216)
Age	-0.0260***	-0.0254***	-0.0252***	-0.0246***	-0.0242***
	(0.00238)	(0.00238)	(0.00242)	(0.00238)	(0.00239)
Age^2	0.000143***	0.000138***	0.000140***	0.000132***	0.00013***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Family size (various dummies)	(+)***	(+)***	(+)***	(+)***	(+)***
Area type (urban)	0.0322	0.0372	0.00584	0.0418*	0.0280
	(0.0196)	(0.0195)	(0.0209)	(0.0196)	(0.0208)
Education>10 years	-0.0639*	-0.0488	-0.111***	-0.0215	-0.0522
	(0.0264)	(0.0266)	(0.0296)	(0.0273)	(0.0313)
Education (university degree)	-0.0699	-0.0401	-0.149**	0.0115	-0.0438
	(0.0475)	(0.0480)	(0.0518)	(0.0477)	(0.0533)
Constant	-1.882**	-1.778**	-2.670***	-1.310*	-1.534*
	(0.634)	(0.635)	(0.651)	(0.637)	(0.645)
Dummy LOW			0.649***		
			(0.101)		
Dummy SPARSE				-0.308***	-0.276***
				(0.0418)	(0.0515)
Dummy HIGH					-0.217***
					(0.0532)
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	72136	72136	72136	72136	72136
R^2 (centered)	0.4971	0.4981	0.4852	0.4992	0.4955

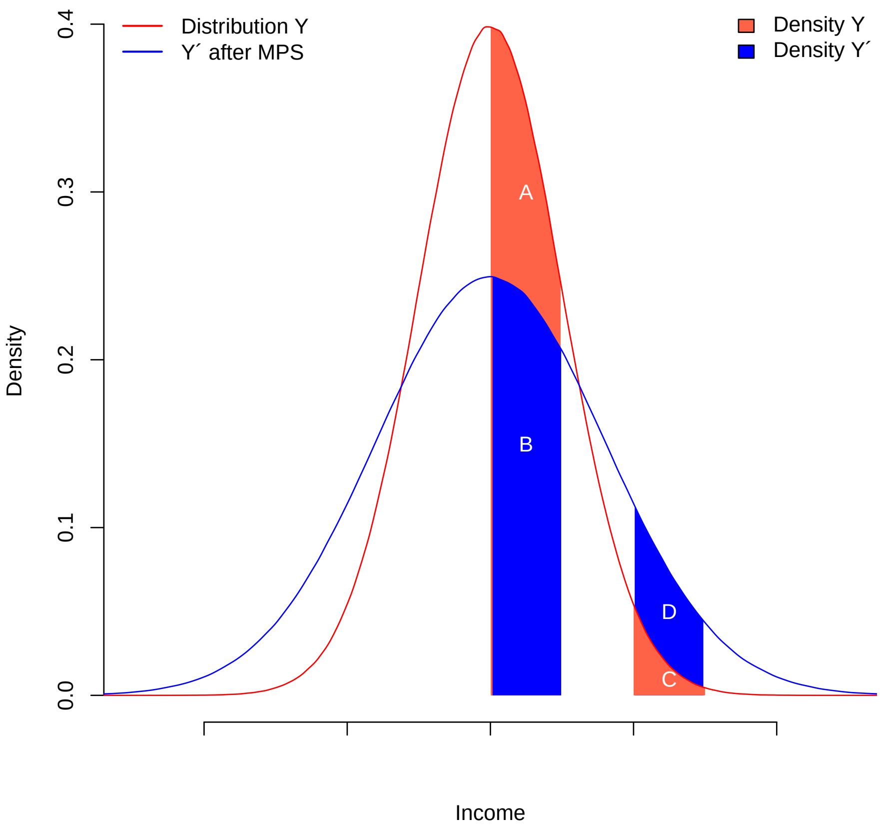
Notes: The regressions use the full sample described in Kaus (2013). Robust standard errors, clustered at PSU level, are indicated in parentheses. *** (**, *) Significant at the 0.1% (1%, 5%) level.

Table 5: Disaggregating the effect of group income dispersion on the household consumption of conspicuous goods and services

Variables	Specifications			
	Clothing	Footwear	Automobiles	Jewelry
Moments of the income distribution				
$Inc^{\mu}_{k,t}$	-0.812***	-0.893***	-0.011**	-0.252***
	(0.106)	(0.118)	(0.004)	(0.065)
interaction effects - partitioning approach				
$Inc^{\gamma}_{k,t}$ * LOW	-0.194	-0.460	-0.034	-0.903*
	(0.608)	(0.638)	(0.047)	(0.391)
$Inc^{\gamma}_{k,t}$ * HIGH	-2.601***	-4.709***	-0.044+	-1.116*
	(0.745)	(0.858)	(0.026)	(0.449)
Household controls				
Household Income	2.049***	1.802***	0.049***	0.829***
	(0.0691)	(0.0800)	(0.007)	(0.049)
Year1995	-0.765***	-1.307***	-0.011***	-0.190***
	(0.0489)	(0.0536)	(0.002)	(0.027)
Year2000	-1.028***	-0.856***	-0.006*	-0.126***
	(0.0475)	(0.0530)	(0.002)	(0.025)
Age	-0.0457***	-0.0471***	0.0003	-0.025***
	(0.00450)	(0.00493)	(0.0003)	(0.003)
Age^2	0.000277***	0.000318***	-4.79e-06	0.0002***
	(0.0000424)	(0.0000458)	(0.0000)	(0.0003)
Family size (various dummies)	(+)***	(+)***	(+)***	(+)***
Area type (urban)	-0.177***	-0.131**	-0.005*	-0.201***
	(0.0410)	(0.0433)	(0.002)	(0.025)
Education>10 years	-0.318***	-0.339***	-0.003+	-0.199***
	(0.0488)	(0.0542)	(0.002)	(0.026)
Education (university degree)	-1.173***	-1.221***	0.0005	-0.297***
	(0.185)	(0.183)	(0.004)	(0.046)
Dummy LOW	-0.672+	-1.727***	-0.003	0.006
	(0.399)	(0.468)	(0.025)	(0.245)
Constant	-2.821**	0.610		
	(1.034)	(1.172)		
R^2 (centered)	0.264	0.217		
Prob>F	0.0000	0.0000		
Obs.	54159	54159	54159	54159

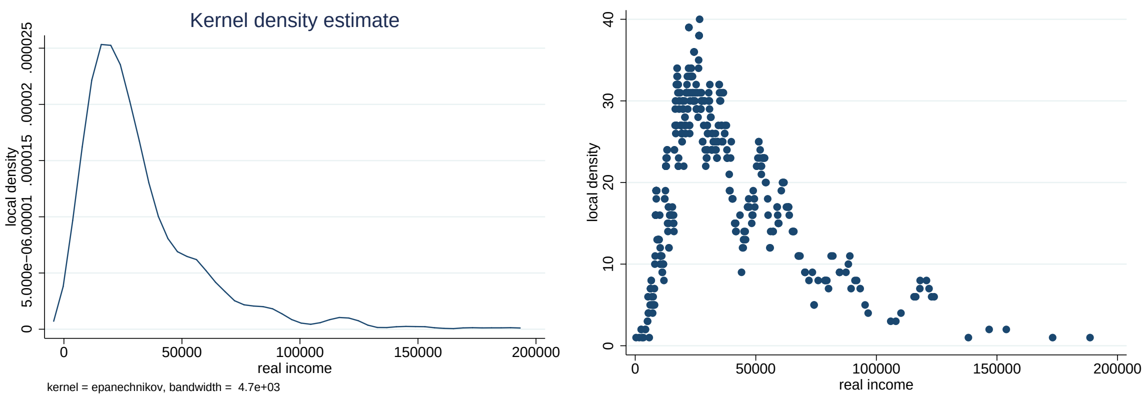
Notes: The regressions use the sample of the Black population described in Kaus (2013). Columns 1 to 4 disaggregate the dependent variable $ln(Vis_i)$. Each specification uses only one subcategory as the dependent variable. Robust standard errors, clustered at PSU level, are indicated in parentheses. *** (**, *, +) Significant at the 0.1% (1%, 5%, 10%) level.

Figure 1: Change of local income share due to a mean preserving spread (MPS)



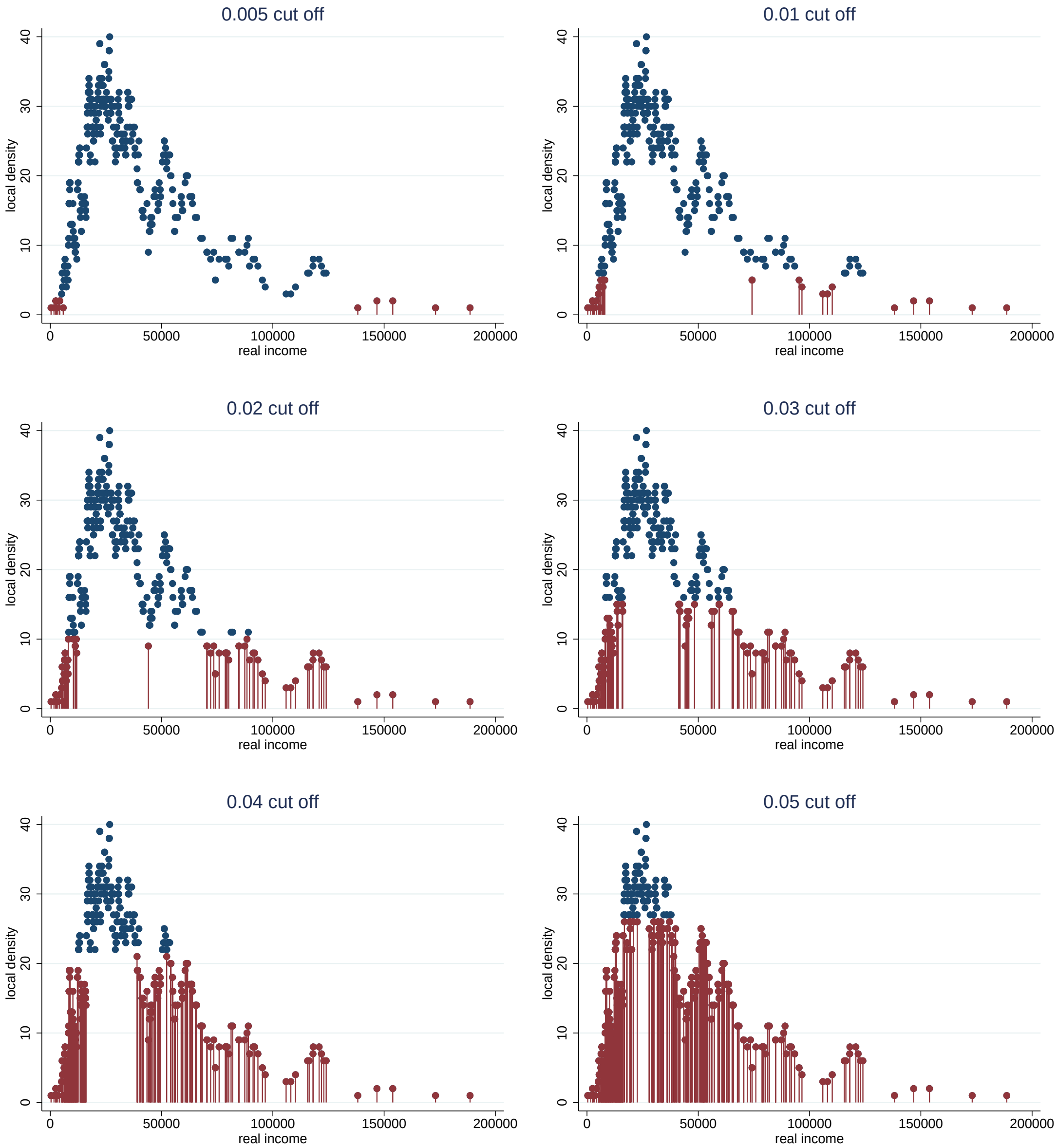
Notes: The figure illustrates how a mean preserving spread in the overall distribution of income from Y to Y' has non-homogeneous effects on local income share since local income share falls close to the mean from A to B and rises at the tails of the distribution from C to D.

Figure 2: Local income share and the distribution of group income



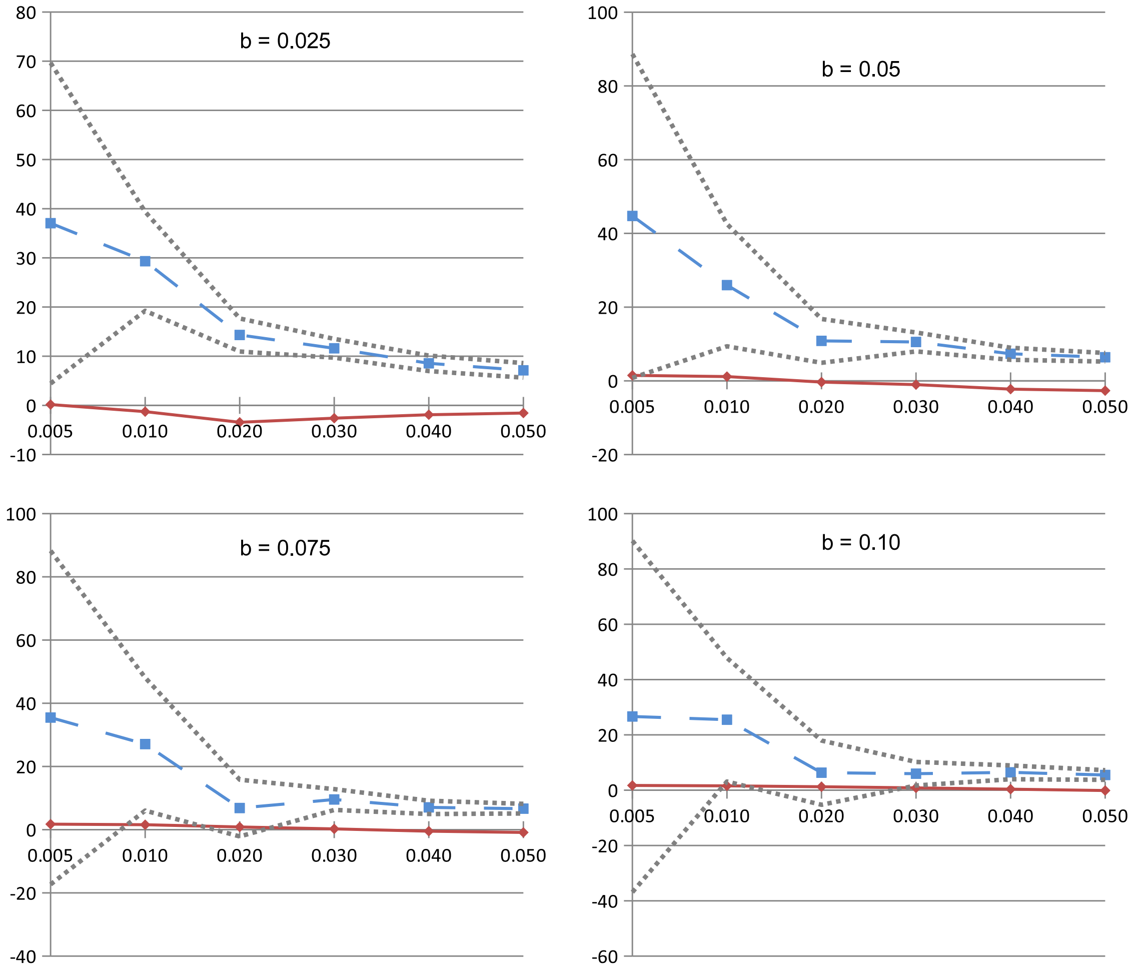
Notes: All amounts are given in 2005 South African Rand. The average exchange rate in 2005 was 6.36 South African Rand per U.S. Dollar (IMF, 2011).

Figure 3: Defining sparse and dense income intervals



Notes: Each figure depicts a scatter plot of the nominal local income share variable of the Black population in 1995 within the Western Cape province. The charts vary with respect to value of the local income share used to define a 'sparse' income interval. The greater is this value, the more households are located in the relatively sparse regions (highlighted in red).

Figure 4: Robustness of $LS_{k,t}$ to varying bandwidth b and cut off point



Notes: The effect of $LS_{k,t}$ on visible spending (vertical axis) partitioned by sparse (square markers) and dense (diamond markers) income intervals as both the cutoff value for defining a sparse income region is altered (horizontal axis) and b is altered. The dotted lines represent the 95% confidence interval for the parameter estimate of $LS_{k,t}$ on visible consumption in relatively sparse income intervals. In Specification (4) a sparse income region is defined as one in which $LS_{k,t} = 2\%$ and $b = 5\%$ (third bin from the left in the top right hand figure).