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INEQUALITY OF HAPPINESS IN THE U.S.: 1972–2010

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It is well accepted that a country's GDP may not fully reflect its level of well-being. In recent years, happiness has emerged as an alternative indicator of well-being, and research has mainly focused on determining the *level* of happiness. While it is important to look at the level, the distribution of happiness is also a salient aspect in any evaluation of *inequality*. There has been a growing interest in the distribution of happiness, although the ordinal nature of the data makes the use of standard inequality measures problematic. Our paper contributes to the literature by exploring the distributions for the U.S. from 1972 to 2010. Based on new methods developed for ordinal data, we are able to overcome the problems associated with ordinality and obtain unambiguous rankings of happiness distributions. We also compute the *level* of happiness inequality using existing measures based on median centred approaches. Further, we decompose the median based inequality measures of happiness by gender, race, and region.

JEL Codes: D39, I39

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1. INTRODUCTION

It is by now well accepted that well-being in a country is more that just its GDP per capita (Sen, 1987). Well-being is a broad concept that is increasingly being evaluated using other dimensions beyond income. One important line of research explores the use of subjective well-being indicators such as happiness (Oswald, 1997; Ng, 1996). Research has focused on finding the levels of happiness in different countries over time and the underlying factors that drive them (Di Tella *et al*., 2003; Alesina *et al*., 2004). While understanding the level of happiness is important, it would also seem to be valuable to understand the distribution of happiness in a population, particularly if the goal is to move to broader measures of well-being.[1] Distributional aspects of happiness have recently received considerable attention in the literature (Veenhoven, 1990; Kalmijn and Veenhoven, 2005;

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[1]The importance of happiness in assessing well-being has been argued strongly by the utilitarians, such as Bentham and Mills (see Sen, 2009; Layard, 2011).

Becchetti *et al.*, 2010; Kalmijn, 2010; Kalmijn and Arends, 2010; Ovaska and Takashima, 2010; Veenhoven, 2011). Our paper contributes to this growing literature by measuring the distribution of happiness in the U.S. from 1972 to 2010 using a particularly appropriate method.

Sen (1994) has convincingly argued that all normative theories of distributional justice have at their core a concern for equality in some space, whether it be in terms of utility or income or capability. If utility is interpreted in terms of happiness, then the utilitarians have long argued for equality in terms of "gains and losses of happiness" (Meade, 1976; Sen, 1994, 2009). Given the emerging prominence of happiness in the evaluation of well-being, it is of particular interest to explore the inequality with which it is distributed.

Interest in happiness has been facilitated by rich datasets spanning the last three decades. When it comes to the subjective evaluation of well-being, surveys often include questions which ask respondents to classify their current level of happiness in one of three or four categories ranging from "*Very Happy*" to "*Not Too Happy*." Typically, therefore, data on happiness come in an ordinal scale. While, "*Very Happy*" may be ranked higher than "*Not Too Happy*," it is not known by how much it is ranked higher. Since we are particularly interested in the "spread of the distribution, information on the difference between these two categories—and indeed any two categories—becomes crucial. In the absence of such information, use of the standard measures of inequality may be problematic.

We evaluate the distribution of happiness with a method that is particularly well suited for an ordinal interpretation of the happiness data. While the assumption of cardinality will be relaxed, we will not be able to dispense with the assumption of interpersonal comparability—where two persons responding with the same category are assumed to have the same level of subjective well-being. There is some support for this commonly made anonymity assumption from the neuroscience literature (see Layard, 2010), but there are also good reasons to be skeptical about it.[2]

Kalmijn and Veenhoven (2005), in measuring the inequality of happiness across nations, assume a cardinal scale across the categories of happiness and thus are able to use and evaluate the standard measures of dispersion and inequality such as the standard deviation and the Gini coefficient.[3] They recommend using the standard deviation, the interquartile range, the absolute Gini index, and the mean absolute difference for measuring inequality of happiness. Most studies in this area, such as Ott (2005), Veenhoven (2005), Kalmijn (2010), and Veenhoven (2011) assume a cardinal scale and use the standard deviation to measure inequality of happiness. Becchetti *et al.* (2010) also assume a cardinal scale but apply the Gini coefficient and variance to measure happiness inequality. We argue later that none these indices is a suitable measure of inequality under an ordinal scale. More importantly, one can question the appropriateness of using a single cardinal scale when dealing with ordinal data, as most of these studies have done, and hence the robustness of the results to changing the scale.

[2]See Fleurbaey *et al.* (2009) for why such assumptions might be problematic and why happiness might not be a good measure of overall welfare.

[3]For a good discussion of the different methods to cardinalize an ordinal variable, refer to Kalmijn and Arends (2010).

One justification for using a cardinal scale has been put forward in van Praag (1991), who argued that when choosing between different categories, respondents have a numerical scale in mind although the numerical scale may differ between respondents. In other words, we can plausibly associate an ordinal scale with at least an interval scale. One serious issue with this study is that all respondents were provided with a common numerical scale and were thus able to associate the given ordinal categories to some range in the numerical scale. It is not apparent how, in the absence of a common numerical scale, respondents will map the ordinal categories to a numerical scale. Even if we were to agree that behind the categorical answers is a numerical scale, surveys do not report any numerical scale associated with the categories. Some surveys ask individuals to quantify their level of happiness or life satisfaction by choosing a numerical score from a bounded interval, say from 0 to 10, instead of asking them to choose between different categories of happiness or life satisfaction. In such case, for two individuals choosing the same numerical score, we cannot be certain whether they have meant the same or different levels of life satisfaction or happiness. In the absence of such information, it is, therefore, not particularly satisfactory to use a cardinal scale.

In a recent paper, Stevenson and Wolfers (2008) calculate the inequality of happiness for the U.S. based on the General Social Survey (GSS). However, they too cardinalize the ordinal data by assuming that happiness is derived from an implicit probit distribution.[4] The variance of that distribution, based on the percentage of people in the different happiness categories, is referred to as the inequality of happiness. In addition to using a particular distribution to cardinalize the variable, they also assume that the distribution itself remains the same over all the years. Moreover their use of variance as a measure of inequality is objectionable, particularly in this context.[5]

To overcome the problems of measuring inequality using an ordinal scale we employ a dominance based method developed by Allison and Foster (2004). We also apply the inequality measures by Allison and Foster (2004) and Abul Naga and Yalcin (2008) which are suited for ordinal data. So far these approaches have mainly been applied in the context of health, where self-reported health also has an ordinal scale (Jones *et al.*, 2010; Madden, 2010). This new method has hardly been applied in the context of measuring inequality of happiness, particularly for the U.S. The only other study that we are aware of is by Madden (2011), who has used this method to study happiness inequality in Ireland. However, unlike previous studies, in the context of happiness in the U.S., we explore some interesting methodological extensions, including providing a tighter link between the dominance based approach and inequality measures of Allison and Foster (2004), and undertaking a decomposition analysis.

The plan of the paper is as follows. The following section discusses the problems with standard measures and explains the Allison–Foster method in the context of happiness. In Section 3, we apply this method to the happiness data

[4]A discussion of the issues around cardinalizing using ordered probit is provided in van Praag and Ferrer-i-Carbonell (2004).

[5]Variance or standard deviation is an unsatisfactory measure of inequality under a cardinal scale (see Sen, 1973). Further, Foster and Ok (1999) show that even the more commonly used variance of logarithms might be unsuitable when it comes to measuring inequality.

from the GSS in the U.S. and discuss the ranking of the different years in terms of greater happiness and lower happiness inequality. Section 4 uses the Allison–Foster measure to decompose happiness inequality across genders, races, and regions. The final section concludes the paper. All the proofs are given in the Supplementary Appendix.

2. Measures of Inequality with Ordinal Data

2.1. *Notation*

Suppose X is an ordinal happiness distribution with n (fixed) categories. We represent happiness distribution X as $p_X = [p_X^1, \ldots, p_X^i, p_X^j, \ldots, p_X^n]$ where p_X^i is the number of people in category i. The categories are ranked in ascending order such that category j is ranked higher than category i, with category n being the highest category. Let f_X^i and F_X^i, respectively, be the proportion of population in the i-th cumulative proportion of population in the category and the category of distribution X. Denote Ω as the set of all ordinal distributions of happiness.

Consider a scale $c = (c_1, c_2, \ldots, c_n)$ where $c_j > c_i$ for $j > i$. Let $\mathcal{C}$ be the set of all such scales. The category to which the median person belongs is defined as the median category. Let k be the median category in distribution X. The overall mean happiness of the distribution is given by:

$$\mu_X(c) = \sum_{i=1}^{n} c_i f_X^i.$$

Consider two distributions X and Y. We say that the mean is order preserving if $\mu_X(c) > \mu_Y(c) \Leftrightarrow \mu_X(c') > \mu_Y(c')$ where $c \neq c'$. Similarly an inequality measure is order preserving if $I_X(c) > I_Y(c) \Leftrightarrow I_X(c') > I_Y(c')$ where $I_X(c)$ and $I_Y(c)$ represent the inequality under scale c for distributions X and Y, respectively. An inequality measure is considered scale independent if for any $c \neq c'$, $I_X(c) = I_Y(c')$. For convenience we may sometimes represent $I^X(c)$ as $I^X(c_1, c_2, \ldots, c_n)$ where $c = (c_1, c_2, \ldots, c_n)$.

2.2. *Problems with Standard Inequality Measures*

When it comes to ordinal or categorical data, standard measures of inequality such as the standard deviation, coefficient of variation, and Gini coefficient may turn out to be inconsistent under different scales. This is because, in order to derive the level of inequality using these measures, the categorical data need to be scaled. For instance, when it comes to the level of happiness, in the U.S. people have three categories to choose from: *Very Happy*, *Pretty Happy*, and *Not Too Happy*. Suppose *Very Happy* is ranked higher than *Pretty Happy*, which in turn is ranked higher than *Not Too Happy*. To measure inequality of happiness we need to know how far apart these categories are from each other. We may use a scale, say $c = (1, 2, 3)$, where *Very Happy* is at 3, *Pretty Happy* is at 2, and *Not Too Happy* is at 1. Once the scale is established, the standard measures can be applied to derive the level of inequality. There is, however, no reason that we should be restricted to a particular scale. We can take another scale, for example, of $c' = (1, 2, 5)$. The levels of inequality calculated using the standard measures will clearly change, but what is worrying is that inequality may not be order preserving. Thus, for instance in the U.S. case, while 1990 may have been a year of lower happiness inequality compared with, say, 2000 under one scale, yet another scale may show the opposite. In such circumstances it becomes difficult to understand whether inequality is increasing or decreasing over time, across regions and between groups.

For most of the inequality measures the source of the problems comes from the fact that inequality is seen as a deviation from the mean and will not be order preserving since the mean itself is not order preserving under scale changes (Allison and Foster, 2004). One may, however, point out that measures such as the absolute Gini or the interquartile range will be free from this criticism since they are not mean dependent. As it turns out, for the absolute Gini, which is the sum of all the pairwise differences, if we change the scales associated with each category by the same amount, the inequality ordering will remain unchanged. Therefore, if we change the scale from $c = (1, 2, 3)$ to $\overline{c} = (3, 4, 5)$, the absolute Gini will be order preserving. This is because, under such transformation of the scale, the difference between each pair remains unchanged. Instead, if the scales are changed to $\underline{c} = (3, 4, 7)$, then there is no guarantee that the absolute Gini will continue to preserve the ranks. Since there is no reason why we should be considering only a certain type of scale transformation, the use of the absolute Gini becomes problematic. The same criticisms will also be true for the relative (or standard) Gini coefficient, apart from the fact that it is also dependent on the mean and hence not order preserving.

The interquartile range, on the other hand, looks at the difference between the first and the third quartile (or in other words the difference between the 75th percentile and the 25th percentile). This is clearly order preserving for any transformation of the scales but it is subject to the criticism that, like the measure of range, it focuses on only part of the distribution and hence does not take into account the whole distribution. Take, for instance, the following distribution of happiness: $p_X = (1, 3, 0)$, i.e. in the context of our example, of a group of four people, one report *Not Too Happy* and the rest report *Pretty Happy*. Let the scale be $c = (1, 2, 3)$. Now suppose with the scales remaining unchanged, the distribution changes to $p_Y = (1, 2, 1)$. Clearly the inequality has changed, yet the interquartile range for both these distributions is the same, i.e. 1.

Another measure of mean independent inequality would be "the percentage outside modus" (Kalmijn and Veenhoven, 2005). In other words, inequality is one minus the share of the population in the modal category. This measure, however, suffers from the same flaw as the interquartile range in that it is not always sensitive to increase in inequality. Consider the following distribution $p_S = (1, 3, 1)$, where one person is reporting *Not Too Happy*, three are reporting *Pretty Happy*, and one is reporting *Very Happy* with a linear scale $c = (1, 2, 3)$. The modal category is *Pretty Happy*. The proportion of the population outside the modus, and thus the level of inequality, is 0.4. Now consider another distribution $p_T = (0, 3, 2)$. We would expect the inequality between the distributions S and T to be different, yet the proportion of people outside the modus remains the same. There are also other issues that arise with mode based measures of inequality: there may be distributions where there is no mode, or there may be multiple modes. In such cases, it is not clear how the inequality should be measured.

Given these issues with both mean based and mode based measures of inequality, Allison and Foster (2004) propose a median based dominance concept to evaluate inequality on categorical data. The next section describes their method.

2.3. *S-Dominance and F-dominance*

Allison and Foster (2004) (henceforth *AF*) note that one of the measures of central tendency that is order preserving under scale transformations is the median. The median, therefore, becomes a natural choice from which to evaluate the dispersion in the distribution.

Under the *AF* framework, inequality in an ordinal setting is considered as the "spread away from the median category" and is captured through the notion of *S-dominance*, which is defined as the following (see Allison and Foster, 2004, p. 512):

Definition 1. *Consider two distributions of happiness, X and Y, such that both have the same median category, k. Distribution Y S-dominates X iff* $\forall i = 1, \ldots, k-1$, $F_Y^i \leq F_X^i$ *and* $\forall i = k, \ldots, n$, $F_Y^i \geq F_X^i$.

Distribution X has a greater population share in the category below the median and a greater population share in the category above the median, compared with Y, which implies that X has a greater spread away from the median compared with Y. More people are concentrated in the middle for distribution Y than distribution X, or in other words, the "spread" of the distribution is lower for Y. Thus *Y S-dominates X* will be associated with X having higher inequality than Y where inequality is interpreted as the spread away from the median.

If X and Y have $n = 3$ categories, with median category $k = 2$, then Definition 1 implies that *Y S-dominates X* iff $f_X^1 > f_Y^1$ and $f_X^3 > f_Y^3$. This is illustrated in Figure 1, where the broken lines represent the cumulative distribution of Y and the solid line represents the cumulative distribution of X.

S_U and S_L in Figure 1 represent the area in the upper and lower tail of the cumulative distributions, respectively.

Before we proceed any further, let us consider a distribution $X \in \Omega$, with k as the median category and $F_X^0 = 0$. The mean happiness of distribution X below the median can be expressed as:

(1) $$\mu_X^L(c) = 2\left(\sum_{i=1}^{k-1} c_i(F_X^i - F_X^{i-1}) + c_k(0.5 - F_X^{k-1})\right),$$

and the mean happiness of distribution X above the median can be written as:

(2) $$\mu_X^U(c) = 2\left(\sum_{i=k+1}^{n} c_i(F_X^i - F_X^{i-1}) + c_k(F_X^k - 0.5)\right).$$

(Allison and Foster, 2004, p. 515) have shown that $S_X^U(c) = \mu_X^U(c) - c_k$, and $S_X^L(c) = c_k - \mu_X^L(c)$, where c_k is the scale applied to the median category k. Any

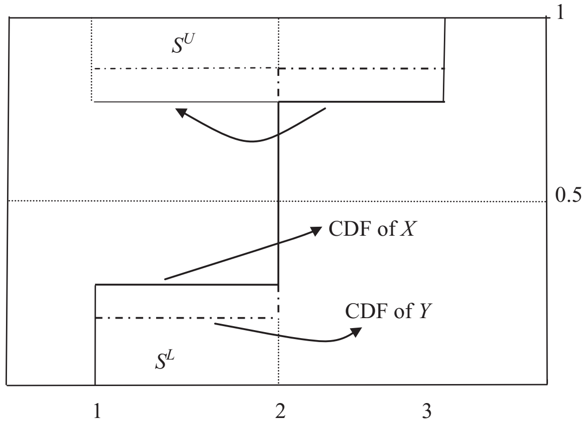

Figure 1. Cumulative Distribution and *S-Dominance* for a Three-Category Case with $k = 2$. Here *Y S-Dominates X*

measure of spread is, therefore, reliant on $\mu_X^U(c)$ and $\mu_X^L(c)$. Thus, Theorem 4 of *AF* can be formulated as:

Proposition 1. *Distribution Y S-dominates X iff* $\forall c \in \mathcal{C}$, $\mu_X^U(c) \geq \mu_Y^U(c)$ *and* $\mu_X^L(c) \leq \mu_Y^L(c)$.

Along with *S-dominance*, we also consider the ranking of the distributions based on first-order dominance (or *F-dominance*).

Definition 2. *Distribution Y F-dominates X iff* $\forall i = 1, \ldots, n,\ F_Y^i \leq F_X^i$.

In other words, *Y* would first order dominate (*F-dominate) X* since *Y* has a lower percentage of people in the inferior categories and a higher percentage in the better categories. If *X* and *Y* have only three categories, with median category $k = 2$, then the above definition of *F-dominance* implies that *Y F-dominates X* iff $f_X^1 > f_Y^1$ and $f_X^3 < f_Y^3$.

When happiness distribution *Y F-dominates X*, it implies that *Y* has a higher average level of happiness than *X*, irrespective of the scale used. Although in this case nothing is said about the distribution of happiness, there is an interesting connection between *F-dominance* and μ^L and μ^U, as shown in Theorem 5 of *AF*, which can be written as:

Proposition 2. *Distribution Y F-dominates X iff* $\forall c \in \mathcal{C}$, $\mu_Y^U(c) \geq \mu_X^U(c)$ *and* $\mu_Y^L(c) \geq \mu_X^L(c)$.

Both *F-dominance* and *S-dominance* are scale independent since they are based on the frequency of the distribution. Hence irrespective of the scale, as long as the distributions remain unchanged, the inequality ordering will always be preserved.

Interestingly, for $n = 3$ categories, if two distributions with median category $k = 2$, cannot be ranked through the *S-dominance* relation, they will invariably be ranked by the *F-dominance* relation and vice versa. This is shown in the next proposition. Before we state the proposition, let the difference in the mean level of happiness above and below the median category between the two distributions be represented by $\Delta\mu^U_{XY}(c) = \mu^U_X(c) - \mu^U_Y(c)$ and $\Delta\mu^L_{XY}(c) = \mu^L_X(c) - \mu^L_Y(c)$ respectively.

Proposition 3. *Let X and Y represent any two distributions with n = 3. Further let X and Y have the same median category k = 2. Then for any scale c, the following will hold: (i)* $\Delta\mu^U_{XY}(c) \geq 0$ *and* $\Delta\mu^L_{XY}(c) \leq 0$ *iff Y S-dominates X, (ii) if* $\Delta\mu^U_{XY}(c) \leq 0$ *and* $\Delta\mu^L_{XY}(c) \geq 0$ *iff X S-dominates Y, (iii)* $\Delta\mu^U_{XY}(c) \leq 0$ *and* $\Delta\mu^L_{XY}(c) \leq 0$ *iff Y F-dominates X, and (iv)* $\Delta\mu^U_{XY}(c) \geq 0$ *and* $\Delta\mu^L_{XY}(c) \geq 0$ *iff X F-dominates Y.*

The above proposition shows that under any scale c, we can use the difference between the two distributions in the mean happiness levels above and below the median to completely rank the two distributions in terms of *S-dominance* or *F-dominance*. This is because the differences in the mean happiness levels above and below the median reduces to the proportion of the population in the upper and lower category respectively. Although *S-dominance* and *F-dominance* on their own will lead to only partial orderings, taken together they will completely order any set of distributions with $n = 3$ categories and $k = 2$.

2.4. *Median Based Measures of Inequality*

While dominance based ranking of distributions is useful, sometimes it becomes necessary to know the level of inequality. In this section we discuss two inequality measures, one based on *AF* and another on Abul Naga and Yalcin (2008) (henceforth *NY*). Both these measures consider dispersion from the median.

A happiness inequality measure is a function $I : \Omega \to \mathbb{R}_+$. *AF* propose a measure of "spread" of the distribution based on the concept of *S-dominance*.

Definition 3. *Consider distribution X, with n categories and scale* $c = (c_1, c_2, \ldots, c_n)$. *Let k be the median category. The AF inequality measure for X is:*

$$I^{AF}_X(c) = \mu^U_X(c) - \mu^L_X(c). \tag{3}$$

It is best to illustrate the concept through an example. Consider a distribution X over three categories, *Not Too Happy*, *Pretty Happy*, and *Very Happy*, such that $p_X = (1, 3, 1)$. Thus, one individual reports *Not Too Happy*, three report *Pretty Happy*, and one reports *Very Happy*. Suppose the scale used is $c = (-1, 0, 1)$. The cumulative percentage of people in each category is (0.2, 0.8, 1). Then, $\mu^L_X = -0.4$, and $\mu^U_X = 0.4$.[6] Thus, $I^{AF}_X = 0.8$. Note that, if the scale is changed, it will lead to a different value of I^{AF}_X.

Although the *AF* measure of inequality is scale dependent, it is closely linked to the notion of *S-dominance* as shown in the following proposition.

[6] Using (1) and (2) we can derive the mean values as follows: $\mu^L_X = 2((-1 \cdot 0.2) + (0 \cdot (0.5 - 0.2)) = -0.4$, and $\mu^U_X = 2((0 \cdot (0.8 - 0.5)) + (1 \cdot (1 - 0.8)) = 0.4$.

Proposition 4. *Consider two distributions X and Y with the same median category. The following two statements are equivalent: (a) X S-dominates Y, and (b)* $\forall c \in \mathcal{C}$, $I_Y^{AF}(c) \geq I_X^{AF}(c)$.

Clearly, if for some $c \in \mathcal{C}$, we find $I_Y^{AF}(c) \geq I_X^{AF}(c)$, it does not necessarily imply that *X S-dominates Y*. However from Proposition 4 we can infer that if for some *c* we find $I_Y^{AF}(c) > I_X^{AF}(c)$, then *Y* can never *S-dominate X* because for *Y* to do so, *Y* must have a higher inequality for all possible scales. Similarly if we find that *X* has a higher inequality than *Y* for any given scale, we can infer that *X* will never *S-dominate Y*.

NY expands on the *AF* inequality measure by considering a weighted difference between the percentage of people in the lower half of the distribution and the upper half of the distribution. If inequality depends on the population of the upper and the lower halves of the distribution, then how much importance should be given to the lower and upper halves in the measure is a subjective judgment. This generalization thus builds the subjective judgments into the inequality measure. The *NY* measure of inequality is presented below.

Definition 4. *Consider any distribution X with n categories. If the median category is k, then the NY inequality measure can be expressed as*

$$I_X^{NY}(\alpha,\beta) = \frac{\sum_{i<k}(F_X^i)^\alpha - \sum_{i\geq k}(F_X^i)^\beta + (n+1-k)}{(k-1)(0.5)^\alpha - (1+(n-k)(0.5)^\beta) + (n+1-k)}, \tag{4}$$

where α, $\beta \geq 1$ *reflect the value judgments of the society.*

When, for instance, $\alpha = \beta = 1$, the cumulative distributions for the lower half and upper halves are given equal weight in the overall inequality. On the other hand, when $\beta > \alpha \geq 1$, the cumulative distributions of the lower half of the distribution are given relatively more weight. The measure also has the appealing property that when everyone is in the median category $I_X^{NY}(1,1) = 0$ and when half of the population is in the lowest category and the other half in the highest category, $I_X^{NY}(1,1) = 1$. Note that $I_X^{NY}(\alpha,\beta)$ is scale independent.

For our empirical application, we have three categories, with the second category being the median category. Under these circumstances, there is an interesting link between the *AF* and the *NY* measure, which is given below.

Proposition 5. *Consider a distribution X, with* $n = 3$ *and* $k = 2$. Suppose $c = (-\theta, 0, \theta)$. *Then,*

$$I_X^{AF}(c) = 2\theta I_X^{NY}(1,1),$$

where $I_X^{NY}(1,1) = (1 - f_X^2)$.

When the number of categories $n = 3$, $I_X^{NY}(1,1)$ is the percentage of people not in the median category. Thus, for any given θ, the *AF* measure of inequality will be a monotonic transformation of the *NY* inequality measure. Note that, although

$I_X^{NY}(1,1)$ is scale independent, it is subject to similar kinds of criticism directed at inequality measures based on mode.

In the next section, we use these dominance criteria and inequality measures to explore the distribution of happiness in the U.S.

3. Empirics

3.1. *Data*

We use the GSS in the U.S., which collects extensive data on individual levels of happiness along with a rich set of personal information. The data are for 28 years from 1972 to 2010, with a gap of a few years in between. In each of these years, a nationally representative sample was chosen. It is one of the longest and most consistent surveys on happiness available for the U.S. and has been extensively used in the literature on happiness (see Di Tella *et al.*, 2003; Alesina *et al.*, 2004; Stevenson and Wolfers, 2008).

Our main interest is in the following GSS question: "Taken all together, how would you say things are these days—would you say that you are very happy, pretty happy or not too happy?" The question is asked to the head of the household. The yearly average age of the respondents is between 44 and 48 years. It does not contain information about the happiness level of other household members. It should also be noted that this is not a panel survey and hence it does not track the same group of people over different years.

The total number of available responses to the happiness questions is 50,357. There was, however, over-sampling of the black population for the years 1982 and 1987. Following Stevenson and Wolfers (2008), we have dropped the over-sampled observations and the interviews that took place in Spanish in 2006. This reduces the total number of responses to 49,433. We weighted the observations according to the sample weights (*WTSALL*) that were provided. The sample weights also ensure that the data are nationally representative at the individual level. Stevenson and Wolfers (2008) found that question order effects can have an impact on how the respondents classify themselves within the happiness categories. Out of the 28 years, this was an issue for five years: 1972, 1980, 1985, 1986, and 1987. They corrected for it and presented the revised percentages in each of these categories for these years.

The weighted distribution of the responses over the three categories of happiness for each year is summarised in Table 1.

The first three columns show the share of the population in the lowest category (*Not Too Happy*), the median category (*Pretty Happy*), and the highest category (*Very Happy*), respectively, and the last column provides the total number of observations in each year. The middle category of *Pretty Happy* turns out to be the median category for all years.

In the next section, we shall present the results for the question order corrected weighted data.

3.2. *Dominance Relations*

For the three-category case, as mentioned above, the *S-dominance* and *F-dominance* will completely order any two distributions. While the *S-dominance*

TABLE 1

Population Shares (for question order corrected data)

	Share of Population in *Not Too Happy*	Share of Population in *Pretty Happy*	Share of Population in *Very Happy*	Total Number of Households
1972	13.600	49.100	37.300	1606
1973	12.286	50.932	36.782	1500
1974	12.515	49.194	38.291	1480
1975	12.973	53.630	33.397	1485
1976	12.249	52.920	34.831	1499
1977	11.013	53.242	35.745	1527
1978	8.369	56.189	35.442	1517
1980	11.600	52.000	36.400	1462
1982	11.700	53.499	34.801	1505
1983	12.092	56.239	31.668	1573
1984	11.614	52.091	36.295	1445
1985	8.600	58.400	33.100	1530
1986	9.200	55.800	35.000	1449
1987	9.700	53.300	37.000	1437
1988	8.241	55.695	36.065	1466
1989	8.793	56.737	34.470	1526
1990	7.740	56.527	35.733	1361
1991	9.485	58.004	32.511	1504
1993	9.736	56.865	33.399	1601
1994	11.287	58.216	30.497	2977
1996	10.502	57.357	32.141	2885
1998	10.896	55.851	33.253	2806
2000	9.644	56.435	33.921	2777
2002	11.282	55.846	32.872	1369
2004	11.696	54.718	33.585	1337
2006	10.552	55.901	33.547	2828
2008	13.289	54.749	31.962	1942
2010	14.192	57.010	28.798	2039
Mean	10.887	54.873	34.243	

focuses on the inequality of the distribution, the *F-dominance* addresses the mean of the distribution. In this section, we present the results for the dominance relations by conducting a pairwise comparison of the happiness distributions for all the years.

We construct a square matrix with 28 rows and 28 columns, with each row and column representing a year from our sample. Each cell of the matrix describes whether the distributions of the concerned two years are based on *F-dominance* or *S-dominance*. We now explore the dominance relationships for the question order corrected data; and the results are presented in Table 2.

To understand the rankings, let us take, for example, the year 1987. The first cell in the row labeled 1987, compares the happiness distribution in 1987 with 1972 and the *S* in that cell shows that 1987 *S-dominates* 1972. If we compare the two distributions (from Table 1), the share of the population in the worst category (*Not Too Happy*) was $f^1_{1987} = 0.097 < f^1_{1972} = 0.136$. The share of the population in the best category (*Very Happy*) was $f^3_{1987} = 0.37 < f^3_{1972} = 0.373$. This implies that 1987 *S-dominates* 1972. In the next cell, we compare the distribution of happiness of 1987 with 1973. If we compare 1987 with 1973, we find that the share of the

TABLE 2

First Order Dominance and S-Dominance for Happiness over 1972–2010 (for question order corrected data)

	72	73	74	75	76	77	78	80	82	83	84	85	86	87	88	89	90	91	93	94	96	98	00	02	04	06	08	10	F	S
72																												F	1	0
73	S		S	F																							F	F	3	2
74	F			F																							F	F	4	0
75	S																										F	F	2	1
76	S	S	S	F																							F	F	3	3
77	S	S	S	F	F			S	F	F	S									F				F	F		F	F	9	5
78	S	S	S	F	F	S		S	F	F	S	F	F	S		F		F	F	F	F	F	F	F	F	F	F	F	18	7
80	S	S	S	F	F				F	F	F														F		F	F	8	3
82	S	S	S	F	S					F																	F	F	4	4
83	S	S	S	S	S																						S	F	1	6
84	S	S	S	F	F				F	F															F		F	F	7	3
85	S	S	S	S	S	S		S	S	F	S		S	S		S		F	S	F	F	S	S	F	S	S	F	F	7	17
86	S	S	S	F	F	S		S	F	F	S			S				F	F	F	F	F	F	F	F	F	F	F	15	7
87	S	F	S	F	F	F		F	F	F	F								F	F	F	F		F	F	F	F	F	17	2
88	S	S	S	F	F	F	F	S	F	F	S	F	F	S		F		F	F	F	F	F	F	F	F	F	F	F	20	6
89	S	S	S	F	S	S		S	S	F	S		S	S				F	F	F	F	F	F	F	F	F	F	F	13	10
90	S	S	S	F	F	S	F	S	F	F	S	F	F	S	S	F		F	F	F	F	F	F	F	F	F	F	F	19	8
91	S	S	S	S	S	S		S	S	F	S			S					S	F	F	S	S	S	S	S	F	F	5	16
93	S	S	S	F	S	S		S	S	F	S									F	F	F		F	S	S	F	F	8	10
94	S	S	S	S	S			S	S	S	S														S		S	F	1	11
96	S	S	S	S	S	S		S	S	F	S									F		S		S	S	S	F	F	4	13
98	S	S	S	S	S	S		S	S	F	S									F				F	S		F	F	5	10
00	S	S	S	F	S	S		S	S	F	S			S					F	F	F	F		F	F	F	F	F	11	9
02	S	S	S	S	S			S	S	F	S									F					S		F	F	4	9
04	S	S	S	F	S				S	F																	F	F	4	5
06	S	S	S	F	S	S		S	S	F	S									F		F		F	S		F	F	7	9
08	S																											F	1	1
10																													0	0
F	1	1	0	17	8	2	2	1	8	19	2	3	3	0	0	3	0	6	7	15	10	9	5	12	10	7	23	27	201	
S	25	21	23	7	13	11	0	15	11	1	15	0	2	8	1	1	0	0	2	0	0	3	2	2	8	4	2	0		177

Note: S represents the S-dominance relation and F represents the F-dominance relation.

population in the worst category is $f_{1987}^{1} = 0.097 < f_{1973}^{1} = 0.123$ and the share of the population in the best category is $f_{1987}^{3} = 0.37 > f_{1973}^{3} = 0.368$. In this case, 1987 *F-dominates* 1973. Overall there are 201 *F-dominating* relations and 177 *S-dominating* relations.

If we concentrate on the *S-dominance*, which reflects happiness inequality, then 1985 seems to be dominating most of the other years. Thus, we can unambiguously say that happiness inequality was lower in 1985 compared with 17 other years. 1985 is closely followed by 1991, which *S-dominates* 16 other years. In fact, on average, the 1990s seem to do better than most other decades in terms of having unambiguously lower happiness inequality. On the other hand, the 1970s and the early 1980s were the worst in terms of having higher happiness inequality compared with other years, with 1972 and 1974 standing out.

When we consider *F-dominance*, 1988 turns out to be one of the best years. Irrespective of the scale used, the mean happiness would be higher in 1988 compared with 20 other years. In particular, 1988, 1989, and 1990 *F-dominate* all the later years including the 1990s and the new millennium. In other words, in terms of the average level of happiness, the late 1980s were the best years for the U.S. and they have not been matched since. One of the worst years in terms of *F-dominance* is 2010, which is dominated by all other years. Thus, the average happiness for 2010 was the lowest compared with all other years in the sample.

3.3. *Inequality of Happiness*

While the dominance results in the previous sections give us unambiguous results, they do not yield a complete ordering. For quite a few of the years, we do not know how they fare compared with other years in terms of inequality. Therefore, in this section we will compute the inequality for each year based on the *AF* and the *NY* measures.

We present the computations for the weighted U.S. data from 1972 to 2010 in Table 3.

The first three columns show the $I_X^{AF}(c)$, where X represents the distribution of happiness for each year. Since the *AF* measure in general is not scale independent, we employ three separate inequality measures: $I_X^{AF}(-2,0,2)$ based on a linear scale $c = (-2, 0, 2)$, $I_X^{AF}(-2,-1,2)$ based on a convex scale $c = (-2, -1, 2)$, and $I_X^{AF}(-2,1,2)$ based on a concave scale $c = (-2, 1, 2)$. The next three columns respectively contain the inequality measures $I_X^{NY}(1,1)$, $I_X^{NY}(1,2)$, and $I_X^{NY}(1,4)$, where increasingly more weight is given to the lower end of the distribution. Similar weighting for the I_X^{NY} measures has been used in Jones *et al.* (2010). The final column calculates $\mu_X(c)$ where $c = (1, 2, 3)$.

First, we discuss the *AF* inequality measure, which is based on the mean level of happiness below and above the median. For clarity let us consider 1990. From Table 1 we know that for 1990 there were 7.74 percent reporting *Not Too Happy*, 56.53 percent reporting *Pretty Happy*, and 35.73 percent reporting *Very Happy*. If we consider the scale (–2, 0, 2), then the mean happiness below the median would be given by $(0.0774 \cdot -2)/0.5 = -0.3096$. Similarly, the mean of the upper half will be $(0.3573 \cdot 2)/0.5 = 1.4299$. The difference between them is 1.7388, which is the inequality for 1990.

TABLE 3

Population Shares and Median Inequality (for question order corrected data)

	$I^{AF}(-2, 0, 2)$	$I^{AF}(-2, -1, 2)$	$I^{AF}(-2, 1, 2)$	$I^{NY}(1, 1)$	$I^{NY}(1, 2)$	$I^{NY}(1, 4)$	Mean $c = (1, 2, 3)$
1972	2.036	2.510	1.562	0.509	0.594	0.683	2.237
1973	1.963	2.453	1.473	0.491	0.579	0.670	2.245
1974	2.032	2.548	1.517	0.508	0.595	0.682	2.258
1975	1.855	2.263	1.446	0.464	0.549	0.649	2.204
1976	1.883	2.335	1.432	0.471	0.558	0.655	2.226
1977	1.870	2.365	1.376	0.468	0.558	0.654	2.247
1978	1.752	2.294	1.211	0.438	0.534	0.633	2.271
1980	1.920	2.416	1.424	0.480	0.569	0.663	2.248
1982	1.860	2.322	1.398	0.465	0.554	0.651	2.231
1983	1.750	2.142	1.359	0.438	0.523	0.628	2.196
1984	1.916	2.410	1.423	0.479	0.568	0.662	2.247
1985	1.664	2.156	1.180	0.416	0.510	0.615	2.247
1986	1.768	2.284	1.252	0.442	0.536	0.635	2.258
1987	1.868	2.414	1.322	0.467	0.560	0.654	2.273
1988	1.772	2.329	1.216	0.443	0.539	0.637	2.278
1989	1.731	2.244	1.217	0.433	0.527	0.629	2.257
1990	1.739	2.299	1.179	0.435	0.532	0.631	2.280
1991	1.680	2.140	1.219	0.420	0.512	0.617	2.230
1993	1.725	2.199	1.252	0.431	0.523	0.627	2.237
1994	1.671	2.056	1.287	0.418	0.504	0.612	2.192
1996	1.706	2.138	1.273	0.426	0.516	0.621	2.216
1998	1.766	2.213	1.319	0.441	0.531	0.633	2.224
2000	1.743	2.228	1.257	0.436	0.528	0.630	2.243
2002	1.766	2.198	1.334	0.442	0.530	0.633	2.216
2004	1.811	2.249	1.373	0.453	0.541	0.642	2.219
2006	1.764	2.224	1.304	0.441	0.531	0.633	2.230
2008	1.810	2.184	1.437	0.453	0.536	0.639	2.187
2010	1.720	2.012	1.427	0.430	0.508	0.616	2.146
Mean	1.805	2.272	1.338	0.451	0.541	0.640	2.234

Figure 2 presents the distribution of the mean happiness levels above the median (μ^U) and mean happiness levels below the median (μ^L) for around every four years from 1972 to 2010 based on the linear scale $c = (-2, 0, 2)$.

From Proposition 3 we know that using μ^U and μ^L we can completely rank the happiness distribution of any two years. For instance in Figure 2, between 1972 and 1976, both μ^U and μ^L are moving inwards towards each other. This implies that $\Delta\mu^U_{XY}(c) \geq 0$ and $\Delta\mu^L_{XY}(c) \leq 0$ where X represents the distribution in 1972 and Y represents the distribution in 1976. From Proposition 3 we know 1976 *S-dominates* 1972. If we compare 1976 and 1980, we can see μ^U is moving away, μ^L is moving inwards. Clearly, $\Delta\mu^U_{YZ}(c) \leq 0$ and $\Delta\mu^L_{YZ}(c) \leq 0$ where Z is the distribution of 1980. Using Proposition 3 we can infer that 1976 *F-dominates* 1980. Thus by observing the direction of the movements of μ^U and μ^L, we can infer the dominance condition. It is interesting to note that the distance between μ^U and μ^L at any point provides the *AF* inequality measure. On the other hand, the middle point between μ^U and μ^L reflects the average happiness of that year.

Under $I^{AF}_X(-2, 0, 2)$, on average, the 1970s had happiness inequality of 1.913; it decreased in the 1980s to 1.806; in the 1990s it further reduced to 1.715. However, since 2000, the average inequality has increased again and stands at

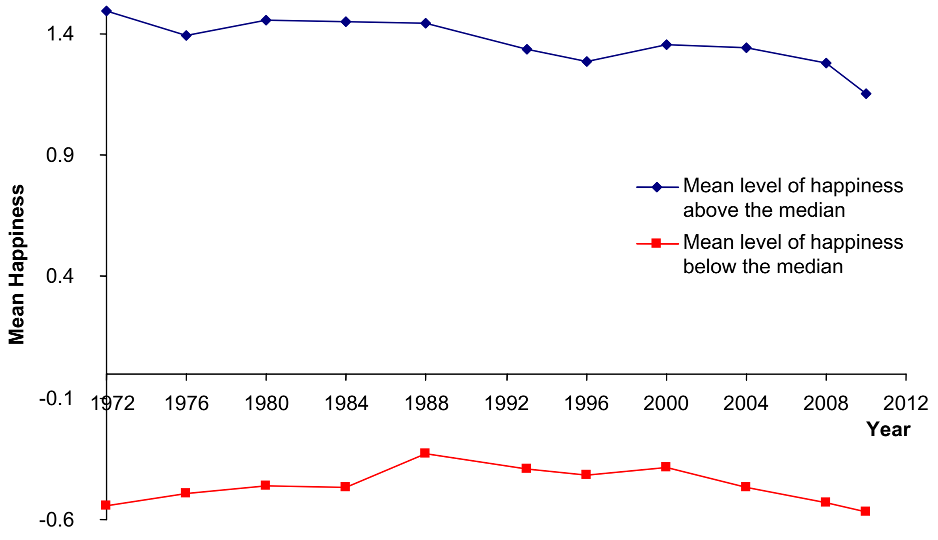

Figure 2. Mean Level of Happiness, $c = (-2, 0, 2)$

1.769. The inequality in the 2000s is thus higher than the 1990s but not as high as the 1980s or 1970s. Thus, in some sense, the progress made in reducing happiness inequality through the 1990s was wiped out in the 2000s. We find similar trends for the other two scales for the I_X^{AF} measure, where inequality has decreased through the 1980s and 1990s, only to increase again in the last decade. In fact $I_X^{AF}(-2, 1, 2)$ in the last decade is higher than in both the 1980s and the 1990s. All the three I_X^{NY} measures also indicate a similar trend, with happiness inequality reducing through the 1980s and 1990s only to rise in the 2000s. For instance, under $I_X^{NY}(1, 2)$, inequality has reduced for each decade, from 0.567 in the 1970s to 0.543 in the 1980s to 0.519 in the 1990s. In the 2000s the inequality has risen again to 0.529.

When it comes to the year with the highest inequality, the measures are divided between 1972 and 1974. This reflects the fact that both these years are *S-dominated* by most of the other years. For the year with the minimum happiness inequality, however, the different measures lead to a divided outcome. While $I_X^{AF}(-2, 0, 2)$ points to 1985 as the year with the lowest inequality, other measures indicate towards 1990, 1994, and 2010. It is interesting to note that 2010 has low inequality according to these measures compared with many other years, thus reversing to some extent the increasing inequality of the previous years during the 2000s.

In terms of the mean happiness, under the linear scale, we find that while average happiness increased from 2.241 in the 1970s to 2.243 in the 1980s, it decreased to 2.241 in the 1990s and further to 2.232 in the 2000s. We also find that 2010 has the lowest average happiness among all the years, thus corroborating the *F-dominance* results of the previous section. 1990, on the other hand, is the year with the highest average happiness.

4. Decomposition

In this section, we decompose the overall inequalities into group inequalities by gender, race, and region.[7] This will help us in picking up interesting trends within groups that aggregate inequalities may mask. Decomposition allows us to see whether the group happiness inequalities follow the national trends; it captures the difference between groups in terms of happiness inequality and can show what proportion of the total inequality is contributed by each of the groups.

For decomposition purposes, we use the *AF* measure of inequality. The *AF* measure is closely linked to the *S-dominance* rankings since it is based on the area below the *S*-curve. In particular, as discussed earlier, Proposition 4 implies that, if, for a given scale, we find that $I_X^{AF}(c) > I_Y^{AF}(c)$, then *X* can never *S-dominate Y*. This connection with the *S-dominance* based ranking is not apparent for other ordinal inequality indices. To check for robustness, as in the previous sections, we compute the values for $I_X^{AF}(-2,0,2)$, $I_X^{AF}(-2,-1,2)$ and $I_X^{AF}(-2,1,2)$. Note that from Proposition 5, we know that $I_X^{AF}(-2,0,2)$ is a monotonic transformation of the scale independent inequality measure, $I_X^{NY}(1,1)$. Further, the I_X^{AF} measures are fully decomposable, as shown in the Supplementary Appendix.

4.1. *Gender*

It is well established that there are significant differences between men and women when it comes to income and labor market outcomes. In the happiness literature, also, there is growing evidence of such differences. Clark (1997) finds that very different things make women and men happy; women were more satisfied with their lives despite being paid less than men.

To understand if there are any differences between the genders when it comes to happiness inequality, we decompose the overall happiness inequality to the inequality between males and females. Our sample, over the 28 years, consists of 26,760 women and 22,673 men. The results are presented in Table 4.

For all the years, the second category (*Pretty Happy*) is the median category for both genders.

One of the broad patterns that emerge from Table 4 is that, on average, women have higher happiness inequality relative to men. This result is consistent across all the three different measures and each of the four decades, although there may be some years in which women have less inequality. Compared with the other decades, for both genders, the 1990s had the lowest happiness inequality on average.

Both men and women followed the national trend, with happiness inequality decreasing from the 1970s to the 1980s, and with further falls in the 1990s. Although inequality has risen in the last decade, according to most measures,

[7]For this part, we use the question order uncorrected weighted data. The revised sample weights taking into account the question order effects are unavailable. Only the percentage of individuals in each of the happiness categories for the whole sample is reported for the five years. Therefore, we do not have the question order corrected distribution for different sub-samples based on race, sex, or geographical location. For both the question order corrected and uncorrected weighted data, however, we have found that the broad trends have remained the same. The maximum difference between the two datasets for the *AF* inequality measures is of the order 0.03, and for *NY* inequality measures, is around 0.004.

TABLE 4
Decomposition of Median Inequality by Gender

	Inequality Women $I^{AF}(-2, 0, 2)$	Inequality Women $I^{AF}(-2, -1, 2)$	Inequality Women $I^{AF}(-2, 1, 2)$	N_W	Inequality Men $I^{AF}(-2, 0, 2)$	Inequality Men $I^{AF}(-2, -1, 2)$	Inequality Men $I^{AF}(-2, 1, 2)$	N_M
1972	1.918	2.270	1.567	758	1.843	2.002	1.683	848
1973	2.055	2.581	1.528	782	1.862	2.313	1.412	718
1974	2.119	2.731	1.508	763	1.940	2.353	1.526	717
1975	1.934	2.348	1.520	794	1.764	2.166	1.362	691
1976	1.929	2.430	1.429	803	1.830	2.226	1.434	696
1977	2.014	2.549	1.478	816	1.706	2.154	1.258	711
1978	1.734	2.290	1.178	859	1.777	2.300	1.255	658
1980	1.969	2.491	1.448	809	1.803	2.194	1.412	653
1982	1.917	2.431	1.403	832	1.790	2.188	1.392	673
1983	1.748	2.138	1.359	871	1.753	2.147	1.359	702
1984	1.966	2.524	1.409	834	1.848	2.255	1.441	611
1985	1.589	1.957	1.222	809	1.621	2.023	1.219	721
1986	1.756	2.260	1.253	809	1.711	2.121	1.302	640
1987	1.792	2.265	1.319	788	1.808	2.211	1.405	649
1988	1.806	2.325	1.288	805	1.731	2.333	1.128	661
1989	1.758	2.278	1.238	836	1.697	2.202	1.191	690
1990	1.735	2.299	1.171	742	1.744	2.299	1.188	619
1991	1.700	2.119	1.281	837	1.655	2.167	1.142	667
1993	1.855	2.371	1.339	889	1.564	1.984	1.144	712
1994	1.652	2.021	1.283	1623	1.695	2.097	1.292	1354
1996	1.694	2.112	1.275	1532	1.719	2.169	1.270	1353
1998	1.825	2.284	1.365	1545	1.694	2.126	1.262	1261
2000	1.764	2.257	1.272	1518	1.716	2.193	1.239	1259
2002	1.772	2.108	1.436	696	1.761	2.291	1.230	673
2004	1.780	2.295	1.266	699	1.845	2.199	1.491	638
2006	1.791	2.252	1.330	1558	1.730	2.189	1.272	1270
2008	1.857	2.242	1.472	1037	1.756	2.117	1.396	905
2010	1.726	2.067	1.384	1116	1.712	1.945	1.480	923
Mean	1.827	2.296	1.358		1.753	2.177	1.328	

Note: N_W refers to number of women in each year; N_M refers to number of men in each year.

inequality has fallen sharply in 2010. In terms of the distribution, there is a lower proportion of women in the bottom two categories (*Not Too Happy* and *Pretty Happy*) compared to men. The happiness inequality gap between men and women, however, has continued to fall through all the four decades and now stands at the lowest.

4.2. *Race*

In the GSS, race has been classified into three groups: Whites, Blacks, and Others. The sample consisted of 41,197 Whites, 5,946 Blacks, and 2,293 from other races. In this section we focus mainly on Blacks and Whites because the number of individuals surveyed under Others in some years is extremely small and further, for some years, the median category for Others is different from those of Blacks and Whites. For the latter two groups, the median category is *Pretty Happy* for all the years. Table 5 captures the *AF* measure of happiness inequality for the three sub-groups under different scales.

TABLE 5

Decomposition of Median Inequality by Race

	Inequality White $I^{AF}(-2, 0, 2)$	Inequality White $I^{AF}(-2, -1, 2)$	Inequality White $I^{AF}(-2, 1, 2)$	N_W	Inequality Black $I^{AF}(-2, 0, 2)$	Inequality Black $I^{AF}(-2, -1, 2)$	Inequality Black $I^{AF}(-2, 1, 2)$	N_B	Inequality Others $I^{AF}(-2, 0, 2)$	Inequality Others $I^{AF}(-2, -1, 2)$	Inequality Others $I^{AF}(-2, 1, 2)$	N_{OTH}
1972	1.875	2.219	1.531	1330	1.895	1.708	2.082	271	1.816	0.908	2.724	5
1973	1.985	2.570	1.400	1302	1.867	1.708	2.026	184	1.160	1.352	0.967	14
1974	2.013	2.573	1.453	1311	2.131	2.263	1.999	162	3.430	2.006	1.436	7
1975	1.871	2.340	1.402	1317	1.723	1.655	1.791	165	2.000	2.000	2.000	4
1976	1.894	2.420	1.368	1361	1.876	1.538	2.215	126	0.666	0.998	0.333	12
1977	1.859	2.397	1.320	1347	2.012	2.192	1.832	165	1.333	1.333	1.333	15
1978	1.771	2.356	1.186	1346	1.634	1.785	1.484	155	1.334	2.001	0.667	17
1980	1.898	2.428	1.368	1308	1.922	1.795	2.049	145	1.053	1.368	0.737	10
1982	1.852	2.366	1.338	1323	1.898	1.918	1.878	153	2.037	2.474	1.601	28
1983	1.752	2.195	1.309	1406	1.723	1.607	1.838	150	1.881	2.469	1.294	17
1984	1.914	2.464	1.364	1233	1.811	1.856	1.765	158	2.291	2.815	1.767	53
1985	1.584	2.015	1.154	1330	1.773	1.752	1.794	151	1.627	1.982	1.272	50
1986	1.784	2.293	1.275	1233	1.360	1.518	1.202	173	1.882	2.212	1.552	43
1987	1.822	2.341	1.303	1207	1.518	1.441	1.594	172	2.172	2.534	1.810	59
1988	1.783	2.388	1.179	1224	1.775	1.964	1.586	179	1.546	2.219	0.874	63
1989	1.762	2.331	1.193	1309	1.603	1.638	1.568	146	1.410	1.885	0.935	71
1990	1.759	2.353	1.165	1141	1.417	1.736	1.097	153	2.144	2.672	1.616	67
1991	1.671	2.192	1.149	1249	1.696	1.875	1.518	203	1.837	1.939	1.735	52
1993	1.762	2.281	1.244	1347	1.475	1.650	1.300	169	1.640	1.987	1.292	85
1994	1.700	2.164	1.236	2467	1.562	1.484	1.640	376	1.451	1.661	1.242	134
1996	1.675	2.136	1.214	2333	1.668	1.802	1.533	372	2.181	2.862	1.500	180
1998	1.772	2.292	1.252	2228	1.648	1.726	1.569	378	1.918	2.252	1.584	201
2000	1.761	2.323	1.200	2185	1.708	1.895	1.522	394	1.602	1.840	1.365	198
2002	1.767	2.271	1.264	1102	2.037	2.198	1.877	175	1.237	1.322	1.152	92
2004	1.812	2.299	1.324	1061	2.014	2.365	1.663	147	1.575	1.702	1.448	128
2006	1.787	2.301	1.274	2135	1.758	1.979	1.537	363	1.621	1.998	1.244	330
2008	1.775	2.237	1.312	1519	2.034	1.911	2.158	264	1.775	2.124	1.425	159
2010	1.720	2.092	1.348	1543	1.786	1.876	1.697	297	1.614	1.588	1.641	199
Mean	1.799	2.308	1.290		1.762	1.816	1.708		1.723	1.947	1.377	

Note: N_w refers to number of White households, N_B refers to number of Black households, N_{OTH} refers to number of households in Other Races.

Over the whole period from 1972 to 2010, Blacks on average had a lower happiness inequality compared with Whites for two of the three inequality indices. $I_X^{AF}(-2,0,2)$ and $I_X^{AF}(-2,-1,2)$ exhibit a lower inequality for Blacks, while under $I_X^{AF}(-2,1,2)$ the opposite result holds. To understand these results, when we focus on the distribution, we find that Blacks do have a higher share of their population in the median category compared to Whites, reflecting a greater dispersion among Whites, which is picked up by $I_X^{AF}(-2,0,2)$. It is interesting to note that most of the Black population is in the lower two categories whereas most of the White population is in the upper two categories of the happiness distribution. Thus, when the gap in the scale is reduced for the lower two categories, as happens with the convex scale $c = (-2, -1, 2)$, the happiness inequality among Blacks reduces relatively more, leading to an increase in the gap between Blacks and Whites, compared with the linear scale $c = (-2, 0, 2)$. On the other hand, when the gap in the scales is reduced for the top two categories, as is the case with the concave scale $c = (-2, 1, 2)$, the inequality among Whites is reduced sharply so that Whites now on average have lower inequality than Blacks.

Broadly, in terms of happiness inequality, both Blacks and Whites follow the general trend, with inequality decreasing from the 1970s all the way to the 1990s. In recent years, for both groups, the inequality has been on the increase, and this is consistent across all the three indices. There are, however, significant differences in the experience of inequality among the groups. When we consider $I_X^{AF}(-2,0,2)$ and $I_X^{AF}(-2,-1,2)$, on average, Blacks had lower inequality than Whites in the 1970s through to the 1990s. It is only in the last decade that the gap between groups has reduced substantially and Blacks under the concave scale reflect a higher inequality than Whites. For $I_X^{AF}(-2,1,2)$, the happiness inequality of Whites has been always lower than that of Blacks for all four decades.

4.3. *Region*

There is growing evidence that happiness and the factors that affect it vary across regions (Alesina *et al.*, 2004; Graham and Felton, 2006). Our primary interest here is whether the distribution of happiness varies across regions within the U.S. GSS reports happiness levels for nine zones. We have followed the U.S. Census definitions and collapsed them into four regions: the Mid-West, the North-East, the South, and the West. Our sample consists of 10,105 observations from the North East, 12,785 observations from the Mid West, 17,033 observations from the South, and 9,509 observations from the West. Table 6 presents the decomposition of the happiness inequality across different regions.

The results show considerable variations in happiness inequality across regions. Over all the three inequality indices, on average the South comes out with the highest inequality, closely followed by the West. On the other hand, the Mid-West and the North-East have the lowest inequality, depending on which inequality index we look at. When we examine the distribution of happiness across the years, we find that these two regions have a much higher proportion of their population in their median category compared with the West and the South. Compared with the other regions, the North-East has a greater percentage of the population in the bottom two categories and this is reflected in the relatively lower

TABLE 6

Decomposition of Median Inequality by Region

	Inequality North-East $I^{AF}(-2, 0, 2)$	Inequality North-East $I^{AF}(-2, -1, 2)$	Inequality North-East $I^{AF}(-2, 1, 2)$	N_{NE}	Inequality Mid-West $I^{AF}(-2, 0, 2)$	Inequality Mid-West $I^{AF}(-2, -1, 2)$	Inequality Mid-West $I^{AF}(-2,1,2)$	N_{MW}	Inequality South $I^{AF}(-2, 0, 2)$	Inequality South $I^{AF}(-2, -1, 2)$	Inequality South $I^{AF}(-2, 1, 2)$	N_S	Inequality West $I^{AF}(-2, 0, 2)$	Inequality West $I^{AF}(-2, -1, 2)$	Inequality West $I^{AF}(-2, 1, 2)$	N_W
1972	1.983	2.156	1.810	402	1.705	1.960	1.450	444	2.026	2.292	1.760	486	1.744	2.071	1.416	274
1973	1.746	2.194	1.299	357	1.896	2.477	1.315	424	2.186	2.718	1.654	476	1.959	2.270	1.649	244
1974	1.961	2.528	1.394	343	1.972	2.352	1.592	431	2.240	2.878	1.603	468	1.835	2.281	1.389	238
1975	1.801	2.182	1.420	327	1.802	2.231	1.373	443	2.013	2.481	1.544	506	1.669	1.932	1.407	209
1976	1.789	2.199	1.379	345	2.083	2.570	1.595	424	1.790	2.241	1.339	486	1.856	2.306	1.407	244
1977	1.866	2.272	1.461	310	1.766	2.287	1.244	459	1.991	2.488	1.494	507	1.824	2.374	1.273	251
1978	1.453	1.902	1.004	342	1.674	2.215	1.133	450	2.019	2.602	1.436	489	1.785	2.377	1.193	236
1980	1.794	2.092	1.495	308	1.762	2.301	1.223	400	2.012	2.509	1.516	494	1.996	2.475	1.517	260
1982	2.096	2.584	1.608	365	1.681	2.139	1.224	421	1.925	2.343	1.506	482	1.682	2.200	1.164	237
1983	1.599	1.859	1.338	354	1.676	2.089	1.264	467	1.893	2.300	1.485	482	1.823	2.322	1.324	270
1984	1.838	2.256	1.420	293	1.903	2.410	1.395	414	1.967	2.468	1.466	475	1.933	2.475	1.392	263
1985	1.551	1.870	1.232	295	1.585	2.005	1.166	400	1.683	2.085	1.281	542	1.538	1.905	1.171	294
1986	1.734	2.076	1.392	310	1.651	2.134	1.169	386	1.770	2.268	1.272	467	1.799	2.304	1.295	285
1987	1.532	1.982	1.083	287	1.874	2.272	1.477	393	1.843	2.287	1.399	491	1.897	2.390	1.404	266
1988	1.751	2.263	1.240	303	1.760	2.268	1.251	388	1.883	2.502	1.263	487	1.625	2.187	1.062	288
1989	1.760	2.259	1.261	311	1.699	2.273	1.125	393	1.825	2.357	1.293	520	1.578	1.997	1.160	303
1990	1.809	2.360	1.257	278	1.616	2.247	0.986	371	1.766	2.255	1.277	459	1.794	2.388	1.200	253
1991	1.592	2.000	1.183	301	1.519	1.902	1.136	366	1.829	2.385	1.272	545	1.695	2.127	1.262	292
1993	1.528	1.866	1.189	293	1.663	2.130	1.197	417	1.810	2.339	1.281	551	1.835	2.342	1.328	340
1994	1.557	1.896	1.218	587	1.647	2.032	1.262	705	1.769	2.171	1.367	1077	1.637	2.032	1.242	608
1996	1.670	2.022	1.317	562	1.731	2.132	1.331	657	1.774	2.262	1.285	1019	1.604	2.051	1.157	647
1998	1.598	1.917	1.280	572	1.735	2.226	1.245	677	1.819	2.285	1.353	1002	1.881	2.373	1.389	554
2000	1.782	2.247	1.316	577	1.545	1.961	1.128	652	1.865	2.419	1.310	986	1.718	2.183	1.252	562
2002	1.838	2.224	1.452	290	1.641	2.029	1.254	346	1.862	2.399	1.325	454	1.690	2.053	1.328	278
2004	1.748	2.157	1.339	232	1.688	2.131	1.245	309	1.919	2.413	1.425	515	1.802	2.154	1.450	281
2006	1.766	2.292	1.239	485	1.725	2.130	1.321	632	1.795	2.248	1.343	1056	1.749	2.225	1.273	655
2008	1.686	2.038	1.334	339	1.884	2.298	1.471	452	1.911	2.324	1.498	712	1.665	1.950	1.380	439
2010	1.725	2.156	1.295	337	1.627	1.964	1.290	464	1.792	2.067	1.517	799	1.681	1.851	1.511	438
Mean	1.734	2.137	1.330		1.733	2.184	1.281		1.892	2.371	1.413		1.761	2.200	1.321	

Note: N_{NE} refers to number of households in North-East; N_{MW} refers to number of households in Mid-West; N_S refers to number of households in South; N_W refers to number of households in West.

average inequality for the North-East in terms of $I_X^{AF}(-2,-1,2)$. The Mid-West has a higher share of the population in the top two categories compared with the other regions, thus leading to a lower inequality for the Mid-West under the concave scale, $c = (-2, 1, 2)$.

Broadly, all the four regions followed the national trend, where inequality decreased through the 1980s and the 1990s, only to increase in the 2000s.[8] The regional experience over time has been quite varied. Over the decades the Mid-West seems to have been able to reduce its inequality more, relative to other regions such as the North-East and the West. In the last decade, the North-East has exhibited a greater level of happiness inequality compared with the West. We see these broad trends continuing in 2010; however, we find that, while for the South and the West, the share of the population in the top category has decreased and the share of the bottom category has increased, for the Mid-West, the middle category has gained relative to the top and the bottom category. For the North-East, the share of the top category has increased and the bottom two categories have decreased.

5. Conclusion

Since happiness is an important indicator of subjective well-being, understanding the distribution of happiness across the population is crucial. However, given the ordinal nature of the happiness data, use of the standard inequality indices to measure happiness inequality may be problematic. This is because, in an ordinal setting, to use the standard inequality measures one has to rely on specific scales. The justification to use a particular cardinal scale to evaluate the levels of happiness inequality is limited and unsatisfactory. More importantly, the standard inequality measures are scale dependent, which leads to the possibility that using different scales may lead to inconsistency in ranking in terms of inequality.

In this paper, we apply a dominance based approach, which is scale independent, to rank the different years in terms of happiness inequality in the U.S. The 1990s seem to dominate other decades and hence have the lowest inequality compared to the other decades. Further, using some recently developed measures of ordinal inequality indices, we compute the happiness inequality in the U.S. from 1972 to 2010. In terms of broad trends, happiness inequality decreased from its highest level in the 1970s, through the 1980s and 1990s. Only in the 2000s did it start to rise again. However, in 2010 there has been a remarkable decline in inequality, making it the year with the lowest inequality under the linear scale of the *AF* measure. This achievement is offset, to some extent, by the fact that the average level of happiness in 2010 turns out to be the lowest among all the years.

The decomposition results allow us to focus on sub-groups within the population. For robustness purposes, we used the *AF* inequality index under three different scales. Among the broad results, we find that women typically have a greater happiness inequality compared with men, although the differences between the genders have reduced over the years. Our analysis also indicates that happiness

[8]The only exception is the West under $I_{AF}^{X}(-2,0,2)$, where the inequality has reduced for each of the four decades.

inequality among Whites is not necessarily always lower than Blacks.[9] For two of the three inequality indices, averaging over all the years, Blacks have a lower happiness inequality than Whites. Among the four regions in the U.S., the South seems to have the highest inequality followed by the West, and it is consistent across all three indices. Although most of the sub-groups have followed the general trend of happiness inequality in the U.S., there are considerable variations across different groups and regions.

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[9]When it comes to income inequality, for instance, Whites typically have a lower inequality compared with Blacks (see Goldsmith and Blakley, 2010).

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix: Proofs of Propositions