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THE ANALYSIS OF HUMAN FEELINGS: A PRACTICAL SUGGESTION FOR A ROBUSTNESS TEST

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Governments, multinational companies, and researchers today collect unprecedented amounts of data on human feelings. These data provide information on citizens' happiness, levels of customer satisfaction, employees' satisfaction, mental stress, societal trust, and other important variables. Yet a key scientific difficulty tends to be downplayed, or even ignored, by many users of such information. Human feelings are not measured in objective cardinal units. This article aims to address some of the ensuing empirical challenges. It suggests an analytical way to approach the scientific complications of ordinal data. The article describes a dichotomous-around-the-median (DAM) test, which, crucially, uses information only on direction within an ordering and deliberately discards the potentially unreliable statistical information in ordered data. Applying the proposed DAM approach, this article shows that it is possible to check and replicate some of the key conclusions of previous research—including earlier work on the effects upon human well-being of higher income.

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1. INTRODUCTION

"Feelings data" are all around us. International policy-makers have begun to incorporate measures of citizens' well-being into official statistics and the evaluation of public policies (Stiglitz et al. 2009; Durand 2015; Graham 2016, 2018; OECD conference 2019). Businesses across the world now collect enormous amounts of information on customer satisfaction and employee engagement: such numbers long ago seemingly passed a key market test (to use Chicago-esque jargon). Organizations like Gallup provide regular surveys of people's feelings across

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the globe.[1] For many decades, moreover, scientific researchers have included concepts such as life satisfaction, mental health, trust, and political corruption in formal regression analysis. Highly cited articles, published in journals such as the *Economic Journal*, the *Journal of Public Economics*, the *Journal of Development Economics*, the *American Economic Review*, the *Quarterly Journal of Economics*, *Review of Income and Wealth*, and the *Proceedings of the National Academy of Sciences of the USA*, empirically analyze such data (e.g., Frey and Stutzer 2000; Easterlin 2001; Alesina et al. 2004; Blanchflower and Oswald 2004; Ferrer-I-Carbonell and Frijters 2004; Booth and van Ours 2008; Di Tella and MacCulloch 2008; Fafchamps and Shilpi 2008; Luechinger 2009; Clark and Senik 2010; Nunn and Wantchekon 2011; Verme 2011; Benjamin et al. 2012; Kahneman and Deaton 2010; Clark et al. 2016). Major portions of particular disciplines, such as psychology and psychiatry, rest on the analysis of this form of ordinal data. As described in recent reviews by Diener et al. (2017) and Clark (2018), there are now, as one example, tens of thousands of published articles on the empirical study of human well-being. Easterlin (1974) was a seminal paper.

The appropriate use of these kinds of data, however, presents scientific challenges. Those have typically been downplayed or ignored by government agencies, by commercial organizations, and often also in published academic research. This is the issue on which we focus. Our article builds particularly upon the work of researchers such as Ferrer-I-Carbonell and Frijters (2004), Oswald (2008), Abul Naga and Yalcin (2008), Lv et al. (2015), Ravallion et al. (2016), Schröder and Yitzhaki (2017), Bond and Lang (2019), Chen et al. (2019), Kaiser and Vendrik (2019), Apouey et al. (2020), and Bloem (2021).

By definition, an ordinal variable (measuring, e.g., human happiness or customer satisfaction or feelings of trust) cannot be converted into objective cardinal units. Consider a question such as "All in all how satisfied are you with your life right now?" with several ordered answer categories: "very satisfied," "satisfied," "unsatisfied," and "very unsatisfied." The lack of information about the interval between response categories presents a conceptually deep empirical problem. Because ordered-response categories only provide information about rank, and not the interval between categories, standard empirical methods—such as comparisons of means or linear regression analysis—can lead to invalid estimates.

These challenges have been known for many decades. Recent writings, however, help to clarify their nature. The work of Schröder and Yitzhaki (2017), for instance, explains the possible perils of assuming arbitrary and fixed intervals between each of the categories on an ordinal scale. The practice of comparing means or using a linear regression ignores the fact that, in principle, any transformation of the ordinal scale is theoretically permissible if it preserves the ordered rank of categories but changes the interval between categories. In addition, the work of Bond and Lang (2019) argues that empirical results using ordinal response regression approaches (e.g., an ordered logit or probit regression) implicitly assume a specific distribution on the error term. Allowing for possible deviations from the assumed functional forms of the error term, Bond and Lang (2019) suggest that prominent results in the microeconomic literature on happiness might be

[1]Gallup Global Research. Available online: https://news.gallup.com/poll/101905/gallup-poll.aspx.

uninformative. Because the true distribution of the error term is unknown, Bond and Lang (2019) are not able to establish that this literature is *definitively* incorrect. Previously published results may be either correct or incorrect, but careful analysis is necessary. In this article, we aim to describe a simple robustness check for quantitative analysis where the dependent variable is measured on an ordinal scale.[2]

One response to these conceptual challenges would be to decline to use ordinal data. This extreme stance, however, has not been taken by modern governments and multinational companies. That is probably because its implied nihilism has a fundamental disadvantage. It means turning our backs, as a community, on a great deal of potentially valuable statistical information about the perceptions and attitudes that are central to people's lives. Despite the potential complications of using ordinal data, nihilism carries its own empirical dangers. Some balance, between conceptual purity and practical relevance, must be struck, whatever the branch, in applied statistical science. One aim of this article is to try to find a central ground that offers such balance.

As one example of these dangers, Ronald A. Fisher, then the most famous statistician in the world, famously refused to accept the early evidence that smoking caused lung cancer. He went to his grave assuring everyone that it was safe to smoke (Pearl and Mackanzie 2018). Fisher objected to the early researchers' cross-sectional statistical methods. He believed those methods were potentially flawed. "The curious associations with lung cancer found in relation to smoking habits do not [...] lend themselves easily to [...] simple conclusion. [...] Such results suggest that an error has been made of an old kind, in arguing from correlation to causation. There is nothing to stop those who greatly desire it from believing that lung cancer is caused by smoking cigarettes. [...] To believe this is, however, to run the risk of failing to recognize [...] more genuine causes" (Fisher 1958, p. 596). Unfortunately for Fisher's standing in medical history, he turned out to be deeply wrong, in a substantive sense, even though his methodological concerns were in principle technically appropriate. If the world had listened to Fisher, large numbers of humans would have died prematurely. Of course, *ex ante*, we cannot know which statistical results are robust to future more rigorous analysis. Therefore, caution and pragmatism, of a scientifically constructive kind, are appropriate in the face of potential methodological concerns.

If ignoring all ordinal "feelings data" is unsatisfactory, how should researchers handle these ordinal variables in empirical analysis? Although some researchers object to the aforementioned critiques, see interesting counter-arguments raised by Chen et al. (2019) and Kaiser and Vendrik (2019), the goal of the current article is to be pragmatic and to attempt to be constructive. Given the foregoing, it seems imperative that empirical researchers use credible methods when using an ordinal dependent variable.[3]

[2]Previous research focuses on other areas of analysis and address complications associated with the use of ordinal variables. One example is in the measurement of inequality when only ordinal variables are available for analysis (Allison and Foster 2004; Abul Naga and Yalcin 2008; Lv et al. 2015; and Apouey et al. 2020).

[3]In this article, we focus on the use of ordinal *dependent* variables, as these tend to present applied researchers with a more difficult problem than compared to the use of ordinal explanatory variables. Indeed, one common approach for using an ordinal explanatory variable is to separate the ordinal variable into distinct dichotomous variables.

This article discusses a robustness test on ordinal feelings variables. This test, which we call the dichotomous-around-the-median (DAM) test, relies only on the direction within ordinal data. This approach builds on the premise that one of the major challenges with the empirical analysis of ordinal variables is absent when analyzing dichotomous variables. To implement the method, we deliberately discard some information captured by the ordinal scale—namely, information about the full ordering of all the answers. This is performed to ensure that our method does not rely on arbitrarily assumed interval information. In the DAM test, the ordinal dependent variable is redefined as a dichotomous variable for threshold points around the median value of answers on the ordinal scale, and relies on two elements (what we later call the upper and lower dichotomous tests).

As we discuss in more detail in Section 4, the median is only one way to define a dichotomous variable. There are, of course, other approaches (see, e.g., Apouey et al., 2020), and some settings may have an internally valid threshold level in the ordinal scale (see, e.g., Alloush and Bloem 2021). If any choice of cut in the data must be made, and we believe it does, the median seems the natural candidate as it possesses intuitive and useful properties. First, it is invariant to monotonic transformations of the ordinal scale. Second, it is simple, is widely understood, and can be applied in any empirical context with an ordinal dependent variable. Third, it ensures that sufficient variation will persist in the dichotomous variable. By its nature, cutting at the median leaves a large amount of statistical information on both sides of the cut. Fourth, because the notion of a mean is not in general defined with ordinal data, we view—and believe most researchers would and will view—a cut at the median as the least arbitrary assumption to be made by an investigator who wishes to divide a dependent variable into a high category and a low category. We believe that applied researchers are likely to eschew a complicated alternative, which is one reason why our dichotomous analysis is a practical compromise. Fifth, our method does not require a statistical investigator to implement only a cut at the median. Other divisions of the data, pursued in a complementary way, could be undertaken by any investigator who wished to do so. However, a DAM test is a natural benchmark case from which to begin.

Robustness to these DAM tests suggests robustness to rank-preserving transformations of the ordinal scale. This DAM test, it should be emphasized, consciously fails to use all the potential statistical information in an ordered data set. It does this precisely because some researchers object to, and doubt the reliability of, within-ranking information.

We then revisit a number of previous and familiar empirical results. First, we show the DAM test by reanalyzing the effect of unconditional cash transfers on psychological well-being in Kenya (Haushofer and Shapiro 2016) and the effect of the slave trade on trust in sub-Saharan Africa (Nunn and Wantchekon 2011). Second, we use the same approach to check the conclusions of prominent research articles on well-being, life satisfaction, and corruption. This analysis relates to the findings in work such as Blanchflower and Oswald (2004), Fan et al. (2009), Triesman (2000), Kahneman and Deaton (2010), and Stone et al. (2010).

The rest of this article is organized as follows. The next section highlights the challenge of empirically analyzing ordinal variables. In Section 3, we make

TABLE 1
Which Group, A or B, Is More Satisfied (Under Different Reporting Functions)?

	Very Dissatisfied	Dissatisfied	Satisfied	Very Satisfied	The Most Satisfied Group?
A	1	0	0	1	
B	0	1	1	0	
Linear Reporting	0	1	2	3	Tie
Concave Reporting	0	1.75	2.5	3	B
Convex Reporting	0	0.5	1.25	3	A

the point that, despite the deep challenges, the use of ordinal variables is not going away anytime soon. Section 4 introduces and describes our DAM approach. Finally, we conclude in Section 5.

2. An Intuitive Introduction to the Analytical Challenge

The challenge of empirically analyzing ordinal variables can be explained as follows. Think of a person who is about to fill in a questionnaire about her feelings. Call the "reporting function" the way the person looks inside herself and then writes answers about how she feels. Imagine that this individual actually has constant marginal utility of income. But now consider the possibility that, as she feels cheerier, she marks herself happier on a questionnaire scale in a way in which she is intrinsically reluctant to approach the highest level on the questionnaire form (e.g. the 5 on a 1–5 scale). Then the reporting function itself is curved. In this case, we will have the illusion, when we study her pay increases over time and analyze the patterns in subjective well-being data, that true diminishing marginal utility of income has been established empirically. Yet it has not. The numbers written down by the person will be due, in part, to the sheer curvature of the reporting function. The root of the problem here is not simply caused by the—perhaps inevitable—reality that subjective well-being is measured on an ordinal scale with discrete boxes for happiness of 5, 4, 3, etc. The problem would persist even if surveys got people to provide exact numerical answers anywhere on the real number line (Oswald 2008).

Consider a further example, as set out numerically in Table 1. A survey asks respondents to answer the following question: "All in all how satisfied are you with your life right now?" using the following ordered response categories: "Very Satisfied," "Satisfied," "Dissatisfied," and "Very Dissatisfied." To simplify this example even further, suppose there are two groups of people, each with only two members. Group A includes one person who is "Very Dissatisfied" and another who is "Very Satisfied." Group B includes one person who is "Dissatisfied" and another who is "Satisfied." A seemingly simple question is: Which group is more satisfied? The answer, however, is not simple. That is because the answer depends on the interval between the response categories. Perhaps a natural way to empirically answer this question is to assume a linear set of values for the response categories. In this case, "Very Dissatisfied" has a value of zero, "Dissatisfied" is one, "Satisfied" is two, and "Very Satisfied" is three. The average satisfaction of the two groups is equal, with an average score of 1.5, and the groups are equally satisfied.

Similar to utility functions, however, ordinal scales only offer information about the relative rank of response categories and thus provide no information about the interval between categories. Therefore, a potentially valid alternative way to answer this question is to assume a concave set of values for the response categories. In this case, "Very Dissatisfied" again has a value of 0, "Dissatisfied" has a value of 1.75, "Satisfied" has a value of 2.5, and "Very Satisfied" again has a value of 3. With this set of values, group B is more satisfied than group A. Finally, another valid alternative is to assume a convex reporting function over the responses. In this case, "Very Dissatisfied" again has a value of 0, "Dissatisfied" has a value of 0.5, "Satisfied" has a value of 1.25, and "Very Satisfied" again has a value of 3. With this set of values, group A is more satisfied than group B. Table 1 illustrates this example and shows that the answer to the seemingly elementary question depends on the assumed intervals between the response categories.

An additional issue is that of possible cross-sectional heterogeneity. That is, not only do we not have information about the intervals between response categories, but it is also possible—intuitively—that different individuals might interpret the distances between the response categories differently. Although this is an area for future research, we follow previous literature that analyzes an ordinal variable and assume no cross-sectional heterogeneity.

3. The Potential Use and the Potential Misuse of Ordinal Variables

Over past decades, researchers have increasingly studied variables measured on an ordinal scale. To date, for example, the single most-cited paper published in the history of the well-known *Journal of Public Economics* analyzes corruption using a 0 through 3 ordinal scale as the dependent variable (Treisman 2000). While discussing the psychology literature on subjective well-being, Diener et al. (2017) note that in 2015 alone over 14,000 publications on Google Scholar mentioned subjective well-being. In addition, while reviewing the economics literature on human happiness, Clark (2018) notes that 4 of the 20 most-cited articles ever published in the *Economic Journal* have the word "happiness" in their title—including Easterlin (2001)—and two of the three most-cited articles ever published in the *Journal of Public Economics* investigate subjective well-being.

The challenge is not limited to a huge research literature on "subjective well-being" (e.g., Easterlin 1974; Oswald 1997; Luttmer 2005; Graham 2005; Fafchamps and Shilpi 2008; Di Tella and MacCulloch 2008; Dedehouanou et al. 2013; Aghion et al. 2016; Boertien and Vignoli 2019; Perelli-Harris et al. 2019). It applies in contexts where any of the following variables are used as primary outcomes of interest: "satisfaction" (Frijters et al. 2004; Clark and Oswald 1994, 1996; Ritter and Anker 2002; Luechinger et al. 2010), "trust" (Nunn and Wantcheckon 2011; Putnam 2001), "corruption" (Treisman 2000; Fan et al. 2009; Martimort and Straub 2009), "work feelings" (Bryson and MacKerron 2017); "feelings of comparison" (Clark and Senik 2010; Budria and Ferrer-I-Carbonell 2019), "visibility" (Heffetz 2011), "hope" (Bloem et al. 2018; Glewwe et al. 2018), measures of mental well-being and personality traits (Borghans et al. 2008; Baird et al. 2013; Cornaglia et al. 2014), measures of "affect" (Krueger et al. 2009; Krueger 2017), measures of "quality" (Acemoglu et al. 2001), and standardized test scores (Bond and Lang 2013; Glewwe 1997; Jacob and Rothstein 2016; Lang 2010; Schröder and Yitzhaki 2016). Therefore, the matters discussed in this article are in principle relevant to a variety of disciplines, including also medicine, psychology, politics, marketing, biometrics, labor relations, psychiatry, and sociology.

Nor is the valid use of ordinal variables just an academic issue. Large corporations use ordinal scales to measure information about how their customers feel about their products and services. Delta and British Airways send customer-satisfaction surveys via email to customers after a flight. Amazon has a five-star ranking system to record customer satisfaction. Currently, Amazon reports an aggregate score that simply takes the average of the one-through-five ordinal scale, assuming a linear set of values associated with each interval. In addition, the ride-share apps Uber and Lyft employ the same method to evaluate the quality of their drivers based on customer reports.[4]

As explained earlier, recent work raises questions on the validity and robustness of some of the academic studies and corporate practices discussed earlier. In particular, Schröder and Yizhaki (2017) examine the reliability of the results reported by Ferrer-i-Carbonell and Frijters (2004) and find that the empirical conclusions are not robust to all the potential monotonic increasing transformations (i.e., transformations of the ordinal scale that maintain the relative rank of categories but change the interval between categories). Similarly, Bond and Lang (2019) attempt to re-evaluate several well-known results from the economics of happiness literature. These include: Easterlin's paradox (Easterlin 1974, 2001), U-shaped life-cycle happiness (Blanchflower and Oswald 2004), the unemployment-inflation trade-off (Di Tella et al. 2001), ranking countries based on happiness, results from the Moving to Opportunity project (Ludwig et al. 2012), the effect of marriage and children on happiness (Diener et al. 2000; Blanchflower and Oswald 2004), declining female happiness (Stevenson and Wolfers 2009), and adaption to disability (Kahneman 2011; Oswald and Powdthavee 2008). Ultimately, Bond and Lang (2019) argue that none of these pass their (admittedly rather extreme) theoretical requirements for the valid use of ordinal variables. Finally, using a vignette approach to investigate heterogeneity across ordinal scales, Ravallion et al. (2016) find evidence of systematic heterogeneity in ordinal response scales. However, this heterogeneity only leads to small biases in their estimated coefficients.

The core point of Schröder and Yitzhaki (2017) is that results using ordinal scales must be robust to monotonic increasing transformations of the *observed*

[4]On their Community Guidelines page, Uber seems to acknowledges the ambiguity of ordinal scales but ultimately sets a minimum average rating that must be met for drivers to maintain access to their account. "There is a minimum average rating in each city. This is because there are cultural differences in the way people in different cities rate each other. We will alert you over time if your rating is approaching this limit, and you'll also get information about quality improvement courses that may help you improve. However, if your average rating still falls below the minimum after multiple notifications, you will lose access to your account." See https://www.uber.com/legal/community-guidelines/us-en/.

scale. That is, empirical results must be robust to rank-preserving transformations of the ordinal scale that change the interval between the observed categories. A related but slightly different point of Bond and Lang (2019) is that results should ideally be robust to monotonic increasing transformations of the *latent variable* (e.g., the unobserved distribution of happiness states). They show that nonparametric estimation techniques are likely not feasible in most empirical settings. There are two feasible approaches for parametric estimation. First, the researcher can assume that the ordinal scale is, in fact, an interval scale. Although this assumption is common, any rank-preserving cardinalization of the ordinal scale is, in principle, theoretically permissible. Second, the researcher can use an ordered-response regression and make the assumption that the distribution of the latent variable is normal (i.e., when using an ordered probit) or logistic (i.e., when using an ordered logit). Bond and Lang (2019) proceed to show that results using an ordered probit or ordered logit can in certain cases be reversed when assuming a different, and theoretically permissible, functional form of the distribution of the latent variable.

4. Dichotomous-Around-the-Median Tests

In introducing and discussing the following robustness test, we attempt to take seriously these critiques and provide advice for how to validate empirical results when using ordinal variables. This proposed test does not diminish the importance of acknowledging the underlying challenges. We hope, however, that the test allows for the valuable information stored in ordinal variables to credibly inform empirical analysis.

One way to think of the complication of ordinal scales is that some researchers have come to put too much emphasis on the multiple levels of ordinal responses—- e.g., the four levels of possible responses in Table 1. It is this multiple ordering, and the unknown intervals between categories, that generates the key problem.

Therefore, we begin in what may seem a counter-intuitive way—by deliberately discarding statistical information (about, in particular, some of the levels). First, and crucially, we exploit a property that can be relied on, namely, the known qualitative direction within an ordinal response scale. No matter how many ostensible levels there are on an ordinal scale, the direction—which way is high and which way is low—is known and unambiguous. Second, the multiple-ordering aspect can then be avoided by compressing multiple scales into a single dichotomous scale. In the case of a customer-satisfaction scale in marketing science, for example, this would mean taking the multiple answers "Completely Satisfied," "Very Satisfied," [...], "Not Satisfied" and reclassifying them into only two categories.

The idea here is consciously to reduce an ordinal scale down into a dichotomous variable. Robustness of results to dichotomous tests suggests that core results are robust to rank-preserving transformations of the ordinal variable. Where exactly should the dichotomous split be inserted? We suggest that the use of a dichotomous test around the median of responses is particularly natural (Allison and Foster 2004). This is because to divide the data at the median is one way to allow as much statistical information as possible into the upper and lower parts of the distribution.

It should be emphasized that other choices about the position of the dichotomous split are feasible. For example, as one reviewer points out, a more sophisticated approach is to apply the axiomatic principles from Apouey et al. (2020) to define where to make the dichotomous split in the ordinal variable. This alternative approach may possess some advantages, namely relying on reasonable axioms, and also relies on the judgment of the researcher and is less straightforward than simply using the median. In certain special cases, it is important to note that researchers may reasonably want to use a more sophisticated approach. In other cases there may already be an internally valid threshold level in the ordinal scale—such as borrowing a critical threshold used in clinical settings to screen for depressive symptoms (Alloush and Bloem 2021). The goal of this article, however, is to develop a simple robustness test that can be quickly applied to the many fields of study using ordinal information as a dependent variable. In addition, one could imagine defining many dichotomous variables using every threshold point in the ordinal scale. Although this is certainly permissible, in some cases a dichotomous variable defined by a relatively extreme threshold point may lack sufficient variation to detect an effect estimate even when there is in fact a nonzero effect, and in cases when the ordinal scale has many threshold values this procedure will become computationally intensive. This motivates our suggestion to use the median value of the ordinal variable to define two dichotomous variables: one that includes the median value within the "upper" category and a second that includes the median value within the "lower" category. This is akin to our DAM test having sufficient power to statistically detect an effect when the true effect is indeed nonzero. Finally, as we will show with the following mathematical sketch, the median is invariant to monotonic increasing transformations of the ordinal scale.

4.1. *A Mathematical Sketch*

A brief mathematical sketch will help illustrate the DAM test approach. Let Y^* be the latent happiness variable, for example. Because, Y^* cannot be directly observed, let Y be the observed ordinal variable that measures Y^*. The observed ordinal variable Y is measured with various values of μ corresponding to threshold points on the ordinal scale:

$$Y = \begin{cases} 0 \text{ if } \quad Y^* \leq 0, \\ 1 \text{ if } 0 < Y^* \leq \mu_1, \\ 2 \text{ if } \mu_1 < Y^* \leq \mu_2 \\ \vdots \\ N \text{ if } \mu_{N-1} < Y^* \end{cases} \tag{1}$$

Next, we calculate the median of the observed ordinal scale and define both the upper and lower dichotomous variables as follows: Dichotomous Upper = 1 if $Y \geq Med(Y)$ and Dichotomous Lower = 1 if $Y > Med(Y)$, where $Med(Y)$ is the median of the observed scale Y.

Now, let $\tau(\cdot)$ be a monotonic increasing function. Transforming the latent variable Y^* with this monotonic increasing function, $\tau(Y^*)$, also transforms the observed ordinal, $\tau(Y)$, given the same set μ's as follows:

$$\tau(Y)=\begin{cases} 0 \text{ if } \quad \tau(Y^*)\leq 0, \\ 1 \text{ if } 0<\tau(Y^*)\leq \mu_1, \\ 2 \text{ if } \mu_1<\tau(Y^*)\leq \mu_2 \\ \vdots \\ N \text{ if } \quad \mu_{N-1}<\tau(Y^*) \end{cases} \tag{2}$$

Note that $Med(\tau(Y)) = \tau(Med(Y))$. Therefore, the "new" dichotomous variables are defined as follows: Dichotomous Upper = 1 if $\tau(Y) \geq \tau(Med(Y))$ and Dichotomous Lower = 1 if $\tau(Y) > \tau(Med(Y))$, which is equivalent to Dichotomous Upper = 1 if $Y \geq Med(Y)$ and Dichotomous Lower = 1 if $Y > Med(Y)$, where $Med(Y)$ is the median of the observed scale Y.

4.2. *Empirical Applications*

We initially use two applications to illustrate our DAM method. In the first, we re-examine the effects of randomly distributed unconditional cash transfers on psychological well-being in Kenya (Haushofer and Shapiro 2016). Among other outcomes of interest, the authors examine the treatment effect on happiness and life satisfaction measured using the questions included in the World Values Survey. Specifically, happiness is measured via the following question: "Taking all things together, would you say you are 'very happy,' 'quite happy,' 'not very happy,' or 'not at all happy?' with the categories enumerated 1 through 4." Similarly, life satisfaction is measured via the following question: "All things considered, how satisfied are you with your life as a whole these days on a scale of one to ten?" with one indicating "very dissatisfied" and ten indicating "very satisfied."

In the second application, we re-examine the effects of the trans-Atlantic slave trade on trust in sub-Saharan Africa (Nunn and Wantchekon 2011). Trust is measured via the Afrobarometer survey along five dimensions—trust of relatives, neighbors, the local council, intra-group trust, and inter-group trust—with the following categories: "not at all," "just a little," "somewhat," and "a lot." The authors code these categories from 0 through 3, with 0 representing "not at all" and 3 representing "a lot."

In each of these data sources, the use of the default cardinalizations of the ordinal data implicitly makes the assumption that the intervals between each of the categories are known, represented by a unitary change of an integer value, and consistent across the entire scale. Yet, as noted earlier, any monotonic transformation of these numerical values that preserves the order of the response categories is theoretically permissible. To test the robustness of the core results to this assumption, we apply our DAM test.

Implementing the approach is simple. For each application, we first calculate the median of the ordinal dependent variable. One complication is that many statistical distributions are asymmetric, so that the median can lie within an answer category. Thus, for completeness, we construct two dichotomous variables. The first includes the median value within the "upper" category, and the second includes the median value within the "lower" category. To ensure comparability

TABLE 2
DAM Tests—Cash Transfers and Well-Being in Kenya (Haushofer and Shapiro 2016)

	Original Ordinal Scale (1)	Dichotomous Upper (2)	Dichotomous Lower (3)
Panel A: Happiness (World Values Survey)			
Treatment	0.165***	0.119**	0.160***
	(0.0503)	(0.0488)	(0.0534)
Village fixed effects	Yes	Yes	Yes
Observations	1473	1473	1473
R^2	0.079	0.082	0.081
Panel B: Life Satisfaction (World Values Survey)			
Treatment	0.170***	0.178***	0.185***
	(0.0480)	(0.0482)	(0.0511)
Village fixed effects	Yes	Yes	Yes
Observations	1473	1473	1473
R^2	0.135	0.180	0.133

Notes: The dependent variable in Panel A measures happiness and the dependent variable in Panel B measures life satisfaction. Both variables are measured using the survey question found on the World Values Survey. Following Haushofer and Shapiro (2016), each dependent variable is standardized, so the control group has a mean of zero and a standard deviation of one. The original results are reported in Table 4 of Haushofer and Shapiro (2016). Standard errors clustered at the household level are shown in parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

with results using the "original" ordinal scale, these variables are then standardized into z-scores.

Table 2 reports the results from our DAM tests of the effect of unconditional cash transfers on psychological well-being in Kenya (Haushofer and Shapiro 2016). Panel A shows the results on happiness, and Panel B shows the results on life satisfaction. Column 1 replicates the original OLS effect estimates as reported by Haushofer and Shapiro (2016). The remaining columns report OLS results from our DAM tests around the median. In column 2, the dependent variable is a standardized dichotomous variable that equals one if the original scale value is greater than *or equal to* the median. In column 3, the dependent variable is a standardized dichotomous variable that equals one if the original scale value is strictly greater than the median.

Both columns 2 and 3 in Panel A of Table 2 show that the original estimate of the effect on happiness is approximately robust to our DAM tests. Similarly, in Panel B, both columns 2 and 3 show that the original estimate of the effect on life satisfaction is robust to our DAM tests. The original effect-size estimate suggests that receiving the cash transfer increased happiness by 0.16 standard deviations and increased life satisfaction by 0.17 standard deviations. Our DAM tests report a slightly larger range of effect sizes on happiness, 0.12 through 0.16 standard deviations, but these estimates are qualitatively consistent. The DAM tests for the effects on life satisfaction have a relatively narrow range, 0.17 through 0.19 standard deviations. Taken together, the original estimates of the effect of unconditional cash transfers on psychological well-being seem to hold up encouragingly in the face of our DAM checks.

TABLE 3
DAM Tests—Trust in Africa (Nunn and Wantchekon 2011)

	Original Ordinal Scale (1)	Dichotomous Upper (2)	Dichotomous Lower (3)
Panel A: Trust of relatives (Afrobarometer)			
ln(export area)	−0.139***	−0.112***	n.a.
	(0.0376)	(0.0327)	
Observations	20,062	20,062	n.a.
R^2	0.133	0.126	n.a.
Panel B: Trust of neighbors (Afrobarometer)			
ln(export area)	−0.158***	−0.149***	−0.119***
	(0.0335)	(0.0347)	(0.0262)
Observations	20,027	20,027	20,027
R^2	0.156	0.112	0.146
Panel C: Trust of local council (Afrobarometer)			
ln(export area)	−0.100***	−0.0909***	−0.0642**
	(0.0196)	(0.0194)	(0.0273)
Observations	19,733	19,733	19,733
R^2	0.196	0.166	0.179
Panel D: Intra-group trust (Afrobarometer)			
ln(export area)	−0.143***	−0.141***	−0.0845***
	(0.0313)	(0.0334)	(0.0246)
Observations	19,952	19,952	19,952
R^2	0.144	0.106	0.136
Panel E: Inter-group trust (Afrobarometer)			
ln(export area)	−0.0971***	−0.0879***	−0.100***
	(0.0279)	(0.0238)	(0.0273)
Observations	19,765	19,765	19,765
R^2	0.112	0.057	0.089

Notes: The dependent variable in each panel measures a different type of trust as measured by the Afrobarometer survey. The dependent variable is standardized to have a mean of zero and standard deviation of one in each column. The original OLS results are reported in Table 3 of Nunn and Wantchekon (2011). Standard errors clustered at the ethnicity and district levels are shown in parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3 reports the results from our DAM tests of the effect of the slave trade on trust in sub-Saharan Africa (Nunn and Wantchekon 2011). Each panel shows the results on a different dimension of trust as measured via the Afrobarometer survey. Aside from the fact that the original scale is standardized to have a mean of zero and a standard deviation of one, column 1 replicates the original OLS effect estimates as reported by Nunn and Wantchekon (2011). Again, in column 2 the dependent variable is a standardized dichotomous variable that equals one if the original scale value is greater than *or equal to* the median. In column 3, the dependent variable is a standardized dichotomous variable that equals one if the original scale value is strictly greater than the median.

In Panel A of Table 3, the "Dichotomous lower" results are not applicable. This is because the median response for trust in relatives is the uppermost category (e.g., "a lot"), and therefore it is impossible to generate results with a variable in which every category is coded as zero. In all other panels, the median response for interpersonal trust was in the "somewhat" category. In all panels the qualitative result—that the slave trade decreased interpersonal trust in sub-Saharan Africa—persists in our dichotomous tests. In some cases, for example in Panel D for the effect on intra-group trust, the dichotomous tests suggest perhaps some additional uncertainty about the specific size of the effect. However, the effects remain both statistically significant and economically meaningful.

Tables 4–6 provide additional applications of the DAM test. The tables are to be read by comparing the left-hand columns (which, in each case, give the original authors' approach) with the later dichotomous-estimate columns on the right-hand side of the tables.

In Tables 4 and 5, we examine a form of the well-being regression equation, as in Blanchflower and Oswald (2004) and Stone et al. (2010), using subjective well-being data from the US collected by Gallup—in Table 4—and the Behavioral Risk Factor Surveillance System (BRFSS)—in Table 5. The Gallup data use "Cantril's Ladder of Life" which asks respondents to: "Imagine a ladder with steps numbered from zero at the bottom and ten at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life. On which step of the ladder would you say you personally feel you stand at this time?" The BRFSS data use a life satisfaction question that asks: "In general, how satisfied are you with your life?" Respondents choose between four possible categories: "Very satisfied," "Satisfied," "Dissatisfied," and "Very dissatisfied." By default, these categories are enumerated on a 1 through 4 scale, with 1 indicating "Very satisfied" and 4 indicating "Very dissatisfied."

In Table 6, we examine the effect of political decentralization and political corruption (Fan et al. 2009). To measure political corruption, these authors use several ordinal scales. In our illustration, we focus on their primary outcome which is based on the following survey questions included in the World Business Environment Survey (WBES): "Is it common for firms in your line of business to have to pay some irregular 'additional payments' to get things done?" Respondents had six response categories: "never," "seldom," "sometimes," "frequently," "usually," and "always." In the regression analysis, these response categories are enumerated by assuming a linear set of intervals, numbered one through six.

In Tables 4 and 5, we see evidence of a U-shaped relationship between age and subjective well-being (Stone et al. 2010), a positive relationship between marriage and subjective well-being (Diener et al. 2000; Blanchflower and Oswald 2004; Perelli-Harris et al. 2019), and a positive relationship between income and subjective well-being (Blanchflower and Oswald 2004; Stevenson and Wolfers 2013). These estimated relationships are robust to our DAM tests using both Gallup and BRFSS data.

Table 6 reports the effect of democratic decentralization on political corruption, originally reported by Fan et al. (2009). Specifically, we re-examine their core results reported in columns 1 and 10 in Table 5 of their paper. The dependent variable is an ordinal variable that measures political corruption, specifically the frequency of bribes. The coefficient of interest is the estimate on the *Tiers* variable, which measures the level of democratic decentralization by describing the number of levels of government within a given country. Additional covariates aim to control for factors that may lead to biased estimates of the correlation between

TABLE 4
DAM Tests—Cantril's Ladder of Life (Gallup)

	(1)	(2)	(3)	(4)	(5)	(6)
	Original Ordinal Scale		Dichotomous Upper		Dichotomous Lower	
Age	−0.052***	−0.051***	−0.044***	−0.043***	−0.044***	−0.043***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age^2	0.0005***	0.0005***	0.0005***	0.0004***	0.0005***	0.0005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.154***	0.145***	0.132***	0.123***	0.170***	0.162***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Log of household income	0.262***	0.263***	0.235***	0.236***	0.169***	0.171***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
MSA-level log of income		−0.0282		0.00735		−0.0146
		(0.029)		(0.029)		(0.030)
U-curve results:						
Turning point (age)	48.19	48.07	48.64	48.53	44.35	44.17
Fieller 95% C.I.	[47.8; 48.7]	[47.6; 48.6]	[48.1; 49.2]	[48.0; 49.1]	[44.0; 44.7]	[43.8; 44.6]
Sasabuchi p-value	0.000	0.000	0.000	0.000	0.000	0.000
Slope at Min	−0.032	−0.032	−0.028	−0.027	−0.026	−0.025
Slope at Max	0.013	0.013	0.010	0.010	0.015	0.015
Year and month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Other individual-level controls	Yes	Yes	Yes	Yes	Yes	Yes
MSA fixed effects	No	Yes	No	Yes	No	Yes
Other MSA-level controls	No	Yes	No	Yes	No	Yes
Observations	556,300	461,054	556,300	461,054	556,300	461,054
R^2	0.117	0.120	0.104	0.106	0.062	0.065

Notes: The dependent variable in each column is the subjective well-being measure from Gallup. The first two columns show the original ordinal scale. The middle two columns show the results using a dichotomous dependent variable that equals one for all values greater than or equal to the median. The last two columns show results using a dichotomous dependent variable that equals zero for all values less than or equal to the median. In each column, the dependent variable is standardized to have a mean of zero and standard deviation of one. Individual-level controls include sex, race, and six education attainment categories. Additional MSA-level controls include the unemployment rate, the crime rate, and the population size. Standard errors clustered at the MSA level are shown in parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 5
DAM Tests—Life Satisfaction (BRFSS)

	(1)	(2)	(3)	(4)	(5)	(6)
	Original Ordinal Scale		Dichotomous Upper		Dichotomous Lower	
Age	−0.045***	−0.044***	−0.032***	−0.031***	−0.038***	−0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age^2	0.0005***	0.0005***	0.0003***	0.0003***	0.0004***	0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.203***	0.190***	0.087***	0.076***	0.218***	0.207***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Log of household income	0.287***	0.295***	0.235***	0.241***	0.223***	0.230***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
MSA-level log of income		−0.011		0.001		−0.013
		(0.020)		(0.020)		(0.020)
U-test results:						
Turning point (age)	46.52	46.52	49.70	49.88	44.93	44.89
Fieller 95% C.I.	[46.2; 46.8]	[46.2; 46.9]	[49.1; 50.4]	[49.18; 50.67]	[44.6; 45.3]	[44.5; 45.3]
Sasabuchi *p*-value	0.000	0.000	0.000	0.000	0.000	0.000
Slope at Min	−0.027	−0.027	−0.020	−0.020	−0.023	−0.022
Slope at Max	0.013	0.013	0.007	0.006	0.013	0.013
Year and month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Other individual-level controls	Yes	Yes	Yes	Yes	Yes	Yes
MSA fixed effects	No	Yes	No	Yes	No	Yes
Other MSA-level controls	No	Yes	No	Yes	No	Yes
Observations	846,269	738,770	846,269	738,770	846,269	738,770
R^2	0.126	0.130	0.065	0.067	0.093	0.097

Notes: The dependent variable in each column is the life satisfaction measure from BFRSS. The first two columns show the original ordinal scale. The middle two columns give the results using a dichotomous dependent variable that equals one for all values greater than or equal to the median. The last two columns presents the results using a dichotomous dependent variable that equals zero for all values less than or equal to the median. In each column the dependent variable is standardized to have a mean of zero and standard deviation of one. Individual-level controls include sex, race, and six education attainment categories. Additional MSA-level controls include the unemployment rate, the crime rate, and the population size. Standard errors clustered at the MSA level are shown in parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 6
DAM Tests—Political Corruption (Fan et al. 2009)

	(1)	(2)	(3)	(4)	(5)	(6)
	Original Ordinal Scale		Dichotomous Upper		Dichotomous Lower	
Tiers	0.227***	0.197**	0.229***	0.192**	0.226**	0.197**
	(0.0827)	(0.0740)	(0.0674)	(0.0786)	(0.0900)	(0.0757)
Bottom unit size		−0.0260		−0.0164		−0.0342
		(0.0396)		(0.0431)		(0.0358)
Subnational revenues		−0.0294***		−0.0285***		−0.0166**
		(0.00841)		(0.00918)		(0.00762)
Total government revenues		−0.0165**		−0.0117		−0.0181**
		(0.00745)		(0.00737)		(0.00737)
Subnational government employment share		0.00602*		0.00551		0.00449
		(0.00330)		(0.00360)		(0.00289)
Total government employees		−0.0201		−0.0182		−0.0167
		(0.0218)		(0.0232)		(0.0206)
State ownership	−0.430***	−0.439***	−0.440***	−0.451***	−0.321***	−0.360***
	(0.0524)	(0.0494)	(0.0532)	(0.0482)	(0.0467)	(0.0497)
Foreign ownership	−0.0642	−0.112***	−0.0575	−0.0676**	−0.0606	−0.110***
	(0.0404)	(0.0279)	(0.0376)	(0.0326)	(0.0382)	(0.0337)
Exporter	0.0439	0.0516**	0.0555*	0.0628*	0.0485	0.0486
	(0.0326)	(0.0251)	(0.0319)	(0.0364)	(0.0340)	(0.0306)
Firm size	−0.00639	−0.00785	−0.00919	−0.00936	−0.00219	−0.00214
	(0.00665)	(0.00501)	(0.00592)	(0.00592)	(0.00697)	(0.00435)
GDP per capita	−0.247***	−0.126	−0.214***	−0.140	−0.191***	−0.0871
	(0.0571)	(0.0845)	(0.0497)	(0.0853)	(0.0574)	(0.0794)
Democratic	0.000351	0.157	0.0414	0.188	−0.0941	0.0582
	(0.125)	(0.161)	(0.117)	(0.160)	(0.116)	(0.150)
Fuel	0.000484	0.00207	0.000130	0.00349	0.000333	−0.00122
	(0.00196)	(0.00440)	(0.00142)	(0.00423)	(0.00191)	(0.00420)
Imports	0.000465	0.00234	0.00100	0.00281	−1.24e-05	0.00186
	(0.00268)	(0.00317)	(0.00230)	(0.00291)	(0.00287)	(0.00349)
Protestant	−0.591**	0.363	−0.630**	0.197	−0.378	0.316
	(0.267)	(0.367)	(0.262)	(0.385)	(0.268)	(0.355)
British colony	−0.0178	−0.225	−0.0130	−0.191	−0.00998	−0.251
	(0.0991)	(0.157)	(0.0943)	(0.166)	(0.0905)	(0.156)

(Continues)

TABLE 6 (CONTINUED)

	(1)	(2)	(3)	(4)	(5)	(6)
	Original Ordinal Scale		Dichotomous Upper		Dichotomous Lower	
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6676	4101	6676	4101	6676	4101
R^2	0.146	0.196	0.125	0.153	0.113	0.165

Notes: The dependent variable in each column is the frequency of political corruption measure from Fan et al. (2009). The original results are reported in columns (1) and (10) of Fan et al. (2009). The first two columns of this table show the original ordinal scale. The middle two columns show the results using a dichotomous dependent variable that equals one for all values greater than or equal to the median. The last two columns show results using a dichotomous dependent variable that equals zero for all values less than or equal to the median. In each column, the dependent variable is standardized to have a mean of zero and standard deviation of one. Standard errors clustered at the country level are shown in parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

democratic decentralization and political corruption.[5] We find that these results are robust to our DAM approach.

4.3. *Discussion*

These kinds of DAM checks seem to have several benefits. First, by using a dichotomous-dependent variable—defined at the median value—the DAM tests directly address a potential concern about robustness to monotonic increasing transformations of the *observed scale* and *latent variable*. Although this method relies on the observed median value, which is manipulable with monotonic increasing transformations of the ordinal scale, this value is used only when creating the dichotomous variables which remain unchanged for any monotonic increasing transformation of the ordinal scale.

Second, the technique is simple and straightforward to execute, which is not necessarily the case for other methods for testing robustness (see, e.g., Bloem 2021). It only requires two additional regressions. One uses a dependent variable defined with the median value of the ordinal scale in the upper part and the other with the median value of the ordinal scale in the lower part of the dichotomous split. Focusing the dichotomous split on either side of a median simplifies calculations. Theoretically, any existing threshold point in an ordinal scale could be used to define the dichotomous split. Implementing this full approach with a large number of categories, however, can quickly become computationally intensive. In addition, some dichotomous splits will suffer from very little variation. Therefore, following previous work (Allison and Foster 2004), we advocate using a median value in the ordinal scale to guide choices about defining dichotomous dependent variables.

With that said, this approach is not without limitations. Perhaps chief among these is that to generate dichotomous variables we are forced to discard potentially valuable information captured in multiple layers of an ordinal scale. How much this limitation matters will depend on the specific details of a given empirical setting and research question. Of course the reason, in the first place, to discard the extra information is because some critics will object to its use.

Another potential issue is that the DAM tests, as they are implemented here, rely on OLS estimates. This is deliberate. It is due to possible concerns about assuming a specific and potentially incorrect functional form of the error term when using more sophisticated regression techniques—such as logit or probit. Although the use of OLS is less sensitive to the distribution of the error term, the standard possible concerns associated with using OLS regression with a dichotomous dependent variable will persist. This, we argue, is less objectionable in empirical applications primarily concerned with estimating the causal effect of some variable X on an ordinal dependent variable Y—as is the case in both Haushofer and Shapiro (2016) and Nunn and Wantchekon (2011).

[5]More detailed descriptions of these variables can be found in Fan et al. (2009).

5. Conclusion

Feelings are central to the lives of human beings. The reason that we study income and wealth and the business cycle and optimal taxes and pollution and minimum wage laws (and so on) is because those variables are believed to affect human feelings. Feelings are an end. Nearly everything else is a means to that end.

This article argues that, with sufficient care, data on people's reported feelings can provide useful empirical insights. The article introduces a validity check approach, namely, a DAM test. The idea behind the article's proposed DAM method is a simple one. The test builds on the fact that the qualitative direction of an ordinal variable *is* reliably known—even though the size of intervals between multiple ranks is not.

By applying our DAM test, which uses no information on interval sizes, we show that it is possible to reanalyze and confirm the substantive findings in a range of well-known journal articles that have relied, even if technically inappropriately, on cardinality. These reanalyzed results can be seen by comparing the estimates across each column in Tables 2 through 6.

Finally, it should be emphasized that the analysis in this article is likely to be far from the last word on this complex set of issues. It is possible that the future will see the collection of ever-increasing amounts, and perhaps even new varieties, of feelings data. We would argue that a nihilistic rejection of all forms of such data (which are widely used by the world's organizations, and thus have passed the long-standing "Chicago market test") would be inappropriate for economists and other social scientists. Nevertheless, the empirical challenges associated with ordinal information demand careful and constructive attention. Much remains to be understood about the optimal way to handle such data.

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