**Online Supplementary Material**

**Appendix A. Data Assembly for Meta-Analysis**

Appendix A provides more information on our dataset and its construction. Table A1 displays the full set of studies assembled for our paper, along with their corresponding temperature and damage estimates. In some select circumstances, we adjusted the temperature and damage estimates reported in the study to reflect global willingness to pay to avoid the impacts of climate change, as measured by a change in global average surface temperature in °C (see Appendices A1 to A3). In determining duplicate estimates, we make classification decisions with respect to which estimates are overly reliant on previous estimates; see Appendix A4. See below for a discussion of these decisions.

*Appendix A1. Aggregation of Regional Damage Estimates*

There are several studies that provide only regional damage estimates. If the authors also provide GDP data, we use them to create GDP weights for aggregation purposes. Otherwise, we use estimates of GDP from NASA’s Socioeconomic Data and Application Center’s Country Level GDP Projections, based on the SRES A2 market scenario (Gaffin et al., 2002), corresponding to when the level of warming was predicted to occur according to the original paper.

All of the Policy Analysis of the Greenhouse Effect (PAGE) estimates (Plambeck and Hope, 1996; Hope, 2006; Hope, 2011) provide regional growth rates and base GDP data, from which we construct GDP estimates. In aggregating these estimates, care was taken to account appropriately for Hope’s adaptation assumptions and for catastrophic impacts. At the calibration temperature, catastrophic impacts are non-existent and therefore are excluded.

Several other studies require aggregation by region using their own data. Manne and Richels (2005) provide GDP data for the MERGE 5.1 model online. Before aggregation, willingness to pay for each region must be constructed. Nordhaus and Yang (1996) provide GDP estimates and regional damages. However, given that we drop this study based on our *a priori* criteria, we use the Tol (2009) estimate.

None of Maddison’s studies (Maddison, 2003; Rehdanz and Maddison, 2005; Maddison and Rehdanz, 2011) provide GDP data. Therefore, we use NASA’s Socioeconomic Data and Application Center’s Country Level GDP Projections for Scenario A2 to create GDP weights for the appropriate year. We then sum national impacts using these weights. Like Nordhaus and Yang (1996), we drop these estimates based on our *a priori* criteria, though we include them in sensitivity analysis (see Appendix C9).

*Appendix A2. Calculation of Temperature Change Relative to Paper’s Base Period*

Several types of temperature adjustments are necessary to ensure that each paper measures temperature change in terms of global average surface temperature (°C) relative to the study’s base period.

Dell et al. (2008; 2012) discusses a 3°C increase by 2100. However, that study uses the A2 scenario to estimate a -0.3% GDP decline by 2100. According to the Intergovernmental Panel on Climate Change (IPCC) (2007)’s Working Group I, the A2 scenario implies a 3.4 °C increase from the base period of 1980-1999 to 2090-2099. We use the 3.4 °C temperature increase.

Several estimates capture average land temperature instead of average surface temperature: G-ECON (Nordhaus, 2006; Nordhaus, 2008b; Ng and Zhao, 2011); Horowitz (Choiniere and Horowitz, 2006; Horowitz, 2009); Gunasekera et al. (2008), and Bluedorn et al. (2010). We multiply their temperature change by the ratio between global land and surface temperatures as defined by NOAA’s State of the Climate dataset to convert to global surface temperature.

Using a small sample of experts, Schauer (1995) estimates the impacts of climate change as a % of GDP for a doubling of CO2. Because Schauer (1995) does not provide a specific climate scenario (i.e., the amount of warming for a particular date) to these experts, we impute the implied temperature change. We use the central estimate equilibrium climate sensitivity of 2.5 °C from the most up-to-date IPCC report at the time of publication.

*Appendix A3. Adjustment of Damage Estimates*

The one damage estimate that we adjust is Meyer and Cooper (1995), which significantly augments the Fankhauser (1995) estimate to account for a higher level of warming by 2050 (3°C instead of 2.5°C), to convert from willingness to pay to willingness to accept, and to include additional damage categories (migration, malaria, and malnutrition). As stated in the main text, we are solely interested in willingness to pay (WTP) estimates and so we convert the Meyer and Cooper (1995) damage estimate to a willingness to pay estimate; we were unable to make a similar adjustment for the Maddison studies (Maddison, 2003; Rehdanz and Maddison, 2005; Maddison and Rehdanz, 2011). To do this, we must undo Meyer and Cooper’s (1995) choice to use OECD’s value of statistical life (VSL) and parity-unit-damage valuation (PUDV) for non-OECD regions; this implies removing the adjustment from Columns C to D in Table A of Meyer and Cooper (1995), removing the adjustment from Columns D to E, and converting the adjustment from E to F into WTP units. This adjustment is done in several steps: (1) we calculate the share of health impacts in Column B of Figure A of Meyer and Cooper (1995) using Fankhauser (1995); (2) we calculate the cost of health impacts in Column C (a switch from 2.5°C to 3°C in 2050) by multiplying total damage by the health share derived in step 1; (3) we calculate the health cost in Columns D and E by assigning all increases from column C to D as health impacts (due to increases in the VSL) and all increases from D to E as non-health impacts (due to increases in PUDV); (4) we assign all increases from Columns E to F to health impacts because the joint impact of malaria and malnutrition dominate the impact of migration (as noted by Fankhauser and Tol in Appendix D of Meyer and Cooper (1995)); (5) we calculate the ratio of health impact increases from Column C to D (i.e., attributable to using OECD VSL values) and divide the increase in health impacts from E to F by this ratio to calculate the WTP to avoid migration, malaria, and malnutrition impacts; (6) we add this WTP estimate to the non-health impacts in Column C (i.e., the value of non-health impacts for a 3°C increase by 2050); and (7) we divide this value by global GDP in 2050 as assumed by Fankhauser (1995) and Meyer and Cooper (1995). The final value represents global willingness to pay to avoid the climate change as estimated by Meyer and Cooper (1995). Given that the adjustments made by Meyer and Cooper does not produce a willingness to accept estimate in the traditional sense (as noted by Fankhauser and Tol in Appendix D of Meyer and Cooper (1995)), an alternative interpretation of our adjustment is as a correction of the assumption to use OECD values for all regions.

After undoing Meyer and Cooper (1995)’s use of uniform damage values (per unit of impact) across regions to ensure a willingness to pay estimate, the first and third modifications remain, the most significant of which is an additional 10 million deaths per year from malnutrition. Fankhauser and Tol argue that that malnutrition mortality estimates are out-of-date, and greatly overestimate the potential impact. While this may be true, the same could be said for virtually all enumerative damage estimates whose impact estimates date back to the 1990s (Revesz et al., 2014). Instead of dropping the estimate, we classify the study as containing catastrophic impacts.

*Appendix A4. Duplication Classification*

In general, the classification of which estimates are duplicates is straightforward. There are a few exceptions, particularly with respect to duplication.

There are several studies that present two potentially independent estimates. Several studies produce estimates for two different temperature changes, including Nordhaus (1994b), Eboli et al. (2010), Roson and van der Mensbrugghe (2012), Weitzman (2012), McCallum et al. (2013), and Howard and Sylvan (2015). Like Tol (2014), we maintain these two estimates despite concerns about dependence. Also like Tol (2014), we maintain the two estimates from Mendelsohn et al. (2000b) because they use separate estimation methodologies: statistical (i.e., Ricardian analysis) and experimental (i.e., reduced-form response functions, assembled by combining U.S. based scientific models and economic models). However, the estimates overlap because experimental reduced-form estimates were used to fill in omitted sectors (i.e., water and coastal) in the Ricardian analysis (Mendelsohn, 2000a). Therefore, while we classify this latter estimate as an experimental method, we reclassify it as statistical for purposes of clustering in order to keep the estimates together, due to likely dependences and because no other damage estimates are similarly constructed. Finally, we choose to keep both scientific estimates from Nordhaus (2014) because they rely on two very different assumptions about temperature limits, with very different final impact estimates. Unlike Tol (2014), we conduct sensitivity analysis to maintaining two data points from these studies instead of one.

In a related discussion with regard to the uniqueness of an estimate (i.e., whether it is a citation of a previously included estimate), we assume that studies that make significant changes to a previous estimate are unique. Specifically, these are estimates for which their authors used the original estimates as starting points, such that the final estimates represent a significant departure from the original estimates. Hanemann (2008) uses Nordhaus (2008a)’s U.S. estimate as a starting point, but develops a fundamentally different estimate for the United States; the ratio of these estimates is then used by Ackerman et al. (2012) to adjust the global Nordhaus (2008a) estimate. Similarly, as seen in the previous section, Meyer and Cooper (1995) fundamentally change Fankhauser (1995). Finally, Environmental Impact and Sustainability Applied General Equilibrium Model (ENVISAGE) (Roson and van der Mensbrugghe, 2012) and the Inter-temporal Computable Equilibrium System (ICES) (Bosello and Parrado, 2014) calibrate their health impacts using Bosello et al. (2006), which translates mortality estimates from Tol (2002) – also used to calibrate the Framework for Uncertainty, Negotiation and Distribution (FUND) – into impacts to labor productivity and demand for health care. We conduct sensitivity analysis to this assumption (see Appendix C4).

**Appendix B: Additional Tables and Figures for Section 6**

Appendix B provides additional tables and figures estimated in our main results (Section 6).

**Appendix C: Sensitivity analyses**

Appendix C discusses our sensitivity analyses, which are briefly summarized in Section 7 of the main text. Beyond our primary analysis, we run a series of sensitivity analyses to test the robustness of our results. Specifically, we re-run the preferred specifications for excluding and including the high-temperature estimates – i.e., Regressions (4) and (8) in Table 2 – under a variety of alternative assumptions. Sensitivity analyses are essential in all meta-analyses given the variety of assumptions that analysts face. In the case of meta-analyses of global damage estimates, they have additional importance because of the small sample size of these studies. While these sensitivity analyses are discussed in Section 7 of the paper, we provide a more extensive discussion below.

*Appendix C1. Re-estimating Tol (2014)’s Temperature-Damage Relationship*

Following Tol’s (2009; 2014), we re-run Table 2, including an additional linear temperature term and its interaction with the various indicator variables; see Table C1. We also re-estimate Tables 3 and B3 assuming the Tol (2009; 2014) functional form; see Tables C2 and C3. As part of these latter tables, we calculate the social cost of carbon (SCC), interpreting the temperature-damage relationships found in our regressions as damage functions and using them to replace the DICE-2013R damage function. Following Tol (2009; 2014), we do not apply a 25% adjustment to non-catastrophic damages when calculating the SCC, as was done by Nordhaus (2013).

When we exclude high-temperature estimates (i.e., >4°C), we find that the coefficients are jointly significant and their signs correspond to theory. Also, the coefficients corresponding to temperature and temperature squared are jointly significantly different from Tol (2014), regardless of whether we account for catastrophic and/or productivity impacts of climate change. As in Table 2, only coefficients corresponding to temperature (and its square) and its interaction with the market indicator variable are individually significant, while the cross-sectional indicator variable is no longer significant. Like Tol (2009) – which also omits high-temperature damage estimates – we find evidence of initial benefits from climate change.

When we include high-temperature estimates (>4°C), we find that the coefficient corresponding to linear temperature shifts from negative to positive, supporting the findings in Tol (2014) of no initial benefits from climate change and a flatter damage function. Additionally, the coefficients corresponding to temperature and temperature squared are now no longer individually significantly different from zero and are not jointly significantly different than those of Tol (2014), unless productivity and/or catastrophic impacts are included. With respect to the original Tol (2014) regression (Specification (1) in Tables C2 and C3), we also find that the inclusion of the sole high-temperature estimate – Roson and van der Mensbrugghe (2012)’s estimate of a -4.6% decline in GDP for a 5.4°C increase – significantly impacts the final coefficients and the corresponding SCC estimate. Together, these results again highlight the sensitivity of the temperature-damage relationship to high-temperature damage estimates.

Regardless of our treatment of high-temperature damage estimates, we find strong evidence of duplication bias. Using seemingly unrelated regression, we reject the null that the coefficients corresponding to the temperature variables and their interactions are unaffected by the decision to exclude duplicate estimates, at the 5% significance level. Again at the 5% significance level, these results also hold when we consider only the coefficients corresponding to non-catastrophic damages (i.e., temperature squared) and total damages (i.e., temperature squared and its interaction with the catastrophic indicator variable), regardless of whether we consider productivity jointly. When we exclude high-temperature estimates, duplication bias is the second most important adjustment that we make to the Tol (2014) results with respect to the percentage change in the social cost of carbon, and the magnitude of the impact is quite large. With the inclusion of high-temperature damage estimates, duplication bias becomes relatively less important.

Overall, our adjustments significantly influence the SCC, particularly when we exclude high-temperature impacts, include catastrophic climate impacts, and/or account for climate impacts on productivity. When we focus solely on damage estimates corresponding to low-temperatures (i.e., ≤ 4°C), addressing potential biases increases the SCC (in 2015) that corresponds solely to non-catastrophic impacts by one-fifth to three-fold from Specification (1) to (5) in Table C2, depending on whether we account for the impact of climate change on economic productivity; however, this represents a six-fold to thirteen-fold increase relative to the original Tol (2014) temperature-damage relationship (i.e., Specification (0) in Table C2) of $18/ton. If we consider total climate impacts (both non-catastrophic and catastrophic), addressing the above biases increases the SCC (in 2015) by two-fifths to three-fold, depending on the treatment of productivity (eight-fold to fifteen-fold relative to the original Tol (2014) estimate).

Unsurprisingly given the flattening effect on the temperature-damage relationship when damage estimates corresponding to high-temperature increases are included, we generally find a smaller impact of our modifications on the SCC when we include them; see Table C3. However, the 2015 SCC estimates corresponding to this dataset are still far above the $18 estimated using the original Tol (2014) damage function; the increase of the SCC is in the range of one-quarter to eleven-fold when considering only non-catastrophic climate impacts and four-fold to sixteen-fold when considering total climate impacts, where the range is dependent on the inclusion of the impact of climate change on productivity.

*Appendix C2. Alternative Functional Forms*

The higher adjusted-R2 squares and log likelihood values of the Tol (2014) damage specification relative to the Nordhaus (2013) damage specification highlights the need to consider alternative functional forms for the damage function. Most alternatives in the literature (Tol, 2015a; Kopp et al. 2012) are a variant of the functional form

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To derive a new estimation equation (i.e., Equation (4) in the main text), we replace in Equation (2) in the main text with the various author assumptions: (1) Nordhaus (2013) assumes ; (2) Burke et al. (2015) find that is a potential alternative; (3) Tol (2009; 2014) support ; (4) Azar and Lindgren (2003) adopt ; (5) Weitzman (2012) backs as another alternative; and (6) Newbold and Marten (2014) introduce a piecewise linear function where and *b* is the breaking point above which the slope of the linear damage function switches from to (we choose the breaking point that maximizes adjusted R-squared and that happens to maximize the log-likelihood value). Given the sensitivity of the Tol (2014) damage specification to high-temperature estimates, we re-estimate the preferred specifications in Table 2 using these variants with and without high-temperature estimates (i.e., >4°C); see Table C4. In general, we find that the signs of the coefficients correspond to our *a priori* hypothesis regardless of functional form and that many of the similar coefficients are significant.

The functional forms that best explain the variation in the data depends on whether we include high-temperature damage estimates. When we exclude high-temperature damage estimates, we find that the Azar and Lindgren (2003) functional form best fits the data (as measured by adjusted R-squared), followed by the damage specifications (in descending order) of Tol (2014), Weitzman (2012), Newbold and Marten (2014), and Nordhaus (2013) – although the variation in fit is relatively small for the latter four. However, our estimate of the Azar and Lindgren (2003) functional form implies unlikely high damages for high-temperature increases (particular above 6°C). Furthermore, that functional form does not perform well in terms of fit when these higher temperature estimates are included. Instead, the Newbold and Marten (2014) damage specification followed by the functional forms (in descending order) of Weitzman (2012), Tol (2009), and Nordhaus (2013) best fit the data when high-temperature estimates are included; again, however, the variation in fit between these four options is relatively small. If we instead use log-likelihood value to rank functional forms instead of adjusted R-squared, the Newbold and Marten (2014) functional form performs best and the Azar and Lindgren (2003) specification no longer performs as well when we exclude high-temperature estimates. The strong performance of the Newbold and Marten (2014), Weitzman (2012), Tol (2014), and Nordhaus (2013) functional forms corresponds to the results of Tol (2015a) and Tol (2015b).

Although the Nordhaus (2013) functional form is outperformed by the Weitzman (2012), Tol (2014), and Newbold and Marten (2014) functional forms with regard to fit, there are two strong arguments for choosing the Nordhaus (2013) specification. First, the inclusion of two polynomial temperature terms in the Weitzman (2012), Tol (2014), and Newbold and Marten (2014) damage specifications requires a significant increase in the number of regressors given our inclusion of methodological control variables. This is a problem in our study because of the small sample size relative to the large number of control variables, which raises the risk of multicollinearity and overfitting the regression; this is an even greater concern in the case of the piecewise linear functional form because the optimal breaking point also requires determination. Therefore, the Weitzman (2012), Tol (2014), and Newbold and Marten (2014) specifications are less useful for our purposes of prediction. For example, as in the Azar and Lindgren (2003) specification, if we interpret the results as damage functions and make damage predictions for higher temperatures (i.e., above 4°C), our estimate of the Weitzman (2012) specification leads to unlikely high damage predictions. Second, partially as a result of this overfitting, the Weitzman (2012) and Tol (2014) functional forms are more sensitive than the Nordhaus (2013) functional form to the inclusion of high-temperature data, implying potential instability. Specifically, the shape of the non-catastrophic damage function corresponding to both specifications significantly shifts between flat to steep depending on the inclusion of high-temperature estimates; the Azar and Lindgren (2003) functional form suffers a similar shortcoming, though the Newbold and Marten (2014) specification is relatively robust. Because of the modest nature of the improvements in the fit of the Weitzman (2012), Tol (2009), and Newbold and Marten (2014) specifications relative to the Nordhaus (2013) specification and the risk of overfitting, we select the Nordhaus (2013) specification as the preferred functional form for the purposes of this analysis.

*Appendix C3. Alternative Clustering Scales*

In the main text of the paper, we hypothesized that the standard errors are potentially clustered at the author, estimation methodology, and model levels. We tested this hypothesis at these alternative levels including and excluding duplicates and high-temperature damage estimates. Note that, when we excluded data to address duplication, we re-assembled each group (author, method, and model) in order to conduct the Breusch-Pagan LM Test of Independence; these re-assembled groups were used in the tests and in our subsequent analyses. We found strong evidence of clustering at all levels; see Table B2.

To test the robustness of our results, we re-estimated the preferred specifications (Specifications 4 and 8 in Table 2) clustered at the author and method levels, as well as two alternative model definitions. In the first alternative model definition (*model\_2*), we define a model as the interaction of author and method. In the second alternative model definition (*Primary\_model*), we use the original classification for model before we re-assembled the groups. The results (available from the authors upon request) are generally robust to alternative levels of clustering.

*Appendix C4. Alternative Definitions*

We re-run the preferred specifications under a variety of alternative definitions – variables, temperature cutoffs, and duplication – to test the robustness of our earlier results to alternative assumptions; see Tables C5 and C6.

First, analysts may be interested in focusing their impact analyses solely on non-catastrophic impacts. In other words, we redefine our primary variable of interest as the willingness to pay to avoid non-catastrophic damages. Therefore, we re-run the preferred specifications after removing catastrophic impacts from enumerative estimates and dropping science-based damage estimates, which cannot be adjusted.

Second, some CGE models account for the impacts of lost ecosystems services due to climate change. While in the main text we assume that these estimates exclude non-market impacts, some could potentially disagree. Therefore, we re-run the preferred specifications assuming that CGE models that capture the impacts of ecosystem services on the market account for non-market impacts.

Third, as discussed in our main text, our 4°C cutoff for climate damage estimates corresponding to high-temperature increases – i.e., the temperature increase above which damage estimates become increasingly speculative – is not the sole candidate. We re-run Specification (4) in Table 2 under two alternative cutoffs: 3°C, which is the most likely value of the equilibrium climate sensitivity parameter according to IPCC (2007); and 4.5°C which is slightly above the temperature increase predicted by 2100 under BAU by IPCC (2013) (Scenario RCP 8.5).

Fourth, we analyze the impact of a more restrictive definition of duplication that further restricts our choice of data (relative to our previous definition) to one estimate per study (even if they are independent according to the author(s)) (Nelson and Kennedy, 2009). Duplication bias is potentially still an issue in the preferred specifications because most high-temperature damage estimates (i.e., above 4°C) are drawn from studies from which a low-temperature damage estimate is already drawn (i.e., below 4°C), such that one estimate is potentially an extrapolation of the other. Thus, a stricter definition requires us to choose which damage estimates to drop when two estimates are provided by a study. For CGE, enumerative, and survey based studies, we drop the estimate corresponding to a higher temperature increase, assuming that they rely on extrapolation. The exception is Howard and Sylvan (2015) because their damage estimate at 1°C is derived in a more indirect manner than their estimate at 3°C; this latter estimate is derived using a question identical to that used in Nordhaus (1994b). For scientific studies, we maintain the estimate that is based more on scientific principles: the 12°C Weitzman (2012) damage estimate is more soundly based on Sherwood and Huber (2010)’s global limit of human adaptability to heat stress than Weitzman’s 6°C estimate; and the Nordhaus (2014) estimate based on a strict 2°C limit is more in the spirit of (and a more literal reading of) the 2°C goal than the estimate based on an average increase of 2°C over the 2050 to 2250 period (particularly given the recent strengthening of the goal under the Paris Agreement to well below 2°C with the aims of achieving a 1.5°C limit if possible). This stricter definition of duplication reduces our data to 18 and 20 observations, depending on whether we exclude high-temperature damage estimates.

Last, we analyze a stricter definition of citation. Some may be concerned by our decision in the main text to maintain damage estimates in our data that we definite as unique despite using another estimate as a starting point. Therefore, we re-run the preferred specifications dropping Meyer and Cooper (1995) and Hanemann (2008). Though not shown, we find that also dropping CGE models that calibrate portions of their model using FUND inputs (Roson and van der Mensbrugghe, 2012; Bosello and Parrado, 2014) has little impact.

We find that our results are fairly robust (particularly the coefficient corresponding to *t2*) to these alternative specifications. There are four changes of note when focusing on instances where we exclude high-temperature estimates. Focusing solely on non-catastrophic impacts (Specification (2)) slightly decreases the coefficient corresponding to temperature squared, but the result is well within the range of uncertainty expressed in Table 2. Redefining the *market* indicator to account for loss of ecosystem services as non-market impacts (Specification (3)) slightly shifts non-catastrophic impacts to catastrophic impacts (such that total impacts remain relatively constant), while greatly decreasing the *market* coefficient and its significance; a similar result holds when including high-temperature damage estimates. Increasing the cutoff for speculative estimates from 4 °C to 4.5 °C (Specification (5)) increases the coefficient corresponding to productivity by including Burke et al. (2015) in the dataset, and it results in its statistical significance. Last, applying our stricter definition of citation (Specification (7)) halves the coefficient corresponding to catastrophic damages (though it still remains insignificant). There are two changes of note when we include high-temperature estimates. Applying a stricter definition of duplication (Specification (6)) shifts catastrophic impacts to non-catastrophic impacts. Because the regression results corresponding to the low-temperature estimates are robust to this new definition, the coefficient corresponding to temperature squared is now insensitive to the treatment of high-temperature damage estimates (this is unsurprising given that there are only two high-temperature estimates remaining). If instead we apply weights of one-half to estimates drawn from studies with multiple damage estimates (regression available from the authors upon request), we find a very small shift of non-catastrophic damages to catastrophic damages relative to the preferred specification (Specification (4) in Table 2). Finally, while a stricter definition of citation (Specification (7)) – dropping Meyer and Cooper (1995) and Hanemann (2008) – has little impact on our results, also dropping Roson and van der Mensbrugghe (2012) and Bosello and Parrado (2014) (in a regression available from the authors) increases the coefficient and significance of productivity.

*Appendix C5. Alternative Estimators*

Despite the literature’s recommendation to use GLS and panel fixed effects, we elected to avoid these methodologies in the main text due to our limited number of observations. With respect to fixed effects at the method level in particular, this limits our ability to compare estimates across different methodologies – an issue raised by the editors of the Journal of Economic Perspectives (JEP) (2015). With respect to GLS estimates, it also limits our ability to model heteroskedasticity and dependence simultaneously. To address these shortcomings, we re-estimate the preferred specification using alternative estimators: OLS, GLS, panel fixed effects at the method scale, and a combination of GLS and fixed effects; see Table C7.

When excluding high-temperature estimates, our results are generally robust to these alternative estimators. The non-catastrophic and total climate damages implied by weighted least squares – i.e., the preferred estimator used in the main text – are, if anything, lower bounds. However, we should be careful in reading too much into these results because of these estimators’ poor sample size properties.

Using data corresponding to all temperature increases, the WLS coefficient corresponding to temperature squared is above the other estimators, while the WLS coefficients corresponding to productivity and catastrophic impacts are generally below the other estimators (the exception being GLS without fixed effects). As a consequence, total impacts (non-catastrophic plus catastrophic) tend to be comparable across the estimators, regardless of whether we account for productivity impacts.

*Appendix C6. Sensitivity Analysis with Respect to Outliers*

As discussed in the literature on meta-analysis methods, testing the sensitivity of the results to outlier estimates is critical when conducting meta-regression. There are generally three types of outliers. Vertical outliers are data whose absolute residuals (or residuals squared) are high, so that they reside far from the regression line. Leverage points are data that are far from the bulk of the other data in the explanatory variable space (i.e., hyperplane); this is traditionally measured using Cook’s distance. Leverage points can be further subdivided into good and bad, where the latter group are also far from the regression line (Verardi and Croux, 2009; Alma, 2011).

We address outliers in three ways. First, we re-run the preferred specifications – i.e., Specifications (4) and (8) in Table 2 – dropping each of the observations in turn to determine their relative impacts on the coefficients; see Figures C1 and C2. Second, we re-run the preferred specification, dropping each study in turn to determine their relative impacts; these results are available from the authors upon request. Third, we re-estimate the model using outlier robust estimators; see Table C8 and Figure C3. Specifically, we employ multiple robust estimators (m-estimators, s-estimators, and mm-estimators). While together all of the robust estimators provide us with information about the impact of outliers, we focus primarily on the mm-estimator. The mm-estimator was designed to have a high breaking point (i.e., it is relatively robust to a higher percentage of outlier estimates) and to be highly Gaussian efficient (i.e., is efficient if the true distribution is normal) (Verardi and Croux, 2009). The purpose of this design is to address the shortcomings of other estimators: the OLS estimator has a 0 breaking point; the m estimator collapses in the presence of leverage points (i.e., it has a high breaking point relative to vertical outliers only); and the s estimator is relatively inefficient despite having a high breaking point (Verardi and Croux, 2009; Alma, 2011; Jann, 2012). We find that the results are fairly robust to these exercises.

We combine a visual inspection of Figure C3 with a review of the *mm* regression weights (generated using the *robreg* command) to identify outlier estimates, and then analyze Figures C1 and C2 to understand the impacts of these individual outliers on regression results. When we exclude high-temperature damage estimates, we find that the magnitude of the catastrophic impact of climate change (*cat\_t2*) is sensitive to the inclusion of Meyer and Cooper (1995), Nordhaus (2008a), and one of the estimates in Howard and Sylvan (2015), while the non-catastrophic impact of climate change (*t2*) is sensitive to the inclusion of the latter point only (in the opposing direction). Schauer (1995), Horowitz (2009), and both Nordhaus (2014) estimates are also potential outliers impacting the coefficient corresponding to *t2, cat\_*t2, and/or the productivity impact of climate change (*prod\_t2*). When we include high-temperature damage estimates, we find that temperature squared and catastrophic impacts are more unstable relative to when we exclude damage estimates corresponding to temperatures above 4°C. We find that one point from Weitzman (2012), Burke et al. (2015), and one point estimate from Howard and Sylvan (2015) are strong candidates as outliers, while Meyer and Cooper (1995), Schauer (1995), Nordhaus (2008a), and one point from Nordhaus (2014) are also potential outliers.

In addition to individual outlier estimates, we may be concerned about outlier studies. Given that the majority of studies in our paper provide only one observation to our dataset, the previous paragraph’s discussion applies to most studies. The exception is when a study provides two estimates. Of the six studies that supply two estimates, half have no impact on the coefficients (Nordhaus, 2014) or affect only the division of total damages between non-catastrophic and catastrophic impacts (Nordhaus, 1994b; Howard and Sylvan, 2015). However, Mendelsohn et al. (2000b) and Roson and van der Mensbrugghe (2012) push up and hold down, respectively, the impact of climate change via productivity, while Weitzman (2012) holds down the coefficient according to catastrophic impacts. Overall, like individual damage estimates, the total (non-catastrophic plus catastrophic) impact estimates are fairly robust to the removal of studies.

Finally, we estimate three robust estimators: m regression (using *mregress*), s regression (using *sregress*), and mm regression (using *mmregress*). Again, the preferred estimator is *mmregress* because it is efficient and robust. We also re-estimate the preferred specifications, dropping estimates with *mm* regressor weights below 0.8 (this is roughly equivalent to the outlier estimates identified earlier with the exception of Schauer (1995) when we exclude high-temperature estimates). On the one hand, we find a flatter temperature-non-catastrophic damage relationship (i.e., the coefficients corresponding to *t2* and *prod\_t2* are smaller in magnitude), though the relationship remains well within the 95th confidence intervals of the preferred specification. On the other hand, we find a steeper temperature-catastrophic damage relationship – in some cases outside the 95% confidence interval of the preferred specification – particularly when we exclude high-temperature estimates. As a consequence, total damages (i.e., non-catastrophic plus catastrophic) are relatively stable, in that outlier estimates affect how total impacts are divided between non-catastrophic and catastrophic impacts rather than the absolute magnitude of the total impact. Therefore, the temperature-damage relationship implied by the robust regression is still steeper than that found earlier in Nordhaus (2013), though this steeper relationship is dependent on the inclusion of productivity and catastrophic impacts when we include high-temperature damage estimates in our regression analysis.

We conduct two additional sensitivity tests (available upon request from the authors) of our outlier results. First, due to a tradeoff between bias and efficiency (Verardi and Croux, 2009), we re-estimate the mm estimator for three efficiency levels: 0.7 (the default of *mregress*); 0.85 (the default of *robreg*) and 0.95 (the maximum under *robreg*); 0.85 is the suggested value according to Jann (2010). The results are robust to the differing efficiency levels. Second, we also run an alternative Stata command *robreg* (which requires a constant, so we run robreg and then rerun WLS without a constant using these weights), and find that overall results are robust to the *mm* regressor chosen. While the general results are robust when we exclude high-temperature estimates, we should note that the coefficient corresponding to temperature squared increases and the coefficient corresponding to catastrophic impacts is approximately halved and slightly less significant as compared to the *mmregress* command (though the catastrophic coefficient is still substantially greater than our original WLS results, such that total impact of climate change is equivalent to WLS).

We should carefully interpret these robust regressions, particularly when we include high-temperature damage estimates. Due to our small sample size, many of the asymptotic properties of these regressions – including asymptotic efficiency – may not hold (Alma, 2011; Koller and Stahel, 2011). Furthermore, many of these high-temperature damage estimates are potential extrapolations of low temperature damage estimates – potentially confounding the determination of outliers when they are included in the data. Finally, some of the robust estimator results are unstable in that they vary by the random draw (i.e., the initial seed). For some random draws (approximately 12.8% of the time), the *mmregress*’s coefficient corresponding to catastrophic impacts declines to approximately its OLS value when we exclude high-temperature estimates. This may partially be due to the potential for multiple solutions when using bi-weights, though the alternative (i.e., Huber weights) has trouble with extreme outliers (Institute for Digital Research and Education, 2016).

*Appendix C7. Alternative Error Distribution Assumptions*

We do not conduct sensitivity analysis to whether the error term is non-normal. Despite expecting more bad surprises than good surprises from climate change (Tol, 2009), we find little evidence of non-normal error terms, particularly for the preferred regression (i.e., excluding duplicate and high-temperature estimates) when the full set of explanatory variables is included. Even if we did relax this assumption, it is unclear what distribution to choose as an alternative. We leave this for future research.

While we do not model non-normal error terms, we re-estimate the preferred specifications using robust regression techniques, as discussed in the previous sub-section. The goal of robust regression is to be robust to incorrect specifications of the underlying data-generating process, so robust outlier regression techniques are (relatively) efficient even when error terms are non-normal (Jann, 2012). Given that our regression results are relatively robust to using these alternative estimators (i.e., moving from WLS to robust estimators) – particularly when we exclude higher temperature damage estimates – we should interpret our results as relatively robust to the potential of a non-normal distribution, despite assuming a normal error structure. In general, robust regression appears to shift non-catastrophic damages toward catastrophic impacts, as would be expected under a right-skewed distribution.

*Appendix C8. Sensitivity to Groups of Damage Estimates*

The Journal of Economic Perspectives (JEP, 2015) expressed concern that some estimates cannot be compared because each type of estimate captures differing – but potentially overlapping – sets of climate impacts. Similarly, the meta-regression standards recommend either studying comparable estimates or controlling for the underlying differences using explanatory variables. To the extent that our methodological controls and our clustering at the model level insufficiently address these shortcomings (and to the extent that our sensitivity analysis with fixed effects in a previous sub-section was insufficiently convincing due to sample size), we explore the impact of specific climate damage estimation methodologies (i.e., enumerative, CGE, statistical (cross-section and panel), survey, science, and compensating surplus) on the preferred regression results: Specifications (4) and (8) in Table 2. This analysis is based on the hypothesis that estimates constructed in similar manner are more likely to be comparable because they capture comparable impacts. This type of sensitivity analysis also allows us to determine whether estimates derived using a particular methodology impact the final, pooled results.

We conduct two types of analysis. First, we re-estimate the preferred specifications using only data derived using each methodology discussed in the second section of the main text; see Tables C9 and C10. Second, we re-estimate the preferred specification, removing data derived using each methodology one by one; see Tables C11 and C12. Together, these regressions demonstrate the relative importance of each type of identification strategy on the global impacts of climate change.

We estimate the temperature-damage relationship for each methodology. While the earlier methodologies (enumerative, CGE, and cross-section regressions) predict a flatter temperature-damage relationship, more recent methodologies (panel regressions and science) and surveys predict a steeper impact of temperature. Some of these relative differences may be due to certain methods’ inability to capture particular types of damages. For instance, CGE and statistical methods omit impacts to non-market services, and all but the enumerative and scientific methods omit catastrophic climate impacts. However, many of these estimates do not significantly differ from one another in a statistical sense.

We also re-estimate the preferred specifications, dropping data corresponding to each methodology in turn. With respect to the coefficient corresponding to temperature squared, the enumerative and survey methodologies respectively hold down and push up its value. Survey estimates also hold down the catastrophic coefficient, as do scientific estimates to a lesser extent; enumerative estimates also push up catastrophic impacts to some extent. With respect to the productivity coefficient, CGE studies appear to hold down the coefficient (particularly when high-temperature estimates are included), while statistical studies (cross-section and panel) appear to be key in the coefficient’s insignificance. Total (non-catastrophic plus catastrophic) damages are relatively stable to the removal of these estimation methods, implying that the removal of most methods appears to shift impacts between non-catastrophic and catastrophic impacts; the exception is methodologies that impact productivity.

*Appendix C9. Sensitivity to Including Compensating Surplus Data*

An alternative to dropping compensating surplus (CS) data (Maddison, 2003; Rehdanz and Maddison, 2005; Maddison and Rehdanz, 2011) is to include the data, along with an indicator variable equal to one if the estimate measures CS interacted with adjusted temperature squared, in the preferred specifications. However, these CS estimates are also the sole estimates to exclude market impacts, providing this indicator with a dual interpretation. We re-estimate Table 2, including compensating surplus estimates from Maddison and Rehdanz; see Table C13. The coefficient corresponding to our new variable is in fact positive (and frequently statistically significant), indicating that the positive impact of CS on the temperature-damage relationship outweighs the negative impact of excluding market impacts. The coefficients corresponding to temperature squared and catastrophic impacts remain unchanged. While there is some limited impact on the coefficient corresponding to productivity, it remains insignificant. The only change of note is that cross-sectional bias appears inconsequential with an increase in the corresponding standard errors.

*Additional References for Online Supplementary Material*

Azar C, Lindgren K (2003) Catastrophic events and stochastic cost-benefit analysis of climate change. Climatic Change 56(3):245-255

Berz G (2000) Insuring against catastrophe. Our Planet 11(3):19-20. <http://www.ourplanet.com/imgversn/113/berz.html>. Cited 07 Dec 2015

Bluedorn JC, Valentinyi A, Vlassopoulos M (2010) The long-lived effects of historic climate on the wealth of nations. 2010 Meeting Papers No. 627. Society for Economic Dynamics

Bosello F, Roson R, Tol RSJ (2006) Economy-wide estimates of the implications of climate change: Human health. Ecological Economics 58(3):579-591

Bosetti V, Massetti E, Tavoni M (2007) The WITCH model: structure, baseline, solutions. FEEM Working Paper No. 10.2007, Fondazione Eni Enrico Mattei, Milano

Dell M, Jones BF, Olken BA (2008) Climate change and economic growth: evidence from the last half century. NBER Working Paper No. 14132, National Bureau of Economic Research, Cambridge MA. DOI 10.3386/w14132

Dellink R, Lanzi E, Château J et al (2014) Consequences of Climate Change Damages for Economic Growth. OECD Economics Department Working Papers No. 1135, OECD Publishing, Paris. DOI 10.1787/5jz2bxb8kmf3-en.

Gaffin SR, Xing X, Yetman G (2002) Country-Level GDP and Downscaled Projections Based on the SRES A1, A2, B1, and B2 Marker Scenarios, 1990-2100. NASA Socioeconomic Data and Applications Center (SEDAC), Palisades NY. <http://sedac.ciesin.columbia.edu/data/set/sdp-downscaled-gdp-a1a2b1b2-1990-2100/metadata>. Cited 21 Nov 2013. DOI <http://dx.doi.org/10.7927/H4XW4GQ1>

Gunasekera D, Ford M, Heyhoe E et al (2008). Global integrated assessment model: a new analytical tool for assessing climate change risks and policies. Australian Commodities 15(1):195-216

Hope C (2006) The marginal impact of CO2 from PAGE2002: An integrated assessment model incorporating the IPCC's five reasons for concern. Integrated Assessment 6(1):19-56

Hope CW (2011) The social cost of CO2 from the PAGE09 model. The Open-Access, Open-Assessment E-Journal. Discussion Paper 2011-39

Horowitz JK (2009) The income–temperature relationship in a cross-section of countries and its implications for predicting the effects of global warming. Environmental and Resource Economics 44(4):475-493

Institute for Digital Research and Education (IDRE) (2016) Stata Data Analysis Examples: Robust Regression. <http://www.ats.ucla.edu/stat/stata/dae/rreg.htm>. Cited 21 Dec 2016

Jann B (2010) ROBREG: Stata module providing robust regression estimators. Statistical Software Components, Boston College Department of Economics. <http://econpapers.repec.org/software/bocbocode/s457114.htm>. Cited 21Dec 2016

Jann B (2012) Robust regression in Stata. 10th German Stata Users’ Group Meetings, Berlin, 1 June 2012. <http://fmwww.bc.edu/RePEc/dsug2012/desug12_jann.pdf>. Cited 21 Dec 2016

Koller M, Stahel WA (2011) Sharpening Wald-type inference in robust regression for small samples. Computational Statistics and Data Analysis 55(8):2504-2515

Kopp RE, Golub A, Keohane NO et al (2012) The influence of the specification of climate change damages on the Social Cost of Carbon. Economics: The Open-Access, Open-Assessment E-Journal 6(13):1-40.

Manne A, Mendelsohn R, Richels R (1995) MERGE: A model for evaluating regional and global effects of GHG reduction policies. Energy Policy 23(1):17-34.

Manne AS, Richels RG (2005) MERGE: an integrated assessment model for global climate change. In: Loulou R, Waaub J-P, Zaccour G (eds) Energy and Environment. Springer, New York

McCallum S, Dworak T, Prutsch A et al (2013) Support to the development of the EU Strategy for Adaptation to Climate Change: Background report to the Impact Assessment, Part I - Problem definition, policy context and assessment of policy options. Environment Agency Austria, Vienna

Ng P, Zhao X (2011) No matter how it is measured, income declines with global warming. Ecological Economics, 70(5):963-970

Nordhaus WD (2008b) New metrics for environmental economics: Gridded economic data. Integrated Assessment, 8(1):73-84

Socioeconomic Data and Applications Center (2002) Country-level GDP and downscaled projections based on the A1, A2, B1, and B2 marker scenarios, 1990-2100. NASA's Earth Observing System Data and Information System. <http://sedac.ciesin.columbia.edu/data/set/sdp-downscaled-gdp-a1a2b1b2-1990-2100>. Cited 21 Nov 2013

Tol RSJ (2013) The economic impact of climate change in the 20th and 21st centuries. Climatic Change 117(4):795-808

***Figure A1. Data, by Whether Deleted or Duplicated***

*Figure A1 displays our paper’s data points, where X are data points deleted based on a priori conditions, light grey circles are duplicate data points, and dark circles are non-duplicate data points.*

***Figure A2. Kernel Weighted Local Polynomial Smoothing of Climate Damage as a Function of Temperature Change, by Dataset***

1. *(b)*

*Figure A2 displays kernel-weighted local polynomial smoothing of climate damage as a function of temperature. In Panel (a), all temperature data are included. In Panel (b), only temperature data equal to or below 4°C are included. In each sub-figure, the black line corresponds to data including duplicate estimates and the grey line corresponds to data excluding duplicate estimates.*

***Figure C1. Effect of Each Observation on Parameter Estimates in Preferred Specification for Low-Temperatures* *(Regression (4) in Table 2)***

*Figure C1 displays the coefficients corresponding to temperature squared and its interaction with indicator variables for catastrophic impacts and productivity impacts, corresponding to the preferred specification for low-temperature, estimated removing one observation at a time. Observation 0 is no observations dropped. The remaining numbers on the x-axis correspond to the following estimates: (1) Nordhaus (1994b); (2) Meyer and Cooper (1995); (3) Fankhauser (1995); (4) Schauer (1995); (5) Mendelsohn et al. (2000b)’s statistical estimate; (6) Mendelsohn et al. (2000b)’s experimental estimate; (7) Manne and Richels (2005); (8) Dell et al. (2008); (9) Nordhaus (2008a); (10) Nordhaus (2008b); (11) Horowitz (2009); (12) Bluedorn et al. (2010); (13) Ng and Zhao (2011); (14) Ackerman et al. (2012), adjusting Hanemann (2008); (15) Roson and van der Mensbrugghe (2012); (16) Tol (2013); (17) Bosello and Parrado (2014); (18) Nordhaus (2014)’s estimate for an average increase of 2°C over the 2050 to 2250 period; (19) Nordhaus (2014)’s strict 2°C limit estimate; (20) Howard and Sylvan (2015)’s 1°C damage estimate; (21) Howard and Sylvan (2015)’s 3°C damage estimate.*

***Figure C2. Effect of Each Observation on Parameter Estimates in Preferred Specification for All Data (Regression (8) in Table 2)***

*Figure C2 displays the coefficients corresponding to temperature squared and its interaction with indicator variables for catastrophic impacts and productivity impacts, corresponding to the preferred specification for all data, estimated removing one observation at a time. Observation 0 is no observations dropped. The remaining numbers on the x-axis correspond to the following estimates:* *(1) Nordhaus (1994b)’s 3°C damage estimate; (2) Nordhaus (1994b)’s 6°C damage estimate; (3) Meyer and Cooper (1995); (4) Fankhauser (1995); (5) Schauer (1995); (6) Mendelsohn et al. (2000b)’s statistical estimate; (7) Mendelsohn et al. (2000b)’s experimental estimate (8) Manne and Richels (2005); (9) Dell et al. (2008); (10) Nordhaus (2008a); (11) Nordhaus (2008b); (12) Horowitz (2009); (13) Bluedorn et al. (2010); (14) Ng and Zhao (2011); (15) Ackerman et al. (2012), adjusting Hanemann (2008); (16) Roson and van der Mensbrugghe (2012)’s 2.3°C damage estimate; (17) Roson and van der Mensbrugghe (2012)’s 4.8°C damage estimate; (18) Weitzman (2012)’s 6°C damage estimate, via Ackerman et al. (2012); (19) Weitzman (2012)’s 12°C damage estimate, via Ackerman et al.(2012); (20) Tol (2013); (21) Bosello and Parrado (2014); (22) Nordhaus (2014)’s estimate for an average increase of 2°C over the 2050 to 2250 period; (23) Nordhaus (2014)’s strict 2°C limit estimate; (24) Burke et al. (2015); (25) Howard and Sylvan (2015)’s 1°C damage estimate; (26) Howard and Sylvan (2015)’s 3°C damage estimate.*

***Figure C3. Graphical Representations of Outliers, by Dataset***

*(a-i) (a-ii)*

*(b-i) (b-ii)*

*Each panel graphically represents the data in a manner that determines outliers for the Preferred Specifications (4) and (8) in Table 2 in the main text of the paper. The (a) panels display scatter plots of the normalized residual squared versus leverage for a WLS regression, including a constant. The (b) panels are scatter plots of Mahalanobis distance versus robust residuals squared for an mm regression (using mmregress), where the hollow points are outliers. The (i) panels exclude damage estimates corresponding to high-temperatures (>4°C) and the data labels correspond to Figure C1. The (ii) panels include high-temperature estimates and the data labels correspond to Figure C2.*

**Table A1.** Damage Studies Cited in Nordhaus (2013), Tol (2014), and Our Paper

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Study** | **Temperature Increase (°C) Cited in Nordhaus (2013) and Tol (2014)** | **Damage Cited in Tol (2014)** | **Damage Cited in Nordhaus (2013)** | **Corrected Temperaturea** | **Corrected Damagea** | **In Non-Duplicate Dataset** |
| Cited in Nordhaus (2013) | | | | | | |
| Nordhaus (1994a) | 3 | 1.3% | 1.6% | 3 | 1.3% |  |
| Nordhaus (1994b) | 3 | 4.8% | 6.0% | 3 | 3.6% | Yes |
| Fankhauser (1995) | 2.5 | 1.4% | 1.8% | 2.5 | 1.4% | Yes |
| Tol (1995) | 2.5 | 1.9% | 2.4% | 2.5 | 1.9% |  |
| Nordhaus and Yang (1996) | 2.5 | 1.7% | 2.1% | 2.5 | 1.7% |  |
| Plambeck and Hope (1996) | 2.5 | 2.5% | 3.1% | 2.5 | **2.6%** |  |
| Mendelsohn et al. (2000b) | 2.5 | 0.0% | 0.0% | 2.5 | 0.0% | Yes |
| -0.1% | -0.1% | -0.1% | Yes |
| Nordhaus and Boyer (2000) | 2.5 | 1.5% | 1.9% | 2.5 | 1.5% |  |
| Tol (2002) | 1 | -2.3% | -2.9% | 1 | -2.3% |  |
| Maddison (2003) | 2.5 | 0.1% | 0.1% | 2.5 | **1.2%** |  |
| Rehdanz and Maddison (2005) | 1 | 0.4% | 0.5% | 1 | **0.6%** |  |
| Hope (2006) | 2.5 | -0.9% | -1.1% | 2.5 | **0.9%** |  |
| Nordhaus (2006) | 2.5 | 0.9% | 1.1% | **2.1** | **1.0%** |  |
| Added in Tol (2014) | | | | | | |
| Nordhaus (2008a) | 3 | 2.5% | - | **2.5** | **1.8%** | Yes |
| Maddison and Rehdanz (2011) | 3.2 | 11.5% | - | 3.2 | **16.3%** |  |
| Bosello et al. (2012) | 1.92 | 0.5% | - | 1.9 | 0.5% |  |
| Roson and van der Mensbrugghe (2012) | 4.8 | 4.6% | - | 4.8 | 4.6% | Yes |
| Roson and van der Mensbrugghe (2012) | 2.3 | 1.8% | - | 2.3 | 1.8% | Yes |
| Added in This Study | | | | | | |
| Nordhaus (1994b) | - | - | - | 6 | 6.7% | Yes |
| Meyer and Cooper (1995) | - | - | - | 3 | 11.5% | Yes |
| Manne et al. (1995) | - | - | - | 2.5 | 1.4% |  |
| Schauer (1995) | - | - | - | 2.5 | 5.2% | Yes |
| Berz (2000) | - | - | - | 2.5 | 1.5% |  |
| Manne and Richels (2005) | - | - | - | 2.5 | 1.9% | Yes |
| Choiniere and Horowitz (2006) | - | - | - | 0.8 | 7.4% |  |
| Bosetti et al. (2007) | - | - | - | 2.6 | 2.5% |  |
| Dell et al. (2008) | - | - | - | 3.4 | 0.3% | Yes |
| Gunasekera et al. (2008) | - | - | - | 1.7 | 6.0% |  |
| Nordhaus (2008b) | - | - | - | 2.1 | 0.3% | Yes |
| Horowitz (2009) | - | - | - | 0.7 | 3.8% | Yes |
| Bluedorn et al. (2010) | - | - | - | 0.7 | 0.0% | Yes |
| Eboli et al. (2010) | - | - | - | 3 | 1.3% |  |
| Eboli et al. (2010) | - | - | - | 1.5 | 0.2% |  |
| Weitzman (2012) via Ackerman et al. (2012) | - | - | - | 12 | 99.0% | Yes |
| Weitzman (2012) via Ackerman et al. (2012) | - | - | - | 6 | 50.0% | Yes |
| Hope (2011) | - | - | - | 3 | 0.8% |  |
| Ng and Zhao (2011) | - | - | - | 0.7 | 1.6% | Yes |
| Ackerman et al. (2012) adjusting Hanemann (2008) | - | - | - | 2.5 | 4.2% | Yes |
| McCallum et al. (2013) | - | - | - | 2 | 0.7% |  |
| McCallum et al. (2013) |  |  |  | 4 | 1.8% |  |
| Tol (2013) |  |  |  | 1 | -1.4% | Yes |
| Bosello and Parrado (2014) |  |  |  | 2.5 | 0.9% | Yes |
| Dellink et al. (2014) |  |  |  | 2.5 | 1.1% |  |
| Nordhaus (2014) |  |  |  | 3 | 10.6% | Yes |
| Nordhaus (2014) |  |  |  | 3 | 4.9% | Yes |
| Burke et al. (2015) |  |  |  | 4.3 | 23.0% | Yes |
| Howard and Sylvan (2015) |  |  |  | 3 | 10.2% | Yes |
| Howard and Sylvan (2015) |  |  |  | 1 | 0.0% | Yes |

a Differences between our paper and Nordhaus (2013) or Tol (2014) are in bold.

**Table A2.** Variable Definitions

|  |  |
| --- | --- |
| **Variable** | **Description** |
| *Damage Variables* | |
| *D\_orig* | Original damage estimate (% GDP) cited by Tol (2009) and used by Nordhaus (2013) |
| D\_new | Climate Damage as a % of GDP corrected for this paper |
| damage | Non-catastrophic damages (D\_new with catastrophic damages removed) |
| *Factual Causes -Temperature Variables* | |
| T | Original temperature change (°C) cited by Tol (2009) and used by Nordhaus (2013) |
| T2 | *T* squared |
| T\_new | Increase in average surface temperature (°C) corrected for this paper |
| T2\_new | *T\_new* squared |
| t | Increase in average surface temperature (°C) adjusted for study's base period |
| t2 | *t* squared |
| *Methodological Causes* | |
| cat | Dummy equal to 1 if estimate includes catastrophic damages |
| cross | Dummy equal to 1 if study uses cross-sectional data without country fixed effects |
| current | Dummy equal to 1 if study measures temperature change relative to current temperature |
| Eco\_Market | Dummy equal to 1 if estimate includes the ecosystem services/non-market effects on market production sector |
| Grey | Dummy equal to 1 if study is drawn from the grey literature |
| Market | Dummy equal to 1 if estimate includes only market damages |
| prod | Dummy equal to 1 if estimate captures the impacts of climate change on GDP through economic productivity |
| Time | Year published minus 1994 |
| *Interaction Variables* | |
| *mkt\_t* | Interaction of *Market* with t |
| mkt\_t2 | Interaction of *Market* with t2 |
| cat\_t2 | Interaction of *cat* with t2 |
| prod\_t | Interaction of *prod* with t |
| prod\_t2 | Interaction of *prod* with t2 |
| *Cluster Groups* | |
| author | Primary author of study |
| method | Estimation method |
| model | Estimation model |
| model2 | Interaction of *author* and *method* |
| Primary\_model | Original classification for model before regroupings to ensure tractability of the Breusch-Pagan test of independence |

***Table B1. P-values of Cameron & Trivedi's decomposition of IM-test for Preferred Specification using D\_new, by Set of Variables and Dataset***

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dataset | Damages for Temp. Increases≤4°C | | Damages for All Temp. Increases | |
| Include Duplicates | Exclude Duplicates | Include Duplicates | Exclude Duplicates |
| Shorter Variable Seta | | | | |
| Heteroskedasticity | 0.460 | 0.123 | 0.000 | 0.002 |
| Skewness | 0.033 | 0.104 | 0.146 | 0.289 |
| Kurtosis | 0.174 | 0.360 | 0.147 | 0.159 |
| Total | 0.093 | 0.073 | 0.000 | 0.003 |
| Extended Variable Setb | | | | |
| Heteroskedasticity | 0.650 | 0.289 | 0.000 | 0.013 |
| Skewness | 0.077 | 0.314 | 0.343 | 0.599 |
| Kurtosis | 0.272 | 0.249 | 0.148 | 0.169 |
| Total | 0.273 | 0.259 | 0.001 | 0.032 |

a Shorter variable set includes temperature squared (*t2)* and its interaction with market (*mkt\_t2*) and catastrophic (*cat\_t2*) dummies.

b The extended variable set expands on the shorter variable set to include the interaction of temperature squared with an indicator variable for productivity (*prod\_t2*) and an indicator variable for a cross-sectional dataset without country fixed effects (*cross*).

***Table B2. P-values of Breusch-Pagan LM Test of Independence, by Cluster-level and Dataset***

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dataset / Cluster Levela | Damages for Temp. Increases≤4°C | | Damages for All Temp. Increases | |
| Include Duplicates | Exclude Duplicates | Include Duplicates | Exclude Duplicates |
| Author | 0.001 | 0.062 | 0.000 | 0.012 |
| Method | 0.029 | 0.029 | 0.109 | 0.020 |
| Model | 0.000 | 0.000 | 0.000 | 0.000 |

**a** *See variable definitions in Table A2 in Appendix A.*

***Table B3.*** *Potential Bias of the Social Cost of Carbon for All Temperature Data: OLS and WLS with Cluster-Robust Standard Errors at the Model Level, by Specification and Dataset*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Datasets and Specificationsa | Damages for All Temp. Increases and Excludes Duplicates | | | | | |
| Nordhaus (2013) | Original | Correct Data | New Data | Omitted Variables | Duplication Bias |
| - | (1) | (2) | (3) | (4) | (5) |
| VARIABLESb | - | D\_orig | D\_new | D\_new | D\_new | D\_new |
| T2 | 0.214 | 0.212\*\*\* |  |  |  |  |
|  |  | (0.0644) |  |  |  |  |
| t2 |  |  | 0.192\*\* | 0.551\*\*\* | 0.263\*\*\* | 0.318\*\* |
|  |  |  | (0.0574) | (0.0943) | (0.0606) | (0.102) |
| mkt\_t2 |  |  |  |  | 0.014 | -0.345\* |
|  |  |  |  |  | (0.254) | (0.156) |
| cat\_t2 |  |  |  |  | 0.413\*\*\* | 0.362\*\*\* |
|  |  |  |  |  | (0.0614) | (0.103) |
| prod\_t2 |  |  |  |  | 0.001 | 0.398 |
|  |  |  |  |  | (0.290) | (0.237) |
| Cross |  |  |  |  | 1.170\*\*\* | 1.700\*\*\* |
|  |  |  |  |  | (0.181) | (0.331) |
| Observations |  | 13 | 9 | 43 | 43 | 26 |
| R2 |  | 0.475 | 0.390 | 0.756 | 0.844 | 0.869 |
| Adjusted R-squared |  | 0.431 | 0.313 | 0.751 | 0.824 | 0.837 |
| Likelihood |  | -22.86 | -16.63 | -123.5 | -113.9 | -72.41 |
| F-statistic |  | 10.84 | 11.18 | 34.11 | 1645 | 776.2 |
| Prob>F |  | 0.006 | 0.016 | 0.000 | 0.000 | 0.000 |
| Hypothesis: non-catastrophic (captured by t2) impacts equal Nordhaus (2013)'s estimate of 0.2136 | | | | | | |
| p-value | - | - | 0.719 | 0.003 | 0.428 | 0.330 |
| Hypothesis: total impacts (captured by t2 + cat\_t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | | |
| p-value | - | - | - | - | 0.000 | 0.000 |
| 2015 SCCc (2015 USD per metric ton of CO2e) – without productivity | | | | | | |
| Non-cat (5%) | - | $7 | $5 | $38 | $14 | $9 |
| Non-cat (50%) | $22 | $22 | $20 | $62 | $28 | $34 |
| Non-cat (95%) | - | $38 | $36 | $90 | $43 | $62 |
| Total (50%) | - | - | - | - | $68 | $70 |
| 2015 SCCc (2015 USD per metric ton of CO2e) - with productivity | | | | | | |
| Non-cat (5%) | - | - | - | - | -$46 | -$4 |
| Non-cat (50%) | - | - | - | - | $28 | $84 |
| Non-cat (95%) | - | - | - | - | $130 | $213 |
| Total (50%) | - | - | - | - | $68 | $127 |
| Robust standard errors in parentheses | | | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | | |

*a The specifications are: (1) Nordhaus (2013), (2) correcting data and improving the estimation strategy, (3) introducing additional damage estimates, (4) accounting for omitted variable bias, and (5) accounting for duplication bias (the preferred specification).*

*b See variable definitions in Table A2 of Appendix A.*

*c 2015 SCC corresponding to the use of the regression estimates as the DICE-2013R damage function.* *Following Nordhaus (2013), we multiply the coefficients corresponding to non-catastrophic impacts (t2 and prod\_t2) by 25% when constructing the damage functions to account for potential omitted non-catastrophic impacts of climate change.*

***Table C1. Tol’s (2014) Regression Specification Estimated Using WLS with Cluster-Robust Standard Errors at the Model Level, by Dataset***

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | Damages for Temp. Increases≤4°C | | | | Damages for All Temp. Increases | | | |
| *Include Duplicates* | | *Exclude Duplicates* | | *Include Duplicates* | | *Exclude Duplicates* | |
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| VARIABLESa | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new |
| t2 | 0.925\*\*\* | 0.925\*\*\* | 1.703\*\*\* | 1.703\*\*\* | 0.095 | 0.095 | 0.013 | 0.013 |
|  | (0.275) | (0.289) | (0.304) | (0.338) | (0.162) | (0.169) | (0.176) | (0.190) |
| mkt\_t2 | -1.091\*\* | -0.891 | -2.164\*\*\* | -3.855\*\*\* | 0.233 | -0.061 | 0.441 | -2.165\*\* |
|  | (0.364) | (1.575) | (0.465) | (0.782) | (0.404) | (1.517) | (0.526) | (0.690) |
| cat\_t2 | 0.433\*\* | 0.433\* | 0.187 | 0.187 | 0.519\*\*\* | 0.519\*\*\* | 0.547\*\*\* | 0.547\*\*\* |
|  | (0.188) | (0.198) | (0.237) | (0.263) | (0.118) | (0.123) | (0.126) | (0.137) |
| prod\_t2 |  | -0.007 |  | 0.829 |  | 0.489 |  | 3.006\*\* |
|  |  | (1.584) |  | (0.660) |  | (1.621) |  | (1.230) |
| t | -1.740\* | -1.740\* | -2.940\*\*\* | -2.940\*\* | 0.639 | 0.639 | 1.302 | 1.302 |
|  | (0.841) | (0.882) | (0.860) | (0.954) | (0.629) | (0.655) | (0.720) | (0.778) |
| mkt\_t | 2.880\* | 2.395 | 4.875\*\* | 8.412\*\*\* | -0.821 | 0.016 | -1.782 | 4.170\*\* |
|  | (1.313) | (3.769) | (1.600) | (1.868) | (1.392) | (3.599) | (1.767) | (1.698) |
| prod\_t |  | -0.387 |  | 0.227 |  | -1.835 |  | -7.968 |
|  |  | (3.740) |  | (1.456) |  | (4.007) |  | (4.416) |
| cross |  | 0.991 |  | 0.381 |  | 0.991 |  | 0.381\* |
|  |  | (0.987) |  | (0.207) |  | (0.968) |  | (0.195) |
| Observations | 38 | 38 | 21 | 21 | 43 | 43 | 26 | 26 |
| R2 | 0.571 | 0.591 | 0.757 | 0.808 | 0.846 | 0.851 | 0.877 | 0.889 |
| Adjusted R-squared | 0.507 | 0.481 | 0.681 | 0.689 | 0.826 | 0.817 | 0.848 | 0.840 |
| Likelihood | -82.90 | -82.04 | -42.96 | -40.50 | -113.7 | -113.0 | -71.55 | -70.21 |
| F-statistic | 17.82 |  | 19.01 |  | 6845 |  | 5036 |  |
| Prob>F | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  |
| Hypothesis: non-catastrophic impacts (without productivity) equal to Tol (2014) estimate | | | | | | | | |
| p-value | 0.0531 | 0.0656 | 0.0026 | 0.0049 | 0.8032 | 0.8170 | 0.2387 | 0.2861 |
| Hypothesis: total impacts (without productivity) equal to Tol (2014) estimate | | | | | | | | |
| p-value | 0.0033 | 0.0046 | 0.0019 | 0.0036 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Hypothesis: non-catastrophic impacts (with productivity) equal to Tol (2014) estimate | | | | | | | | |
| p-value | . | 0.5856 | . | 0.0021 | . | 0.7754 | . | 0.0119 |
| Hypothesis: total impacts (with productivity) equal to Tol (2014) estimate | | | | | | | | |
| p-value | . | 0.1091 | . | 0.0129 | . | 0.7603 | . | 0.0331 |
| Robust standard errors in parentheses | | | | | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | | | | |

*a See variable definitions in Table A2 in Appendix A.*

***Table C2. Bias of Tol’s (2014) Regression Specification for Low-Temperature Data: OLS and WLS with Cluster-Robust Standard Errors at the Model Level, by Specification and Dataset***

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Datasets and Specificationsa | Damages for Temp. Increases≤4°C and Excludes Duplicates | | | | | |
| Tol (2014) | Originalc | Correct Data | New Data | Omitted Variables | Duplication Bias |
| - | (1) | (2) | (3) | (4) | (5) |
| VARIABLESb | - | D\_orig | D\_new | D\_new | D\_new | D\_new |
| T | 0.28 | -3.833\*\* |  |  |  |  |
|  |  | (1.372) |  |  |  |  |
| T2 | 0.16 | 1.747\*\*\* |  |  |  |  |
|  |  | (0.510) |  |  |  |  |
| t |  |  | -1.196\* | 1.157 | -1.740\* | -2.940\*\* |
|  |  |  | (0.633) | (0.659) | (0.882) | (0.954) |
| t2 |  |  | 0.604\*\* | -0.057 | 0.925\*\*\* | 1.703\*\*\* |
|  |  |  | (0.193) | (0.196) | (0.289) | (0.338) |
| mkt\_t |  |  |  |  | 2.395 | 8.412\*\*\* |
|  |  |  |  |  | (3.769) | (1.868) |
| mkt\_t2 |  |  |  |  | -0.891 | -3.855\*\*\* |
|  |  |  |  |  | (1.575) | (0.782) |
| cat\_t2 |  |  |  |  | 0.433\* | 0.187 |
|  |  |  |  |  | (0.198) | (0.263) |
| prod\_t |  |  |  |  | -0.387 | 0.227 |
|  |  |  |  |  | (3.740) | (1.456) |
| prod\_t2 |  |  |  |  | -0.007 | 0.829 |
|  |  |  |  |  | (1.584) | (0.660) |
| cross |  |  |  |  | 0.991 | 0.381 |
|  |  |  |  |  | (0.987) | (0.207) |
| Observations |  | 18 | 13 | 38 | 38 | 21 |
| R2 |  | 0.657 | 0.512 | 0.391 | 0.591 | 0.808 |
| Adjusted R-squared |  | 0.614 | 0.423 | 0.357 | 0.481 | 0.689 |
| Likelihood |  | -37.15 | -21.34 | -89.57 | -82.04 | -40.50 |
| F-statistic |  | 15.35 | 20.02 | 9.717 |  |  |
| Prob>F |  | 0.000 | 0.001 | 0.004 |  |  |
| Hypothesis: non-catastrophic (without productivity) impacts equal to Tol (2014) estimate | | | | | | |
| p-value | - | 0.0201 | 0.0580 | 0.4194 | 0.0656 | 0.0049 |
| Hypothesis: total impacts (without productivity) equal to Tol (2014) estimate | | | | | | |
| p-value | - | - | - | - | 0.0046 | 0.0036 |
| 2015 SCCd (2015 USD per metric ton of CO2e) - without productivity | | | | | | |
| Non-cat (50%) | $18 | $96 | $31 | $15 | $51 | $112 |
| Total (50%) | - | - | - | - | $98 | $136 |
| 2015 SCCd (2015 USD per metric ton of CO2e) – with productivity | | | | | | |
| Non-cat (50%) | - | - | - | - | $43 | $242 |
| Total (50%) | - | - | - | - | $89 | $276 |
| Robust standard errors in parentheses | | |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | |  |  |  |  |  |

*a The specifications are: (1) Tol (2014), (2) correcting data and improving the estimation strategy, (3) introducing additional damage estimates, (4) accounting for omitted variable bias, and (5) accounting for duplication bias (the preferred specification).*

*b See variable definitions in Table A2 in Appendix A; the exception is that now T, T2, and D\_orig are the temperature (linear and quadratic) and damage variables cited in Tol (2014).*

*c We exclude Nordhaus (2013) as a previous meta-analysis using Tol (2009) estimates – a subset of Tol (2014) – on the grounds that it is a linear combination of these estimates.*

*d 2015 SCC corresponding to the use of the regression estimates as the DICE-2013R damage function. Following Tol (2009; 2014), the SCC estimates do not include a 25% adjustment of regression coefficients to account for omitted impacts, as in Nordhaus (2013).*

***Table C3. Bias of Tol’s (2014) Regression Specification for All Data: OLS and WLS with Cluster-Robust Standard Errors at the Model Level, by Specification and Dataset***

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Datasets and Specificationsa | Damages for All Temp. Increases and Excludes Duplicates | | | | | |
| Tol (2014) | Originalc | Correct Data | New Data | Omitted Variables | Duplication Bias |
| - | (1) | (2) | (3) | (4) | (5) |
| VARIABLESb | - | D\_orig | D\_new | D\_new | D\_new | D\_new |
| T | 0.28 | 0.333 |  |  |  |  |
|  |  | (0.630) |  |  |  |  |
| T2 | 0.16 | 0.154 |  |  |  |  |
|  |  | (0.184) |  |  |  |  |
| T |  |  | -0.107 | -0.966\*\* | 0.639 | 1.302 |
|  |  |  | (0.344) | (0.333) | (0.655) | (0.778) |
| t2 |  |  | 0.201\*\* | 0.688\*\*\* | 0.095 | 0.013 |
|  |  |  | (0.0776) | (0.0537) | (0.169) | (0.190) |
| mkt\_t |  |  |  |  | 0.016 | 4.170\*\* |
|  |  |  |  |  | (3.599) | (1.698) |
| mkt\_t2 |  |  |  |  | -0.061 | -2.165\*\* |
|  |  |  |  |  | (1.517) | (0.690) |
| cat\_t2 |  |  |  |  | 0.519\*\*\* | 0.547\*\*\* |
|  |  |  |  |  | (0.123) | (0.137) |
| prod\_t |  |  |  |  | -1.835 | -7.968 |
|  |  |  |  |  | (4.007) | (4.416) |
| prod\_t2 |  |  |  |  | 0.489 | 3.006\*\* |
|  |  |  |  |  | (1.621) | (1.230) |
| Cross |  |  |  |  | 0.991 | 0.381\* |
|  |  |  |  |  | (0.968) | (0.195) |
| Observations |  | 19 | 14 | 43 | 43 | 26 |
| R2 |  | 0.486 | 0.544 | 0.780 | 0.851 | 0.889 |
| Adjusted R-squared |  | 0.426 | 0.468 | 0.770 | 0.817 | 0.840 |
| Likelihood |  | -43.54 | -23.72 | -121.3 | -113.0 | -70.21 |
| F-statistic |  | 8.047 | 27.76 | 82.59 |  |  |
| Prob>F |  | 0.003 | 0.000 | 0.000 |  |  |
| Hypothesis: non-catastrophic (without productivity) impacts equal to Tol (2014) estimate | | | | | | |
| p-value | - | 0.9863 | 0.1810 | 0.0000 | 0.8170 | 0.2861 |
| Hypothesis: total impacts (without productivity) equal to Tol (2014) estimate | | | | | | |
| p-value | - | - | - | - | 0.0000 | 0.0000 |
| 2015 SCCd (2015 USD per metric ton of CO2e) - without productivity | | | | | | |
| Non-cat (50%) | $18 | $19 | $15 | $43 | $19 | $23 |
| Total (50%) | - | - | - | - | $68 | $76 |
| 2015 SCCd (2015 USD per metric ton of CO2e) – with productivity | | | | | | |
| Non-cat (50%) | - | - | - | - | $29 | $197 |
| Total (50%) | - | - | - | - | $75 | $292 |
| Robust standard errors in parentheses | | | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | | |

*a The specifications are: (1) Tol (2014), (2) correcting data and improving the estimation strategy, (3) introducing additional damage estimates, (4) accounting for omitted variable bias, and (5) accounting for duplication bias (the preferred specification).*

*b See variable definitions in Table A2 in Appendix A; the exception is that now T, T2, and D\_orig are the temperature (linear and quadratic) and damage variables cited in Tol (2014).*

*c We exclude Nordhaus (2013) as a previous meta-analysis using Tol (2009) estimates – a subset of Tol (2014) – on the grounds that it is a linear combination of these estimates.*

*d 2015 SCC corresponding to the use of the regression estimates as the DICE-2013R damage function. Following Tol (2009; 2014), the SCC estimates do not include a 25% adjustment of regression coefficients to account for omitted impacts, as in Nordhaus (2013).*

***Table C4. Alternative Functional Forms: Preferred Regression Specification Estimated Using WLS with Cluster***-***Robust Standard Errors at the Model Level, by Dataset and Functional Form***

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Datasets | Damages for Temp. Increases≤4 °C | | | | | | Damages for All Temp. Increases | | | | | |
| Functional Form | Nordhaus (2013) | Linear | Tol (2014) | Azar and Lindgren (2003) | Weitzman (2012) | Newbold and Marten (2014) with breakpoint at 1.7°Cb | Nordhaus (2013) | Linear | Tol (2014) | Azar and Lindgren (2003) | Weitzman (2012) | Newbold and Marten (2014) with breakpoint at 0.8°C b |
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| VARIABLESa | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new |
| t2 | 0.595\*\* |  | 1.703\*\*\* |  | 0.013 |  | 0.318\*\* |  | 0.013 |  | 0.977\*\*\* |  |
|  | (0.190) |  | (0.338) |  | (0.365) |  | (0.102) |  | (0.190) |  | (0.125) |  |
| mkt\_t2 | -0.622\*\* |  | -3.855\*\*\* |  | 1.395\*\* |  | -0.345\* |  | -2.165\*\* |  | 0.432 |  |
|  | (0.226) |  | (0.782) |  | (0.475) |  | (0.156) |  | (0.690) |  | (0.312) |  |
| cat\_t2 | 0.260 |  | 0.187 |  |  |  | 0.362\*\*\* |  | 0.547\*\*\* |  |  |  |
|  | (0.267) |  | (0.263) |  |  |  | (0.103) |  | (0.137) |  |  |  |
| prod\_t2 | 0.113 |  | 0.829 |  | -1.117\*\*\* |  | 0.398 |  | 3.006\*\* |  | -1.062\*\*\* |  |
|  | (0.125) |  | (0.660) |  | (0.297) |  | (0.237) |  | (1.230) |  | (0.296) |  |
| T |  | 1.348\*\* | -2.940\*\* |  |  |  |  | 1.284\*\*\* | 1.302 |  |  |  |
|  |  | (0.523) | (0.954) |  |  |  |  | (0.359) | (0.778) |  |  |  |
| mkt\_t |  | -1.249\* | 8.412\*\*\* |  |  |  |  | -1.185\*\* | 4.170\*\* |  |  |  |
|  |  | (0.660) | (1.868) |  |  |  |  | (0.529) | (1.698) |  |  |  |
| cat\_t |  | 1.009 |  |  |  |  |  | 4.404\*\* |  |  |  |  |
|  |  | (0.713) |  |  |  |  |  | (1.754) |  |  |  |  |
| prod\_t |  | 0.267 | 0.227 |  |  |  |  | 1.670 | -7.968 |  |  |  |
|  |  | (0.437) | (1.456) |  |  |  |  | (0.985) | (4.416) |  |  |  |
| t4 |  |  |  | 0.081\*\*\* |  |  |  |  |  | 0.007\*\*\* |  |  |
|  |  |  |  | (0.0219) |  |  |  |  |  | (0.00160) |  |  |
| mkt\_t4 |  |  |  | -0.094\*\*\* |  |  |  |  |  | -0.020 |  |  |
|  |  |  |  | (0.0253) |  |  |  |  |  | (0.0123) |  |  |
| cat\_t4 |  |  |  | 0.025 |  |  |  |  |  | -0.003 |  |  |
|  |  |  |  | (0.0301) |  |  |  |  |  | (0.00160) |  |  |
| prod\_t4 |  |  |  | 0.019 |  |  |  |  |  | 0.028 |  |  |
|  |  |  |  | (0.0127) |  |  |  |  |  | (0.0160) |  |  |
| t6 |  |  |  |  | 0.010 |  |  |  |  |  | -0.001\*\*\* |  |
|  |  |  |  |  | (0.00776) |  |  |  |  |  | (9.83e-05) |  |
| mkt\_t6 |  |  |  |  | -0.048\*\*\* |  |  |  |  |  | -0.037\*\*\* |  |
|  |  |  |  |  | (0.0113) |  |  |  |  |  | (0.00772) |  |
| cat\_t6 |  |  |  |  | 0.003 |  |  |  |  |  | 0.001\*\*\* |  |
|  |  |  |  |  | (0.00402) |  |  |  |  |  | (9.36e-05) |  |
| prod\_t6 |  |  |  |  | 0.037\*\*\* |  |  |  |  |  | 0.038\*\*\* |  |
|  |  |  |  |  | (0.00815) |  |  |  |  |  | (0.00772) |  |
| t\_1 |  |  |  |  |  | -0.893 |  |  |  |  |  | -0.838 |
|  |  |  |  |  |  | (0.653) |  |  |  |  |  | (1.283) |
| Mkt\_ t\_1 |  |  |  |  |  | 2.690\*\*\* |  |  |  |  |  | 3.187\*\* |
|  |  |  |  |  |  | (0.656) |  |  |  |  |  | (1.287) |
| cat\_ t\_1 |  |  |  |  |  | -2.989 |  |  |  |  |  | -16.99\*\*\* |
|  |  |  |  |  |  | (1.974) |  |  |  |  |  | (2.838) |
| prod\_ t\_1 |  |  |  |  |  | -0.485\*\*\* |  |  |  |  |  | -10.64 |
|  |  |  |  |  |  | (0.0920) |  |  |  |  |  | (9.688) |
| t\_2 |  |  |  |  |  | 6.056\*\*\* |  |  |  |  |  | 2.183\*\* |
|  |  |  |  |  |  | (1.461) |  |  |  |  |  | (0.715) |
| mkt\_ t\_2 |  |  |  |  |  | -10.67\*\*\* |  |  |  |  |  | -3.389\*\*\* |
|  |  |  |  |  |  | (1.542) |  |  |  |  |  | (0.716) |
| cat\_ t\_2 |  |  |  |  |  | 5.944 |  |  |  |  |  | 8.493\*\*\* |
|  |  |  |  |  |  | (3.521) |  |  |  |  |  | (0.747) |
| prod\_ t\_2 |  |  |  |  |  | 3.423\*\*\* |  |  |  |  |  | 6.002 |
|  |  |  |  |  |  | (0.526) |  |  |  |  |  | (3.904) |
| Cross | 1.700\*\*\* | 1.563\*\*\* | 0.381 | 1.735\*\*\* | 0.407 | 0.629\*\*\* | 1.700\*\*\* | 1.563\*\*\* | 0.381\* | 1.735\*\*\* | 0.407 | 0.233\*\* |
|  | (0.343) | (0.414) | (0.207) | (0.268) | (0.280) | (0.108) | (0.331) | (0.399) | (0.195) | (0.259) | (0.263) | (0.0826) |
| Observations | 21 | 21 | 21 | 21 | 21 | 21 | 26 | 26 | 26 | 26 | 26 | 26 |
| R2 | 0.722 | 0.652 | 0.808 | 0.774 | 0.808 | 0.814 | 0.869 | 0.733 | 0.889 | 0.667 | 0.913 | 0.924 |
| Adjusted R-squared | 0.635 | 0.543 | 0.689 | 0.704 | 0.689 | 0.675 | 0.837 | 0.670 | 0.840 | 0.588 | 0.875 | 0.883 |
| Likelihood | -44.36 | -46.72 | -40.50 | -42.17 | -40.49 | -40.13 | -72.41 | -81.63 | -70.21 | -84.51 | -67.02 | -65.36 |
| F-statistic | 21.95 | 16.82 |  | 28.3 |  |  | 776.2 | 9.733 |  | 10952 |  |  |
| Prob>F | 0.000 | 0.000 |  | 0.000 |  |  | 0.000 | 0.001 |  | 0.000 |  |  |
| Robust standard errors in parentheses | | |  |  |  |  |  |  |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | |  |  |  |  |  |  |  |  |  |  |  |

*a See variable definitions in Table A2 in Appendix A. These names are slightly modified for the corresponding polynomial, each of which is adjusted for its base period. The exceptions are t\_1 and t\_2, which represent the piecewise linear coefficients below and above, respectively, the temperature breakpoint (i.e., 0.8°C or 1.7°C), such that cat\_ t\_1 represents the Interaction of cat with t\_1.*

*b In Appendix C2, the notation for the piecewise linear damage function (Newbold and Marten, 2014) assumes marginal coefficients. Instead, the above results present the coefficients as cumulative for ease of comparison, such that the marginal coefficients are t\_1 below the breaking point and t\_2-t\_1 thereafter.*

**Table C5. *Sensitivity Analysis: Re-estimating the Preferred Specification for Low-Temperature Data (Specification (4) in Table 2), by Specification***

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | Damages for Temp. Increases≤4 °C and Excludes Duplicates | | | | | | |
| Specificationsa | Preferred Specification | Alt. Variable Definition | | High-Temperature Cut Off | | Drop Estimates | |
| Non-catastrophic Damages Only | Ecosystem Services Reclassified | 3 Degree Celsius | 4.5 Degree Celsius | More Restrictive Definition of Duplication | More Restrictive Definition of Citation |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| VARIABLESb | D\_new | Damage | D\_new | D\_new | D\_new | D\_new | D\_new |
| t2 | 0.595\*\* | 0.482\*\* | 0.507\*\* | 0.595\*\* | 0.595\*\* | 0.601\*\* | 0.595\*\* |
|  | (0.190) | (0.155) | (0.186) | (0.192) | (0.214) | (0.186) | (0.193) |
| mkt\_t2 | -0.622\*\* | -0.508\*\* | -0.315 | -0.622\*\* | -0.622\*\* | -0.523\*\* | -0.622\*\* |
|  | (0.226) | (0.195) | (0.230) | (0.228) | (0.246) | (0.183) | (0.229) |
| cat\_t2 | 0.260 |  | 0.348 | 0.260 | 0.260 | 0.352 | 0.137 |
|  | (0.267) |  | (0.256) | (0.269) | (0.296) | (0.258) | (0.193) |
| prod\_t2 | 0.113 | 0.113 | -0.205 | 0.167 | 0.550\*\* | 0.009 | 0.113 |
|  | (0.125) | (0.123) | (0.176) | (0.123) | (0.216) | (0.088) | (0.127) |
| cross | 1.700\*\*\* | 1.700\*\*\* | 1.318\*\* | 1.700\*\*\* | 1.700\*\*\* | 1.813\*\*\* | 1.700\*\*\* |
|  | (0.343) | (0.336) | (0.488) | (0.345) | (0.341) | (0.088) | (0.348) |
| Observations | 21 | 19 | 21 | 20 | 22 | 18 | 19 |
| R2 | 0.722 | 0.550 | 0.691 | 0.725 | 0.664 | 0.741 | 0.660 |
| Adjusted R-squared | 0.635 | 0.430 | 0.594 | 0.633 | 0.565 | 0.641 | 0.539 |
| Likelihood | -44.36 | -38.34 | -45.49 | -42.39 | -54.13 | -38.35 | -39.40 |
| F-statistic | 21.95 | 18.09 | 83.36 |  | 25.28 |  |  |
| Prob>F | 0.000 | 0.000 | 0.000 |  | 0.000 |  |  |
| Hypothesis: non-catastrophic impacts (captured by t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | | | |
| p-value | 0.0800 | 0.1210 | 0.1531 | 0.0816 | 0.1124 | 0.083 | 0.0835 |
| Hypothesis: total impacts (captured by t2+cat\_t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | | | |
| p-value | 0.0031 | - | 0.0031 | 0.0032 | 0.0010 | 0.078 | - |
| Hypothesis: non-catastrophic impacts (captured by t2 + prod\_t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | | | |
| p-value | 0.0618 | 0.0895 | 0.6174 | 0.0424 | 0.0154 | 0.003 | 0.0648 |
| Hypothesis: total impacts (captured by t2 + prod\_t2 + cat\_t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | | | |
| p-value | 0.0052 | - | 0.1096 | 0.0035 | 0.0014 | 0.004 | 0.0011 |
| Robust standard errors in parentheses | | | | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | | | |

*a Specifications include: (1) Preferred estimate; (2) dropping science-based damage estimates and removing catastrophic impacts from non-science-based damage estimates; (3) assuming that CGE models that capture the impacts of ecosystem services on the market account for non-market impacts, (4) and (5) redefining the cutoff for high-temperatures at 3°C and 4.5 °C increases, respectively; (6) imposing a stricter definition of duplication that further limits data to one estimate per study; (7) imposing a stricter definition of citation that drops estimates that use other estimates as starting points for their unique estimates (Meyer and Cooper, 1995; Hanemann, 2008).*

*b See variable definitions in Table A2 in Appendix A.*

***Table C6. Sensitivity Analysis: Re-estimating the Preferred Specification for Damage Estimates Corresponding to All Temperature Increases (Specification (8) in Table 2), by Specification***

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Dataset | Damages for All Temp. Increases and Excludes Duplicates | | | | |
| Specificationsa | Preferred Specification | Alt. Variable Definition | | Drop Estimates | |
| Non-catastrophic Damages Only | Ecosystem Services Reclassified | More Restrictive Definition of Duplication | More Restrictive Definition of Citation |
| (1) | (2) | (3) | (6) | (7) |
| VARIABLESb | D\_new | Damage | D\_new | D\_new | D\_new |
| t2 | 0.318\*\* | 0.312\*\*\* | 0.280\*\*\* | 0.601\*\* | 0.318\*\* |
|  | (0.102) | (0.085) | (0.085) | (0.180) | (0.103) |
| mkt\_t2 | -0.345\* | -0.339\*\* | -0.009 | -0.523\*\* | -0.345\* |
|  | (0.156) | (0.144) | (0.193) | (0.177) | (0.157) |
| cat\_t2 | 0.362\*\*\* |  | 0.401\*\*\* | 0.018 | 0.356\*\*\* |
|  | (0.103) |  | (0.086) | (0.184) | (0.103) |
| prod\_t2 | 0.398 | 0.398 | 0.100 | 0.446\* | 0.398 |
|  | (0.237) | (0.235) | (0.283) | (0.196) | (0.239) |
| Cross | 1.700\*\*\* | 1.700\*\*\* | 1.181\*\* | 1.813\*\*\* | 1.700\*\*\* |
|  | (0.331) | (0.327) | (0.526) | (0.085) | (0.333) |
| Observations | 26 | 22 | 26 | 20 | 24 |
| R2 | 0.869 | 0.487 | 0.866 | 0.905 | 0.871 |
| Adjusted R-squared | 0.837 | 0.374 | 0.834 | 0.873 | 0.837 |
| Likelihood | -72.41 | -55.64 | -72.69 | -51.06 | -66.94 |
| F-statistic | 776.2 | 11.65 | 770.4 | - | 14486 |
| Prob>F | 0.000 | 0.001 | 0.000 | - | 0.000 |
| Hypothesis: non-catastrophic impacts (captured by t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | |
| p-value | 0.3303 | 0.2696 | 0.4552 | 0.064 | 0.3342 |
| Hypothesis: total impacts (captured by t2+cat\_t2) equal Nordhaus (2013)'s estimate of 0.2132 | | | | | |
| p-value | 0.0000 | - | 0.0000 | 0.000 | 0.0000 |
| Hypothesis: non-catastrophic impacts (captured by t2 + prod\_t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | |
| p-value | 0.0804 | 0.0746 | 0.5685 | 0.011 | 0.0825 |
| Hypothesis: total impacts (captured by t2 + prod\_t2 + cat\_t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | |
| p-value | 0.0045 | - | 0.0727 | 0.003 | 0.0049 |
| Robust standard errors in parentheses | | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | |

*a See Table C5 for specification definitions.*

*b See variable definitions in Table A2 in Appendix A.*

***Table C7. Alternative Estimators: Re-estimating Preferred Specification Regressions (4) and (8) in Table 2 using Alternative Estimators, by Estimator***

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | Damages for Temp. Increases≤4 °C and Excludes Duplicates | | | | | Damages for All Temp. Increases and Excludes Duplicates | | | | |
| Estimator | Preferred | OLS | GLS | Fixed Effectsb | GLS and Fixed Effectsb | Preferred | OLS | GLS | Fixed Effectsb | GLS and Fixed Effectsb |
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| VARIABLESa | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new |
| t2 | 0.595\*\* | 0.626\*\* | 0.545\*\*\* | 0.825\*\* | 0.718\*\*\* | 0.318\*\* | 0.264\*\*\* | 0.265\*\*\* | 0.226 | 0.132 |
|  | (0.190) | (0.198) | (0.124) | (0.288) | (0.150) | (0.102) | (0.0711) | (0.0938) | (0.168) | (0.0902) |
| mkt\_t2 | -0.622\*\* | -0.670\*\* | -0.598\*\*\* | -1.184\*\*\* | -1.002\*\*\* | -0.345\* | -0.309\*\* | -0.305\* | -0.577\*\* | -0.411\*\*\* |
|  | (0.226) | (0.212) | (0.191) | (0.297) | (0.161) | (0.156) | (0.101) | (0.175) | (0.247) | (0.105) |
| cat\_t2 | 0.260 | 0.248 | 0.292 | 0.444 | 0.407\*\* | 0.362\*\*\* | 0.380\*\*\* | 0.442\*\*\* | 0.403\*\* | 0.527\*\*\* |
|  | (0.267) | (0.275) | (0.208) | (0.397) | (0.162) | (0.103) | (0.0712) | (0.127) | (0.171) | (0.124) |
| prod\_t2 | 0.113 | 0.120 | 0.188 | 0.233\*\*\* | 0.002 | 0.398 | 0.433\* | 0.245 | 0.809\*\*\* | 0.524\*\*\* |
|  | (0.125) | (0.0767) | (0.155) | (0.0650) | (0.188) | (0.237) | (0.234) | (0.192) | (0.0655) | (0.168) |
| Cross | 1.700\*\*\* | 1.358\* | 1.132 | 0.245\*\*\* | -0.196 | 1.700\*\*\* | 1.358\* | 0.911 | 0.284 | -0.213 |
|  | (0.343) | (0.693) | (0.959) | (0.0515) | (0.288) | (0.331) | (0.669) | (1.067) | (0.797) | (0.280) |
| Observations | 21 | 21 | 21 | 21 | 21 | 26 | 26 | 26 | 26 | 26 |
| R2 | 0.722 | 0.783 |  | 0.824 |  | 0.869 | 0.933 |  | 0.897 |  |
| Adjusted R-squared | 0.635 | 0.715 |  | 0.631 |  | 0.837 | 0.916 |  | 0.821 |  |
| Hypothesis: non-catastrophic impacts (captured by t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | | | | | | |
| p-value | 0.0800 | 0.0710 | 0.0078 | 0.0666 | 0.0008 | 0.3303 | 0.4906 | 0.5812 | 0.9409 | 0.3673 |
| Hypothesis: total impacts (captured by t2 + cat\_t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | | | | | | |
| p-value | 0.0031 | 0.0027 | 0.0002 | 0.0295 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Hypothesis: non-catastrophic impacts (captured by t2 + prod\_t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | | | | | | |
| p-value | 0.0618 | 0.0367 | 0.0091 | 0.0212 | 0.0349 | 0.0804 | 0.0766 | 0.1652 | 0.0010 | 0.0201 |
| Hypothesis: total impacts (captured by t2 + prod\_t2 + cat\_t2) equal Nordhaus (2013)'s estimate of 0.2136 | | | | | | | | | | |
| p-value | 0.0052 | 0.0020 | 0.0004 | 0.0128 | 0.0001 | 0.0045 | 0.0042 | 0.0004 | 0.0000 | 0.0000 |
| Robust standard errors in parentheses |  |  |  |  |  |  |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 |  |  |  |  |  |  |  |  |  |  |

*a See variable definitions in Table A2 in Appendix A.*

*b Fixed effects are at the method level.*

***Table C8. Robust Regression for Preferred Specifications (4) and (8) in Table 2, by Robust Estimators***

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | Damages for Temp. Increases≤4 °C and Excludes Duplicates | | | | | Damages for All Temp. Increases and Excludes Duplicates | | | | |
| Specification | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| Regressor | OLS | m regressor | s regressor | mm regressor | Drop Outliersb | OLS | m regressor | s regressor | mm regressor | Drop Outliersb |
| Preferred specification | mregress (Huber weights) | sregress | mmregress (efficiency 0.85) | Preferred specification | mregress (Huber weights) | sregress | mmregress (efficiency 0.85) |
| VARIABLESa | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new |
| t2 | 0.595\*\* | 0.546\*\* | 0.329\*\*\* | 0.344\*\*\* | 0.404\*\* | 0.318\*\* | 0.231\*\* | 0.190\*\*\* | 0.200\*\*\* | 0.209\*\*\* |
|  | (0.190) | (0.190) | (0.0746) | (0.0661) | (0.132) | (0.102) | (0.0869) | (0.00488) | (0.0171) | (0.00153) |
| mkt\_t2 | -0.622\*\* | -0.590 | -0.312\*\*\* | -0.315\*\*\* | -0.336\* | -0.345\* | -0.275 | -0.170\*\*\* | -0.189\*\*\* | -0.236\* |
|  | (0.226) | (0.387) | (0.0764) | (0.0692) | (0.152) | (0.156) | (0.375) | (0.0177) | (0.0603) | (0.122) |
| cat\_t2 | 0.260 | 0.322 | 0.898\*\*\* | 0.875\*\*\* | 0.268\* | 0.362\*\*\* | 0.382\*\*\* | 0.417\*\*\* | 0.406\*\*\* | 0.397\*\*\* |
|  | (0.267) | (0.260) | (0.0893) | (0.0855) | (0.132) | -0.103 | (0.0893) | (0.00488) | (0.0171) | (0.00197) |
| prod\_t2 | 0.113 | 0.120 | 0.033 | 0.044 | 0.019 | 0.398 | 0.228 | 0.131\*\*\* | 0.124\* | 0.153 |
|  | (0.125) | (0.374) | (0.0461) | (0.0479) | (0.0903) | (0.237) | (0.374) | (0.0191) | (0.0610) | (0.127) |
| cross | 1.700\*\*\* | 1.358 | -0.115 | -0.159 | -0.178 | 1.700\*\*\* | 1.358 | -0.126 | 0.236 | 1.700\*\*\* |
|  | (0.343) | (2.072) | (0.0921) | (0.119) | (0.168) | (0.331) | (2.245) | (0.0961) | (1.077) | (0.344) |
| Observations | 21 | 21 | 21 | 21 | 15 | 26 | 26 | 26 | 26 | 19 |
| R-squared | 0.722 | 0.672 |  |  | 0.648 | 0.869 | 0.978 |  |  | 0.977 |
| Robust standard errors in parentheses | | | | | | | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | | | | | | |

*a See variable definitions in Table A2 in Appendix A.*

*b We define an outlier as a datum for which the mm regressor weight is below 0.8.*

***Table C9: Method-Specific Estimates: WLS with Huber White Corrected Standard Errors, Estimated Using Data for Each Method Corresponding to a Temperature Increase of 4°C or Less, by Method***

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | Damages for Temp. Increases≤4 °C and Excludes Duplicates | | | | | | | | |
| Estimation Method | Original | Enumerative | CGE | Statistical | Statistical-Cross Section | Statistical-Panel | Survey | Science | Compensating Surplus |
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| VARIABLESa | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new |
| t2 | 0.595\*\* | 0.212\* | 0.141 | 0.234 | 0.234 | - | 0.770\*\* | 0.861 | 0.849 |
|  | (0.190) | (0.0822) | (0.0606) | (0.254) | (0.232) | - | (0.230) | (0.317) | (0.429) |
| mkt\_t2 | -0.622\*\* |  |  |  |  | - |  |  |  |
|  | (0.226) |  |  |  |  | - |  |  |  |
| cat\_t2 | 0.260 | 0.637 |  |  |  | - |  |  |  |
|  | (0.267) | (0.321) |  |  |  | - |  |  |  |
| prod\_t2 | 0.113 |  |  | -0.213 |  | - |  |  |  |
|  | (0.125) |  |  | (0.254) |  | - |  |  |  |
| Cross | 1.700\*\*\* |  |  |  |  | - |  |  |  |
|  | (0.343) |  |  |  |  | - |  |  |  |
| Observations | 21 | 6 | 2 | 6 | 5 | - | 4 | 2 | 2 |
| R2 | 0.722 | 0.769 | 0.841 | 0.0810 | 0.0800 | - | 0.841 | 0.881 | 0.768 |
| Adjusted R-squared | 0.635 | 0.653 | 0.682 | -0.378 | -0.150 | - | 0.788 | 0.762 | 0.536 |
| Likelihood | -44.36 | -13.00 | -1.729 | -12.75 | -10.76 | - | -8.361 | -4.933 | -6.141 |
| F-statistic | 21.95 | 7.083 | 5.401 |  | 1.016 | - | 11.23 | 7.395 | 3.907 |
| Prob>F | 0.000 | 0.049 | 0.259 |  | 0.370 | - | 0.044 | 0.224 | 0.298 |
| Robust standard errors in parentheses | | | | | | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | | | | | |

*a See variable definitions in Table A2 in Appendix A.*

***Table C10: Method-Specific Estimates: WLS with Huber White Corrected Standard Errors, Estimated* *Using Data for Each Method Corresponding to All Temperature Increases, by Method***

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | Damages for All Temp. Increases and Excludes Duplicates | | | | | | | | |
| Estimation Method | Original | Enumerative | CGE | Statistical | Statistical-Cross Section | Statistical-Panel | Survey | Science | Compensating Surplus |
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| VARIABLESa | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new |
| t2 | 0.318\*\* | 0.212\* | 0.151\*\* | 0.234 | 0.234 | 0.672 | 0.330\* | 0.677\*\*\* | 0.849 |
|  | (0.102) | (0.0822) | (0.0159) | (0.245) | (0.232) | (0.411) | (0.151) | (0.0940) | (0.429) |
| mkt\_t2 | -0.345\* |  |  |  |  |  |  |  |  |
|  | (0.156) |  |  |  |  |  |  |  |  |
| cat\_t2 | 0.362\*\*\* | 0.637 |  |  |  |  |  |  |  |
|  | (0.103) | (0.321) |  |  |  |  |  |  |  |
| prod\_t2 | 0.398 |  |  | 0.439 |  |  |  |  |  |
|  | (0.237) |  |  | (0.422) |  |  |  |  |  |
| Cross | 1.700\*\*\* |  |  |  |  |  |  |  |  |
|  | (0.331) |  |  |  |  |  |  |  |  |
| Observations | 26 | 6 | 3 | 7 | 5 | 2 | 5 | 4 | 2 |
| R2 | 0.869 | 0.769 | 0.954 | 0.596 | 0.0800 | 0.698 | 0.545 | 0.938 | 0.768 |
| Adjusted R-squared | 0.837 | 0.653 | 0.930 | 0.434 | -0.150 | 0.396 | 0.431 | 0.917 | 0.536 |
| Likelihood | -72.41 | -13.00 | -2.313 | -18.15 | -10.76 | -7.094 | -13.24 | -14.59 | -6.141 |
| F-statistic | 776.2 | 7.083 | 90.16 | 2.364 | 1.016 | 2.675 | 4.766 | 51.77 | 3.907 |
| Prob>F | 0.000 | 0.049 | 0.011 | 0.189 | 0.370 | 0.349 | 0.094 | 0.006 | 0.298 |
| Robust standard errors in parentheses | | | | | | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | | | | | |

*a See variable definitions in Table A2 in Appendix A.*

***Table C11: WLS Using Cluster***-***Robust Standard Errors at the Model Level, Estimated Using Low-Temperature Increase Data and Dropping Data Corresponding to Each Data Method, by Method Dropped***

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | Damages for Temp. Increases≤4 °C and Excludes Duplicates | | | | | | | |
| Dropped Estimation Method | Original | Enumerative | CGE | Statistical | Statistical-Cross Section | Statistical-Panel | Survey | Science |
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| VARIABLESa | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new |
| t2 | 0.595\*\* | 0.770\*\* | 0.595\*\* | 0.595\*\* | 0.595\*\* | 0.595\*\* | 0.212\*\*\* | 0.595\*\* |
|  | (0.190) | (0.231) | (0.195) | (0.196) | (0.192) | (0.192) | (0.00991) | (0.193) |
| mkt\_t2 | -0.622\*\* | -0.797\*\* | -0.622\*\* | -0.595\*\* | -0.595\*\* | -0.622\*\* | -0.239 | -0.622\*\* |
|  | (0.226) | (0.266) | (0.231) | (0.196) | (0.192) | (0.228) | (0.129) | (0.229) |
| cat\_t2 | 0.260 | 0.091 | 0.260 | 0.260 | 0.260 | 0.260 | 0.643\*\*\* | 0.254 |
|  | (0.267) | (0.231) | (0.273) | (0.275) | (0.269) | (0.269) | (0.155) | (0.392) |
| prod\_t2 | 0.113 | 0.113 | 0.047 | 0.141\*\*\* | 0.087 | 0.167 | 0.113 | 0.113 |
|  | (0.125) | (0.135) | (0.125) | (0) | (0.0501) | (0.123) | (0.132) | (0.127) |
| Cross | 1.700\*\*\* | 1.700\*\*\* | 1.700\*\*\* |  |  | 1.700\*\*\* | 1.700\*\*\* | 1.700\*\*\* |
|  | (0.343) | (0.369) | (0.350) |  |  | (0.345) | (0.360) | (0.348) |
| Observations | 21 | 15 | 19 | 15 | 16 | 20 | 17 | 19 |
| R2 | 0.722 | 0.757 | 0.724 | 0.781 | 0.778 | 0.725 | 0.730 | 0.668 |
| Adjusted R-squared | 0.635 | 0.636 | 0.625 | 0.702 | 0.704 | 0.633 | 0.617 | 0.549 |
| Likelihood | -44.36 | -29.83 | -40.66 | -33.16 | -35.14 | -42.39 | -34.44 | -39.56 |
| F-statistic | 21.95 |  |  |  |  |  | 138.2 | 16.01 |
| Prob>F | 0.000 |  |  |  |  |  | 0.000 | 0.001 |
| Robust standard errors in parentheses | | | | | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | | | | |

*a See variable definitions in Table A2 in Appendix A.*

***C12: WLS Using Cluster-Robust Standard Errors at the Model Level, Estimated Using All Temperature Increase Data and Dropping Data Corresponding to Each Data Method, by Method Dropped***

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | Damages for All Temp. Increases and Excludes Duplicates | | | | | | | |
| Dropped Estimation Method | Original | Enumerative | CGE | Statistical | Statistical-Cross Section | Statistical-Panel | Survey | Science |
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| VARIABLESa | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new |
| t2 | 0.318\*\* | 0.330\*\* | 0.318\*\* | 0.318\*\* | 0.318\*\* | 0.318\*\* | 0.212\*\*\* | 0.318\*\* |
|  | (0.102) | (0.126) | (0.104) | (0.105) | (0.103) | (0.104) | (0.00942) | (0.104) |
| mkt\_t2 | -0.345\* | -0.356\* | -0.345\* | -0.318\*\* | -0.318\*\* | -0.345\* | -0.239\* | -0.345\* |
|  | (0.156) | (0.176) | (0.159) | (0.105) | (0.103) | (0.158) | (0.122) | (0.159) |
| cat\_t2 | 0.362\*\*\* | 0.347\*\* | 0.362\*\*\* | 0.362\*\* | 0.362\*\*\* | 0.362\*\*\* | 0.468\*\*\* | 0.532 |
|  | (0.103) | (0.126) | (0.105) | (0.106) | (0.104) | (0.105) | (0.0111) | (0.317) |
| prod\_t2 | 0.398 | 0.398 | 0.699\*\*\* | 0.151\*\*\* | 0.372 | 0.177 | 0.398 | 0.398 |
|  | (0.237) | (0.248) | (0.120) | (0) | (0.207) | (0.119) | (0.246) | (0.242) |
| Cross | 1.700\*\*\* | 1.700\*\*\* | 1.700\*\*\* |  |  | 1.700\*\*\* | 1.700\*\*\* | 1.700\*\*\* |
|  | (0.331) | (0.345) | (0.337) |  |  | (0.335) | (0.343) | (0.337) |
| Observations | 26 | 20 | 23 | 19 | 21 | 24 | 21 | 22 |
| R2 | 0.869 | 0.874 | 0.888 | 0.914 | 0.877 | 0.904 | 0.881 | 0.543 |
| Adjusted R-squared | 0.837 | 0.832 | 0.856 | 0.891 | 0.848 | 0.879 | 0.844 | 0.409 |
| Likelihood | -72.41 | -57.43 | -63.16 | -53.33 | -62.86 | -62.53 | -58.97 | -56.47 |
| F-statistic | 776.2 | 2231 |  |  |  |  | 721.6 | 9.892 |
| Prob>F | 0.000 | 0.000 |  |  |  |  | 0.000 | 0.001 |
| Robust standard errors in parentheses | | | | | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | | | | |

*a See variable definitions in Table A2 in Appendix A.*

***Table C13. WLS with Cluster-Robust Standard Errors at the Model Level Using Data that Includes Compensating Surplus Estimates, by Dataset***

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | Damages for Temp. Increases≤4°C | | | | Damages for All Temp. Increases | | | |
| *Include Duplicates* | | *Exclude Duplicates* | | *Include Duplicates* | | *Exclude Duplicates* | |
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| VARIABLESa | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new | D\_new |
| t2 | 0.328\*\* | 0.328\*\* | 0.595\*\*\* | 0.595\*\* | 0.263\*\*\* | 0.263\*\*\* | 0.318\*\*\* | 0.318\*\* |
|  | (0.122) | (0.126) | (0.182) | (0.193) | (0.0596) | (0.0610) | (0.0989) | (0.103) |
| mkt\_t2 | -0.186 | -0.00367 | -0.487\*\* | -0.578\*\* | 0.023 | 0.061 | 0.032 | -0.301\* |
|  | (0.132) | (0.277) | (0.184) | (0.233) | (0.146) | (0.251) | (0.205) | (0.164) |
| nmkt\_t2 | 0.508\*\*\* | 0.459\*\* | 0.253 | 0.140 | 0.572\*\*\* | 0.523\*\*\* | 0.530\*\*\* | 0.417\*\*\* |
|  | (0.122) | (0.152) | (0.182) | (0.205) | (0.0596) | (0.104) | (0.0989) | (0.124) |
| cat\_t2 | 0.403\* | 0.403\* | 0.260 | 0.260 | 0.413\*\*\* | 0.413\*\*\* | 0.362\*\*\* | 0.362\*\*\* |
|  | (0.189) | (0.195) | (0.256) | (0.270) | (0.0603) | (0.0618) | (0.0998) | (0.104) |
| prod\_t2 |  | -0.232 |  | 0.070 |  | -0.046 |  | 0.355 |
|  |  | (0.257) |  | (0.131) |  | (0.288) |  | (0.244) |
| Cross |  | 0.483 |  | 1.311 |  | 0.483 |  | 1.311 |
|  |  | (0.845) |  | (0.817) |  | (0.833) |  | (0.788) |
| Observations | 41 | 41 | 23 | 23 | 46 | 46 | 28 | 28 |
| R2 | 0.593 | 0.611 | 0.707 | 0.725 | 0.838 | 0.838 | 0.858 | 0.862 |
| Adjusted R-squared | 0.549 | 0.545 | 0.645 | 0.628 | 0.822 | 0.814 | 0.834 | 0.824 |
| Likelihood | -93.44 | -92.48 | -52.98 | -52.23 | -122.2 | -122.1 | -79.12 | -78.71 |
| Robust standard errors in parentheses | | | | | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | | | | |

*a See variable definitions in Table A2 in Appendix A. nmkt\_t2 is adjusted temperature squared interacted with an indicator variable equal to one when the study omits market impacts. For all estimates for which this indicator variable is one, damages are measured in compensating surplus and not WTP.*