Raising the Temperature on Food Prices: Climate Change, Food Security, and the Social Cost of Carbon

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Abstract

Climate change will directly affect food availability and security. Because food production is fundamentally a biological process that is a function, in part, of temperature and moisture, the agricultural sector's potential vulnerability is particularly large. While there is ongoing scientific debate over the magnitude of the effect of climate change on overall agricultural production, the welfare effects of increased food insecurity could be substantial. This is because food is a necessary good, such that climate change driven food shortages could significantly raise food costs relative to traditionally manufactured goods. However, U.S. policymakers rely on climate change models that do not reflect these fundamental differences between agriculture and other economic sectors. This paper modifies DICE-2010, an integrative assessment model, by disaggregating agricultural goods from the aggregate consumption good and updating the agricultural damage function. By more accurately measuring the cost of potential food shortages due to climate change and similar shortages in non-market goods, we find that the social cost of carbon increases by a magnitude of approximately one-third In preliminary results.

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Peter Howard and Thomas Sterner

Climate change is the preeminent policy issue that this generation will face. One of the key threats of climate change is the potential that it will undermine humanity's ability to feed itself. Food production is fundamentally a biological process. Unlike many market goods and services, climate, in terms of sunlight and rain, is an essential input into the agricultural production function. As a consequence, the agricultural sector's potential vulnerability to climate change is particularly large. The 2007-2008 world food price crises, when agricultural prices soured partly due to decreased supply, only helped to stoke these fears given the resulting socio-political and economic stability that this event wrought. Food, like water, shelter, and clothing, is essential to life – few people care about manufactured goods when they cannot eat. Thus, the possibility of increased food insecurity from climate change and the potential for rapid rises in food prices are serious concerns for policymaker given the strain they place on the fabric of our society. Some wonder if a Malthusian catastrophe brought on by climate change awaits.

While policymakers and society in general fear that climate change will undermine world food security, there is an extensive debate on how climate change will affect world food consumption. Undoubtedly, climate change will negatively affect food production in some locales, but it is highly uncertain how climate change will affect global food production and consumption; this uncertainty remains even as agriculture is the "sector with the best underlying data and the most extensive research (Nordhaus and Boyer, 2000)." This debate partly stems from countervailing effects of climate change, which make possible the potential for increased production in the short-run, and humanity's ability to adapt locally and globally through changing agricultural practices, shifting crop production, research and development and increase trade. In particular, some question whether human ingenuity will be enough to maintain agricultural growth rates about population growth given the potential strain of adaptation on general agricultural research and development and the potential for increased weather variability to wreak havoc on our current agricultural system. Thus, some fear our society may fall prey to a new Malthusian trap brought on by the same Industrial Revolution that helped us escape it in the first place.

While we would hope that the current policy tools to analyze the effects of climate change would be able to aid us in determining whether fears of food insecurity, rising food prices, and/or a Malthusian collapse are justified, this is sadly not the case. Currently, the preeminent policy tool in the United States to address climate change is the social cost of carbon (SCC). The SCC is an estimate of the total cost of damages done by each ton of carbon dioxide that is spewed into the air. As of 2008, the federal government must include the SCC in all federal cost-benefit analyses. To ensure uniformity at the federal level, the 2010 Interagency Working

Group on the Social Cost of Carbon was formed to develop official U.S. estimates of the SCC. The Working Group used three integrated assessment models (IAMs) – models that integrate simple global models of the climate and the economy together to capture each step in the transformation of a unit of carbon emissions into a welfare loss – to produce the official U.S. estimates: Nordhaus' DICE-2007, Tol's FUND 3.5, and Hope's PAGE2002. In 2013, the Interagency Working Group was again formed to update these numbers using updated versions of these three models: DICE-2010, FUND 3.8, and PAGE09. The current estimate is approximately $40.[1] While each of these models internalizes the cost of climate change on agriculture in some way, as currently structured, they are unable to capture fundamental aspects of food insecurity and the Malthusian threat.

Each of these models has the same structural assumptions that prevent the modeling of food price increases. Currently, the integrated assessment models (IAMs) that estimate the social cost of carbon (SCC) assume constant relative prices for all goods and services. Because goods and services produced outdoors are more sensitive to climate change, climate-driven declines in environmental services and agricultural goods that increase their prices relative to manufactured goods are likely. Combined with the outdated agricultural damage estimates used to calibrate the IAMs' damage functions, the failure to capture the increase in value of outdoor produced goods relative to other traditional consumption goods biases current SCC estimates downwards. To correct for this bias, this research modifies DICE-2010 to model agricultural, other-market, and non-market goods separately and to limit substitutability between these goods on the consumption and production sides of the economy. In doing so, this research develops an IAM that more realistically captures issues relating to food security, particularly the effects of food shortages on the SCC. Thus, our model can potentially capture that climate-driven food shortages could result in the relative value of agricultural goods increasing from its currently insignificant level in most developed nations (Heal, 2009).

Each of these IAMs relies on outdated agricultural damage estimates dating back to the 1990s. Currently, the three IAMs that underlie the U.S. government's SCC estimate rely on optimistic assumptions about the positive effect of the CO_2 fertilization effect on crop yields, and fail to capture the more recent statistical studies that capture a less optimistic picture.[2] To address the possible shortcomings of current IAMs' agricultural damage estimates, future work will test the sensitivity of our results to calibrating our agricultural damage function to differing

[1] The precise, central value for a ton of carbon dioxide emitted in 2015 is $37, in 2007 USD (http://www.whitehouse.gov/sites/default/files/omb/assets/inforeg/technical-update-social-cost-of-carbon-for-regulator-impact-analysis.pdf).

[2] The failure to integrate the more recent statistical estimates of the effects of climate change on agriculture is mostly likely due to several factors: (1) these recent studies analyze crop yields and not dollar effects, (2) these estimates are mostly U.S. centric, and (3) these estimates often fail to account for future adaptation through research and development and trade.

agricultural damage estimates. The current work focuses on analyzing the effect of including relative prices into DICE-2010 using the current agricultural assumptions implicit within DICE-2010.

The goal of addressing the current shortcoming in the IAM literature by differentiating between agriculture and other market sectors is multi-fold. First, we are able to address how future threats to food security from climate change affect the SCC. Given the policy importance of the SCC, capturing a fundamental fear of climate change, such as escalating food insecurity and food prices, is essential to the validity of this instrument. The paper finds preliminary evidence that accounting for the relative prices of agricultural and non-market goods may increase the social cost of carbon by as much as one-third. Second, we are able to assess how differing preference structures, growth in agricultural productivity, and agricultural damage functions affect the SCC. This assessment is key to understanding how various predications about agriculture will affect the SCC, and allow policymakers to determine the potential value of climate policy by assigning their own weights to the various outcomes. Finally, we are able to partially capture the potential cost of a Malthusian like-crisis. Large run ups in the price of agriculture, such that climate damages soar, will partially internalize the cost of a Malthusian collapse into policy. However, IAMs do not currently capture the cost of declining populations from lack of food and the resulting social and political unrest that a dramatic rise in food prices will cause. Thus, the resulting SCC should be interpreted as lower bound estimates of the cost of emitting a unit of carbon.

In this paper, we focus on improving the estimation of the SCC by modifying the DICE-2010 to explicitly model the agricultural sector and integrate various agricultural modeling assumptions into this model. First, we review the IAM and the climate damage literature with a focus on how they address agriculture. Second, we describe our modification of the DICE-2010 model. Third, we present our preliminary results. Fourth, given that our results are preliminary, this paper lays out future work. Finally, we conclude with a summary of this paper and its important preliminary results, and their potential policy implications.

Literature Review

Currently, all three IAMS explicitly or implicitly model agriculture with different levels of transparency. On the one extreme, in FUND, Tol explicitly models the effect of climate on agriculture by calibrating three agricultural damage equations: an impact from the rate of climate change, an impact due to the level of climate change, and an impact capturing the CO_2 fertilization effect.[3] These equations are calibrated using five agricultural studies from the

[3] This first impact captures the rigidity costs in agriculture from farmer maladaptation due to climate change; this impact is always negative and increasing in the rate of temperature change. The second impact captures the effect of temperature level on agricultural production, and can be positive or negative. The third impact captures the effect of CO_2 fertilization on agricultural production, and is always positive.

1990s.[4] Tol finds a positive net effect of climate change agriculture throughout the 21st century (Tol, 2013).[5] On the other extreme, in PAGE, Hope implicitly models damages to agriculture, which are contained within the economic damage function. Due to the relative opaque nature of the calibration of the PAGE09 damage function, which combines earlier damage estimates of DICE and FUND using author discretion, it is impossible to determine how damages to agriculture affect the SCC in PAGE.

The calibration of the DICE damage function is somewhere in between these two extremes. Agricultural damages are implicitly captured using an aggregate global damage function like PAGE. Unlike PAGE, Nordhaus and Boyer (2000) and Nordhaus (2008) explicitly present the region-sector damage estimates for a 2.5 °C increase in global average surface temperature used to calibrate the DICE-1999, DICE-2007, and DICE-2010 aggregate damage functions; the data used to calibrate the DICE-2010 damage function is identical to that of DICE-2007. In DICE-2007 and DICE-2010, DICE's aggregate global damage function is made of seven sectors (agriculture, other vulnerable market,[6] coastal, health, non-market amenities, settlements and ecosystems, and catastrophic impacts) and twelve regions.[7] In DICE-1999, most regional agricultural impact estimates are drawn from Darwin et al (1995),[8] particularly Table B6, using the second most favorable GCM scenario and unrestricted land use (Nordhaus and Boyer, 2003; Warren et al., 2006). Thus, all of the assumptions in Darwin et al (1995) are implicitly included in DICE's agricultural damage estimates, including the assumption that there is no fertilization effect and resource constraints (land and water) are not included. In DICE-2007 and DICE-2010, Nordhaus updated the calibration source of his agricultural damage estimates to a "judgmental average" of various estimates from Cline – though the specific sources are unclear.[9] Given the inclusion of CO_2 fertilization effect in the Cline estimates, agricultural impacts are less severe, though not universally so. To make matters difficult, Nordhaus (2008) does not provide the globally weighted damage estimates for each sector in DICE-2007 and DICE-2010; see Table 4a.

[4] The five data sources for the FUND agricultural damage function are: Kane et al. (1992), Reilly et al. (1994), Morita et al. (1994), Fischer et al. (1996), and Tsigas et al. (1996).

[5] In fact, FUND predicts a 0.8% increase in GDP from climate change due to agriculture. This increase is solely due to the positive effects of CO_2 fertilization (Tol, 2013).

[6] The other market sector includes climate sensitive market sectors other than agriculture: forestry, fisheries, water transportation, hotels and other lodging places, outdoor recreation, and energy.

[7] The twelve regions in DICE-2007 and DICE-2010 include: United States, Western Europe/European Economic Zone, Other-High Income, Russia, Eastern Europe/Former Soviet Union, Japan, China, India, Middle Easter, Sub-Saharan Africa, Latin America, and Other Asian.

[8] Because Darwin et al (1995) uses slightly different regions than DICE/RICE, Nordhaus and Boyer (2003) use two Ricardian studies to adjust two of DICE/RICE's regional estimates: Dinar et al (1998) for India and Sanghi et al. (1997) for Brazil in the Middle Income Region.

[9] Nordhaus (2007) states that "we introduced Cline's agricultural studies. These were generally more positive than our earlier estimates, and we took a judgmental average."

Despite the difficulties of isolating the agricultural damage function in DICE-2010, we choose to utilize the DICE-2010 model for the purposes of this project. Primarily, this choice is due to the relative ease of modeling relative prices in DICE (and RICE) compared to FUND and PAGE. Unlike FUND and PAGE, DICE is an optimization model. The maximization structure allows us to avoid adjusting the Ramsey discount rate, adjusting equity weights, and including parametric equations for the relative prices of agriculture and environmental goods. The other reason for choosing DICE is that its structure also allows us to model agricultural production explicitly with some model modification. With this modification, the optimization structure of DICE allows us to capture the substitution of inputs between production activities.

Relative Prices[10]

Climate change is predicted to affect market and non-market goods produced outdoors (such as agricultural, fisheries, forestry, and environmental goods and services) more than market goods produced indoors; market goods insensitive to climate change account for the majority of GDP (Nordhaus and Boyer, 2000). As a consequence, outdoor produced goods will become relatively scarcer than indoor produced goods over time. Based on the law of scarcity, the value of outdoor produced goods and services will increase relative to indoor produced market goods. However, current damage estimates to climate sensitive goods and services reflect the current ratio of their economic value to climate insensitive goods, which is based on the current ratio of their quantities. By extrapolating these estimates to future time periods without making any explicit adjustment for relative prices, that is, without accounting for relative change in value of outdoor produced goods and services to indoor produced goods over time, the developers of IAMs implicitly assume constant relative prices, and bias the SCC downward.

A methodically sound way to address this issue is to explicitly model relative prices. However, most IAMs (including DICE, FUND, and PAGE) include only an aggregate consumption good, as measured by per capita consumption, in the social welfare function.[11] On the consumer side of the economy, this assumption implies all goods and services, including market goods and non-market goods, are perfectly substitutable (even in the long-run), and that they have constant relative prices (Gerlagh and van der Zwaan, 2002; Sterner and Persson, 2008).[12] Constant relative prices imply the ratio of the prices of any two goods must remain constant, regardless of the amounts available of either good.[13] As a consequence, the current IAMs fail to capture

[10] This sub-section is a direct citation of Howard (2014).

[11] This aggregate consumption good, often referred to as a numéraire, equals the combined economic values of all market and non-market goods divided by the global population. However, in practice, it often equals only the value of market goods.

[12] All three IAMs include only an aggregate consumption good in the social welfare function, and so assume constant relative prices and perfect substitutability. While FUND 3.6 does account for the increase in the relative value of habitat services due to the loss of species, this is done in a very limited way.

[13] Constant relative prices imply that a decline in the supply of a consumption good (market or non-market) does not affect its price relative to all other goods and services. If the relative price of the good were to increase in

the increase in value of outdoor produced goods and services relative to other traditional consumption goods produced indoor (Gerlagh and van der Zwaan, 2002; Sterner and Persson, 2008). [14] Therefore, the simplifying assumption of modeling only one generalized consumption good biases the social cost of carbon estimates downward because future damage estimates to climate sensitive goods and services fail to account for the increase in relative value of these goods and services, as discussed in the previous paragraph.

Recent work has looked at the effect of disaggregating per capita consumption into market goods and non-market goods. Developing a simple social welfare function with two sectors (market and non-market) that grow at different rates, Hoel and Sterner (2007) find that increasing consumption of market goods and constant or decreasing consumption of environmental services will increase the relative value of environmental services due to their increasing relative price when the elasticity of substitution is less than one, that is, it is difficult to substitute market goods for non-market goods.[15,16] Hoel and Sterner (2007) demonstrate, as Gerlagh and van der Zwaan (2002) did before them, that the value of market goods will collapse to zero in the long run if these paths continue. After deriving an updated equation for the discount rate (similar to the Ramsey equation) resulting from the new specification, Hoel and Sterner (2007) also find that the combined effect of a newly derived discount rate and the change in relative prices can result in damage estimates that exceed those calculated under traditional discounting.[17] The work in Hoel and Sterner (2007) applies to any two sectors of the economy.

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response to this decline in supply, there would be no demand for the good because consumers could obtain more utility (i.e., welfare) by switching their expenditure to all other goods and services (due to the perfectly substitutable assumption). This would put downward pressure on the good's price until it reached its original value relative to all other prices.

[14] Discussions about changing relative prices date back to earlier literatures. Neumayer (1999) calls this argument the Krutilla-Fisher rationale from Krutilla and Fisher (1975). In the context of manufactured and public goods, Baumol (1967) describes a similar phenomenon called Baumol's disease. The discussion of changing relative prices also has roots in the earlier literatures of weak sustainability and strong sustainability.

[15] In this context, the elasticity of substitution measures the ease at which market goods can be substituted for non-market goods. An elasticity of substitution less than one implies that market goods and non-market goods are complements in the long run. In the extreme, perfect complements are when market goods cannot be substituted at any level to make up for the loss of non-market goods. An example would be subsistent water levels, where no amount of a market good can replace its value. An elasticity greater than one implies that market goods and non-market goods are substitutes (Heal, 2009). In the extreme, perfect substitutes are when market goods can be substituted at a constant rate to make up for a loss of non-market goods, regardless of the level of non-market goods available.

[16] In the language of sustainability, elasticity less than one implies strong sustainability in the long run and an elasticity greater than one implies weak sustainability in the long run.

[17] It should be unsurprising that the discount rate requires updating because growth rates of man-made and environmental goods and services differ. In addition, the rationale for discounting, i.e., that the future will be better off due to continued economic growth, is weakened with the elimination of the perfect substitutability assumption.

To empirically capture the effects of modeling the relative price of non-market goods on the optimal emissions path, Sterner and Persson (2008) modify DICE to restrict substitutability between non-market and market goods. Like Hoel and Sterner (2007) and Neumayer (1999) before them, Sterner and Persson (2008) find that allowing a change in relative prices can increase the costs of climate change relative to a model assuming constant relative prices. More specifically, the authors find that damages double from 1.05 percent of GDP for a 2.5 degree Celsius increase to 2.1 percent of GDP; this implies that the SCC would also increase with a switch away from constant to relative prices. Using their base parameters, Sterner and Persson (2008) also find that allowing for a change in relative prices achieves a lower optimal emissions path than the Stern Review (Sterner and Persson, 2008; Heal, 2009).[18] In this sense, relative prices can be as important as the discount rate in determining the optimal climate change prevention policy. However, their results are highly dependent on the assumed elasticity of substitution. The lower the actual elasticity of substitution is, that is, the more difficult it is to substitute market goods for lost non-market goods to make society as equally well off under climate change, the more likely the current integrated assessment models are to underestimate the environmental cost of climate change by assuming perfect substitutability. Thus, we are left with uncertain parameters determining model outcomes – the elasticity of substitution determining the SCC.[19]

There has been little attempt to integrate the relative price of agricultural goods into integrated assessment models. While the agricultural damage estimates used in IAMs are drawn from CGE studies, which capture some relative price changes, these changes are limited because they model only the effects of limited agricultural damages in the near short-run. Given then work of

[18] Initially, Sterner and Persson (2008) assume that elasticity of substitution is equal to 0.5, 10 percent of current utility comes from non-market goods, and that 50 percent of damages are attributable to non-market goods. The remaining parameters follow the standard assumptions of DICE.

[19] In the context of market and non-market goods, this recasts the argument about whether or not to act now from a disagreement about the discount rate into a debate of whether poor (strong) sustainability or perfect (weak) sustainability, that is, an elasticity of substitution less than or greater than 1 in the context of the CES utility function, holds in the long run (Gerlagh and van der Zwaan, 2002). Unlike the pure rate of time preference and the elasticity of the marginal utility of consumption, the elasticity of substitution is not an ethical parameter. However, there is still considerable uncertainty about this parameter due to a lack of empirical data (Neumayer, 1999). Sterner and Persson (2008) argue that a lower elasticity of substitution is more likely because some environmental goods are unique and irreplaceable (for example, drinking water), and these goods are likely to dominate the calculation of the elasticity of substitution as environmental goods become more scarce. In a similar argument, Heal (2009) states that market goods and environmental services are complements because some of the services in the former group are irreplaceable and essential to life (Heal, 2009; Dasgupta and Heal, 1979). Heal (2009) points out that this has two implications: some level of environmental services is essential and that the elasticity of substitution is not a constant. Gerlagh and van der Zwaan (2002) demonstrate that even if the substitutability varies with the amount of environmental services, there often exists a level of environmental services below which poor substitutability occurs in the long run. While these arguments support an elasticity of substitution below which it is difficult to substitute consumption goods for environmental goods (elasticity of substitution of less than one), future debate is likely to ensue as current statements are more a matter of belief due to a lack of empirical evidence (Neumayer, 1999).

Hoel and Sterner (2007) and Sterner and Persson (2008), IAMs current failure to model the relative price of agriculture has the potential to significantly bias the social cost of carbon downwards. However, there are some key ways in which the agricultural sector is different than the non-market sector. First, while the work in Hoel and Sterner (2007) theoretically applies to any two sectors of the economy, including agricultural and other-market sectors, a major real-world difference between non-market goods and agricultural goods that will undoubtedly affect the results of this paper is that the latter are market produced goods. Thus, in response to agricultural price increases, society can transfer labor to, increase capital investment in, and increase research and development in the agricultural sector. Second, unlike non-market goods, many of the preference parameters for the agricultural sector are empirical available. Specifically, the elasticity of substitution between food and other market goods has been estimated, and is, in general, found to be inelastic.

Agricultural damage estimation

The realized price effects of climate change on agricultural goods are highly dependent on the magnitude of agricultural climate damages. While a substantial literature analyzing the potential effects of climate change on agriculture exists, there is little consensus due to considerable scientific uncertainty (Schlenker and Roberts, 2008). The uncertainty partially arises due to the large number of existing methods to estimate the effects of climate change on agriculture.

In this literature, there are three predominant methods of analysis (Schlenker, Hanemann, and Fisher, 2006). The agronomic approach is to develop a complex theoretical model of plant growth and seed formation to simulate yields. While this approach has the advantages of accounting for the whole distribution of weather outcomes (not just average outcomes) and avoiding econometric problems such as misspecification and omitted variable bias, it cannot model adaptation through changes in farmer behavior and technological development. As a consequence, the resulting damage estimates tend to be on the higher end of agricultural damage estimates (Schlenker, Hanemann, and Fisher, 2005).

The empirical method uses current variation in climate to analyze the effects of climate on land values, crop yields, or crop output.[20] The most common empirical strategy is the Ricardian approach whereby farmland value is regressed on land characteristics, including climate characteristics. While this method captures farm-level adaptation and allows for small scale analysis (e.g. farm and county level), this approach is only a partial equilibrium analysis (e.g. prices are exogenous), suffers from the typical econometric problems of misspecification and

[20] Some categorize the empirical production function approach of regressing yields on property characteristics, including climate, as an empirical agronomic approach. Like the agronomic approach, it assumes the farmers do not adapt by planting a different crop or changing their land use allocation (Mendelsohn, Nordhaus, and Shaw, 1994).

omitted variable bias (Schlenker, Hanemann, and Fisher, 2005), and fails to capture CO_2 fertilization effects. Early Ricardian work by Mendelsohn, Nordhaus, and Shaw (1994) was believed to demonstrate that the agronomic approach greatly overestimated the resulting climate damages to agriculture. However, more recent work by Schlenker, Hanemann, and Fisher (2005, 2006. 2007) demonstrated that early Ricardian analyses, such as Mendelsohn, Nordhaus, and Shaw (1994), incorrectly pooled irrigated and non-irrigated (dryland) crop lands producing downwardly biased loss estimates.[21] By introducing agronomic-based climate, soil, and water availability variables, adjusting for spatial autocorrelation using finer spatial scale models, and correcting for these pooling errors, the authors demonstrate that the cost of climate change to U.S. agriculture under more recent climate scenarios are likely to be more in line with the agronomic literature than the early Ricardian studies.[22,23]

The general equilibrium approach integrates the results from the previous two approaches into a computable general equilibrium (CGE) model.[24] While CGE models capture sector-level adaptation through shifts in geographical locations of crops and changes in resource reallocation (including land), they rely on analyst specified farm-level adaptation and CO_2 fertilization assumptions (Schlenker, Hanemann, and Fisher, 2006). Using the CGE approach,

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[21] Schlenker, Hanemann, and Fisher (2005) demonstrate that previous empirical estimates are biased due to a pooling of irrigated and non-irrigated (dryland) crop lands because precipitation does not measure available water supply. Specifically, Schlenker, Hanemann, and Fisher (2005) point out that California and Arizona are high value agricultural states in spite of their high temperatures, not because of them. Thus, pooling implies that as currently cooler regions increase in temperature that they will also obtain water supplies similar to that of the currently warmer regions.

[22] Schlenker, Hanemann, and Fisher (2005) estimate a negative impact on non-irrigated U.S. agriculture of between \$5 billion and \$5.3 billion in 1982 dollars for a uniform five degree Fahrenheit and an eight percent precipitation increase, Schlenker, Hanemann, and Fisher (2006) estimates the economic cost of climate change to U.S. dryland agriculture east of the 100 meridian to be between a 10% and 25% decline in current cropland value (a cost of between \$3.1 billion to \$7.2 billion a year) from 2020-2049 and between 27% and 69% of cropland value from 2070-2099 under five different climate scenarios. Controlling for effective water supply, Schlenker, Hanemann, and Fisher (2007) demonstrate that a loss of two acre feet per acre in California due to a reduced snowpack will decrease California agriculture value by 40%; this assumes that no capital investment is made to reduce the loss of California's snowpack.

[23] Deschenes and Greenstone (2007) argue that the work of Schlenker, Hanemann, and Fisher suffers from omitted variable bias. Fisher et al. (2009) finds significant yield and profit losses for both U.S. corn and soybean using the panel data from Deschenes and Greenstone (2007) after correcting for several empirical issues including data construction errors. Under the Hadley III-B2 scenario, the authors find yield losses of 65.6% and 75.7% for corn and soybean, respectively, and combined profit losses of 53%. Furthermore, Fisher et al. (2009) argue that short-run cost estimates do not represent upper bounds because of the ability to engage in unsustainable practices, such as storage and ground water pumping.

[24] In a similar approach, results from agronomic models can be plugged into non-linear programming models, e.g. Adams et al (1995), to capture farmer-level adaptation. Schlenker, Hanemann, and Fisher (2006) criticize these non-linear programming models for being partial equilibrium models, ignoring fixed costs, and making arbitrary calibration assumptions. The latter two criticisms are slightly unfounded because there are no fixed costs in the long-run and calibration constraints can capture economic meaning and are not necessarily arbitrary (Howitt, Medellín-Azuara, and MacEwan, 2009). These partial equilibrium models are sometimes classified as part of the agronomic approach.

several authors have argued that regardless of the effect on an individual country's agricultural production that overall production should not significantly decrease as increases in higher latitude countries (often developed countries) balances out decreases in lower latitude countries (often developing countries); trade further helps to minimizes welfare losses by re-allocating production benefits from higher latitude to lower latitude nations (Reilly, Hohmann, and Kane,1994; Rosenzweig and Parry, 1994; Darwin et al, 1995). Currently, IAMs predominately use agricultural damage estimates from the CGE approach to calibrate their damage functions. This approach is mostly likely chosen because it produces regional cost estimates for the entire world that are convenient to plug into IAMs, rather than producing yield or output effects for particular countries or regions that are difficult to integrate into current IAMs.

Several economists, most notably Ackerman, criticize the use of the particular subset of 1990s CGE studies used in IAMs for several reasons. First, these studies are outdated. Since the 1990s, estimates of yield loss (without the CO_2 fertilization effect) have increased and estimates of the CO_2 fertilization effects have decreased (Ackerman, 2010; Warren et al., 2006)**.** In other words, the CGE model estimates are only as reliable as their data, and these CGE model estimates rely on outdated effects as evidence by recent work by Schlenker and other economists that highlight the importance of weather variability and land temperature.[25] Second, these studies are missing potentially important sub-regional effects due to their aggregate spatial scale (Hanemann, 2008). Third, several of these studies allow for regional agricultural expansions without considering binding resource constraints (Warren et al, 2006; Kane et al., 1992). In the limited cases where resource constraints were considered, the effects of climate change on these constraints are ignored: the loss of agricultural land (to sea level rise and erosion) and changes in temporal-spatial water availability. Fourth, some of these studies allow for high levels of adaptation that are not supported by the data. In particular, Schlenker and Roberts (2008) find that crop yields rapidly decline above critical temperature thresholds (Hanemann, 2008), and argue that the robustness of this result indicates a lack of increasing heat tolerance over time as predicted by many adaptation assumptions. Last, Cline (2007) argues that these models make over-optimistic assumptions about technological advancement.

There are several other alternative global agricultural damage estimates to the recent CGE models. First, using both an agronomic model and a Ricardian model to estimate yield effects, Cline (2007) estimates a loss of world-wide agricultural productivity of 16% and 3% without and

[25] Cline (2007) points out that the temperature above land is higher than the temperature above water, which results in the temperature above land exceeding the average global temperature. An increase in the average global temperature of 3 degrees Celsius implies an increase in temperatures above land and agriculture of 5 and 4.4 degrees Celsius, respectively. Hanemann (2008) makes a similar argument that the aggregate spatial and temporal scales of damage estimates can mask higher damages. An increase in the average global temperature of 2 degrees Celsius implies an increase of five degrees in the Central Valley of California during the summer.

with fertilization, respectively. Unlike the studies in the previous paragraph, Cline (2007) does not plug these effects in a CGE model, he makes a more conservative CO_2 fertilization assumption, and assumes no technological advancement.[26,27] Second, using a panel dataset, Lobell, Schlenker, and Costa-Roberts (2011) analyze the effect of temperature trends on worldwide maize, rice, soybeans, and wheat from 1980 to 2008 using a panel dataset; these four crops account for 75% of human calorie consumption. By detrending temperature and precipitation to estimate the effects of climate change, the authors find a global net loss of maize and wheat of 3.8% and 5.5%, respectively, and no effect on rice and soybeans; this estimation strategy allows the author to capture both short-run adaptation and technological advancement. After accounting for a 14% increase in yields of C3 crops due to the fertilization effect (Ainsworth et al. 2008), the authors find an increase in rice and soybean yields and a decline in maize and wheat yields; food prices increase regardless.[28] As in the other studies, agriculture in high elevation regions initially benefits from climate change, and agriculture in low elevations regions loses.

In this paper, we aim to estimate the effect of including the relative price of agriculture on the SCC using DICE-2010. While there is debate over the effects of climate on agriculture in the U.S. and worldwide, we maintain the implicit agricultural damage estimates in DICE that likely correspond to the CGE approach. The CGE models estimated in the 1990s find little effect of climate change on agriculture at the international scale; these predictions differ from more recent empirical papers that find declines using different estimation strategies. Additionally, while there is consensus that agriculture in poorer nations will be negatively affected by climate change, given the aggregate nature of DICE-2010, we are unable to model the effect of this regional disparity. This is particularly problematic given that poor nations are less able to adapt to climate change and their economies are more dependent on agriculture. Finally, while the shifting location of agricultural activities and trade will most likely decrease the economic costs of climate change, as captured by CGE estimates, rigidity will result in a corresponding cost of movement; these costs are excluded from the CGE estimates included in DICE-2010 (Freeman and Guzman, 2009). Future work will attempt to address these shortcomings – particularly the effects of updating global agricultural damage estimates. In the meantime, the current SCC estimates should be interpreted as a lower bound.

[26] Cline (2007) assumes a CO_2 fertilization effect of 15%. This is a decrease with respect to earlier laboratory experiments. Cline (2009) justifies this assumption by emphasizing that "in one such open-air study, at 550 parts per million (ppm) of CO_2, wheat yields only went up 13 percent, in contrast to 31 percent in lab studies. Likewise, soybean yields in the field only went up 14 percent, compared to 32 percent in lab studies."

[27] Cline (2007; 2009) argue that technological advancement will not make up for losses due to climate change because (1) global populations will continue to increase, (2) income growth will result in further increases in demand for food, particularly resource intense food like meat, (3) technological advancements in agriculture have slowed since the 1960s and 1970s, and (4) increases in ethanol production.

[28] Overall, world food prices increase by 18.9% and 6.4% with and without CO_2 fertilization effects, respectively.

Modifications

We make several modifications to the DICE-2010 model to capture the relative price of agriculture. Specifically, we replace the utility function, include an additional production function for agricultural goods, and specify the agricultural, other market, and non-market damage equations. Each of these equations is calibrated using the existing literature, including the amount of technological progress in the agricultural sector. With respect to the inclusion of the relative price of non-market goods, we internalize many of the assumptions made in Sterner and Persson (2008).

Utility function

This paper extends the work of Sterner and Persson (2008) by imposing imperfect substitutability between agricultural and other market goods. To capture the change in the relative price of agricultural goods, the isoelastic utility function in DICE is replaced with a nested utility function where the consumption good (C) is a weighted combination of per capita agricultural consumption (A) and per capita consumption of other-market goods (X); the utility function now takes the form:

$$U(C,E) = L * \left[(1-\gamma_2)C(X,A)^{\frac{\sigma_2-1}{\sigma_2}} + \gamma_2 E^{\frac{\sigma_2-1}{\sigma_2}}\right]^{(1-\alpha)\sigma_2/(\sigma_2-1)} \Big/ (1-\alpha)$$

and

$$C(X,A) = \left[(1-\gamma_1)X^{\frac{\sigma_1-1}{\sigma_1}} + \gamma_1 A^{\frac{\sigma_1-1}{\sigma_1}}\right]^{\sigma_1/(\sigma_1-1)}$$

where L is the world population, E is the non-market good (this is a gross measure), α is the elasticity of the marginal utility of consumption, γ is the share parameter, σ is the elasticity of substitution, and $j \in \{1,2\}$ gives the level within the utility function.[29] The agricultural goods should be thought of as agricultural food stuffs, and not fuel, forestry, or fabrics. Currently, we include fisheries in the other-market sector.[30]

There are two options with respect to determining the elasticity of substitution between food and other-market goods. First, we can estimate σ_1 and γ_1 by estimating global demand equations for other-market goods and agricultural goods assuming that the amount of non-market goods is exogenously determined. A time series of world GDP, value of agricultural consumption, and prices of market and agricultural goods is necessary over several decades in

[29] As in Stone-Geary preferences, positive minimum consumption levels for agricultural, non-market, and other-market goods could be set or estimated. Currently, I assume that these values are equal to zero.

[30] Alternatively, we could include forestry and/or fishery production in agriculture to fully capture the relative price of highly sensitive market sectors.

order to estimate these equations. Second, we can try to find this elasticity of substitution in the literature, and conduct a sensitivity analysis over its value. Regardless of the method chosen, sensitivity analysis over the value of σ_2, as in Sterner and Persson (2009), is still necessary. This paper chooses the latter method.

The parameters in the first stage of the utility function are drawn from macroeconomic literature. There is a general consensus that the elasticity of substitution between food and non-food is less than one because the demand for food is inelastic (Pourroy, Carton, and Coulibaly 2013). Focusing on the monetary policy of developing countries, Anand and Prasad (2012) calibrate an elasticity of substitution between food and non-food of 0.6, such that own price elasticity of demand for food is -0.3 matching the USDA value. However, this value is dependent on a subsistence level of food consumption. Based on the Anand and Prasad (2012) estimate, Pourroy, Carton, and Coulibaly (2013) find that the elasticity of substitution between food and non-food is 0.3 when the subsistence level of food consumption is set equal to zero. While we may be concerned that elasticity of substitution is higher in developed countries, Ishikawa, Ueda, Arai (2012) assumes an elasticity of substitution between food and non-food of 0.5 for Japan, and Petith (1976) assumes an elasticity of substitution between food and manufactured goods of 0.6 for Western Europe. Based on this range of results, we assume $\sigma_1 = 0.5$. Following Sterner and Persson (2009), we assume that $\sigma_2 = 0.5$ in the base scenario.

A similar argument follows for the share of food in the market good consumption index, γ_1. Anand and Prasad (2010) find a share parameter value of 0.2585 such that average household expenditure on food is equal to 42% given their assumed subsistence level of food consumption; 42% is clearly the food expenditure level of a developing country. Alternatively, Pourroy, Carton, and Coulibaly (2013) calibrates share parameters of 0.48, 0.31, and 0.2 for low, medium, and high income countries assuming a zero subsistence level of food consumption. Unlike Pourroy, Carbon, and Coulibaly (2013), Ishikawa, Ueda, and Arai (2012) assume a share parameter of 0.042 for Japan, a high income country. Based on these values, we assume a value of 0.1 as the halfway point between the share parameters of high income countries in Pourroy, Carton, and Coulibaly (2013) and Ishikawa, Ueda, and Arai (2012). Following Sterner and Persson (2009), we assume that $\gamma_2 = 0.1$ in the base scenario.

Sensitivity of the results to the specification structure and the various preference parameters will be tested. First, we test the sensitivity of results to the nested functional form by also modeling utility as

$$U(C,E) = L * \left[(1-\gamma_1-\gamma_2)X^{\frac{\sigma_2-1}{\sigma_2}} + \gamma_1 A^{\frac{\sigma_2-1}{\sigma_2}} + \gamma_2 E^{\frac{\sigma_2-1}{\sigma_2}}\right]^{(1-\alpha)\sigma_2 / (\sigma_2-1)} \Big/ (1-\alpha).$$

This specification allows for different substitution relationships between the various goods and services in the model. Second, we will also vary the elasticity of substitution and the share parameters. We will run alternative specifications where σ_1 is equal 0.3 and 0.9, σ_2 is equal 0.3 and 0.9, and where γ_1 is equal to 0.05, 0.2, and 0.3.

Production functions

In DICE, the production of market goods is modeled because growth is endogenous. Currently, the use of an aggregate consumption good in DICE imposes an identical production function on all goods and services; $Q = f(L, K) = AL^{\beta}K^{1-\beta}$ where L is total labor (equivalent to the population size) and K is the amount of capital. The splitting of market goods into agricultural and other-market goods provides the unique opportunity to relax this assumption by assuming unique production functions for each market good. For the agricultural good, a Cobb-Douglas production function of the form $Q_2 = g(L_2, K_2) = \mathrm{A}_2 {L_2}^{\beta_2} {K_2}^{1-\beta_2}$ will be used where L_2 and K_2 are the labor and capital used in agricultural production.[31] Other market goods (Q_1) is equal to $Q_1 = Q - Q_2$; the choice to not explicitly model the production function of other market goods reduces the number of parameters that require estimation.

<u>Agricultural production function</u>. There are two options with respect to determining the agricultural production function. First, we can estimate the parameters: β_2 and A_2. β_2 is an exogenous static parameter equal to the ratio of the total cost of agricultural labor to the value of agricultural output. Total factor productivity, A_2, is an exogenous dynamic parameter that captures (Hicks neutral) technological change. Following the functional form of total factor productivity of the overall economy

$$A(t) = \frac{0.03}{\prod_{t=1}^{T}\left(1 - 0.16 * e^{-0.09\mathrm{t} * e^{-0.02t}}\right)},$$

technical innovation in the agricultural sector will have the form

$$A_2(t) = \frac{\mathrm{A}_{2,0}}{\prod_{t=1}^{T}\left(1 - \mathrm{A}_{2,1} * e^{-\mathrm{A}_{2,2}\mathrm{t} * e^{-\mathrm{A}_{2,3}t}}\right)}.$$

The functional form can be calibrated using the method described in Nordhaus and Boyer (2000) on pages 47 and 50 using studies that measure and predict total factor productivity; see Table 2. Second, we can try to find this production function in the literature; the resulting

[31] An alternative would be to assume an agricultural production function of the form $g(L_{2,r}, K_{2,r}) = \mathrm{A}_{2,r} {L_{2,r}}^{\alpha_{2,r}} {K_{2,r}}^{\beta_{2,r}} {E_r}^{1-\alpha_{2,r}-\beta_{2,r}}$ where $L_{2,r}$ and $K_{2,r}$ are the labor and capital used in the production of the market good in region *r* and E_r is the level of non-market (environmental) services in region *r*. Non-market services (E_r) in the agricultural production function captures the indirect effects of climate change, such as declines in the available water supply, and excludes the direct effects of temperature and CO_2 on agricultural production. This functional form will be make the solution more difficult to find, and is avoided for reasons of tractability.

equation may be inconsistent with Nordhaus' estimate of total factor productivity for the overall economy and the use of the functional form specified above. Regardless of the method chosen, we will also need to determine the initial values for the amount of labor, capital, and output in agriculture.

This paper mostly follows the Nordhaus and Boyer (2000) calibration methods. First, the elasticity of agricultural output with respect to labor, i.e., β_2, is taken from the literature. Based on the estimates in Table 1, we choose an elasticity of 0.35; this value is approximately equal to the mean, median, and mode of all studies in Table 1 that assume constant returns to scale.[32] This number is far lower than the elasticity of the overall economy of 0.7; agricultural production is more labor intensive, and thus, we should expect agricultural output to be more inelastic with respect to labor.

Second, we assume that agricultural accounts for 5.2% of GDP in 2005. According to the FAO, the gross production value of world agriculture is $2.03955 trillion in constant 2004-2006 U.S. dollars; 5.2% is the resulting percentage from dividing this number by the World Bank's measure of GDP in 2005. This number is close to the CIA's measure of 5.9% in 2012.[33] Using DICE's measure of output after damages before abatement of $55.225 trillion and the percentage of agricultural damage from climate change (calculated later on), agriculture output in 2005 is assumed to equal $55.22 trillion*0.052*(1+0.0055)=$2.88748 trillion.[34]

Third, we assume that the 36.4% of the world labor force is in agriculture in 2005 based on the CIA's measurement. This is similar to the finding of Pourroy, Carton, and Coulibaly (2013) that the agricultural sector accounts for approximate one-third of employment. However, this number is slightly lower than the 40.09% of the population that is in agriculture in 2005 according to the FAO.

Fourth, we assume that capital in agriculture accounts for 5.44% of total capital. According to the FAO, the gross capital stock in world agriculture in 2005 was $5.28845273 trillion in constant 2005 prices; this measure of agricultural capital stock includes $1.671665 trillion in land development, $1.444389 in livestock (fixed assets), $1.24413 in machinery and equipment, $0.404196 trillion in plantation crops, $0.269174 trillion in structures for livestock, and 0.254892 livestock (inventory). The 5.44% is derived by dividing the value of agricultural capital by the value of total capital in the DICE 2010 model, which is $97.3 trillion. To give these numbers some perspective, the ratio of FAO's measure of gross capital stock in agriculture to

[32] It should be noted that the corresponding mean and median of the literature written in the last two decades is approximately 0.29.

[33] According to the World Bank, the value added of agriculture (farming, forestry, hunting, and fishing) to the world economy is 3.14% of GDP in 2010 where "value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs (http://data.worldbank.org/indicator/NV.AGR.TOTL.ZS/countries?display=default)."

[34] Agricultural output after damages before abatement equals $55.22 trillion*0.052=$2.87169 trillion.

the value of agricultural production is 259% and the ratio of DICE's measure of gross capital stock to GDP is 176%; a similar ratio holds for agriculture in DICE.[35] Given that DICE's measure of the aggregate capital stock is calibrated, such that other factors (like land) are included in capital, this lower ratio in DICE is surprising. As will be discussed later, the amount of capital in agricultural may also need to be calibrated as evidenced from the results.

Last, we calibrate the total factor productivity term over time in three steps. In the first step, we calculate total factor productivity in the base year. Rearranging $Q_2(0) = \Omega_2(0)[\mathrm{A}_2(0)\mathrm{K}_2(0)^{\gamma}\mathrm{L}_2(0)^{1-\gamma}]$ where $Q_2(0)$, $\Omega_2(0)$, $\mathrm{A}_2(0)$, $\mathrm{K}_2(0)$, and $\mathrm{L}_2(0)$ are the value of agricultural output, climate damages to agriculture as a percentage of agricultural output, total factor productivity, capital, and labor in 2005, respectively, we calculate total factor productivity in 2005 as $\mathrm{A}_2(0) = \frac{Q_2(0)}{\Omega_2(0)\mathrm{K}_2(0)^{\gamma}\mathrm{L}_2(0)^{1-\gamma}} = \frac{2.88748}{(1-0.0055)5.28845^{1-0.35}(0.364*6411)^{0.35}} = 0.06515$; $\Omega_A(0)$ is the percentage damage to agriculture in 2005 due to climate change, and it is equal to $\Omega_A(0) = \frac{h_A(0.830,0.11)}{1+h_A(0.830,0.11)}$ where $h_A(0.830,0.11)$ is defined later in the paper.

In the second step, we calibrate total factor productivity growth. As mentioned above, we assume an exogenous exponential trend in technological progress. We calibrate the three parameters in the agricultural total factor productivity growth rate function ($\mathrm{A}_{2,1}$, $\mathrm{A}_{2,2}$, and $\mathrm{A}_{2,3}$) to match current estimates and future predictions of total factor productivity and to match the growth rate in total factor productivity of the overall economy in the final time period.[36] A variety of point estimates exist in the literature, see Table 2, which can result in a large array of total factor productivity curves. However, we restrict these curves to those that are monotonically decreasing over time so as to match the shape of total factor productivity growth in DICE for the overall economy; see Figure 1. We select the curve that corresponds to total factor productivity growth equaling 1.34% in 2005 (Fugile, 2010), 1% in 2025 (Linehan et al, 2013), and the same growth rate as DICE-2010 for the overall economy in 2395. The resulting parameters are: $\mathrm{A}_{2,1} = 0.02819972$, $\mathrm{A}_{2,2} = 0.00792198$, and $\mathrm{A}_{2,3} = 0.0001889$. The resulting curve is below the DICE-2010 total factor productivity curve for all market goods, and it converges to DICE-2010 over time. Future work will test the sensitivity of the results to this total factor productivity curve.[37]

[35] Interestingly, a World Bank dataset measuring aggregate capital stock found that the ratio of the value of capital stock to GDP ranged between 263% and 295% between 1975 and 1990 (Nehru and Dhareshwar, 1993). These percentages are much closer to the FAO ratio than to the DICE ratio.

[36] Nordhaus and Boyer (2000) calculate the parameters in the growth function for the overall economy by (1) choosing the initial rate of productivity growth so that growth between the first and second periods in per capita output matches the assumed rates, and (2) calculating the decline in this rate of growth at an exponential rate to fit the assumed asymptotic level of output per capita.

[37] Alternatively, we could choose an agricultural total factor productivity curve that exceeds the growth rate of the overall economy equaling 1.29% in 1990 (Ludena, 2007), 1.38% in 2025 (Ludena, 2007), and the same rate as DICE-

A third step is necessary for calibration given that that capital and labor are endogenous, and the solution for the amount of labor and capital in agriculture is such that agricultural output differs from its initial observed value. As a solution, we iterate the initial agricultural technology value $\mathrm{A}_2(0)$ until the solution path has initial agricultural output equal it observed value. As will be discussed later, given the preliminary results of this paper, future work will also need to calibrate the initial amount of agricultural capital.

Non-market production function. There is no production function for non-market goods and services. Following Sterner and Persson (2008), non-market goods and services are set equal to the value of market goods and services in the base year, 2005; this value is $55.34 trillion. The amount of non-market services is assumed constant, except for the effect of climate change. In other words, human behavior only affects the non-market sector through the emission of carbon. Consequently, $55.34 trillion is the maximum value of non-market services in any given time period of the model.

Other-market production function. We do not assume a production function for other-market goods and services. Instead, the value of other-goods and services produced is equal to the overall value of goods and services produced less the value of agricultural goods and services produced.

Damage functions

To solve this modified version of DICE, the amount of agricultural, other-market, and environmental goods in every period must be determined. This requires that a damage function for each of these goods be determined.

Non-market damage function. Using DICE, Sterner and Persson (2008) specify a relationship between global average surface temperature and non-market damage functions. They assume a quadratic relationship of

$$E = \frac{E_0}{1 + h_E(T_{AT})} = \frac{E_0}{1 + aT_{AT}{}^2}$$

where E_0 is the level of consumption of non-market goods in 2005, h_E is the non-market damage function, and T_{AT} is the global average surface temperature. Based on the approach employed by the Stern Review, Sterner and Persson (2008) assume that the magnitude of non-market goods (E_0) and impacts are equal to the value of market goods and impacts, respectively, in the base year. In other words, they normalize the level of environmental amenities in the base year (2005) to the value of market good consumption in 2005, and then

2010 in 2395. The resulting parameters are: $\mathrm{A}_{2,1} = 0.02819972$, $\mathrm{A}_{2,2} = -0.00284845$, and $\mathrm{A}_{2,3} = 0.01852561$. The resulting curve is above the DICE-2010 total factor productivity curve for all market goods. Alternatively, we could also set total factor productivity growth in agriculture equal to total factor productivity growth in the overall economy.

calibrate the quadratic damage function assuming the same level of non-market damages as in the economic sector for a 2.5 degree temperature increase.

We only partially follow Sterner and Persson (2008) in their treatment of the non-market good. Specifically, like them, we assume that

$$E = \frac{E_0}{1 + h_E}$$

where we normalize the amount of non-market goods in the base period, i.e., E_0, to equal the value of market goods in the base period. However, we differ from Stern and Persson (2008) in that assume that $\mathrm{h}_E(T_{AT}, SLR) = \theta_{1,E}T_{AT} + \theta_{2,E}{T_{AT}}^2 + \theta_{3,E}SLR + \theta_{4,E}SLR^2$ to match the DICE-2010 damage function, such that

$$E = \frac{E_0}{1 + h_E(T_{AT}, SLR)} = \frac{E_0}{1 + \theta_{1,E}T_{AT} + \theta_{2,E}{T_{AT}}^2 + \theta_{3,E}SLR + \theta_{4,E}SLR^2},$$

where *SLR* equals sea level rise. Furthermore, we follow the calibration method discussed below.

<u>Market damage functions.</u> Like the original damage function in DICE-2010, the other-market and agricultural damage functions are quadratic in mean surface temperature. They are of the form

$$\mathrm{h}_k(T_{AT}) = \theta_{1,k}T_{AT} + \theta_{2,k}{T_{AT}}^2 + \theta_{4,k}SLR + \theta_{4,k}SLR^2$$

where T_{AT} is the mean surface temperature (atmospheric temperature), SLR is the sea level rise, and *k* is the type of market damage function: other-market (*M*) and agriculture (*A*).

Calibration of damage functions

As mentioned above, each of these damage functions must be calibrated. This is a difficult task for two reasons. First, Nordhaus assembled the damage function using eight types of damage classifications that do not correspond to the three sectors in our model. Second, while the damage estimates by sector used to calibrate DICE-1999 and DICE-2007 are well documented, this is not true for DICE-2010. However, based on correspondence with Nordhaus, it is clear that the DICE-2010 damage function is calibrated using the data from DICE-2007. However, several additional steps are taken: (1) he fits a linear temperature term in addition to the quadratic temperature term, and (2) he disaggregates a sea level rise damage function; it is still unclear how exactly these two additional steps were performed. Third, while region-sector specific damage estimate are available for DICE-2007, global-sector specific damage estimates are not available. Due to these complications, the DICE-1999 and DICE-2007 damage functions are used to disaggregate the DICE-2010 damage function. This section discusses this process.

Disaggregation of damages. The original damage function in DICE-2010 is a combination of market (agricultural and other-market) and non-market damages. In order to calibrate the damage functions in this paper, i.e. the agricultural, non-market, and other-market damage functions, the DICE-2010 damage function must be divided up into the components from which it is built (i.e. agriculture, sea level rise, other market sectors, human health, non-market amenity impacts, human settlements and ecosystems, and catastrophes) and then re-assigned to one of the three damage functions. While agricultural damages can be clearly allocated to the agricultural sector and human health and non-market amenity impacts are attributable to the non-market sector, the other types of damages must be divided up between the three sectors. Human settlements and ecosystem damages must be divided into damages to the other market-sector (human settlements) and the non-market sector (ecosystems). Damages from sea level rise, which is represented by a separate damage function in DICE-2010, must be divided into agricultural, other-market, and non-market damages. This is because damages from sea level rise include damages from storms, which affects all three sectors, and undeveloped land, agricultural and non-market sectors; the majority of land lost in developing countries is agricultural land and wetlands according to Dasgupta et al (2009). Similarly, catastrophic damages would affect all three sectors. Finally, whether other market damages (as defined by Nordhaus), which are attributable to damages to forestry, energy systems, water systems, construction, fisheries, and outdoor recreation, should be divided between the other-market sector (as defined in this paper) and the agricultural sector depends if we define agricultural goods to include fisheries and fiber. For simplicity, we define agriculture as farm-based food stuff, and assign all other market damages (as defined by Nordhaus) to the non-market sector. Even though the documentation is better for the DICE-1999 model, we utilize the damage estimates for a 2.5 degree Celsius increase from DICE-2007 to separate out agricultural and non-market damages from total damages.

The disaggregation of the DICE-2007 climate damages for a 2.5 degree Celsius rise into agricultural, other-market, and non-market damages is done in two steps. First, in order to calculate damage estimates by component for a 2.5 degree Celsius increase in temperature at the global scale (which Nordhaus does not do for each component of non-catastrophic damages), we weigh regional damages using GDP weights from the base run of DICE-2010. In DICE-2007, Nordhaus utilizes GDP weights from 2105, which is the year that a 2.5 degree Celsius increase in temperature over pre-industrial levels occurs in the base run of DICE-2007. Instead, we calculate weighted damages using GDP from 2065, which corresponds to the year when a 2.5 degree Celsius increase in temperature is achieved in DICE-2010's base run; the results from this weighting system also more closely match the global damage estimates in DICE-2007 for total non-catastrophic damages, catastrophic damages, and total damages than when we utilize GDP weights from 2105 (see Table 3).

Second, we divide up Nordhaus' component damages into the three sectors of our model using additional weights when the division is unclear. This includes three sectors: human settlements and ecosystems, sea-level rise, and catastrophic damages. It is assumed that market and non-market damages receive equal weighting based on the Sterner and Persson (2008) assumption that 50% of the DICE damages are attributable to non-market goods. Within market goods, agricultural and other-market goods are weighted based on the relative economic size of their climate sensitive components. While overall the agricultural sector is assumed to be sensitive to climate change, Nordhaus and Boyer (2000) argue that only part of the other-market sector is sensitive to climate change; this includes" forestry, energy systems, water systems, construction, fisheries, and outdoor recreation." According to Nordhaus and Boyer (2000), sensitive other-market sectors in the U.S. are equivalent to 5.9% of the U.S. economy in 1994 and agriculture is equivalent to 1.7% of the U.S. economy. Therefore, 22.4% of climate damages to the U.S. market sector are attributable to damages to U.S. agriculture. We make a similar attempt at a global calculation. According to the FAO, agriculture, forestry and fisheries are equivalent to 5.2%, 1% and 0.34% of world GDP, respectively, in 2010 (FAO 2013, 2012a, 2012b). According to the Institute for Energy Research, world energy expenditure was between 7.9% and 8.2% of GDP (IEI, 2010). Assuming that the total value of water transportation, real estate (coastal property), hotels and other lodging places, and outdoor recreation is equivalent to forestry, fisheries, and energy sectors, agricultural damages are equivalent to 21.8% of damages to the market sector. For simplicity, we will assume the value of agricultural damages is equivalent to 22.5% of the value of market damages. The resulting breaking down of damages is given in Tables 5a-c.

Calibration of the DICE-2010 Damage Functions. To calibrate the three damage functions in this paper, it is important to note the three key differences between the DICE-2007 damage function

$$\mathrm{g}(T_{AT}) = 0.002839 * {T_{AT}}^2$$

and the DICE-2010 damage function

$$\begin{aligned}\mathrm{g}(T_{AT}) &= g_T(T_{AT}) + g_S(SLR) \\ &= 0.000082 * T_{AT} + 0.002046 * {T_{AT}}^2 + 0.005182 * SLR + 0.003058 * SLR^2,\end{aligned}$$

where T_{AT} is average surface temperature and SLR is sea level rise. First, the magnitude of damages differs significantly between the two models. Second, the DICE-2007 damage function has only a quadratic term in temperature, whereas, DICE-2010 has both a linear and quadratic terms. Nordhaus calibrates the DICE-2007 damage function using only the damage estimates for a 2.5 degree Celsius temperature increase. We assume that DICE-2010 follows the DICE-1999 method for calibrating both linear and quadratic coefficients, such that the climate damage estimates for 2.5 degree Celsius increase are extended out to a 6 degree Celsius increase using the method describe on pages 89 to 95 in Nordhaus and Boyer (2000). Last, the DICE-2007 includes the damages from sea-level rise implicitly in the coefficient; DICE-2010 explicitly models the damages from sea-level rise.

These differences imply the following three-step calibration method for the three sector specific damage functions in DICE-2010. First, excluding sea-level rise, normalize the sector specific damages from a 2.5 degree Celsius increase (seen in Table 4a) by the ratio of the direct economic damages from a 2.5 degree Celsius increase in DICE-2007 to the direct economic damages from a 2.5 degree Celsius increase DICE-2010, i.e. $\frac{0.002839*2.5^2}{g_T(2.5)} = \frac{1.77}{1.3}$. Second, using a single point calibration method, split the temperature portion of the DICE-2010 damage function, i.e., $g_T(T_{AT})$, into sector specific components, which assumes that the ratio of sector specific damages (agriculture, other-market, and non-market), derived in the previous step, to total damages (excluding sea-level rise) at a 2.5 degree Celsius increase holds at all temperatures, including a 6 degree Celsius increase. The sector specific damage functions excluding sea-level rise are then obtained by multiplying the temperature portion of the DICE-2010 damage function, i.e., $g_T(T_{AT})$, by these ratios.[38] Last, the sea-level rise component of the DICE-2010 damage function is split up using the GDP weighting system discussed in the previous section.

The resulting sets of damage functions are

$$\mathrm{h}_A(T_{AT}, SLR) = 0.00001585 * T_{AT} + 0.000397252 * {T_{AT}}^2 + 0.00000583 * SLR + 0.00000344 * SLR^2$$

for the agricultural sector,

$$\mathrm{h}_M(T_{AT}, SLR) = 0.00003064 * T_{AT} + 0.00076827 * {T_{AT}}^2 + 0.00002008 * SLR + 0.00001185 * SLR^2$$

[38] An alternative methods is a the two point calibration method, which utilizes the methods discussed in Nordhaus and Boyer (2000) to extend the 2.5 degree damage estimates to 6 degrees for DICE-2007. The resulting estimates must be broken up into sectors utilizing the methods discussed in the previous sub-section and then normalized utilizing the ratio of the direct economic damages from 6 degree Celsius increase in DICE-2007 to the direct economic damages from 6 degree Celsius increase in DICE-2010, i.e. $\frac{0.002839*6^2}{g_T(6)} = \frac{10.22}{7.42}$.[38] The quadratic sector specific damage functions are then calibrated using the sector specific damage estimates at 2.5 and 6 degrees Celsius. This alternative calibration method requires econometric analysis using the RICE-2007 damage estimates, i.e. regional-component specific damage estimates as seen in Table 4, and regional temperatures. Because no regional temperatures were found in the documentation of DICE-2007/RICE-2007, regional temperatures from Nordhaus and Boyer (2000)'s Table 4.3 could be utilized assuming that the Middle East region in RICE-2010 is equivalent to the high income OPEC region in RICE-1999 and that Latin American and Other Asian regions in RICE-2010 are part of the Lower Middle Income region in RICE-1999. The resulting damage functions are not utilized because this method is overly complicated, and, as a consequence, produces unrealistic damage functions for the agricultural sector.

for the other-market sector, and

$$\mathrm{h}_E(T_{AT}, SLR) = 0.00003513 * T_{AT} + 0.000880736 * {T_{AT}}^2 + 0.00002591 * SLR + 0.00001529 * SLR^2$$

for the non-market sector.

Social cost of carbon

The adjustment of the utility function in DICE-2010, as discussed earlier, automatically accounts for the change in the relative price and the corresponding change in the Ramsey discount rate. However, the social cost of carbon calculation must be explicitly adjusted for these changes. In the original DICE model, utility is a function of only per capita consumption *C*, such that the social cost of carbon equaled

$$SCC_{original} = \sum_{t=1}^{2395} B_t\left(C_{Base,t} - C_{Pert,t}\right)$$

where B_t is the discount factor in period *t*, $C_{Base,t}$ is consumption per capita in period *t* on the base emissions path, and $C_{Pert,t}$ is consumption per capita in period *t* with an one unit emissions perturbation (i.e. a unit increase in CO_2 emissions in the base period) above the base emissions path. In our model, the social cost of carbon is

$$SCC_{new} = \sum_{t=1}^{2395} B_t\left(X_{Base,t} - X_{Pert,t}\right) + B_t * p_{a,t} * \left(A_{Base,t} - A_{Pert,t}\right) + B_t * p_{E,t} * \left(E_{Base,t} - E_{Pert,t}\right)$$

where B_t is the discount factor in period t, $X_{Base,t}$ is other-market consumption per capita in period *t* on the base emissions path, $X_{Pert,t}$ is other-market consumption per capita in period *t* with an one unit emissions perturbation above the base emissions path, $A_{Base,t}$ is agricultural consumption per capita in period *t* on the base emissions path, $A_{Pert,t}$ is agricultural consumption per capita in period *t* with an one unit emissions perturbation above the base emissions path, $E_{Base,t}$ is non-market consumption in period *t* on the base emissions path, $E_{Pertebautino,t}$ is non-market consumption in period *t* with an one unit emissions perturbation above the base emissions path, $p_{a,t}$ is the relative price of agriculture in period *t*, and $p_{E,t}$ is relative price of non-market goods in period *t.*

There are several parameters for which we derive specific parametric expressions. First, we derive relative prices, which are equal to $p_{a,t} = \frac{U_{A(t)}}{U_X(t)}$ and $p_{E,t} = \frac{U_E(t)}{U_X(t)}$**.** An important feature of the relatives prices of agricultural and non-market goods and services is that they now vary over time. The growth rates of these prices depend on the relative growth rates of the various sectors: agricultural, other-market, and non-market goods and services. Second, we derive the effective discount rate, which is equal to

$$r = r_{Ramsey} + \gamma_2^* \dot{p}_{\boldsymbol{E}} + \gamma_1^*(1-\gamma_2^*)\dot{p}_{\boldsymbol{A}}$$

where $\dot{p}_E$ and $\dot{p}_A$ are the growth rates of relative price of non-market goods and services and agricultural goods, respectively, over time and γ_1^* and γ_2^* are parametric weights derived by the authors. The discount rate equals the original Ramsey equation plus an adjustment for the growth rates of the relative prices. The exact parametric expressions derived by the authors are available upon request.

Results

The following results are preliminary. These results are based on a MATLAB version of DICE-2010 developed by the EPA, which we modified for our purposes. The current solver is *fmincon*. As will be discussed below, these results are preliminary in that additional work is necessary to ensure a global solution and to adjust the initial amount of capital in agricultural. This will be discussed in more detail below.

Accounting for relative prices increased the social cost of carbon from \$38 in DICE-2010 to approximately \$52. Given the particular parameter values chosen, this increase is irrespective of the utility function chosen; the social cost of carbon is \$51 per ton for the non-nested utility function and \$52 in the nested model; see Figure 2. This is a significant increase in the social cost of carbon, and, if this result is robust to future calibrations, accounting for relative prices should be considered a necessary structural change in all IAMs.

There are three qualifications for these results. First, these are tentative results, and may change with the additional calibration of agricultural capital. If we look at Figures 3 and 4, we can see that capital investment (i.e. savings) and capital accumulation in agriculture spikes in the initial period. This indicates that the initial capital stock is likely insufficient. This should not be surprising given that Nordhaus calibrates capital in DICE, such that it represents a catch all input (including potentially the value of land) instead of the overall value of physical capital. While recalibrating the initial value of capital in agriculture may change the current result, it is unlikely to significantly do so given that this peak happens in the base and perturbation runs. Second, we are concerned that *fmincon* finds a local rather than a global maximum. This is a problem with *fmincon*, and, as a consequence, we will be switching to *KNITRO-MATLAB* in future work. If the current result is not a global maximum, the results may significantly change. Third, these results could differ significantly under different parameter assumptions and starting values, particularly parameters in the utility function and agricultural production function. Future sensitivity analysis is discussed below. While sensitivity analysis will not invalidate the current results, it may indicate that they are not robust to parameter values.

From the current results, it is unclear how much of the increase in the social cost of carbon is driven by an increase in the relative price of agriculture versus the relative price of non-market damages. To answer this question, like Sterner and Persson (2008), we allow only the relative price of non-market goods to vary over time by assuming that the price of agricultural goods remains constant; this is accomplished by assuming that the other-market good and the agricultural good are perfect substitutes, such that σ_1 approaches infinity. We find that the SCC of carbon decreases to $32 from the $38 in the original DICE-2010 model; the same four qualifications apply as discussed in the previous paragraph. This result is unexpected given the results of Sterner and Persson (2008) using similar parameters. The key difference between these our paper and Sterner and Persson (2008) is that the damage function is significantly less in our paper; this is because we disaggregate the DICE-2010 damage function rather than adopting their assumption that non-market damage function is equivalent to the current DICE damage function. Additionally, like Sterner and Persson (2008), we assume that the non-market good should be included in the social welfare function as an aggregate, while market (i.e. agricultural and other-market) goods enter the social welfare function on a per capita basis. If instead, we instead allow non-market goods to enter the social welfare function on a per capita basis, this increases the social cost of carbon in excess of $100; see Figure 5. Given that there is reason to believe that society cares about non-market services as some combination of aggregate services and per capita service levels (or at least local level of services), we will calculate a range of damage estimates using sensitivity analysis over preference parameters for non-market goods, the non-market damage function, and whether to include non-market damages in the social welfare function on an aggregate or per capita basis.[39]

Future Work

As discussed earlier, these results are preliminary for several reasons. First, given the current solutions, we are concerned that the model is not properly calibrated. Second, there are concerns that the current solutions are not global maxima. Third, due to the uncertainty surrounding many of the parameters, sensitivity analysis over the parameter values is necessary to determine whether the current findings are robust.

Calibration

Future work needs to better calibrate the unknown model parameters, so the solution in base year matches observation in real world. In particular, we are currently setting the agricultural capital ratio in the initial time period based on the observed value of capital in world agriculture versus the value of capital in the overall economy as specified in DICE. However, the amount of capital in the overall economic is a calibrated parameter in DICE. As a consequence, it is a catch

[39] Ideally we would include both local and global non-market services in the social welfare function, but this is impossible in DICE given its global structure.

all parameter that likely contains land, which is excluded from the Cobb-Douglas production function. Therefore, we need to better calibrate the parameter that captures the amount of agricultural capital in the base period, such that the spikes in capital investment evident in the current model solutions do not occur. Potentially, we should switch from calibrating the initial agricultural technology value to the initial capital value, such that the solution for the amount of agriculture in the real world matches the DICE value.[40]

Solver

We are currently using the *fmincon* solver - the default solver for optimization problems in MATLAB. For non-linear programming (NLP), *fminco*n does not guarantee to return the global minimum. As a consequence, the results from using it are often sensitive to the initial conditions. In future work, we will switch to using the KNITRO-MATLAB solver.[41]

Future Sensitivity Analysis

Future work will check the robustness of this paper's results to the various parameter assumptions discussed above.

<u>Preference and production parameters.</u> As discussed earlier, sensitivity of results to the various preference and production function parameters will be tested. In terms of preference parameters, we will vary the elasticities of substitution and the share parameters at both stages of the utility function. We will run alternative specifications where elasticities are equal to 0.3 and 0.9 and the share parameters are equal to 0.05, 0.2, and 0.3. These sensitivity analyses will be conducted with the nested and non-nested utility functions. In terms of the production parameters, we will vary the elasticity of output with respect to labor using the range of values in the literature: 0.2, 0.5, and 0.7.

<u>Total factor productivity.</u> Currently, we restrict agricultural total factor productivity growth to monotonically decreasing, and assume that total factor productivity growth is below the overall economy. This assumption may very well note be true. We will test the sensitivity of our results in this paper using three different agricultural total factor productivity growth curves. First, we will assume that agricultural total factor productivity curve exceeds the growth rate of the overall economy equaling 1.29% in 1990 (Ludena, 2007), 1.38% in 2025, and the same growth rate as DICE-2010 in 2395. The resulting parameters are: $\mathrm{A}_{2,1} = 0.02819972$, $\mathrm{A}_{2,2} =$

[40] Alternatively, it may be necessary to add an additional constraint to the model, such as setting the value of the marginal product of capital equal across sectors in the base period.

[41] An alternative solution is to reprogram our model using DICE-2013. Unlike DICE-2010 which Nordhaus programmed in only Microsoft excel, Nordhaus programs DICE-2007 and DICE-2013 in excel and GAMS. In GAMS, Nordhaus uses the CONOPT solver. This solver uses a generalized reduced gradient (GRG) algorithm, which essentially linearizes the non-linear equations. While this solver is efficient at solving non-linear programming problems when the constraints are smooth, it does not guarantee a global optimum in complex problems like DICE. However, Nordhaus has found that it finds a global optimum in GAMs. Matlab does not have a GRG solver; several premium solvers are available as alternatives including: *KNITRO-MATLAB* and TOMLAB /MINOS.

-0.00284845, and $A_{2,3} = 0.01852561$. The resulting curve is above the DICE-2010 total factor productivity curve for all market goods, and it converges to DICE-2010 over time. Second, we will assume that the, the growth rate of total factor productivity growth in agriculture equals the growth rate of total factor productivity in the overall economy. See Figure 2. Last, another possibility is that agricultural R&D is going to help maintain yields, and does not expand yields in the future. To model this scenario, we will assume that total factor productivity growth stops for warming above a particular rate of increase.

Agricultural damage function. Agricultural damage estimates will require updating. As discussed earlier, the general damage functions in DICE-1999 are calibrated using agricultural damage estimates derived using the general equilibrium approach. In DICE-2007, as mentioned earlier, it is unclear exactly where the damage estimates are drawn; we only know that they are a judgmental average of some of Cline's estimates, which produce less negative results. Currently, we run our model using the best approximation of agricultural damage estimates contained in DICE-2007.

Future work will run DICE-2010 drawing on several agricultural damage estimates in order to represent the scientific debate. There are many options with respect to updating the agricultural damage estimates, including DICE-1999, Cline (2007),[42] the latest Ricardian estimates from Schlenker, Fisher and Hanemann (2005, 2006, 2007),[43] the latest general equilibrium damage estimates from Calzadilla et al (2010; 2011);[44] the U-shaped damage function with benefits in the short-run from Tol (2013), and non-linear agricultural damage functions from Schlenker and Roberts (2008).[45] Sensitivity analysis over the parameters in the agricultural damage function will be utilized to capture these various alternative scenarios.

For each of the estimates, we will run the DICE model with and without the corresponding CO_2 fertilization effect if possible. While the CO_2 fertilization effect has been confirmed, there are several sources of agricultural damages omitted from these studies: extreme weather, ozone (some of which is the result of methane emissions), weeds and other pests, and fire. As a consequence, the CO_2 fertilization effect may not be realized.

[42] Schlenker, Hanemann, and Fisher (2006, 2007, and 2008) are U.S. estimates and not world estimates. These estimates will need to be extrapolated globally for use in DICE-2010.

[43] While Cline (2007) does not account for technological growth, the DICE-2010 model already explicitly models the growth of total factor productivity.

[44] Calzadilla et al (2010; 2011) accounts for water availability in irrigation. The damage estimates are given below in Table 7 with the CO_2 fertilization effect approximated for some of these estimates; these calculations assume that ¾ of crops are C3 crops and do not account for general equilibrium effects of the inclusion of the CO_2 fertilization effect. It should be mentioned that these models assume high levels of adaptation, which results in a corresponding rise in price due to higher costs, which is not captured in the DICE-2010 model.

[45] This analysis will aim to replicate the work of Schlenker and Roberts (2008), which finds that crop yields look more like mesas or cliffs than symmetric hills.

Non-market damage function. As mentioned earlier, the non-market damage function is much lower than in Stern and Persson (2008). In addition to conducting sensitivity analysis to the agricultural damage function, sensitivity analysis will be conducted with respect to the non-market damage function. First, we will conduct sensitivity analysis to the inclusion of non-market damages on an aggregate or per capita basis. Second, we will replace our non-market damage function with the Sterner and Persson (2008) non-market damage function and the PAGE09 non-market damage function.

Conclusion

Climate change will directly affect the provision of market and non-market goods and services, including agricultural goods, through the direct effects of temperature, precipitation, and other climatic changes. Because food production is fundamentally a biological process that is a function, in part, of temperature and moisture, the agricultural sector's potential vulnerability is particularly large. This vulnerability has led to some raising alarms about the world falling back into a Malthusian trap. While a Malthusian catastrophe is an extreme possibility, rises in food insecurity and world food prices are serious possibilities. Specifically, while there is a significant debate over the magnitude over the effect of climate on agriculture, these concerns are legitimate given the potentially significant damages that may arise due to the price inelasticity of agricultural goods. Given the social instability that resulted from the 2007-2008 world food price crisis, the future threat of climate to agriculture is a serious policy concern.

As of 2008, the federal government must include the SCC in all federal cost-benefit S analyses. As a consequence, the SCC has become the primary policy tool for policymakers with respect to climate change. The U.S. government's published estimates rely on three IAMs: DICE, FUND, and PAGE. Currently, these models assume away agricultural price increases and internalize outdated agricultural damage estimates dating back from the 1990s. Thus, the U.S. government is relying on a climate policy tool that is unable to address one of their fundamental concerns about climate change: climate change driven food insecurity. As a consequence, these IAMS underestimate the social cost of carbon, and provide misleading policy prescriptions.

To address the downward bias in the SCC associated with the modeling of agriculture in IAMs, this paper improves DICE-2010 - an important economic model of climate damages - by extending the work of Sterner and Persson (2008) and dividing the aggregate consumption good in DICE-2010 into agricultural, non-market, and other-market goods. This significant modification requires two modeling changes. On the consumption side, I replace the isoelastic utility function in DICE-2010 with a CES utility function to capture the change in the relative prices of agricultural and non-market goods. Additionally, I model the effects of using a nested and non-nested CES utility function. On the production side, I replace DICE's Cobb-Douglas production function for all goods and services with two separate production functions for agriculture and other-market goods to allow for substitution of resources between production activities. These production functions are calibrated using readily available data.

Preliminary results indicate that inclusion of relative prices can significantly increase the SCC. First, the SCC increases from $38 to approximately $52 using a base set of parameters in DICE-2010, including the outdated agricultural damage estimates contained within DICE. Future work will need to test the sensitivity of results to this damage function. Second, though specific to the base parameter choices, this result is relatively insensitive to the choice of utility model: nested versus non-nest CES utility functions. Third, this increase is predominately drive by an increase in the price of agriculture. Finally, the results are highly dependent on other modeling choices, and future work will need to test the sensitivity of our results to these assumptions. Future work is also necessary to improve the calibration and solution of this modified DICE model.

The potential for significant increases in the social cost of carbon by including relative prices has several important modeling and policy implications. First, this work re-emphasizes the need for structural changes to current IAMs to account for relative prices. While many of the authors of IAMs have been reluctant to make structural changes to their models, significant increases in damages may help U.S. policymakers push IAM modelers to make the necessary changes if the results prove robust in future work. Second, this work emphasizes the need for further disaggregation of market goods, such as forestry and water resources, to more accurately estimate the SCC, and thus, better inform climate change policy. Additionally, there is a need to disaggregate non-market damages between local and global benefits; this is difficult given the global welfare function used in DICE. Third, this work potentially aids U.S. policymakers in making cost-benefit justified policies, particularly as they relate to climate change and food security. A significantly higher social cost of carbon from a rise in the relative price of agricultural goods indicates that the costs of climate are greater than we are currently considering, and action is more urgent than currently assumed in U.S. policy. In particular, it indicates the need for policies to incentivize agricultural adaptation to avoid future costs. Finally, if future work finds that dramatic agricultural price increases occur under some reasonable set of assumptions, it will indicate that Malthusian fears are at least partially valid, and policymakers should take note.

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Table 1. Elasticity of output with respect to labor by study

Source	Year	Elasticity of output with respect to labor	Returns to scale
Lau and Yotopoulos (1988)	1988	0.325	1.245
Kawagoe, Hayami, and Ruttan (1985)	1985	0.503	1.066
Kawagoe, Hayami, and Ruttan (1985)	1985	0.509	1.066
Hayami & Ruttan (1985)	1985	0.5	1.06
Kawagoe, Hayami, and Ruttan (1985)	1985	0.473	1.042
Craig et al (1997)	1997	0.25	1.03
Kawagoe, Hayami, and Ruttan (1985)	1985	0.436	1.026
Fuglie (2008)	2008	0.35	1
Bravo-Ortega & Lederman (2004)	2004	0.11	1
Gutierrez & Gutierrez (2003)	2003	0.29	1
Martin & Mitra (2002)	2002	0.64	1
Mundlak et al. (1999)	1999	0.08	1
Kawagoe and Hayami (1985)	1985	0.45	1
Mundlak-Hellinghausen (1982)	1982	0.4	1
Yamada-Ruttan (1980)	1980	0.35	1
Nguyen (1979)	1979	0.35	1
Hayami-Ruttan (1970)	1970	0.4	1
Hayami (1969)	1969	0.45	1
Bhattacharjee (1955)	1955	0.3	1
Antle (1983)	1983	0.4	0.85
Evenson-Kislev (1975)	1975	0.2	0.85

All studies			
Mean	1985.904762	0.369809524	1.011190476
Median	1985	0.4	1
Mode	1985	0.35	1
Studies with constant returns to scale			
Mean	1985.845238	0.3475	1
Median	1985	0.35	1
Mode	1985	0.35	1
Studies with constant returns to scale and since 1990			
Mean	1993.6	0.294	1
Median	2002	0.29	1
Mode	-	-	-

Table 2. Estimates of total factor productivity by time period and study

Source	Study Year	First Year	Midpoint Year	End Year	Growth
Fuglie (2008)	2008	1970	1979.5	1989	0.87%
Fuglie (2008)	2008	1990	1998	2006	1.56%
Coelli and Rao (2005)	2005	1980	2000	2020	1.10%
Coelli and Rao (2005)	2005	1980	2000	2020	2.10%
Ludena (2007)	2007	1961	1970.5	1980	0.60%
Ludena (2007)	2007	1981	1990.5	2000	1.29%
Ludena (2007)	2007	2001	2020.5	2040	0.49%
Fuglie (2010)	2010	1960	1964.5	1969	0.63%
Fuglie (2010)	2010	1970	1974.5	1979	0.77%
Fuglie (2010)	2010	1980	1984.5	1989	0.92%
Fuglie (2010)	2010	1990	1994.5	1999	1.54%
Fuglie (2010)	2010	2000	2003.5	2007	1.45%
O'Donnell (2008)	2008	1970	1985.5	2001	1.00%
Linehan et al. (2013)	2013	2007	2028.5	2050	1.00%
Linehan et al. (2013)	2013	2007	2028.5	2050	1.12%
The OECD/FAO (2012)	2012	2001	2020.5	2040	1.38%

Table 3. Summary of impacts to different sectors in DICE-1999 for 2.5 °C warming

Sector	% of 2100 GDP*	$1990 billions
Agriculture	-0.13%	-4
Other vulnerable market	-0.50%	-
Energy	-	0
Timber	-	0
Water	-	0
Coastal /sea level rise	-0.32%	-6
Health	-0.10%	1
Non-market time use	0.29%	17
Settlements and ecosystems	-0.17%	-
Settlements	-	-6
Migration	-	NA
Species loss	-	NA
Catastrophic impact (2.5 degrees)	-1.02%	-25
Market (includes sea level rise)	-	-11
Non-market (everything else)	-	-17
Total	-1.50%	-28

*Regional damages are output-weighted using GDP in 2100 of RICE's base case scenario

Table 4a. Summary of impacts to different sectors in DICE-2007 for 2.5 °C warming[46]

	Agriculture	Other vulnerable mkt	Coastal	Health	non-market time use*	Settlements and ecosystems*	Total non-catastrophic		Catastrophic impact		TOTAL	
							2.5 degrees Celcius	6 degrees Celcius	2.5 degrees Celcius	6 degrees Celcius	2.5 degrees Celcius	6 degrees Celcius
US	0.03%	0.00%	0.10%	0.02%	-0.28%	0.10%	-0.03%	1.34%	0.94%	4.00%	0.70%	5.34%
WE/Euro	0.03%	0.00%	0.46%	0.02%	-0.43%	0.25%	0.33%	4.26%	1.09%	4.80%	3.65%	9.06%
OHI	-0.05%	-0.32%	0.09%	0.02%	-0.35%	0.10%	-0.50%	4.19%	1.11%	4.80%	-2.79%	8.99%
Russia	-0.82%	-0.80%	0.05%	0.02%	-0.75%	0.05%	-2.25%	3.63%	1.12%	4.80%	-16.36%	8.43%
EE/FSU	0.03%	0.00%	0.01%	0.02%	-0.36%	0.10%	-0.21%	0.76%	0.94%	4.00%	-0.66%	4.76%
Japan	0.02%	0.00%	0.27%	0.02%	-0.31%	0.25%	0.24%	4.04%	1.07%	4.80%	2.96%	8.84%
China	0.02%	0.32%	0.08%	0.09%	-0.26%	0.05%	0.30%	3.92%	1.04%	4.00%	3.33%	7.92%
India	0.32%	0.29%	0.09%	0.40%	0.30%	0.10%	1.51%	6.94%	1.57%	6.00%	13.29%	12.94%
MidEast	0.35%	0.20%	0.04%	0.23%	0.24%	0.05%	1.12%	4.41%	0.96%	4.00%	9.61%	8.41%
SSA	0.67%	0.32%	0.02%	1.00%	0.25%	0.10%	2.35%	9.55%	1.78%	7.00%	20.00%	16.55%
LA	0.42%	0.28%	0.10%	0.32%	-0.04%	0.10%	1.18%	5.16%	1.30%	5.20%	10.47%	10.36%
OthAsia	0.52%	0.21%	0.09%	0.32%	-0.04%	0.10%	1.20%	5.00%	1.23%	5.00%	10.55%	10.00%
Global: 2105 weights: 2.5 degrees Celcius												
Output weighted							0.61%	3.51%	1.16%	4.72%	1.77%	8.23%
Population weighted							0.97%	5.60%	1.26%	5.05%	2.24%	10.65%

[46] This table is reproduced from

Table 4b. Summary of impacts to different sectors in DICE-2007 for various GDP (based on RICE-2010) weights

	Agriculture	Other vulnerable mkt	Coastal	Health	non-market time use*	Settlements and ecosystems*	Total non-catastrophic		Catastrophic impact		TOTAL	
							2.5 degrees Celcius	6 degrees Celcius	2.5 degrees Celcius	6 degrees Celcius	2.5 degrees Celcius	6 degrees Celcius
2005 GDP	0.10%	0.05%	0.19%	0.12%	-0.23%	0.14%	0.40%	3.80%	1.10%	4.60%	1.50%	8.50%
2055 GDP	0.19%	0.11%	0.14%	0.22%	-0.13%	0.11%	0.64%	4.56%	1.18%	4.84%	1.80%	9.40%
2065 GDP (2.5 degrees Celcius)	0.20%	0.14%	0.14%	0.22%	-0.12%	0.11%	0.70%	4.50%	1.20%	4.80%	1.90%	9.40%
2105 GDP	0.25%	0.16%	0.12%	0.26%	-0.08%	0.11%	0.80%	4.80%	1.20%	4.90%	2.00%	9.70%
2105 Population	0.34%	0.22%	0.09%	0.39%	0.02%	0.10%	1.20%	5.80%	1.30%	5.30%	2.50%	11.10%
Average of 2005 and 2105 GDP	0.19%	0.12%	0.14%	0.20%	-0.14%	0.12%	0.60%	4.40%	1.20%	4.80%	1.80%	9.20%

Table 5a: Market and Non-market Damages as a % of GDP in RICE-2007 from a 2.5 degree Celsius Increase without Damages from Sea-Level Rise Included

Model – Weighting	Agriculture	Other-Market	Non-Market	Total Damages
RICE2007-2065 GDP Weights (weights from RICE2010 base)	0.34%	0.65%	0.75%	1.73%
RICE2007-2105 GDP Weights (weights from RICE2010 base)	0.38%	0.68%	0.84%	1.91%

Table 5b: Market and Non-market Damages as a % of GDP in RICE-2007 from a 2.5 degree Celsius Increase with Damages from Sea-Level Rise Included

Model – Weighting	Agriculture	Other-Market	Non-Market	Total Damages
RICE2007-2065 GDP Weights (weights from RICE2010 base)	0.35%	0.70%	0.81%	1.87%
RICE2007-2105 GDP Weights (weights from RICE2010 base)	0.40%	0.73%	0.91%	2.03%

Table 5c: Market and Non-market Sea-Level Rise Damages as a % of Total Sea-Level Rise Damages from a 2.5 degree Celsius Increase

Damages from Sea Level Rise	New Agriculture at 2.5 degrees	New Other-Market Damages at 2.5 degrees	New Non-Market Damages at 2.5 degrees
All models	11.25%	38.75%	50.00%

Table 6. Summary estimates of the impact of global warming on world agricultural output potential by the 2080s (percent) in Cline (2007)

	Without carbon fertilization	With carbon fertilization
Global		
Output-weighted	-15.9	-3.2
Population weighted	-18.2	-6
Median by country	-23.6	-12.1
Industrial countries	-6.3	7.7
Developing countries*	-21	-9.1
Median	-25.8	-14.7
Africa	-27.5	-16.6
Asia	-19.3	-7.2
Middle East North Africa	-21.2	-9.4
Latin America	-24.3	-12.9

*Excluding Europe.

Table 7. Agricultural Damage estimates from Calzadilla et al (2010) for 2020 and 2050

Paper	**Year**	**Scenario**	**Temperature Increase (degrees Celsius) based on IPCC 4th Assessment**	**CO_2 fertilization effect**	**Damage (% of agricultural production)**
Calzadilla et al (2010)	**2020**	A1B	0.64 to 0.69	Yes	-0.45%
Calzadilla et al (2010)	**2050**	A1B	1.8	Yes	-2.28%
Calzadilla et al (2010)	**2020**	A2	0.69	Yes	-0.53%
Calzadilla et al (2010)	**2050**	A2	1.7	Yes	-2.38%
Calzadilla et al (2010)	**2020**	A1B	0.64 to 0.69	No	-5.2%
Calzadilla et al (2010)	**2050**	A1B	1.8	No	-13.0%
Calzadilla et al (2010)	**2020**	A2	0.69	No	-5.0%
Calzadilla et al (2010)	**2050**	A2	1.7	No	-13.1%

Table 8. Preference parameters

First stage utility function	
Elasticity of substitution	0.5
Share Parameter (agriculture)	0.1
Elasticity of MU of consumption	1.5
Second stage utility function	
Elasticity of substitution	0.5
Share Parameter (non-market)	0.1

Table 9. Production parameters

	Output	**Agriculture**	**Other-market**	**Non-market**
Parameters (Non-TFP)				
Elasticity of output with respect to capital	0.3	0.65	-	-
Elasticity of output with respect to labor	0.7	0.35	-	-
Initial quantity (2005)	55.34	2.887484	52.38394	55.34
Initial capital (2005)	97.3	5.288453	92.01155	-
Initial labor (2005)	6411	2333.604	4077.396	-
Total factor productivity (TFP)				
Initial TFP	0.030322		-	0
TFP growth - parameter 1	0.160023	0.028200	-	0
TFP growth - parameter 2	0.009426	0.007922	-	0
TFP growth - parameter 3	0.001924	0.000189	-	0
Time period adjustment	-1	-39	-	-

Table 10. Climate damage parameters

	Output	**Agriculture**	**Other-market**	**Non-market**
Temperature				
Linear parameter	0.00008162	0.00001585	0.00003064	0.00003513
Quadratic Linear	0.00204626	0.00039725	0.00076827	0.00088074
Sea Level Rise				
Linear parameter	0.00005182	0.00000583	0.00002008	0.00002591
Quadratic Linear	0.00003058	0.00000344	0.00001185	0.00001529

Figure 1. Total Factor Productivity Growth over Time

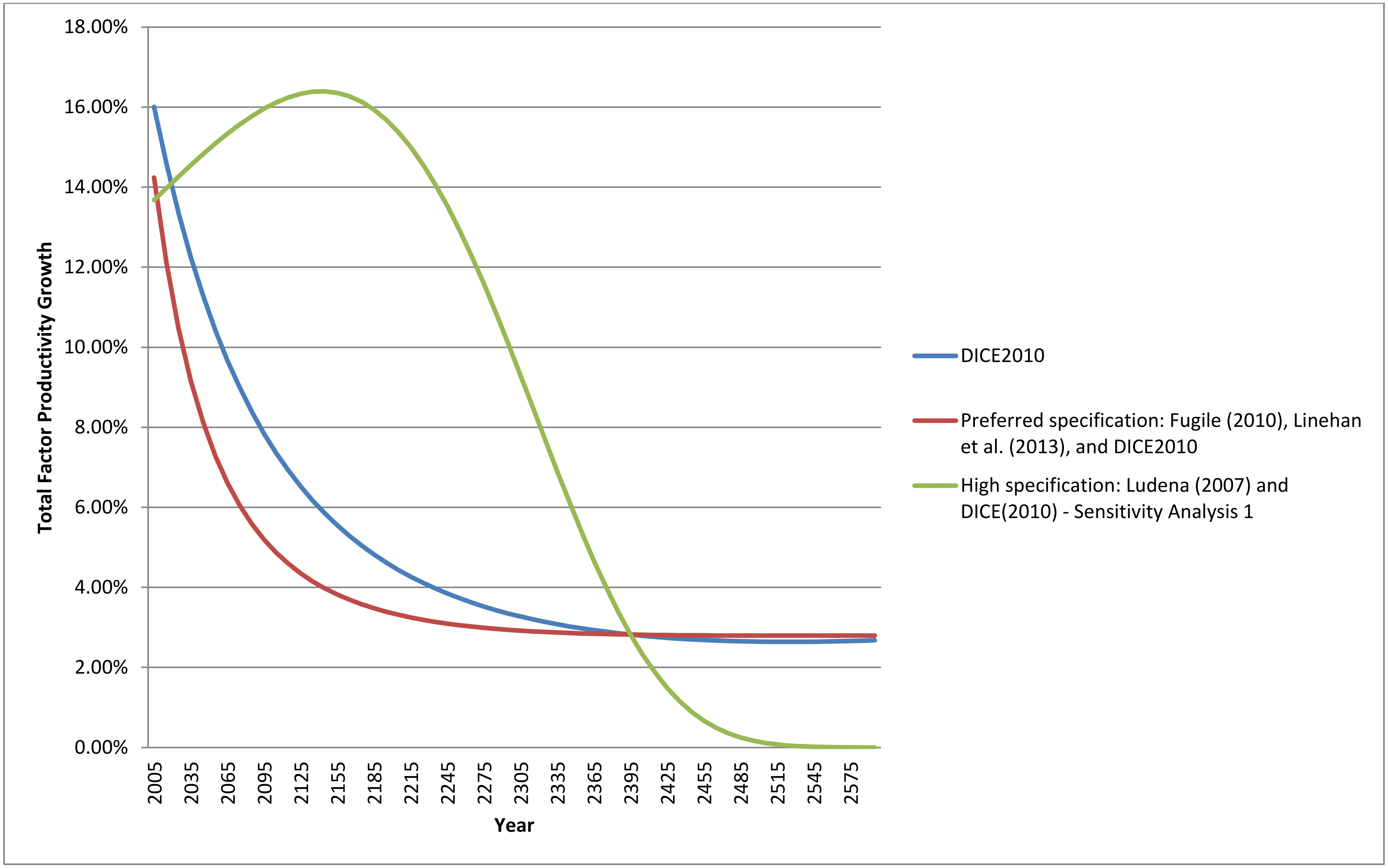

Figure 2. 2015 social cost of carbon with a 3% pure rate of time preference: original model; nested preferences accounting for the relative prices of agricultural and non-market goods; and non-nested preferences accounting for the relative prices of agricultural and non-market goods

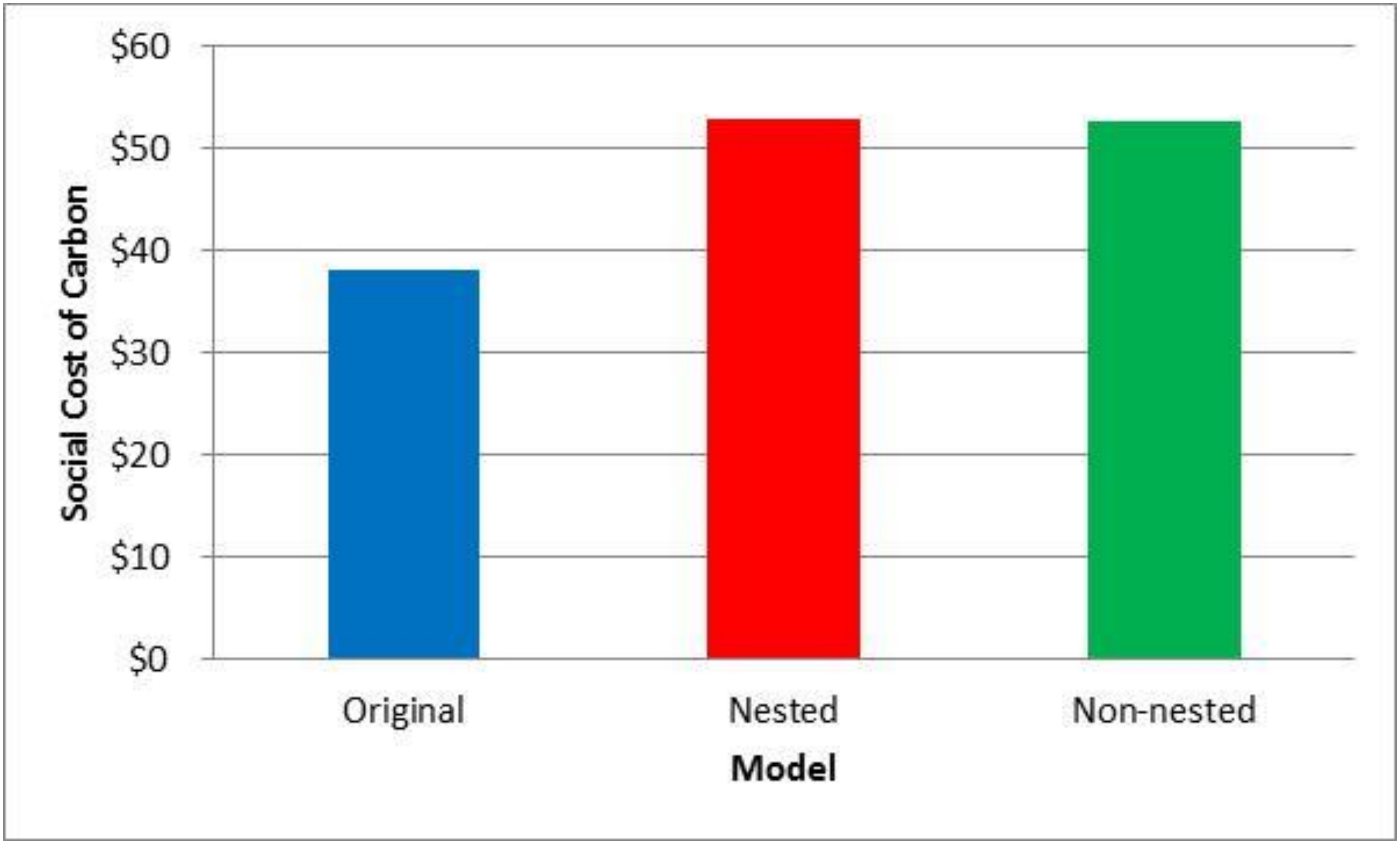

Figure 3. Savings Rate over Time

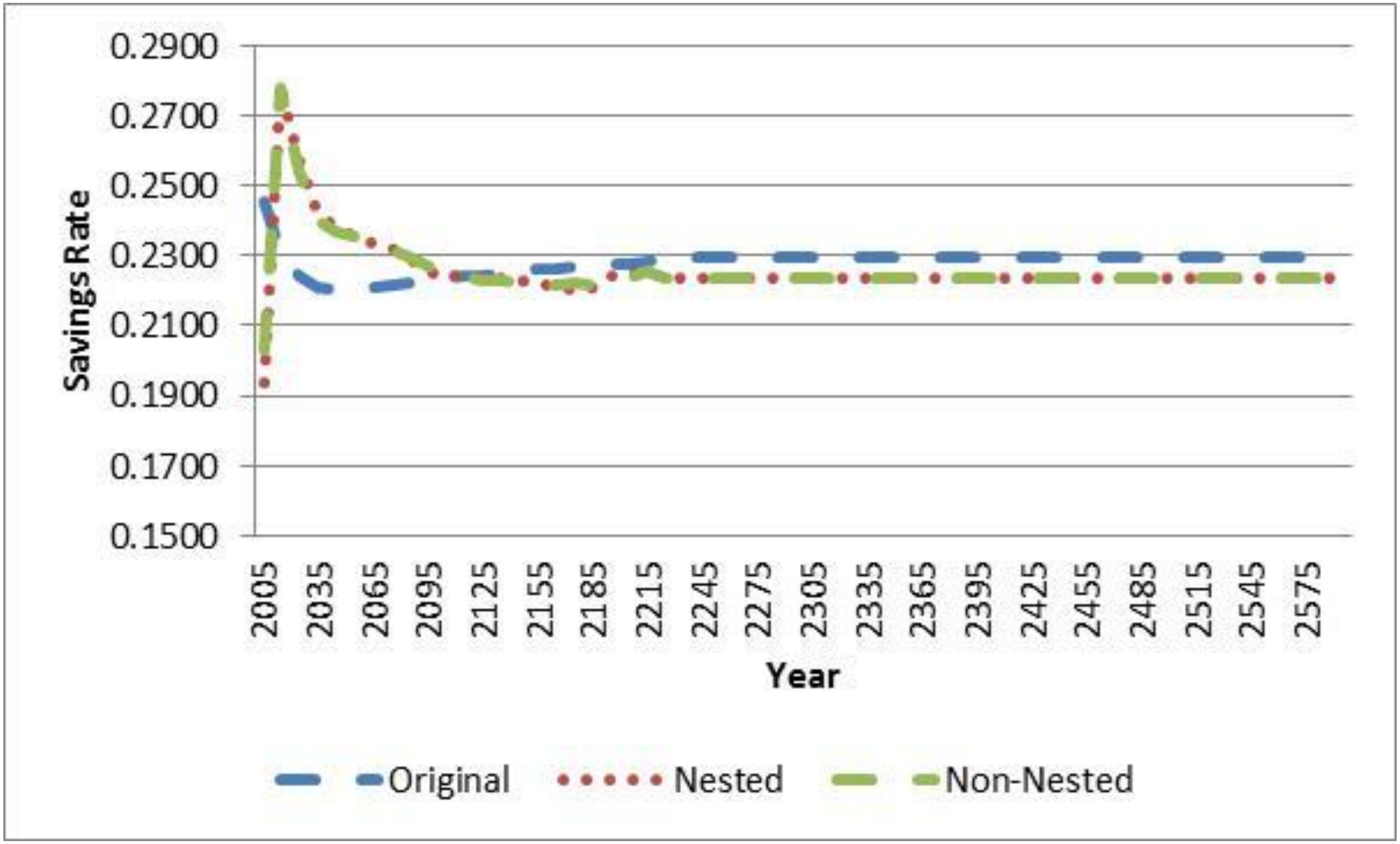

Figure 4. Investment and Labor in Agriculture over Time

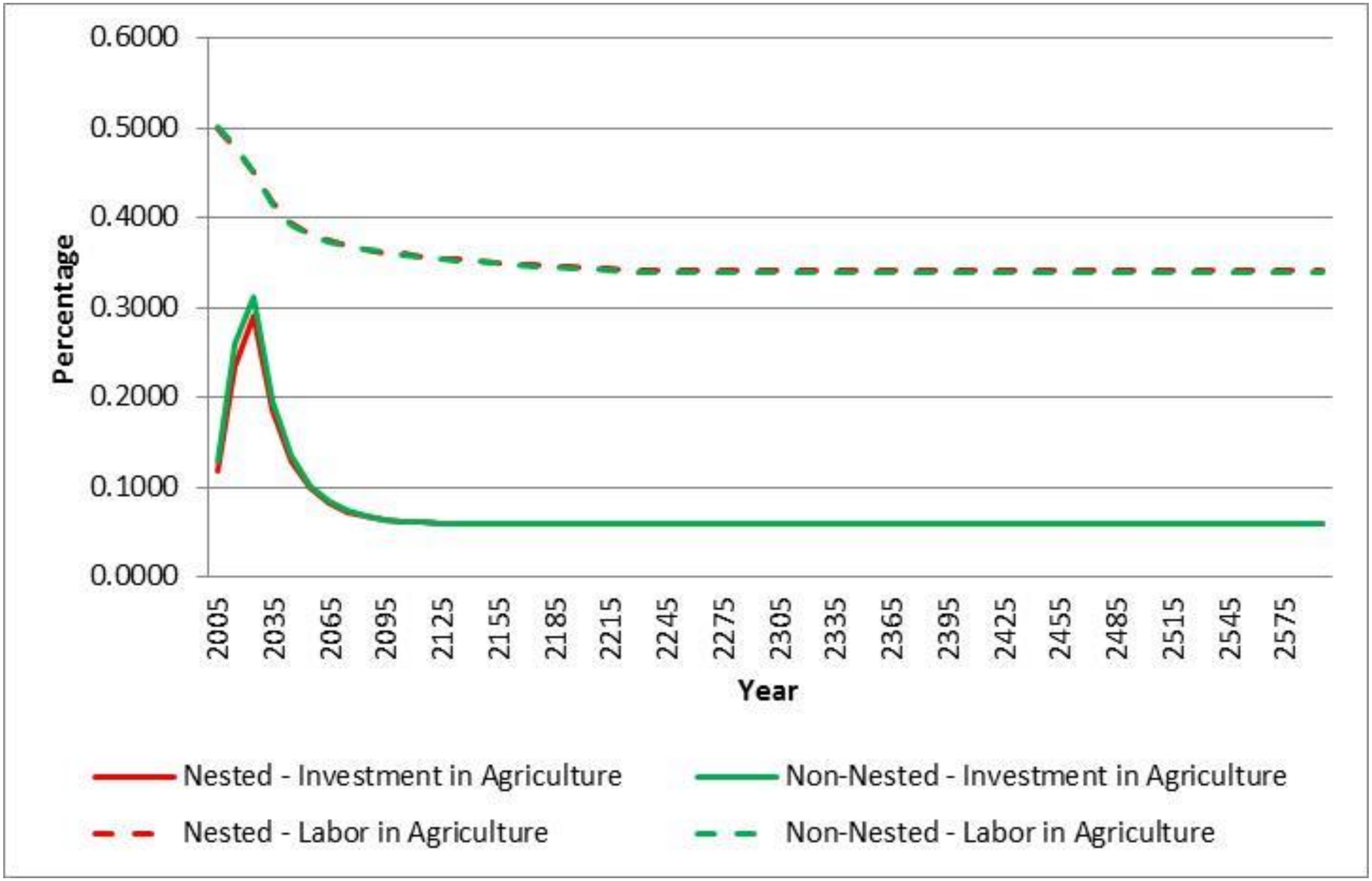

Figure 5. 2015 social cost of carbon with a 3% pure rate of time preference: original model; nested preferences accounting for the relative price of an aggregate measure of non-market goods and services; and nested preferences accounting for the relative price of non-market goods and services on a per capita basis