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Agricultural research spending must increase in light of future uncertainties ☆

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ABSTRACT

Agricultural productivity depends critically on investments in research and development (R&D), but there is a long lag in this response. Failing to invest today in improvements of agricultural productivity cannot be simply corrected a few decades later if the world finds itself short of food at that point in time. This fundamental irreversibility is particularly problematic in light of uncertain future population, income, and climate change, as portrayed in the IPCC's Shared Socio-Economic Pathways (SSPs). This paper finds the optimal path of agricultural R&D spending over the 21st century for each SSP, along with valuation of those regrets associated with investment decisions later revealed to be in error. The maximum regret is minimized to find a robust optimal R&D pathway that factors in key uncertainties and the lag in productivity response to R&D. Results indicate that the whole of uncertainty's impact on R&D is greater than the sum of its individual parts. Uncertainty in future population has the dominant impact on the optimal R&D expenditure path. The robust solution suggests that the optimal R&D spending strategy is very close to the one that will increase agricultural productivity fast enough to feed the World under the most populous scenario. It also suggests that society should accelerate R&D spending up to mid-century, thereafter moderating this growth rate.

1. Introduction

Despite abundant and affordable food throughout much of the developed world, currently 12.9% of the population in developing countries is undernourished (World Food Program, 2016). From 2005 to 2050, world population is expected to increase by 50%, from 6.5 in 2005 to 9.7 billion (United Nations, 2015). When coupled with increases in income and changing diets, this translates into substantial growth in the demand for agricultural production (Pingali, 2007), which is expected to rise by somewhere between 60 and 100% (Alexandratos and Bruinsma, 2012; Tilman et al., 2011). Studies looking at the future supply and demand for food indicate that meeting this demand may pose significant challenges for the food and environmental systems (Piesse and Thirtle, 2010). The extent of environmental pressure and the resulting food price changes will hinge critically on the evolution of productivity growth in agriculture (Baldos and Hertel, 2015).

Since the 1950s, increased agricultural productivity has allowed food availability to outpace demand on a global scale, resulting in a long run downward trend in world prices. Public and private investments into agricultural research and development (R&D) have been the foundation for this achievement. Studies have shown that public investment in agricultural research has resulted in significant economic benefits (Fuglie and Heisey, 2007).[1] However, while R&D spending globally has continued to rise, its rate of growth has fallen, and this growth has shifted in favor of developing countries (Pardey et al., 2016).

Global R&D picked up strongly over the 2000–2008 period, rising by 22%, coinciding with rising food prices. Accelerated spending in China and India accounted for close to half of the increase

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[1] The magnitudes of returns to investments into agricultural R&D vary across studies. For example, range of returns to public agricultural research reported in Fuglie and Heisey (2007) is 20–60% per year. On the other hand, Hurley et al. (2014) report much wider range with the mean return over 270 prior studies just 13.6%.

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(Beintema et al., 2012). Several studies report estimates of the additional investment in agricultural R&D needed to meet projected increases in demand by 2050 (Beintema and Elliot, 2009; von Braun et al., 2008; Rosegrant et al., 2008). It is likely that an increasing part of the R&D expenditures over the coming decades will be focused on adaptation to climate change which is expected to act as a brake on productivity growth (IPCC, 2014). The most important determinants of the demand for food in the future are the size of global population and per capita income growth (Baldos and Hertel, 2016). Developments in these variables in the 21st century are very uncertain. Based on the Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2014; IIASA, 2015), the spread between low and high global population levels in 2100 is 5.8 billion people, and average global per capita income in 2100 ranges between 22 and 138 thousand 2005USD across the SSPs. This translates into greatly differing global food requirements by the end of this century. On the supply side, future agricultural productivity is also highly uncertain—a problem which is confounded by the uncertain impacts of climate change on agriculture (Rosenzweig et al., 2014).

The problem posed by this future uncertainty in the demand and supply of agricultural products is further complicated by the extremely long lag time involved in translating agricultural research expenditures into realized productivity gains. For example, it took more than 80 years after the invention of hybrid corn for this important innovation to be fully disseminated in the United States and, in the case of Bt corn, this lag was more than a century (Pardey and Beddow, 2013). The fact that it takes decades for research spending to have an impact means plans cannot simply be adjusted in 2050 or 2100 if the world finds itself in food shortfall or surplus at that point in time. Long run planning is required, and this must be done in an environment of great uncertainty. Unfortunately, published work on this topic to date has not brought to bear the necessary tools for robust decision making under uncertainty. This study aims to do so by building on the FABLE model of optimal global land use (Steinbuks and Hertel, 2016). We begin by characterizing the lagged relationship between R&D spending and agricultural productivity and use this to estimate the optimal path of R&D spending over the 21st century. Since this depends on the uncertain global economic environment, we do so for each of the SSPs, generating five markedly different paths of optimal R&D spending. We then find the preferred path of spending by applying a criterion which seeks to minimize the maximum regret associated with making decisions based on one SPP, when another one turns out to be the realization.

2. Literature review and knowledge gaps

There is a rich literature on the impacts of agricultural research on farm productivity, much of it originating with the work of T.W. Schultz and his students at the University of Chicago (Alston et al., 2010). Griliches (1957, 1963) who sought to understand the dissemination of new technologies and their role in determining aggregate productivity growth. Hayami and Ruttan (1970) identified the role of relative prices in 'inducing innovation' in agriculture. Huffman and Evenson (2008) measured the contribution of public and private science to US agricultural productivity growth. Alston et al. (2010) find that the lag between R&D spending and farm productivity outcomes can persist for as long as five decades. Fuglie (2012) has taken this work to the global scale, documenting the links between agricultural knowledge capital, human capital and agricultural productivity growth across many different countries.

More recently, researchers have sought to understand the contribution of agricultural technologies to environmental outcomes, including climate mitigation (Burney et al., 2010; Stevenson et al., 2013). These researchers have found that higher yielding varieties historically reduced the amount of land conversion which would otherwise have occurred, thereby reducing global greenhouse gas (GHG) emissions. Lobell et al. (2013) find that future R&D can contribute to both effective climate adaptation as well as contributing to future mitigation of GHGs. Other recent research has sought to understand the link between agricultural R&D, technology adoption and agricultural development more generally (Maredia et al., 2014). However, to date, none of these studies have formally addressed the question of agricultural R&D investments as a problem of irreversible decision making under uncertainty. Yet, with the extremely long lag between such investments today and their potential future payoffs (Alston et al., 2010; Pardey and Beddow, 2013), along with the sizable demographic, economic and climatic uncertainties which the world faces, developing an optimal investment strategy is a very difficult task. There is a clear knowledge gap calling for the application of robust decision tools to the determination of optimal pathways for agricultural research.

Robust decision making has a very rich tradition (Lempert et al., 2006). It has grown increasingly important in the context of global change and decision making under alternative futures. In this context, there has been a resurgence of interest in scenario analysis (Trutnevyte et al., 2016). In an effort led by Brian O'Neill at NCAR, a set of Shared Socio-economic Pathways (SSPs) have been developed for use in Integrated Assessment Models for global change analysis (O'Neill et al., 2014). It lays out a set of future scenarios for global demographic, economic and climatic changes which are internally consistent, and which, taken together, span the two-dimensional space characterized by alternative socio-economic challenges for adaptation, on the one hand, and mitigation challenges on the other. Among others, the five scenarios include a low economic growth with high population future, a high economic growth with high emissions future, and a sustainable development future. Together, the five SSPs span the global uncertainty space which should be considered by those formulating global agricultural research policy over the 21st century.

In this paper, we seek to fill these knowledge gaps by leveraging earlier work on the linkage between agricultural R&D and productivity. We combine this knowledge with the latest developments in robust decision making under uncertainty in order to understand how future uncertainties, such as those posed by the alternative SSPs, should influence decision making about agricultural research at the global scale.

3. Theory and methods

3.1. A dynamic model of R&D investment

To understand the impacts of uncertainty in future population, income and climate change on the optimal level of global investment in agricultural R&D over the 21st century, we build on a dynamic, forward-looking, partial equilibrium (PE) model of land use (Steinbuks and Hertel, 2016). In our model, a social planner maximizes the sum of discounted payoffs, subject to endowments, production functions and other constraints. The social planner's payoff in each period takes into account global population and per capita welfare (utility). Per capita utility is derived from the consumption of land-based, as well as other, goods and services. The land-based final consumption goods include: crop-based food, livestock-based food, wood products, and energy (including bioenergy). Consumer preferences are represented with An Implicit, Directly Additive Demand System (Rimmer and Powell, 1996) which has been estimated on international cross-section data (Reimer and Hertel, 2004). This demand system is very flexible in its description of the evolution of consumer demands as per capita incomes grow (Cranfield et al., 2002), with the marginal budget share for food products falling towards zero as per capita income rises.

Production of the land-based final consumption goods, as well as intermediate inputs, is explicitly modeled within the PE framework. A schematic diagram of this stylized economy, with a focus on land-based goods and services is presented in Table 1, where the rows refer to inputs, including endowments and intermediate inputs, and the columns pertain to sectors in the PE model, as well as final consumption. Here it can be seen that production of crops requires land and fertilizers. The agrochemical sector converts fossil fuels into nitrogen fertilizer that is used in production of crops used for food, feed and biofuels. The energy sector combines petroleum and biofuels to produce energy services. The forestry sector produces timber, which is further processed into wood products. A composite of all other goods and services is used as other intermediate inputs, as well as representing competing final consumption. The production of these other goods and services is not captured within the PE model, but rather is given exogenously.

We solve a social planner's problem with perfect foresight. The social planner's objective is to maximize the total welfare (i.e., present value of global utilities over time):

$$\max_{I,\mathbf{X}} \quad \sum_{t=0}^{\infty} \delta^t U(\mathbf{y}_t)\Pi_t \tag{1}$$

where I is the R&D spending path, $\mathbf{X}$ is the vector path of resource allocation variables, δ is the discount factor, U is per capita utility derived from per capita consumption of five final goods, $\mathbf{y}_t$, and Π_t is global population at time t. Per capita utility is given by:

$$U(\mathbf{y}_t) = \frac{(C(\mathbf{y}_t))^{1-\gamma}}{1-\gamma} \tag{2}$$

where $\gamma > 0$ represents inverse of the intertemporal elasticity of substitution. Here $C(\mathbf{y}_t)$ is the per-capita consumption aggregator of the multiple goods and services $\mathbf{y}_t$, and is computed implicitly using AIDADS preferences (see Appendix for details).

Agricultural output depends on inputs used and the overall level of technology represented by Total Factor Productivity (TFP), as well as climate. TFP, in turn, depends on investments in agricultural research. In the model, both TFP and R&D are endogenous variables, with increases in the global stock of R&D driving growth in TFP. As previously noted, the diffusion of innovations in agriculture takes many years, so there is a lag between the R&D expenditures and the productivity gains at the farm level that can take decades to be fully felt (Piesse and Thirtle, 2010). In seeking to find a lag structure which best explains the relationship between R&D spending and total factor productivity (TFP) in agriculture in the United States, Alston et al. (2010) choose a distribution of weights which peaks at around 25 years (for the logarithmic model), with R&D impacts persisting for nearly half a century after the initial expenditure. This long lag is confirmed by Baldos et al. (2015) who adopt a Bayesian approach to estimating the US R&D-to-farm productivity lag structure, thereby providing estimates of the two parameters in the underlying gamma distribution.

We use the log-linear model and its parameter values from Baldos et al. (2015) for the relationships between TFP (A_t) and R&D knowledge stock (S_t), and treat R&D knowledge stock (S_t) as a weighted combination of annual average decadal investments in R&D (I_{t-i} for the decadal period $[t-i, t-i+1]$):

$$\ln(A_t) = \phi_0 + \phi_1 \ln(S_t) \tag{3}$$

$$S_t = \sum_{i=1}^{5} c_i I_{t-i} \tag{4}$$

where ϕ_0, ϕ_1 and c_i are estimated mean values taken from Baldos et al. (2015).[2] Specifically, the elasticity of TFP with respect to R&D knowledge stock, the "R&D elasticity", ϕ_1 is 0.3.

In light of the productivity spillover effects from developed to developing countries, on the one hand, and rapid improvements in the quality of agricultural R&D activities worldwide on the other, instead of using relatively poor quality global data on R&D to estimate the parameters above, we use parameters estimated on U.S. data to inform the relationship between agricultural R&D and productivity at global scale over the coming century. This lag structure suggests that the maximum impact of an increase in R&D spending today will be felt between two and three decades from now, while its total effects linger for the next 50 years Baldos et al. (2015). This poses a significant challenge for decision makers, as the decision not to invest today is irreversible. If events in 2040 call for higher levels of agricultural productivity, it is not possible to immediately attain these higher productivity levels by spending more on R&D in 2040. That process should have been started today.

In this framework, agricultural output depends not only on inputs used and TFP, but also climate – specifically the global mean temperature increase. Meta-analysis of crop impacts of climate change (Challinor et al., 2014) shows that global yields will be damaged by global warming with yields dropping on average 4.9% per 1ºC increase in temperature T_t. To reflect the impact of climate change on crop yields in the model, we multiply TFP (i.e., A_t) by $(1-\eta T_t)$ where $\eta = 0.049$, resulting in an outcome whereby past R&D becomes less efficient in delivering agricultural output under warmer climate – an approach consistent with the latest IPCC analysis (IPCC, 2014). Since the temperature pathway varies by SSP, this means that climate uncertainty will also affect our optimal investment decisions.

3.2. Characterizing future global uncertainties using SSPs

It is extraordinarily difficult to characterize future economic, demographic and climate uncertainties. Ideally, we would like to obtain a joint probability distribution specifying the likelihood of any combination of global GDP, population and temperature to be realized at each point in time over the next century. This would allow us to find the investment pathway which maximizes the present value of the stream of expected utilities over the time horizon in question. Unfortunately, developments in these global economic variables over the 21st century are very uncertain and they depend on a host of drivers, including government policies, civil conflict and climate response to elevated CO_2 concentrations in the atmosphere. Furthermore, these drivers are inter-related, with high income growth tending to generate greater CO_2 emissions, but also contributing to lower fertility rates and therefore slower population growth. It is simply not possible to develop the requisite multi-variate probability distribution. Therefore, we turn to the work undertaken by the global change community in the context of integrated assessment modeling. Specifically, a set of Shared Socioeconomic Pathways (SSPs) has been developed to cover the broad range of potential global economic and climate futures (O'Neill et al., 2014; IIASA, 2015).

Fig. 1 reports the evolution of global population, total income, income per capita and global average temperature for the five SSPs.[3] SSP2 is dubbed the 'middle of the road' scenario, since population and income growth rates, as well as the development of global temperature, are based on business-as-usual (BAU) conditions. SSP1 is the 'sustainability scenario' in which population growth peaks at

[2] In a robustness check, we also experimented with five-year time steps, in place of decadal time steps, and found that it did not change our results significantly.

[3] For interpretation of color in 'Figs. 1 and 3', the reader is referred to the web version of this article.

Table 1
Partial equilibrium model of land use.

Inputs	Sectors										Final consumption
	Crop	Livestock	Timber	Fertilizer	Crop-based food	Lvstk-based food	Biofuels	Wood products	Petroleum	Energy	
Crop		x			x		x				
Livestock						x					
Timber								x			
Fertilizer	x										
Crop-based food											x
Lvstk-based food											x
Biofuels										x	
Wood products											x
Petroleum										x	
Energy											x
Endowments											
Land	x	x	x								
Fossil Fuels				x					x		
Other g&s	x	x	x	x	x	x	x	x	x		x

mid-century and the global mean temperature rise in 2100 is just 2.5 °C. SSP3 contrasts sharply with these scenarios, with 'fragmentation' of the world economy leading to low income growth and population reaching nearly 13 billion (and still rising) at the end of the century. SSP5, 'conventional development', entails heavy fossil fuel consumption, which in turn fuels high income growth, thereby leading to the highest temperature increase of all—almost +4 °C above current levels by 2100. SSP4, the 'inequality scenario', has lower rates of income growth with slightly higher population in 2100 than SSP2. Inspection of the values of key variables in 2100 give a sense of the tremendous uncertainty foreseen by these SSPs: the spread between low and high global population levels in 2100 is 5.8 billion people, and the average global per capita income in 2100 ranges between 22 and 138 thousand 2005USD across the SSPs. Global average surface temperature in 2100 varies from 2.5 to 4 °C.

3.3. The Minmax Regret (MMR) method for robust decision making

Absent an explicit probability distribution for the uncertain drivers of global change, we must find another means of determining the optimal response to future uncertainties. The approach taken here involves choosing the future path of investment in R&D which minimizes the maximum regret (MMR) associated with future choices. Such regrets arise when we plan for one future – SSP2 (business as usual) for example – and the actual outcome is different – possibly SSP3 (the high population scenario). In this case, we might wish that we could turn back the clock and invest more in agricultural R&D in order to feed nearly 13 billion people at the end of this century. However, given the long lag from R&D to TFP, this would be problematic. The MMR solution factors in such regrets, and thereby proposes a different pathway which is deemed an acceptable outcome irrespective of which candidate scenario may be correct. In this way, it ameliorates the conservatism of the min-max criterion's dependence upon the worst-case scenario. The MMR solution selects a specific path of investment in agricultural R&D which is robust to future global economic, demographic and climate uncertainties.

To clearly represent the dependence of the production functions on the population, global income and change in global surface temperature, we represent them as follows:

$$\mathbf{y}_{t,k} = \mathbf{F}(A_t, \mathbf{X}_t; \Pi_{t,k}, E_{t,k}, T_{t,k}) \tag{5}$$

where $\Pi_{t,k}$ is the kth SSP projected world population path, $E_{t,k}$ is the kth SSP income path, $T_{t,k}$ is the kth SSP temperature path, A_t is level of technology in agriculture resulted from R&D spending path I, $\mathbf{X}_t$ is the vector of resource allocation variables $X^{i,j}$, and $\mathbf{y}_{t,k}$ is the vector of per-capita consumption of final goods produced under the decision path $(I, \mathbf{X})$ and the kth SSP scenario at time t. The production functions (5) represent the relationships between total output and per capita consumption of each good produced in the land-based economy, the constraint on other goods and services, as well as the market clearing constraints ((A.4)–(A.19) in the Appendix) with the kth SSP scenario.

To find the optimal path of R&D spending in the face of future uncertainties, we compute:

$$\mathcal{W}(I, \mathbf{X}; k) \triangleq \sum_{t=0}^{\infty} \delta^t U(\mathbf{y}_{t,k}) \Pi_{t,k}$$

which is the total welfare associated with policy paths $(I, \mathbf{X})$ and SSP scenario k. We then solve for:

$$G(k) \triangleq \max_{I,\mathbf{X}} \mathcal{W}(I, \mathbf{X}; k) \tag{6}$$

subject to the constraints (2), (3), and (5), corresponding to the kth SSP scenario. That is, for each SSP scenario we find the optimal path of agricultural R&D spending I and resource allocation $\mathbf{X}$. The regret function is defined as

$$R(I; k) \triangleq G(k) - \max_{\mathbf{X}} \mathcal{W}(I, \mathbf{X}; k) \tag{7}$$

for a given R&D spending path I and SSP scenario k. That is, for the kth realized SSP scenario, the regret is difference between (a) wealth attained when social planner can choose both optimal R&D spending and resource allocation and (b) wealth attained when social planner can choose resource allocation, but R&D spending is pre-determined. We then solve the MMR model as follows:

$$\min_I \max_k \quad R(I; k) \tag{8}$$

by using the computational method in Cai and Sanstad (2016). Note, the resulting vector of optimal per capita consumption $\mathbf{y}^*_{t,k}$ is now given by:

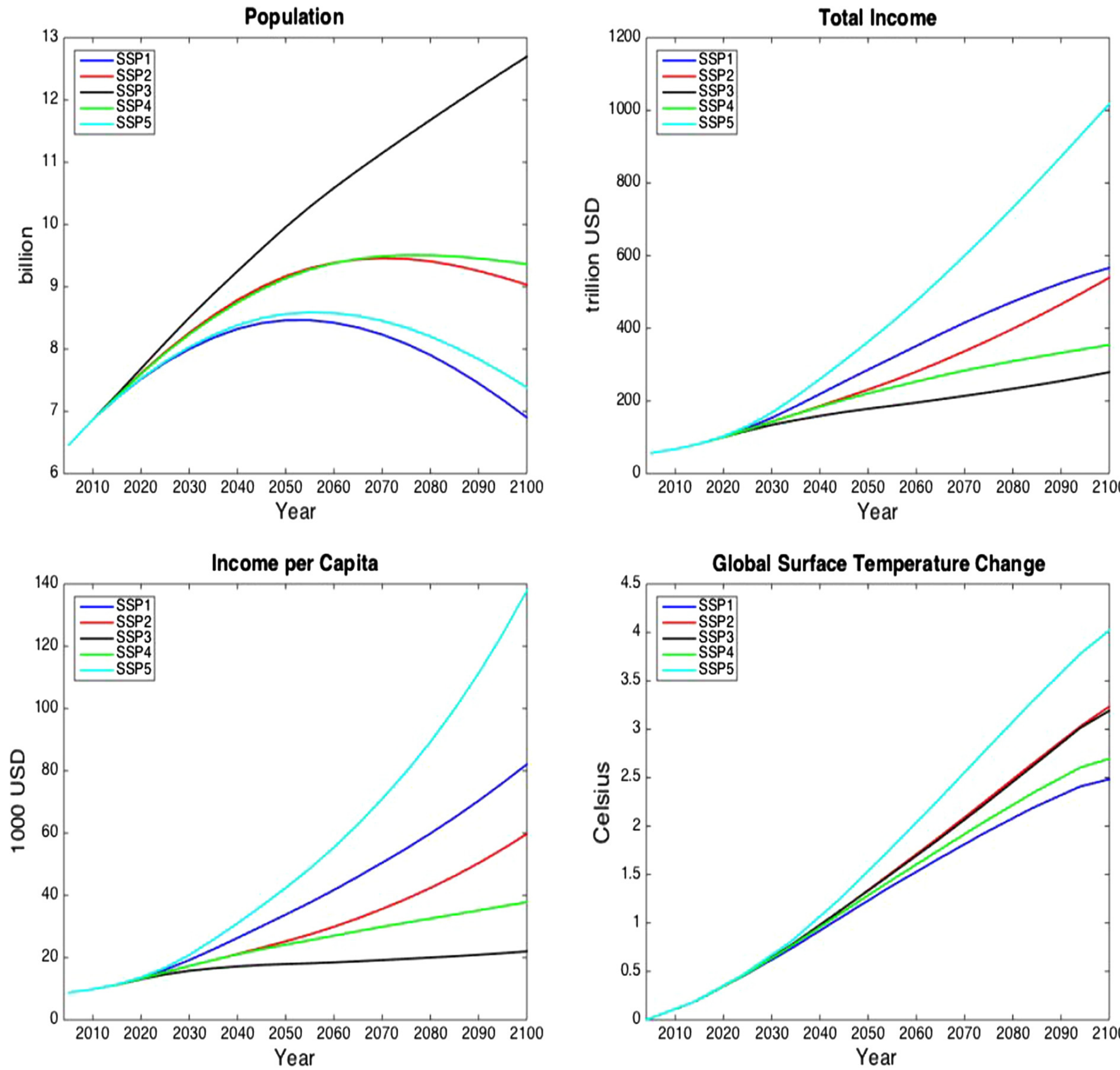

Fig. 1. SSP population (in billion), income (in trillion USD), their associated per-capita income (in 1000 USD), and changes in global surface temperature (in Celsius) relative to the beginning of the 21st century.

$$\mathbf{y}^*_{t,k} = \mathbf{F}\left(A^*_t, \mathbf{X}^*_{t,k}; \Pi_{t,k}, E_{t,k}, T_{t,k}\right) \tag{9}$$

where A^*_t is the optimal TFP resulting from the optimal R&D spending I^* in the MMR model (8), and $\mathbf{X}^*_{t,k}$ is the corresponding optimal solution of the maximization problem in the right-hand side of (7) for the given kth SSP scenario.

This formulation of MMR assumes that the R&D spending path I is the robust decision that is independent of scenarios (and I determines optimal A_t), while the optimal decision variables $\mathbf{X}$ are assumed to be dependent on scenarios, because these resource allocations $\mathbf{X}$ can be optimally adjusted as the world realizes which scenario will actually unfold. Scaling of the regret function $R(I, k)$ will not change the choice of optimal decisions. Here, we use the present value of the flow of global consumption loss to quantitatively measure the regrets (see Appendix for details). (In the Appendix, we also present MMR results when both uncertainty in the drivers of food demand and supply, as well as the elasticity of TFP with respect to R&D stock (i.e., ϕ_1) are simultaneously taken into account.)

4. Results

4.1. Results from the deterministic analysis

The dashed lines in Fig. 2 display the optimal deterministic path for R&D spending, and hence agricultural productivity, for each of the five SSP scenarios. These are calibrated to match observed, annual average global public R&D spending, \$30 billion, over the 2004–2011 period (constructed using data in Pardey et al. (2016)). SSP3 (high population) shows the highest rates of optimal R&D spending. The lowest spending paths are for SSP1 and SSP5, which have slower population growth, accompanied by higher income per capita growth. This illustrates the interaction between policies which moderate population growth (e.g., investments in female education) and agricultural R&D policy. Overall, optimal agricultural R&D spending in 2100 varies by a factor of 3.4—ranging from about \$105 billion to \$360 billion, depending on the SSP scenario. This raises the important question: given the inherent uncertainty about the future, which spending path should be chosen? If we plan for the sustainability outcome (SSP1), but fail to

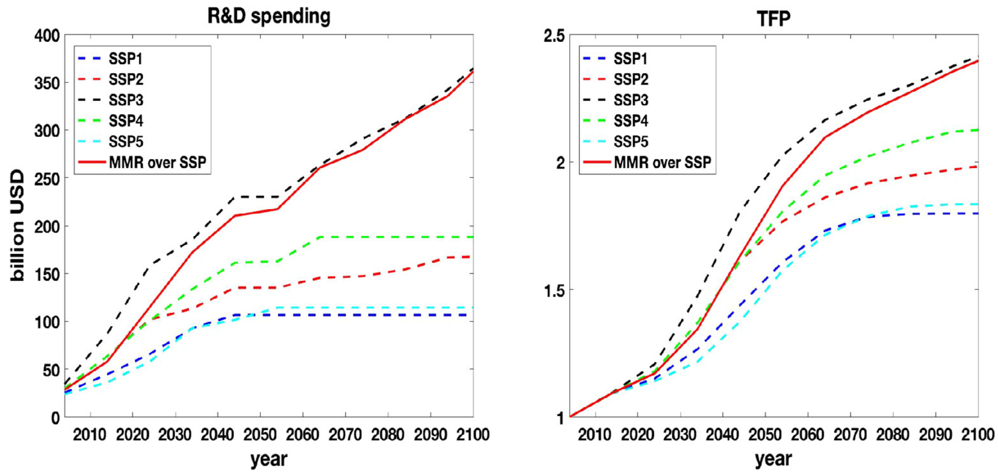

Fig. 2. Optimal Paths of R&D spending and TFP. The solid line represents the optimal path of the min-max regret (MMR) problem, and each dashed line represents solution of the deterministic model for specific SSP scenario path (e.g., the black dashed line represents solution of the deterministic model assuming population, income, and climate change paths are given exogenously by SSP3).

achieve this and instead revert to a fragmented global economy (SSP3), there will be serious shortfalls over the 21st century in R&D stock and productivity levels. This leads us naturally to the MMR approach.

4.2. Minimizing the maximum regret

As noted above, if we could assign probabilities to each of these SSPs, we might logically seek to maximize the expected value of our objective function. However, the alternative pathways represented by the SSPs are simply alternative storylines intended to encompass a wide range of possible future states of the world. There are no associated probabilities, although some, like the middle of the road (SSP2), appear more likely than others. The essential challenge in this decision making problem boils down to the following: what if we choose the optimal R&D action today with one SSP in mind, and then discover that the world economy is, in fact, following a different SSP? Given the long lag between R&D expenditures and productivity, it is not possible to return to the present day and chart a new course of R&D spending. How large is the regret which we would experience if we set off on the wrong path today? As noted above, we measure this as the present value of the flow of global consumption forgone by choosing the wrong SSP path for R&D spending, as opposed to the SSP which is actually realized. A complete matrix of regrets under alternative actions/outcomes is reported in Table 2.

The rows in Table 2 refer to actions taken. For example, the first row refers to the case where the investment path is chosen assuming that SSP1 will be realized. There are six rows, corresponding to the five SSPs as well as the MMR solution whereby we consider all SSPs as possible outcomes and seek to minimize the maximum regret across all outcomes. The columns in Table 2 refer to different realizations, comprising each of the five SSPs. Therefore, entries in the table report the regrets which arise when a given row action is taken and the associated column outcome is realized. It makes sense that the diagonal elements in this table are all equal to zero, since these are the cases where the planner accurately anticipates the future outcome. The off-diagonal elements detail the non-zero regrets which arise when the planner is wrong about the future.

Based on the entries in Table 2, we see that the largest regret occurs when the planner makes R&D investment decisions based on SSP5 (low pop, high temperature, high income per capita), yet SSP3, the high population and low income per capita path, is the true outcome. The associated loss is \$250 billion—a discounted value which is more than eight times the amount of initial R&D spending. This is followed closely by the level of regret (\$200 billion) which arises when we plan for SSP1, the low population and low temperature trajectory, therefore investing relatively less in R&D today, however, we end up on SSP3. SSP3 is the scenario with high population, low per capita income and higher temperature increase—a scenario which calls for greater investment in R&D from the start. The other regrets are much smaller, but even in the best case, when we base our R&D spending decisions on the SSP4 scenario, the largest loss (final column in Table 2) still reaches \$50 billion and amounts to considerably more than the current flow of global public R&D spending.

As explained in the methods section, we believe that the most natural approach to decision making under this type of uncertainty is to avoid choosing a path which is tailored to just a single SSP. Rather, we propose finding the R&D pathway which minimizes the maximum regret (MMR) (Cai and Sanstad, 2016; Hall et al., 2012; Iverson and Perrings, 2012). The MMR investment and productivity pathways are shown by the solid red line in Fig. 2. Note that the MMR path lies between the extremes of the deterministic paths up to 2030, but then deviates toward SSP3 optimal R&D spending path and essentially follows SSP3 to the end of the century. To put these total figures in perspective, the MMR expenditures on agricultural R&D represent about 0.05%, 0.1% and 0.07% of business as usual Global World Product in the beginning, middle and end of the 21st century, respectively. The final row in Table 2 demonstrates that the largest loss using the MMR solution is \$33 billion, which is much less than the largest loss using the deterministic solution associated with any one specific SSP scenario.

4.3. Assessing the interaction between different types of uncertainty

Given the interplay between optimal R&D policy and the multiple sources of long-run uncertainty in the global economy, it is important to see how different the long-run policy would be if it were built up from a sequence of analyses, each of which considers just one source of uncertainty at a time. Fig. 3 reports results from these experiments, designed to isolate the interaction effects among different sources of uncertainty (see appendix for details on the methodology used to do this). The plotted lines report the *additional R&D spending* called for under the MMR criterion if the underlying sources of uncertainty are considered one-at-a-time (the three dashed lines). In this case, we see that climate

Table 2
Present value of the flow of global consumption loss (in billion USD).

	Realization of SSP scenario					Largest
	SSP1	SSP2	SSP3	SSP4	SSP5	Loss
Sol. using SSP1	0	24	200	30	3	200
Sol. using SSP2	18	0	68	1	32	68
Sol. using SSP3	80	33	0	29	100	100
Sol. using SSP4	20	1	50	0	34	50
Sol. using SSP5	3	45	250	51	0	250
Sol. using MMR	32	27	33	32	33	33

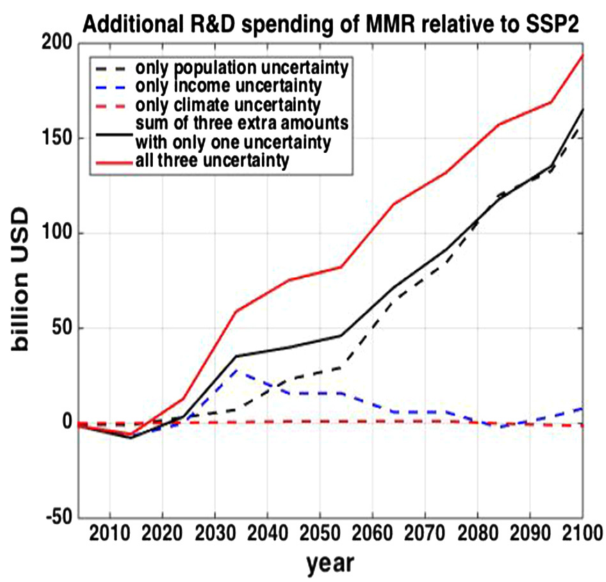

Fig. 3. Additional R&D spending of MMR solutions relative to the deterministic solution with SSP2.

uncertainty (red dashed line) does not significantly affect the optimal R&D spending path. In contrast, considering only population uncertainty gives rise to much higher levels of R&D than under the BAU scenario (i.e., SSP2). This reflects the very wide range of possible population outcomes in 2100 (7 billion vs. nearly 13 billion). The impact of income uncertainty is most important in the first half of the century, before the world's population reaches higher average income levels at which point the income elasticity of demand for food declines sharply. When we sum all three of the one-at-a-time MMR solutions together, we obtain the solid black line in Fig. 3. This suggests that, ignoring interactions amongst the different sources of uncertainty, society should move to higher levels of R&D spending, with the increment gradually increasing and reaching roughly $160 billion in the end of the century (relative to optimal R&D spending in SSP2).

By way of contrast, Fig. 3 also reports the MMR solution (the solid red[3] line) when all three sources of uncertainty are simultaneously considered. The difference between this and the summation of the individual MMR solutions is a useful measure of the policy impact of interacting uncertainties. When the uncertainties are simultaneously considered, the optimal R&D path (the solid red line) begins rising sooner and rises to a spending level which remains higher than the individual uncertainty path (the solid black line) from 2040 to the end of the century. In summary, the interaction effects among economic, demographic and climate uncertainties result in a substantial reallocation of the time path of R&D spending, calling for a substantial increase in the additional R&D desired.

5. Discussion

From a methodological point of view, this work has demonstrated, for the first time, how long run uncertainties affect society's optimal allocation of spending on agricultural R&D. In order to address this complex problem, we have made a number of simplifying assumptions which should be relaxed in future work. Firstly, we have focused on public agricultural R&D investments and have not included private expenditures, the share of which in total R&D has been rapidly expanding during the last three decades. One reason we have not included private investments is that they are less studied and data on global private R&D are not readily available. Another reason is that these investments are fundamentally different in character, with private R&D expenditures being directed to investments with faster payoffs. Private sector investments also tend to leverage public sector advances, suggesting a much more complex model of public–private interaction (Huffman, 2001).

Perhaps the most obvious limitation of this study is the global scale of our analysis. In reality, the productivity of R&D expenditures in improving agricultural technology varies greatly by region, and this depends on investments in human capital and extension services (Fuglie, 2012). With sufficient data, one could estimate Eqs. (3) and (4) for every major producing region, globally. Of course, R&D investments in one region can spillover and benefit other regions (Alston et al., 2010)—a factor which becomes important once one disaggregates individual regions. Population and income growth rates, as well as climate impacts, also vary dramatically by country. However, in a globally integrated market, international trade can facilitate the exchange of commodities between deficit and surplus regions, thereby facilitating adjustment to differential supply and demand growth rates (Baldos and Hertel, 2015). In this study, we are implicitly assuming that such arbitrage will occur over the long run.

Another, more subtle limitation of our global analysis is the absence of any consideration of the importance of the spatial location of crop production. Beddow and Pardey (2015) show that as much as one-fifth of the growth in US corn output over the period: 1879–2007 was due to the spatial movement of production in response to changes in climate and technology. By adopting an aspatial approach, we are likely understating the potential for adaptation to climate change, as well as new technological opportunities.

Uncertainty in the TFP 'production function' is also an important consideration. When we take into account both uncertainties in future population, income and climate change, represented by SSPs, as well as the elasticity of TFP with respect to R&D knowledge stock, we find that uncertainty in TFP response to R&D has little impact on the robust R&D spending (see Appendix). But the maximum regret increases significantly due to the additional source of uncertainty. Without using the MMR solution, the worst case regret rises to $456 billion, while the largest loss using the MMR solution is $63 billion.

Given the growing literature on R&D-based adaptation to climate impacts in agriculture (Lobell et al., 2013; Nelson et al., 2010), it is perhaps surprising that uncertainty in climate change plays a relatively small role in the optimal investment decisions within our framework. There are several reasons for this outcome. Firstly, when compared to the demand-side uncertainty emanating from population and income, the supply-side impacts of temperature changes envisioned under the SSPs are modest. Population in 2100 varies by a factor of nearly 2, while the ratio of high to low per-capita income in 2100 is almost 5. Against this backdrop, the 1.5°C temperature difference in 2100 between the most extreme SSPs is quite modest and does not reflect the full range of possible temperature outcomes in 2100 (IPCC, 2013). Moreover, the 1.5 °C temperature translates into only a 7.35% crop yield difference as we assume 4.9% decrease in crop yields per 1 °C increase in temperature. We find that the climate uncertainty foreseen by the SSPs leads to about 17% difference of R&D spending in 2100. Of course, there is also great uncertainty in the response of agricultural yields to these higher temperatures and we have not factored this type of response uncertainty into our analysis.

Finally, note that, while there is great uncertainty in future per capita incomes, this type of uncertainty has a relatively modest impact on optimal path of R&D spending. The reason for this outcome is that marginal budget share spent on food approaches zero at very high levels of income. Of course, how quickly marginal budget shares fall at higher levels of income is itself uncertain. Inclusion in the analysis of this type of parametric uncertainty, along with uncertainty in the response of productivity to R&D would increase the uncertainty associated with demographic and economic growth. Overall, we believe that the finding that population uncertainty dominates climate and income uncertainties as determinants of optimal R&D in agriculture over the 21st century is robust. However, in the longer run, beyond 2100, as temperatures continue to rise, and critical thresholds are exceeded, climate impact uncertainty will surely loom large.

6. Conclusions and policy implications

The central finding in this paper is that public spending on agricultural R&D should be increased, and this increase should be 'front-loaded' towards the first half of the 21st century. Specifically, we estimate that the growth rate in agricultural R&D spending should rise to 4.2% per year up to 2050, thereafter falling off, for an overall average growth rate of 2.6% per year over the entire 21st century. Investments in agricultural productivity in the near term are important due to the great uncertainty associated with environmental and socio-economic outcomes after 2050. According to the SSP scenarios utilized here, world population in 2100 could be as low as 7 billion or as high as 13 billion. World per capita income could be anywhere from $20,000 to $140,000. In addition, temperature anomalies could be in the range from 2.5 to 4 °C. Complicating this massive uncertainty is the long lag between public R&D investments and increases in agricultural productivity which means that we cannot afford to wait till 2050 to act. Given our analysis of society's potential regrets associated with planning for one future and ending up with another, it is clear that the most dire outcomes arise when we plan for the low population trajectories (SSP1 or SSP5), yet we end up on a high population path such as SSP3, in which case feeding the world becomes a significant challenge. In this context, agricultural R&D investments in the coming decade offer an important insurance policy against uncertainty in the evolution of the global economy over the 21st century.

Future research on the subject of optimal agricultural R&D under uncertainty should be a high priority. As previously noted, our findings lack geographical specificity. Yet, we know that the locus of agricultural R&D spending is rapidly shifting from developed to large developing economies, including China, India and Brazil. Assuming less than perfect spillovers from innovating regions to other countries, this will have important implications for the pattern of future productivity and agricultural output growth. Unfortunately, R&D investments in Sub-Saharan Africa (SSA) remain far below that in other regions, even though the SSA region continues to experience extremely rapid population growth. Without significant investments in improved agricultural productivity, many of the countries in Africa will be forced to import ever more of their food supply. This, in turn, raises important questions about their ability to pay for these imports, as well as the importance of maintaining a free and open world trade policy regime which will guarantee unfettered access to the world's food supplies. In summary, investments into agricultural R&D cannot be viewed in isolation from other key elements of food and economic policy.

Appendix A. Specification of the PE land use model

As noted in the text, we build on a dynamic forward looking partial equilibrium (PE) model of land use (Steinbuks and Hertel, 2016) in which a representative consumer derives utility from land-based and other goods and services. The land-based final consumption goods include: crop-based food, livestock-based food, wood products, and energy (including bioenergy). Here, we provide more detail on the underlying consumption and production relationships in the model employed in the analysis. Recall that, in the deterministic model, we solve a social planner's problem with perfect foresight. The social planner's objective is to maximize the total welfare (i.e., present value of global utilities):

$$\max_{I,\mathbf{X}} \quad \sum_{t=0}^{\infty} \delta^t U(\mathbf{y}_t)\Pi_t \tag{A.1}$$

where I is the R&D spending path, $\mathbf{X}$ is the vector path of resource allocation variables, δ is the discount factor, U is per capita utility derived from per capita consumption of five final goods, $\mathbf{y}_t$, and Π_t is global population at time t. Per capita utility is given by:

$$U(\mathbf{y}_t) = \frac{(C(\mathbf{y}_t))^{1-\gamma}}{1-\gamma} \tag{A.2}$$

where $\gamma > 0$ represents inverse of intertemporal elasticity of substitution. Here $C(\mathbf{y}_t)$ is the per-capita consumption aggregator of the multiple goods and services $\mathbf{y}_t$, and is computed implicitly using AIDADS preferences:

$$\ln(C(\mathbf{y}_t)) = \left[\sum_{q=cfood,lfood,e,w,o} \left(\frac{\alpha_q + \beta_q C(\mathbf{y}_t)}{1 + C(\mathbf{y}_t)} \right) \ln\left(y_t^q - \underline{y}^q \right) \right] - 1 - \ln(\Upsilon) \tag{A.3}$$

where α, β, and Υ are parameters, and $\underline{y}^q$ is subsistence level. When $\gamma = 1$, the utility is $U(\mathbf{y}_t) = \ln(C(\mathbf{y}_t))$, equivalent to the AIDADS utility (Rimmer and Powell, 1996).

The social planner's optimization problem is subject to endowment availability, production function, market clearing and transition law constraints defined below. The objective function of the maximization problem (A.1) has infinite horizon and cannot be computed exactly. In our computational examples, we use the summation of discounted utility over 300 years as its approximation, and focus on first 100 years of simulation in the analysis. The model is solved with decadal time steps.

Production activities in the partial equilibrium model of land use are indexed with superscript j. Let $X_t^{i,j}$ denote quantity of intermediate input i used in production sector j. Market clearing for each produced good i is $Q_t^i = \sum_j X_t^{i,j}$. $X_t^{o,j}$ denotes quantity of other g&s used in production sector j. Production output i that is used as an intermediate input and not as a final consumption good is denoted by Q_t^i. If output i is used as an intermediate input in activity j only, then market clearing condition is $Q_t^i = X_t^{i,j}$. To eliminate this "dummy" constraint, Q_t^i is used to denote both output i and input i used in production sector j. For example, the land-fertilizer composite is used in crop production only. So, Q_t^{lf} denotes both land-fertilizer composite output and land-fertilizer composite input in crop production. Subscript "0" refer to observation at the point of normalization (i.e., year 2004). L_t^C, L_t^P, and L_t^F denote cropland, pasture land, and forest land, θ_t^i represent exogenous technological improvement, and A_t represents endogenous level of technology in agriculture (TFP). Y_t^j denotes total consumption of final good j and output of respective sector, so the per-capita consumption is

$$\mathbf{y}_t = (y_t^{cfood}, y_t^{lfood}, y_t^e, y_t^w, y_t^o) = (Y_t^{cfood}, Y_t^{lfood}, Y_t^e, Y_t^w, Y_t^o)/\Pi_t \tag{A.4}$$

where $y_t^{cfood}, y_t^{lfood}, y_t^e, y_t^w$, and y_t^o denote per capita consumption of crop-based food, livestock-based food, energy services, wood products, and other g&s, respectively. Each production activity is represented with a constant elasticity of substitution (CES) production function, where α^j represents base year cost share of specific input used in production of j (e.g. crop input used in food production), $(1-\alpha^j)$ represents base year cost share of other g&s input, and $\rho^j = \frac{(\sigma^j - 1)}{\sigma^j}$ where σ^j is the elasticity of substitution. These production functions are as follows:

- Petroleum production function:

$$Q_t^p = Q_0^p \left(\alpha^p \left(\frac{X_t^{ex,p}}{X_0^{ex,p}} \right)^{\rho^p} + (1-\alpha^p) \left(\frac{X_t^{o,p}}{X_0^{o,p}} \right)^{\rho} \right)^{1/\rho^p} \tag{A.5}$$

where $X_t^{ex,p}$ denotes fossil fuels used in petroleum production.

- Fertilizer production function:

$$Q_t^{fert} = Q_0^{fert} \left(\alpha^{fert} \left(\frac{X_t^{ex,fert}}{X_0^{ex,fert}} \right)^{\rho^{fert}} + (1-\alpha^{fert}) \left(\frac{X_t^{o,fert}}{X_0^{o,fert}} \right)^{\rho^{fert}} \right)^{1/\rho^{fert}} \tag{A.6}$$

where $X_t^{ex,fert}$ denotes fossil fuels used in fertilizer production.

- Cropland and fertilizer composite production function:

$$Q_t^{lf} = Q_0^{lf} \left(\alpha^{lf} \left(\frac{L_t^C}{L_0^C} \right)^{\rho^{lf}} + (1-\alpha^{lf}) \left(\frac{Q_t^{fert}}{Q_0^{fert}} \right)^{\rho^{lf}} \right)^{1/\rho^{lf}} \tag{A.7}$$

- Crop production function:

$$Q_t^c = (1 - \eta T_t) A_t Q_0^c \left(\alpha^c \left(\frac{Q_t^{lf,c}}{X_0^{lf,c}} \right)^{\rho^c} + (1-\alpha^c) \left(\frac{X_t^{o,c}}{X_0^{o,c}} \right)^{\rho^c} \right)^{\frac{1}{\rho^c}} \tag{A.8}$$

where T_t is the temperature increase relative to base year of analysis, and A_t is the agricultural TFP.

- Crop-based food production function:

$$Y_t^{cfood} = \theta_t^{cfood} Y_0^{cfood} \left(\alpha^{cfood} \left(\frac{X_t^{c,cfood}}{X_0^{c,cfood}} \right)^{\rho^{cfood}} + (1-\alpha^{cfood}) \left(\frac{X_t^{o,cfood}}{X_0^{o,cfood}} \right)^{\rho^{cfood}} \right)^{1/\rho^{cfood}} \tag{A.9}$$

where $X_t^{c,cfood}$ denotes crops used in crop-based food production.

- Pasture land and feed composite production function:

$$Q_t^{lfeed} = Q_0^{lfeed} \left(\alpha^{lfeed} \left(\frac{L_t^P}{L_0^P} \right)^{\rho^{lfeed}} + (1-\alpha^{lfeed}) \left(\frac{X_t^{c,feed}}{A_t X_0^{c,feed}} \right)^{\rho^{lfeed}} \right)^{1/\rho^{lfeed}} \tag{A.10}$$

where $X_t^{c,feed}$ denotes crops used for livestock feed.

- Livestock production function:

$$Q_t^l = A_t Q_0^l \left(\alpha^l \left(\frac{Q_t^{lfeed}}{Q_0^{lfeed}} \right)^{\rho^l} + (1-\alpha^l) \left(\frac{X_t^{o,l}}{X_0^{o,l}} \right)^{\rho^l} \right)^{1/\rho^l} \tag{A.11}$$

- Livestock-based food production function:

$$Y_t^{lfood} = \theta_t^{lfood} Y_0^{lfood} \left(\alpha^{lfood} \left(\frac{Q_t^l}{Q_0^l} \right)^{\rho^{lfood}} + (1-\alpha^{lfood}) \left(\frac{X_t^{o,lfood}}{X_0^{o,lfood}} \right)^{\rho^{lfood}} \right)^{1/\rho^{lfood}} \tag{A.12}$$

- Biofuel production function:

$$Q_t^b = Q_0^b \left(\alpha^b \left(\frac{X_t^{c,b}}{X_0^{c,b}} \right)^{\rho^b} + (1-\alpha^b) \left(\frac{X_t^{o,b}}{X_0^{o,b}} \right)^{\rho^b} \right)^{1/\rho^b} \tag{A.13}$$

where $X_t^{c,b}$ denotes crops used in biofuel production.

- Energy production function:

$$Y_t^e = \theta_t^e Y_0^e \left(\alpha^e \left(\frac{Q_t^b}{Q_0^b} \right)^{\rho^e} + (1-\alpha^e) \left(\frac{Q_t^p}{Q_0^p} \right)^{\rho^e} \right)^{\frac{1}{\rho^e}} \tag{A.14}$$

- Timber production function:

$$Q^{tim} = Q_0^{tim} \left(\alpha^{tim} \left(\frac{L^F}{L_0^F} \right)^{\rho^{tim}} + (1-\alpha^{tim}) \left(\frac{X^{o,tim}}{X_0^{o,tim}} \right)^{\rho^{tim}} \right)^{1/\rho^{tim}} \tag{A.15}$$

- Wood production function:

$$Y_t^w = \theta_t^w Y_0^w \left(\alpha^w \left(\frac{Q_t^{tim}}{Q_0^{tim}} \right)^{\rho^w} + (1-\alpha^w) \left(\frac{X_t^{o,w}}{X_0^{o,w}} \right)^{\rho^w} \right)^{1/\rho^w} \tag{A.16}$$

- The other g&s consumption:

$$Y_t^o = E_t - \sum_{i \in \{fert, c, b, cfood, l, lfood, p, tim, w\}} X_t^{o,i} - I_t \tag{A.17}$$

where E_t is total annual other g&s, given exogenously, Y_t^o is other g&s consumed, and I_t is the annual global R&D spending.

- Market clearing condition for extracted fossil fuel:

$$X_t^{ex,p} + X_t^{ex,fert} - Q_t^{ex} = 0 \tag{A.18}$$

- Market clearing condition for crops:

$$X_t^{c,b} + X_t^{c,cfood} + X_t^{c,feed} - Q_t^c = 0 \tag{A.19}$$

For simplicity, in this paper we assume that cropland L_t^C, pasture land L_t^P, and forest land L_t^F have fixed areas over the analyzed time horizon, and the path of extracted fossil fuels Q_t^{ex}, used for liquid fuels and production of fertilizer in the model, is given exogenously and follows extraction growth rate in the SSP2 scenario.

The model is benchmarked to the year 2004 using FAOSTAT (FAOSTAT, 2015) and GTAP v.7 data bases (Narayanan and Walmsley, 2008). The AIDADS parameters for this study are estimated on the cross-section of countries recorded in GTAP v.7 data base following methodology documented in Reimer and Hertel (2004). To implement AIDADS in the partial equilibrium model, the estimated parameters must be calibrated for our global representative consumer to ensure equality of fitted AIDADS budget shares and ones observed in the initial year of the analysis. The calibration procedure follows approach described in Golub (2006). The elasticity of substitution between land and fertilizer in crop production is calibrated using econometric analysis reported in Hertel et al. (1996). The elasticity of substitution between biofuel and petroleum is calibrated using econometric analysis reported in Anderson (2012). The elasticity of substitution between pasture and feed in global livestock sector is calibrated using elasticities reported in Keeney and Hertel (2005). Other input-output relationships are assumed to occur in (nearly) fixed proportions.

Appendix B. Computing the value of regrets

The regret function is defined as

$$R(I;k) \triangleq G(k) - \max_{\mathbf{X}} \mathcal{W}(I,\mathbf{X};k) \tag{A.20}$$

for a given R&D spending path I and SSP scenario k. That is, for the kth realized SSP scenario, the regret is difference between (a) wealth attained when social planner can choose both optimal R&D spending and resource allocation and (b) wealth attained when social planner can choose resource allocation, but R&D spending is given. We then solve the MMR model

$$\min_{I} \max_{k} \quad R(I;k) \tag{A.21}$$

by using the computational method in Cai and Sanstad (2016). As explained in the main text, we use the present value of the flow of global consumption loss to quantitatively measure the regrets. Let $c_{t,l}^* = C(\mathbf{y}_{t,l}^*)$ be the optimal per capita consumption aggregator of the maximization problem (6) for scenario l, and let $c_{t,k,l}$ be the per capita consumption aggregator when we implement the optimal solution I of (6) for scenario k but the world ends up on scenario l.

To convert the units of consumption aggregators $c_{t,l}^*$ and $c_{t,k,l}$ to real market dollars we divide the aggregators by $\frac{\partial C}{\partial y^o}(\mathbf{y}_{t,l}^*)$, where y^o, other goods and services, are measured in real market dollars. Thus, the per capita consumption loss at time t is

$$\frac{c_{t,l}^* - c_{t,k,l}}{\frac{\partial C}{\partial y^o}(\mathbf{y}_{t,l}^*)} \tag{A.22}$$

Therefore, the present value of the flow of global consumption loss (the regret) is

$$\sum_{t=0}^{\infty} \frac{c_{t,l}^* - c_{t,k,l}}{\frac{\partial C}{\partial y^o}(\mathbf{y}_{t,l}^*)\prod_{s=0}^{t-1}(1+r_s)} \tag{A.23}$$

where r_s is the real net interest rate in period s, which is computed by

$$r_s = \frac{U'(c_{s,l}^*)\frac{\partial C}{\partial y^o}(\mathbf{y}_{s,l}^*)}{\delta U'(c_{s+1,l}^*)\frac{\partial C}{\partial y^o}(\mathbf{y}_{s+1,l}^*)} - 1 \tag{A.24}$$

Appendix C. Decomposing the sources of uncertainty

The model (8) assumes that population, income, and climate uncertainty are fully correlated within any given SSP scenario. We conduct decomposition analysis (Fig. 3 in the main text) which assumes that only one uncertainty, e.g., population uncertainty, is represented by the SSP scenarios, and the other two components of SSPs (e.g. income and temperature) are assumed to be certain and given exogenously by one specific SSP scenario (e.g., SSP2). For such a decomposition, we change the production functions (5). For example, with only population uncertainty, the production functions in the associated MMR problem become $\mathbf{y}_{t,k} = \mathbf{F}(A_t, \mathbf{X}_t; \Pi_{t,k}, E_{t,2}, T_{t,2})$ where $E_{t,2}$ and $T_{t,2}$ are SSP2 income and temperature paths, respectively.

Fig. A.1 shows the optimal MMR paths of TFP and R&D spending for models with only population uncertainty, only income uncertainty, and only climate uncertainty, respectively, where the other two exogenous paths are chosen to be SSP2. It shows that population uncertainty is, individually, the greatest source of R&D uncertainty. Clearly it is important both that R&D has a delayed impact and that there are multiple sources of uncertainty which are tightly intertwined.

The decomposition analysis in Fig. 3 shows that the whole of uncertainty's impact on R&D is greater than the sum of its individual parts over the century. This decomposition is conducted with respect to SSP2 scenario. To check if the result is robust with respect to the choice of reference scenario, the decomposition is also conducted with respect to SSP1, SSP3, SSP4 and SSP5 scenarios. Fig. A.2 indicates that the finding is indeed robust, despite the fact that the contribution, both magnitude and direction, of each source of the uncertainty, depends on reference scenario. In each case, the combined scenario (simultaneous uncertainties) shows a higher level of R&D spending over the 21st century than that obtained by simply summing the individual uncertainties.

Appendix D. Minmax regret model with both SSP and R&D elasticity uncertainty

In addition to the uncertainties surrounding the SSP scenarios, there are many other sources of uncertainty influencing the future path of R&D knowledge capital and associated TFP in agriculture. Perhaps most central to this question is the responsiveness of TFP with respect to knowledge capital. Baldos et al. (2015) estimate this elasticity to be 0.3 – the central value used in our paper – with a standard deviation of 0.1. With this in mind, we introduce this added source of uncertainty into MMR dynamic optimization as follows. We assume that ϕ_1 ranges from 0.2 to 0.4, and has potential discretized values $\phi_{1,j}$ for $j = 1, \ldots, n$ (we choose $n = 3$ with $\phi_{1,1} = 0.2, \phi_{1,2} = 0.3$ and $\phi_{1,3} = 0.4$ to represent low, medium and high R&D elasticity respectively). For each SSP scenario k and value $\phi_{1,j}$, the production functions become

$$\mathbf{y}_{t,k,j} = \mathbf{F}(A_{t,j}, \mathbf{X}_t; \Pi_{t,k}, E_{t,k}, T_{t,k}) \tag{A.25}$$

with

$$\ln(A_{t,j}) = \phi_0 + \phi_{1,j}\ln(S_t)$$

The total welfare associated with policy paths $(I, \mathbf{X})$ becomes

$$\mathcal{W}(I,\mathbf{X};k,j) \triangleq \sum_{t=0}^{\infty} \delta^t U(\mathbf{y}_{t,k,j})\Pi_{t,k}$$

We then solve

$$G(k,j) \triangleq \max_{I,\mathbf{X}} \mathcal{W}(I,\mathbf{X};k,j) \tag{A.26}$$

and the MMR model

$$\min_{I} \max_{k,j} \quad R(I;k,j) \tag{A.27}$$

where the regret function R is defined as

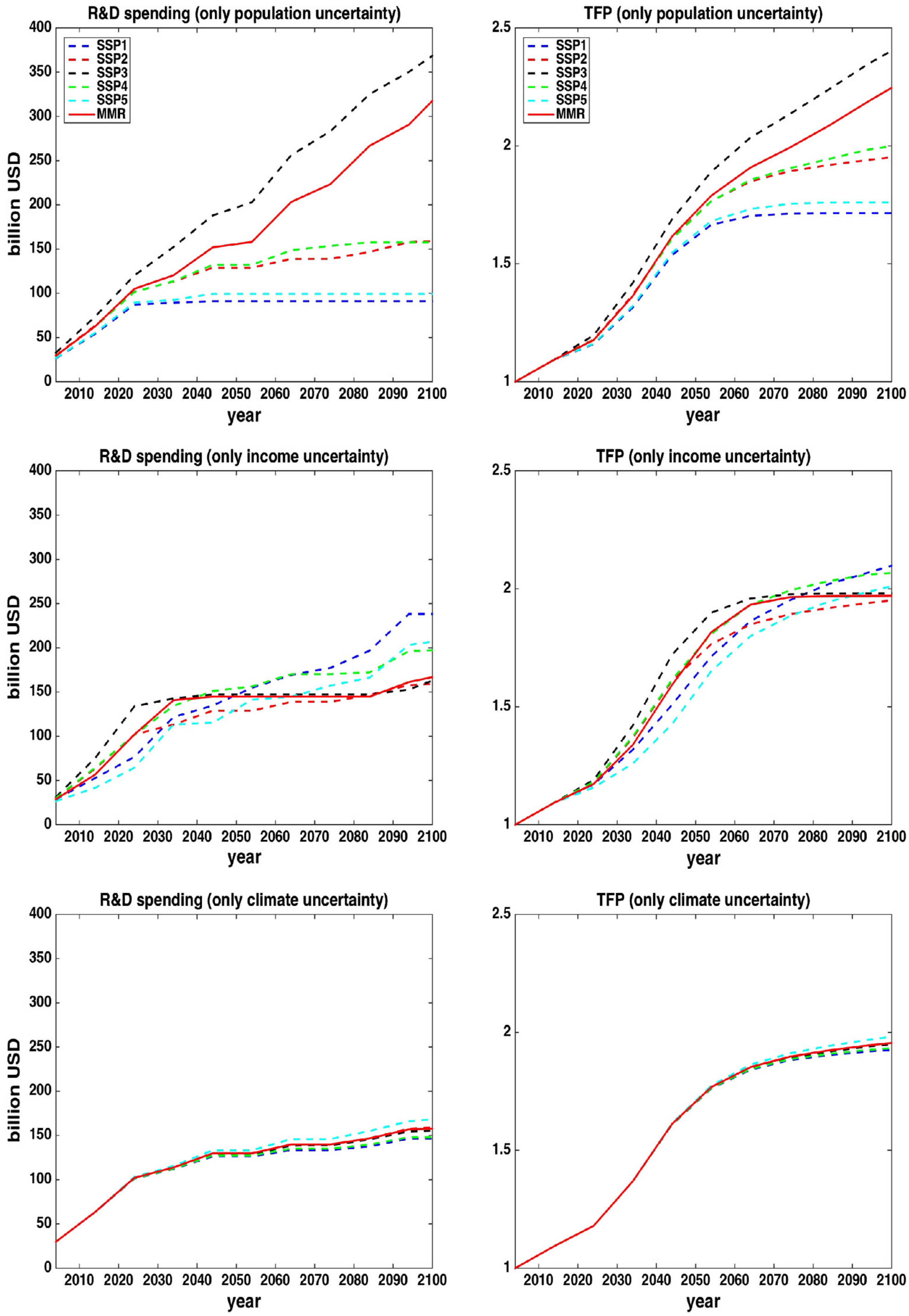

Fig. A.1. Optimal Paths of R&D and TFP spending under population, income, and climate uncertainties, considered one at a time.

$$R(I;k,j) \triangleq G(k,j) - \max_{\mathbf{X}} \mathcal{W}(I,\mathbf{X};k,j) \tag{A.28}$$

for a given R&D spending path I, SSP scenario k and elasticity value $\phi_{1,j}$.

When we solve the MMR model (A.27), we find that the optimal path for R&D spending is not very different from that reported in the paper (see Fig. A.3 for this comparison). However, with this added source of uncertainty, the maximum regrets are now much larger. For example, when planning for SSP5 (low population growth – recall Fig. 1 from the text), in the face of a low TFP elasticity (0.2), sizable R&D investment results in large regrets ($456 billion) if SSP3 (fragmentation scenario leading to high population growth) and a high TFP elasticity comprise the true realization. This high level of regret arises from underinvesting in R&D (investments are less productive with the low elasticity) during the early part of the century, followed by a flattening of real expenditures after 2050 (see Fig. 2), even as the optimal path of R&D should have been rising strongly. The smallest regret across all SSPs is for SSP2/medium TFP elasticity, but even this reaches $74 billion in the face of a SSP5/low elasticity realization.

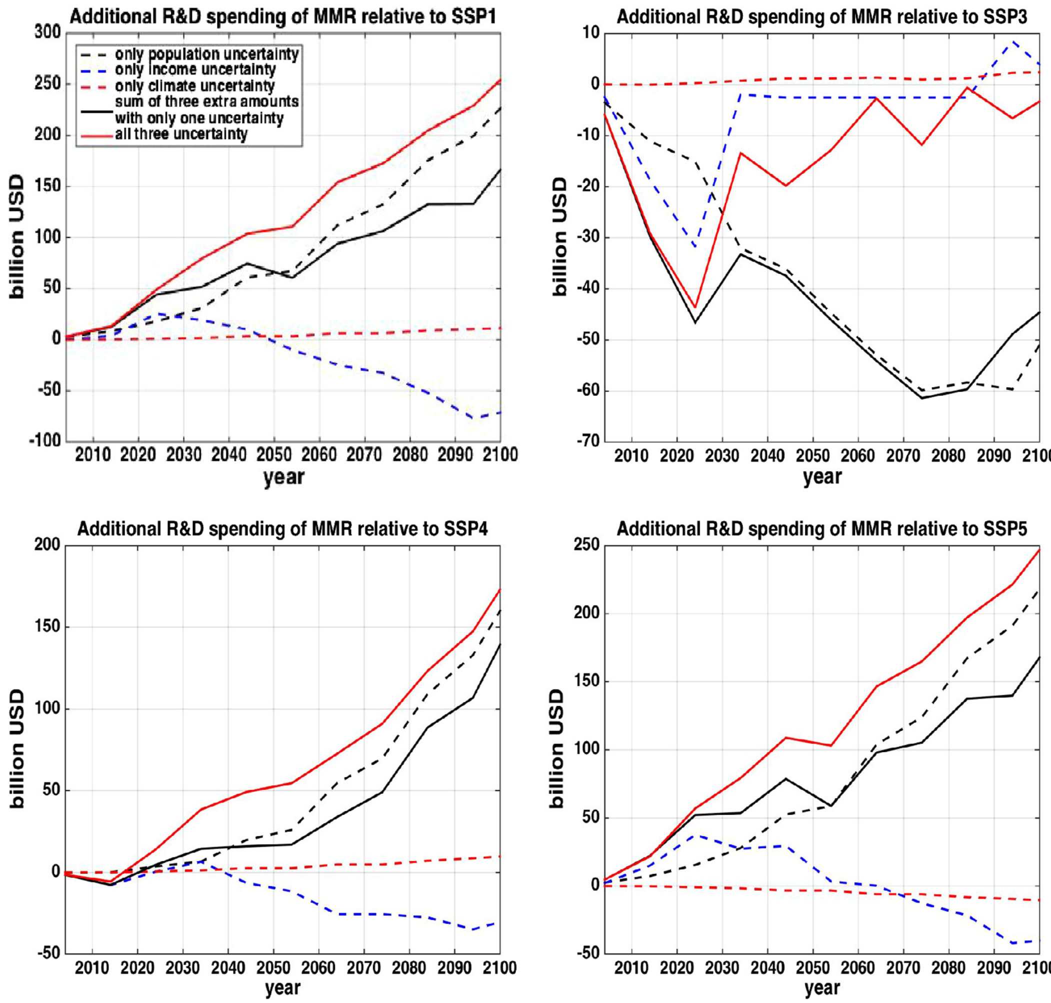

Fig. A.2. Additional R&D spending of MMR relative to SSP1, SSP3, SSP4, and SSP5.

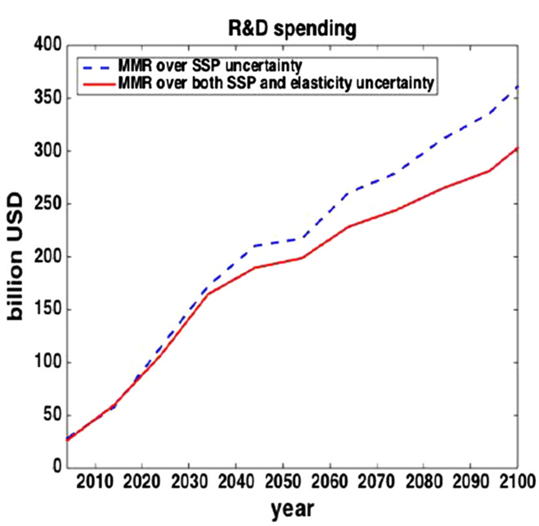

Fig. A.3. R&D spending of MMR with SSP and R&D Elasticity Uncertainty.

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