Developing long-run agricultural R&D policy in the face of uncertain economic growth*

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Abstract

Projecting economic growth, population and climate over the 21st century is challenging. One approach to this problem has been the development of "Shared Socio-economic Pathways" (SSPs) designed to provide a consistent characterization of alternative evolutions of population, per capita income and climate. However, recent analysis has shown that the true extent of future growth uncertainty is likely far greater than that embodied in the SSPs. We build on the innovative work of Christensen et al., in order to construct 13 independent probability distributions of economic growth in the 21st century. For each of these distributions, we use a stochastic dynamic partial equilibrium model of global land use to compute the optimal rate of R&D investment as well as the ensuing path of Total Factor Productivity (TFP) growth to 2100. When there is a significant probability of non-positive growth, the optimal response is to invest a lot in R&D today, and maintain a fairly flat trajectory over the entire century. This is in sharp contrast to the optimal path when growth rates are strictly positive. In this case, R&D spending starts out slow, and accelerates over time. Since we do not know which expert, if any, is correct, we propose a novel approach to dealing with this ambiguity by minimizing the maximum regret across all 13 optimal growth paths. This results in 40% higher R&D spending early in the century than that dictated by a mean growth rate deterministic model. However, by mid-century, optimal R&D spending levels off, and the resulting TFP plateaus by the end of the century at a level which is about twice as high as at the start.

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1 Introduction

Over the past 50 years, most of the increase in demand for agricultural products was met through improvements in agricultural productivity, arising from innovations and changes in technology (Evenson, 2001). Public and private investments into agricultural research and development (R&D) have been playing an important role in this achievement. High rates of return on these investments (Fuglie and Heisey, 2007; Alston et al., 2000; Evenson, 2001) are generally taken as evidence of underinvestment in agricultural R&D and suggest that increasing investment will further increase agricultural output (Beintema and Elliot, 2009). More aggressive R&D spending is often considered as a vehicle to end hunger and poverty, and meet expected increase in demand for agricultural products in the 21st century. However, the rate of growth in global public agricultural R&D spending declined during 1981-2000 and became negative in developed countries over the 1991-2000 decade (Pardey et al., 2006), raising concerns about the world's future ability to feed a growing population (Alston et al., 2009). This, in turn, spurred literature on how much investment in agricultural R&D is required and how this should be targeted.

Piesse and Thirtle (2010) review the literature that discusses additional investment in agricultural R&D needed to meet current and future demands for food (Bientema and Elliot 2009, Von Braun et al. 2008, Rosegrant et al. 2008). Estimates of the additional agricultural R&D needed to meet poverty or hunger reduction targets often involve assumptions about elasticity of agricultural output with respect to R&D stock and stylized representation of R&D stock dynamics. Piesse and Thirtle (2010) assume a relatively low elasticity of agricultural output with respect to R&D expenditure (0.05), and estimate that to increase annual growth in output from current 1% to the 1.34%, potentially needed to meet increase in global demand by 2050, current global annual spending on agricultural R&D of US$36 billion should increase by 6.8%, or US$2.5 billion per annum. Von Braun et al. (2008) simulate the impact of doubling R&D funding in developing countries, from about US$4.6 billion to US$9.3 billion per annum over 2008-2013 period, and then keeping R&D expenditure at the new higher level. They assume that inputs are fixed at the base year of analysis, and agricultural output depends only on R&D stock. Under some reasonable assumptions on R&D elasticities, they find that targeting new resources toward maximizing total agricultural output results in increase in output growth from 0.5% in 2008 to 1.5% in 2020. This analysis was further refined in Pratt and Fan (2010) who consider sensitivity of the results with respect to assumption on elasticity of output with respect to stock of R&D.

On a global scale, the answer to the question how much investment shall be put into agricultural R&D, depends on the demand for food in the future. The most important determinants of this demand are the size of global population and per capita income growth (Hertel et al., 2016). Developments of these variables in the 21st century are highly uncertain. According to the Shared Socioeconomic Pathways (SSPs) (IIASA, 2015), the spread between low and high global population levels in 2100 is about 5.8 billion people, and average global per capita income ranges between 22 and 138 thousand 2005US$, while results of the Yale Long-Run Growth Survey indicate much wider range of possible global per capita income outcomes in the end of this century (Christensen et al., 2016). On the supply side, there are many uncertainties as well, including the effectiveness with which R&D spending translates into increased agricultural productivity growth, which, in turn, depends on uncertain impacts of climate change.

Studies that quantify changes in agricultural productivity over time consider different measures of productivity, including physical crop yield, land and labor productivity, as well as total factor productivity (TFP). TFP accounts for input substitution. Piesse and Thirtle (2010) point out that although yield growth has slowed in aggregate and labor productivity growth varies by region, TFP has improved in most regions. Studies of the contributions of agricultural research and extension to productivity growth often use TFP as a measure of agricultural productivity. These studies highlight that technological innovation – from new technologies to commercial development and transmission to farmers – takes time, and represent TFP as a function of a weighted sum of R&D expenditures over some number of past years (Alston et al., 2010).

The goal of the present study is to analyze optimal path of global agricultural R&D spending in the 21st century and understand impacts of uncertainty in future growth of per capita income on decisions to invest in agricultural R&D, while factoring in the long time lag in response of agricultural productivity to R&D expenditures. Quantification of uncertainty in future economic growth rates, however, is a very difficult task. Such an exercise involves assumptions about new technologies, future educational attainment, institutional reforms and political stability (Gillingham et al., 2015). In the absence of this information, researchers rely on scenario-based forecast or experts opinions regarding possible growth rates in the 21st century and their probability distributions. Christensen et al. (2016) document, however, that uncertainty in global growth rates quantified with experts' forecast is substantially higher than what is implied by scenario-based estimates currently used in policy research. Following this new finding, this study quantifies uncertainty using economic experts' opinions regarding probability distribution of the long-run economic growth using the survey results reported in Christensen et al. (2016).

The paper is organized as follows. Section 2 is devoted to mathematical formulation of the problem and presents a dynamic forward looking model of land use with endogenous investments into agricultural R&D to improve agricultural productivity, and uncertain economic growth. In the model, the social planner chooses a path of R&D spending and resource allocation from now to 2100 to maximize expected global welfare. The planner takes into account increasing global population and realizes that it will take several decades before investments in R&D spent today translate into increases in agricultural productivity. Resources available each period to the social planner depend on future economic growth rates, but the growth rates are not known with certainty. Therefore, the social planner employs experts forecast regarding the economic growth rates. However, different experts have different opinions regarding the probability distribution of productivity growth in this century. In an effort to come up with the best plan, the social planner takes into account the opinions of all the experts and chooses the path of R&D spending that minimizes maximum regret (MMR) associated with not choosing one specific distribution from the provided ones by the experts. Section 3 is devoted to the results and presents optimal R&D spending when opinion of each expert is separately taken into account and then, the MMR R&D spending path. The MMR R&D spending path is then compared with a path obtained from maximizing expected global welfare when probability distribution of growth rates is constructed by averaging across experts' forecasts. Section 4 discusses the findings and concludes.

2 Modeling Framework

2.1 Dynamic model of land use with endogenous agricultural R&D and uncertain economic growth

To understand how uncertainty in future economic growth affects the optimal level of global investments in agricultural R&D, we develop a dynamic forward looking partial equilibrium (PE) model of global land use with endogenous R&D spending that determines agricultural TFP. Economic growth in the 21st century is described by annual growth rate in per capita income g. Let us assume that cumulative distribution function of growth rate g is known, and is discretized into n possible values $\{g_k : 1 \leq k \leq n\}$ with respective probabilities $\{p_k : 1 \leq k \leq n\}$. The social planner's expected welfare maximization problem becomes:

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

subject to endowment availability, production functions, market clearing and transition law constraints. In equation (1), $I = \{I_t : t \geq 0\}$ is the agricultural R&D spending path, $\mathbf{X}^k$ is the vector path of resource allocation variables under scenario k with annual growth rate g_k, h is number of years within one period in the model, δ is the annual utility discount factor, U is per capita utility, $\mathbf{y}_t^k$ is the vector of per-capita consumption of goods produced in period t under the decision $(I, \mathbf{X}^k)$, and Π_t is global population at time t. Per capita utility is given by:

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

where $\gamma > 0$ represents degree of relative risk aversion, and $C(\mathbf{y}_t^k)$ is the per-capita consumption aggregator of the multiple final consumption goods and services $\mathbf{y}_t^k$. Consumer preferences are represented with An Implicit, Directly Additive Demand System (AIDADS) (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 income rises (Cranfield et al., 2002). The consumption aggregator $C(\mathbf{y}_t)$ is computed implicitly using the following AIDADS preferences (scenario index k is omitted):

$$\ln(C(\mathbf{y}_t)) = \left[\sum_q \left(\frac{\alpha_q + \beta_q C(\mathbf{y}_t)}{1 + C(\mathbf{y}_t)}\right) \ln\left(y_t^q - \underline{y}^q\right)\right] - 1 - \ln(\Upsilon) \tag{3}$$

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

A representative consumer derives utility from land-based, and other, goods and services. The land-based final consumption goods include food, wood products, energy (including bioenergy), and ecosystem services. Production of these final consumption goods, as well as intermediate inputs, is explicitly modeled within the PE framework. A schematic diagram of this stylized economy with focus on land-based goods and services is presented in Table S1 in Appendix. For example, the agrochemical sector converts fossil fuels into nitrogen fertilizer that is used in production of crops used for food 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 to represent competing final consumption and as intermediate inputs in the land-based production sectors modeled in this PE framework. For example, production of crops requires not only land and fertilizer, but also other goods and services, such as labor and capital. The production of the other goods and services is not captured within the PE model, but rather is given exogenously and depends on future uncertain productivity growth rate g. For each scenario k, its corresponding exogenous path of other goods and services available in the economy is given by:

$$E_t^k = E_0(1 + g_k)^{ht}\Pi_t/\Pi_0 \tag{4}$$

where Π_0 and E_0 are base year global population and endowment of other goods and services, respectively.

In the dynamic model of land use, both TFP and R&D are endogenous variables, and TFP is a function of past R&D. 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 extend over several decades (Piesse and Thirtle, 2010). For example, Alston et al. (2010) find that resources invested in agricultural R&D today will have their maximum impact 25 years from now, with R&D impacts persisting nearly half a century after the initial expenditure. This finding is confirmed by Baldos et al. (2015) who employ Bayesian analysis to relate R&D spending to knowledge capital stocks and finally to agricultural productivity growth. The long lag structure documented in econometric studies leads to the following specification of the relationship between TFP and past R&D. In the model with decadal time steps, next period agricultural TFP (A_{t+1}) is a concave function of historical annual average over decade investments in R&D (I_{t-i}) i decades ago, as well as linear function of historical productivity levels (A_{t-3}):

$$A_{t+1} = \sum_{i=0}^{3} c_i \sqrt{I_{t-i}} + \phi A_{t-3} \tag{5}$$

where c_i and ϕ are calibrated parameters (Cai et al., 2016). Lagged TFP is included to prevent current TFP and agricultural production from falling to zero in a situation of zero lagged R&D spending. In fact, a significant share of the R&D expenditures goes to support research aimed at preventing agricultural productivity from declining in the face of co-evolving pests and diseases (Alston et al., 2009). To parameterize this relationship, we use U.S. annual time series data on agricultural TFP and R&D expenditures. We employ United States Department of Agriculture, Economic Research Service data on U.S. agricultural TFP growth over 1948-2007 (USDA-ERS, 2015). Information on R&D expenditures for this time period is constructed using data available in USDA-ERS (2012) and Huffman and Evenson (2008). When estimating equation (5), regression coefficients on lagged R&D expenditure are restricted according to the Bayesian lag weights estimated in Baldos et al. (2015). In light of the productivity spillover effects from developed to developing countries, on one hand, and rapid improvements in the quality of agricultural R&D activities worldwide on the other, we use the relationship estimated on U.S. data to inform the relationship between agricultural R&D and productivity at the global scale over the coming century. Specifically, we assume that, in the 21st century, U.S. investments, when scaled up to the global level, are capable of bringing a level of global TFP comparable to that in the U.S.

Agricultural output depends on inputs used and the overall level of technology, represented by TFP, as well as the changing climate. 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 ºC increase in temperature. To reflect the impact of climate change on crop output in the model, we pre-multiply TFP by $(1 - \eta T_t)$ with $\eta = 0.049$, where T_t is change in global surface temperature relative to beginning of the 21st century. This results in an outcome whereby past R&D spendings become less efficient in delivering agricultural output under a warmer climate.

To summarize, the vector of per-capita consumption of final goods $\mathbf{y}_t^k$ in period t produced under the decision $(I, \mathbf{X}^k)$ and the k-th growth scenario can be represented with the following production function vector:

$$\mathbf{y}_t^k = \mathbf{F}(A_t, \mathbf{X}_t^k; E_t^k) \tag{6}$$

where E_t^k is the k-th income path, A_t is level of technology in agriculture resulted from R&D spending path $I = \{I_t : t \geq 0\}$, $\mathbf{X}_t^k$ is the vector of resource allocation variables. The production functions (6) stand for the set of equations (S1)-(S14) representing sectoral production functions, market clearing and resource availability constraints given in the Appendix. Thus, the social planner solves the expected welfare maximization problem subject to the constraints (2)-(6).

2.2 Robust decision making in the face of ambiguity over probability distributions

The social planner is provided with probability distributions of per capita income growth in the 21st century by several economic experts. For each distribution, the expected welfare maximization method (1) can be applied to find the optimal path of R&D spending. However, no weights are provided for each distribution. Thus, the social planner is faced with ambiguity over probability distributions (Lange and Treich, 2008). To find optimal R&D spending, the social planner takes into account the opinions of all the experts and chooses the path of R&D spending that minimizes maximum regret associated with not choosing one specific distribution from those provided by the experts. Let us assume that there are m experts providing different probability distributions of per capita income annual growth rate g. Each distribution have the same set of possible values of g, $\{g_k : 1 \leq k \leq n\}$, but their respective probabilities are dependent on the corresponding distribution, denoted $\{p_{j,k} : 1 \leq k \leq n\}$ for the j-th distribution.[1]

Thus, the possible future annual income scenarios are the same as (4), while their corresponding probabilities may differ across experts. Let

$$\mathcal{W}(I, \mathbf{X}^1, ..., \mathbf{X}^n; j) \triangleq \sum_{k=1}^{n} p_{j,k} \sum_{t=0}^{\infty} \delta^{ht} U(\mathbf{y}_t^k)\Pi_t$$

denote the total expected welfare with given policy paths $(I, \mathbf{X}^1, ..., \mathbf{X}^n)$, and the j-th distribution (j-th expert). We first solve

$$G(j) \triangleq \max_{I, \mathbf{X}^1, ..., \mathbf{X}^n} \mathcal{W}(I, \mathbf{X}^1, ..., \mathbf{X}^n; j) \tag{7}$$

subject to the constraints (2)-(6) corresponding to the j-th distribution. That is, for each distribution we find its corresponding optimal solution of agricultural R&D spending I and resource allocations $\mathbf{X}^1, ..., \mathbf{X}^n$. The regret function is defined as

$$R(I, \mathbf{X}^1, ..., \mathbf{X}^n; j) \triangleq G(j) - \mathcal{W}(I, \mathbf{X}^1, ..., \mathbf{X}^n; j) \tag{8}$$

for a given distribution j. We then solve the MMR model

$$\min_{I, \mathbf{X}^1, ..., \mathbf{X}^n} \max_{j} \quad R(I, \mathbf{X}^1, ..., \mathbf{X}^n; j) \tag{9}$$

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

$$\mathbf{y}_t^{k*} = \mathbf{F}(A_t^*, \mathbf{X}_t^{k*}; E_t^k) \tag{10}$$

where A_t^* is the robust optimal TFP resulted from the robust optimal R&D spending I^*, and $\mathbf{X}_t^{k*}$ is the corresponding robust optimal solution for the given

[1] If some g_k is not a possible value of g for distribution j, then its corresponding probability is $p_{j,k} = 0$.

k-th income scenario in the MMR model (9). This formulation of the MMR method assumes that the R&D spending path I is the robust decision that is independent of both distribution and income scenarios (and I determines optimal A_t), while the optimal decision variables $\mathbf{X}$ are assumed to be independent of distributions but dependent on income scenarios, because these resource allocations $\mathbf{X}$ can be optimally adjusted as the true scenario unfolds.

2.3 Expert forecasts

Gillingham et al. (2015) study the uncertainty of major outcomes of climate change using multiple integrated assessment models. One of the uncertain factors they attempt to quantify is growth in per capita output, or productivity. To develop estimates of the associated uncertainty, they employ results of a survey of economic experts on economic growth to determine both the central tendency and the uncertainty about long-run growth trends. The survey procedure and its results are documented in Christensen et al. (2016). In the survey, a panel of experts is asked to characterize uncertainty in estimates of economic growth, where the growth is defined as the average over 2010-2100 period annual rate of growth of real per capita GDP. Christensen et al. (2016) collect 13 experts' opinions about the 10%, 25%, 50%, 75% and 90% quantiles of the uncertain annual growth rate, and then use their sample means to provide the corresponding summary quantiles. In the present study, we apply piecewise linear interpolation and extrapolation to the data reported in Figure 9 in Christensen et al. (2016), excluding negative growth rates since they result in violations of the AIDADS subsistence, to construct expert-specific cumulative distribution functions for average annual growth rate in the 21st century. Then, each cumulative distribution function is discretized over $n = 21$ possible values of growth rates, $\{g_k : 1 \leq k \leq n\}$, and their respective probabilities $\{p_k : 1 \leq k \leq n\}$ are computed, where p_k is the difference between the cumulative probability at $(g_{k-1} + g_k)/2$ and the cumulative probability at $(g_k + g_{k+1})/2$, where $g_0 = -\infty$ and $g_{n+1} = \infty$. The resulting cumulative distribution functions (CDFs) are presented in Figure S1 in the Appendix.

3 Results

In order to illustrate the basic economic mechanisms in this model, we present three illustrative simulations in Figure 1. These are all deterministic simulations, such that there is no uncertainty about the underlying rate of per capita income growth. The assumed growth rates are 1%, 2% and 3%/year over the entire 21st century. Economic growth produces two competing forces in the model. First, higher per capita income growth means that food demand will grow faster and, ceteris paribus, it is desirable to produce more food. However, this food can be produced in two different ways. With current technology (fixed TFP), food production can be increased by using more of non-land inputs per unit of land. Alternatively, we can invest in improved technology, thereby boosting TFP over time, and eventually conserving both land and non-land inputs. Since the question of investment is problem of intertemporal allocation over time, it will depend on the consumption discount rate, defined as $u'(C(\mathbf{y}_t))/(u'(C(\mathbf{y}_{t+1}))\delta^h) - 1$.

The first panel in Figure 1 reports paths of the consumption discount rate for three deterministic growth scenarios, each one with a successively higher rate of economic growth: 1%, 2% and 3%/year, over the course of the 21st century. Note that, with the high rate of growth (3%/year), the initial consumption discount rate is nearly twice as high as that under the low growth scenario. This translates into a relatively lower rate of investment in R&D in the initial period (see the second panel in Figure 1). As we forward in time, this consumption discount rate changes relatively little for the low growth scenario – hence the flat optimal path of investment. However, the consumption discount rate for the high growth scenario falls dramatically with time, thereby explaining the rapid acceleration in R&D spending. That is, the opportunity cost of deferring consumption falls, thereby encouraging relatively more investment. In the long run, with high growth, food demand is much higher and the level of TFP is also much higher than under the low growth scenario (see the third panel in Figure 1).

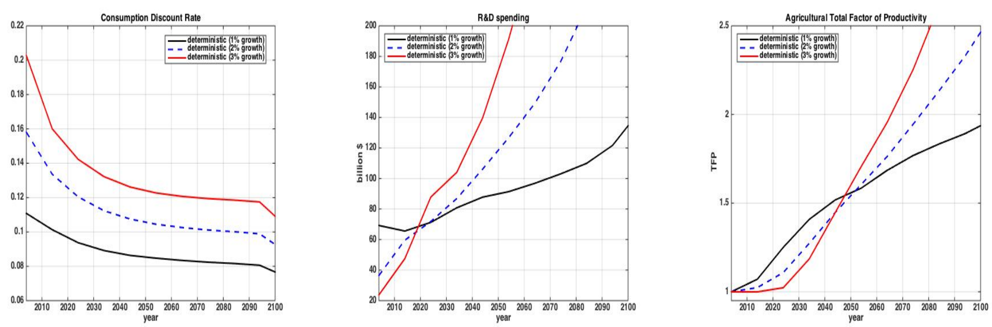

Figure 1: Consumption discount rate, optimal R&D spending and TFP with deterministic economic growth

The first column of Figure 2 presents the results from three different expert CDFs built up from the data points reported in Figure 9 of Christensen et al (2016). We call these three experts, respectively, the bear, the turtle and the bull. As can be seen from the CDFs, the differences across expert opinions can be dramatic! In the opinion of the bear, there is a 40% probability that average growth over the coming century will be zero or negative. (We truncate these CDFs at zero, as negative entries create infeasibilities owing to the subsistence parameters in the AIDADS utility function.) The bull, on the other hand, rules out zero growth rates, beginning the CDF just about where the bear leaves off (about 2.5%), and reaching as high as 6%/year at the high end of the probability distribution. In between, we have the turtle, who believes in a slow and steady growth rate of about 2%/year over the century, with a high degree of confidence. The fourth row in the first column of this figure represents the summary CDF created by averaging the individual CDFs from all 13 experts in the growth survey (see S1).

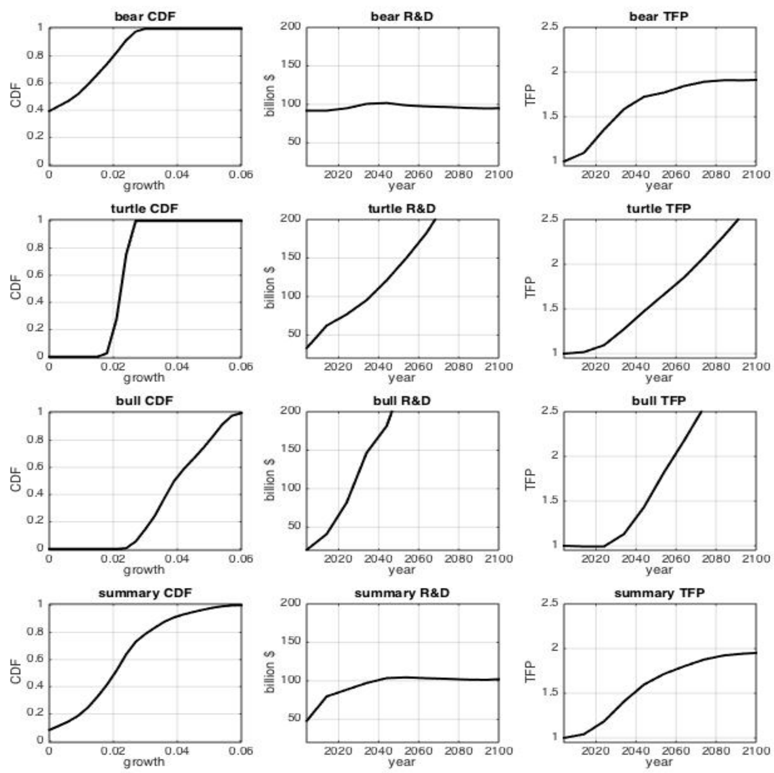

Figure 2: CDFs of three experts and summary CDF, and optimal R&D spending and agricultural productivity resulted from solving expected welfare maximization problem for each CDF

The second and third columns in Figure 2 draw out the implications of these different views of the future. As can be seen, the optimal R&D paths (column two) differ dramatically. In the case where there is significant probability of zero growth in the future, R&D spending starts out high – about $90 billion/year, or more than twice current levels, globally (recall the flatter path associated with the low growth rate in Figure 1), and it remains roughly constant through the entire century. This 'bear scenario' reflects the significant probability that growth will come to a halt, thereby raising the opportunity cost of future R&D. This stands in stark contrast to the bullish case, wherein the expert is confident of future growth, with the only question being how high this will be. So it makes sense to postpone investments until the consumption discount rate falls. However, with strong growth in per capita income and demand, the R&D trajectory is steep, reaching a level double that associated with the bear expert, by mid-century. Turtle's optimal spending trajectory falls in between the bear and the bull, starting out higher than the bull, but growing more slowly.

Finally, we have the implications of the summary CDF which was created by averaging the CDFs of the 13 original experts. This spending path is quite different from the turtle, even though their mean growth rates are quite similar. This difference stems from the non-zero probability of a zero rate of economic growth over the 21st century. For this reason, initial spending based on the summary CDF starts out at \$50 billion, rising thereafter to \$100 billion at 2040, and remaining at that level going forward.

The final column in Figure 2 shows the consequences of these spending paths for TFP in agriculture. In the case of the bear scenario, TFP rises rapidly for the first forty years, and then flattens out. In contrast, the bull expert CDF results in TFP staying flat until 2030, then rising linearly at a rapid rate going forward. The turtle follows a similar path to the bull case, but growth starts sooner and the ensuing slope is lower. Finally, the summary CDF results in steady growth in TFP to mid-century, followed by a leveling off. Productivity in 2100 is about double current levels under the summary CDF.

Based on the diverse growth expectations of the 13 experts in the Christensen et al. survey, there is massive uncertainty regarding future economic growth. And this is not only uncertainty about the expected long run rate of economic growth, but also about the probability distribution of these growth rates. This puts decision makers in a world of ambiguity (Lange and Treich, 2008): we have 13 different probability distributions instead of just one, and we have no idea which one is more likely to be correct.

Christensen et al. (2016) recommend creating an aggregate (across experts) forecast distribution which can be used in subsequent uncertainty analysis. This is similar in spirit to our summary CDF which results in the optimal paths for R&D spending and TFP reported in the final row of Figure 2. However, given the dramatic difference between optimal paths which include, and exclude, the probability of zero economic growth, it is not clear that simply averaging the quantile probabilities is the most sensible approach to this ambiguity. An alternative approach is to apply the MMR method (9) to get the robust optimal solutions of R&D spending and TFP.

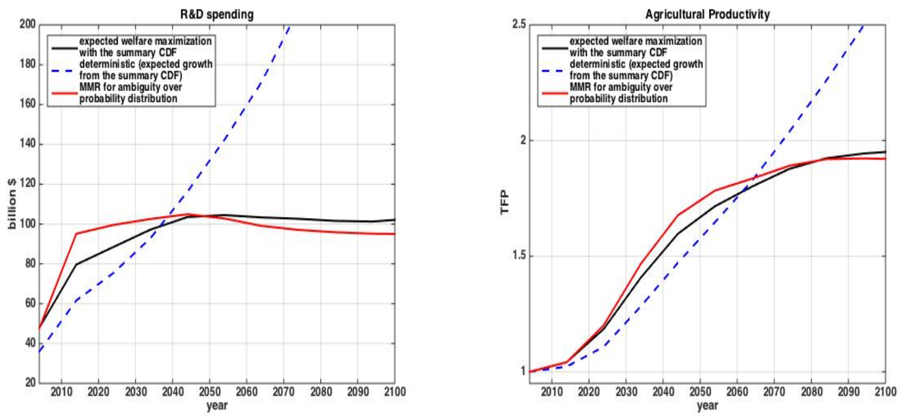

Figure 3: Optimal R&D spending and TFP with MMR for ambiguity over probability distributions

To understand the implications of these different approaches to ambiguity, Figure 3 presents three different optimal paths for R&D and TFP. In the first case, we simply adopt a 2.2%/year growth rate, which is the expected growth rate under the summary CDF, and solve this as a deterministic problem. This results in a steadily rising rate of R&D investment and TFP (with global R&D spending starting at level close to \$36 billion observed in the beginning of this century). The second optimal path in the face of ambiguity is based on the summary CDF. In this case, there is a non-negligible probability of zero growth over the course of the century, and so the decision maker builds up the R&D stock more quickly, before letting it level off at mid-century. The final approach to ambiguity uses the MMR solution which, rather than averaging the 13 different CDFs, actually factors in the optimal path under each and every one of those cases. The choice of optimal R&D path under this approach is made in order to minimize the maximum regret associated with not choosing one specific distribution from those provided by the experts. This approach further accentuates the response to potential zero growth rates, as it includes the probability distribution belonging to the 'bear' forecaster, who foresees a 40% probability of non-positive growth over the 21st century. In 2020, the MMR path dictates about 15% more spending on R&D, relative to the summary CDF approach, and about 40% more R&D spending than in the deterministic case. The extra R&D spending in the early periods in the MMR case leads to higher TFP before 2060. By the end of this century, MMR TFP stays flat at a level about 92% higher than at the start.

4 Summary and Conclusions

When viewed from a global economic perspective, the world is a very uncertain place at the moment. Projecting economic growth, population and climate (as well as its impacts) over the 21st century is a daunting task. One approach to this problem has been the development of SSPs (O'Neill et al., 2014) designed to capture a variety of different story-lines around political and economic conditions over the coming century. This approach is currently in widespread use by integrated assessment modelers. Its great advantage is that it provides a consistent characterization of these alternative futures, such that the evolution of population is consistent with the evolution of per capita income, and both of those are consistent with the emissions of greenhouse gases and climate change. In related work Cai et al. (2016) have explored the implications of these multiple sources of uncertainty over the 21st century for optimal agricultural R&D.

The path-breaking work of Gillingham et al. (2015) analyzes long run uncertainties in integrated assessment modeling and concludes that the most important source of uncertainty over the coming century is the rate of economic growth – which in turn is tied to the underlying rate of economy-wide productivity growth. When they take a deeper look into the uncertainty associated with long run growth, they find that the IAM community has vastly understated the extent of such uncertainty. This is perhaps not surprising, given that the SSPs and associated IAM projections are the result of lengthy consultations and discussions – leading inevitably to a gravitation to the mean. By picking a set of independent researchers, giving them the same information, and asking for purely independent forecast distributions, Christensen et al. (2016) have shown that the true extent of future growth uncertainty is likely far greater than that embodied in the SSPs.

We build on the innovative research of Christensen et al. (2016), who report quantiles for economic growth rates over the course of the 21st century from 13 independent experts. From these data points, we build 13 CDFs, as well as a summary CDF. The latter is built from averages of the individual probabilities across all 13 experts. For each of these 21st century per capita income growth CDFs, we compute the optimal rate of R&D investment as well as the ensuing path of TFP to 2100. The individual paths vary greatly across the experts. We highlight three particular forecast distributions of interest: the 'bull', the 'bear' and the 'turtle'. As their names suggest, they embody very different views of the future. The bear foresees a high probability of non-positive growth in the coming century. The bull's CDF starts where the bear's leaves off – about 2.5% growth per year, with potential growth rates as high as 6% per year! The turtle believes in slow and steady growth of around 2.2% per year over the course of this century. Using these independent probability distributions, we compute 13 different optimal R&D investment and TFP trajectories. These vary greatly, both in level and in shape. When there is a significant probability of non-positive growth over the next century, the optimal response is to invest a lot in R&D today, and maintain a fairly flat trajectory over the entire century. This is in sharp contrast to the optimal path when growth rates are strictly positive.

In this case, R&D spending starts out slow, and accelerates over time. The summary CDF results in a level of R&D which is about one third higher than that observed today, and then rises fairly sharply till 2040, before leveling off.

In this paper, we propose a novel approach to dealing with the ambiguity posed by having 13 independent growth forecasts. The summary CDF implicitly gives each forecaster equal weight. However, in light of the risk aversion associated with economic stagnation, it would appear desirable to take a different approach. Here, we seek to minimize the maximum regret across all 13 optimal growth paths. This results in higher R&D spending early in the century – in 2020 roughly 15% higher than that suggested by the summary CDF, and nearly 40% higher than that dictated by a deterministic model using 2.2% growth rate. However, by mid-century, R&D spending levels off, and TFP plateaus by the end of the century at a level which is about twice as high as at the start.

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Supporting Information

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 (1) has infinite horizon and cannot be computed exactly. In our computational examples, we use the summation of discounted utility over 400 years as its approximation, and focus on first 100 years of simulation in the analysis. The model is solved with decadal time step.

A schematic diagram of the stylized partial equilibrium economy with focus on land-based goods and services is presented in Table S1:

Inputs	Sectors									Final consumption
	Crop	Timber	Fertilizer	Food	Biofuels	Wood products	Petroleum	Energy	Eco-system services	
Crop				x	x					
Timber						x				
Fertilizer	x									
Food										x
Biofuels								x		
Wood products										x
Petroleum								x		
Energy										x
Eco-system services										x
Endowments										
Land	x	x							x	
Fossil Fuels			x				x			
Other g&s	x	x	x	x	x	x	x		x	x

Table S1: **Partial equilibrium model of land use**

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^F and L_t^N denote cropland, commercial forest and natural areas. 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

$$\mathbf{y}_t = (y_t^{food}, y_t^e, y_t^w, y_t^r, y_t^o) = (Y_t^{food}, Y_t^e, Y_t^w, Y_t^r, Y_t^o)/\Pi_t \tag{S1}$$

where y_t^{food}, y_t^e, y_t^w, y_t^r and y_t^o denote per capita consumption of food, energy services, wood products, eco-system and recreation services, and other g&s, respectively. Each production activity is represented with a constant elasticity of substitution (CES) production function, where α^j represents cost share of specific input used in production of j (e.g. crop input used in food production), $(1-\alpha^j)$ represents 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:

$$Q_t^p = Q_0^p \left(\alpha^p \left(\frac{X_t^{ex,p}}{X_0^{ex,p}} \right)^{\rho^p} + (1-\alpha_0^p) \left(\frac{X_t^{o,p}}{X_0^{o,p}} \right)^{\rho^p} \right)^{1/\rho^p} \tag{S2}$$

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

- Fertilizer production function:

$$Q_t^{fert} = Q_0^{fert} \left(\alpha^{fert} \left(\frac{X_t^{ex,fert}}{X_0^{ex,fert}} \right)^{\rho^{fert}} + (1-\alpha_0^{fert}) \left(\frac{X_t^{o,fert}}{X_0^{o,fert}} \right)^{\rho^{fert}} \right)^{1/\rho^{fert}} \tag{S3}$$

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

- Cropland and fertilizer composite production function:

$$Q_t^{lf} = Q_0^{lf} \left(\alpha^{lf} \left(\frac{L_t^C}{L_0^C} \right)^{\rho^{lf}} + (1-\alpha_0^{lf}) \left(\frac{Q_t^{fert}}{Q_0^{fert}} \right)^{\rho^{lf}} \right)^{1/\rho^{lf}} \tag{S4}$$

- Crop production function:

$$Q_t^c = (1-\eta T_t) A_t Q_0^c \left(\alpha^c \left(\frac{Q_t^{lf,c}}{X_0^{lf,c}} \right)^{\rho^c} + (1-\alpha_0^c) \left(\frac{X_t^{o,c}}{X_0^{o,c}} \right)^{\rho^c} \right)^{1/\rho^c} \tag{S5}$$

where T_t is the temperature increase, and A_t is a function of past R&D spending and historical productivity level:

$$A_{t+1} = \sum_{i=0}^{3} c_i \sqrt{I_{t-i}} + \phi A_{t-3}$$

- Crop-based food production function:

$$Y_t^{food} = \theta_t^{food} Y_0^{food} \left(\alpha^{food} \left(\frac{X_t^{c,food}}{X_0^{c,food}} \right)^{\rho^{food}} + (1 - \alpha_0^{food}) \left(\frac{X_t^{o,food}}{X_0^{o,food}} \right)^{\rho^{food}} \right)^{1/\rho^{food}} \tag{S6}$$

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

- Biofuel production function:

$$Q_t^b = Q_0^b \left(\alpha^b \left(\frac{X_t^{c,b}}{X_0^{c,b}} \right)^{\rho^b} + (1 - \alpha_0^b) \left(\frac{X_t^{o,b}}{X_0^{o,b}} \right)^{\rho^b} \right)^{1/\rho^b} \tag{S7}$$

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

- Energy production function:

$$Y_t^e = \theta_t^e Y_0^e \left(\alpha_0^e \left(\frac{Q_t^b}{Q_0^b} \right)^{\rho^e} + (1 - \alpha_0^e) \left(\frac{Q_t^p}{Q_0^p} \right)^{\rho^e} \right)^{1/\rho^e} \tag{S8}$$

- Timber production function:

$$Q^{tim} = Q_0^{tim} \left(\alpha^{tim} \left(\frac{L^F}{L_0^F} \right)^{\rho^{tim}} + (1 - \alpha_0^{tim}) \left(\frac{X^{o,tim}}{X_0^{o,tim}} \right)^{\rho^{tim}} \right)^{1/\rho^{tim}} \tag{S9}$$

- Wood production function:

$$Y_t^w = \theta_t^w Y_0^w \left(\alpha_0^w \left(\frac{Q_t^{tim}}{Q_0^{tim}} \right)^{\rho^w} + (1 - \alpha_0^w) \left(\frac{X_t^{o,w}}{X_0^{o,w}} \right)^{\rho^w} \right)^{1/\rho^w} \tag{S10}$$

- Ecosystem and recreation services:

$$Y_t^r = Y_0^r \left(\alpha_0^r \left(\frac{L^N}{L_0^N} \right)^{\rho^r} + (1 - \alpha_0^r) \left(\frac{X^{o,r}}{X_0^{o,r}} \right)^{\rho^r} \right)^{1/\rho^r} \tag{S11}$$

- The other g&s consumption:

$$Y_t^o = E_t - \sum_{i \in \{fert, c, b, food, p, tim, w, r\}} X_t^{o,i} - I_t \tag{S12}$$

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:

$$X_t^{ex,p} + X_t^{ex,fert} - Q_t^{ex} = 0 \tag{S13}$$

- Market clearing condition for crops:

$$X_t^{c,b} + X_t^{c,food} - Q_t^c = 0 \tag{S14}$$

For simplicity, in this paper we assume that cropland L_t^C, natural land L_t^N, and commercial 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 driven by growth in global population and technological improvements in production of energy services θ_t^e.

The model is benchmarked to the year 2004 using FAOSTAT (FAOSTAT, 2015) and GTAP v.7 data bases (Narayanan and Walmsley, 2008). In addition to the AIDADS parameters, which have been estimated for this study using the GTAP data base, the elasticity of substitution between land and fertilizer in crop production is calibrated using econometric analysis in Hertel et al. (1996). The elasticity of substitution between biofuel and petroleum is calibrated using econometric analysis from Anderson (2012). Other input-output relationships are assumed to occur in (nearly) fixed proportions.

Figure S1 shows 13 probability distribution functions of per capita income growth constructed with opinions of 13 experts. The CDFs are constructed using experts quantiles information presented in Figure 9 in Christensen et al. (2016), with negative growth rates excluded. Figure S1 also shows the summary CDF which is the average of these 13 CDFs.

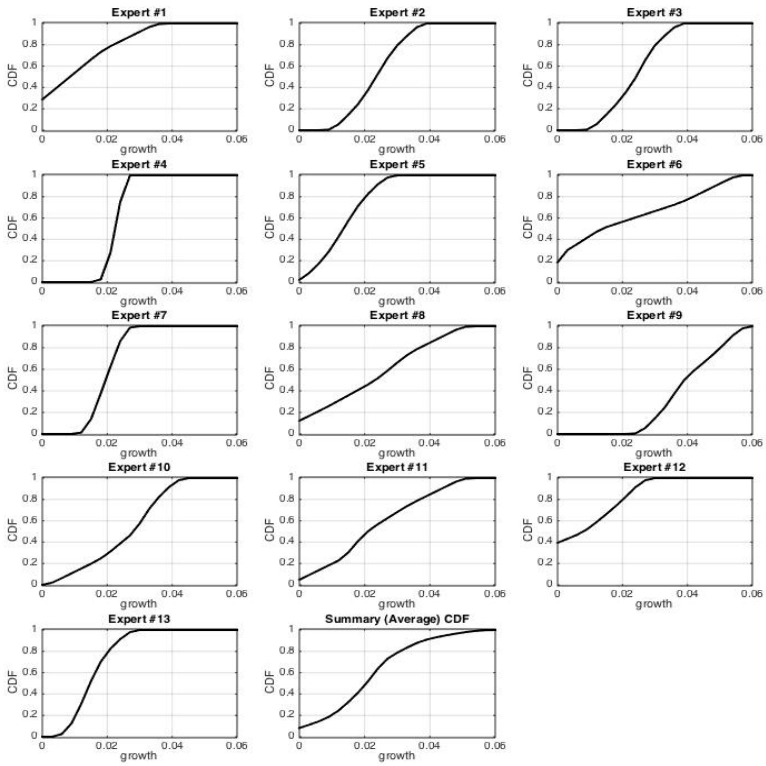

Figure S1: Cumulative distribution functions of 13 experts, constructed with survey data reported in Christensen et al. (2016), and the summary distribution

Figures S2 and S3 show optimal solutions of R&D spending and TFP for each probability distribution using the expected welfare maximization method.

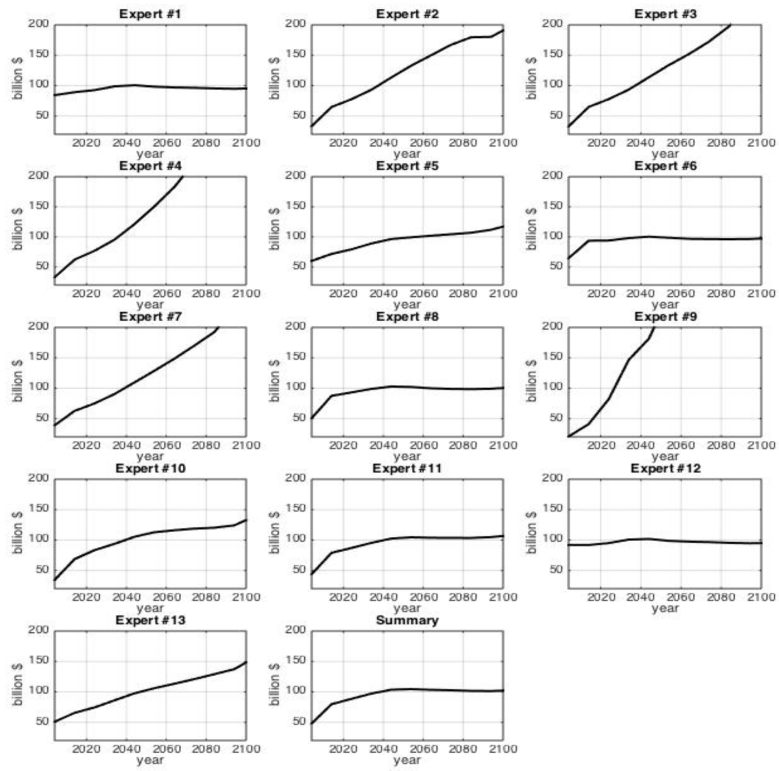

Figure S2: Optimal R&D spending using the expected welfare maximization method

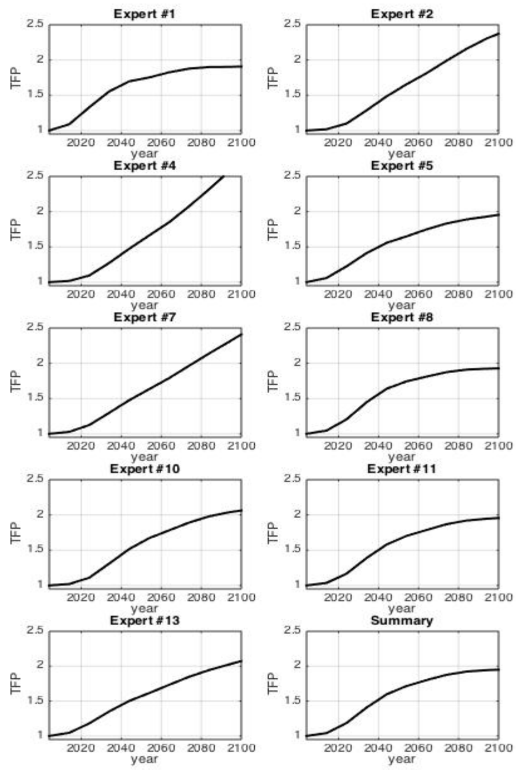

Figure S3: Optimal TFP using the expected welfare maximization method