Investing in Public R&D for a Competitive and Sustainable US agriculture

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I. Introduction

Sustained productivity growth in US agriculture is crucial to ensure competitiveness in the world markets. US farm output has grown remarkably since the 1950s – by more than two-folds and this historic rise was mainly driven by productivity growth (USDA ERS, 2021). Efforts to develop and disseminate of new technologies can be traced back to public research and development (R&D) activities conducted in universities and government institutions. To influence long-term farm productivity, continued investments in public agricultural R&D are needed. The economic gains from R&D-driven productivity growth are well researched (Alston et al., 2011; Andersen & Song, 2013; K. Fuglie, 2017; Jin & Huffman, 2016). In a recent meta-analysis of the returns to agricultural R&D, Rao et al (2019) estimated that the median reported internal rate of return from R&D investments is around 34.0% per annum for developed countries. But despite these economic benefits, there has been a slowdown in investments in the US public agricultural R&D systems. The stagnation of public funding for US agricultural scientific research is alarming when contrasted with the growth in R&D investments in middle income countries, particularly in China which has recently surpassed US R&D spending (Clancy et al., 2016; Pardey et al., 2018). The slower R&D spending at home and greater investments in the rest of the world could potentially erode the competitiveness of US in the global agricultural markets.

Rising agricultural productivity can also provide environmental co-benefits. Several model-based assessments have shown that greater agricultural productivity could dampen future agricultural land expansion and farm GHG emissions. For example, Valin et al (2013) examined the global GHG emissions impacts of productivity growth in several crop and livestock sectors as well as other land-based sectors. The authors focused on methane emissions from paddy rice and livestock, emissions from fertilizer use, as well as land use change emissions. They find that under business as usual, world agricultural GHG emission is expected to increase by around 30% between 2000 and 2050 (from 3.5 to 4.6 GtCO2-eq /yr). The authors also found that greater productivity thru higher yield trends and yield convergence across crops and livestock sectors could reduce global GHG emissions in agriculture in 2050 by up to 10% relative to the baseline. Jones and Sands (2013) calculated the GHG emissions reduction from total factor productivity growth in the crop and livestock sectors. The authors examined changes in GHG emissions from agriculture, forestry as well as energy sectors. In the absence of farm productivity growth, the authors estimated that global agricultural GHG emissions could increase by 47% between 2004 to 2034 (from 5.1 to 7.5 GtCO2-eq /yr). WRI (2019) used a global accounting model to calculate future changes in agricultural production, land use and greenhouse gas emissions between 2010 and 2050. The authors estimated several scenarios using different assumptions regarding future diets, food waste mitigation, productivity and emission reduction in crops and livestock animals. They also estimated alternative scenarios based on the level of effort needed to drastically reduce in agricultural GHG emissions, including new technologies. The estimates show that under business as usual global agricultural GHG emissions is expected to increase by around 25% between 2010 to 2050. The results also show that significant reduction in emissions is possible under alternative scenarios with new technologies reducing global farm GHG emissions.

This study examines both the economic and environmental benefits from greater farm productivity growth due to increased US public R&D investments over 2025-2035. Compared to previous work, this study directly calculates the implied growth in agricultural productivity from R&D spending increase using the latest data and parameter estimates on the historical gains from US R&D spending (Baldos et al., 2018) as well as technological spillovers estimates to the rest of the world (Fuglie, 2017). The results suggest that increased R&D investments in the US could significantly boost US agricultural production over 2017-2050. There is also some reduction in farm input use and associated GHG emissions per agricultural output produced in the US as R&D investments intensify. However, significant reduction in agricultural GHG emissions can only be achieved when imposing both R&D investment and farm input constraint policies.

II. Models and Methods

Modelling R&D investments and knowledge stock accumulation

The empirical literature on the linkages between the flow of R&D spending, the stock of accumulated knowledge capital and subsequent productivity growth is well established (Alston et al., 2011; Griliches, 1979; Heisey et al., 2011; Huffman, 2009). The framework involves two main stages. In the first stage, knowledge capital stocks are constructed from the stream of R&D spending using R&D lag weights. Knowledge capital consists of the technological and human capital needed to develop and propagate high-yielding crop varieties as well as modern farm management techniques and machineries. More importantly, how R&D spending today contributes to the R&D knowledge stock in the future is summarized by the R&D lag weights.

Initially, the R&D spending contributes little to knowledge capital accumulation, but its effect builds over time as technology arising from that research matures and is eventually disseminated to farmers. Eventually, the effects peak when technology is fully disseminated, but then wane due to technology obsolescence. In the second stage, after converting the R&D spending flows to knowledge capital stocks, the growth in stocks is then linked to growth in agricultural total factor productivity (TFP) growth via elasticities which describe the percent rise in TFP given a 1 percent rise in knowledge capital stock.

This study borrows heavily from the data and parameter estimates from Baldos et al (2018) which examines the historical gains in US R&D spending using Bayesian econometrics. The authors compiled annual public agricultural R&D expenditures (in billion 2005 USD) from spending data by USDA intramural research agencies in particular the Agricultural Research Service (ARS) and the Economic Research Service (ERS), State Agricultural Experiment Stations (SAES), and Schools of Veterinary Medicine. Following the authors, this study adapts the gamma structure with a 50-year lag span when calibrating the R&D lag weights. Furthermore the R&D lag weight structure is parametrized by $\delta = 0.74$ and $\lambda = 0.86$ which Baldos et al (2018) estimated. Note that the sum of the weights (i.e. $\beta_{RD,0} \ldots \beta_{RD,49}$) is equal to 1 due to normalization.

$$\beta_{RD,i} = (i+1)^{\delta/1-\delta} (\lambda)^i \Big/ \sum_{i=0}^{L} (i+1)^{\delta/1-\delta} \lambda^i \; ; \; \sum_{i=0}^{49} \beta_{RD,i} = 1$$

The estimated R&D stock TFP elasticity (0.34) in Baldos et al (2018) is also adopted. (i.e. a 0.34 percent rise in TFP given a 1 percent rise in knowledge capital stock). R&D investments in the US results in technical improvements which is transmitted to the rest of the world. To explore the technological spillovers to the rest of the world from increased US R&D spending, the methods and parameters from Fuglie (2017) is used. The author reviewed the literature on the estimated R&D stock TFP elasticities as well as R&D spillover elasticities for key world regions. The author also calculated the international R&D stocks - which generate R&D spillovers - from the knowledge capital stocks in the developed world specifically in Western Europe, North America, Oceania + South Africa and Developed Asia. Since the full data used by Fuglie (2017) is not publicly available, side calculations are necessary to calculate the international R&D stocks from the available US data. Shares of R&D stocks for US and other key regions from Fuglie (2017) are combined with the estimated US R&D knowledge capital stocks in this study to calculate total international R&D stocks. Going forward into the future, it is assumed that the contribution of R&D stocks from non-US regions are fixed (i.e. international R&D stocks are mainly driven by R&D stocks from the US). Regions which historically benefited from R&D spillovers include Western Europe, Oceania + South Africa, Developed Asia and Latin America. Actual agricultural TFP data for these regions for 2017 are taken from USDA-ERS (2021) and are projected to 2050 using the year-on-year change in international R&D stocks and R&D spillover TFP elasticities from Fuglie (2017) (Appendix Table 1).

The SIMPLE Model

To quantify economic and environmental benefits from increased US R&D spending, we employ the SIMPLE model (a Simplified International Model of agricultural Prices, Land use and the Environment) – a global economic model of agriculture (Figure 3). As the name suggests, SIMPLE focuses on the key drivers and economic responses which govern long run developments in the farm and food system (Baldos & Hertel, 2013). In the SIMPLE model, per capita food demands are driven by exogenous per capita income growth and respond to endogenous changes in food prices with these responses varying by income level. Consumers in wealthy regions are less responsive to price and income changes than those residing in low income regions. Aggregated food commodities in SIMPLE include crops, livestock products and processed foods, and consumption patterns evolve to reflect observed shifts in dietary preferences – moving away from crops towards livestock and processed foods as incomes rise.

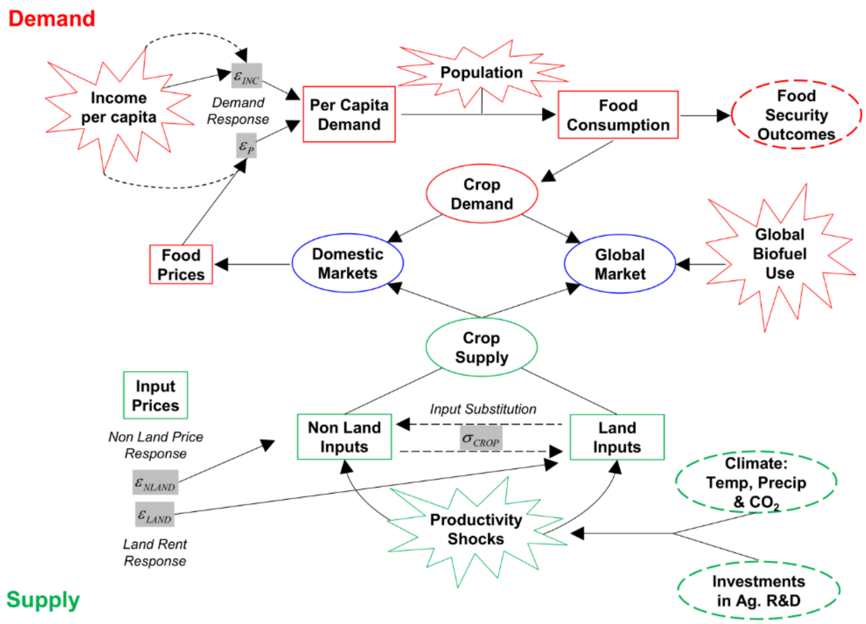

Figure 3. Schematic of the SIMPLE Model

Regional production systems in SIMPLE are modelled using a constant elasticity of substitution (CES) production framework. Crops are produced by combining land and an aggregate noncropland input, with the latter input representing all other factors of production – excluding land – which are used by the crops sector, including fertilizer, labor and machinery, among other farm inputs. Crop outputs are demanded in four uses, namely: direct food consumption, feed use in the livestock sectors, raw input use in the processed food industries, as well as feedstocks in the global biofuel sector. The capacity for input substitution between land and noncropland inputs makes it possible to endogenously increase crop yields. Livestock and processed food sectors use crop and non-crop inputs. Crop outputs are traded across regions. In the original version of SIMPLE, livestock and processed foods are traded within a region. However, the model is modified to incorporate regional trade for these commodities for this study. The evolution of the global farm system is also driven by exogenous productivity trend effects owing to climate change as well as endogenous productivity responses to past and future investments in agricultural R&D.

Agricultural GHG emissions which are reported in the model include emissions from crop and livestock production as well as cropland land use change emissions. West et al. (2010) estimated these carbon stocks using spatially explicit datasets on potential vegetation and soil carbon. These are considered as one-time carbon emissions associated with bringing that land into crop production. Data on GHG emissions from agricultural production is based on the GTAP v.10 standard database (Aguiar et al., 2019) which reports CO2 emissions from fossil fuel combustion using detailed energy volume data from the International Energy Agency (IEA, 2016) and combustion factors from the Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC/OECD/IEA, 1997). GHG emissions from methane, nitrous oxide and fluorinated gases are based on the GTAP non-CO2 GTAP database (Chepeliev, 2020) which use FAOSTAT (2020) for agricultural emissions. We rely on the global carbon stocks calculated by West et al. (2010) to quantify the one-time GHG emissions when cropland expands in natural lands. West et al. (2010) estimated these carbon stocks using spatially explicit datasets on potential vegetation and soil carbon.

Experimental design

Projections for the period 2017 to 2050 using the SIMPLE model require future growth rates in the population, income, biofuel demand and total factor productivity in the crops, livestock and processed food sectors. In this study, sources of these future growth rates are as follows. The population and income growth rates are based on the Shared Socio-economic Pathways (SSP) Database v.2 (Gidden et al., 2019; Riahi et al., 2017; Rogelj et al., 2018). These SSPs have been specifically designed for climate change impact assessment by providing alternative trends in socio-economic development when climate change impacts are ignored (Kriegler et al., 2012; O'Neill et al., 2012). In this study, SSP2 is used, which assumes that future socio-economic and technological development permits successful implementation of climate change adaptation and mitigation strategies (Kriegler et al. 2012). In addition to population and income, future food demand will also be affected by crop feedstock demand for biofuel production. Projections of global biofuel consumption is based on the "Current policies" scenario published in the World Energy Outlook (IEA, 2019) which serve as a business-as-usual-scenario. With the "Current policies" scenario, all existing energy policies for the power and transportation sectors are accounted for. In this study, estimates of total factor productivity (TFP) growth rates – a measure of productivity which accounts for *total* output given *over-all* input use – are used in future projections. Regional TFP growth rates for the crops and livestock sectors are based on adjusted historical estimates from Fuglie (2012) and projections from Ludena et al. (2007), respectively. Lacking detailed TFP projections for the processed food sector, historical rates from Griffith et al. (2004) is used, assuming that these rates apply in the future and across all regions. Future growth rates for key variables mentioned above are used to generate the 'S1 Baseline' which is the business-as-usual scenario.

Alternative scenarios are simulated to show the implications of input restrictions and greater US R&D spending over the future baseline. 'S2 – Restricted Input Use' assumes 10% reduction in both land and non-land inputs which represent efforts to directly curb GHG emissions in the US crop sector. Additional increases in US R&D spending over the baseline growth (around 1.9% per annum based on 1971-2010 average annual growth rate) by 7% per year over 2025 to 2035 is represented by 'S3 - Greater US R&D spending'. 'S4 - No R&D Spillovers' build on S3 and shows the impacts of ignoring international R&D spillovers from US R&D investments. 'S5 Combined Policy' shows the outcomes when both input restrictions and increased US R&D policies are pursued to reduce US agricultural GHG mitigation. The last two scenarios consider the uncertainty in the transmission of R&D spending to agricultural productivity growth. The upper and lower bound values of the estimated US R&D stock TFP elasticities (0.27 and 0.43, respectively) from Baldos et al (2018) are used. Also, the R&D spillover elasticities from Fuglie (2017) are adjusted based on scalars calculated using the mean and extreme values of US R&D stock TFP elasticities.

III. Results and Discussions

US-level results: Changes in US agricultural production and GHG emissions over the period 2017-2050 under different scenarios are summarized in Table 1. Looking at the baseline (S1), US agricultural productivity rises by 38.7% while farm output grows by 50.0% over the period 2017-2050. US crop and livestock output are expanding by around 58.4% and 38.6%, respectively, despite falling supply prices (by -19.0% and -28.7%, respectively). These results show strong farm productivity growth under the baseline which improves US producers' competitiveness and incentivize agricultural output expansion. However, output expansion results in more land being used in agriculture. Under the baseline, US cropland area expands by 6.7 M ha (by 4.2% relative to Y2017 area). Average agricultural GHG emissions in the baseline is around 490.4 M MT CO2e/year while average GHG emissions per farm output is at 1.57 kg CO2e/year per USD.

The impacts of input restrictions on US agricultural production and GHG emissions are simulated in S2. The results show trade-offs in farm production when farmers face restrictions in input use. Compared to the baseline, US farm output growth is much slower with lower input use (increasing by 44.3%). US crop production increases by 49.1 % but this is less than the growth under baseline. Livestock output growth is roughly the same as in S1. Crop and livestock supply prices are still falling by -15.8% and -28.5% despite lower input use. Policies aimed at directly curbing land and non-land input use are quite effective in reducing agriculture's environmental impacts. US cropland use contracts by around -7.9 M ha (-4.9%) when crop input use are reduced by 10%. Average farm GHG emissions and emissions per output are also much lower at 416.3 M MT CO2e/year and at 1.39 kg CO2e/year per USD, respectively. The results in S2 shows that directly reducing farm input use is effective in achieving environmental goals but at the expense of agricultural output growth and food price reduction in the future.

Greater US agricultural R&D spending over 2025 to 2035 is simulated in S3. Given a 7% per annum increase in R&D investments over 2025 to 2035, US agricultural productivity is expected to grow by 62.1%. This results in significantly faster output growth relative to the baseline (by 69.5%). Both US crop and livestock output increase more with greater productivity (by 86.2% and 50.9%, respectively) while supply prices for these commodities experience further reduction (by -30.4% and -39.5%, respectively). Greater productivity results in an environmental trade-off since it incentivizes farmers to expand production and use more land and non-land inputs. US cropland area expands by around 7.0 M ha (by 4.4%). Average agricultural GHG emissions is around 486.2 M MT CO2e/year which is much higher than in S2. These results suggest that increasing productivity alone is not sufficient to reduce input use and GHG emissions in US agriculture. However, greater productivity leads to greater GHG efficiency with lower GHG emissions per farm output at 1.38 kg CO2e/year per USD.

Scenario S4 is a counterfactual scenario of S3 and show how the absence of international R&D spillovers from US public R&D spending affect changes in the agricultural sector. Note that these spillovers allow other regions to benefit from increased US R&D spending thru transfer of knowledge across countries. Without these spillovers, other regions do not benefit from US R&D spending. This results in greater expansion in agricultural production, cropland use and GHG emissions within the US. Agricultural output grows by 73.8% and most of this increase is due to crop output expansion (by 93.2%). Livestock production also increase by 54.6%. Both crop and livestock supply price falls at a slower rate at -28.1% and -39.4%, respectively. Cropland use expands by 8.9 M ha which is higher than in the baseline. With greater input use, average agricultural GHG emissions is at 502.5 M MT CO2e/year which is much higher than in the baseline. Even without the R&D spillovers, average GHG emissions per output remains low at 1.39 kg CO2e/year per USD.

Policies aimed at increasing US agricultural productivity and reducing farm input use are both implemented in S5 and the results show that there are synergistic effects between these strategies. With greater R&D spending, US agricultural output increases by 62.3%. This is well above the output growth in S2 where only input constraints are implemented. Production in US crop and livestock sectors increase by 74.7% and 50.7%, respectively while supply prices for these commodities fall by -27.9% and -39.4%, respectively. Unlike S3 where only R&D investments policies are considered, cropland area in S5 contracts by -4.9% (around -7.8 M ha) as crop producers face constraints in land and non-land input use. Average agricultural GHG emissions is around 410.5 M MT CO2e/year while average GHG emissions per output is at 1.22 CO2e/year per USD. Note that the value of these GHG metrics are much lower under this scenario than under S2 and S3. By implementing these policies in tandem, the adverse trade-offs in terms of output reduction and cropland expansion are avoided while average GHG emissions and GHG emissions per output are further dampened.

Building on S5, scenarios S6 and S7 shows the uncertainty in the impact of R&D spending on agricultural productivity growth. These scenarios represent the upper and lower bounds on the expected farm productivity growth from R&D spending, respectively. The results show that US agricultural productivity growth is between 69.7% and 56.7% given a 7% per annum increase in US R&D spending over 2025 to 2035. Agricultural output growth is around 68.3% and 58.0% under S6 and S7, respectively. Under S6 where the productivity gains are greater, US crop and livestock output expands by 83.3% and 54.7%, respectively. But even with lower benefits from R&D investments, crop and livestock output growth are still above the baseline at 68.5% and 47.9%, respectively. US crop supply price reduction is between -30.9% and -25.4% while for livestock the change between -42.2% and -37.1%. Note that input restrictions are also imposed under S6 and S7 scenarios. Given this policy, US cropland contracts by around -7.7 and -7.9 M ha, respectively. The upper and lower bounds of average agricultural GHG emissions are around 410.0 and 411.3 M MT CO2e/year, respectively. For GHG emissions per output, the bounds are at 1.17 and 1.25 kg CO2e/year per USD. The results show that even under the lower bound scenario there are substantial gains in agricultural production and reduction in GHG emissions from increased R&D spending.

Global-level results: Global markets adjust to changes in US agriculture. Productivity gains from US R&D spending increases the competitive advantage of US farm products while input restrictions make farmers less competitive. At the same time, the rest of the world also benefit from US R&D investments via knowledge spillovers. Table 1 reports the global changes in agricultural production and GHG emissions over the period 2017-2050 under different scenarios. Under S1 global average agricultural productivity increases by 40.0% while total farm output rises by 56.2%. World production of livestock grows faster than crop which shows the impact of changing diets on the composition of agricultural production (around 61.6% and 54.2%, respectively). World average supply prices for these commodities are also expected to fall (by -21.8% and -30.2%, respectively) owing to strong productivity growth in the baseline. Globally, cropland area is expected to rise by 93.6 M ha (by 6.0%). World average agricultural emissions are around 8218.6 M MT CO2e/year while GHG emissions per output are at 2.13 kg CO2e/year per USD. Note that the global GHG emissions per output are roughly 36% more than the US estimates under S1. This shows that US agriculture is more efficient in terms of GHG emissions per output relative to the world average.

At the global level, the magnitude of the changes across scenarios are much smaller. This is expected since only the US and a few regions benefit from US R&D policies while farm input restriction mandates are limited to the US. But even with limited input use in the US (S2), global agricultural output still expands by 56.1% which is comparable to the baseline growth. Global crop and livestock output growth are roughly the same as in S1 (54.0% and 61.6%, respectively). Changes in average supply prices for these commodities are also similar to the baseline (-21.1% and -30.2%, respectively). With international trade, the impacts of lower US output growth in the world markets is partly offset by output expansion in the rest of the world. Input restrictions in the US are effective in slowing down global cropland expansion at 81.5 M ha. Under S2, world average agricultural GHG emissions is at 8167.2 M MT CO2e/year while GHG emissions per output is at 2.12 kg CO2e/year per USD.

Greater US R&D spending results in improved productivity at home and in selected regions thru technical spillovers. Global farm productivity under S3 increases by 44.3% which leads to output expansion at 57.7%. World livestock production rises faster than crop output with greater US R&D spending (63.5% and 55.5%, respectively). Global average supply prices for these commodities also fall faster than in the baseline (-32.7% and -28.2%, respectively). Even with the expansion in US cropland area in S3, globally cropland use under this scenario is 18% lower (at 76.7 M ha) compared to S1. Similarly, world average agricultural emissions and emissions per output are also lower at 8005.2 M MT CO2e/year and 2.06 kg CO2e/year per USD. These results show that the accounting of the economic and environmental benefits from US R&D spending policies should consider the gains achieved beyond its borders.

In absence of R&D spillovers, the global gains from US R&D investments are dampened which shows that knowledge transfers to the rest of the world are important co-benefits of any agricultural R&D policy (S4). Global farm productivity under S4 increases at a slower rate by 42.1% while output expands by 57.0%. When knowledge transfers are ignored, the growth in world crop and livestock production (63.0% and 54.8%, respectively) and the decline in their prices are reduced relative to the baseline (-24.7% and -30.3%, respectively). The environmental gains in terms of avoided cropland expansion and agricultural GHG emissions mitigation are also lower. Global cropland use grows by 86.1 M ha which is 12% more than when spillovers are considered. Average agricultural emissions and emissions per output are also slightly higher in S4 than in S3 (at 8132.1 M MT CO2e/year and 2.10 kg CO2e/year per USD, respectively).

The global outcomes in S5 shows that the combined R&D and input restriction policies result in similar output growth and price reduction compared to S1 but greater gains in avoided GHG emissions and cropland expansion compared to S2 and S3 - scenarios where these policies are implemented separately. World agricultural output expands by 57.5% with faster growth in livestock than in crop production (63.5% and 55.3%, respectively). Relative to the baseline, global average supply prices for these goods falls faster over this period (-32.7% and -27.3%, respectively). Around 64.9 M ha of additional cropland (expanding by 4.1%) is needed globally but this is roughly 31% less than the expansion in S1. The rise in agricultural GHG emissions and emissions per output are also much smaller (7957.1 M MT CO2e/year and 2.05 kg CO2e/year per USD).

The upper and lower bounds of the global changes due to uncertainties in the productivity gains from US R&D spending are reported in S6 and S7, respectively. Note that these scenarios also consider restrictions in US farm input use. The range of changes are much smaller at the global level. World farm productivity growth is between 45.6% and 43.3% while agricultural output increase is around 58.0% and 57.2%. The upper bound for crop and livestock production growth is around 55.7% and 64.0% while the lower bound of these changes are around 55.0% and 63.0%, respectively. Global average change in crop price is bounded between -29.1% and -26.0% while for livestock the range is between -33.4% and -32.2%. The range of global cropland expansion is between 68.5 and 60.0 M ha. The global average agricultural GHG emissions is between 8000.3 and 7895 M MT CO2e/year while the global average GHG emissions per hectare is around 2.06 and 2.02 kg CO2e/year per USD. Note that the lower bounds for cropland area and GHG emissions are below the expected changes under S2 and S3. This suggest that the global environmental gains from the combined R&D and input restriction policy are much larger than if these policies were pursued individually even with uncertainty in the impacts of US R&D spending on farm productivity.

IV. Summary and Conclusions

The future economic and environmental benefits from increased US public R&D investments is examined in this study using the latest empirical estimates on the historical linkages between US R&D spending and agricultural productivity growth as well as technological spillover effects across developed countries. The benefits from increased US R&D spending is then calculated using a global economic model of agriculture. The results suggest that increasing the growth rate of US R&D investments over the period 2025-35 results in additional expansion in US crop production by 2050 - most of which are sold in the world market as greater productivity increases competitiveness of US crop exports. However, the environmental benefits to these economic gains are limited since additional production requires more cropland and noncropland inputs which in turn drives up GHG emissions from these inputs. Including technological spillovers from the US to other regions slightly erodes the growth in US crop production.

Agricultural GHG emissions in the US can only be reduced significantly when stringent input restrictions are implemented but these restrictions also limits US crop production. Greater R&D spending combined with restrictions in input use in the US provides both economic gains from increased production as well as reduced GHG emissions from lower input use.

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Table 1. Summary of US and World agricultural production and GHG emissions under different R&D spending and input restriction scenarios

United States

	Scenarios	Agricultural Productivity	Agricultural Output	Crop Output	Livestock Output	Crop Price	Livestock Price	Cropland Use	Average Annual Agricultural GHG Emissions	Average Annual Agricultural GHG Emissions per Output
		%	%	%	%	%	%	M ha	M MT CO2e/year	kg CO2e/year per USD
S1	Business-As-Usual	38.7	50.0	58.4	38.6	-19.0	-28.7	6.7	490.4	1.573
S2	Reduced US Input Use	38.7	44.3	49.1	38.5	-15.8	-28.5	-7.9	416.3	1.388
S3	Greater US R&D spending	62.1	69.5	86.2	50.9	-30.4	-39.5	7.0	486.2	1.380
S4	No R&D Spillovers	62.1	73.8	93.2	54.6	-28.1	-39.4	8.9	502.5	1.391
S5	Combined Policy	62.1	62.3	74.7	50.7	-27.9	-39.4	-7.8	410.5	1.217
S6	Combined Policy - Upper Bound	69.7	68.3	83.3	54.7	-30.9	-42.2	-7.7	410.0	1.172
S7	Combined Policy - Lower Bound	56.7	58.0	68.5	47.9	-25.4	-37.1	-7.9	411.3	1.252

World

	Scenarios	Agricultural Productivity	Agricultural Output	Crop Output	Livestock Output	Crop Price	Livestock Price	Cropland Use	Average Annual Agricultural GHG Emissions	Average Annual Agricultural GHG Emissions per Output
		%	%	%	%	%	%	M ha	M MT CO2e/year	kg CO2e/year per USD
S1	Business-As-Usual	40.0	56.2	54.2	61.6	-21.8	-30.2	93.6	8218.6	2.131
S2	Reduced US Input Use	40.0	56.1	54.0	61.6	-21.1	-30.2	81.5	8167.2	2.120
S3	Greater US R&D spending	44.3	57.7	55.5	63.5	-28.2	-32.7	76.7	8005.2	2.056
S4	No R&D Spillovers	42.1	56.9	54.8	63.0	-24.7	-30.9	86.1	8132.1	2.100
S5	Combined Policy	44.2	57.6	55.3	63.5	-27.3	-32.7	64.9	7957.1	2.046
S6	Combined Policy - Upper Bound	45.6	58.0	55.7	64.0	-29.1	-33.4	60.0	7895.7	2.025
S7	Combined Policy - Lower Bound	43.3	57.2	55.0	63.0	-26.0	-32.2	68.5	8003.0	2.062

Appendix Table 1. Average Agricultural R&D Elasticities for Key Regions from Fuglie (2017)

Region	TFP R&D Elasticity from International R&D stocks
Developed	0.210
Western Europe	0.240
Australia-NZ-S Africa	0.120
Japan-Korea-Taiwan	0.210*
Developing	0.070
Latin America	0.360