Forecasting the Fallout from AMR: Economic Impacts of Antimicrobial Resistance in Food-Producing Animals

A report from the EcoAMR series

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World Organisation for Animal Health · AID Animal Industry Data · CGD Center for Global Development · Institute for Health Metrics and Evaluation · RAND Europe · The World Bank IBRD • IDA | World Bank Group

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Foreword

Antimicrobial resistance (AMR) is a silent pandemic that must be curbed via a multidisciplinary, multi-sectoral One Health approach, backed by political will, government commitment and public–private partnerships. This global threat affects the health of humans, animals and plants. Using a One Health approach, this EcoAMR study provides current estimates and up-to-date predictions of the health and economic burdens associated with AMR in humans and livestock, to facilitate policy action.

EcoAMR findings underscore the severe threat caused by AMR if no action is taken. Forecasts for 2025–2050 show that 38.5 million human deaths will be associated with bacterial AMR. Moreover, the global health care costs of AMR could rise to US$ 159 billion a year by 2050. In the animal sector, cumulative global gross domestic product (GDP) loss due to AMR in livestock is predicted to be US$ 575 billion by 2050. These multi-sectoral results provide strong evidence that calls for urgent action to curb AMR.

In light of this threat, the second United Nations General Assembly High-Level Meeting (UNGA HLM) on AMR, scheduled for September 26, 2024, aims to advocate to members of the UN General Assembly that concrete resolutions to combat AMR must be made. It is only through global and ambitious actions that this severe threat can be contained, preventing a return to treatment failure challenges and its consequences.

Across the global One Health spectrum, a bold and concrete political declaration is needed, informed by evidence. Obtaining this supportive evidence depends largely on the availability of high-quality, relevant data. However, data are sparse on the topic of antimicrobial use (AMU) and resistance, particularly from low- and middle-income countries. This gap is even wider in the animal health sector. Underpinning this lack of data that would help generate evidence are weak information systems; this is partly due to inadequate financial resources to support such systems that could synthesise evidence across sectors. In particular, the animal health sector requires adequate support to accelerate the response to the growing threat of AMR. Antimicrobials are critical medicines, and their effectiveness must be preserved for the treatment, control and prevention of infectious diseases in animals, humans and plants when needed.

Making an economic case for investment in the fight against AMR has been a challenge across the world, partly due to competing priorities at all levels. Paramount to establishing the required business case for sustainable investment to tackle AMR is cooperation – both within and across human and animal sectors – as well as collaboration with national and global stakeholders, and engagement of private partnerships. Thus, the World Organisation for Animal Health (WOAH) is collaborating with the United Kingdom Department of Health and Social Care (UK DHSC) to pool a consortium of international partners across the human and animal health sectors, who can implement this groundbreaking EcoAMR series. The project aims to generate the necessary evidence that will inform bold and concrete commitments to mitigate AMR by member states at the UNGA HLM on AMR in 2024 and future actions by governments and policy-makers. Among this team are global experts from the Centre for Global Development and the Institute for Health Metrics and Evaluation, who have partnered with Global Research on Antimicrobial Resistance to develop the human health component. Meanwhile, RAND Europe, Animal Industry Data and WOAH have addressed the animal health component of this cross-sector initiative. The World Bank has provided quality assurance via a team of global experts serving as peer reviewers of this study's methodologies and outputs. The results from this study will guide action-oriented declarations at the UNGA HLM on AMR, inform governments and policy-makers on effective interventions and policy-making, and facilitate sustainable financing.

We all have a role to play to contain AMR around the world, and I extend my gratitude to the UK DHSC for their global leadership role in curbing AMR and funding this cross-sectoral initiative on the economics of AMR. My thanks also go to the editors and authors for generating this new evidence, as well as the global peer reviewers assembled by the Work Bank for reviewing the study. Finally, I wish to thank our collaborators in Bangladesh, where field studies were conducted, and all staff who ensured that this project was implemented promptly and successfully to meet its overarching goal of informing UNGA HLM on AMR 2024 and to provide evidence for governments and policy-makers.

Dr Emmanuelle Soubeyran

Director General, World Organisation for Animal Health

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We also wish to thank collaborators from the government of Bangladesh's Department of Livestock Services and Department of Fisheries for its support in conducting the field studies that survey frontline animal health professionals and farmers, as well as for carrying out key informant interviews with senior professionals.

Abbreviations and acronyms

AGP	Antimicrobial Growth Promoter
AHHME	Agriculture Human Health Micro-Economic
AI	Artificial Intelligence
AMR	Antimicrobial Resistance
AMU	Antimicrobial Use
ANIMUSE	ANImal antiMicrobial USE Global Database
BRD	Bovine Respiratory Disease
CES	Constant Elasticity of Substitution
CM	Clinical Mastitis
DCGE	Dynamic Computable General Equilibrium (Model)
EcoAMR	Economic Impact of Antimicrobial Resistance
FAO	Food and Agriculture Organization of the United Nations
GDP	Gross Domestic Product
GTAP	Global Trade Analysis Project
KAP	Knowledge, Attitudes and Practices
LMICs	Low- and Middle-Income Countries
LPD	Livestock Production Disease
NAP	National Action Plan
NCD	Neonatal Calf Diarrhoea
ODE	Ordinary Differential Equations
OHHLEP	One Health High-Level Expert Panel
PCU	Population Correlation Unit
ROI	Return on Investment
SAM	Social Accounting Matrix
SC	Swine Colibacillosis
SSP	Shared Socioeconomic Pathway
TFP	Total Factor Productivity
UK DHSC	United Kingdom Department of Health and Social Care
UNGA	United Nations General Assembly
WOAH	World Organisation for Animal Health

Executive summary

Antimicrobial resistance (AMR) poses a significant threat to global health and economic stability, affecting human, animal and plant health, and rendering lifesaving drugs ineffective. This multifaceted issue requires the consistent implementation of interventions using a One Health approach. Previous studies have estimated AMR's economic implications to trigger a gross domestic product (GDP) loss of between US$ 1 trillion and 3.4 trillion annually, by 2050. Despite the potential economic impacts on food-producing animals and the spillover threats to human health and other sectors, research on the economic impacts of AMR in animal health remains limited, with only sparse relevant data. Furthermore, quantifying the exact impact of antimicrobial use (AMU) in food-producing animals on AMR in humans remains a challenge due to lack of high-quality data.

OBJECTIVES

The overarching objective of this study is to generate evidence on the economic burden of AMR in food-producing animals, to inform response and decision-making, and to support more effective evidence-based implementation of National Action Plans (NAPs).

More specifically, this study aims to:

- identify the major economic impact pathways by which AMR is thought to impact productivity in food-animal production;
- estimate the global economic effects of AMR and the potential economic value of interventions to reduce AMU in food-animal production up to 2050;
- estimate the potential economic return on investment (ROI) of interventions to address AMU and AMR in livestock;
- and to identify the knowledge, attitudes and practices (KAP) of the farming sector in a setting of low- and middle-income countries (LMICs) against the backdrop of the implementation of their NAPs for AMR.

METHODOLOGY

This study used various methodologies to address its objectives. A literature review was conducted to identify the major economic impact pathways of AMR in food-producing animals. Economic modelling assessed AMR-attributable effects on the productivity of different livestock sectors. This method compared a reference scenario against a series of 'what-if' counterfactual scenarios, using a livestock production disease (LPD) model and computable general equilibrium (CGE) model. To understand the ROI of interventions to tackle AMR, an economic evaluation was conducted, leveraging a low-cost artificial intelligence (AI) based intervention suitable for all settings, including LMICs, with the aid of a cost–benefit analysis. To understand the challenges involved in implementing NAPs in LMICs, a comprehensive fieldwork case study was conducted in Bangladesh. The resulting data was evaluated using different qualitative and quantitative data analysis approaches.

Livestock production disease and macroeconomic models

The livestock production disease (LPD) model simulates production outputs of different livestock sectors for three animal species: (1) cattle, (2) chicken and (3) swine. It also analyses five different output goods: (1) cattle meat, (2) cattle (raw) milk, (3) swine meat, (4) chicken meat and (5) chicken eggs. Within the

LPD model, animals move over time through a sector-specific production system and are at risk of having bacterial infections that can lead to treatment failure due to AMR. In turn, this leads to excess levels of mortality and morbidity, thus impacting sector productivity. The projected productivity effects attributable to AMR in the modelled livestock sectors are then passed on to the macroeconomic model to assess wider economic impacts on selected economic indicators, such as GDP. The analysis covers seven regions, based on the current World Bank regional classification: (1) East Asia and the Pacific, (2) Europe and Central Asia, (3) Latin America and the Caribbean, (4) the Middle East and North Africa, (5) North America, (6) South Asia and (7) Sub-Saharan Africa.

In the LPD and macroeconomic models, the global economic effects of AMR in livestock sectors were simulated for the period 2025–2050 under different scenarios. First, a reference scenario was established, beginning in the year 2025; this scenario tracks production trends in the modelled livestock sectors based on current levels of antimicrobial consumption and rates of resistance, to then project them for future years up to 2050. Projections estimated by the Food and Agriculture Organization of the United Nations (FAO) show that, in most regions, the number of livestock in production systems follow a rising trend due to a predicted increase in demand for food products These trends are associated with an increase in antimicrobial consumption over time as well as rising rates of resistance. The reference scenario was compared to six 'what-if' counterfactual scenarios, which vary in their assumptions regarding current and future AMU and AMR input parameters (see Table 1).

To put the study's findings in the right context, some important caveats for the economic analysis must be highlighted. First, due to data limitations, only a subset of livestock animals and diseases are included in the analysis. Second, the analysis uses business-as-usual scenario projections for future levels of livestock production provided by FAO, yet it does not model the potential economic impacts resulting from negative externalities by livestock (e.g. cattle) on climate change through greenhouse gas emissions, deforestation and biodiversity loss.

A return-on-investment analysis of an early disease detection intervention using artificial intelligence

The intervention was assessed for its real-time potential to detect the onset of disease or abnormalities. This would result in prompter disease management and thereby a reduction in the use of antimicrobials

TABLE 1 Macro-modelling scenarios for animal health

Scenario	Label	Description
1	Very low resistance scenario	Resistance rates across all modelled pathogens and sectorial diseases are set to 5% across all regions and sectors.
2	Pessimistic scenario	AMR-attributable disease burden doubles in all regions. AMU and subsequently AMR rates rise faster than in the reference scenario.
3	AMU reduction in line with global targets scenario	In line with current discussions on global targets, the scenario assumes a 30% reduction in AMU across all regions within the next five years.
4	Substantial AMU reduction scenario	All regions reduce AMU in livestock production to 20 mg of AMU per kg of biomass over the next 20 years.
5	Small negative externality from animals to humans scenario	AMR has a negative impact on the health of humans and reduces the productivity of those in the workforce in all economic sectors by 1.5% each year. It is assumed that 5% of the AMR impact on humans is attributable to AMU and AMR in food-producing animals.
6	Pessimistic with large negative externality from animals to humans scenario	AMU and AMR trajectory in livestock sectors follows pessimistic scenario 2, adding a more pronounced negative externality from AMU and AMR in livestock on human health than scenario 5. It also assumes a 3% AMR shock on labour productivity, and that 10% is attributable to AMR in livestock.

with overall positive effects on animal health and productivity. The study includes a calculation of the costs *versus* benefits of this intervention. The AI solution supports farmers in continually monitoring individual pigs to track changes in their health and productivity, facilitating early disease detection, diagnosis and treatment. The solution can be implemented in LMIC settings on small-, medium- and large-scale farms, where the ROI could be even greater due to lower baseline levels of biosecurity and animal husbandry practices.

Case study in Bangladesh

Key informant interviews, a survey of animal health professionals and a field survey of livestock and aquaculture farmers were conducted in Bangladesh from January to March 2024. Semi-structured key informant interviews aimed to identify policy interventions and strategies designed to reduce AMU and AMR in livestock and aquaculture, including regulation of antimicrobials at the farm level, and the main drivers of AMR emergence and spread. Surveys of animal health professionals (n = 100) assessed respondents' KAP regarding access to antimicrobials, off-label use, presence of substandard and falsified medicines, affordability, and the role of the government and private sector in influencing farmers. Interviews with farmers (n = 1459) aimed to determine their KAP regarding antimicrobials and the economic burden of disease and impact on their farm operations and families.

MAIN FINDINGS

- Without further action to curb AMR, its negative impacts on livestock production and the global economy will intensify over time:
  - By 2050, it is estimated that the annual livestock production losses due to AMR equal the consumption needs of 746 million people (comparing the reference scenario to scenario 1 with a low resistance rate of 5%). Under a more pessimistic assumption about the future AMR-disease burden (comparing the reference scenario to scenario 2), the estimated yearly production losses equal the consumption needs of about two billion people globally. Livestock production losses are heaviest in cattle and poultry meat production compared to the other livestock output types assessed in both scenarios 1 and 2.
  - By 2050, the estimated cumulative global GDP loss for 2025–2050 due to AMR in livestock is US$ 575 billion (comparing the reference scenario to scenario 1 with a low resistance rate of 5%). Under the more pessimistic assumptions on the future AMR-disease burden (comparing the reference scenario to scenario 2), the estimated cumulative GDP loss between 2025 and 2050 is US$ 953 billion.
- Considering even moderate harmful spillover effects of AMR in livestock on human health, cumulative global GDP losses between 2025 and 2050 associated with lower labour productivity are estimated at US$ 1.1 trillion (comparing the reference scenario to scenario 5). Considering a pessimistic scenario for both, the direct AMR burden on livestock and the potential spillover effects on humans (comparing the reference scenario to scenario 6) the cumulative GDP loss for 2025–2050 could rise to US$ 5.2 trillion by 2050.
- The economic projections highlight the potential economic gain from interventions that aim to reduce AMU in livestock. Results suggest that a global reduction in AMU of around 30% is predicted to lead to a cumulative increase in the global GDP by US$ 120 billion between 2025 and 2050 (comparing the reference scenario to scenario 3). Interventions targeting AMU and AMR can mitigate resistance rates and offer economic benefits that potentially outweigh the costs of implementing these interventions.
- Statistical analysis suggests that countries using antimicrobials for growth promotion in livestock have an estimated average of 45% higher antimicrobial use per kilogram of animal biomass than countries that do not use growth promoters. This estimate accounts for all classes of antimicrobials except ionophores. As previously reported by WOAH,

the use of antimicrobials as growth promoters is still a practice among 20% of its Members, with 75% of those being in the regions of the Americas, and in Asia and the Pacific.

- An AI-based innovative low-cost intervention for early disease detection was evaluated in a case study on swine farms, revealing a benefit-to-cost ratio of four. This indicates an average yearly ROI of more than 400% per pig, with a range of 225% in the first year, to 537% in the third year of implementation. Medical costs to farms that implemented this AI solution were consistently lower and even decreased over the study period in comparison to conventional farms. Moreover, this AI solution has been successfully implemented in LMICs in small-, medium- and large-scale farms with encasements.
- Evidence from a KAP case study of over 1,450 livestock and aquaculture farms in Bangladesh (with high-intensity food-animal production) shows the following highlights:
  - there is a persistent lack of AMU and AMR awareness, with evidence of AMU practices that contribute to AMR emergence and spread among farms, which often rely on untrained professionals for disease management. This exacerbates and promotes the indiscriminate use of antimicrobials, including propagation of substandard and falsified medicines;
  - high expenditures on antimicrobials are driven by AMU in animal feed, the use of untrained service providers, disease outbreaks, resistant disease management and farm size.
- Evidence from key informant interviews in Bangladesh also suggests that implementation of current policies to tackle AMR lack the required financial investment and human resources.

RECOMMENDATIONS

Based on these findings, this report offers seven main recommendations to mitigate the potential economic ramifications of AMR in food-producing animals:

1. Prioritise preventive interventions to reduce the burden of disease in animals. This leads to a reduced need for AMU in livestock, and the economic benefits would likely outweigh the costs associated with implementing such interventions. This involves the following:
   a. The development and deployment of strategies to reduce the need for AMU, including vaccination, evidence-based effective alternatives to antimicrobials, as well as good farm management practices based on biosecurity and nutrition.
   b. The implementation of cost-effective real-time early disease detection interventions (e.g. AI-enabled solutions or equivalent alternatives) for prompt disease management. This avoids the need for AMU and reduces the selection pressure for AMR emergence and spread.
2. Enforce formal prescription practices and improve access and affordability to essential antimicrobials. This includes using preventive measures (e.g. vaccines), facilitating regulations and promoting research and development (R&D).
3. Phase out AMU for growth promotion in food-producing animals.
4. Strengthen and institutionalise surveillance systems for AMU and AMR, including comprehensive data capture on diseases, as well as risk factors associated with food-producing animals, via a One Health perspective for data sharing and evidence-based decision-making across sectors. This should also include the establishment of a global baseline for AMR resistance in food-producing animals.
5. Establish and quantify the spillover linkages and impacts of AMR between food-producing animals and humans, determining their interconnectedness and enabling accurate risk estimations of the real-world economic impact of AMR, to better inform policy-makers and responses.
6. Improve awareness by educating farming communities on AMR and training health professionals on the prudent and responsible use of antimicrobials in food-producing animals. Promote mechanisms

to reward farmers who comply with policies and regulations, and who undertake available training as necessary.

7. Sustainably invest and finance initiatives such as:
    a. infrastructure development (e.g. sentinel diagnostic laboratories and rapid in-field diagnostics) to generate high-quality data needed for analyses to provide evidence;
    b. R&D to mitigate the gap crisis in the animal health sector to reduce AMU and AMR;
    c. analyses to establish the economic impact and to build a case for greater investment in AMR using a One Health approach. In this way, WOAH Members and other key stakeholders can remain appropriately informed on cost-effective interventions that reduce AMU and AMR on a global level.

CHAPTER 1

Overview of the EcoAMR project: animal sector report

INTRODUCTION

Antimicrobial resistance (AMR) occurs when bacteria, viruses, fungi and parasites no longer respond to antimicrobial agents (WHO, 2024). As a result of drug resistance, antibiotics and other antimicrobial agents become ineffective, making infections difficult or even impossible to treat, thereby increasing the risk of disease spread, severe illness and death (WHO, 2024). AMR has been characterised as a silent pandemic that requires a multidisciplinary, multi-sectoral One Health approach that recognises the interconnectedness between the environment and the health of humans, animals and plants. The One Health High-Level Expert Panel (OHHLEP) has defined One Health as an:

> *'integrated, unifying approach that aims to sustainably balance and optimize the health of people, animals, and ecosystems. It recognizes the health of humans, domestic and wild animals, plants, and the wider environment (including ecosystems) are closely linked and interdependent. The approach mobilizes multiple sectors, disciplines, and communities at varying levels of society to work together to foster well-being and tackle threats to health and ecosystems, while addressing the collective need for healthy food, water, energy, and air, taking action on climate change and contributing to sustainable development.' (OHHLEP* et al.*, 2022).*

The misuse of antibiotics in humans, animals and agriculture contributes to the emergence and spread of resistant bacteria through various channels. For example, resistant bacteria can be transmitted to humans via contaminated food, direct contact with animals, and the environment via water contaminated with resistant bacteria (WHO, 2023a).

The societal burden of AMR from a One Health perspective

AMR has a significant societal burden that will continue to rise if no further action is taken to tackle it. AMR threatens the effective treatment of infections caused by bacteria, viruses and fungi and therefore represents a global public health threat. Updated findings from this EcoAMR project estimate 4.9 million human deaths associated with bacterial AMR in 2022, with a forecast to 2050 of 7.73 million deaths (Vollset *et al.*, 2024). Furthermore, rising resistance increases animal disease burden, as well as the risk of disease spread, severe illness and death, particularly among vulnerable populations such as the elderly, immunocompromised individuals and those undergoing surgery (Cecchini *et al.,* 2015). The health burden of AMR is further exacerbated by the limited development of new antimicrobials and access to existing ones, presenting a significant challenge to global health security (Laxminarayan *et al.,* 2013). From an animal health perspective, antimicrobials are used in livestock production for managing diseases. However, increased use causes increased resistance rates, thus reducing the effectiveness of antimicrobials. Overall, this leads to higher costs for food-producing sectors due to elevated levels of animal mortality and morbidity, as well as reduced productivity (Pokharel *et al.,* 2020). This can have negative consequences for food production, especially in light of a growing population, lack of food security and contamination risk for the environment (Pokharel *et al.,* 2020).

It is challenging to accurately estimate the economic burden of AMR, as it has a multifaceted impact on human and animal health, as well as on the broader economy. Via a variety of scenarios, the World Bank (2017) projected that, by 2050, AMR could decrease annual global GDP by 1.1–3.8%, corresponding to between US$ 1 trillion and US$ 3.4 trillion. Similarly, a report by the UK AMR Review estimates that AMR could lead to a cumulative cost of US$ 100 trillion by 2050 if left unchecked (O'Neill, 2016). From a healthcare perspective, Thorpe *et al.* (2018) estimate that, in the United States of America (US) alone, the additional healthcare costs due to multidrug-resistant bacterial infections range from US$ 2 billion to US$ 20 billion annually. While the economic impact of AMR on humans has received considerable attention in the existing literature, there are limited studies that focus on the economic impacts of AMR in food-producing animals (Poudel *et al.,* 2023). The World Bank (2017) estimates that, by 2050, AMR could be associated with a decline in livestock production by approximately 11% in low-income countries, and 6–9% in middle- and high-income countries.

Mitigating the impact of AMR requires a One Health approach as defined by OHHLEP. This includes prudent use of antimicrobials in all sectors, surveillance of AMR and AMU, infection prevention and control, as well as R&D (O'Neill, 2016). Although there is only limited evidence on the economic impact of AMR in the livestock sector, there has been increasing interest in understanding the burden of AMR on livestock within the context of One Health, which has highlighted the importance and interconnectedness of sectors in the context of AMR and pathogen transmission (WOAH, 2023a). The Organisation for Economic Co-operation and Development (OECD) therefore recommends implementing multiple One Health policies as packages rather than in isolation, as this is more beneficial (OECD, 2023).

Progress in the implementation of National Action Plans varies due to financing gaps in animal health

The World Health Organization (WHO), in collaboration with FAO and WOAH, has provided guidelines for the development of NAPs against AMR, emphasising a One Health approach that integrates human, animal and environmental health (WHO, 2015). NAPs typically include objectives related to awareness and understanding of AMR, surveillance and research, infection prevention and control, optimisation of AMU and sustainable investment in countering AMR. They also involve a range of stakeholders, including government agencies, healthcare providers, veterinarians, farmers and the general public. As of 2023, 159 countries have developed multi-sectoral governance or coordination mechanisms on AMR; however, significant challenges persist in implementing these plans and progress varies widely by income region (WHO, 2023b). Lack of funding has impeded the implementation of measures to combat AMR and much of the public funding is allocated to AMR in humans, with limited funds available to implement measures for AMR in animal health (Ryan, 2021).

OBJECTIVES

This study's key objective is to generate evidence on the economic burden of AMR in food-animal production to inform responses and decision-making that support the implementation of NAPs. Accurate estimates of the economic burden depend on high-quality relevant data. However, a major challenge is the limited data available in the animal sector, as well as inadequate financial support for the sustainable implementation of NAPs on AMR for most countries, particularly LMICs. While a few existing studies have considered the economic impact of AMR on livestock production, they did not consider the underlying pathways on how changes in AMU and AMR impact these sectors (Fernando and McKibbin, 2022, 2024; World Bank, 2017).

To bridge this gap, this study has the following aims:

1. Identify the major economic impact pathways by which AMR is thought to impact productivity in food-animal production, with a focus on livestock.
2. Estimate the global economic effects of AMR and the potential economic value of interventions to curb AMU in food-animal production, forecast up to 2050.

3. Estimate the potential economic ROI of interventions to address AMU and AMR in livestock.
4. Identify the KAPs of the farming sector in an LMIC setting for the implementation of its NAP for AMR.

METHODOLOGY

To achieve these research objectives, the study used a mix of research methodologies, as outlined in Table 2.

Below are brief overviews of each methodology. For more technical details on each type, see the technical annexes provided at the end of this report.

Literature review

At the start of the literature review, generic strings of search terms were devised to capture as many scientific publications as possible. Peer-reviewed scientific literature was searched for on the PubMed platform using the following strings: AMR + livestock (503 papers); AMR + livestock + economic pathways (7 papers); AMR + livestock + economic (20 papers). These papers were then screened by three reviewers based on the title and abstract. Inclusion and exclusion of papers were based on the criteria listed in Annex F: **Literature reviews**, which identified 76 papers for inclusion. A grey literature review supplemented the scientific peer-reviewed literature. For this step, relevant inclusion and exclusion criteria from the peer-reviewed literature were followed, identifying 48 sources of grey literature. Three of these met all the inclusion criteria. Further details can be found in Annex F: **Literature reviews**.

Economic modelling using livestock production disease and macroeconomic models

To find new evidence on the potential economic cost of AMR in food-producing animals, a livestock production disease (LPD) model was developed to provide productivity output parameters. These were then passed on to a multi-sectorial, multi-region dynamic computable general equilibrium (DCGE) model to assess the economic impacts of changes in the productivity of livestock sectors. The LPD model uses production and disease inputs to simulate production outputs of different livestock sectors under varying scenarios. Three animal species are considered in this model: (1) cattle, (2) chicken and (3) swine. In addition, five different output goods are considered: (1) cattle meat, (2) cattle (raw) milk, (3) swine meat, (4) chicken meat and (5) chicken eggs. Within the LPD, animals move over time through a sector-specific production system where the prevalence of treatment-resistant bacterial pathogens can cause treatment failure. In turn, this leads to AMR-attributable excess levels of mortality and morbidity, adversely affecting productivity. The simulated sector-specific AMR productivity effects are then passed on to a DCGE model to assess the wider economic impacts.

TABLE 2 Research methodologies

	Research objective	Methodology
1	Identify the major economic impact pathways by which AMR is thought to affect productivity in food-producing animal production.	Literature review of the existing academic and grey literature.
2	Estimate the global economic effects of AMR and the potential economic value of interventions to reduce AMU in food animal production up to 2050.	Livestock production disease (LPD) model producing sectorial productivity parameters, which are passed on to a global macroeconomic model to assess impact on economic indicators, such as gross domestic product (GDP).
3	Estimate the potential economic return on investment (ROI) of interventions to address AMU and AMR in livestock.	Economic evaluation of an AI-based intervention for early disease detection aimed to reduce AMU in pig farming.
4	Identify the knowledge, attitudes and practices (KAP) of the farming sector in a setting of lower- and middle-income countries (LMICs) on the implementation of their National Action Plans (NAPs) for AMR.	Key informant interviews, survey of health professionals, and in-person interviews with livestock and aquaculture farmers.

The rationale for assessing the effects on GDP from a macroeconomic perspective is that livestock sectors do not operate in isolation within an economy. In fact, they demand inputs from other sectors, or indeed are themselves suppliers of inputs to other sectors. Using a DCGE model accounts for some of these indirect economic effects. The DCGE model uses the Global Trade Analysis Project (GTAP) database for inputs as calibration (Purdue University, 2023). GTAP is a globally consistent database, widely considered the standard for global computable general equilibrium modelling. Technical details on the economic modelling approach are outlined in Annexes A to D.

At this point, it is important to highlight the scope and limitations of the economic analysis (limitations of other research objectives can be found in the following chapters). This study's focus lies on how AMR affects food-producing animals and its consequences on the productivity of livestock sectors. Specifically, the economic analysis aims to assess what economic effects are attributable to AMR, rather than animal disease in general. Thus, the economic impact of zoonoses was not in the scope of this analysis. Although calculating the burden of animal disease is a challenging task due to limitations in data availability, specifically calculating the burden of AMR in livestock may be even more challenging given the vast diversity of data requirements (Gilbert *et al.,* 2024; Martins *et al.,* 2024). While a number of analytical limitations are highlighted throughout the report where necessary, there are two overarching caveats that frame the study's findings in the right context.

First, due to major limitations in data availability on animal diseases and the extent of AMR rates and AMU, this analysis only includes a sub-set of livestock production diseases, exclusively focusing on bacterial infections. Furthermore, the analysis only considers AMR in terrestrial animals, excluding aquatic animals. Due to data limitations, it is difficult to assess the impact of the exclusion of other types of infections and sectors on this study's findings. Their exclusion may cause an under-estimation of this study's reported costs attributable to AMR in food-producing animals.

Second, within this study's applied economic modelling framework, AMR negatively affects livestock production outputs, eventually leading to a lower supply of animal source foods (e.g. meat, milk, eggs) and higher prices for these products. All else being equal, this is associated with negative dietary consequences, especially for populations in lower-income regions. These regions are projected to experience stronger population growth over the coming decades, and therefore also increasing food demands. The analysis applies the business-as-usual scenario projections for future levels of livestock production provided by FAO (2024a). However, it is important to note that livestock production (e.g. cattle) has negative externalities on climate change, primarily through greenhouse gas emissions, deforestation and biodiversity loss. The analysis does not consider the potential economic impacts of climate change, yet global mitigation strategies will need to be implemented to offset the climate effects of increased production and demand of animal-source foods. These strategies include substitution between food animal types (e.g. from cattle to chicken) to improve the environmental sustainability of livestock production.

Economic evaluation of an AI-based intervention

An intervention based on Artificial Intelligence (AI) was assessed for its real-time potential to detect the onset of disease or abnormalities. Its aim is to provide prompt disease management and thereby a reduction in the use of antimicrobials, with overall positive effects on animal health and productivity. A calculation of the costs *versus* the benefits of the intervention was also carried out. Chapter 4 of this report provides details on the study objective.

KAP interviews and surveys

Key informant interviews

An interview guide was developed with questions focusing on the following: policy interventions or strategies designed to reduce AMR or AMU in livestock and fisheries; regulation of antimicrobials at the farmer level; costs associated with these interventions; and the main sources/drivers of AMR emergence and spread in livestock and fisheries. Semi-structured interviews were carried out with 25 key informants from Bangladesh livestock services, and 15 from fisheries. Each informant was familiar with or involved in policies and scientific developments to tackle AMU and AMR in Bangladesh. The key informants were contacted via email, then interviewed virtually using Microsoft Teams at a time most suitable to them. Of the 15 fisheries and 25 livestock informants, six and five agreed to participate in an interview, respectively. The interviewers took notes, while the interviews were audio recorded then transcribed using Microsoft Teams' built-in functionality. Findings from the interviews were mapped onto a coding framework developed using Microsoft Excel, and a narrative synthesis of the responses was written up.

Online surveys of frontline food-producing animal health professionals

Two surveys were conducted: the first with animal health professionals working with livestock (n = 73) and the second with fisheries (n = 27). Respondents were identified by the Department for Livestock and Department for Fisheries in Bangladesh, who facilitated the sharing of the survey online. Surveys were conducted via the SmartSurvey platform (SmartSurvey, 2024). Questions were developed by the interdisciplinary study team, with input from stakeholders in Bangladesh.

Field surveys of livestock and fisheries farmers

Mixed method cross-sectional KAP surveys were deployed in Bangladesh from January to March 2024, targeting farmers in livestock and fisheries departments (livestock n = 1054 and fisheries n = 405). The surveys were administered in-person and translated into the local language by Bangladeshi survey enumerators. Survey responses were documented in English.

A literature review was conducted to identify themes with potential to influence KAPs regarding AMU and AMR among the target audiences. The survey questions were subsequently developed with information from the literature review and with input from a team of subject-matter experts. The survey consisted of both qualitative and quantitative questions to assess the KAP of the target audiences, successful interventions implemented to curb AMR, and pathways through which AMR impacts productivity and the economy.

A stratified purposive sampling approach was implemented in the livestock and fisheries sectors to target areas with intensive production, maximising relevant inputs from participants, as opposed to a uniform sampling approach across the entire country. For the livestock sector, two high production districts of Sirajganj and Tangail were selected. For the fisheries sector, two high production districts of Mymensingh and Khulna were selected. More samples were allocated to the larger farms within each farm type to maximise responses from farmers of intensive livestock and fishery operations. Large farms were prioritised in this survey, as these may be more dependent on AMU for higher productivity. Considering these weighted factors, farmers were randomly selected for interview within each farm type and size. KoboToolbox was used for data collection and all survey data was analysed in R statistical software (R Core Team, 2023; KoboToolBox, 2024.) Further details of the descriptive and regression analysis can be found in Annex G.

CHAPTER 2

Economic pathways and impacts of antimicrobial use and resistance and food-producing animals

LITERATURE REVIEW

Approximately 20% of livestock production each year is lost due to animal diseases (WOAH, n.d.). This includes a wide variety of animal diseases, such as viral and bacterial infections, diseases caused by other parasites and treatment-resistant infections. Animal diseases incur considerable economic costs in livestock production. At the farm level, these costs primarily arise from (i) alterations in input utilisation on farms, including increased veterinary treatments for sick animals; (ii) changes in input requirements beyond the farm, such as additional labour cost for carcass trimming at slaughter facilities; (iii) variations in the quantity of outputs sold, including lower product sales due to disease; and (iv) modifications in the quality of marketable production outputs, such as decreased egg quality (Niemi, 2021). Unlike highly contagious outbreaks of animal diseases (e.g. African swine fever), which incur a substantial cost burden, bacterial infections in food-producing animals are often associated with a continuous economic burden, steadily affecting disease control expenditures and productivity. This can have substantial economic ramifications for national economies, as food-producing animal sectors are a major source of employment and income for many regions, especially in LMICs. For example, these sectors employ approximately 70% of the workforce living in rural Bangladesh; in Indonesia, this is 40% of the workforce and 12% of the GDP; and in Bhutan, crop production and livestock farming are the main sources of income, employing 51.1% of the population (Gurung *et al.*, 2023; Coyne *et al.*, 2020; Al Amin *et al.*, 2020). Furthermore, the demand for animal products is increasing: in Sub-Saharan Africa, for example, the demand for meat is predicted to rise by 246% and for fish by 196% by 2050 (Mikecz *et al.*, 2020). Thus, negative effects on food production caused by infections can have negative consequences for global food security. To sustain the rising demand for animal-food production and sources of employment in many countries, it is vital to understand the potential trade-offs in the interplay between AMU and AMR in livestock sectors.

Antimicrobials have a range of purposes ranging from treating ill animals to growth promotion

Antimicrobials have various applications in food-producing animals: for veterinary medical purposes (e.g. for the prevention, control or treatment of disease) and non-veterinary medical purposes, including to increase the rate of weight gain or the efficiency of feed utilisation in animals, also known as growth promotion (Al Amin *et al.*, 2020; Coyne *et al.*, 2019; Magnusson *et al.*, 2021; Albernaz-Gonçalves *et al.*, 2022a, 2022b; WOAH, 2024b). For veterinary purposes, for example, antimicrobials are used to treat bovine mastitis, liver abscesses in calves, parasitic infections in beef cattle, and gastrointestinal nematodes, liver flukes and bovine lungworms in ruminant livestock (Khan *et al.,* 2021; Rushton *et al.,* 2014). However, many farmers rely on antimicrobials to alleviate the results of poor animal husbandry and biosecurity, particularly in the context of intensive farming (Al Amin *et al.,* 2020; Coyne *et al.,* 2019; Magnusson *et al.,* 2021; Albernaz-Gonçalves *et al.,* 2022a). In such cases, antimicrobials are used as a substitute for good husbandry and biosecurity measures.

Antimicrobials used for veterinary medical purposes help maintain good animal health and levels of production in cases of disease outbreaks, yet when they are used for growth promotion, their purpose is to directly enhance sectoral production outputs. Some studies suggest that, from an economic perspective, it is challenging to replace AMU for rapid animal growth if there is no viable alternative for farmers (Albernaz-Gonçalves *et al.,* 2022b). For example, an economic analysis of a small commercial broiler chicken system has shown a positive relationship between AMU and productivity (Coyne *et al.,* 2020). Furthermore, reducing AMU in large livestock-producing countries (i.e. Brazil, the People's Republic of China, India and the US) may have led to a decline in meat production, accompanied by substitution to lower-priced meat (Ryan, 2019). This type of evidence has exacerbated perceptions held by the farming community on AMU and its value. Pig production stakeholders in Brazil, for example, believe that it is more economical to raise pigs on antimicrobials, and that limiting their use to treatment purposes would lead to high mortality rates, which they are not prepared to deal with (Albernaz-Gonçalves *et al.,* 2022b). Indeed, studies report that livestock farmers believe AMU to be economically advantageous because it prevents illnesses that could negatively impact their farms (Coyne *et al.,* 2020, 2019). However, the mechanisms for antimicrobial-mediated growth enhancement in food-producing animals are still not fully understood; in fact, the true growth response may be smaller than users expect, especially in high-income and more industrialised countries (Laxminarayan *et al.,* 2015).

Excessive use of antimicrobials is associated with a rising prevalence of resistant infections and negative ramifications for livestock sector productivity

The use of antimicrobials in agricultural sectors is expected to rise, especially in emerging economies (Mulchandani *et al.,* 2023; Buchy *et al.,* 2020; Albernaz-Gonçalves *et al.,* 2022a). For example, a 205% rise in antimicrobial consumption is expected in Myanmar, 202% in Indonesia and 163% in Nigeria (Hickman *et al.,* 2021; Hosain *et al.,* 2021). If used frequently and inappropriately, AMU in animals can lead to resistance to therapeutics (Kalam *et al.,* 2022; Gilbert *et al.,* 2021). This makes existing treatments less effective (Kalam *et al.,* 2022; Gilbert *et al.,* 2021). Multiple studies document the strong correlation between prolonged AMU and development of resistance. An analysis of publicly available data from seven European countries compared AMU and the prevalence of resistance in commensal *Escherichia coli* isolates from pigs, poultry and cattle; statistically significant correlations were found between the use of specific antimicrobial and development of resistance (Chantziaras *et al.,* 2014). A further study shows that the unfettered use of colistin in pigs for prophylaxis and growth promotion has likely resulted in widespread colistin resistance in pigs (Rhouma *et al.,* 2016). Poultry farming, which is primarily intensive and accounts for 37% of global meat production, uses a disproportionate number of antimicrobials with a high global incidence of resistant *E. coli* infections (Nhung *et al.,* 2017; Hedman *et al.,* 2020).

While the prevalence of AMR in food-producing animals is predicted to rise globally, LMICs have the highest predicted resistance rates increases in animals. This is due to a relative faster rise in demand, with the production going forward having an increasing proportion of intensive farming practices (necessitating higher AMU). A further cause is limited implementation and monitoring of NAPs. Thus, it is anticipated that the impact of AMR will be felt more acutely in LMICs, impacting farmers through rising production costs, rising costs of medication and treatments and rising rates of morbidity and mortality (Allel *et al.,* 2023). Given the increasing prevalence of AMR in the livestock sector, it is likely that costs will grow over time due to the need for multiple antimicrobials as well as other drugs to combat multidrug-resistant infections (Azabo *et al.,* 2022; Lhermie *et al.,* 2022). This will likely be compounded by the increasing costs of medication itself and production losses caused by rising morbidity and mortality as a result of resistant infections (Ryan, 2019).

The use of antimicrobials in animals has potential negative externalities on humans

The issues around AMU in livestock production are complex and may extend to other sectors, with negative externalities on human and environmental health (Ryan, 2019). For example, food-producing animals can act as hotbeds of AMR-genes due to high levels of exposure to low-dose antimicrobials, which can then be transmitted to humans through the food chain, through direct contact with animals in a farm or community setting, or through the environment (e.g. wastewater and drainage systems) (Almansour *et al.,* 2023). While existing studies have noted transmission of resistance, this is further compounded by AMU that is considered 'critically important' for human medicine, such as colistin in food and livestock production (Magouras *et al.,* 2017; Hickman *et al.,* 2021; Andrade *et al.,* 2020; Vidovic and Vidovic, 2020). In the US and Europe, a high proportion of antimicrobials that are used for treating human infections (up to 70%) are sold for use in food production (Pokharel *et al.,* 2020).

While there is evidence that suggests a link between animal AMU and AMR in humans, it is crucial to highlight that the rate and scale of transfer of resistance from animals to humans is currently contested in the scientific literature. Some empirical studies have shown positive associations, indicating transfer of resistance, yet some have shown the opposite: restriction of AMU in animals has resulted in a decrease in AMR bacteria in humans (Innes *et al.,* 2020; Emes *et al.,* 2024; Rahman and Hollis, 2023; Allel *et al.,* 2023; ECDC *et al.,* 2024; Ardakani *et al.,* 2023). Despite recent improvements in data availability (e.g. longitudinal data on animal AMU), these studies suffer from a sparsity of data and a lack in its quality, which hinders the empirical identification of causal pathways or even the magnitude of the associations between AMU in animals and AMR in humans. Future research based on more and better data is needed to fully understand these links.

Multiple mitigation measures for tackling excessive AMU and AMR exist, yet suitability varies depending on geography and farming context

Given the health and economic challenges associated with AMR in livestock, and the need for alternatives to antimicrobials, multiple approaches are currently being tested to mitigate AMR. The two main categories of prevalent mitigation measures include biological and policy interventions. However, it can be challenging to implement and scale up these interventions due to lack of enforcement and oversight, perceived costs, lack of available infrastructure, and the cultural and habitual use of antimicrobials (Coyne *et al.,* 2020; Magnusson *et al.,* 2021). Hence, interventions require further analysis to determine which regions and scenarios they are best suited for, as discussed below.

Firstly, vaccinations have emerged as an effective tool to prevent the occurrence of infectious diseases in high- to middle-income countries. Multiple preventive vaccination regimes against disease-causing pathogens have proven to inhibit the occurrence of infections that would ordinarily require AMU (Sharma *et al.,* 2017; Magnusson *et al.,* 2021; Hosain *et al.,* 2021; Rushton *et al.,* 2014; Miranda *et al.,* 2018; Jansen *et al.,* 2018; Marquardt and Li, 2018; Cardoso, 2019; Emes *et al.,* 2023; Gozdzielewska *et al.,* 2020; Roskam *et al.,* 2019; Laxminarayan *et al.,* 2015). In a given population, unvaccinated animals that are exposed to vaccinated animals have been shown to gain protection to certain pathogens through herd immunity (Hosain *et al.,* 2021). Aquaculture in Norway has provided perhaps the most compelling case: rates of AMU have fallen by 95% since the introduction of vaccination programmes in aquaculture (Henriksson *et al.,* 2018). In particular, salmon farming has very low rates of AMU, with mainly viral infections now occurring (Henriksson *et al.,* 2018).

However, there is a need for improvements to the currently available vaccines, as protection provided by vaccines against infections caused by *Staphylococcus aureus* or *E. coli* are limited and many strains of disease-causing pathogens can evolve, reducing the efficacy of these vaccines and prompting the need for regular vaccinations (Sharma *et al.,* 2017; Krömker and Leimbach, 2017). Ultimately, the cost of regular vaccinations is seen as a substantial financial burden on farmers and animal health professionals (Sharma *et al.,* 2017).

Secondly, a promising and cost-effective alternative to antimicrobials are bacteriophages. Multiple biology-based interventions to combat AMR and reduce AMU are either being established or are in development; these include bacteriophages, probiotics, herbal medicines, antimicrobial peptides and engineered compounds (Sharma *et al.,* 2017; Krömker and Leimbach, 2017; Hosain *et al.,* 2021; Henriksson *et al.,* 2018; Rushton *et al.,* 2014; Miranda *et al.,* 2018; Marquardt and Li, 2018; Cardoso, 2019; Huang *et al.,* 2022; Sneeringer *et al.,* 2016). Bacteriophages are considered a cost-effective way to inhibit bacterial growth (Krömker and Leimbach, 2017). An estimated US$ 1.5 billion is needed to produce a new antimicrobial; on the other hand, a phage product can be produced for US$ 8,000–20,000 (Makumi *et al.,* 2021). Antimicrobial peptides are also being considered as a viable alternative to antimicrobials as they display a broad spectrum of activity against bacteria, fungi and viruses, and can promote growth (Rodrigues *et al.,* 2021). Despite the benefits of these peptides, there are ongoing concerns, such as challenges in their transportation due to their lack of stability, insufficient data on toxicity, and other safety issues that require further R&D (Sharma *et al.,* 2017).

Further biotechnological innovation has focused on the development of plant antibodies to help control infections in domestic animals (Marquardt and Li, 2018). While the production of plant antibodies is safe, convenient, cost-effective and scalable, more research is necessary to determine the number of antibodies needed to treat specific infections (Marquardt and Li, 2018). Despite the potential benefits of vaccine alternatives, more research must be done to investigate their safety and viability (Albernaz-Gonçalves *et al.,* 2022b). To exemplify the value of these alternatives, Box 1 highlights a notable intervention carried out in Colombia, using colostrum to reduce AMU.

Box 1

Colombia colostrum case study

Pig farming in Colombia is a prolific and growing sector, necessitating new strategies to maintain favourable production costs for farmers. A nationwide survey conducted across 22 pig farms revealed that 20% of farms experienced productivity losses due to diarrhoea in pig litters at the post-weaning stage. This led to AMU to treat infections, without knowledge on infection aetiology.

A three-year randomised control trial (RCT) has been implemented by PorkColombia in partnership with the International Centre for Antimicrobial Resistance Solutions (ICARS), due for completion in January 2025. Prior to the study, a wide variation was noted between therapeutic and preventive AMU on farms. The RCT focuses on measuring the impact of improved uptake of colostrum and vaccines to enhance piglets' immune systems. It also investigates its impact on the need for AMU. The study design incorporates elements of capacity building and improved agricultural practices.

Interventions are complete on three of the study's five farms. Preliminary findings are positive and suggest that a 20% reduction in AMU could occur as a result of the intervention. While the intervention analysis continues, and a formal cost–benefit analysis is in development, the scale of AMU reduction and the costs associated with implementation across five farms (approx. US$ 548K) provide initial estimates of cost and value.

Note: This information is from an active research project that has been found via publicly available information and direct engagement with the on-the-ground delivery team at PorkColombia, as well as the support partners at ICARS. They are currently analysing their findings to develop a cost–benefit analysis of the intervention.

Source: ICARS, n.d.

Thirdly, farmer education and improvement in biosecurity has had positive impacts on reducing indiscriminate use of antimicrobials. However, practices are inconsistent, and their effect is unquantified. Improving education for farmers and the public on the topics of AMU and AMR, veterinary practice, AMR stewardship, and enforcing prescription requirements has proven to help tackle AMR across a variety of settings and geographies (Pholwat *et al.,* 2020; Dadgostar, 2019; Ström *et al.,* 2018; Coyne *et al.,* 2019; Naylor *et al.,* 2018; Mataragka *et al.,* 2023; Gondam *et al.,* 2016; Busch *et al.,* 2020). Other approaches, such as rapid testing systems and susceptibility testing, have allowed for pathogen identification to prevent unnecessary AMU and mitigate the spread of AMR (Krömker and Leimbach, 2017; Thanner *et al.,* 2016; Mataragka *et al.,* 2023). Improved animal husbandry measures, such as sanitary protocols, segregation of animals by age, ventilation systems, adjustments to feed rations and improved biosecurity (e.g. reduced entry of disease-causing pathogens), can also help combat the spread of AMR (Luu *et al.,* 2021; Henriksson *et al.,* 2018; Laxminarayan *et al.,* 2015). While there are positive examples of this practice (see the Ontario and Vietnam case studies in Boxes 2 and 3), a scaled-up approach can help find the extent to which biosecurity and education measures may reduce AMU, and how best to achieve this in practising communities, particularly in LMICs.

Box 2

Ontario dairy farming case study

Neonatal diarrhoea in dairy calves is a prevalent condition linked to AMU. Education and medicine management interventions have been proposed to reduce AMU in this sector. For this study, a multidisciplinary intervention was carried out across ten small-scale dairy farms in Ontario, evaluating its impacts on AMU volume for therapeutics and on calf mortality. The intervention involved training farmers in calf health assessment, streamlining disease prevention management protocols, and developing a decision-algorithm for AMU in the treatment of diarrhoea. Farms were evaluated over a twelve-month period, before and after the intervention.

The intervention led to a decrease in the volume of antimicrobials used, with an average reduction of 37%. The highest noted reductions were 81% and 74% at two of the largest farms, with no impact on calf mortality. Furthermore, the algorithm predicted an 80% reduction in the risk of inappropriate AMU.

Source: Gomez *et al.,* 2021.

Box 3

Vietnam broiler chicken case study

In LMICs, small scale poultry farming is a critical component of ensuring the livelihoods of rural communities. AMU is highest in chickens, compared to all other animal species. In Vietnam, AMU on chicken farms is primarily for preventative reasons, as it is considered a cheap alternative to disease monitoring and control measures. The intervention consisted of a randomised trial, with provision of farmer education and advice *versus* none provided. The advice focused on using antimicrobial replacement products, improving biosecurity, litter management and vaccination. Advice was intended to be a persuasive rather than restrictive, which has proven to be more sustainable in the long-term. The intervention measured the effect of this advice on AMU by assessing the volume of antimicrobials used in feeds and mortality rates. Overall, the intervention resulted in a 66% AMU reduction and a 40% reduction in mortality. However, this study did not evaluate the cost-effectiveness and benefit analysis.

Source: Phu *et al.,* 2021.

Fourthly, policies to reduce practices of growth promotion curb indiscriminate AMU for disease prevention and improve food safety have been put in place across multiple jurisdictions with varying results (Hosain *et al.,* 2021). In Denmark, for example, when veterinarians could no longer profit from antimicrobial sales, there was a shift toward helping farm staff improve animal husbandry and reduce reliance on AMU (Gilbert *et al.,* 2021). Similarly, a European Union regulation restricts prophylactic AMU in farm animals (European Union, 2019). Moreover, several countries have now banned AMU for growth promotion. In fact, the Food and Drug Administration (FDA) in the US has placed limits on antimicrobial residues from animals in the environment (Rodrigues *et al.,* 2021). Following the ban of antimicrobials as growth promoters, there has been a demonstrable decrease in AMR; a 69.6% reduction was observed on Dutch farms from 2009 to 2019 as a result of multifaceted legislative change (Scott *et al.,* 2018; Mallioris *et al.,* 2022).

However, not all AMU alternatives and policy changes are beneficial in every context. In Indonesia, banning AMU as growth promoters has led to high animal mortality rates and economic loss, whereas a similar ban in Denmark did not cause a reduction in productivity (Aarestrup *et al.,* 2010; Coyne *et al.,* 2020). The economic effects of a ban on AMU as growth promoter may be miniscule in optimised production systems in comparison to LMICs. This may be due to suboptimal hygiene and farming practices in such settings (Laxminarayan *et al.,* 2015).

Lastly, taxation is another potential intervention that would encourage appropriate AMU. Antimicrobial taxation schemes have been implemented in a limited number of countries (Morgan *et al.,* 2023). Economic and epidemiological models show that taxation strategies could have a comparable impact to bans on AMU in food-producing animals regarding resistance prevalence and infection prevention (Morgan *et al.,* 2023). Additionally, revenue generated from taxation could be reinvested into antimicrobial development or agricultural biosecurity in high-income countries or LMICs, or even reinvested into non-agricultural purposes with indirect benefits for farmers (Morgan *et al.,* 2023). Taxation as a strategy to control AMU is not a standalone solution; it must be carried out in tandem with other AMU reduction efforts. Indeed, many studies have proposed a diverse ‘toolkit’ of approaches, and alternatives should be made available to tailor to every context. The UK mastitis case study in Box 4 is an example of a multifaceted approach to reducing AMU.

Box 4

United Kingdom national mastitis control case study

AMU in dairy cows is most used for treating bovine mastitis. The United Kingdom Agriculture and Horticulture Development Board developed a Dairy Mastitis Control Plan (DMCP), which was launched in 2009 as a structured scheme for nationwide enrolment. A multitude of interventions and studies ensued. One of these interventions took place on a large 600-herd dairy farm. The DMCP questionnaire was completed by the farm owners and herd manager to capture the following factors relevant for mastitis control: herd management practices on lactating and dry cow environment management, milking routine, basic milking machine function, treatment, biosecurity and more. The responses shaped a tailor-made priority plan for the farm to discuss and implement based on best practice in mastitis reduction. Implementation of the plan resulted in a 50% reduction in clinical mastitis cases over a twelve-month period, a 50% reduction of AMU in the daily defined dose amount and a 35% reduction of AMU in mg/Population Correction Unit (PCU).

Source: Breen *et al.,* 2017.

DISCUSSION

Evidence on AMU trends in the livestock sector makes a strong case for the control of AMU in dairy and poultry production, as well as in aquaculture, since food-producing animals are a reservoir for AMR infections (Gurung *et al.,* 2023; Krömker and Leimbach, 2017; Kalam *et al.,* 2022; Gilbert *et al.,* 2021). This incurs productivity losses for livestock sectors that have substantial economic ramifications for national economies, since food-producing animal sectors are a major source of employment and income for many regions. Paired with a predicted increase in future demand for more efficient, environmentally and economically sustainable meat production, particularly in LMICs, the negative impacts on food production caused by infections and AMR can, in turn, have negative consequences for global food security. Furthermore, if AMU in animals has negative externalities on humans through the transfer of resistance and by rendering many critical antimicrobials ineffective to treat microbial infections in humans, then the economic ramifications from AMU in food-producing animals would increase substantially, as demonstrated by the economic burden of AMR in humans (World Bank, 2017).

Alternatives (preventive and treatment options) to antimicrobials are critical to curbing AMR. On its own, a reduction in AMU is unlikely to generate a large-scale positive impact and may not gain traction in the agricultural community. Scientific studies and farmer assessments in Bangladesh show positive effects of AMU on productivity when there is no alternative; this has fortified beliefs in a positive correlation between AMU and high-production value. While there are multiple mitigation measures for tackling excessive AMU, their suitability varies by geography and farming context. It can also be challenging to implement and scale-up interventions due to lack of enforcement and oversight, as well as the perceived associated costs and lack of infrastructure. A multifaceted toolkit of options and interventions could be beneficial for each country to adapt to its own context.

CHAPTER 3

Economic effects of antimicrobial resistance and the value of interventions to curb the use of antimicrobials

BACKGROUND

The previous chapter discussed potential economic pathways and impacts of AMU and AMR, as well as the current and future trade-offs with emerging treatment failures. In addition, Chapter 2 highlighted certain interventions (e.g. vaccinations, better husbandry and biosecurity measures) that could prevent disease burden and tackle excessive use of antimicrobials to mitigate AMR. Nonetheless, there is a lack of an assessment of the opportunity-cost of not taking further action to tackle AMR in livestock sectors, and a calculation of the economic value of interventions to reduce AMU at the global scale.

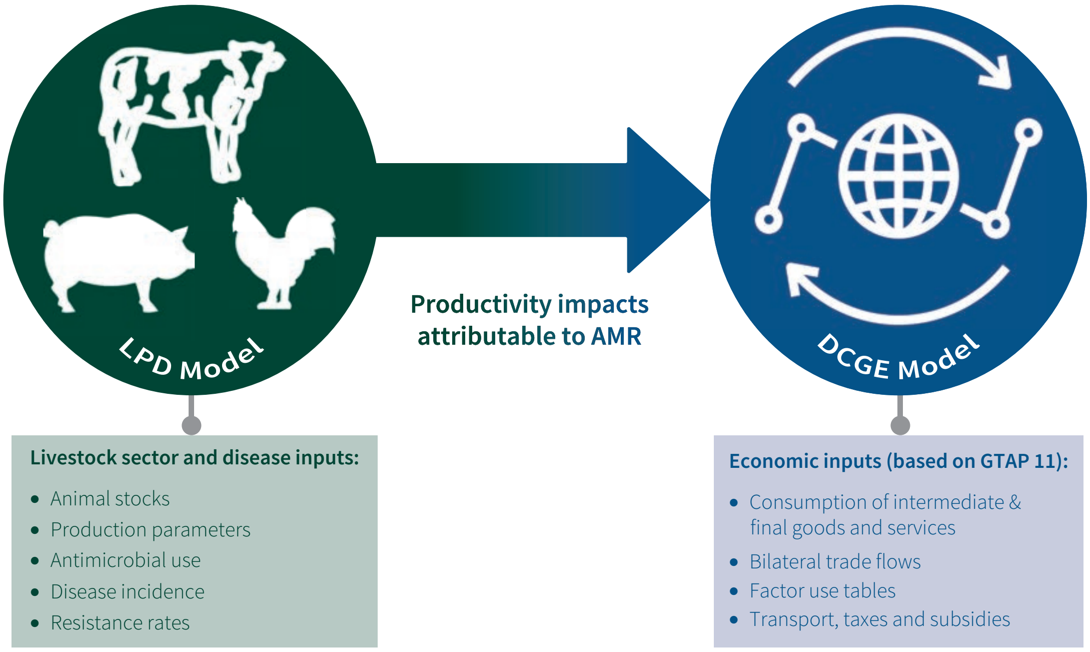
METHODOLOGY

The methodological framework to assess the economic burden of AMR in food-producing animals

The analysis focuses on the economic effects of AMR on livestock production associated with treatment failures due to resistant infections. That is, within the analysis, resistance to existing antimicrobial treatments affects the number of animals that die prematurely of an infection due to treatment failure, before they reach the time of slaughter (e.g. for meat producing sectors); or, if they survive, there is an additional productivity loss (e.g. through impaired growth performance). Both the mortality and morbidity effects attributable to AMR have a negative impact on the sector's production outputs. It is vital to note that the analysis only considers the foregone production quantities that are attributable to AMR, and not the loss in production caused by bacterial infections (susceptible or resistant) in general. That is, the analysis does not compare the cost of resistant infections against no infection, instead comparing it to the counterfactual scenario of the animal having a bacterial infection that would have been susceptible to treatment.

A few economic studies have aimed to assess the potential economic impact of AMR for livestock production. However, these studies have a key shortcoming in common: they do not consider the underlying epidemiology of AMR in livestock in sufficient detail (Fernando and McKibbin, 2022, 2024; World Bank, 2017; Council of Canadian Academies, 2019). For example, studies by the World Bank (2017) and Fernando and McKibbin (2024) assumed that production losses attributable to AMR in livestock sectors were 3–7%; these results were based on estimates of the productivity effects associated with the withdrawal of antimicrobials as growth promoters (World Bank, 2017; Fernando and McKibbin, 2024).

FIGURE 1 Applied modelling framework using a livestock production disease and macroeconomic DCGE model



Notes: LPD = Livestock Production Disease. DCGE = Dynamic Computable General Equilibtium. GTAP = Global Trade Analysis Project.

To improve on previous modelling efforts, this analysis uses a LPD model to simulate the AMR-attributable productivity effects. These are then passed on as input parameters into a multi-sectorial, multi-region DCGE model (see Figure 1). First, the LPD model uses production and disease inputs to simulate production outputs of different livestock sectors. The model considers three animal species: (1) cattle, (2) chicken and (3) swine; and five output goods: (1) cattle meat, (2) cattle (raw) milk, (3) swine meat, (4) chicken meat and (5) chicken eggs. Within the LPD, animals move through a sector-specific production system over time, at risk of infections that can lead to treatment failure in the prevalence of AMR. In turn, this leads to excess levels of mortality and morbidity, thereby impacting sector productivity.

Second, the predicted AMR productivity impacts on the modelled livestock sectors are then passed on to the DCGE model to assess the wider economic impacts. Livestock sectors do not operate in isolation within an economy; in fact, they demand input from other sectors, or indeed supply input to other sectors themselves. Furthermore, while livestock sectors in many modern economies only contribute a small proportion to overall economic output, they are still major employers in many developing countries. It is therefore important to capture these wider indirect economic effects of productivity changes in livestock sectors. For its inputs, the DCGE model uses the GTAP database of Purdue University for calibration. GTAP is a globally consistent database, widely considered the standard for global CGE modelling (Purdue University, 2024). It must be noted that the LPD and DCGE models are not fully integrated; LPD productivity parameters are used as inputs for the DCGE model, but there are currently no feedback loops between the two. That is, changes in economic indicators (e.g. GDP or prices) determined in the DCGE model do not affect production decisions in the LPD model. All technical details regarding this study's modelling approach to assess the economic effects of AMR in livestock production sectors are outlined in detail in Annexes A to D.

For the analysis, countries are mapped into seven regions based on the current World Bank regional classification.[1] These vary by income level and differences in their livestock production systems (e.g. predominant livestock species). The regions are:

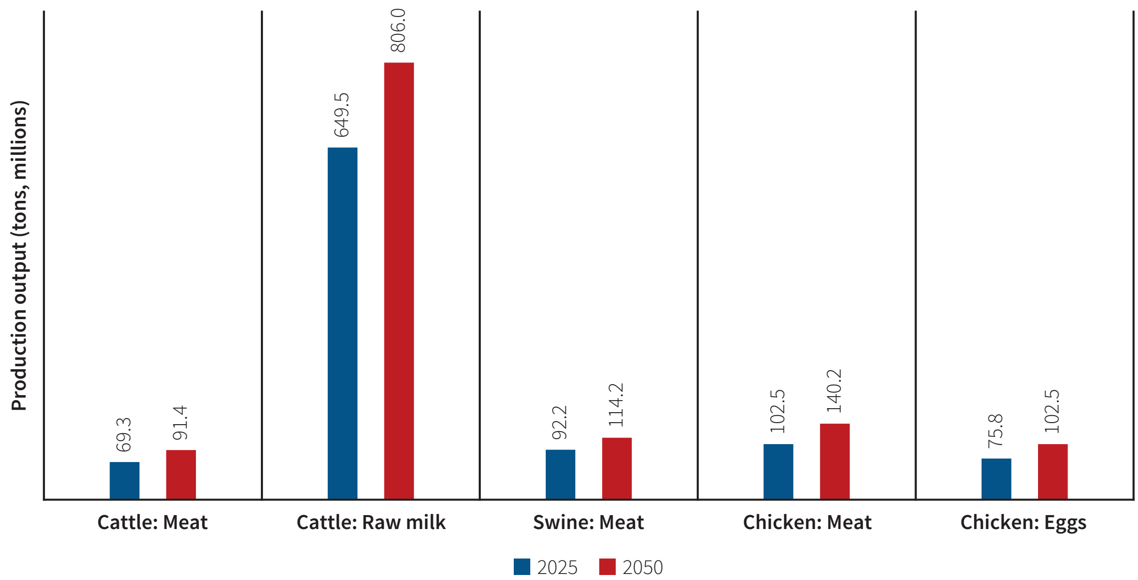
- East Asia and the Pacific
- Europe and Central Asia
- Latin America and the Caribbean
- The Middle East and North Africa
- North America
- South Asia
- Sub-Saharan Africa

Across these seven regions, the study models potential production effects attributable to AMR for five disease areas: (1) bovine (clinical) mastitis, (2) bovine respiratory disease, (3) neonatal calf diarrhoea, (4) swine colibacillosis, and (5) chicken colibacillosis, as well as the impact of each disease on animal mortality and morbidity. The disease areas were selected due to their reported significance as prevalent production diseases and their data availability.

Using different scenarios to assess the economic effects of AMU and AMR in livestock production

The applied combined modelling approach simulates the disease and associated economic impacts for the time range 2025–2050, across different scenarios. A reference scenario is defined, starting in the year 2025, to track production trends in the modelled livestock sectors based on current rates of antimicrobial consumption and resistance. It then projects them into the future based on past empirical associations between antimicrobial consumption and the resistance prevalence.[2] Within the reference scenario, based on existing food and agricultural production projections estimated by FAO, in many regions the number of placed livestock in six production systems follows a rising trend due to a predicted increase in demand for food products, as determined by factors such as population and economic growth (FAO, 2024a). Figure 2 shows the predicted reference global production outputs for 2025 and 2050 in each of the modelled livestock sectors.

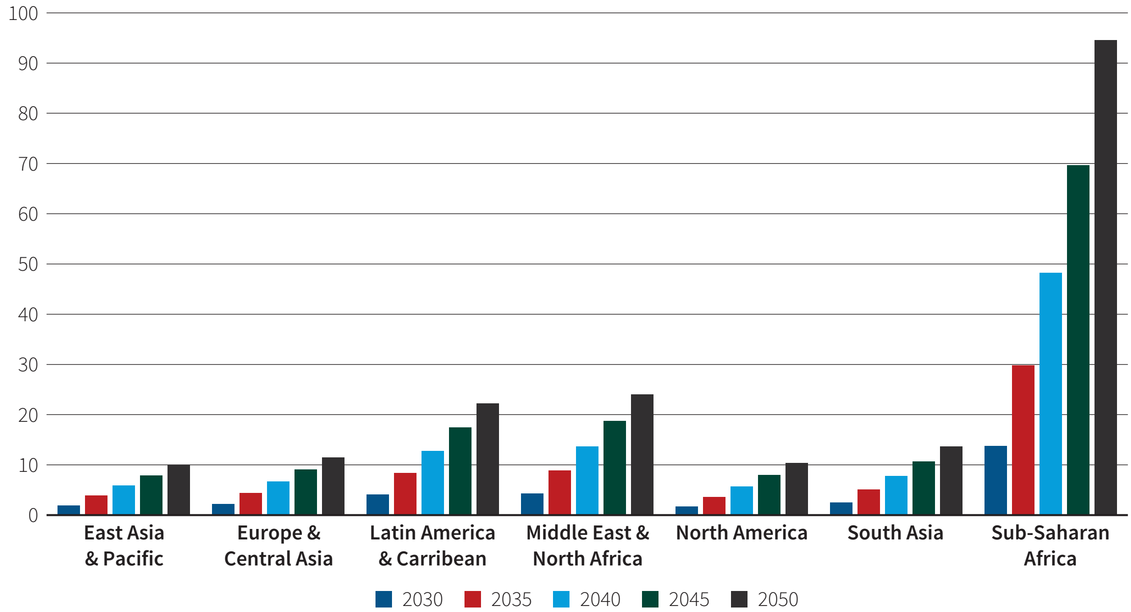
FIGURE 2 Predicted global production quantities (tons, millions) under reference scenario by modelled livestock sector (2025 and 2050)



Note: more detailed predicted production quantities based on livestock production disease (LPD) for the reference scenario by region and year are reported in Annex B (Table B.16).

1 For more information on the World Bank region classification system, see: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups
2 As summarised in Annex B, a 1% increase in the one-year lag of AMU is associated with a 0.0119% increase in the average resistance rate across different pathogens.

FIGURE 3 Predicted change in AMU by region 2025–2050 (per cent)



Note: entries report percentage change in AMU by year and region based on livestock production disease (LPD) model simulations for the reference scenario.

All else being equal, within the LPD model these trends are associated with a rise in antimicrobial consumption over time. Figure 3 shows the predicted changes in total AMU for the reference scenario across the three modelled livestock species (cattle, chicken and swine) in the reference scenario. The model simulations predict that, in relative terms, Sub-Saharan Africa will experience the greatest increase in AMU across the three livestock sectors by 2050, predicting an almost 100% increase in comparison to 2025 estimated levels. Other regions that are predicted to experience a relatively large increase based on the simulation analysis of the livestock disease model are Latin America and the Caribbean as well as the Middle East and North Africa, both having a predicted increase of over 20% by 2050.[3]

In absolute terms, initial and future levels of AMU in the regions predicted to experience the largest relative increase in consumption are not necessarily those with the highest absolute consumption, as reported in Table 3. For example, across the three animal types and five livestock sub-sectors modelled, the reference scenario simulations predict a consumption of approx. 28,492 tons for East Asia and the Pacific in 2025, and approx. 2,486 and 1,247 tons for South Asia and Sub-Saharan Africa respectively.

Among other factors, the association between AMU intensity and the use of antimicrobial growth promotion (AGP) practices were examined using data from WOAH's ANImal antiMicrobial USE (ANIMUSE)

3 Applying the production disease model for the 2020–2030 period to compare with Mulchandani *et al.* (2023), the present study predicts an increase in AMU by region for 2020–2030 as follows: East Asia and the Pacific: + 3.5%; Europe and Central Asia: + 3.8%; Latin America and the Caribbean: +7.4%; the Middle East and North Africa: + 7.9%; North America: + 3%; South Asia: +4.5%; Sub-Saharan Africa: + 26%. Methodologies and data inputs differ (this analysis used ANIMUSE data for antimicrobial consumption, among others), meaning that direct comparisons are not straightforward. Yet, the study's predicted changes in AMU for 2020–2030 are within similar ranges as predicted by Mulchandani *et al.* (2023). For example, Mulchandani *et al.* (2023) estimated an increase for Sub-Saharan Africa by approx. 25%, for Europe of approx. 5%, North America 4% and Asia approx. 6%. The present study's estimate for Latin America and the Caribbean is smaller than the 14% increase predicted by Mulchandani *et al.* (2023) and as this study's regional disaggregation is not equal to that of Mulchandani *et al.* (2023) it is impossible to fully compare the Asian regions. However, overall, the present study's disease production model predicts similar changes in AMU for the period 2020–2030 (Mulchandani *et al.*, 2023).

TABLE 3 Predicted antimicrobial consumption (tons) for reference scenario by region (2025–2050)

Year	East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
2025	28,492	6,632	11,918	1,556	8,739	2,486	1,247	*61,070*
2030	29,041	6,778	12,406	1,624	8,893	2,548	1,419	*62,708*
2035	29,600	6,926	12,914	1,695	9,060	2,613	1,618	*64,427*
2040	30,171	7,078	13,444	1,770	9,241	2,681	1,848	*66,233*
2045	30,754	7,233	13,995	1,848	9,438	2,751	2,115	*68,135*
2050	31,348	7,392	14,569	1,931	9,651	2,825	2,425	*70,141*

Note: entries are reported in tons and represent absolute changes in AMU by year and region based on livestock production disease (LPD) model simulations for the reference scenario.

database (described in Annex B, Table B.16). The statistical analysis at the country-level found a positive association between reporting the use of AGP practices and AMU intensity, suggesting that a country with AGP practices has on average a 45% higher intensity than a country that reports not using AGP practices (Annex B, Table B.17). It must be noted that this is true for all antimicrobials except ionophores, which include critically important and less critically important ones.

Within the projected reference scenario, all else being equal, the rise in antimicrobial consumption, especially for lower-and middle-income regions, is associated with a rise in resistance rates over time.[4] In comparison to the reference projections, different 'what-if' or counterfactual scenarios are introduced to highlight potential effects of changing rates of antimicrobial consumption and resistance can have on production levels by sector and regions' GDP. Of course, the reference and counterfactual scenarios in the simulations for both the LPD and DCGE models contain the same underlying future projections; however, differences between the scenarios are driven by changes in varying key input variables (e.g. antimicrobial consumption, prevalence of resistance). The scenarios have been chosen to demonstrate different economic effects. Scenario 1 aims to demonstrate how current and future AMU and AMR projected under the reference scenario without further action affect livestock productivity in comparison to a hypothetical situation with very low resistance. Scenario 2 aims to demonstrate the associated economic cost if no further action is taken and if the predicted AMU consumption and AMR burden is higher than assumed under the reference scenario. Scenarios 3 and 4 aim to demonstrate the potential economic value of reducing unnecessary AMU via a set of interventions (e.g. vaccinations or better husbandry and biosecurity measures), assuming no adverse impact on animal health and welfare.[5] Lastly, scenarios 5 and 6 aim to demonstrate an order of magnitude for potential economic effects associated with even small or medium negative spillover effects from AMU in food-producing animals on AMR in humans. Table 4 provides more detail on the applied and modelled counterfactual scenarios.

4 A detailed breakdown of the predicted changes in average resistance rates for each modelled livestock animal by year and region can be found in Annex B, Table B.18.

5 Note that the scenarios do not directly model interventions within the LPD framework; they only assume a reduction in AMU by a certain per cent over different time horizons.

TABLE 4 Modelled counterfactual scenarios for animal health

Scenario	Label	Description
1	Very low resistance scenario	Resistance rates across all modelled pathogens and sectorial diseases are set to 5% across all regions and sectors. This demonstrates current and future AMR burden compared to a hypothetical situation with very low resistance rates. Previous studies (e.g. World Bank, 2017; O'Neill, 2016) have applied zero resistance as a reference to assess the 'full' cost of AMR. However, as zero resistance is implausible in a real-life setting, a fixed low rate of 5% resistance was applied.
2	Pessimistic scenario	This demonstrates the economic burden if AMU and AMR in livestock production follow a more pessimistic trajectory than anticipated under the reference scenario. AMR-attributable disease burden doubles in all regions. AMU and subsequently AMR rates rise faster than under the reference scenario, especially in lower- and middle-income regions, such as South Asia and Sub-Saharan Africa.[a] Currently, South Asia reports an average antimicrobial use of 42 mg/kg and Sub-Saharan Africa reports 22 mg/kg. It is assumed that both regions will increase gradually to 96 mg/kg over the next 20 years (as currently observed for Latin America & the Caribbean region, which shares a similar biomass composition).
3	AMU reduction in line with global targets scenario	This demonstrates the economic value of reducing AMU in livestock production via a set of interventions (e.g. vaccinations, improved husbandry and biosecurity measures) that are assumed to reduce unnecessary AMU and do not adversely affect animal health and welfare. In line with current discussions on global targets, the scenario assumes a 30% reduction in AMU across all regions within the next five years.[b]
4	Substantial AMU reduction scenario	This demonstrates the economic value of a substantial AMU reduction in livestock but over a longer time horizon. All regions will reduce their AMU in livestock production to 20 mg of AMU per kg of biomass over the next 20 years.
5	Small negative externality from animals to humans scenario	While it is currently difficult to quantify the magnitude of the potential negative spillover effect from AMU and AMR in food-producing animals, the scenario aims to demonstrate the potential economic impact if even a relatively small negative externality exists. AMR has a negative impact on human health and reduces the productivity of workforces across all economic sectors by 1.5%[c] each year. It is assumed that 5% of the AMR impact on humans is attributable to AMU and AMR in food-producing animals.
6	Pessimistic with large negative externality from animals to humans scenario	While it is currently difficult to quantify the magnitude of the potential negative spillover effect from AMU and AMR in food-producing animals, the scenarios aim to demonstrate the potential economic impact if the negative externality is larger than under scenario 5. AMU and AMR trajectory in livestock sectors follows pessimistic scenario 2 and adds a more pronounced negative externality from AMU and AMR in livestock on human health than scenario 5, assuming a 3%[d] AMR shock on labour productivity and that 10% is attributable to AMU and AMR in livestock.

Notes: [a]The pessimistic scenario uses the upper value of the 95% confidence interval for the parameter, measuring the magnitude of the association between the one year lag of AMU and the average resistance rate across different pathogens. Thus, rather than a 0.0119% increase applied to the baseline, a 0.0225% increase is applied for every per cent increase in AMU (see Table B.18 in Annex B). [b]This broadly mimics the AMU targets set by the Third Global High-Level Ministerial Conference on Antimicrobial Resistance, hosted in Muscat 2022, Oman. See http://www.amrconference2022.om/MuscatManifesto.html. [c]Based on a 'low-AMR' scenario; see World Bank (2017). [d]Based on a 'medium-AMR' scenario; see World Bank (2017).

RESULTS AND DISCUSSION

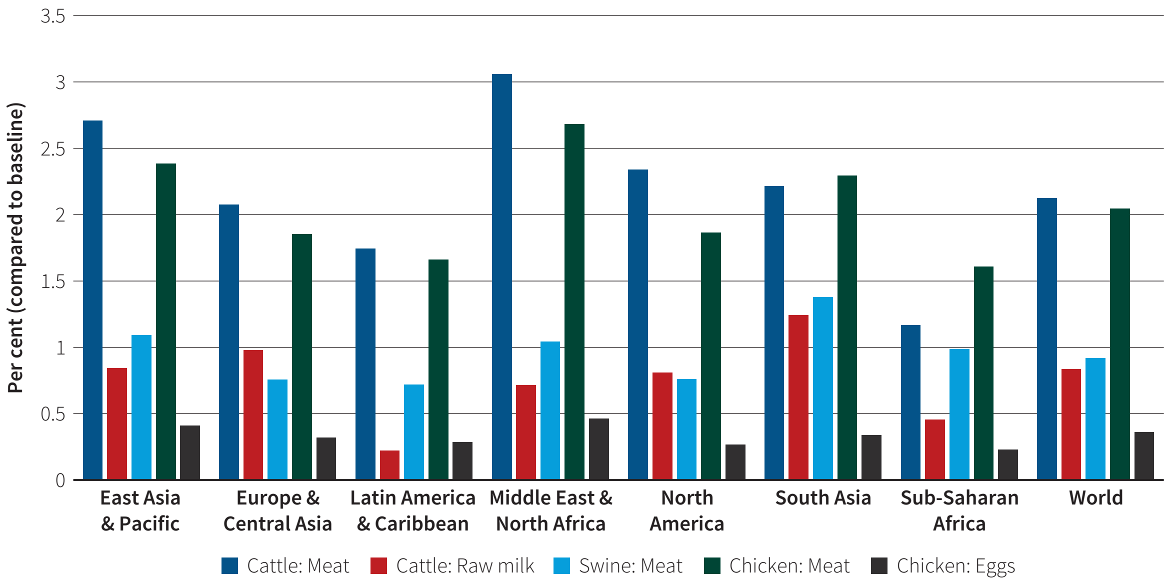
AMR is already adversely affecting livestock production outputs, with negative effects projected to grow over time

Comparing the current rates of resistance against relative low resistance rates (scenario 1) in 2025, Figure 4 shows the simulated effects for the global production output of the modelled livestock sectors.[6] Compared to the reference scenario, very low resistance rates (5%) will result in a global increase in cattle meat production of approx. 2.1%. Equally, current resistance rates will lead to a loss of 0.84% of cattle (raw) milk, 0.92% of swine meat, 2.05% of chicken meat and 0.36% of chicken egg production. The latter corresponds to about 0.27 million tons of chicken eggs, which is roughly equivalent to half of the UK's annual egg production as of 2023.[7]

When comparing scenario 1 to the reference scenario, the estimated relative production effects vary across the seven regions modelled (see Table 5). For example, the regions of East Asia and the Pacific, as well as the Middle East and North Africa show a relative increase in production associated with very low resistance rates.[8] It must also be noted that the foregone production outputs within each region as well as globally are increasing over time due to a rising trend in antimicrobial consumption and an associated rise in resistance rates in the reference scenario. Notably, Sub-Saharan Africa is projected to experience some of the largest foregone production outputs when comparing scenario 1 to the reference scenario; the percentage increase in production outputs by 2050 is relatively more pronounced than in other regions (see Table 5).

To put the production effects attributable to AMR for scenario 1 compared to the reference scenario into

FIGURE 4 Estimated production loss attributable to AMR in 2025 by region (scenario 1 *versus* reference)



Note: based on simulations of the livestock production disease (LPD) model.

6 Note that the production effects for all scenarios, measured in tons by region, are reported in Annex D.
7 Assuming annual production of 9.96 billion eggs a year and an average weight per egg of 60 grams. See: https://www.egginfo.co.uk/egg-facts-and-figures/industry-information/data.
8 However, in absolute terms, overall losses are greater for regions with a larger biomass in a given modelled livestock sector. See Table D.3 in Annex D.

TABLE 5 Simulated effects on livestock sector production outputs (scenario 1 *versus* reference) – differences in per cent

Livestock output type	Year	East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	2025	2.71	2.07	1.74	3.06	2.34	2.21	1.17	*2.13*
	2030	2.72	2.09	1.78	3.11	2.34	2.22	1.22	*2.13*
	2040	2.77	2.17	1.91	3.36	2.34	2.26	1.44	*2.2*
	2050	2.85	2.31	2.15	3.77	2.34	2.31	1.81	*2.34*
Cattle: Raw milk	2025	0.85	0.98	0.22	0.71	0.81	1.24	0.46	*0.84*
	2030	0.85	0.98	0.23	0.72	0.81	1.24	0.47	*0.84*
	2040	0.86	1.01	0.24	0.76	0.81	1.26	0.52	*0.85*
	2050	0.87	1.05	0.26	0.81	0.81	1.28	0.62	*0.88*
Swine: Meat	2025	1.09	0.76	0.72	1.04	0.76	1.38	0.99	*0.92*
	2030	1.1	0.76	0.73	1.05	0.76	1.38	1.02	*0.92*
	2040	1.11	0.78	0.77	1.06	0.78	1.4	1.14	*0.94*
	2050	1.13	0.8	0.83	1.07	0.8	1.43	1.34	*0.98*
Chicken: Meat	2025	2.38	1.85	1.66	2.68	1.86	2.29	1.61	*2.05*
	2030	2.39	1.86	1.67	2.69	1.88	2.31	1.66	*2.05*
	2040	2.42	1.89	1.72	2.73	1.96	2.37	1.85	*2.1*
	2050	2.48	1.94	1.8	2.8	2.09	2.48	2.19	*2.2*
Chicken: Eggs	2025	0.41	0.32	0.29	0.46	0.27	0.34	0.23	*0.36*
	2030	0.41	0.32	0.29	0.46	0.27	0.34	0.24	*0.36*
	2040	0.42	0.33	0.3	0.47	0.28	0.35	0.26	*0.37*
	2050	0.42	0.33	0.31	0.48	0.3	0.36	0.3	*0.37*

Note: based on simulations of the livestock production disease (LPD) model. In this heatmap, the blue colour represents the lowest values, red represents the highest values, and white represents the average/midpoint values.

perspective, Table 6 shows the consumption equivalent for each output good of the modelled livestock sectors per million people.[9] For example, in the presence of very low resistance rates (5%), by 2025, the equivalent of the beef consumed by approx. 175 million people globally could have been produced. In addition, lost production of cattle milk is estimated to equal the consumption needs of approx. 55 million people per year; for swine meat this is 80 million, for chicken meat 129 million and for chicken eggs 47 million. As in the production effects reported in Table 5, the equivalent consumption needs reported in Table 6 increase over time, following AMU and AMR projection trends. Moreover, the production loss risk is highest in cattle meat, followed by chicken meat over the same period.

Under the more pessimistic scenario 2, the simulated foregone production effects are projected to be even more substantial (see Tables 7 and 8). Compared to

9 See Annex D for more detail on the calculation of the consumption equivalent per million people. Essentially, the projected production difference between a scenario and the baseline projections are divided by the per capita consumption in kg (as provided by FAO, then processed and made available by Our World in Data).

TABLE 6 Simulated effects on livestock sector production outputs (scenario 1 *versus* reference) – differences in consumption equivalents (million people)

Livestock output type	Year	East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	59	16.6	11.2	7.3	8.8	56.3	15.5	*174.7*
	2030	61.6	17.6	12.2	8.2	8.9	59.4	18.7	*186.7*
	2040	67.7	20.3	14.9	10.7	9.3	66.8	29.3	*219.1*
	2050	75.2	24	19	14.5	9.6	75.9	49	*267.1*
Cattle: Raw milk	**2025**	11.5	13.1	1.3	3.6	3.7	12.7	8.7	*54.6*
	2030	11.8	13.6	1.4	4	3.7	13.6	10.4	*58.4*
	2040	12.4	14.9	1.6	4.8	3.7	15.6	15.8	*68.8*
	2050	13.2	16.5	1.9	6	3.7	18	25.3	*84.6*
Swine: Meat	**2025**	17.1	6.4	4.2	1.2	4	35.1	11.6	*79.6*
	2030	17.8	6.6	4.6	1.2	4.1	36.7	14.3	*85.4*
	2040	19.4	7.2	5.5	1.3	4.5	40.4	22.9	*101.2*
	2050	21.3	8	6.7	1.4	4.9	44.9	38.6	*125.9*
Chicken: Meat	**2025**	44	12.7	8.9	10	6.7	34.9	11.8	*128.9*
	2030	46.1	13.2	9.4	10.5	7.3	38.3	15.5	*140.2*
	2040	50.8	14.5	10.7	11.7	8.7	46.7	28.4	*171.4*
	2050	56.6	15.9	12.3	13.1	10.7	57.9	54.5	*221*
Chicken: Eggs	**2025**	8.8	2.5	1.8	2.6	1.3	6.1	3.3	*26.4*
	2030	9.2	2.6	1.9	2.7	1.4	6.7	4.4	*28.8*
	2040	10.1	2.8	2.2	3	1.7	8.1	7.9	*35.8*
	2050	11.2	3.1	2.5	3.4	2.1	10	15	*47.3*

Notes: based on simulations of the livestock production disease (LPD) model. Entries report the projected production effects in tons from Table D.3 (see Annex D) as consumption equivalents of millions of people by dividing estimated production losses by the average consumption of the modelled livestock sectors' products in kg per capita. In this heatmap, the blue colour represents the lowest values, red represents the highest values, and white represents the average/midpoint values.

the reference scenario, it is estimated that cattle meat production will be over 2% lower, globally.[10] However, poultry meat has the highest production loss, followed by cattle meat, when compared to the other livestock output types, representing the consumption equivalent of almost 200 million people globally. The difference in production output when comparing scenario 2 to the reference scenario for the other sectors in 2025 are lower by an estimated 3.2% (cattle raw milk), 1.32% (swine meat), 3.76% (chicken meat) and 0.87% (chicken eggs). These represent the following consumption equivalents: about 200 million people (cattle raw milk), 110 million people (swine meat), 228 million people (chicken meat) and 63 million people (chicken eggs) globally in 2025, with rising losses projected up to 2050.

Note that the production effects reported in Tables 5 and 6 represent a loss when compared to the reference scenario. If scenario 2 is compared to scenario 1, the

10 This represents an additional loss in production if scenario 2 is compared to scenario 1, which assumes a constant low resistance rate of 5%.

TABLE 7 Simulated effects on livestock sector production outputs (scenario 2 *versus* reference) – differences in per cent

Livestock output type	Year	East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	−2.82	−2.3	−2.03	−3.17	−2.56	−2.55	−1.73	*−2.38*
	2030	−2.85	−2.35	−2.11	−3.31	−2.56	−2.93	−2.59	*−2.54*
	2040	−2.97	−2.55	−2.46	−3.91	−2.56	−4.35	−5.57	*−3.2*
	2050	−3.17	−2.9	−3.05	−4.94	−2.56	−6.49	−9.35	*−4.29*
Cattle: Raw milk	**2025**	−2.85	−4.12	−1.12	−2.21	−3.25	−3.44	−2.02	*−3.21*
	2030	−2.86	−4.15	−1.13	−2.25	−3.25	−3.67	−2.41	*−3.27*
	2040	−2.91	−4.27	−1.19	−2.41	−3.25	−4.55	−3.76	*−3.55*
	2050	−2.98	−4.48	−1.29	−2.7	−3.25	−5.87	−5.47	*−4.06*
Swine: Meat	**2025**	−1.47	−1.17	−1.14	−1.42	−1.17	−1.77	−1.5	*−1.32*
	2030	−1.48	−1.18	−1.17	−1.43	−1.18	−1.93	−1.93	*−1.34*
	2040	−1.52	−1.23	−1.29	−1.47	−1.23	−2.54	−3.45	*−1.46*
	2050	−1.6	−1.31	−1.49	−1.52	−1.3	−3.46	−4.02	*−1.6*
Chicken: Meat	**2025**	−4.05	−3.63	−3.47	−4.32	−3.65	−3.75	−3.19	*−3.76*
	2030	−4.08	−3.66	−3.52	−4.36	−3.73	−4.07	−3.95	*−3.85*
	2040	−4.22	−3.79	−3.73	−4.53	−4.07	−5.31	−6.66	*−4.26*
	2050	−4.46	−4	−4.09	−4.81	−4.64	−7.23	−6.82	*−4.75*
Chicken: Eggs	**2025**	−0.93	−0.85	−0.81	−0.99	−0.8	−0.74	−0.62	*−0.87*
	2030	−0.93	−0.85	−0.82	−0.99	−0.81	−0.8	−0.75	*−0.88*
	2040	−0.96	−0.88	−0.86	−1.03	−0.87	−1.01	−1.22	*−0.95*
	2050	−1.01	−0.92	−0.93	−1.08	−0.98	−1.34	−1.24	*−1.04*

Note: based on simulations of the livestock production disease (LPD) model. In this heatmap, the blue colour represents the lowest values, red represents the highest values, and white represents the average/midpoint values.

effects reported in Tables 5 and 6 must be added to those reported in Tables 3 and 4. For example, under the pessimistic scenario 2, the loss in production of cattle meat compared to scenario 1 with very low resistance rates (5%) would be the consumption equivalent of approx. 904 million people in 2050.[11]

The simulated production effects projected in scenarios 3 and 4 can be found in Annex D. Estimated production effects are positive; thus, in comparison to the reference scenario, further actions to reduce antimicrobial consumption and resistance can lead to a rise in production outputs over time.

11 Calculated as 267.1 + 636.4 million people.

TABLE 8 Simulated effects on livestock sector production outputs (scenario 2 *versus* reference) – differences in consumption equivalents (million people)

Livestock output type	Year	East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	−61.4	−18.4	−13	−7.6	−9.6	−64.7	−23.1	*−197.8*
	2030	−64.5	−19.8	−14.5	−8.7	−9.8	−78.3	−39.8	*−235.3*
	2040	−72.5	−23.9	−19.2	−12.5	−10.1	−128.8	−113.7	*−380.6*
	2050	−83.7	−30.1	−27.1	−19	−10.4	−212.9	−253.2	*−636.4*
Cattle: Raw milk	**2025**	−38.8	−55.3	−6.4	−11.2	−14.8	−35.1	−38.4	*−200.1*
	2030	−39.8	−57.5	−6.9	−12.3	−14.8	−40	−53.4	*−224.7*
	2040	−42.1	−63.1	−8	−15.3	−14.8	−56.4	−113.5	*−313.3*
	2050	−45.1	−70.5	−9.7	−19.9	−14.8	−82.8	−224.4	*−467.2*
Swine: Meat	**2025**	−23	−9.8	−6.7	−1.6	−6.1	−45.1	−17.7	*−110*
	2030	−24	−10.2	−7.3	−1.7	−6.4	−51.4	−27.2	*−128.3*
	2040	−26.7	−11.4	−9.2	−1.8	−7	−73.5	−69.5	*−199.1*
	2050	−30.1	−13.1	−12.1	−2	−7.9	−109	−115.7	*−290*
Chicken: Meat	**2025**	−74.8	−24.9	−18.5	−16	−13.1	−57	−23.4	*−227.8*
	2030	−78.7	−26.1	−19.7	−17	−14.4	−67.6	−37	*−260.4*
	2040	−88.6	−29	−23.1	−19.4	−18.1	−104.7	−101.8	*−384.6*
	2050	−101.9	−32.9	−28	−22.6	−23.7	−169.1	−169.6	*−547.8*
Chicken: Eggs	**2025**	−19.8	−6.5	−5.2	−5.5	−3.9	−13.3	−9	*−63.3*
	2030	−20.8	−6.8	−5.5	−5.9	−4.3	−15.6	−13.9	*−72.8*
	2040	−23.3	−7.5	−6.4	−6.7	−5.3	−23.6	−36.8	*−109.6*
	2050	−26.6	−8.5	−7.7	−7.7	−6.8	−37.2	−61.5	*−156*

Notes: based on simulations of the livestock production disease (LPD) model. Entries report the projected production effects in tons from Table D.12 (see Annex D) as consumption equivalents of millions of people by dividing estimated production losses by the average consumption of the modelled livestock sectors' products in kg per capita. In this heatmap, the blue colour represents the lowest values, red represents the highest values, and white represents the average/midpoint values.

Key messages

Without further action to curb AMR, its negative impacts on livestock production loss will deepen over time

By 2050, in comparison to the reference scenario (resistance rate for 2025):

- annual livestock production losses due to AMR are estimated to equal the consumption needs of 746 million people, relative to an assumed low resistance rate of 5% (scenario 1);
- yearly global production losses are predicted to equal the consumption needs of approx. 2 billion people under a more pessimistic assumption of the future increased use of antimicrobials and associated doubled AMR-disease burden (scenario 2);
- livestock production losses are heaviest in cattle and poultry meat production compared to the other livestock output types assessed in both scenarios 1 and 2.

Economic effects of AMR in livestock sectors adversely affect GDP, yet potential effects may be much larger if negative externalities on human health are factored in

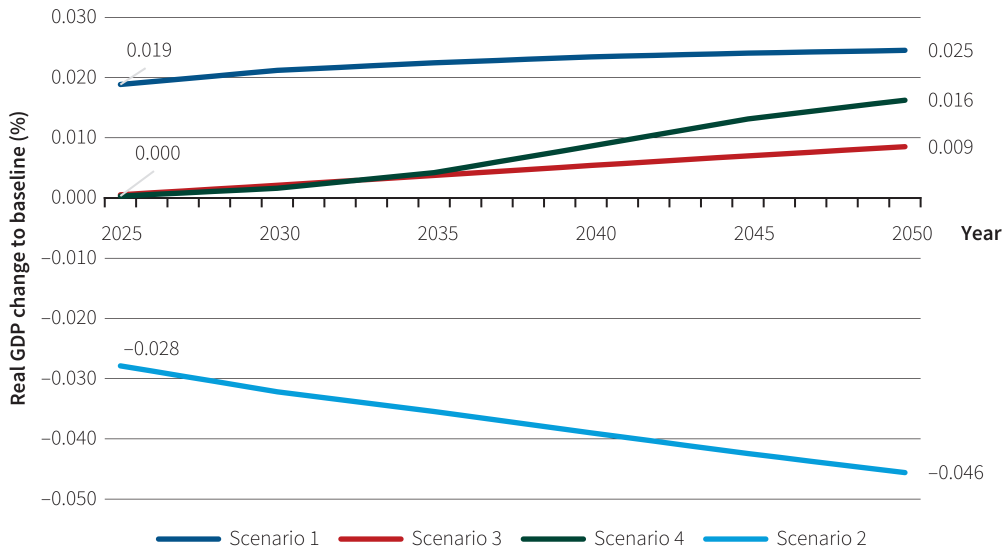
The effects on GDP associated with livestock sector productivity effects under different scenarios are assessed using the global macroeconomic DCGE model. Results are presented in the following series of tables and graphs, which report the difference in real GDP (US$ at 2017 value, constant) between the different counterfactual scenarios and the reference scenario, at various points in time (from 2025 to 2050). In most regions, livestock only has a relatively small direct contribution to the overall economy, yet it plays a larger role for LMIC economies (World Bank, 2017).

Figure 5 and Tables 8 and 9 show the simulated AMR effects that livestock sectors have on global real GDP by year, between 2025 and 2050. In comparison to scenario 1 with very low resistance rates (5%), global GDP by 2025 is estimated to be 0.02% higher. By 2050, it is projected to be 0.025% higher. This is equivalent to approximately US$ 39.7 billion per year (see Table 10), which is akin to the estimated cost in lost GDP associated with the SARS outbreak in the 2000s (Keogh-Brown and Smith, 2008).

Under the more pessimistic scenario 2, by 2050, the global real GDP could be 0.046 lower than in the reference scenario. This figure is equivalent to approximately US$ 74 billion per year, demonstrating the profound economic risks if disease burden and productivity losses show a larger increase over time than expected in the reference projections, all else being equal.

Scenarios 3 and 4 demonstrate the potential economic value of strategies and interventions that aim to reduce the use of antimicrobial consumption in the modelled livestock sectors. It is important to note that both scenarios assume that a basket of interventions is implemented in each region, including vaccinations and improvements to animal husbandry and biosecurity measures, thus replacing the need for unnecessary AMU and without adversely affecting animal health and welfare.[12] For example, with the more moderate interventions of scenario 3, global real GDP by 2050 is projected to be 0.01% greater than the reference scenario (approx. US$ 13.8 billion per year, see Table 9). With the more ambitious interventions of scenario 4, global real GDP by 2050 is projected to be 0.02% greater (approx. US$ 26.3 billion per year, see Table 10). Under a more pessimistic scenario, by 2050, the global real

FIGURE 5 Predicted changes in global real gross domestic product (GDP) by year and scenario



12 The simulations do not consider the costs of these interventions. That is, only the economic effect of reducing AMU and the subsequent reduction in AMR are modelled. It is assumed that the costs of these interventions do not exceed the costs of the AMU that would have been used in the absence of intervention efforts.

GDP could be 0.046% lower than the reference scenario, representing the equivalent of approx. US$ 74 billion. This is evidence for the profound economic risks if the disease burden and productivity losses increase at a greater pace than expected over time, all else being equal.

The economic effects of AMR in livestock production are not equally distributed across the modelled regions. As shown in Tables 9 and 10, the projected effects tend to be more pronounced in lower- and middle-income regions (Sub-Saharan Africa, South Asia, the Middle East and North Africa, Latin America and the Caribbean). This is especially evident in scenario 2, which assumes a greater rise in antibiotic consumption than the reference scenario: Sub-Saharan Africa's GDP is predicted to be 0.15% lower by 2050 compared to the reference scenario, and this is 0.13% lower in the case of South Asia's GDP.

TABLE 9 Predicted changes in gross domestic product (GDP) by year, region and scenario (in per cent compared to the reference scenario)

Scenarios	Year	East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Real GDP by year in per cent relative to reference scenario									
Scenario 1	**2025**	0.03	0.01	0.03	0.03	0.01	0.03	0.03	*0.02*
	2030	0.03	0.01	0.03	0.03	0.01	0.03	0.03	*0.02*
	2040	0.03	0.01	0.03	0.03	0.02	0.04	0.03	*0.02*
	2050	0.03	0.01	0.03	0.04	0.02	0.04	0.04	*0.03*
Scenario 2	**2025**	−0.04	−0.02	−0.06	−0.05	0.00	−0.07	−0.07	*−0.03*
	2030	−0.04	−0.02	−0.06	−0.05	−0.01	−0.08	−0.08	*−0.03*
	2040	−0.04	−0.03	−0.06	−0.06	−0.01	−0.10	−0.12	*−0.04*
	2050	−0.05	−0.03	−0.06	−0.07	−0.01	−0.13	−0.15	*−0.05*
Scenario 3	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2030	0.00	0.00	0.01	0.00	0.00	0.00	0.00	*0.00*
	2040	0.01	0.00	0.01	0.01	0.01	0.01	0.01	*0.01*
	2050	0.01	0.01	0.02	0.01	0.01	0.01	0.01	*0.01*
Scenario 4	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2030	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2040	0.01	0.00	0.02	0.01	0.01	0.01	0.00	*0.01*
	2050	0.02	0.01	0.03	0.02	0.01	0.01	0.01	*0.02*
Scenario 5	**2025**	−0.04	−0.04	−0.04	−0.03	−0.04	−0.04	−0.04	*−0.04*
	2030	−0.04	−0.04	−0.04	−0.03	−0.04	−0.04	−0.04	*−0.04*
	2040	−0.05	−0.04	−0.04	−0.04	−0.05	−0.05	−0.04	*−0.05*
	2050	−0.05	−0.04	−0.04	−0.04	−0.05	−0.05	−0.04	*−0.05*
Scenario 6	**2025**	−0.19	−0.17	−0.20	−0.16	−0.17	−0.22	−0.21	*−0.18*
	2030	−0.21	−0.18	−0.20	−0.18	−0.18	−0.24	−0.23	*−0.20*
	2040	−0.24	−0.19	−0.21	−0.21	−0.19	−0.28	−0.28	*−0.22*
	2050	−0.26	−0.20	−0.21	−0.24	−0.20	−0.32	−0.32	*−0.24*

Note: in this heatmap, the blue colour represents the lowest values, red represents the highest values, and white represents the average/midpoint values.

As discussed in Chapter 2, current evidence on the existence and potential magnitude of a transmission link between AMR in animals and humans is still subject to debate. To provide an order of magnitude for a relatively small or medium spillover effect from AMU and AMR in livestock to humans, scenarios 5 and 6 offer comparisons to the reference scenario. Even with moderate assumptions, there are substantial relative GDP effects associated with a potential spillover effect on humans. As illustrated in Tables 8 and 9, by 2050, global GDP is projected to be 0.05% smaller than the reference scenario (equivalent to US$ 77.4 billion). Assuming a higher AMR-attributable burden in livestock production and a larger spillover effect on humans (scenario 6), global real GDP by 2050 could be 0.24% lower (equivalent to approx. US$ 384 billion per year). That is, if scenarios 2 and 6 are compared, the inclusion of a potential negative externality on human

TABLE 10 Predicted changes in gross domestic product (GDP) by year, region and scenario (US$ at 2017 value compared to reference)

Scenarios	Year	East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Real GDP by year relative to reference (US$ at 2017 value in billions)									
Scenario 1	**2025**	7	2.2	2.3	1.1	2.4	1.5	0.7	*17.2*
	2030	9.3	2.7	2.6	1.5	3.5	1.9	0.8	*22.3*
	2040	12.9	3.6	3.2	2.2	5.3	2.9	1.2	*31.2*
	2050	16.1	4.3	3.6	3	7.1	3.7	1.9	*39.7*
Scenario 2	**2025**	−10	−4.3	−3.8	−1.8	−0.9	−3.3	−1.4	*−25.5*
	2030	−13.3	−5.3	−4.4	−2.5	−1.7	−4.6	−2	*−33.8*
	2040	−19.1	−7.3	−5.6	−4.1	−3	−8.1	−4.8	*−51.9*
	2050	−25.2	−9.2	−7	−6.2	−4.7	−13.7	−8	*−73.9*
Scenario 3	**2025**	0.2	0.1	0.1	0	0.1	0	0	*0.5*
	2030	0.8	0.3	0.4	0.1	0.4	0.1	0.1	*2.2*
	2040	2.5	0.9	1.1	0.4	1.5	0.5	0.3	*7.2*
	2050	4.8	1.7	1.8	0.8	3.2	1	0.5	*13.8*
Scenario 4	**2025**	0.1	0	0.1	0	0	0	0	*0.3*
	2030	0.7	0.2	0.3	0.1	0.3	0.1	0	*1.7*
	2040	5	1	2	0.7	2.2	0.5	0.1	*11.5*
	2050	12.3	2.3	3.1	2.1	4.7	1.4	0.3	*26.3*
Scenario 5	**2025**	−10.9	−8.5	−2.4	−1.2	−9.9	−1.7	−0.7	*−35.3*
	2030	−14.3	−9.7	−2.8	−1.5	−11.5	−2.3	−1	*−43.1*
	2040	−21.6	−12.1	−3.7	−2.4	−14.7	−3.7	−1.5	*−59.8*
	2050	−29.5	−14.4	−4.5	−3.5	−18.1	−5.1	−2.2	*−77.4*
Scenario 6	**2025**	−53.4	−38.5	−13.4	−6.5	−40.6	−9.9	−4.4	*−166.7*
	2030	−70.6	−44	−15.7	−8.6	−47.6	−13.8	−6	*−206.4*
	2040	−105.6	−55.6	−20.4	−13.8	−61.8	−22.8	−10.9	*−291*
	2050	−143.1	−67	−24.8	−20.2	−77.3	−34.2	−16.9	*−383.5*

Note: in this heatmap, the blue colour represents the lowest values, red represents the highest values, and white represents the average/midpoint values.

health could increase GDP effects of AMR from livestock sectors by more than a factor of five. However, it must be noted that the inclusion of a potential negative externality on human health – despite the conservative modelling – is for solely illustrative purposes. More evidence is needed to better understand the magnitude of the overlap between AMU in livestock sectors and the occurrence of AMR and burden in humans. Based on the relative change in regional GDP in per cent in scenarios 1 to 6, the differences in country-specific GDP effects (in US$ at 2017 value) for each scenario relative to the reference scenario are reported in Tables D.17 to D.23 in Annex D.[13]

Lastly, Table 11 summarises the cumulative economic effects across the scenarios for each region. To that end, present values (PVs) of the differences in GDP are calculated for each scenario and the reference scenario over the period 2025–2050, using the social discount rates previously applied by the World Bank (2017). The following discount rates are applied: 0%, 1.4%, 3.5% and 5.5%. Lower discount rates yield higher present values, suggesting that future costs associated with resistance are considered of higher relative importance than under higher social discount rates. Table 11 shows calculations of the present values for the cumulative economic effects across the different scenarios and regions using the discount rates of 1.4% and 5.5%.[14]

Using a 1.4% discount rate, the global economic cost of lost livestock production attributable to AMR under scenario 1, for 2025–2050, is predicted to amount to US$ 575 billion in GDP. Using a discount rate of 5.5%, the corresponding difference in cumulative GDP between scenario 1 and the reference scenario is US$ 246 billion. The projected cumulative GDP costs in pessimistic scenario 2 are profound: in 2025–2050, these are estimated to amount to US$ 950 billion, or almost a trillion dollars. The cumulative economic costs under this scenario are approx. US$ 468 billion for a discount rate of 5.5%. Note that regarding the production effects shown in Tables 4 and 5, if scenario 2 is compared to scenario 1, which assumes very low resistance rates (5%), then the cumulative effects shown in Table 11 for scenarios 2 and 1 would have to be added together. For example, assuming a 1.4% discount rate, the lost cumulative GDP when comparing scenario 2 to the reference scenario (US$950 billion) is added to the lost cumulative GDP when comparing scenario 1 to the reference scenario (US$575 billion). This results in an approximate lost cumulative GDP of US$ 1.5 trillion for the period 2025–2050, when comparing scenario 2 to scenario 1. To put this into perspective, in 2022, Germany's GDP was about US$ 4 trillion (World Bank Group, 2024b). For a discount rate of 1.4%, the potential GDP benefits of reducing AMU in livestock in scenarios 3 and 4 are US$ 119 and US$ 191 billion, respectively. The equivalent cumulative GDP gains for a discount rate of 5.5% are US$ 52.1 billion and US$ 78.5 billion. However, projected cumulative economic costs of AMR in livestock sectors rise substantially when moderate externalities on human health are considered. For a 1.4% discount rate, the cumulative GDP effects in scenario 5, compared to the reference scenario, are US$ 1.1 trillion. For the more pessimistic scenario 6, this is approx. US$ 5.3 trillion.

13 For example, when the GDP of a region is projected to decrease by 0.01% in 2050, 0.01% is applied for each country in that region. Then the country-specific GDP value of 0.01% is calculated in US$ at 2017 value, in billions.

14 The estimated cumulative GDP effects for the discount rates of 0% and 3.5% are shown in Table D.17 in Annex D.

TABLE 11 Predicted changes in cumulative real gross domestic product (GDP) by year, region and scenario (cumulative US$ at 2017 value compared to reference)

Scenarios	Year	East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
A. Discount rate 1.4%									
Scenario 1	**2030**	43.8	13.1	13.1	7.1	15.7	9.2	4.2	*106.2*
	2040	134.1	38.4	36.5	22.3	51.3	28.9	12.6	*324.1*
	2050	236.7	66.2	60.5	40.9	95.2	52.2	23.4	*575.1*
Scenario 2	**2030**	−62.6	−25.9	−22.1	−11.6	−6.8	−21.1	−9.2	*−159.4*
	2040	−194.6	−77	−62.5	−38.6	−25.5	−72.4	−36.2	*−507*
	2050	−351.3	−135.5	−107	−74.9	−52.6	−149.1	−81.9	*−952.6*
Scenario 3	**2030**	2.5	1	1.2	0.3	1.3	0.4	0.2	*7.1*
	2040	15.9	6.1	7.1	2.3	9	3.1	1.6	*45.2*
	2050	41.9	15.6	17.3	6.4	25.6	8.5	4.4	*119.7*
Scenario 4	**2030**	2.2	0.6	1	0.2	0.9	0.2	0.1	*5.2*
	2040	23.4	5	9.5	3	10.3	2.4	0.6	*54.2*
	2050	86.9	16.8	28.1	12.7	35.8	9.2	2.1	*191.7*
Scenario 5	**2030**	−67.6	−49.1	−14.1	−7.2	−57.7	−10.6	−4.7	*−211.1*
	2040	−214.5	−137.5	−40.8	−23.3	−164	−34.9	−15	*−630*
	2050	−395.7	−231.2	−69.6	−44.3	−280.1	−66.1	−28.4	*−1,115.50*
Scenario 6	**2030**	−333.1	−222.7	−78.5	−40.4	−237.7	−63.6	−27.8	*−1,004.20*
	2040	−1,052.50	−627.9	−225.5	−131.9	−681.7	−212.1	−96.1	*−3,028.40*
	2050	−1,884.10	−1,025.40	−372.9	−246.2	−1,135.40	−404.5	−191.2	*−5,260.50*
B. Discount rate 5.5%									
Scenario 1	**2030**	32.5	9.7	9.7	5.3	11.6	6.8	3.1	*78.7*
	2040	58.2	17	16.6	9.5	21.5	12.3	5.5	*140.7*
	2050	101.6	29	27.3	17	39.3	22	9.7	*245.8*
Scenario 2	**2030**	−46.4	−19.2	−16.4	−8.6	−5	−15.6	−6.8	*−118.1*
	2040	−117.7	−46.9	−38.4	−23.1	−15	−43.2	−21.2	*−305.6*
	2050	−174.9	−68.2	−54.6	−36.3	−24.9	−70.9	−37.7	*−467.7*
Scenario 3	**2030**	1.8	0.7	0.9	0.2	1	0.3	0.2	*5.1*
	2040	8.9	3.4	4	1.3	5	1.7	0.9	*25.2*
	2050	18.3	6.9	7.7	2.8	11	3.7	1.9	*52.1*
Scenario 4	**2030**	1.6	0.4	0.7	0.2	0.7	0.2	0	*3.7*
	2040	12.5	2.7	5.1	1.6	5.5	1.3	0.3	*29.1*
	2050	35.3	6.9	11.9	5	14.7	3.7	0.9	*78.5*
Scenario 5	**2030**	−50.1	−36.5	−10.5	−5.3	−42.9	−7.8	−3.5	*−156.7*
	2040	−129.4	−84.5	−24.9	−14	−100.6	−20.9	−9	*−383.4*
	2050	−195.4	−118.8	−35.5	−21.6	−143	−32.3	−13.9	*−560.6*
Scenario 6	**2030**	−246.8	−165.6	−58.3	−30	−176.6	−47	−20.6	*−745.2*
	2040	−635.2	−385.5	−138	−79.2	−417.4	−127	−57.2	*−1,840.10*
	2050	−915.5	−514.6	−186.3	−118	−565.9	−192.6	−89.8	*−2,583.30*

Note: in this heatmap, the blue colour represents the lowest values, red represents the highest values, and white represents the average/midpoint values.

Key messages

The predicted negative impact associated with no further action to curb AMR on the global economy will be enormous and will intensify over time

Between 2025 and 2050, when compared to the reference scenario:

- cumulative global GDP loss due to AMR in livestock is predicted to be US$ 575 billion, relative to an assumed low resistance rate of 5% (scenario 1);
- cumulative GDP loss is estimated at US$ 953 billion under a more pessimistic assumption of future AMU and the associated AMR-disease burden (scenario 2);
- cumulative global GDP is predicted to increase by US$ 120 billion if global AMU is reduced by around 30% (scenario 3);
- cumulative global GDP losses associated with lower labour productivity are estimated to be US$ 1.1 trillion under moderate harmful spillover effects on human health by AMU and AMR in livestock (scenario 5);
- cumulative GDP loss could reach US$ 5.2 trillion under a more pessimistic prediction of spillover effects on human health by AMU and AMR in livestock (scenario 6).

LIMITATIONS OF THE ECONOMIC ANALYSIS

This analysis of the potential economic effects of AMR in livestock production has highlighted the fact that if no action is taken to tackle AMR, this translates to significant adverse impacts on GDP and food production. The analysis also highlights the potential gains if interventions are put in place to curb AMU to varying extents over a period of 5–20 years. Moreover, while only illustrative in nature, the analysis also shows the projected impacts of any potential externalities from antimicrobial consumption in livestock on human health and labour productivity; this could further add to the potential costs if AMU and AMR in livestock is not addressed, and it increases the benefit of interventions.

While this analysis has focused solely on the effects that AMR has on the economy through the disruption and productivity impacts of livestock sectors (and, to some extent, on labour productivity, depending on the scenario), it must be mentioned that other effects exist that could be monetised, yet these are not considered in this analytical approach. It is possible that this may cause an under-estimation of the potential cost of AMR in food-producing animals. Some of these are analysed below.

First, the analysis only includes a sub-set of bacterial infections and livestock types. Due to limitations in data availability, the potential impacts of AMR on the fisheries sector and other livestock types were not considered. However, the fisheries sector is a vital source of protein in many countries and is predicted to play an even greater role in the future. Furthermore, many other bacterial, viral and fungal infections exist but were not modelled. While it is not a straightforward task to assess the real attributable and marginal impacts that the exclusion of other infection types has, due to many co-morbidity issues and the lack of data, it is likely that their exclusion may cause an under-estimation of the costs attributable to resistance.

Second, as resistance rates in livestock sectors may rise in future, countries may opt to close their borders and prohibit the movement of live animal and food products from AMR hotspots. This would lead to additional economic losses, especially for countries with relatively high food exports (at least in the short-term, before production systems are adjusted). However, accurately quantifying these potential future trade restrictions is a challenge. For example, it is difficult to predict at what level of resistance such potential fear factors would set in. Furthermore, it is not *a priori* clear to what extent these trade embargoes would hurt the exporting economy, since the closed export markets could be substituted with markets not under embargo.

Third, the future may see a change in consumer preferences. This would naturally lead to a shift in demand for goods produced by livestock sectors affected by high resistance rates and certain practices that lead to excess AMU (e.g. growth promotion). As with trade restrictions, changes in product demand could (at least in the short-term) lead to additional economic losses associated with AMU and fear of resistance or animal welfare practices. However, if one were to model such changes in consumer preferences, parameterising these effects with existing empirical data would be a challenge. In summary, while it must be acknowledged that these effects could lead to an increase in the estimated costs associated with AMR in livestock production, it was out of the scope of this analysis to model these additional cost drivers.

CHAPTER 4

Evaluation of the cost-effectiveness of an AI-based intervention for real-time disease diagnostics to reduce antimicrobial consumption and resistance

BACKGROUND

Previous studies have demonstrated the potential economic value of interventions aimed at reducing AMU and curbing AMR in livestock, such as the case studies of Ontario dairy farming and Vietnam broiler chickens (see Boxes 2 and 3), and others that include policy interventions, compulsory behavioural change interventions, disease management strategies and vaccination programmes (Guenin *et al.,* 2023; Costa *et al.,* 2023). Although these interventions have proven effective, the studies did not estimate the costs of implementation. It is therefore necessary to evaluate the cost-effectiveness of each intervention. While there are preventive alternatives to reduce AMU, they are often inaccessible due to lack of affordability and infrastructure, as well as other barriers, such as lack of knowledge or skills. It is key for stakeholders in livestock sectors to understand the ROI of interventions, as this will likely vary, even at the individual farm level. Consequently, there is a need for comprehensive data on the cost of intervention at a global scale. Estimating the ROI for specific interventions can help stakeholders understand their feasibility and cost-effectiveness, making it possible to scale up the interventions to national, regional and global levels, as well as to offer the necessary evidence to decision-makers to target cost-effective interventions.

Effective interventions in the animal sector are limited. This chapter discusses the retrospective evaluation of a promising intervention in the swine sector, which uses AI to monitor animal health. The intervention has the potential to be used not only in high-income countries or the swine sector, but more broadly in different country-settings and across animal species. This specific AI-based intervention, including its cost–benefit analysis, was assessed to provide insights on its economic viability and cost-effectiveness.

Intervention for monitoring animal health with innovative AI technology

As the global population grows, so too does the demand for animal-sourced proteins. To alleviate global hunger and poverty – especially in LMICs – this necessitates an increase in food-animal production, yet there are only finite resources. Intensive production systems are then adopted to increase production. In the livestock sector, such systems contribute to AMU for growth promotion and disease prevention. However, these practices are linked to the growing threat of AMR, which is a global health challenge that affects both humans and animals (CDC, 2022; Pandey *et al.,* 2024).

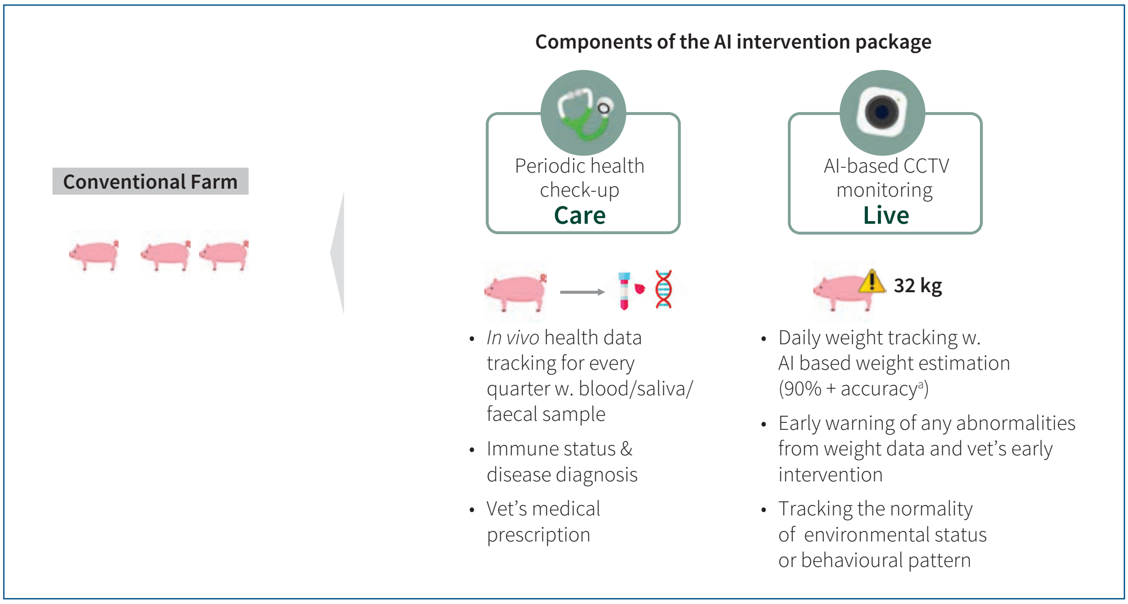
Recent technological advances have ushered in the use of AI in agriculture, including in livestock farming, to increase farm productivity and reduce disease burden (Arshad *et al.,* 2024; Fuentes *et al.,* 2022). Ensuring livestock health ultimately supports the reduction in AMU. In turn, this decreases the pressure for the emergence and spread of AMR in livestock. Such a reduction could also lead to improved health for humans and the environment, underscoring the importance of decreasing AMU in livestock, which can positively impact animal health as well as human health and wellbeing.

The aim of this case study was to conduct a cost–benefit analysis of a particular AI-intervention package, and to examine its role in improving farm productivity and animal health, through its impact on AMU and early disease detection. The AI-intervention package combines AI and biotechnology to improve farm productivity and livestock health.

In this analysis, AI-intervention farms are defined as farms that implemented the AI technology. This technology service consists of two main components (see Figure 6). The first component is a periodic health check-up, which enables farm owners to monitor the health status of their animals and receive customised medical care from veterinarians, based on health data provided by the AI solution. The second component is AI-based closed-circuit television (CCTV) monitoring, which is a live digital surveillance system using digital AI technology to track and document parameters. Such parameters include animal weight, abnormal behaviours or changes (e.g. temperature variation, gait, etc.) within and among the animals. This information enables the rapid detection of disease onset or other disorders, alerting professionals/owners to implement the appropriate interventions. Early disease diagnosis is critical to limiting transmission and spread of resistant and susceptible pathogens within and between farms, and it reduces the overall disease burden in the farm, optimising animal health and increasing productivity and profitability for the farmer.

When a farm employs AI technology, AI helps the farm manager monitor individual pigs or the entire herd more frequently. For example, the AI technology tracks the herd status, documenting changes, such as daily herd weight gain (an important index of pig health). If the herd does not attain an ideal weight gain within 3–4 days, the manager can then identify this abnormal

FIGURE 6 Components of the AI intervention package



Notes: [a]Computer vision algorithm has been trained by certified veterinarians based on data sets from 1M+ pigs. Global patent pending in 150 countries (PCT).

status before the herd shows severe clinical signs or even death. The manager can then opt to consult a veterinarian to treat the herd with antimicrobials, or choose to enhance herd immunity levels via alternate methods, such as feed additives, a change in feed, change in climate conditions or disinfection of surfaces. Furthermore, in a sow farm, AI technology can monitor pregnant sows 24 hours a day to detect abnormalities in the farrowing condition and subsequently notify the manager. This feature offers a suitable alternative to induction drugs to manage delivery timings, as managers cannot monitor delivery at all times.

In contrast to AI-intervention farms, conventional farms with only human farm managers must monitor thousands of pigs at once. Here, it is extremely difficult to pay attention to each individual pig, making the timely detection of negative health changes and subsequent prompt intervention less likely. Hence, the farm manager may notice abnormalities only after a number of pigs have died or show advanced clinical signs. At this point, it is already too late into the disease process, with a graver risk of the potential spread of disease, necessitating AMU to treat sick pigs. When the disease is already widespread, the best option is to treat the entire herd on the assumption that other animals are also infected despite not showing clinical signs, rather than treating only those individuals that present with clinical signs.

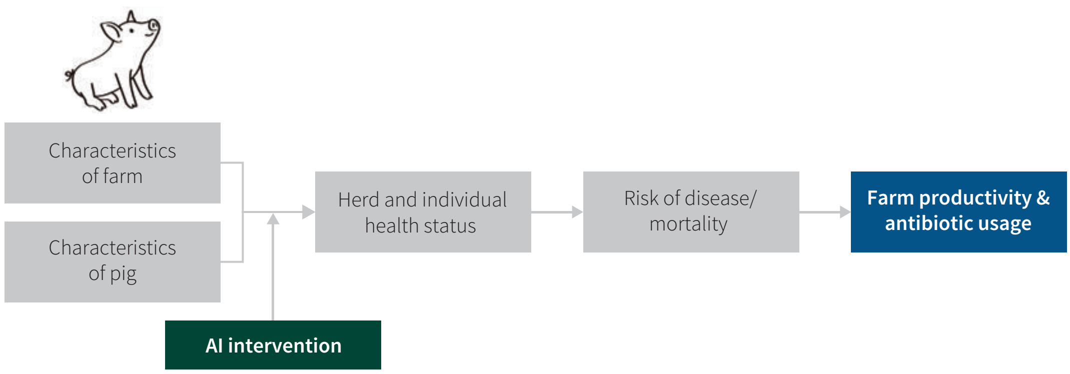
Overall, AI technology enables farm managers to monitor the herd more thoroughly and rapidly, facilitating early detection of disease onset and other abnormal conditions. In turn, this reduces the need for AMU. Figure 7 is a generalised diagram of these examples. When certain factors, such as farm specifications, management methodology and the biological characteristics of pigs are determined, the AI intervention can improve the health status of groups or individuals (via early detection and response to abnormal signs), which reduces the risk of disease outbreaks, decreases mortality rates and ultimately increases farm productivity, reducing the incidence of antimicrobial prescriptions.

The purpose of this analysis is to observe the potential of AI interventions to eventually foster change in farm productivity and AMU. As outlined in Figure 7, this effect is assumed to follow a necessary path via an intermediate factor, which is a change in animal health status. In addition, the term ‘productivity’ has many definitions, yet for this particular study, farm productivity refers to the ‘benefit’ per pig.

This benefit is calculated via a return-on-investment (ROI) analysis. The net benefit of AI-intervention farms is compared to that of conventional farms in Component 1 of the study (cost–benefit analysis). Component 2 evaluates micro-level data from two AI-intervention farms over a set period. Finally, Component 3 examines the difference in immune indicators based on haematological analysis (health data analysis) of individual samples obtained from both AI-intervention and conventional farms. For further technical detail on the ROI calculation, see Annex E.

The health status of individual pigs is pivotal for both the farm’s overall productivity and its use of antimicrobials. Despite the significance of individual health,

FIGURE 7 Effect of the health of an individual pig on farm productivity



given the scale of pig farming, individual health management is often overlooked. Since most pig farms raise dozens to hundreds of pigs within a single building, the health status of individual pigs significantly influences the overall health of the group. Consequently, the health status at the individual pig level directly impacts the overall farm productivity and its likelihood of AMU.

METHODOLOGY

To investigate the economic viability of the AI technology, a cost–benefit analysis was conducted using data from both AI-intervention and conventional farms. Information from conventional farms was exclusively sourced from the Korean Statistical Information Service (KOSIS), and was limited to reported data, including format and aggregation levels. In contrast, data for the AI-intervention farms was collected from 27 finisher pig farms that successfully employed the AI technology from 2020 to 2022. These farms were selected for their clean, time-balanced and consistent farm size data, providing high-quality data for analysis. To ensure a thorough and balanced comparison between the two farm types, only relevant key variables that existed in both comparison groups were retained for analysis (see Table 12).

Comparable data for conventional farms were obtained from the KOSIS, which conducts annual surveys of a sample of finisher farms to analyse farm economics and gauge national productivity levels (KOSIS, 2023a; 2023b). This nationally sourced data is openly available and is aggregated annually for the years 2020 to 2022. The data are categorised into four farm size ranges: 1) under 1,000 pigs, 2) 1,000–2,000, 3) 2,000–3,000 and 4) over 3,000 pigs, with average values calculated for each category. Annual farm surveys collect data on benefits and costs, employing a stratified sampling methodology to ensure representative selection. Analysing the yearly differences in cost–benefit ratios across these categories provides insight to national trends in farm economic performance.

The key differences between the KOSIS national data and the private data from AI-intervention farms, as well as adjustments made to account for disparities, are as follows:

1. *Time point:* AI-intervention farm data are collected monthly, providing detailed insight yet occasionally showing gaps due to operational disruptions, such as service terminations, national disease control policies or data omissions. To mitigate this, only AI-intervention farms with the most consistent monthly data were analysed.
2. *Farm size:* in contrast to the national data, which uses a structured sampling method to ensure balance, the AI-intervention farm data comes from all farms that opt for AI services. This results in an unbalanced representation that is skewed towards larger farms. For more accurate comparison, data from farms with over 1,000 heads are analysed in addition to the overall dataset.

TABLE 12 Selected variables for cost–benefit analysis in conventional and AI-intervention farms

Variable	Description
Total Revenue (A)	Sales revenue from meat production
Operational Cost (B)	Farm operation costs
Cost: Feed	Feed expenditure
Cost: Medical	Medical expenditure
Cost: AI-package fee*	Fee for the AI technology
Benefit (A – B)	Farm income (Revenue – Operational Cost)
Net Profit (A – C)	Net profit (Revenue – Total Cost)

Note: total cost includes operational cost (B), self-labour costs and Interest-related costs, which includes capital service cost and land service cost.

3. *Farm type:* the Republic of Korea has three categories for pig farms: breeding farms, finisher farms and integrated farms. National data solely focuses on finisher farms, whereas AI data includes all three types. To align with the national data, the analysis of AI data filters out breeding farms, focusing only on finisher and integrated farms.
4. *Operational costs:* AI farm operational costs include specific expenditures on medical care, feed and an AI-package fee, reflecting the added services that come with the use of AI technology. For comparison purposes, only medical care and feed costs were retained for conventional farms to compute the ROI, adjusting for all other factors.
5. *Revenue sources:* national data only includes revenue from meat sales of finisher pigs. For AI farms, revenue generated from selling piglets is also included. To ensure data comparability, when analysing integrated farms, revenue from piglet sales is excluded, focusing solely on revenue from meat sales.

RESULTS AND DISCUSSION

The AI intervention is associated with a positive return on investment

The AI intervention demonstrates the cost-effectiveness of ROI in pig farms ranging from small to commercial-scale farm sizes, as shown in Table 13.A.

Benefits attributable to AI per pig are calculated on an annual basis, and ROI values are calculated in Table 13.B. Thus, for every single South Korean Won (KRW) invested in the AI intervention, an average return of KRW 4.17 is realised. This result is highly profitable and suggests that the AI intervention is very cost-effective. It must be noted that the profitability increases over time during the study period, starting at 255% in the first year and increasing to 537% by the third year of implementation, suggesting greater long-term benefits.

In addition to the ROI results, two key points are worth highlighting as a mechanism by which AI intervention impacts the ROI. First, AI farms had lower medical costs, which even decreased over the study period (see Figure 8). This exemplifies the effectiveness of the AI-intervention package in early detection of disease clinical signs and the resulting decrease in medical expenditures. The result implies that the costs associated with early detection and intervention at AI farms are likely lower than the costs of treatment after disease occurs at conventional farms.

Second, despite the higher up-front cost of adopting the AI-technology package, AI farms can achieve greater benefits via higher revenues and lower medical costs. Figure 9 shows the benefit comparison between conventional and AI farms across the study period.

TABLE 13.A Revenue, cost, and benefit data for conventional and AI farms (unit: per pig, currency: KRW*)

Variable	Conventional farms			AI-intervention farms		
Year	2020	2021	2022	2020	2021	2022
Revenue (R)	358,519	405,970	450,610	365,146	409,251	463,018
Operational Cost** (C)	182,685	201,625	241,834	177,382	186,532	234,127
Feed cost	172,602	190,606	230,297	170,309	179,833	227,582
Medical cost	10,083	11,019	11,537	7,073	6,699	6,545
AI package cost/year (lowest)***	0	0	0	3,360	3,228	3,160
Benefit (R – C)	175,834	204,345	208,776	187,764	222,719	228,891
Benefits attributable to AI/pig/year				11,930	18,374	20,115
Number of sample farms	146	146	146	27	27	27

Notes: *KRW = South Korean Won. **Operational cost includes feed and medical costs. ***The investment represents the cost of an AI package per pig, which is KRW 1,000 according to the pricing policy. The production period for pigs to produce pork is four months; thus, investment for one pig is a maximum of KRW 4,000 per year. After the pricing policy is applied for 1 year, and if the farm size increases within the contracted period, then the AI cost per pig would be lower than KRW 4,000. For this reason, the average cost per pig per year is less than KRW 4,000.

TABLE 13.B Calculation of return on investment (ROI) for AI-intervention farms

Variable	AI-intervention farms			
Year	Benefits attributable to AI/pig/year (KRW*)	AI package cost/year (KRW)	ROI** calculation	ROI (%)
2020	11,930	3,360	(11,930 / 3,360) – 1	2.55 (255%)
2021	18,374	3,228	(18,374 / 3,228) – 1	4.69 (469%)
2022	20,115	3,160	(20,115 / 3,160) – 1	5.37 (537%)
Average	16,806	3,249	(16,806 / 3,249) – 1	4.17 (417%)

Notes: *KRW = South Korean Won. **ROI = Return on Investment.

FIGURE 8 Cost of medical expenditures (per pig per year) in South Korean Won (KRW)

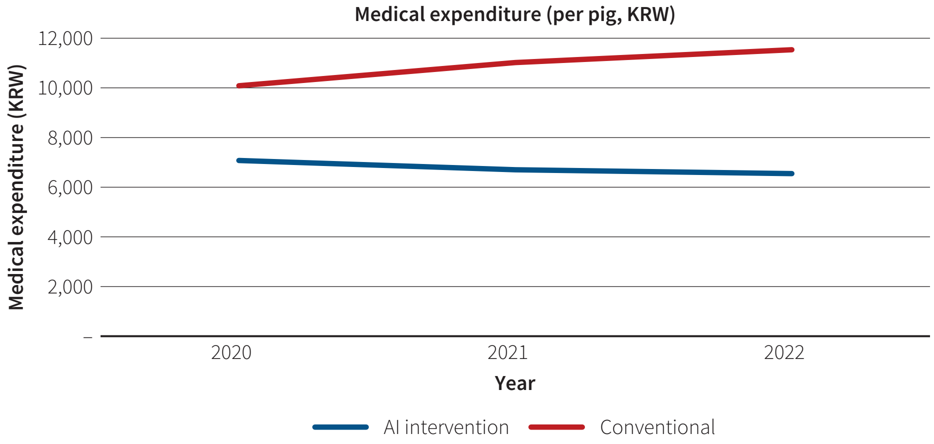
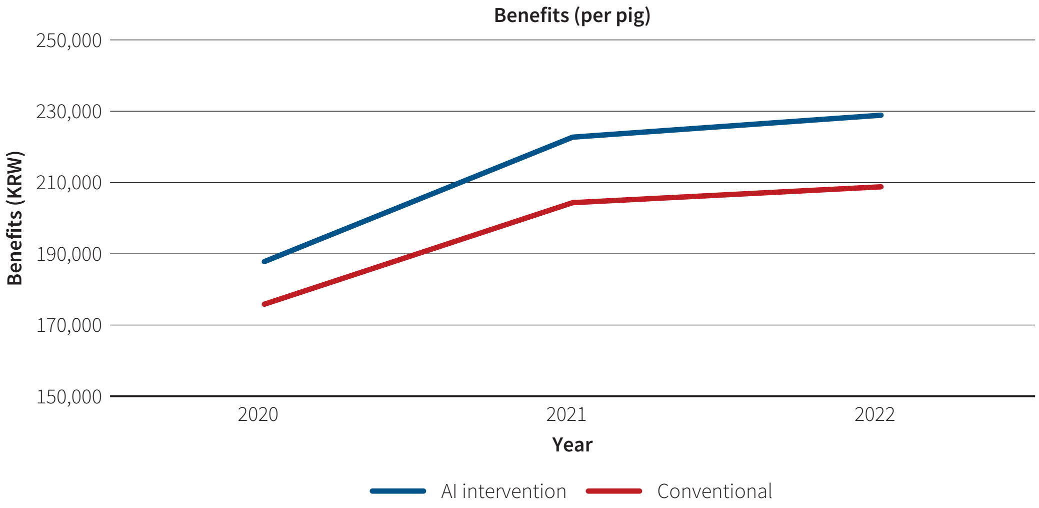


FIGURE 9 Benefits (per pig per year) in South Korean Won (KRW)



Key messages

Evaluation of the cost-effectiveness of the AI-intervention package:

- **Positive ROI:** The AI-intervention package has proven a positive ROI of an average 417% over a three-year period.
- **Increasing ROI:** The ROI shows an increasing trend over time, ranging from 255% to 537% during the first three years of investment.
- **Lower health care costs:** AI-intervention farms experienced lower and decreasing medical costs compared to conventional farms during the study period.
- **Scale-up potential:** This cost-effective AI solution has been implemented successfully in LMICs and in small-, medium- and large-scale farms.

The AI intervention is associated with a positive impact on productivity and reduced AMU

The following section provides an additional detailed analysis of two selected AI-intervention farms. The report illustrates the impact of AI technology on farm productivity, disease burden and AMU. The chosen farms have consistently implemented the AI services for at least two years, while maintaining a farm size of over 3,000 pigs. In addition, these farms demonstrate advanced swine management skills on the part of the farm owners, who are receptive to new technologies and capture meticulous high-quality data on a daily basis. The farm with the most significant improvement has been selected to showcase gains in productivity indicators, demonstrating the best case of AI-intervention in ROI.

The study focused on specific indicators related to health status improvements due to AI technology and subsequent productivity enhancements. These indicators also validate the effectiveness in both internal and external farm environments. As Table 14 illustrates, several reproductive performance indicators (e.g. pregnancy rate, mortality rate and number of births) are analysed. These are closely linked to the herd's health status, including immune status, which is found via blood sample analysis. Additionally, the study tracks the monthly average medical expenses and,

TABLE 14 Farm productivity and health management indicators for AI-intervention farms

Indicator	Description
Immune grade	Focuses on the portion of medical expenses specifically attributed to antimicrobials
Pregnancy rate	Represents the herd's health status, assessed via periodic health check-ups, using an immunity grading system developed by Animal Industry Data
Average number of piglets	The number of successful pregnancies among sows in a given period
Average number of weaning pigs	The number of living piglets delivered by each sow
Mortality rate in lactation	Indicates the monthly average number of piglets weaned per sow
Average number of weaning pigs	The yearly average number of piglets weaned per sow
Average number of marketed pigs	The yearly average number of marketed piglets (sales for pork) per sow (alive from lactation to finish)
Mortality rate from weaning to finish	The monthly mortality rate at the lactation level = (total birth count – number of weaning pigs) / total birth count × 100%
Cost of medical expenditure (KRW*)	The monthly mortality rate at the growth level = (number of marketed pigs – number of weaning pigs) / number of marketed pigs × 100%
Cost of antimicrobial expenditure (KRW)	The monthly average medical expenses incurred per sow

Note: *KRW = South Korean Won.

more specifically, the costs associated with purchasing antimicrobials. This helps assess the impact of the AI intervention on reducing AMU.

The analysis examines the before- and after-effects of adopting AI technology, while also tracking the serial impacts at different intervals (e.g. six months, one year and two years) post-intervention. This aimed to identify when the marginal effects caused by the AI technology are most pronounced, as well as their evolution over time.

Table 15 provides an example of a farm that benefited from the introduction of AI technology in February 2021, with baseline data from January 2021. Follow-up measurements were taken at six months, one year and annually thereafter to observe changes in productivity. Key findings include improvements in immune grade, pregnancy rate and a reduction in medical expenses, which all indicate effective health management through AI. However, certain metrics, such as mortality rates during different growth stages, showed delayed improvement. This suggests that some management practices might be slower to respond to technological interventions.

Table 16 examines the effects of AI technology on a Grand Parent (GP) farm, known for managing high-value breeding stock. Despite optimal management, initial challenges, such as suboptimal immune grades, were observed. However, the farm demonstrated a high initial pregnancy rate, with minimal increases after the AI intervention due to pre-existing efficient practices. The data also suggests a shift toward preventive care, with reductions in antimicrobial expenditures. These case studies offer insight to the effects of AI interventions, highlighting how AI can improve farm health status and operations, as well as the temporal dynamics of such improvements.

An added potential benefit of the AI solution is improvements in animal health status. However, the evaluation of health status comparing AI-intervention to conventional farms revealed that only a few haematological parameters were statistically significant. The majority fell within normal reference ranges. This is likely due to the short duration of follow-ups in the case study. Future studies should allow for sufficient time to observe changes in health status.

In summary, it is challenging to address AMR within the livestock industry, and it is separate to addressing productivity issues on livestock farms. AMR on livestock farms generally stems from farming practices aimed at increasing farm profitability, where more pigs are raised in confined and narrower spaces with fewer labour inputs (Manyi-Loh *et al.,* 2018; Sneeringer *et al.,* 2016). Simply requiring larger spaces, more labour or

TABLE 15 Integrated farm case study

	Before AI application	After AI application			
	1 month (M)	ca. 6M	ca. 1 year (Y)	ca. 2Y	ca. 3Y
Variable	Jan. 2021	Jul. 2021	Dec. 2021	Dec. 2022	Dec. 2023
Immune grade	Grade C	Grade A	Grade A	Grade A	Grade A
Pregnancy rate	65%	93%	95%	94%	95%
Average number of piglets	10.09	12.47	12.92	13.31	13.5
Average number of weaning pigs per sow	8.8	10.9	11.2	11.9	12.4
Mortality rate in lactation	12.78%	12.59%	13.31%	10.59%	8.15%
Average number of weaning pigs per sow	20.48	23.11	23.74	25.70	27.16
Average number of marketed pigs	17.92	20.50	22.80	24.28	26.90
Average mortality rate from weaning to finish	12.59%	16.67%	9.52%	8.05%	1.10%
Cost of medical expenditure (KRW*)	32,200	25,400	21,000	18,000	18,000
Cost of antimicrobial expenditure (KRW)	17,500	12,100	8,400	8,200	8,200

Note: *KRW = South Korean Won.

TABLE 16 Grand Parent farm case study

Variable	Before AI application	After AI application		
	1 month (M)	ca. 6M	ca. 1.5 years (Y)	Ca. 2.5Y
	Jun. 2021	Dec. 2021	Dec. 2022	Dec. 2023
Immune grade	Grade C	Grade A	Grade A	Grade A
Pregnancy rate	89%	90%	93%	94%
Average number of piglets	10.10	10.20	10.50	10.90
Average number of weaning pigs per sow	9.90	10.00	10.50	10.70
Mortality rate in lactation	1.98%	1.96%	0.00%	1.83%
Average number of weaning pigs per sow	21.78	22.10	23.10	23.86
Average number of marketed pigs	21.50	21.60	22.90	23.80
Average mortality rate from weaning to finish	1.38%	2.26%	0.87%	0.42%
Cost of medical expenditure (KRW*)	28,300	27,500	26,700	25,100
Cost of antimicrobial expenditure (KRW)	8,490	7,040	6,675	5,800

Note: *KRW = South Korean Won.

Key messages

The impact of AI technology on farm productivity, disease burden and AMU:

- Improved immune grade, pregnancy and fertility rate, higher number of weaning pigs per sow, reduced mortality and increased number of marketed pigs.
- Reduced medical expenses and AMU. This indicates greater benefits and better health management.

the management of fewer animals on farms will not solve the problem. Farm profitability is crucial for the livelihood of farmers, and this underpins most of their management practices. To achieve sustainable animal farming, idealistic methods are not enough when faced with the realities of farms. Ensuring sustainability in animal farming also means ensuring farmer productivity. Therefore, ways to address AMR issues must be found that do not compromise farm profitability and the livelihoods of the families depending on them.

This analysis has demonstrated that raising healthy livestock – a crucial step to increasing farm profitability and addressing AMR emergence and spread – is an attainable and economically viable goal. First, the AI intervention led to a 417% ROI per pig per year, implying a net profit of approx. KRW 4,170 per pig, gained on a KRW 1,000 in comparison to conventional farms (this corresponds to a $1 investment with a return of $4.17). Considering that a swine farm may rear tens of thousands of pigs per year, a 417% return on investment per single pig is a significant annual profit (depending on the farm size). Second, a significant difference was observed in medical expenses per pig in AI-intervention farms compared to conventional farms, and this increased over time. Third, AI-intervention farms have shown a gradual improvement in the immune grade, a long-term decrease in mortality rate and a reduction in the cost of AMU (from KRW 17,500 to KRW 8,200, which is a 53% decrease).

LIMITATIONS OF THE CASE STUDY

Due to limited access and data availability for both AI-intervention and conventional farms, the study was restricted to a comparison of a subset of AI-intervention farms and open-access data for conventional farms. Additionally, there was insufficient time to follow-up on animal health status using haematological indicators during the study.

CHAPTER 5

Practices on-the-ground against a backdrop of a National Action Plan: the case of Bangladesh

BACKGROUND

AMR is a growing concern globally, yet the impact is particularly severe for LMICs. This case study focused on Bangladesh, a nation with intensive farming and a growing economy linked to food production and exports. Poultry production systems are considered a high-risk environment for the emergence of AMR in low-income settings, and Bangladesh has seen a rapid expansion of commercial poultry production (Caputo *et al.,* 2023). Fisheries, vital for food security, have also emerged as a key challenge area for AMR development, primarily through the misuse of antimicrobials. Bangladesh also has a rapidly growing fisheries sector, which serves as a useful case study to understand practices and perceptions on AMU/AMR on the ground (Chowdhury *et al.,* 2022).

Bangladesh developed and implemented its first NAP from 2017 to 2022 (Fleming Fund, 2018). The action plan emphasises effective collaboration across One Health sectors. Since 2012, multi-sectoral committees and working groups have been implementing integrated AMR and One Health activities. To understand the actual practice of AMU against the backdrop of the NAP, this study conducted a multifaceted data collection exercise in Bangladesh from its fisheries and livestock sectors. Hence, this chapter identifies the challenges of NAP implementation and where focused effort is required to contain the rising use of antimicrobials. For details of the methodology and a description of each audience (key informant, health professional, farmer), please refer to Chapter 1.

RESULTS

Livestock sector key informant interviews

Key informants from the livestock sector felt that Bangladesh has enough policies for tackling AMR, but the nation lacks implementation and monitoring where concerted efforts are required

Key informants from the Bangladesh livestock sector (n = 5) indicated that there are already multiple legislations and policies in place that support the more responsible use of antimicrobials in Bangladesh. Namely, the Drug and Cosmetic Act, 2023; Drug Act, 1940; Fish Feed and Animal Feed Act, 2010; High Court Verdict, 2019; Animal Feed Act, 2010; AMR National Action Plan; Animal Disease Act, 2005, as well as specific curbs on the use of select antimicrobials for animal treatment (e.g. Colistin, Fosfomycin, Ciprofloxacin, Azithromycin) by the Directorate General of Drug Administration, 2019.

Key informants have varied views on the level of implementation of the NAPs' strategic policy interventions. However, they all agree that the sector should see increased investment and capacity building, with the government investing in more sentinel diagnostic laboratories around the nation to test for AMR susceptibility.

Focus should lie on targeted pathogens being routinely tested in the poultry sector. Interviewees highlighted some successes from initiatives that sought to curb the occurrence and spread of AMR: more participation in campaigns against AMR/AMU, regular intersectoral meetings to develop targeted strategies on how to reduce AMR and increased investment in research activities. A prime example is the government's development of loan programmes that incentivise farmers to register on their database for the routine collection of AMU data.

Key informants reported challenges with AMU and its reduction: lack of investment and human resources in sentinel diagnostic laboratories across the country, underdeveloped AMR surveillance networks and unregulated AMU by farmers. A further barrier to the implementation of NAPs was the lack of collaboration and communication across government ministries, particularly in data sharing and priority setting. Another issue raised was a lack of political interest in exploring the extent of AMR within livestock for fear of disrupting food supply chains. Moreover, beyond data quality, data sharing was cited as a further barrier, based on confidentiality concerns and ministries being unwilling to share data. However, the One Health secretariat has fostered the adoption of a National One Health Strategic Framework that will address some of the above-mentioned challenges.

Livestock key informants felt that significant workforce upskilling and investment are required to achieve a reduction in AMU

Key informants stated that antimicrobials are mainly used in poultry and cattle (dairy and beef) farming in Bangladesh. Secondary to these groups are fisheries, mainly shrimp and pond fish farming. Among the farm types that use antimicrobials, it was felt that indiscriminate use of antimicrobials is most likely to occur on poultry farms.

Key informants perceived the main drivers of AMR emergence and spread in Bangladesh to be the misuse and overuse of antimicrobials, poor regulatory enforcement, poor animal vaccination coverage, farm biosecurity and lack of resources (i.e. laboratory facilities) and AMU surveillance. The most economically impactful diseases affecting livestock in Bangladesh were cited as mastitis (in dairy animals), salmonellosis, anthrax, fibromuscular dysplasia and lumpy skin disease.

Respondents pointed to contributory factors for the indiscriminate use of antimicrobials, such as easy access to antimicrobials without prescription and farmers' use of antimicrobials without consultation of registered veterinarians. Moreover, respondents highlighted the aggressive marketing of antimicrobials by pharmaceutical companies and feed dealers. As a remedy to these issues, respondents advocated for real-time monitoring of AMU on food-animal farms, more skilled human resources and funding for AMR surveillance activities, as well as a dedicated virtual platform or system to aid with AMR/AMU surveillance.

Livestock sector animal health professionals survey

Livestock health professionals cited rising trends of AMR infections in livestock, with treatment failures and deaths becoming more prevalent. Most professionals in clinical practice are concerned about the impact of AMR

The survey of livestock health professionals elicited key insights on the practices of AMU in Bangladesh. Of the 73 respondents, 87% had been trained on the topic of AMR. Respondents reported that farmers primarily request antimicrobials to increase the animal's recovery speed, to prevent or cure infections, as well as for growth promotion.

Preventive and treatment alternatives to antimicrobials are used less often by animal health professionals. When these are used, over half of respondents indicated that they use vaccines (53%) and probiotics (51%). To help reduce AMU, almost all respondents currently advise farmers to use vaccinations. Most respondents do not commonly perform microbial culture and susceptibility tests before prescribing antimicrobials to sick animals, or to modify treatment. This is mainly because most respondents (76%) cannot afford the necessary laboratory facilities to conduct the right tests before prescribing antimicrobials. Key informants agreed with this, citing a lack of resources and infrastructure access.

Respondents highlighted that they perceive treatment failures and deaths during treatments as becoming more common, where 81% of the respondents indicated a rising trend in the frequency of treatment failures, and 57% indicated an increase in deaths.

The survey also indicated that AMR in Bangladesh is a substantial problem in terms of perceived prevalence and economic burden. Over 70% of respondents reported perceived AMR prevalence, with over half rating perceived prevalence in their region as 'medium'. Almost all respondents (88%) reported experiencing the economic impacts of AMR or AMU. These impacts were described in free form text. Common themes included: rising costs due to the increase in use and duration of antimicrobials and associated veterinary expenses; decrease in animal productivity while on treatments; increase in animal mortality and decrease in reproduction; as well as a decrease in overall farm productivity.

Livestock farmers survey

The survey of large-scale farmers in Bangladesh aimed to understand the extent of farmers' awareness of AMR, AMU practices, disease and disease burden, as well as drivers of AMU among farmers. The livestock sector survey sampled 1,054 farmers across two high livestock production districts of Sirajganj (n = 458) and Tangail (n = 596) in Bangladesh.

AMR awareness and AMU practices

Awareness of AMR among farmers is notably low, offering evidence for policy-makers to address this critical knowledge gap. Most of the surveyed farmers (69%) are not aware of the term 'AMR'. Over half cannot provide a definitive answer on whether excessive AMU makes drugs ineffective over time and whether sick animals and products from sick animals can transmit disease to humans (51%).

A worrying factor is the ease of access to antimicrobials without a prescription through unqualified veterinary service providers. This practice contributes to excessive and unwarranted AMU. Approximately 41% of farmers reported using antimicrobials without a prescription, and 72% indicated that commonly used antimicrobials are readily accessible. Stockpiling (25%) and the use of expired antimicrobials (12%) are further practices observed among farmers.

Large-scale indiscriminate use of antimicrobials to treat viral infections and for disease prevention is a significant concern. Almost two-thirds (73%) of farmers indicated they use antimicrobials to treat viruses. The majority (87%) of farmers reported using antimicrobials in animal feed formulations, with almost half (44%) reporting AMU for disease prevention without any prescription for such use by a competent authority.

Farmers also reported concerning practices that are well-known to contribute to the development of AMR in animals and humans: discontinuing antimicrobial treatment before the course is complete, administering higher doses of medicine after treatments fail to work or slaughtering the animal for human consumption, as well as not waiting after administering antimicrobials before human consumption.

Financial implications of AMU were the primary concerns of farmers when considering a reduction in AMU, both in the sense of cost savings and preventing production loss. Reducing AMU is being considered by 58% of farmers, primarily to reduce costs, while 42% have not considered reducing AMU. About half of farmers (52%) believe that reducing AMU on their farm will have negative consequences, such as reducing sales or profits.

Animal disease and death impacts on farmers

Livestock disease and death have profound impacts on farmers, affecting both the economic and social aspects of their lives. A significant proportion of respondents, 62% (647 farmers), had experienced the death of a sick animal on their farms. A range of economic impacts and losses were cited as a result. Cattle faced an average of 1.3 deaths per report, with a maximum of 15 deaths, based on 591 reports. Death of cattle causes significant economic damage, with an average loss of 1857.19 and a peak loss of 3,00,000, in Bangladeshi taka (BDT), reported in 588 cases. Poultry experienced an even higher average death rate of 560.4, with a maximum of 130,000 deaths across 601 reports. The economic losses for poultry were also significant, averaging BDT 106,503.8 (approx. € 834) and reaching as high as BDT 5,400,000 (approx. € 42,314), based on 597 reports.

Beyond the monetary value, livestock disease and death also cause significant disruption and difficulty to households. Farmers reported that households had to cut back on provisions of clothes, healthcare and school materials for their children. Employment was also affected, as farmers had to let go employees and reduce working hours due to livestock disease or death.

Trusted sources of information on AMU and channels of access to antimicrobials

Farmers trust their peer farmers and untrained service providers as their primary information sources on antimicrobials and to treat sick animals. About 37% (388 farmers) indicated that they sometimes or always purchase medication themselves rather than seeking veterinary advice.

When asked about the major source of advice on AMU for non-sick animals, 57.7% (283 farmers) of the advice comes from untrained service providers, peer farmers, pharmacies and drug sellers, as well as contract buyers. Regarding levels of trust in information about AMU, 40.6% (430 farmers) trust untrained service providers, peer farmers, pharmacies and drug sellers, and contract buyers.

Untrained service providers are commonly used to treat sick animals. Overall, 57.2% (607 farmers) reported rarely or never seeking veterinary services. This is a high result, indicating a predisposition to the potential misuse or overuse of antimicrobials.

Analysis of the responses underscores the diverse sources and practices of AMU among farmers, highlighting the significant role of untrained service providers and the varying levels of trust and pressure from external bodies. Understanding these dynamics is crucial for developing strategies that can influence and improve AMU practices among farmers.

Drivers of spending on antimicrobials among livestock farmers in Bangladesh

A linear regression model was used to identify the primary drivers of spending on antimicrobials (described in Annex G). The analysis of potential factors to impact spending on antimicrobials shows that antimicrobial expenditure is significantly driven by factors related to farm size and type, experience of drug failure and practices linked to treatment and feed. This highlights which areas require targeted policy interventions. Farm size, experience of drug failure, and use of antimicrobials in feed formulation is positively associated with farmers spending on antimicrobials. Annual antimicrobial expenditure was found to be 74% higher if the farmer was the last person to administer antimicrobials to a sick animal, in comparison to a farmer using external service providers. In contrast, farmers who seek health professionals to treat sick animals spend an average 21% less than those who do not. Family farms spend 81% less on antimicrobials per year compared to commercial farms. Table G.1 in Annex G presents the regression results on the main drivers of spending on antimicrobials, alongside a detailed discussion of the results.

Key messages

Bangladesh livestock sector case study: a summary

Key informants and health professionals in the livestock sector reported raised concerns on AMR due to challenges of policy implementation, treatment failures and negative economic impacts. Interviews with 1,054 farmers revealed the following:

- Farmers lack awareness of AMU/AMR and of best practices, and there is widespread misuse of antimicrobials.
- Easy access to drugs emphasises the need for targeted interventions to promote responsible AMU and combat AMR.
- Morbidity and mortality are substantial health and economic burden to farmers with social implications (e.g. children not attending school, etc.).

Fisheries sector key informant interviews

Key informants from the fisheries sector feel that more effort is needed to combat AMR and indiscriminate AMU in Bangladesh

Six key informants from the fisheries sector in Bangladesh were interviewed. Overall, the key informants were aware of Bangladesh's NAP for AMR; however, there was less awareness of how the NAP was being implemented. Respondents could identify specific policies to help combat AMR, such as the Fish Feed and Animals Feed Act of 2010 (a joint effort between the Department of Livestock services and the Department of Fisheries), the National Residue Control Plan, the Fish Inspection and Quality Control Act (revised in 2020) and the Aquacultural Medicinal Product Control Guideline (2015).

The National Residue Control Plan was emphasised as the most successful intervention to help reduce AMU in aquaculture. This plan involves testing for antimicrobial residues in aquaculture products intended for international export. If farmers are found to be non-compliant with the plan, their products cannot be accepted. Farmers are then trained to minimise the risk of future non-compliance. Anecdotal evidence from the respondents suggests that this monitoring process has detected minimal antimicrobial residues in the final aquaculture products. Other interventions mentioned included advocacy, awareness and training programmes.

Despite the highlighted policies, many key informants believed that the efforts to combat AMR are insufficient and that more must be done, with the current policies and interventions being unknown to farmers or not being enforced. Key informants expressed that efforts to curb AMR were more focused on livestock than aquaculture. Notable challenges associated with reducing AMR and AMU in Bangladesh's aquaculture were cited as the influence of pharmaceutical company representatives on farmers, the presence of falsified medicines, and farmers' attitudes, beliefs and lack of knowledge. Key informants highlighted the need for improvements to biosecurity, surveillance, awareness, training, treatment guidelines and diagnostic capacity. They also supported the increased usage of antimicrobial alternatives, such as probiotics (especially indigenous probiotics) and vaccines.

Fish health professionals

AMU awareness and practices

Responses from 27 fish health professionals were analysed. Findings show that interventions targeted at improving the education of fish health professionals may be beneficial to enhance AMU awareness and practices. Forty-four percent of fish health professionals indicated they have not received training or participated in a workshop or conference on AMU and AMR. Almost a quarter of respondents (24%) report that they rarely advise farmers to complete the full course of antimicrobials and 16% admit to writing antimicrobial prescriptions for farmers without visiting their aquaculture farm; both these practices contribute to indiscriminate AMU. Furthermore, respondents alluded to AMU practices being driven by outside influences, such as pressure from farmers (43%) and pharmaceutical companies (31%) to prescribe antimicrobials or to increase the dosage occurring at least some of the time.

The use of alternatives to antimicrobials warrants further promotion among aquatic health professionals. Thirty-one percent of fish health professionals reported rarely or never using alternatives to antimicrobials. However, when alternatives are used, 70% use probiotics. None of the respondents use vaccines as a preventive alternative, which is in keeping with the wider ecosystem in Bangladesh where vaccines have not been introduced in the fisheries sector, as reported by sector key informants in the interviews.

Over half of respondents (62%) are concerned about AMR becoming a problem in their clinical practice. Sixty percent reported that they at least sometimes experience treatment failure on their sick fish, with almost two thirds (73%) reporting at least a small increase in the change in frequency of a treatment not working. However, it is not clear from the survey results if the treatment in reference is specific to antimicrobials or if it was prescribed appropriately.

Aquaculture farmers survey

Aquaculture farmers have low awareness of AMR and commonly use untrained service providers for advice and administration of antimicrobials

Aquaculture farmers in Bangladesh (*n* = 405) were surveyed across the districts of Mymensingh (*n* = 204) and Khulna (*n* = 201). Findings show that aquaculture farmers have limited awareness of key AMR concepts. Over half (66%) of respondents are not aware of the term AMR. Akin to the livestock sector, this is an area where targeted educational interventions to reduce AMU may prove successful. Policies aimed at the affordability of professional health services and availability of antibiotics without a prescription may influence farmers to rely more on trained health professionals, in turn supporting more prudent AMU; currently, only a third (32%) of farmers rely on fish health professionals for treatment of sick fish. Findings further underscore the dependence of aquaculture farmers on untrained service providers and their self-autonomy when treating fish stocks. Moreover, farmers report low trust levels (27%) in fish health professionals when it comes to advice on AMU. Like the livestock sector, inappropriate use of AMU was also reported in the fisheries sector. To influence AMU practices effectively, initiatives should focus on strengthening the role of fish health professionals among farmers, thereby ensuring prudent AMU and building trust in professional advice through community engagement and training for farmers. AMU may be driven by economic perceptions, such as the belief that antibiotics use leads to higher prices for aquaculture products, or the misconception that there will be negative consequences if AMU is reduced. For detailed results, refer to Annex G.

Impact of animal disease and death on aquaculture farm productivity

In the aquaculture farming sector, disease and mass die-offs have had profound impacts on farmers, extending beyond mere productivity losses. Almost half (48%) of farmers reported experiencing mass die-offs on their aquaculture farms, leading to a wide range of economic and social challenges. However, the study's results do not reveal if these deaths are attributable to AMR. Household difficulties resulting from aquaculture loss or disease were reported by 65% of respondents (*n* = 263). Of those that reported household difficulties, many noted the need to reduce spending on essential provisions or services, such as sending children to school (35%), buying school materials (59%), clothing for household members (66%) and healthcare visits for family members (41%). Impacts on employment were also noted, with 41% (*n* = 142) of farmers reporting having to let go of employees and 26% (*n* = 89) of farmers reducing employee work hours.

From a financial perspective, 48% of farmers took out bank loans to re-establish their farms or restock after disease incidents. The reported impacts of losses due to disease and mass die-offs varied across the respondents. Economic losses due to mass die-offs averaged BDT 533,301.35 (approx. € 4,152) across 405 cases, with a maximum loss of BDT 15,000,000 (approx. € 116,790).

Drivers of spending on antimicrobials among aquaculture farms in Bangladesh

Antimicrobial spending among aquaculture farmers in Bangladesh is influenced by a range of demographic and operational factors. A regression modelling approach was used for analysis, as described in Annex G. Variables found to have significantly links to rises in spending on antimicrobials were: farm size, past experience of fish mass die-off, use of fish health professionals to administer the antimicrobials, and use of untrained service providers to treat fish disease. Conversely, using antimicrobials for a single purpose and opting to always visit a fish health professional when animals are sick are associated with decreased antimicrobial expenditure. These insights can inform targeted interventions and policies to optimise AMU and enhance aquaculture farm management practices. More detailed results can be found in Annex G.

Key messages

Bangladesh fisheries sector case study: a summary

- Key informants in the fisheries sector highlighted that current policies to combat AMR are not visible to farmers nor are they enforced. They also advocated for better biosecurity, surveillance, awareness, training, treatment guidelines and diagnostics to curb AMR.
- 44% of fish health professionals lacked training and 66% of farmers lack awareness of AMR, necessitating educational interventions on AMU and AMR.
- Fish health professionals experience pressure from other farmers and the industry to use antimicrobials.
- Fish farmers reported relying on untrained service providers and on self-autonomy for treatment and disease management.

CHAPTER 6

Conclusions and recommendations

CONCLUSIONS

The economic and societal burden of AMR continues to rise, with clear impacts across the sectors of food production, trade, animal welfare, human health and labour, to name just a few. Given the indiscriminate use of antimicrobials in many settings and geographies, the increase in resistant infections in both animals and humans, and the subsequent threats to food security due to production losses, it is critical to focus efforts on understanding the mechanisms and scale of impact of AMR in the greater context of agriculture.

This study has highlighted how current trends of not tackling AMR translate to significant economic and livestock production losses based on counterfactual scenarios. By 2050, it is estimated that the annual livestock production losses due to AMR equal the consumption needs of 746 million people (comparing the reference scenario to scenario 1 with a low resistance rate of 5%). Under a more pessimistic assumption about the future use of AMU and associated AMR-disease burden (comparing the reference scenario to scenario 2), the estimated yearly production losses equal the consumption needs of about two billion people globally. Livestock production losses are heaviest in cattle and poultry meat production compared to the other livestock output types, when assessed in scenarios 1 and 2. By 2050, the estimated cumulative global GDP loss for 2025–2050 due to AMR in livestock is US$ 575 billion (comparing the reference scenario to scenario 1 with a low resistance rate of 5%). Under the more pessimistic assumptions about the future use of AMU and associated AMR-disease burden (comparing the reference scenario to scenario 2) the estimated cumulative GDP loss for 2025–2050 is US$ 953 billion. Considering even moderate harmful spillover effects of AMU and AMR in livestock on human health, cumulative global GDP losses for 2025–2050, associated with lower labour productivity, are estimated to be US$ 1.1 trillion (comparing the reference scenario with scenario 5). Considering a pessimistic scenario for both, the direct AMR burden on livestock and the potential spillover effects on humans (comparing the reference scenario to scenario 6), the cumulative GDP loss for 2025–2050 could rise to US$ 5.2 trillion by 2050.

The study also highlights the potential gains if interventions are made to curb AMU to varying extents from 2025 to 2050. Economic projections highlight the potential economic gain from interventions aimed at reducing AMU in livestock. Results suggest that a global reduction in AMU of around 30% is predicted to increase global GDP cumulatively in the period 2025–2050 by US$ 120 billion (comparing the reference scenario to scenario 3). Moreover, statistical analysis suggests that countries using antimicrobials for growth promotion in livestock are estimated to have an average 45% higher antimicrobial use per kilogram of animal biomass, than countries where there is no use of growth promoters. This estimation concerns all classes of antimicrobials except ionophores. As previously reported by WOAH (2023b, 2024c), the use of antimicrobials as growth promoters is still practised by 20% of its membership, with 75% of those concentrated in the regions of the Americas, and Asia and the Pacific. By mitigating resistance rates by interventions that target AMU and AMR, economic benefits can be realised that potentially outweigh the costs of implementation.

While there are interventions that provide alternatives to AMU, they are often inaccessible due to prohibitive costs and lack of infrastructure. As such, this study also highlights the use case of a low-cost and simple to implement intervention that applies AI and offers high ROI. This strategy and other examples highlighted in this study provide a suite of interventions that could be deployed in various global settings, particularly in LMICs. The case study of swine farms offers an evaluation of an innovative low-cost intervention for early disease detection based on AI, and the results show a benefit-to-cost ratio of four. This indicates an average yearly ROI of 400% per pig, ranging from 225% in the first year to 537% in the third year of implementation. Medical costs of AI-intervention farms were consistently lower and even decreased over the study period in comparison to conventional farms. In addition, this AI solution has seen successful implementation in LMICs in small-, medium- and large-scale farms with encasements.

Furthermore, this EcoAMR study has provided on-the-ground evidence from an LMIC perspective on the practices of AMU, as well as the challenges and barriers to improvements and to implementing NAPs for AMR. A KAP case study was conducted among over 1,450 livestock and aquaculture farms in Bangladesh, and evidence reveals a persistent lack of AMU and AMR awareness, as well as AMU practices that contribute to AMR emergence and spread among farms. Farmers often rely on untrained service providers for disease management; this type of practice promotes indiscriminate use of antimicrobials, and the propagation of substandard and falsified medicines. The Bangladesh case study revealed that high expenditures on antimicrobials are driven by AMU in feed, the use of untrained service providers, disease outbreaks, resistant disease management and farm size. The results suggest that the implementation of current policies to tackle AMR lack the required financial investment and human resources.

RECOMMENDATIONS

A main challenge in this study was access to comprehensive and high-quality data for accurate modelling, and this highlighted a systemic gap in the food-producing animal sector around consistent data collection and sharing. This is a substantial barrier, as a large proportion of AMU or AMR infections may be underreported, especially in LMICs. This study has also highlighted evidence that lack of access to viable alternatives to AMU is a critical driver for their indiscriminate use. At times, the strong reliance on AMU is due to perceptions of its benefits on productivity. Based on these results, the following recommendations are proposed to mitigate potential economic ramifications of AMR in food-producing animals:

1. Prioritise preventive interventions to reduce the burden of disease in animals. This will lead to a reduced need for AMU in livestock, as the economic benefits likely outweigh the costs of implementation. There are two aspects to this recommendation:
    a. strategies must be developed and deployed to reduce the need for AMU, such as vaccination, evidence-based effective alternatives to antimicrobials, and good farm management practices based on biosecurity and nutrition;
    b. cost-effective real-time early disease detection interventions must be implemented (e.g. AI-enabled solutions or equivalent alternatives) that can inform prompt disease management, avert the need for AMU and reduce the selection pressure for AMR emergence and spread.
2. Enforce formal prescription practices and improve access and affordability to essential antimicrobials, including the implementation of preventive measures (e.g. vaccines), facilitation of regulations and promotion of R&D.
3. Phase out AMU for growth promotion in food-producing animals.
4. Strengthen and institutionalise surveillance systems for AMU and AMR, including comprehensive

data capture on diseases, and risk factors associated with food-producing animals, via a One Health perspective for data sharing and evidence-based decision-making across sectors. This should also include the establishment of a global baseline for AMR resistance in food-producing animals.

5. Establish and quantify the spillover linkages and impacts of AMR between food-producing animals and humans, determining the interconnectedness and enabling accurate risk estimations of the real-world economic impact of AMR to better inform policy-makers and responses.
6. Improve awareness by educating farming communities on AMR and training health professionals on the prudent and responsible use of antimicrobials in food-producing animals. Promote mechanisms to reward farmers who comply with policy and regulations, and who undertake available training as necessary.
7. Sustainable investment and financing of initiatives such as:
   a. infrastructure development (e.g. sentinel diagnostic laboratories and rapid in-field diagnostics) to generate the high-quality data necessary for analyses and evidence;
   b. R&D to mitigate the gap crisis in the animal health sector to reduce AMU and AMR;
   c. analyses to establish the economic impact and build a case for investment in AMR using a One Health approach. In this way, WOAH Members and other key stakeholders can be appropriately informed about cost-effective interventions that reduce global AMU and AMR.

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Annex A: Conceptual approach and scope of the modelling work to assess the economic effects of AMR in livestock production

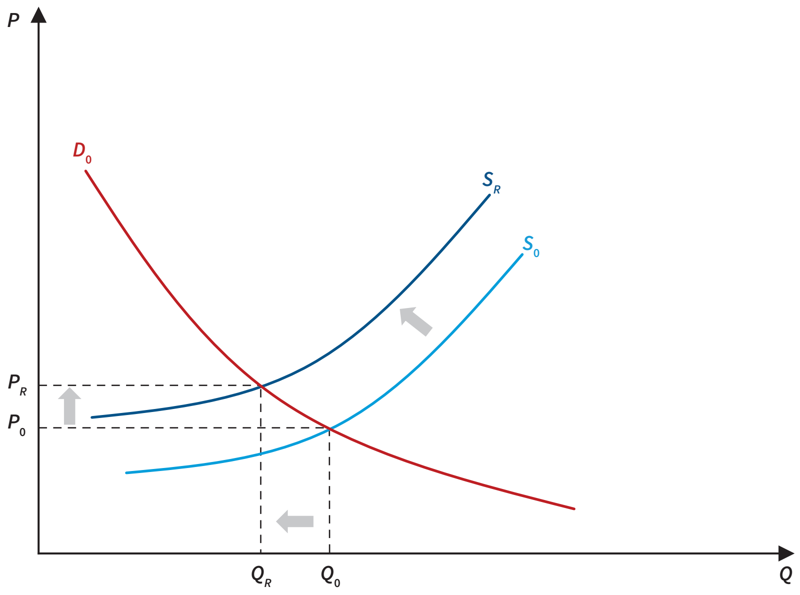
Applying the theory of production economics helps to understand the decision process that farms undertake in a context of disease existence, specifically regarding bacterial infections. The theory outlines how farmers make decisions that satisfy their objective of profit-maximisation (or cost-minimisation). Here, optimal decisions are determined by (1) the market prices of production inputs and outputs, which are exogenous to the individual farm; and (2) the existing production technology that determines the maximum level of production output. The latter refers to the process in which inputs are converted into outputs (e.g. also known as the production function). In this context, bacterial infections affect the quantity of outputs produced per level of inputs. Additional costs are caused by disease control efforts or mitigation results, leading to increased production costs per unit of output. This results in higher expenses needed to cover the production costs, resulting in lower output sold, since market prices are exogenous to individual farms.

The production function can also include scaling factors related to diseases; these reduce output at any given level of the current production technology and production inputs. For example, in relation to the concept of the Animal Health Loss Envelope, Gilbert et al. (2024) outline the following farm-level production function:

$$y = F(z)x\ [1 - L(bx\ (1 - C(x))]$$

In this equation, y represents the farm output, and $F(z)$ is the production function for ordinary production inputs z (e.g. animal food) (Gilbert *et al.,* 2024). L represents a loss function, which takes values between 0 and 1 that describe the impact of an infection-causing pathogen b on production y. Moreover, $C(x)$ is a control function that lies in the interval between 0 and 1 and increases with inputs x, which represent disease control inputs (e.g. antimicrobials), which in turn mitigate the effect of b. When b is equal to 0, there is no loss in output because of disease; this is denoted as y^*. The loss function represents a loss-expenditure frontier due to disease, where farms choose the optimal combination of production loss *versus* expenditure on control inputs to minimise their expenses based on exogenous cost inputs (e.g. market prices for lost production and control inputs). In the presence of resistant infections, treatments become less effective, resulting in a shift of the loss-expenditure frontier to the right, where at any given level of disease control expenditure, the loss in

FIGURE A.1 Supply and demand with and without resistant infections



output is higher or the cost to achieve the same level of output loss requires greater expenditure.

At the aggregate demand level, bacterial infections reduce productivity and income, while also incurring additional production costs. Since farms must increase prices for products to cover their costs, this may lead to a decrease in consumer demand. The occurrence of resistant infections adds to farm costs and further elevates prices. This is depicted in the aggregated sectorial supply curve in Figure A.1. The demand curve D_0 illustrates the quantity of goods of a given livestock sector (e.g. beef) that consumers are willing to purchase at different market prices (P). In the absence of resistant infections, farms can supply quantity Q_0 at prices P_0, and consumers are willing to purchase this quantity at the same price in a state of market equilibrium. As the occurrence of resistant infections is likely to increase the production cost per unit of goods supplied to the market, farms will therefore need to charge a higher price to cover the increase in expenditure. This leads to a shift in the supply curve from S_0 to S_R, where at price P_R consumers choose to consume less. Without a change in consumer preferences (e.g. a shift in the demand curve), the new market equilibrium is at quantity Q_R and price P_R. In practice, this implies that, on aggregate, the reduced quantity supplied either stems from farms exiting the market or choosing to reduce their production output. Note that bacterial infections and increasing resistance could also cause changes in consumer preferences. For example, if consumers dislike the excessive use of antimicrobials in livestock production, they may be willing to pay higher prices for a given quantity if the product is AMU-free. On the other hand, if the product has been produced with AMU, they may be willing to pay less. This change in the consumer's willingness to pay shifts the demand curve to the right.

Furthermore, AMU in food-producing animals has been linked to AMR in humans. As a result, this can have negative externalities on other sectors that are not taken into account by farmers in their decision-making process. Thus, the use of AMU in livestock sectors has been targeted by policy interventions to restrict the use of antimicrobials in livestock production, including measures to encourage the prudent use of antimicrobials, to improve animal husbandry or biosecurity.

MODEL CONCEPTUALISATION

As outlined above, when considering the economics of infectious disease in livestock production sectors, it is important to consider the long-term trade-off between AMU and AMR. As discussed, antimicrobials are used in livestock production for disease management, as well as for productivity enhancement; restricting their use may adversely affect animal productivity, farm income and even the broader food supply. However, increasing resistance rates associated with excessive AMU make the existing disease management practices employing AMU less efficient and more costly for livestock sectors due to elevated levels of animal mortality and morbidity, and reduced productivity.

Previous studies have applied different modelling techniques to quantify the relationship between AMU and AMR, including (1) mathematical compartment models; or (2) empirically driven modelling approaches that use historical data for consumption and resistance (Emes *et al.,* 2022). In the former, mathematical compartment models track populations over time and capture effects of interactions between population groups as functions of transmission rates, antimicrobial exposure and the way resistance evolves over time. The advantage of such deterministic models is that the acquisition of resistance can be modelled via underlying epidemiological foundations. However, these models can be complex and rely on existing data to calibrate key input parameters (e.g. transmission rates), which are often not directly observable and must be estimated indirectly via existing data sources, then validated against observed data or other research studies. In contrast, purely data-driven statistical analyses do not rely as heavily on the knowledge of transmission mechanisms and their precise interactions. Instead, they can determine the contribution of various factors (e.g. antimicrobial consumption) to key dependent variables (e.g. AMR). An important advantage of such empirically driven regression analysis is that these models can accommodate flexible functional forms (including lags, interactions and non-linearities) that can be used to reflect the relationship of interest more accurately and comprehensively. They can also control for a diverse range of factors to isolate the effect of the variables of interest, while holding other factors constant. On the other hand, a purely empirical approach is often constrained by the availability of data. For example, a recent study aimed to empirically link antimicrobial consumption in animals and humans to resistance levels at the national level (Allel *et al.,* 2023). Due to limitations in data availability, specifically for the animal sector, the study had to consider cross-sectional data and could not exploit additional time-varying or country-specific effects.

The present study applied a modelling framework using an LPD model, subsequently passing on simulated productivity parameters by sector to a dynamic multi-regional economy-wide computable general equilibrium. With this method, the study can consider some dynamics between AMU and AMR in livestock sectors and analyse their consequences from a macroeconomic perspective.

The analytical modelling approach of utilising both the LPD and the DCGE model is comparable to the Agriculture Human Health Micro-Economic model (AHHME) (Emes *et al.,* 2023). The AHHME model is a modelling tool that aims to evaluate the impact (e.g. cost-effectiveness) of interventions in food-animal production using a One Health approach. AHHME is a Markov state transition model where different populations are divided at any given point into different states or so-called 'compartments'. Movements between different compartments over time are modelled through transition probabilities. While similar in nature, the present study's modelling approach differs on certain aspects to the AHHME tool for both the epidemiological and economic components. First, regarding the epidemiological component, the study's approach focuses primarily on food-animal producing sectors but can be extended to model humans in future studies. However, it is currently not modelling the potential externalities between antimicrobial consumption in animals and AMR in humans. Second, the AHHME does not include a link between antimicrobial consumption and resistance, and the user must exogenously assume at the outset the value of how much an intervention may reduce AMR. Third, regarding the economic component, AHHME uses standard approaches in health economics to assess productivity losses caused by a disease (e.g. either through a human capital or friction cost approach). However, such a modelling approach does not consider potential spillovers (e.g. to other sectors, either domestically or abroad via trade links with other countries) from food-animal production sectors onto other economic agents. In comparison, the present study integrates the LPD model with an economy-wide DCGE model that considers these potential spillover effects by modelling an economic system and interactions between different economic agents.

SCOPE OF THE ANALYSIS

When conceptualising the economic costs attributable to AMR in livestock production, this study focuses on the effect of treatment failure due to resistance on sectorial production through its negative impact on animal mortality and morbidity. In the LPD model, resistance to existing antimicrobial treatments affects the number of animals that die prematurely of an infection due to treatment failure before they reach the time of slaughter (e.g. for meat producing sectors); or, if they survive, there is an additional productivity loss (e.g. through impaired growth performance). Both the mortality and morbidity effects attributable to AMR negatively affect the production outputs of the modelled livestock sectors. It is important to highlight that this study only considers the losses in production quantities that are attributable to AMR. That is, the cost of resistant infection is assessed against the counterfactual scenarios of animals having a susceptible infection, and not against the comparison of animals without infection. Furthermore, the analysis only considers bacterial infections; WHOA's 20% production loss estimate due to animal disease represents a high upper boundary estimate for this analysis, as it includes a much broader set of diseases (including viral and fungal infections and other diseases).

In this analysis, it is essential to recognise the difference in production systems across the world. For example, lower-income countries have production systems that use on average less intensive production than in higher-income countries (Gilbert *et al.,* 2018). Further differences can be found in the predominant animal species, and therefore in the biomass heterogeneity within food-producing sectors. For example, while countries in Latin America predominantly hold cattle stocks, some Asian countries produce more swine. Since the types of diseases caused by infections vary by animal species as well as by the characteristics of the production system (e.g. intensive *versus* extensive), it is critical to take these geographical nuances into account. As a result, this study's modelling approach consists of seven geographical regions, as determined by the World Bank (n.d.).

Within these geographical regions, the study models the impacts of productivity effects attributable to AMR across a set of economically relevant production diseases.

Annex B: The livestock production disease model

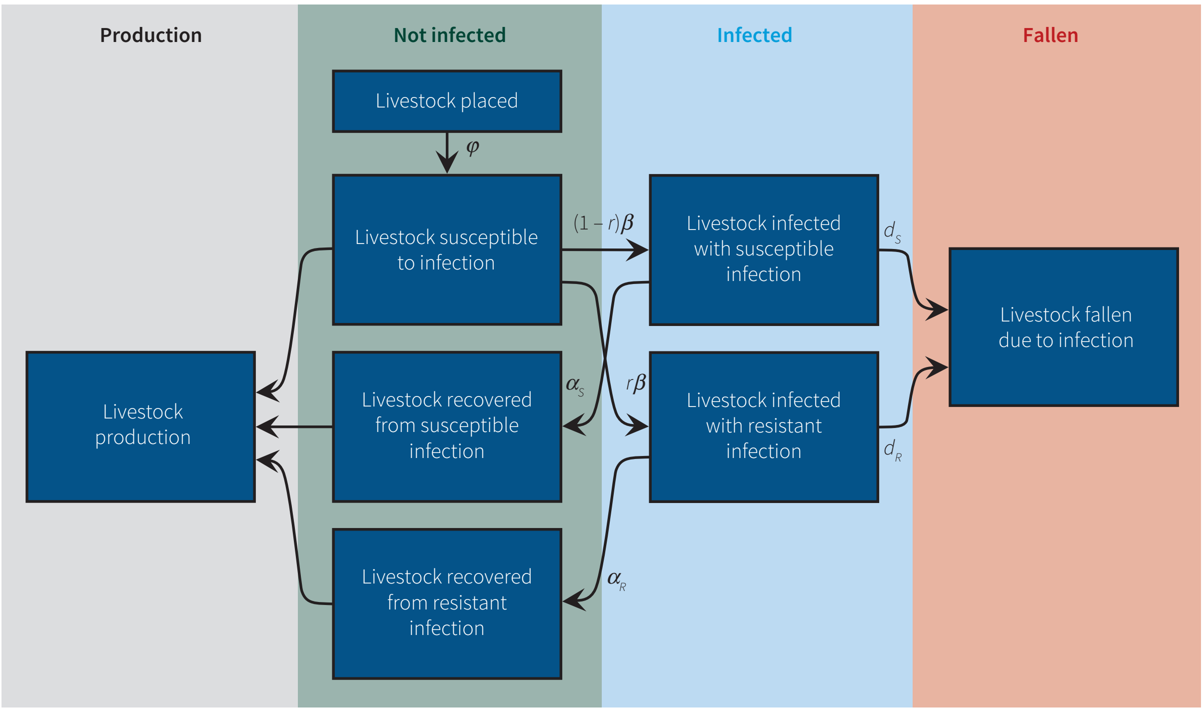
This annex describes the technical details of the livestock production (LPD) model. First, a model overview is provided, followed by a summary of model inputs, and finally, the model analyses and outputs are described.

MODEL OVERVIEW

The LPD is a compartment model based on a system of ordinary differential equations (ODEs) comprising five main compartments: susceptible (i.e. healthy), infected, recovered, fallen, and finally, for animals intended for meat production, the model allows an end state for their move to slaughter. Figure B.1 depicts the four compartments of the epidemiological model component.

Essentially, the model simulates the production process across different livestock sectors I, where animals are placed in sector-specific production cycles of length τ_i. At any given moment in time, each sector i consists of a healthy (susceptible) animal population H, which can become infected by either a susceptible infection I_S or a resistant infection I_R. Infected animals either recover, transitioning to states R_S or R_R respectively, or succumb to the infection and move to the fallen population, F. For the livestock sectors focused on meat production, at the beginning of each production cycle, a cohort of young livestock (ϕ) is introduced into the animal population; then, at the end of each cycle, all surviving livestock are sent to meat production (M). For livestock sectors that do not focus on meat production but rather

FIGURE B.1 Compartments of the epidemiological model component



on products such as raw milk and eggs, it is assumed that in each cycle there is a stock of animals producing these goods, and they do not move to M, instead staying in S or moving to either R_S or R_R if they suffer from an infection, respectively. The model is represented by a system of equations that describe the dynamics of each sector's population:

$$\frac{dH}{dt}=\begin{cases}\phi-H\ for\ t\bmod\tau=0\\ -\beta H\ otherwise,\end{cases}$$

$$\frac{dI_S}{dt}=\begin{cases}-I_S\ for\ t\bmod\tau=0\\ (1-r(t))\beta H-(\alpha_S+d_S)I_S\ otherwise,\end{cases}$$

$$\frac{dI_R}{dt}=\begin{cases}-I_R\ for\ t\bmod\tau=0\\ r(t)\beta H-(\alpha_R+d_R)I_R\ otherwise,\end{cases}$$

$$\frac{dR_S}{dt}=\begin{cases}-R_S\ for\ t\bmod\tau=0\\ \alpha_S I_S\ otherwise,\end{cases}$$

$$\frac{dR_R}{dt}=\begin{cases}-R_R\ for\ t\bmod\tau=0\\ \alpha_R I_R\ otherwise,\end{cases}$$

$$\frac{dF}{dt}=\begin{cases}-F\ for\ t\bmod\tau=0\\ d_S I_S+d_R I_R\ otherwise,\end{cases}$$

$$\frac{dM}{dt}=\begin{cases}H+R_S+R_R\ for\ t\bmod\tau=0\\ 0\ otherwise.\end{cases}$$

Where the expression 't mod τ' represents the modulo operation of t divided by τ, signifying the temporal position within a production cycle.

The rate of infection is denoted as β, and the fraction of infections that are resistant r varies over time. Rates of recovery and death from infection are denoted as α_S, α_R and d_S, d_R, respectively. It is important to note that the rate at which animals move from susceptible to infected states is not dependent on the proportion of infected animals in the population. When modelling infectious disease dynamics, the rate of infection depends on the proportion of infected among the total population, with the likelihood of becoming infected increasing, even at a constant mixing rate. However, due to the scope of the number of modelled livestock sectors and the limitations of data availability for animal diseases (see the next section), there are challenges to the calibration of the relevant parameters. For parsimonious reasons, the study opted that the rate at which animals fall ill is constant. Note that the model implies that an animal can only become sick once, either with a susceptible infection or a resistant infection. After this, the animal moves to the recovered state within a given production cycle and then does not move back to the state H. In reality, animals can become infected more than once within a cycle; thus, the model's simulated mortality and morbidity burden is likely an under-estimation. However, as previously mentioned, due to data limitations on calibrating animal diseases and the risk of re-infections, parsimonious reasons lead to only one allowed infection. For livestock with relatively short cycles (e.g. broiler chickens) this is likely to be a valid assumption, yet in the case of dairy cows and mastitis, this is most likely a conservative assumption, as dairy cows can become infected more than once a year.

The effective productivity of sector i is represented as:

$$P(t)=g\rho(t)\mu(t)m[H(t)+\rho_{R_S}R_S(t)+\rho_{R_R}R_R(t)]$$

where g is a factor taking values larger than 1 for sectors using antimicrobials for growth promotion purposes. $\rho(t)$ is a time-varying factor that accounts for changes in productivity in this sector over time.[15] $\mu(t)=\frac{m(t)}{m(t=\tau)}$ is the relative average animal mass (m) at time t compared to the final mass ($t=\tau$).[16] Furthermore, ρ_{R_S} and ρ_{R_R} represent relative productivity weighting factors for animals that were suffering from a susceptible or resistant infection.[17]

15 For example, livestock sectors may become more productive over time due to factors such as new technologies. This change in productivity within the model is measured in the meat yield per animal liveweight for meat producing sectors, or, for non-meat producing sectors, via the quantity of milk or eggs per animal.

16 For example, the model considers that in livestock sectors for meat production, the mass of an animal increases over time until it reaches its final weight. For parsimonious reasons, a linear growth is assumed.

17 Based on the assumption of a productivity factor of 1 for healthy animals that have never suffered from infection. It is important to highlight that, for many livestock production diseases, evidence suggests that animal morbidity is associated with impaired growth rates. However, in reality, animals within a given group are often slaughtered at the same time, where the loss in weight is a direct loss in output. In some instances, an animal will be raised for longer than healthy animals to catch up on the lost weight. In such cases, loss in productivity is observed indirectly through additional feed days. For the sake of simplicity, this analysis does not distinguish between such cases.

It must be noted that the share of infections that are resistant varies over time; this is modelled as a function of antimicrobial consumption $A(t)$. The relationship between changes in resistance r and AMU is characterised as follows:

$$r(t+1) = r(t) + c[A(t+1) - A(t)]$$

Where c represents a parameter coefficient characterising the strength and direction of the relationship between consumption A and resistance r. The calculation of antimicrobial consumption in each sector at time t is defined by:

$$A(t) = \begin{cases} \vartheta_0 m(\tau)\phi(t) \text{ for } t = 0 \\ \vartheta(t) m(\tau)\phi(t) \text{ for } t > 0. \end{cases}$$

Where $\vartheta(t)$ represents the intensity of antimicrobial consumption in milligrams per kg of animal biomass. $\phi(t)$ signifies the number of livestock heads introduced in the current production cycle.[18] That is, within this model, antimicrobial consumption is determined in the reference by a constant AMU intensity and changes over time mechanically due to changing levels of placed livestock in each sector. This increases consumption due to a rise in biomass. Moreover, within this simplified model, the sole driver of resistance is antimicrobial consumption. However, as demonstrated in existing empirical studies, other factors beyond consumption contribute to the emergence of AMR (Allel *et al.,* 2023).

To simulate the model, the system of ODEs is numerically integrated over time using a finite-step method. This task is carried out in Python utilising the *odeint* function from Python's *scipy.integrate* package.[19] The initial conditions of the ODE system are set to 0 for all parameters, except for the healthy animal population, which begins with H $(t = 0) = \phi$. The integration process is conducted with daily time steps. At the onset of each production cycle, all surviving livestock for meat production from the previous cycle are sent for slaughter, and new livestock are introduced. The model operates on a daily timescale, incorporating the daily probabilities of infection, recovery and mortality. At the conclusion of each cycle duration τ, the population parameters I_S, I_R, R_S, R_R and F are reset to 0, while the healthy population H is reset to ϕ, as defined in the ODEs. To account for variations in introduced livestock over time, due to factors such as changes in demand and population growth, the parameter ϕ adjusts over time with each successive cycle by a factor σ.

It is important to note that, due to the daily temporal resolution for the numerical integration of the model, β, α_S, α_R, d_S, d_R represent the daily rates of infection, recovery and death. That is, for some parameters, this requires a transformation to a daily rate. For example, in many instances the incidence of a certain disease is reported over a given period (e.g. a year). The existing literature provides examples of how to apply rates based on observed risk probabilities. For example, the rate of infection can be approximated as follows (Malloy *et al.,* 2021):

$$\beta = -\ln(1 - B) / n$$

Where B denotes a probabilistic risk of getting an infection over a time period n.[20] Equally, the mortality risk associated with an infection is dependent on its length. The daily rate of death – either due to a susceptible or resistant infection – can be written as:

$$d_{S(R)} = -\ln(1 - D_{S(R)}) / q_{S(R)}$$

Where $D_{S(R)}$ represents a reported mortality risk over the course of an infection lasting q number of days. Accordingly, the rate of recovery is represented as:

$$\alpha_{S(R)} = \frac{1}{q_{S(R)}} - d_{S(R)}$$

The main model parameters are summarised in Table B.1 below, which includes a note on where information is sourced from to calibrate each specific parameter.

18 Note that a baseline intensity of antimicrobial consumption (ϑ_0) is used at the start of the simulation, maintaining a constant value across different regions and scenarios as a reference point.
19 Full details of the *odeint* function in Python's *scipy.integrate* package can be found here: https://docs.scipy.org/doc/scipy/reference/generated/scipy.integrate.odeint.html
20 Equalling to 365 if the infection risk is over a period of one year.

TABLE B.1 List of parameters

Parameter	Description	Source
β	Daily probability of infection	Literature
α_S	Daily probability of recovering from a susceptible infection	Literature
α_R	Daily probability of recovering from a resistant infection	Literature
d_S	Daily probability of mortality from a susceptible infection	Literature
d_R	Daily probability of mortality from a resistant infection	Literature
D_S	Probability of mortality from a susceptible infection	Literature
D_R	Probability of mortality from a resistant infection	Literature
q	Average duration of an infection in days	Literature
τ	Duration of a production cycle in days	Literature
$\rho(t)$	Time-dependent productivity factor	Secondary data analysis
$\Phi(t)$	Number of placed livestock (heads) in a production cycle	Secondary data analysis
$r(t)$	Fraction of infections that are resistant	Secondary data analysis
θ_0	Reference AMU intensity	Secondary data analysis
$\theta(t)$	AMU intensity over time (dependent on scenario)	Calculated within model
$m(t)$	Animal mass	Secondary data analysis
g	Productivity weighting due to AMU for growth promotion	Literature
ρR_S	Productivity weighting of population recovered from susceptible infection	Literature
ρR_R	Productivity weighting of population recovered from resistant infection	Literature
c	Magnitude associated between AMU and AMR in food-producing animals	Secondary data analysis

The following sections describe the sources and explanations for which values are assigned to each of the parameters, based on data obtained from the existing literature or through additional statistical analysis.

MODEL INPUTS

Livestock and animal productivity inputs by region and sector

Data for the reference stock in animals across livestock sectors and regions are sourced from FAO. Through its statistical unit, Food and Agricultural Organization Statistics (FAOSTAT), FAO compiles, validates and disseminates rich global annual statistics on, among other aspects, crops and livestock, production, harvested areas, yields, as well as live and slaughtered animal numbers (FAO, 2024b). Furthermore, FAO provides food and agriculture projections up to 2050. These projections consider trends affecting food and agricultural systems to map out possible future pathways of food and agricultural production and consumption (FAO, 2018). This study employs this data to incorporate how stocks of placed animals and productivity (i.e. yield) by region in each sector will change over time. For example, the data projects that Sub-Saharan Africa will likely see the largest increases due to assumed changes in economic conditions and population growth. On the other hand, regions such as North America or Europe and Central Asia are predicted to experience more moderate growth rates.

The input values for parameters ϕ, σ, $\rho(t)$ and m $(t = \tau)$ are provided in Tables B.2, B.3, B.4, B.5 and B.6. Note that for the growth factor parameters σ and $\rho(t)$, the study employs stock and productivity values provided for each sector from FAO projections for the years 2030 to 2050, and calculates the average annual growth factor using business-as-usual projections.

TABLE B.2 Stocks and productivity parameters: Beef cattle

Beef cattle					
	Reference values (annual)			Growth factor (annual)	
Region	Liveweight per animal (kg): $m(t = \tau)$	Stock (heads): φ	Yield (kg/head)	Stock: σ	Productivity: $\rho(t)$
East Asia & Pacific	366.9	65,277,490	204.47	1.002178	1.003521
Europe & Central Asia	430.6	49,186,460	241.70	1.003383	1.004556
Latin America & Caribbean	367.9	70,653,230	200.15	1.006331	1.004022
Middle East & North Africa	331.7	7,178,344	211.51	1.015463	1.004928
North America	565.5	37,145,960	370.33	0.9990485	1.002672
South Asia	219.9	52,469,820	116.49	0.9990224	1.005667
Sub-Saharan Africa	275.9	38,242,860	159.06	1.017544	1.00535

TABLE B.3 Stocks and productivity parameters: Dairy cattle

Dairy cattle					
	Reference values (annual)			Growth factor (annual)	
Region	Liveweight per animal (kg): $m(t = \tau)$	Stock (heads): φ	Raw Milk (kg/head)	Stock: σ	Productivity: $\rho(t)$
East Asia & Pacific	366.9	25,860,840	2,534.81	1.002178	1.003521
Europe & Central Asia	430.6	45,887,390	5,758.26	1.003383	1.004556
Latin America & Caribbean	367.9	34,795,230	1,889.26	1.006331	1.004022
Middle East & North Africa	331.7	8,279,935	3,876.49	1.015463	1.004928
North America	565.5	10,359,200	10,092.63	0.9990485	1.002672
South Asia	219.9	77,840,110	940.27	0.9990224	1.005667
Sub-Saharan Africa	275.9	63,331,050	718.97	1.017544	1.00535

TABLE B.4 Stocks and productivity parameters: Broiler chicken

Broiler chicken					
	Reference values (annual)			Growth factor (annual)	
Region	Liveweight per animal (kg): $m(t = \tau)$	Stock (heads): φ	Yield (kg/head)	Stock: σ	Productivity: $\rho(t)$
East Asia & Pacific	1.59	22,660,470,000	1.31	1.002482	1.002083
Europe & Central Asia	1.62	10,339,810,000	1.58	1.003735	1.001702
Latin America & Caribbean	1.81	12,418,550,000	1.64	1.005391	1.001588
Middle East & North Africa	1.44	6,015,460,000	1.30	1.004879	1.00229
North America	2.01	10,003,490,000	1.95	1.002501	1.001484
South Asia	1.23	4,628,426,000	1.05	1.01104	1.00287
Sub-Saharan Africa	1.33	2,689,273,000	1.13	1.035573	1.002936

TABLE B.5 Stocks and productivity parameters: Layer chicken

Layer chicken					
	Reference values (annual)			Growth factor (annual)	
Region	Liveweight per animal (kg): $m(t=\tau)$	Stock (heads): φ	Yield (kg/head)	Stock: σ	Productivity: $\rho(t)$
East Asia & Pacific	1.59	4,100,814,000	8.85	1.002482	1.002083
Europe & Central Asia	1.62	731,032,200	13.15	1.003735	1.001702
Latin America & Caribbean	1.81	729,392,800	11.08	1.005391	1.001588
Middle East & North Africa	1.44	294,720,800	12.00	1.004879	1.00229
North America	2.01	424,467,200	17.28	1.002501	1.001484
South Asia	1.23	821,636,200	7.42	1.01104	1.00287
Sub-Saharan Africa	1.33	388,924,200	4.98	1.035573	1.002936

TABLE B.6 Stocks and productivity parameters: Swine meat

Swine meat					
	Reference values (annual)			Growth factor (annual)	
Region	Liveweight per animal (kg): $m(t=\tau)$	Stock (heads): φ	Yield (kg/head)	Stock: σ	Productivity: $\rho(t)$
East Asia & Pacific	78.54	758,682,900	55.32	1.000218	1.002045
Europe & Central Asia	102.41	286,790,900	81.97	1.002896	1.001826
Latin America & Caribbean	89.64	100,909,600	74.57	1.006561	1.001888
Middle East & North Africa	77.86	287,487	54.96	1.001952	1.001835
North America	106.50	149,581,100	98.70	1.005053	1.001494
South Asia	59.75	10,843,430	47.49	1.003444	1.002254
Sub-Saharan Africa	68.18	37,334,890	52.31	1.027097	1.002986

Animal health parameter inputs by region and sector

This section offers a detailed overview of the health parameters used in the analysis. It discusses each of the major production diseases caused by bacterial infections that are considered in the analysis for each sector, including:

- Neonatal calf diarrhoea (dairy and beef cattle)
- Bovine respiratory disease (beef cattle)
- Mastitis (dairy cattle)
- Swine colibacillosis (swine)
- Chicken colibacillosis (layer and broiler chickens)

Each disease section discusses the assumptions made in terms of the incidence of the disease, as well as the morbidity and mortality effects associated with susceptible and resistant infections.

Neonatal calf diarrhoea

Digestive diseases, such as diarrhoea, are a leading cause of morbidity and mortality in calves. Neonatal calf diarrhoea (NCD) is a global disease in the cattle industry associated with economic losses due to high morbidity, mortality, lower productivity and elevated treatment costs. NCD is the most common cause of death in calves during their first 30 days of age, with a case fatality risk of approx. 5% (Windeyer *et al.,* 2014; Svensson *et al.,* 2006; Urie *et al.,* 2018). NCD is characterised as a multifactorial disease linked to exposure to a combination of pathogens. The most common diarrheic pathogens include rotavirus and coronavirus, *Enterotoxigenic Escherichia coli* (*E. coli*), Clostridium perfringens and salmonella, as well as *Cryptosporidium parvum* (Bartels *et al.,* 2010; Izzo *et al.,* 2011).

Systematic data on the incidence of NCD is scarce. A recent meta-analysis examined the prevalence of mixed infections across global regions in both dairy and beef production systems (Brunauer *et al.,* 2021). The highest worldwide mean pooled prevalence was identified for bovine rotavirus and *Cryptosporidium* spp. (6.69%; confidence interval (CI): 4.27–9.51), followed by bovine rotavirus and coronavirus (2.84%; CI: 1.78–4.08), as well as the combined bovine rotavirus and *E. coli* (1.64%; CI: 0.76–2.75). The study also reports prevalences across different global geographies. This analysis approximates the incidence of NCD caused by a bacterial infection, with the estimated prevalence for the combined bovine rotavirus and *E. coli* infections. However, there are two major caveats: first, it accounts for a combined combination of a viral and bacterial infection. However, as the aim is to understand the AMR-attributable mortality and morbidity, antimicrobial treatment failure due to a resistant pathogen would, at least, be partially captured by a combined infection. Second, prevalence of an infection in a given population is not equal to the incidence. However, as an infection most likely has a duration of a couple of days, occurring within the first few days of a calf's life, in the absence of incidence data the prevalence is assumed to be a suitable proxy.

Based on values reported in the literature, this study assumes a case fatality for NCD with a susceptible infection of 5%. The AMR-attributable mortality is proxied using data from an analysis (Bernal-Córdoba *et al.,* 2022) on the efficacy of antimicrobial treatments *versus* different control groups (other antimicrobial or no-treatment). The study reported a relative mortality risk from receiving treatment *versus* no-treatment between 0.06 and 0.8. Furthermore, the relative mortality risk from receiving an antimicrobial treatment with low resistance *versus* one with high resistance was reported as 0.65. Calculating the inverse risks suggests that receiving a treatment at risk of resistance *versus* one with low resistance risk increases the mortality risk by a factor of approx. 1.54. There was not enough evidence available to infer whether any productivity losses are associated with a resistant infection *versus* a non-resistant one; therefore, the study does not apply a productivity effect. Note that due to the absence of region-specific mortality parameters, the study applies the same mortality parameters across all regions. All inputs by region are reported in Table B.7. Within the model, these health parameters are applied to both dairy and beef cattle during the first twenty days after birth.

TABLE B.7 Health inputs: Neonatal Calf Diarrhoea

Neonatal Calf Diarrhoea						
Region	Incidence: B	Mortality risk (susceptible infection)	Mortality risk (resistant infection)	Productivity factor (susceptible infection)	Productivity factor (resistant infection)	Average duration of susceptible infection (days)
East Asia & Pacific	0.0120	0.050	0.077	1	1	5
Europe & Central Asia	0.0097	0.050	0.077	1	1	5
Latin America & Caribbean	0.0015	0.050	0.077	1	1	5
Middle East & North Africa	0.0370	0.050	0.077	1	1	5
North America	0.0362	0.050	0.077	1	1	5
South Asia	0.0340	0.050	0.077	1	1	5
Sub-Saharan Africa	0.0243	0.050	0.077	1	1	5

Note: incidence data applied from Brunauer *et al.* (2021); mortality parameters applied from Bernal-Córdoba *et al*. (2022).

Bovine Respiratory Disease

Bovine respiratory disease (BRD) is a leading contributor to economic costs, morbidity and mortality for the global beef cattle industry, specifically for intensive production systems (Chai *et al.,* 2022). In the US, for example, 90% of feedlots report BRD as the most frequent health condition affecting animals (USDA, 2024). The disease increases mortality but also has a substantial impact on productivity by creating less efficient feed conversion and average daily growth rates (Holland *et al.,* 2010). BRD is a complex disease affecting the respiratory tract of cattle and is characterised by a multifactorial aetiology, with a range of viral and bacterial infectious pathogens: bovine herpesvirus type 1 (BoHV-1), bovine adenovirus (BAdV), bovine viral diarrhoea virus (BVDV), bovine coronavirus (BCoV), bovine respiratory syncytial virus (BRSV), bovine parainfluenza virus (BPiV), *Pasteurella multocida*, *Mannheimia haemolytica*, *Histophilus somni* and *Mycoplasma bovis* (Cirone *et al.,* 2019). It is understood that bacterial pathogens cause the acute syndrome by invading the respiratory tract, which has been previously affected by a viral infection. Bacteria are generally considered causative of BRD at higher prevalence in cattle with respiratory signs, making antimicrobial treatment often the first choice of treatment to avoid progression to more severe BRD (Bateman *et al.,* 1990). The most common bacteria isolated from cattle with respiratory signs include *P. multocida*, *M. haemolytica* and *H. somni*, yet other bacteria have been associated with it as well (e.g. *E. coli*, *S. aureus*, *Enterobacter*) (Confer, 2009). Vaccines and antimicrobials are used around the world to prevent and treat BRD; however, vaccines have not yet reached satisfying effectiveness while AMU is a concern due to rising resistance rates (Baptiste and Kyvsgaard, 2017).

Systematic data on the incidence of BRD is scarce. A recent meta-analysis examined the prevalence of BRD and found broad ranges of 4–80% (Timsit *et al.,* 2016). Evidence from Ireland suggests an incidence of 20% among calves, and a prevalence of 8–20% among veal and yearling populations in Spain (Fernández *et al.,* 2020; Boehringer Ingelheim Animal Health UK Ltd., 2020). The varying incidence of BRD among different cattle populations is corroborated for France by Delabouglise *et al.* (2017). For the purpose of this analysis, incidence risk data is provided by Delabouglise *et al.* (2017) but is adjusted for each region by the relative share of intensive beef cattle farming. This is because BRD is prevalent in more intensive production systems; thus, by applying these incidence risks across all regions, it could overestimate the burden of BRD. To determine the adjustment factors, evidence is taken from Gilbert *et al.* (2018, 2015) on the global distribution patterns of livestock production. Gilbert *et al.* (2015) link the share of intensive farming in pig and poultry production with a country's GDP per capita. This is used to approximate the rough share of intensive farming associated with a region's income level. However, the aforementioned study only includes this analysis for pig and poultry production, but not for cattle. In the absence of this information, the present study uses the provided functional relationship on the link between income and intensive farming for poultry production from Blakebrough-Hall *et al.* (2020) as Gilbert *et al.* (2018)[21] point out that the global distribution for cattle and poultry are most similar. To adjust the predicted distribution of intensive farming in poultry based on GDP per capita, the analysis assumes the same function but changes the levels. For example, in high-income countries, poultry is expected to be almost completely intensive farming; on the other hand, for beef cattle production, even the biggest producer, the US, only has approx. 70% in intensive production systems (Ritchie, 2023). Based on these calculations for the applied adjustment factors for region-wide incidence, the present study predicts a crude back-of-the-envelope prediction about the share of intensive beef production across the whole sector production in each region as follows: (1) East Asia and the Pacific, 61%; (2) Europe and Central Asia, 65%; (3) Latin America and the Caribbean, 0.62%; (4) the Middle East and North Africa, 0.62%; (5) North America, 70%; (6) South Asia, 32%; and (7) Sub-Saharan Africa, 31%.

21 See Figure 1 in Gilbert et al., (2018).

The daily incidence rate of $1.89*10^{(-3)}$ provided by Delabouglise *et al.* (2017) is applied and adjusted for the share of intensive beef farming, assuming that half of BRD infections are caused by a bacterial pathogen. The weighted incidence is therefore multiplied by the factor 0.5 (Delabouglise *et al.,* 2017).

Parameters for mortality and productivity impairment associated with BRD are taken from Blakebrough-Hall *et al.* (2020) who provide experimental data on the BRD-associated mortality risk and productivity impacts for healthy animals in comparison to animals with one or more antimicrobial treatments. Overall, the study suggests a prevalence of 18% among the study population, which is in line with other studies mentioned above. Furthermore, the mortality rate among animals with no infection was 0.15%, whereas a single infection was associated with a mortality of 3%; two infections with a mortality of 11.5%; and three or more infections with a mortality of 57.9%. Thus, the mortality risk for a susceptible infection is approximated at 3%, and the mortality risk associated with a resistant infection is the weighted average of two or more infections (increasing the mortality about tenfold), assuming that treatment failure due to a resistant infection will lead to at least a second round of antimicrobial treatment. Applying the same approach to productivity impairment reported in Blakebrough-Hall *et al.* (2020), which is measured as the weight of the animal when exiting the feedlot for slaughter, productivity loss in terms of average growth impairment can be estimated at approx. 1.4% for one infection, and a weighted average productivity loss for two or more infections is approx. 9.77%. All inputs by region are summarised in Table B.8.

Bovine mastitis

Bovine mastitis is a common global production disease in dairy cattle and a contributing factor to economic losses for the dairy livestock sectors. Mastitis is associated with elevated treatment costs, reduced milk production, increased mortality and lower reproductive capacities (Lam *et al.,* 2013). Mastitis is generally classified into three types: (1) subclinical; (2) clinical; and (3) chronic mastitis. Subclinical mastitis (SCM) tends to cause a major loss to milk production due to the absence of any visible changes in milk and difficulties in detecting the infection. Clinical mastitis (CM) is characterised by the swelling of the udder, milk containing flakes, clots or having a watery consistency (Krishnamoorthy *et al.,* 2021). Pathogens causing mastitis include *E. coli*, *S. aureus* and streptococci (Cobirka *et al.,* 2020). The present study's focus is mainly on CM, as this form is more likely to be detected and subsequently addressed with antimicrobial treatment, where treatment failure due to resistance has a direct consequence. There is also more evidence available on the incidence and associated mortality and productivity effects. SCM often

TABLE B.8 Health inputs: Bovine Respiratory Disease (BRD)

Bovine Respiratory Disease						
Region	Incidence: B (daily rate)	Mortality risk (susceptible infection)	Mortality risk (resistant infection)	Productivity factor (susceptible infection)	Productivity factor (resistant infection)	Average duration of susceptible infection (days)
East Asia & Pacific	0.00061	0.030	0.309	0.986	0.902	7
Europe & Central Asia	0.00063	0.030	0.309	0.986	0.902	7
Latin America & Caribbean	0.00061	0.030	0.309	0.986	0.902	7
Middle East & North Africa	0.00061	0.030	0.309	0.986	0.902	7
North America	0.00067	0.030	0.309	0.986	0.902	7
South Asia	0.00033	0.030	0.309	0.986	0.902	7
Sub-Saharan Africa	0.00030	0.030	0.309	0.986	0.902	7

Note: daily incidence rate of $1.89 \times 10^{(-3)}$ weighted by the share of intensive beef production by region (Delabouglise *et al.*, 2017) and assuming half of BRD infections are caused by bacterial pathogen; mortality and productivity effects from Blakebrough-Hall *et al.*, 2020.

goes undetected but can be prevented through preventive interventions or prophylactic antimicrobials. Moreover, if this analysis focused solely on CM, it could under-estimate the true burden of resistant infections.

Systematic evidence for the incidence of CM is scarce in the literature. Evidence from Europe suggests an annual incidence of 12.7–27.8% (Valde *et al.,* 2004; Santman-Berends *et al.,* 2015), for Japan this is approx. 21% (Fukushima *et al.,* 2020) and for the US it is approx. 24% (Gonçalves *et al.,* 2022). The only systematic review with meta-analysis to assess the occurrence of CM globally reports prevalence rather than actual incidence (Krishnamoorthy *et al.,* 2021), and it also considers cattle and buffalos, albeit the latter only representing a small proportion of the overall study sample for CM. The study suggests that the global average annual prevalence in cattle is estimated at 14% (95% Confidence Interval: 11–18%), with regional variation: Africa (12%); Asia (18%); Europe (29%), Latin America (8%), North America (22%); and Oceania (5%). Overall, the published prevalence data is in line with incidence rates of other studies. This provides more systematic estimates of the health burden of mastitis to proxy incidence with these published prevalence estimates for each of the continents reported. Where possible, this analysis uses the estimates by region, which include the most recent studies (see Table 3, Chapter 1).

Systematic reviews have estimated the mortality of dairy cows at 1–5% and 4% (Compton *et al.,* 2017; Thomsen and Houe, 2006). However, these studies included evidence from higher-income countries, lacking data from lower-income countries. To be conservative, this analysis applied a 1% base mortality across all regions. Bar *et al.* (2008) estimate that one clinical episode of CM increases the mortality risk by a factor of 9, while for two or more episodes it is a factor of 13.3. Note that in the absence of any evidence on the AMR-attributable mortality, this analysis uses 13.3 as its proxy. The productivity loss associated with CM has been estimated previously at 3.2–10.6% milk loss over a 305 day milk-yield period of a dairy cow (Heikkilä *et al.,* 2018). This analysis calculates the productivity loss for a single infection, assuming a duration of treatment of seven days until the infection is cleared (Kumar *et al.,* 2016). In this time, the milk must be discarded. The treatment period is assumed to be followed by a three-day withdrawal period before the milk of the recovered dairy cow can be sold again. Over a lactation period of 305 days, this corresponds to a productivity loss of at least 3.2% for a susceptible infection.[22] Assuming that a resistant infection would take at least twice as long until the infection is cleared (e.g. due to the course of another line of treatment), and that second-line and third-line treatment likely apply antimicrobial treatments that require a longer withdrawal period (e.g. fluoroquinolones), this analysis calculates the loss associated with a resistant infection as 5.9%.[23] All inputs by region are summarised in Table B.9.

Swine Colibacillosis

Porcine infections caused by *E. coli*, also known as Swine Colibacillosis (SC), is associated with a wide range of symptoms including neonatal diarrhoea, post-weaning diarrhoea, polyserositis and urinary tract infections, among others (Fairbrother and Nadeau, 2019). SC causes substantial economic losses to the global swine industry as it is associated with mortality, morbidity, reduced productivity and treatment costs (Luppi, 2017). It is a widespread disease, occurring both in industrialised and developing countries and across all climates. Different approaches are taken to prevent and treat SC, with antimicrobials being the most common treatment strategy (Castro *et al.,* 2022). However, due to the growing selective pressure of antimicrobials when treating *E. coli* infections, and the rising resistance, the available treatment options for the swine industry are narrowing.

SC is associated with high mortality, with some studies reporting a rate of 70% in neonatal piglets with severe

22 Calculated as 10/305, which is most likely a conservative estimate, assuming that on all other days the cow would produce milk as it would without an infection. However, there is evidence that a CM episode can have a detrimental impact on the milk yield over the remaining 305-day lactation period.

23 Calculated as 15/305, which assumes that a second-line treatment will take another seven days plus a further day of withdrawal period, than the first-line treatment.

diarrhoea, and 1.5–2% among post-weaned or finishing pigs with moderate diarrhoea; in untreated animals with moderate to severe diarrhoea, the mortality is approx. 25% (Fairbrother and Nadeau, 2019; AHAW *et al.,* 2022). A Danish study has found a cumulative diarrhoea incidence 14 days post weaning of 40–50% (Eriksen *et al.,* 2021), with approx. 42% associated with *E. Coli*; most piglets were cured after treatment within four days. Evidence from LMICs is scarce, yet existing studies suggest that the burden of diarrhoea among pig producers is not just a substantial issue in high-income countries (Obala *et al.,* 2021; Pabón-Rodríguez *et al.,* 2023). In the absence of systematic evidence on the incidence of SC across countries and regions, and based on the evidence that SC is a global and not geography-specific problem, this analysis applies the incidence reported by Eriksen *et al.* (2021) across all regions. Furthermore, experimental evidence suggests that untreated diarrhoea caused by *E. coli* infections is associated with a 14% mortality and a 4% reduction in average weight gain in the post-weaning period (Madec *et al.,* 2000). Thus, this analysis assumes a reference mortality of 1.5% for susceptible infections, a 14% mortality for resistant infections, and it applies a 4% productivity loss in the post-weaning period. All inputs by region are summarised in Table B.10.

TABLE B.9 Health inputs: Bovine Mastitis

Bovine Mastitis						
Region	Incidence: B	Mortality risk (susceptible infection)	Mortality risk (resistant infection)	Productivity factor (susceptible infection)	Productivity factor (resistant infection)	Average duration of susceptible infection (days)
East Asia & Pacific	0.18	0.090	0.133	0.967	0.941	7
Europe & Central Asia	0.29	0.090	0.133	0.967	0.941	7
Latin America & Caribbean	0.08	0.090	0.133	0.967	0.941	7
Middle East & North Africa	0.12	0.090	0.133	0.967	0.941	7
North America	0.22	0.090	0.133	0.967	0.941	7
South Asia	0.19	0.090	0.133	0.967	0.941	7
Sub-Saharan Africa	0.12	0.090	0.133	0.967	0.941	7

Note: incidence proxied from prevalence rates provided by Krishnamoorthy *et al*., 2021.

TABLE B.10 Health inputs: Swine Colibacillosis

Swine Colibacillosis						
Region	Incidence: B	Mortality risk (susceptible infection)	Mortality risk (resistant infection)	Productivity factor (susceptible infection)	Productivity factor (resistant infection)	Average duration of susceptible infection (days)
East Asia & Pacific	0.19	0.015	0.14	1	0.96	5
Europe & Central Asia	0.19	0.015	0.14	1	0.96	5
Latin America & Caribbean	0.19	0.015	0.14	1	0.96	5
Middle East & North Africa	0.19	0.015	0.14	1	0.96	5
North America	0.19	0.015	0.14	1	0.96	5
South Asia	0.19	0.015	0.14	1	0.96	5
Sub-Saharan Africa	0.19	0.015	0.14	1	0.96	5

Note: incidence taken from Eriksen *et al*., 2021.

Chicken Colibacillosis

Colibacillosis in chickens refers to an infection caused by avian pathogenic *E. coli* (APEC), which can include haemorrhagic septicaemia, air sac disease (chronic respiratory disease), swollen head syndrome, peritonitis, salpingitis and enteritis, among others, with depression, fever, yellowish or greenish droppings, and lesions of internal organs among the main clinical signs (Yousef *et al.,* 2023). Colibacillosis is a contributing factor to excess economic costs in broiler and layer production systems and a driver of AMU and AMR.

Colibacillosis in poultry is associated with elevated mortality risk, with evidence suggesting that up to half of mortality occurring in broiler breeding farms is associated with APEC infections, salpingitis or peritonitis predominant conditions (European Commission, 2019). Other studies suggest a 1–10% mortality rate in layer chickens and a higher mortality in broiler production systems (Zanella *et al.,* 2000; Mellata, 2013). Systematic evidence on the incidence of colibacillosis in chickens is missing, with one comprehensive study suggesting an annual incidence at the animal-level in predominantly intensive farming settings of approx. 5% in layers and approx. 25% in broiler chickens (Landman and van Eck, 2015). The same study estimated excess mortality rates associated with colibacillosis in layer chickens by about 8% (layer) and 11% (broiler). For the purpose of this analysis, the annual incidence risks provided for layer and broiler chickens are used separately, but are adjusted for each region by the relative share of intensively raised chickens.[24] To determine the regional incidence adjustment factors, evidence from Gilbert *et al.* (2015) on the global distribution patterns of livestock production is applied, as this links the share of intensive farming in pig and poultry production with a country's GDP per capita. This is used to approximate the rough share of intensive farming associated with a region's income level. Based on these calculations and using the GDP values provided by Shared Socioeconomic Pathway (SSP), which are aggregated regionally, this analysis applies a crude back-of-the envelope prediction on the share of intensively raised chickens in each region as follows: (1) East Asia and the Pacific, 90%; (2) Europe and Central Asia, 95%; (3) Latin America and the Caribbean, 92%; (4) the Middle East and North Africa, 92%; (5) North America, 95%; (6) South Asia, 65%; and (7) Sub-Saharan Africa, 60%. There is no evidence on the AMR-attributable mortality for colibacillosis in poultry, yet existing economic studies have modelled a reduction of antimicrobials and its impact on mortality risk (Azabo *et al.,* 2022).[25] While this is not a direct measure of this mortality, the analysis proxies it by using parameter values provided by these studies on how a 50% reduction in antimicrobials is associated with higher mortality, using the factor 1.1.[26] It assumes that mortality with a resistant infection is equal to mortality without treatment, though in all likelihood these are not fully comparable. However, the analysis applies a very low mortality factor of 1.4, given that continued treatment failure – especially in poultry, where the average value of an animal is considerably lower than cattle, for example – will most likely lead to death. Thus, one would expect this AMR-attributable mortality risk to be substantially higher. For this reason, this analysis uses a more conservative AMR-attributable mortality risk factor of 1.4. No direct evidence was found on how colibacillosis impacts productivity, measured as average daily weight gain for broiler chickens, nor on the potential quality or quantity of eggs from layer hens. For broiler chickens, this analysis assumes an average of 50 days from placed to slaughter, and an excess number of three days in which the animal does not grow due to resistant infection.[27] All inputs by region are summarised in Tables B.11 and B.12.

24 Multiplying annual incidence by the intensively farmed share of animals by region.
25 This includes the study by Reus (2011).
26 For example, if baseline mortality for a susceptible infection is 0.05, this analysis assumes the mortality associated with a resistant infection is 0.055.
27 Leading to a proxy productivity loss compared to a susceptible infection of 1–(3/50) = 0.94.

TABLE B.11 Health inputs: Chicken (Broiler) Colibacillosis

Chicken Colibacillosis						
Region	Incidence: B	Mortality risk (susceptible infection)	Mortality risk (resistant infection)	Productivity factor (susceptible infection)	Productivity factor (resistant infection)	Average duration of susceptible infection (days)
East Asia & Pacific	0.0248	0.108	0.151	1	0.94	3
Europe & Central Asia	0.0252	0.108	0.151	1	0.94	3
Latin America & Caribbean	0.0251	0.108	0.151	1	0.94	3
Middle East & North Africa	0.0251	0.108	0.151	1	0.94	3
North America	0.0252	0.108	0.151	1	0.94	3
South Asia	0.0185	0.108	0.151	1	0.94	3
Sub-Saharan Africa	0.0169	0.108	0.151	1	0.94	3

Note: incidence taken from Landman and van Eck (2015) and adjusted by prevalence of intensive farming by region based on Gilbert *et al*. (2015).

TABLE B.12 Health inputs: Chicken (Layer) Colibacillosis

Chicken Colibacillosis						
Region	Incidence: B	Mortality risk (susceptible infection)	Mortality risk (resistant infection)	Productivity factor (susceptible infection)	Productivity factor (resistant infection)	Average duration of susceptible infection (days)
East Asia & Pacific	0.0248	0.108	0.151	1	1	3
Europe & Central Asia	0.0252	0.108	0.151	1	1	3
Latin America & Caribbean	0.0251	0.108	0.151	1	1	3
Middle East & North Africa	0.0251	0.108	0.151	1	1	3
North America	0.0252	0.108	0.151	1	1	3
South Asia	0.0185	0.108	0.151	1	1	3
Sub-Saharan Africa	0.0169	0.108	0.151	1	1	3

Note: incidence taken from Landman and van Eck (2015) and adjusted by prevalence of intensive farming by region based on Gilbert *et al*. (2015).

Parameter inputs related to AMU and AMR

This section outlines the statistical analyses that were conducted to inform the applied values for parameters $r(t)$ and c. In addition, the applied values for parameter $\vartheta(t)$ are summarised.

Empirical analysis estimating the association between AMU and AMR in livestock sectors

For an empirical assessment of the association between antimicrobial consumption and AMR in food-producing animals, this analysis employed two major data sources: (1) publicly available data on AMR rates in animals; and (2) non-publicly available data from WOAH on the biomass of food-producing animals and antimicrobial consumption by country over time.

First, AMR data for animals was obtained from ResistanceBank, which is an online platform covering the years 2000–2021 that centralises data on AMR in animals from more than 1,285 surveys from LMICs and data harmonised from high-income countries. This database includes resistance rates for pathogens isolated from cattle, chickens, pigs and sheep, among other species, including *Campylobacter*, *E. coli*, *S. aureus* and salmonella. The ResistanceBank also includes information, among other things, about the year of the sample, sample type (e.g. faecal, dead or killed animal), the class of antimicrobials tested, as well as total number of samples, isolates and how many isolates were found to be resistant. It is by far the most comprehensive database on AMR in animals that is publicly available, and includes relevant data for all regions applied in this analysis except for North America (the US and Canada) (Criscuolo *et al.* 2021).

Second, this analysis used antimicrobial consumption and biomass data from WOAH's ANIMUSE database, which is a specialised platform designed for the collection and dissemination of information related to the use of antimicrobial agents in animals. Its primary intention is to provide a comprehensive and standardised system for monitoring global antimicrobial usage in veterinary settings (Jeannin *et al.,* 2023). This kind of tracking is critical to understanding patterns of AMU, which can help address issues related to AMR. Since 2015, Veterinary Services across the globe have reported information to WOAH on AMU on animals in their countries. The platform officially launched to the public in 2023. Reporting is open to all countries, including WOAH Members and non-members, with degrees of options on what level of quantitative data is shared to the platform. As of 2023, 92 countries have already reported consumption data to ANIMUSE. In addition to consumption data, the platform includes information on the total biomass of food-producing animals in each reporting country, which enables the adjustment of overall consumption by the biomass of animals or the report of AMU consumption levels as intensity (mg of antimicrobials consumed per kg biomass in population correlation unit [PCU]) (WOAH, 2024a).

In addition to ResistanceBank and ANIMUSE, this analysis has complemented its data used with country-level variables obtained from the World Bank Development Indicator Databank (World Bank, 2024b). The following paragraphs describe both analyses in more detail.

At the country-level, existing studies have assessed the correlation between AMU and AMR for humans and food-producing animals, suggesting that antimicrobial consumption in food-producing animals (e.g. measured in mg per kg PCU) is associated with higher resistance rates in animals and humans (Allel *et al.,* 2023). However, due to a lack of comprehensive longitudinal antimicrobial consumption data, these analyses were limited to using cross-sectional AMU data. Longitudinal data, as well as appropriate estimation methods that can exploit variation over time for the same unit of observation, can provide important advantages over existing empirical approaches to assess the association between AMU and AMR (Emes *et al.,* 2022). For example, Rahman and Hollis (2023) examined the associations between antimicrobial consumption in food-producing animals and humans and AMR using longitudinal data for European countries. Their results show an increase in AMU in animals of approx. 10%, which is estimated to increase the prevalence of resistance in animals by approx. 2%, and in humans by approx. 0.3%. Adda (2020) used state level data from the US to estimate the link between AMU in humans and animals and their contribution to AMR in humans, suggesting that antimicrobial consumption in humans is a stronger contributor to resistance in humans than antimicrobial consumption in farming animals; in addition, more recently introduced antimicrobial treatments have greater contribution to resistance than older treatments (Adda, 2020). This may suggest a trend where resistance to treatment builds up faster in the initial stages and then decreases marginally over time. Emes *et al.* (2024) used panel regression methods to examine the associations between AMU in animals and AMR in humans; they found that AMU is related to resistance in humans but with varying effects across use in different animals.

Alongside this emerging literature, the present study has conducted a similar empirical analysis to examine the association between antimicrobial consumption and rates of AMR across countries in food-producing animals over time. In the analysis, the rate of resistance represents the dependent variable, and antimicrobial consumption represents the key independent variable of interest, while adjusting for a set of other country-level variables that could determine resistance rates and consumption simultaneously. Since ANIMUSE data is only available from 2014 onwards, the data sample includes 56 countries observed between

2014 and 2021. Using this longitudinal data sample, the empirical estimate of the association between AMU and AMR, r, is as follows:

$$r_{ict} = cAMU_{ct} + \alpha X_{ict} + \beta Z_{ct} + \gamma_t + \varepsilon_{ict}$$

Where r_{ict} is the observed level of resistance in sample i in country c in year t. AMU_{ct} is the observed level of total antimicrobial consumption across food-producing animals in country c and year t, and c is the parameter used in the model's epidemiological component. For each sample, the dependent variable of interest (percentage of isolates resistant to the relevant tested antimicrobial compound) takes a value between 0 and 1. If AMU_{ct} is positively associated with resistance rates, it is expected to result in $c > 0$.

X_{ict} is a vector of control variables at the sample level, including the sample type, species, pathogen, number of samples and isolates taken, the guidelines followed, as well as the sampling method and the class of antimicrobial tested. Z_{ct} is a vector of country-specific time-varying variables, including GDP per capita, total population size, share of a country's agricultural land among total landmass, as well as the level of corruption, and rule of law indicator, derived from the World Bank Development Indicator Databank (World Bank, 2024b).[28] It also includes biomass data from ANIMUSE, including the total biomass in tons and the share of this biomass by species (pig, chicken, cattle, sheep and others). γ_t are year fixed effects, controlling for common time trends in the prevalence of resistance across countries.[29]

The associations between AMU, sample characteristics, country and time variables and resistance rates are examined based on empirical model specifications using Fractional Logit (FL) regressions. FL considers that the continuous dependent variable is bounded between 0 and 1 (Papke and Wooldridge, 1996). Statistical significance was assessed at a significance level of 5% with robust standard errors (se). Note that different specifications were run, which vary by the inclusion or exclusion of country-specific control variables Z_{ct}, as well as how AMU_{ct} enters the model: (1) total consumption in kg at a scale of $10^{(-7)}$ adjusted for the total biomass of food-producing animals (in kg PCU);[30] (2) natural logarithm of total consumption in kg adjusted for the total biomass of food-producing animals (in kg PCU); and (3) intensity (in natural logarithm) of consumption measured as mg of antimicrobial consumption and divided by the biomass of food-producing animals (in kg PCU) (Tiseo *et al.,* 2020). Due to the application of the natural logarithm across the two specifications, the parameter estimates for $\hat{c}$ are expected to have a similar magnitude between specifications (3) and (2). Furthermore, as in previous longitudinal analyses (Emes *et al.,* 2024; Rahman and Hollis, 2023), both are included: the contemporaneous and 1-year lag values of antimicrobial consumption are used in the model to account for potential lags in the use of antimicrobial treatments and the emergence of resistance (Emes *et al.,* 2024; Rahman and Hollis, 2023).

Table B.13 below reports the parameter estimates for $\hat{c}$ based on different specifications using FL. The coefficients are reported in log-odds. For ease of interpretation and to better understand the magnitude of the parameters, the marginal effects for each specification are also reported in Table B.14. Thus, Table B.14 shows, for example, the parameter estimate reported for the 1-year lag of the absolute value of AMU (scaled as kg*10000000) in Panel A. This suggests that an increase of the total value of AMU consumed by kg*10000000 is associated with a 0.083% increase in the average resistance across all pathogens in the sample. The parameter estimate reported in Panel B, using the 1-year lag of AMU, suggests that a 1% increase in AMU is associated with a 0.0119% increase in the average resistance across the sampled pathogens. This estimate is in line with the lower range of estimates provided by Rahman and Hollis (2023). In this analysis, a 10% increase in AMU is associated with an average 1.2% increase in average resistance among animals, whereas the study by Rahman and Hollis (2023) estimates a 2% increase. The parameter estimates reported in Panel of Table B.14 suggest that a 1% increase in the AMU intensity is associated with a 0.0108% increase in the average resistance rate.

28 Similar control variables have been applied in Allel *et al.* (2023); Rahman and Hollis (2023); Adda (2020) and Emes *et al.* (2024).
29 Note that specifications are also tested that include an interaction effect between year and the WOAH region indicator.
30 Following similar scaling of AMU as in Tiseo *et al.* (2020).

TABLE B.13 Association between AMU and resistance rates in food-producing animals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. AMU & Biomass (scale: kg × 10000000)												
AMU_t	0.236 (0.044)***	0.422 (0.053)***										
$Biomass_t$	−0.000 (0.000)***	0.000 (0.000)										
AMU_{t-1}			0.235 (0.045)***	0.424 (0.053)***								
$Biomass_{t-1}$			−0.000 (0.000)***	0.000 (0.000)								
B. AMU & Biomass (scale: natural logarithm)												
Ln (AMU_t)					0.046 (0.021)**	0.057 (0.027)**						
Ln ($Biomass_t$)					0.013 (0.026)	0.010 (0.042)						
Ln (AMU_{t-1})							0.047 (0.021)**	0.061 (0.028)**				
Ln ($Biomass_{t-1}$)							0.014 (0.026)	0.016 (0.042)				
C. AMU Intensity (scale: natural logarithm)												
Ln (Intensity)									0.053 (0.021)**	0.054 (0.027)*		
Ln ($Intensity_{t-1}$)											0.053 (0.021)**	0.055 (0.028)**
Sample control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	12,743	12,742	12,701	12,701	12,743	12,742	12,701	12,701	12,743	12,742	12,701	12,701

TABLE B.14 Confidence intervals on the association between AMU and resistance rates in food-producing animals

	$\hat{c}$	95% CI: low	95% CI: high
A. AMU (scale: kg × 10000000)			
AMU_t	0.0826	0.0608	0.1044
AMU_{t-1}	0.083	0.0612	0.1048
B. AMU (scale: natural logarithm)			
Ln (AMU_t)	0.0113	0.0008	0.0169
Ln (AMU_{t-1})	0.0119	0.0013	0.0225
C. AMU Intensity (scale: natural logarithm)			
Ln (Intensity)	0.0104	0.0001	0.0209
Ln ($Intensity_{t-1}$)	0.0108	0.0002	0.0213

Note: entries represent marginal effects of model specifications presented in columns (2), (4), (6), (8), (10) and (12) of Table B.13. Marginal values calculated at mean values of all other control variables.

For the input to the production disease model, this study chose the coefficient for $\hat{c}$ based on the logarithmic specification with the lag relationship between consumption and resistance of 0.0119. Applying a log-linear relationship between consumption and the emergence of resistance in practice suggests that changes in antimicrobial consumption initially (e.g. at low use) have a larger effect on the emergence of AMR. Then, as AMU continues to increase, the rate at which resistance rises begins to diminish, leading to a flattening effect. In contrast, reducing AMU at higher levels of resistance would suggest an initially stronger reduction in resistance before a flattening effect, suggesting a level of 'stickiness' to the resistance when observed empirically (Emes *et al.,* 2024; Rahman and Hollis, 2023). While this is an extreme simplification of the complex and multi-faceted relationship pattern between consumption and resistance, it has been proven in the literature (Firsov *et al.,* 2018; ECDC *et al.,* 2024; Olesen *et al.,* 2018; Adda, 2020).

It must be noted that the analysis to assess the associations between AMU and AMR in food-producing animals has several strengths, including the ability to use longitudinal data on consumption and resistance. This includes not just high-income countries but also information from LMICS. However, the study has several limitations, which are outlined below.

First, the longitudinal data is unbalanced, and earlier years include fewer countries due to the scope of the available data in ANIMUSE. Also, the included resistance data for higher-income countries is more frequent for recent years, though there is no resistance data for Canada or the US.

Second, while a set of confounding factors at the sample and country-level were included in the analysis, there are many other factors that could determine the occurrence of resistance which were not included in the analysis.

Third, data on antimicrobial consumption was entered as the total amount of consumption because ANIMUSE consumption data is not directly reported by animal type. While this analysis has adjusted for the prevalent biomass within a country, previous evidence suggests potentially heterogenous associations by animal type (Emes *et al.,* 2024).

Fourth, the associations between AMU and AMR in real-life settings are multifaceted and complex and cannot be represented appropriately by just a few parameters that have been 'fitted' to data that is subject to many limitations. For example, different model specifications were tested, including quadratic and cubic terms for AMU, to check further non-linear associations between AMU and AMR. However, coefficients for these terms were generally not statistically significant from zero. Of course, this is not evidence for the fact that these relationships follow different patterns in reality. Future research based on better data will be able to expand on this.

Calculating reference resistance rates by region and livestock sector

The average AMR rates $r(t)$ by livestock sector and region are obtained from the ResistanceBank data. As the data is at the level of a submitted sample/survey, which varies depending on the pathogens, species, sample sizes or sampling methods, this analysis calculates adjusted values of AMR rates. To calculate the reference resistance rates, data from the ResistanceBank are merged with country-level variables, including GDP per capita, total population, the share of total landmass dedicated to agriculture, level of corruption and rule of law indicator obtained from the World Bank Development Indicator Databank (World Bank, 2024b).

This combined data allows for an empirical estimate of the association between the rate of resistance (transformed to range between 0 and 1) and a set of independent variables at the sample/survey level i and at the country-level c in a given year t and AMR r, as follows:

$$r_{ict} = \alpha X_{ict} + \beta Z_{ct} + \gamma_t + \varepsilon_{ict}$$

For each sample, the dependent variable of interest (the percentage of isolates resistant to the relevant tested antimicrobial compound) takes a value between 0 and 1. X_{ict} is the vector of control variables at the sample level, including the sample type, species, pathogen, number of samples and isolates taken, the guidelines followed as well as the sampling method and the class of antimicrobial tested. Z_{ct} is a vector of country-specific time-varying variables, including GDP per capita, total population size, share of a country's agricultural land among total landmass, as well as the level of corruption and rule of law. For the US and Canada, sample predictions of average resistance rates are based on the parameter estimate values for these countries included in Z_{ct}. γ_t refers to the year fixed effects, controlling for common time trends in resistance rates across countries.[31] The associations between sample characteristics, country and time variables are examined based on different empirical model specifications using Fractional Logit (FL) regressions. FL considers the fact that the continuous dependent variable is bound between 0 and 1 (Papke and Wooldridge, 1996). Statistical significance was assessed at a significance level of 5% with robust standard errors (se). Based on the parameter values from the regression model, this analysis predicts $\hat{r}_t$ at the individual country-level based on the data sample, and then aggregates to the median values from the country-specific predicted resistance rates for each region and sector included in the epidemiological component (cattle, chicken and pig).

Table B.15 reports the predicted AMR rates. For the cattle sector, as the modelled diseases are caused by a variety of pathogens, median resistance rates across

TABLE B.15 Reference AMR rates by sector (cattle, chicken, pig) and region

Region	Reference values AMR		
	Cattle	Chicken	Swine
East Asia & Pacific	0.258	0.388	0.403
Europe & Central Asia	0.195	0.304	0.284
Latin America & Caribbean	0.169	0.276	0.270
Middle East & North Africa	0.275	0.428	0.386
North America	0.196	0.305	0.285
South Asia	0.325	0.486	0.504
Sub-Saharan Africa	0.195	0.376	0.363

Note: based on ResistanceBank data. Entries represent predicted (median) values of AMR by region based on a simple regression model adjusted for sample characteristics, as well as country-specific covariates. Values for North America are predicted out of a sample based on input values for ln (gross domestic product [GDP] per capita), total population size, and the share of a country's agricultural land among total landmass.

31 Note that we also test specifications which include an interaction effect between year and the WOAH region indicator.

TABLE B.16 Reference AMU intensity values by region

Region	AMU (mg/kg biomass)
East Asia & Pacific	128.2
Europe & Central Asia	45.0
Latin America & Caribbean	96.7
Middle East & North Africa	76.0
North America	71.1
South Asia	43.5
Sub-Saharan Africa	22.7

Note: data applied from ANIMUSE and provided by WOAH.

TABLE B.17 Association between antimicrobial growth promoters (AGP) use and antimicrobial use

	AMU intensity (natural logarithm)	
AGP Use (Yes/No)[a]	(1) 0.509 (0.177)***	(2) 0.368 (0.160)**
Year fixed effects	Yes	Yes
Country control variables	No	Yes
Observations	623	616

Notes: data applied from ANIMUSE and provided by WOAH Significance level: **$p < 0.05$; ***$p < 0.01$. [a]Marginal effects are calculated as $(e^{\beta} - 1) * 100$.

pathogens have been calculated and adjusted for treatment class and other sample and country characteristics. For the chicken and pig sector, as the modelled diseases are predominantly caused by *E. coli*, median AMR rates for this pathogen have been calculated, adjusted for treatment class and other sample and country characteristics.

Table B.16 shows the parameter values for the initial values of $\theta(t)$ and the AMU intensities by region applied in the model. Table B.17 shows the parameter estimate of the association analysis between AGPs and AMU.

LIMITATIONS OF THE LIVESTOCK PRODUCTION DISEASE MODEL

While the LPD model provides a tool to simulate the potential implications of changes in AMU and AMR for livestock production, the analysis is associated with several limitations.

First, like all models, the LPD represents a simplification of complex processes that interact in reality. For example, it models a representative 'farm' or producer in each region and sector, but in reality, there is large heterogeneity across farms in each sector, even within countries. However, with more granular data available, the model could be used to disaggregate the analysis and introduce more heterogeneity in the future.

Second, for simplicity, the model currently applies constant infection rates where the number of infected does not depend on the total number of infected. This is unlikely to be the case in reality, as infections can break out in farms where animals live in close proximity. However, animal populations in livestock production sectors differ from human populations, which can interact and mix more freely. This makes it more complicated to accurately calibrate the rate of infection parameters in the absence of data. Calibrating these complex interactions was not possible with the current data availability, yet this can be introduced in future studies. Similarly, the model currently assumes that there are no re-infections, which most likely leads to an under-estimation of the burden; in reality, animals can be repeatedly infected, and this is associated with antimicrobial treatments.

Third, the inclusion of livestock sectors and modelled diseases was driven by data availability; thus, they only represent a subset of areas where AMR could cause negative implications for livestock sector productivity and animal health. This likely causes an under-estimation of the true AMR burden in these sectors. Furthermore, for the current analysis, parameter inputs had to be extrapolated from a variety of different studies. With better data availability in the future, the model can make more accurate predictions of the impact of AMR on livestock.

Fourth, the link between AMU and AMR is an important driver of some of the simulated outcomes, which vary by scenario. A parameter estimate has been applied that is grounded in empirical evidence. However, as the association between AMU and AMR is multifaceted and highly complex, this analysis does not capture all potential drivers of resistance. Furthermore, due to data limitations, the analysis focuses on average resistance rates across a set of pathogens that cause the modelled animal diseases. In reality, diseases are caused by different pathogens with varying resistance rates.

Fifth, due to data limitations, there is a substantial degree of uncertainty related to all parameter inputs to the LPD. In addition, select parameters, such as the association between AMU and AMR, have been statistically estimated and these come with a confidence interval. For the latter, a scenario was included that uses the upper boundary of the 95% confidence interval to demonstrate an association between AMU and AMR, with a higher magnitude than assumed in the reference scenario. This leads to a larger rise in AMR for each per cent increase in AMU, all else being equal. Uncertainty in many other inputs could be addressed using probabilistic distributions for each input parameter. However, current data limitations hinder an understanding of the appropriate distributions and the corresponding first, second and third moment. In addition, as the model depends on several input parameters, such a probabilistic analysis is computationally intensive.

Lastly, the model currently does not consider imported or exported resistance rates. For example, resistant pathogens that affect animals, and which therefore contribute to disease, can be imported or exported to other sectors within the same region or to other regions. The current model assumes no direct cross-sector or cross-regional spillovers.

REFERENCE SCENARIO MODEL OUTPUTS

Table B.18 reports the predicted changes in resistance rates by region for 2025–2050 and for the livestock species of cattle, swine and chicken. It must be noted that the predicted changes in resistance are solely based on changes in overall AMU due to increases in livestock placed over time. In reality, there are other factors and complicated mechanisms at play that lead to the emergence and changes in resistance across different pathogens. Based on the simulation analysis using the LPD model, and the calibrated parameter of the relationship between AMU and AMR, this study predicts that the regions with relative stronger increases in AMU will also experience relative larger increases in resistance rates. For example, for cattle, predicted resistance rates will increase from roughly 19.7% to 30% in Sub-Saharan Africa, whereas other regions will have lower predicted increases. Validating these results with external data is not a straightforward process due to a lack of similar modelling approaches and existing studies, however, predicted changes can be compared to the available literature. For example, Ager *et al.* (2023) estimate that resistance rates across global conventional livestock farms have increased from 18% to 37% between 2000 and 2020; in other words, this is a 19% increase over two decades (Ager *et al.*, 2023). This is roughly in line with predicted changes for the regions with the largest predicted increases in AMU, but overall suggests that this study's simulation results under-estimate the changes in resistance that one would observe in reality, all else being equal.

TABLE B.18 Predicted change in resistance rates for reference scenario by region (2025–2050)

	East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa
A. Cattle							
2025	0.2584	0.1953	0.1700	0.2762	0.1955	0.3256	0.1976
2030	0.2596	0.1972	0.1732	0.2815	0.1938	0.3268	0.2068
2040	0.2642	0.2050	0.1868	0.3035	0.1868	0.3319	0.2448
2050	0.2720	0.2183	0.2097	0.3407	0.1749	0.3405	0.3090
B. Swine							
2025	0.4035	0.2842	0.2710	0.3864	0.2854	0.5045	0.3673
2030	0.4050	0.2858	0.2751	0.3876	0.2870	0.5064	0.3805
2040	0.4112	0.2925	0.2918	0.3923	0.2933	0.5143	0.4352
2050	0.4215	0.3039	0.3200	0.4003	0.3040	0.5277	0.5278
C. Chicken							
2025	0.3890	0.3045	0.2766	0.4285	0.3064	0.4878	0.3812
2030	0.3911	0.3064	0.2798	0.4310	0.3115	0.4932	0.4001
2040	0.3998	0.3143	0.2930	0.4414	0.3323	0.5158	0.4783
2050	0.4145	0.3276	0.3154	0.4590	0.3675	0.5539	0.6106

Note: entries report change in resistance rate by animal type, year and region based on livestock production disease (LPD) model simulations for the reference scenario.

In addition, Table B.19 reports the predicted quantities (in tons) produced for the reference scenario by each of the modelled livestock sectors by region and over time (2025–2050). For example, global cattle annual meat production in 2025 is predicted to be 69 million tons, for swine meat this is 92 million tons and for chicken meat this is 102 million tons. Cattle raw milk is predicted to be about 649 million tons, and chicken eggs are at 75 million tons.

TABLE B.19 Predicted production quantities (1000 tons) for reference scenario by region and modelled livestock sector (2025–2050)

Output type	Year	East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	13,771	12,126	15,054	1,634	13,325	6,424	6,954	*69,288*
	2030	14,310	12,776	16,068	1,797	13,282	6,762	8,019	*73,015*
	2040	15,451	14,178	18,292	2,171	13,200	7,491	10,653	*81,436*
	2050	16,676	15,724	20,804	2,619	13,127	8,296	14,130	*91,375*
Cattle: Raw milk	**2025**	64,830	260,261	68,118	33,343	97,027	75,035	50,902	*649,515*
	2030	66,201	268,707	71,960	35,914	92,840	80,035	59,365	*675,022*
	2040	69,024	286,364	80,297	41,653	85,015	91,047	80,707	*734,107*
	2050	71,960	305,088	89,588	48,289	77,867	103,559	109,644	*805,994*
Swine: Meat	**2025**	42,688	23,935	7,848	16	14,956	525	2,229	*92,197*
	2030	44,296	24,789	8,371	16	15,407	547	2,668	*96,095*
	2040	47,693	26,588	9,523	17	16,350	596	3,816	*104,582*
	2050	51,344	28,513	10,829	18	17,348	649	5,452	*114,152*
Chicken: Meat	**2025**	29,563	16,122	20,500	7,781	19,815	5,051	3,630	*102,462*
	2030	30,850	16,713	21,555	8,155	21,272	5,507	4,641	*108,693*
	2040	33,586	17,956	23,819	8,955	24,497	6,543	7,571	*122,925*
	2050	36,549	19,283	26,306	9,828	28,184	7,766	12,320	*140,237*
Chicken: Eggs	**2025**	37,321	9,835	8,364	3,647	7,721	6,517	2,354	*75,759*
	2030	38,951	10,196	8,796	3,823	8,290	7,107	3,012	*80,175*
	2040	42,424	10,959	9,727	4,201	9,558	8,451	4,928	*90,248*
	2050	46,205	11,778	10,755	4,615	11,018	10,048	8,060	*102,479*

Note: entries report change in production outputs (tons) by sector, year and region based on livestock production disease (LPD) model simulations for the reference scenario.

Annex C: The dynamic computable general equilibrium economic model

This annex describes the technical details of the DCGE model. It first outlines the model overview, before describing the model inputs, and finally describing the model outputs.

MODEL OVERVIEW

To assess the economic impacts of AMR in livestock production, this study uses productivity parameter outputs from the LPD model as inputs to the multi-region DCGE model. Through this model, the study conceptualises the economies of several countries as open economies that are connected to each other and the rest of the world via trade (e.g. intermediate and final goods, services) and investment networks (e.g. foreign direct investment). Recently, the importance of considering the economic system as a whole when evaluating new health interventions has been highlighted (Hafner *et al.,* 2023). The DCGE model resembles Lanz and Rutherford's (2016) multi-region model. In the following paragraphs, further information is provided on the main components of this study's model. Its purpose is to provide extended information for the general audience (Lanz and Rutherford, 2016). For more technically rigorous documentation, please refer to Lanz and Rutherford (2016).

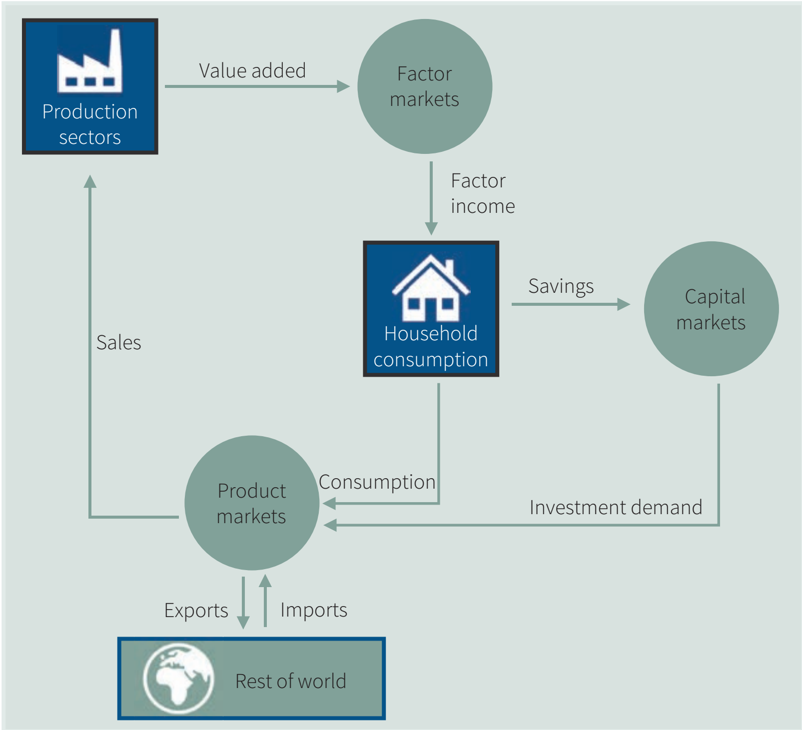
Each geographical region *r* is conceptualised as an open economy. Regions are inter-connected through trade links of goods and services (e.g. intermediate and final goods). The model is calibrated to seven distinct regional households (e.g., North America, Latin America and the Caribbean, etc.), which have been chosen because countries within these regions share similarities in terms of their livestock biomass distribution and income levels. Further information on the calibration of the LPD model is provided in Appendix A, and its analytical scope is provided in Annex B.

Figure C.1 is a simplified illustration of the model. It depicts the interaction of production sectors (e.g. different agricultural, industrial and service sectors) that require capital and labour inputs, which they access through the factor markets. Firms hire labour and rent capital from households, by which households in turn obtain income. Goods are then sold in product markets, which households pay for, given their available income. The economy also trades products with the rest of the world through bilateral international links.

The model also includes government services and investment (not depicted in Figure C.1). The government collects taxes with which it buys (demands) final goods and thus provides public services. Furthermore, regional households and governments save/borrow in capital markets, where an investment account demands final goods used to create new capital for the next period.

The model is programmed in GAMS using the sub-language mathematical programming system for general equilibrium (MPSGE) (GAMS, 2023; Rutherford, 1999). Further details on the static element of this model are provided in Hafner *et al.* (2023).

FIGURE C.1 Depiction of selected key interactions between economic agents in the dynamic computable general equilibrium economic (DCGE) model



To assess the cost of animal AMR, the DCGE compares alternative 'what-if?' counterfactual scenarios to a reference projection. For example, one scenario that captures the cost of AMR compares a counterfactual scenario with very low levels of AMR to the current reference world, which contains current AMR rates and AMU practices.

Further information on this is in the following sections.

Production structure

In each region r and time-period t, sectors y_i produce goods and services (e.g. live animals in the agriculture sectors) with corresponding market prices of p_i. Each sector demands labour L_i, capital inputs K_i and intermediate inputs N_{ij} (with j other sectors). The model further assumes that technological progress A follows a Hicks-neutral assumption (i.e. Total Factor Productivity, or TFP) across all sectors, for the sake of simplicity. Finally, an animal AMR TFP parameter P_i is introduced, obtained from the LPD model discussed previously in Annexes A and B. The AMR TFP affects the three main live animal aggregated sectors: (i) bovine cattle, sheep and goats, (ii) other animal products – mainly swine, poultry, chicken eggs, etc. and (iii) raw milk.

Supressing indices for region r and time-period t, the model uses a multi-level constant return to scale (CRS) production function of the form:

$$y_i = (AP_i) f(K_i, L_i, N_{ij}) \tag{1}$$

This is illustrated in Figure C.2. At the top-nest, a Capital-Labour value is combined with intermediate inputs N_{ij} in fixed proportions (i.e. a Leontief function). In the next level, capital and labour are combined using a Cobb-Douglas function, which has a unitary substitution elasticity (i.e. σ = 1). Intermediate inputs are also combined using a Constant Elasticity of Substitution (CES) function, which has a much lower substitution near zero (i.e. σ = 0.1), signifying different intermediate inputs. Finally, at the lowest-nest, domestic and imported intermediate inputs are combined using a CES function with a high substitution elasticity σ = 5, signifying the high similarity between domestic and imported intermediate products.

FIGURE C.2 Multi-level constant returns to scale (CRS) production structure

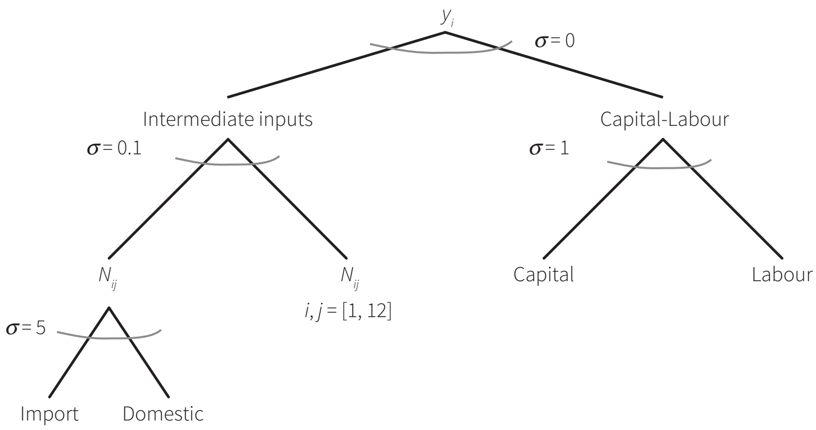
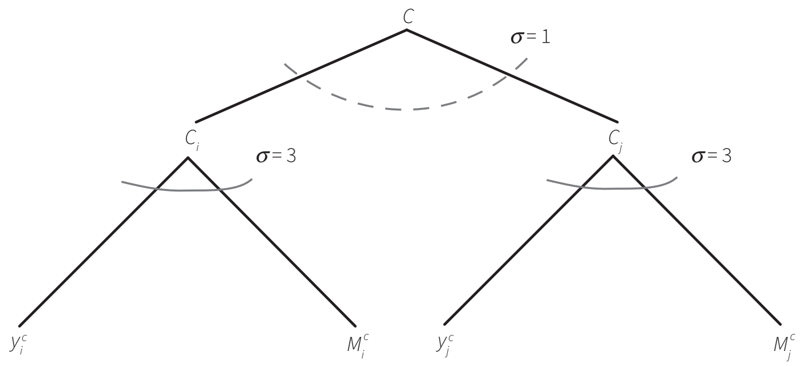


FIGURE C.3 The structure of private consumption



Regional households

As previously mentioned, regional households are a collection of countries that share a similar livestock biomass distribution and income levels. Each region maximises a welfare function W_r of private consumption, public consumption and investment in fixed proportions (i.e. Leontief function), which have a price index P^W This offers the following equation:

$$\begin{aligned} &\text{Max } W_r = f(C_r, G_r, I_r) \\ &s.t.\ R_r K_r + w_r L_r + P_r^{CA} CA_r = P_r^W W_r \end{aligned} \tag{2}$$

This is subject to their intra-temporal budget constraint with R being the rental rate of capital, w the wage rate, and P^{CA} being the price index for the CA current account.[32]

In the next sub-levels, private consumption is structured as a two-level function, $C = f(y_i^C, M_i^C)$, with consumer price index p^C. As Figure C.3 illustrates, at the top level, goods and services $i = [1 \ldots N]$, with $i \neq j$, are assembled as a Cobb-Douglas function. In the second level, domestic y_i^C and imported M_i^C final goods and services are combined using a CES function with a high substitution elasticity $\sigma = 3$, which captures the similarity and substitutability of products within a sector.

Similarly, public consumption $G = f(y_i^G, M_i^G)$ is also a two-level function, with price index p^G. At the top level, products are demanded in fixed proportion, while at the lower level, domestic and imported products are assembled within a CES function with a high substitution elasticity of $\sigma = 3$. Finally, investment $I = f(y_i^I, M_i^I)$ is similar to the government demand with price index p^I.

Though this is not depicted here, all goods and imports are subject to taxes and import duties, which are calibrated accordingly.

32 The current account is part of the balance of payments provided within the Social Accounting Matrix (SAM). It includes trade balance, transaction on transport and marketing services, as well as primary and secondary income flow transfers to/from other countries. To simplify this documentation, a general overview is provided here. Further details can be found in Lanz *et al.*, 2016.

International trade

The model employs an Armington formulation (Armington, 1969), which allows for cross-hauling of goods and services. Regionally differentiated imports are brought in from other regions. These are demanded by the production sectors as intermediate imported goods, or as final goods for private or public consumption and investment. Transportation services (i.e. trade margins) enter on a proportional basis with imports from different regions. In terms of exports, production sectors y_i are split into domestic supply, exported goods and services, as well as transportation services, using a constant elasticity of transformation (CET) function. Supply–demand conditions apply to all goods and factors adhering to the typical market clearance conditions.

Calibration

The underlying economic data used for this analysis is obtained from the GTAP database. This database was developed by the Centre for Global Trade Analysis at Purdue University in 1993. Overall, GTAP covers 160 countries for 65 GTAP commodities and includes all bilateral trade patterns, production, consumption and intermediate inputs of commodities and services. This study includes data from the latest version, GTAP 11. GTAP has a disaggregated structure for many agricultural sectors and is therefore well-suited for the purpose of this project (Purdue University, 2023).

GTAP includes Social Accounting Matrices (SAMs) for individual countries based on national accounts data (e.g. use–supply tables, input–output tables) and information from household survey data and trade data. SAM is a complex table expressed in terms of incomes and expenditures, i.e. a double-entry accounting method. From the GTAP database, countries are aggregated into regions and a regional SAM is extracted.

As previously discussed (see Annex A), countries have been aggregated into seven geographical regions based on similarities regarding livestock biomass and income levels. These seven regions are listed in Table C.1.

GTAP provides 65 distinct production sectors, which have been aggregated into 12 main sectors. It is important to highlight that GTAP 11 aggregates sectors in such a way that requires the inputs by sector from the LPD model to be reweighted and/or aggregated to map them into the GTAP sectors.

First, GTAP sector *'ctl'* includes bovine animals, live, other ruminants, horses and other equines, and bovine semen. As the focus of the LPD model is on cattle, this study uses biomass data from ANIMUSE, which provides the share of biomass per species for each of the regions, and calculates the proportion for cattle in each region. That proportion is then used to weight the productivity effect P_i for the cattle meat sector, which is then passed to the DCGE model.[33]

Second, the GTAP sector *'rmk'* includes likely raw milk from various animal species, including goats and sheep. Thus, the study applies FAO production data to calculate the total quantities of raw milk produced in

TABLE C.1 Geographical regions

1	EAP	East Asia & Pacific
2	ECA	Europe & Central Asia
3	LAC	Latin America & Caribbean
4	MENA	Middle East & North Africa
5	NorthA	North America
6	SA	South Asia
7	SSA	Sub-Saharan Africa

33 For example, if cattle make up 90% of the total biomass among other ruminants, horses and other equines, then the productivity effect is weighted by multiplying it by 0.9 before it is applied in the DCGE model.

kg among all species in each region, then calculates the proportion from cattle. This proportion is then applied as a weight for the sector-specific productivity effect P_i, which is then passed to the DCGE model.

Third, the GTAP sector *'oap'* includes the following: other animal products; swine; poultry; other live animals; eggs of hens or other birds in shell, fresh; reproductive materials of animals; natural honey; snails, fresh, chilled, frozen, dried, salted or in brine, except sea snails; edible products of animal origin n.e.c.; hides, skins and fur skins, raw; insect waxes and spermaceti, whether or not refined or coloured. Similarly, for raw milk, the study applies FAO production data and calculates for each region the total amount produced among all the possible items included in the GTAP sector. Next, the proportion of this total is calculated that goes to swine, poultry and chicken eggs, which is then used as the weight for the sector-specific productivity effect P_i. This is then passed to the DCGE model.

The AMR TFP affects the three main live animal aggregated sectors: (i) bovine cattle, sheep and goats, (ii) other animal products – mainly swine, poultry, chicken eggs, etc. and (iii) raw milk. The sectorial aggregation is outlined in Table C.2.

Model dynamics

The model employs a recursive-dynamic approach, whereby the model is solved for each period and moves all variables forward to the next period. Therefore, this is a myopic approach in which regional households cannot react to foreseeable future events. In other words, regional households make consumption–investment decisions to maximise their welfare only based on past states of the economy, implying that the role of expectation is limited. Lecca *et al.* (2013) discuss the different advantages and disadvantages of using a fully-forward looking approach *versus* a recursive one.

As previously discussed, for each sector *i*, production follows a form of $y_t = AP_t f(K_t, L_t, N_{jt})$, which is Hicks neutral in total factor productivity.

Two variables adjust recursively. First, physical supply of employed labour adjusts by $L_t = L_0(1 + g_t)$, which is introduced exogenously into the model. Demographic data for the working population aged 15–64 drives the rise in labour L_t. Since adequate estimates for changes in participation rates are unavailable, this analysis assumes that L_t is driven by the change in the working population aged 15–64. Furthermore, the analysis uses the total population for other metrics, such as GDP per capita.

TABLE C.2 Sectorial aggregation

1	Crop Food	Various food-producing sectors
2	Beef Live	Bovine cattle, sheep and goats
3	Pig Chick Live	Other animal products, mainly swine, poultry, other live animals, chicken eggs, etc.
4	Dairy	Raw milk production
5	Extraction	Forestry, coal, oil, gas, other minerals
6	Fishing	–
7	Beef Production	Meat production of cattle, sheep and goats
8	Pig Chicken Production	Other meat production, mainly from swine and poultry.
9	Man	Other manufacturing sectors
10	Pharma	Pharmaceutical
11	Ser	Other services sectors
12	Health	Healthcare

Notes: defining sectors $i = [1, 12]$, the counterfactual animal AMR scenarios affect the live animal sectors 2, 3 and 4 through the parameter P_i.
In the reference scenario, $P_i = 1$, while in the counterfactual scenarios, $P_i \neq 1$, which will change the overall Hicks-neutral Total Factor Productivity (TFP).

The demographics used in this model are provided by the Institute for Health Metrics and Evaluation (2020).

Second, capital is adjusted according to a standard capital stock accumulation assumption, with δ being the depreciation rate. Old capital is distinguished from new capital whereby old capital is defined as the remaining capital after depreciation, while new capital is created through new investment.

$$K_{t+1} = (1-\delta)K_t + I_t \tag{3}$$

Since the model is calibrated to regional SAMs, the capital stock is converted to return on capital in monetary values by multiplying both sides of (3) by a five-year internal rate of return ρ, which recognises that investors have a risk–return trade-off in their consumption and saving behaviour. This is different for each region.

For each region r, the following change in return on capital is obtained:

$$VK_{t+1,r} = (1-\delta_r)VK_{t,r} + \rho_r I_{t,r} \tag{4}$$

Calibration of parameters

Three reference parameters from Penn World Tables 10.0 are calibrated: (i) Total Factor Productivity (TFP), (ii) depreciation and (iii) the Internal Rate of Return that is associated with the regional risk–return trade-off in consumption and saving behaviour (provided in Table C.3) (Feenstra *et al.,* 2015). Since values vary and have unknowns, these are broadly grouped by region. Finally, reference regional projections are adjusted to align with those estimated by SSP2 (i.e. a 'middle of the road' scenario) and PWC (2017) (Cuaresma, 2017).

TABLE C.3 Sampling values for non-probability parameters

		Total factor productivity, A		Depreciation, δ		Internal rate of return, ρ	
		Year 0	Year 30	Year 0	Year 30	Year 0	Year 30
EAP	East Asia & Pacific	1.0%	0.95%	4.5%	4.5%	10.0%	8.0%
ECA	Europe & Central Asia	1.1%	0.95%	4.5%	4.5%	10.0%	8.0%
LAC	Latin America & Caribbean	1.5%	1.1%	4.0%	4.0%	15.0%	15.0%
MENA	Middle East & North Africa	1.5%	1.1%	4.0%	4.0%	15.0%	15.0%
NorthA	North America	1.1%	0.95%	4.5%	4.5%	10.0%	8.0%
SA	South Asia	1.5%	1.1%	4.5%	4.5%	18.0%	15.0%
SSA	Sub-Saharan Africa	1.5%	1.1%	4.5%	4.0%	15.0%	15.0%

Annex D: Results from scenario analyses

LIVESTOCK PRODUCTION EFFECTS ATTRIBUTABLE TO AMR BY YEAR AND REGION

The simulated effects of AMR from the LPD model on the production outputs of the modelled livestock sectors under different scenarios are reported in a series of tables below (Tables D.2 to D.16). For each scenario 1 to 4, the effects on outputs in per cent, tons and consumption equivalent are reported. That is, to put the production effects measured in tons, which are attributable to AMR, into perspective, the annual consumption per capita data has been used, based on information from FAO, which was processed and made available by Our World in Data; this is reported in Table D.1 by region (FAO with major processing by Our World in Data, 2023). The production effect in tons is divided by the per capita consumption of the given livestock output; this provides the foregone consumption equivalent. Note that for parsimonious reasons, the consumption per capita has been adjusted so it does not change over time.

TABLE D.1 Annual consumption of livestock sector goods (kilogram per capita)

Region	Beef meat	Milk	Swine meat	Poultry meat	Eggs
kg per capita per year					
East Asia & Pacific	6.3	47.6	27.2	16.0	17.5
Europe & Central Asia	15.2	193.7	28.5	23.5	12.8
Latin America & Caribbean	23.5	119.0	13.3	38.4	13.1
Middle East & North Africa	6.8	65.6	0.1	20.9	6.5
North America	36.1	220.8	28.6	55.1	15.8
South Asia	2.5	73.5	0.2	3.3	3.6
Sub-Saharan Africa	5.2	26.7	1.9	5.0	1.6

Notes: entries represent population weighted kg per capita consumption values based on data by the Food and Agriculture Organization of the United Nations (2023), with major processing by Our World in Data. Population data to weight entries by region is based on country-specific data from the World Bank (World Bank, 2024a). The entries represent average values for 2017–2021.

TABLE D.2 Simulated effects on livestock sector production outputs (scenario 1 *versus* reference) – differences in per cent

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	2.71	2.07	1.74	3.06	2.34	2.21	1.17	*2.13*
	2030	2.72	2.09	1.78	3.11	2.34	2.22	1.22	*2.13*
	2040	2.77	2.17	1.91	3.36	2.34	2.26	1.44	*2.20*
	2050	2.85	2.31	2.15	3.77	2.34	2.31	1.81	*2.34*
Cattle: Raw milk	**2025**	0.85	0.98	0.22	0.71	0.81	1.24	0.46	*0.84*
	2030	0.85	0.98	0.23	0.72	0.81	1.24	0.47	*0.84*
	2040	0.86	1.01	0.24	0.76	0.81	1.26	0.52	*0.85*
	2050	0.87	1.05	0.26	0.81	0.81	1.28	0.62	*0.88*
Swine: Meat	**2025**	1.09	0.76	0.72	1.04	0.76	1.38	0.99	*0.92*
	2030	1.10	0.76	0.73	1.05	0.76	1.38	1.02	*0.92*
	2040	1.11	0.78	0.77	1.06	0.78	1.40	1.14	*0.94*
	2050	1.13	0.80	0.83	1.07	0.80	1.43	1.34	*0.98*
Chicken: Meat	**2025**	2.38	1.85	1.66	2.68	1.86	2.29	1.61	*2.05*
	2030	2.39	1.86	1.67	2.69	1.88	2.31	1.66	*2.05*
	2040	2.42	1.89	1.72	2.73	1.96	2.37	1.85	*2.10*
	2050	2.48	1.94	1.80	2.80	2.09	2.48	2.19	*2.20*
Chicken: Eggs	**2025**	0.41	0.32	0.29	0.46	0.27	0.34	0.23	*0.36*
	2030	0.41	0.32	0.29	0.46	0.27	0.34	0.24	*0.36*
	2040	0.42	0.33	0.30	0.47	0.28	0.35	0.26	*0.37*
	2050	0.42	0.33	0.31	0.48	0.30	0.36	0.30	*0.37*

Note: based on simulations of the livestock production disease (LPD) model.

TABLE D.3 Simulated effects on livestock sector production outputs (scenario 1 *versus* reference) – differences in tons

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	372,936	251,330	262,457	49,932	317,524	142,290	81,104	*1,477,572*
	2030	389,207	267,344	285,444	55,967	322,930	150,320	97,749	*1,568,961*
	2040	427,603	308,316	350,037	72,887	334,019	169,028	153,118	*1,815,007*
	2050	475,004	363,811	446,483	98,719	345,489	191,899	255,543	*2,176,947*
Cattle: Raw milk	**2025**	547,819	2,544,353	152,105	238,193	817,603	931,835	232,224	*5,464,132*
	2030	560,860	2,642,868	162,637	259,531	817,603	996,156	278,670	*5,718,326*
	2040	591,077	2,886,974	190,510	315,287	817,603	1,143,720	423,021	*6,368,192*
	2050	627,312	3,202,686	229,584	393,533	817,603	1,321,097	676,362	*7,268,177*
Swine: Meat	**2025**	466,326	181,307	56,530	167	113,815	7,226	22,034	*847,404*
	2030	485,337	188,654	61,033	172	117,762	7,562	27,134	*887,654*
	2040	528,981	206,236	72,888	184	127,217	8,336	43,392	*987,233*
	2050	581,176	228,231	89,544	197	139,019	9,265	73,104	*1,120,536*
Chicken: Meat	**2025**	704,646	298,754	340,001	208,778	369,231	115,773	58,423	*2,095,606*
	2030	737,704	310,872	360,003	219,584	400,304	127,055	76,893	*2,232,414*
	2040	813,831	339,195	409,318	244,612	479,775	155,038	140,400	*2,582,169*
	2050	905,381	373,751	473,547	274,961	588,633	192,288	270,008	*3,078,567*
Chicken: Eggs	**2025**	153,227	31,482	23,959	16,850	20,555	21,958	5,424	*273,456*
	2030	160,358	32,746	25,349	17,716	22,269	24,079	7,119	*289,634*
	2040	176,648	35,669	28,733	19,703	26,613	29,289	12,864	*329,521*
	2050	196,050	39,195	33,083	22,091	32,508	36,144	24,409	*383,480*

Note: based on simulations of the livestock production disease (LPD) model.

TABLE D.4 Simulated effects on livestock sector production outputs (scenario 1 *versus* reference) – differences in consumption equivalents (million people)

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	59.0	16.6	11.2	7.3	8.8	56.3	15.5	*174.7*
	2030	61.6	17.6	12.2	8.2	8.9	59.4	18.7	*186.7*
	2040	67.7	20.3	14.9	10.7	9.3	66.8	29.3	*219.1*
	2050	75.2	24.0	19.0	14.5	9.6	75.9	49.0	*267.1*
Cattle: Raw milk	**2025**	11.5	13.1	1.3	3.6	3.7	12.7	8.7	*54.6*
	2030	11.8	13.6	1.4	4.0	3.7	13.6	10.4	*58.4*
	2040	12.4	14.9	1.6	4.8	3.7	15.6	15.8	*68.8*
	2050	13.2	16.5	1.9	6.0	3.7	18.0	25.3	*84.6*
Swine: Meat	**2025**	17.1	6.4	4.2	1.2	4.0	35.1	11.6	*79.6*
	2030	17.8	6.6	4.6	1.2	4.1	36.7	14.3	*85.4*
	2040	19.4	7.2	5.5	1.3	4.5	40.4	22.9	*101.2*
	2050	21.3	8.0	6.7	1.4	4.9	44.9	38.6	*125.9*
Chicken: Meat	**2025**	44.0	12.7	8.9	10.0	6.7	34.9	11.8	*128.9*
	2030	46.1	13.2	9.4	10.5	7.3	38.3	15.5	*140.2*
	2040	50.8	14.5	10.7	11.7	8.7	46.7	28.4	*171.4*
	2050	56.6	15.9	12.3	13.1	10.7	57.9	54.5	*221.0*
Chicken: Eggs	**2025**	8.8	2.5	1.8	2.6	1.3	6.1	3.3	*26.4*
	2030	9.2	2.6	1.9	2.7	1.4	6.7	4.4	*28.8*
	2040	10.1	2.8	2.2	3.0	1.7	8.1	7.9	*35.8*
	2050	11.2	3.1	2.5	3.4	2.1	10.0	15.0	*47.3*

Notes: based on simulations of the livestock production disease (LPD) model. Entries report the projected production effects in tons from Table D.3 as consumption equivalents of millions of people by dividing estimated production losses by the average consumption of the modelled livestock sectors' products in kg per capita.

TABLE D.5 Simulated effects on livestock sector production outputs (scenario 2 *versus* reference) – differences in per cent

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	–2.82	–2.30	–2.03	–3.17	–2.56	–2.55	–1.73	*–2.38*
	2030	–2.85	–2.35	–2.11	–3.31	–2.56	–2.93	–2.59	*–2.54*
	2040	–2.97	–2.55	–2.46	–3.91	–2.56	–4.35	–5.57	*–3.20*
	2050	–3.17	–2.90	–3.05	–4.94	–2.56	–6.49	–9.35	*–4.29*
Cattle: Raw milk	**2025**	–2.85	–4.12	–1.12	–2.21	–3.25	–3.44	–2.02	*–3.21*
	2030	–2.86	–4.15	–1.13	–2.25	–3.25	–3.67	–2.41	*–3.27*
	2040	–2.91	–4.27	–1.19	–2.41	–3.25	–4.55	–3.76	*–3.55*
	2050	–2.98	–4.48	–1.29	–2.70	–3.25	–5.87	–5.47	*–4.06*
Swine: Meat	**2025**	–1.47	–1.17	–1.14	–1.42	–1.17	–1.77	–1.50	*–1.32*
	2030	–1.48	–1.18	–1.17	–1.43	–1.18	–1.93	–1.93	*–1.34*
	2040	–1.52	–1.23	–1.29	–1.47	–1.23	–2.54	–3.45	*–1.46*
	2050	–1.60	–1.31	–1.49	–1.52	–1.30	–3.46	–4.02	*–1.60*
Chicken: Meat	**2025**	–4.05	–3.63	–3.47	–4.32	–3.65	–3.75	–3.19	*–3.76*
	2030	–4.08	–3.66	–3.52	–4.36	–3.73	–4.07	–3.95	*–3.85*
	2040	–4.22	–3.79	–3.73	–4.53	–4.07	–5.31	–6.66	*–4.26*
	2050	–4.46	–4.00	–4.09	–4.81	–4.64	–7.23	–6.82	*–4.75*
Chicken: Eggs	**2025**	–0.93	–0.85	–0.81	–0.99	–0.80	–0.74	–0.62	*–0.87*
	2030	–0.93	–0.85	–0.82	–0.99	–0.81	–0.80	–0.75	*–0.88*
	2040	–0.96	–0.88	–0.86	–1.03	–0.87	–1.01	–1.22	*–0.95*
	2050	–1.01	–0.92	–0.93	–1.08	–0.98	–1.34	–1.24	*–1.04*

Note: based on simulations of the livestock production disease (LPD) model.

TABLE D.6 Simulated effects on livestock sector production outputs (scenario 2 *versus* reference) – differences in tons

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	–387,907	–278,393	–305,378	–51,743	–346,500	–163,650	–120,484	*–1,654,055*
	2030	–407,264	–299,704	–339,407	–59,510	–352,399	–198,068	–207,534	*–1,863,886*
	2040	–458,282	–361,921	–449,978	–84,949	–364,500	–325,773	–593,160	*–2,638,563*
	2050	–528,537	–456,496	–634,429	–129,232	–377,016	–538,624	–1,321,190	*–3,985,525*
Cattle: Raw milk	**2025**	–1,847,857	–10,717,599	–762,456	–736,264	–3,277,918	–2,578,829	–1,026,814	*–20,947,737*
	2030	–1,894,184	–11,144,551	–815,414	–807,475	–3,277,917	–2,939,341	–1,428,512	*–22,307,395*
	2040	–2,006,301	–12,226,490	–955,927	–1,005,914	–3,277,917	–4,142,086	–3,034,804	*–26,649,439*
	2050	–2,146,842	–13,655,999	–1,153,367	–1,302,330	–3,277,917	–6,081,791	–6,001,492	*–33,619,739*
Swine: Meat	**2025**	–626,738	–279,305	–89,238	–227	–174,975	–9,291	–33,531	*–1,213,306*
	2030	–655,112	–292,177	–97,621	–235	–181,951	–10,586	–51,565	*–1,289,247*
	2040	–726,579	–326,279	–122,518	–255	–200,537	–15,147	–131,501	*–1,522,814*
	2050	–820,843	–373,300	–161,392	–280	–226,149	–22,461	–219,113	*–1,823,539*
Chicken: Meat	**2025**	–1,197,441	–584,961	–710,692	–335,837	–722,966	–189,307	–115,935	*–3,857,138*
	2030	–1,259,994	–611,555	–758,352	–355,325	–793,434	–224,395	–183,224	*–4,186,279*
	2040	–1,418,701	–679,993	–888,861	–405,383	–996,508	–347,682	–503,984	*–5,241,111*
	2050	–1,630,417	–772,030	–1,076,741	–473,185	–1,308,017	–561,501	–839,736	*–6,661,626*
Chicken: Eggs	**2025**	–346,112	–83,202	–67,853	–35,974	–61,567	–48,186	–14,697	*–657,591*
	2030	–363,798	–86,881	–72,252	–38,016	–67,360	–56,538	–22,689	*–707,534*
	2040	–407,852	–96,150	–84,003	–43,163	–83,630	–85,213	–59,886	*–859,897*
	2050	–465,567	–108,366	–100,555	–50,010	–108,037	–134,282	–100,192	*–1,067,009*

Note: based on simulations of the livestock production disease (LPD) model.

TABLE D.7 Simulated effects on livestock sector production outputs (scenario 2 *versus* reference) – differences in consumption equivalents (million people)

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	−61.4	−18.4	−13.0	−7.6	−9.6	−64.7	−23.1	*−197.8*
	2030	−64.5	−19.8	−14.5	−8.7	−9.8	−78.3	−39.8	*−235.3*
	2040	−72.5	−23.9	−19.2	−12.5	−10.1	−128.8	−113.7	*−380.6*
	2050	−83.7	−30.1	−27.1	−19.0	−10.4	−212.9	−253.2	*−636.4*
Cattle: Raw milk	**2025**	−38.8	−55.3	−6.4	−11.2	−14.8	−35.1	−38.4	*−200.1*
	2030	−39.8	−57.5	−6.9	−12.3	−14.8	−40.0	−53.4	*−224.7*
	2040	−42.1	−63.1	−8.0	−15.3	−14.8	−56.4	−113.5	*−313.3*
	2050	−45.1	−70.5	−9.7	−19.9	−14.8	−82.8	−224.4	*−467.2*
Swine: Meat	**2025**	−23.0	−9.8	−6.7	−1.6	−6.1	−45.1	−17.7	*−110.0*
	2030	−24.0	−10.2	−7.3	−1.7	−6.4	−51.4	−27.2	*−128.3*
	2040	−26.7	−11.4	−9.2	−1.8	−7.0	−73.5	−69.5	*−199.1*
	2050	−30.1	−13.1	−12.1	−2.0	−7.9	−109.0	−115.7	*−290.0*
Chicken: Meat	**2025**	−74.8	−24.9	−18.5	−16.0	−13.1	−57.0	−23.4	*−227.8*
	2030	−78.7	−26.1	−19.7	−17.0	−14.4	−67.6	−37.0	*−260.4*
	2040	−88.6	−29.0	−23.1	−19.4	−18.1	−104.7	−101.8	*−384.6*
	2050	−101.9	−32.9	−28.0	−22.6	−23.7	−169.1	−169.6	*−547.8*
Chicken: Eggs	**2025**	−19.8	−6.5	−5.2	−5.5	−3.9	−13.3	−9.0	*−63.3*
	2030	−20.8	−6.8	−5.5	−5.9	−4.3	−15.6	−13.9	*−72.8*
	2040	−23.3	−7.5	−6.4	−6.7	−5.3	−23.6	−36.8	*−109.6*
	2050	−26.6	−8.5	−7.7	−7.7	−6.8	−37.2	−61.5	*−156.0*

Notes: based on simulations of the livestock production disease (LPD) model. Entries report the projected production effects in tons from Table D.6 as consumption equivalents of millions of people by dividing estimated production losses by the average consumption of the modelled livestock sectors' products in kg per capita.

TABLE D.8 Simulated effects on livestock sector production outputs (scenario 3 *versus* reference) – differences in per cent

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2030	0.31	0.31	0.30	0.28	0.35	0.20	0.17	*0.29*
	2040	0.76	0.77	0.75	0.76	0.87	0.49	0.43	*0.71*
	2050	1.21	1.23	1.19	1.25	1.38	0.78	0.69	*1.12*
Cattle: Raw milk	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.03*
	2030	0.10	0.17	0.04	0.08	0.14	0.12	0.08	*0.12*
	2040	0.26	0.41	0.11	0.20	0.33	0.29	0.19	*0.30*
	2050	0.41	0.65	0.17	0.32	0.53	0.47	0.30	*0.47*
Swine: Meat	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2030	0.08	0.08	0.08	0.08	0.08	0.08	0.08	*0.08*
	2040	0.20	0.20	0.20	0.20	0.20	0.20	0.20	*0.20*
	2050	0.32	0.32	0.32	0.32	0.32	0.32	0.32	*0.32*
Chicken: Meat	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2030	0.19	0.19	0.19	0.19	0.19	0.14	0.13	*0.19*
	2040	0.47	0.47	0.47	0.47	0.47	0.35	0.33	*0.45*
	2050	0.74	0.75	0.75	0.76	0.75	0.56	0.52	*0.72*
Chicken: Eggs	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2030	0.02	0.02	0.02	0.02	0.01	0.01	0.01	*0.01*
	2040	0.07	0.07	0.07	0.07	0.04	0.03	0.02	*0.05*
	2050	0.12	0.12	0.12	0.12	0.06	0.04	0.03	*0.10*

Note: based on simulations of the livestock production disease (LPD) model.

TABLE D.9 Simulated effects on livestock sector production outputs (scenario 3 *versus* reference) – differences in tons

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	0	0	0	0	0	0	0	*0*
	2030	44,066	39,974	48,684	5,085	48,613	13,510	13,989	*213,921*
	2040	117,012	109,134	136,435	16,602	123,604	36,802	45,787	*585,376*
	2050	201,375	193,106	247,805	32,715	203,688	64,973	97,127	*1,040,791*
Cattle: Raw milk	**2025**	0	0	0	0	0	0	0	*0*
	2030	69,170	444,316	31,893	29,567	137,469	95,618	45,428	*853,463*
	2040	177,317	1,164,517	87,503	84,350	337,928	267,445	151,969	*2,271,029*
	2050	294,600	1,978,106	155,593	155,961	538,387	484,819	329,486	*3,936,952*
Swine: Meat	**2025**	0	0	0	0	0	0	0	*0*
	2030	35,912	20,031	6,763	13	12,450	445	2,161	*77,776*
	2040	95,066	52,823	18,918	35	32,484	1,191	7,611	*208,127*
	2050	163,100	90,280	34,302	58	54,929	2,066	17,371	*362,106*
Chicken: Meat	**2025**	0	0	0	0	0	0	0	*0*
	2030	58,541	32,063	41,124	15,723	40,822	7,920	6,118	*202,310*
	2040	156,754	84,721	111,808	42,472	115,722	23,154	24,621	*559,251*
	2050	272,038	145,088	197,018	74,355	212,612	43,871	64,218	*1,009,200*
Chicken: Eggs	**2025**	0	0	0	0	0	0	0	*0*
	2030	7,881	2,098	1,802	785	1,159	132	19	*13,875*
	2040	28,994	7,615	6,730	2,913	2,919	2,562	856	*52,590*
	2050	53,815	13,948	12,684	5,454	6,435	3,224	2,136	*97,697*

Note: based on simulations of the livestock production disease (LPD) model.

TABLE D.10 Simulated effects on livestock sector production outputs (scenario 3 *versus* reference) – differences in consumption equivalents (million people)

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	*0.0*
	2030	7.0	2.6	2.1	0.7	1.3	5.3	2.7	*21.8*
	2040	18.5	7.2	5.8	2.4	3.4	14.5	8.8	*60.7*
	2050	31.9	12.7	10.6	4.8	5.6	25.7	18.6	*109.9*
Cattle: Raw milk	**2025**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	*0.0*
	2030	1.5	2.3	0.3	0.5	0.6	1.3	1.7	*8.1*
	2040	3.7	6.0	0.7	1.3	1.5	3.6	5.7	*22.6*
	2050	6.2	10.2	1.3	2.4	2.4	6.6	12.3	*41.4*
Swine: Meat	**2025**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	*0.0*
	2030	1.3	0.7	0.5	0.1	0.4	2.2	1.1	*6.4*
	2040	3.5	1.9	1.4	0.2	1.1	5.8	4.0	*17.9*
	2050	6.0	3.2	2.6	0.4	1.9	10.0	9.2	*33.3*
Chicken: Meat	**2025**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	*0.0*
	2030	3.7	1.4	1.1	0.8	0.7	2.4	1.2	*11.2*
	2040	9.8	3.6	2.9	2.0	2.1	7.0	5.0	*32.4*
	2050	17.0	6.2	5.1	3.6	3.9	13.2	13.0	*61.9*
Chicken: Eggs	**2025**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	*0.0*
	2030	0.5	0.2	0.1	0.1	0.1	0.0	0.0	*1.0*
	2040	1.7	0.6	0.5	0.4	0.2	0.7	0.5	*4.6*
	2050	3.1	1.1	1.0	0.8	0.4	0.9	1.3	*8.6*

Notes: based on simulations of the livestock production disease (LPD) model. Entries report the projected production effects in tons from Table D.9 as consumption equivalents of millions of people by dividing estimated production losses by the average consumption of the modelled livestock sectors' products in kg per capita.

TABLE D.11 Simulated effects on livestock sector production outputs (scenario 4 *versus* reference) – differences in per cent

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2030	0.28	0.18	0.26	0.21	0.27	0.11	0.06	*0.21*
	2040	1.54	0.85	1.37	1.28	1.36	0.52	0.26	*1.09*
	2050	2.35	1.81	1.67	3.10	1.77	1.16	0.56	*1.66*
Cattle: Raw milk	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2030	0.09	0.09	0.04	0.06	0.10	0.07	0.03	*0.08*
	2040	0.52	0.45	0.20	0.33	0.53	0.31	0.11	*0.38*
	2050	0.80	0.96	0.24	0.78	0.68	0.69	0.24	*0.70*
Swine: Meat	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2030	0.07	0.05	0.07	0.06	0.06	0.04	0.03	*0.06*
	2040	0.41	0.22	0.36	0.32	0.31	0.21	0.12	*0.33*
	2050	1.02	0.49	0.75	0.77	0.71	0.47	0.26	*0.77*
Chicken: Meat	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2030	0.17	0.11	0.16	0.15	0.14	0.08	0.04	*0.14*
	2040	0.95	0.52	0.86	0.77	0.74	0.38	0.20	*0.74*
	2050	2.38	1.16	1.74	1.83	1.74	0.83	0.42	*1.67*
Chicken: Eggs	**2025**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	*0.00*
	2030	0.03	0.02	0.03	0.03	0.03	0.01	0.00	*0.01*
	2040	0.16	0.09	0.15	0.13	0.07	0.04	0.02	*0.12*
	2050	0.41	0.20	0.30	0.32	0.24	0.09	0.03	*0.29*

Note: based on simulations of the livestock production disease (LPD) model.

TABLE D.12 Simulated effects on livestock sector production outputs (scenario 4 *versus* reference) – differences in tons

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	0	0	0	0	0	0	0	*0*
	2030	40,001	22,487	41,079	3,745	36,594	7,375	4,624	*155,906*
	2040	237,868	120,074	249,789	27,758	194,230	39,101	27,833	*896,653*
	2050	392,102	285,027	347,155	81,080	260,874	96,033	79,112	*1,541,381*
Cattle: Raw milk	**2025**	0	0	0	0	0	0	0	*0*
	2030	62,790	249,925	26,911	22,899	103,480	52,198	15,018	*533,220*
	2040	360,462	1,281,146	160,202	137,556	531,006	284,142	92,379	*2,846,893*
	2050	573,621	2,919,709	217,973	376,986	689,539	716,560	268,369	*5,762,758*
Swine: Meat	**2025**	0	0	0	0	0	0	0	*0*
	2030	32,599	11,268	5,706	10	9,372	243	714	*59,913*
	2040	193,254	58,118	34,637	56	51,044	1,265	4,627	*343,001*
	2050	524,476	138,674	81,256	141	122,379	3,054	14,149	*884,129*
Chicken: Meat	**2025**	0	0	0	0	0	0	0	*0*
	2030	53,140	18,036	34,700	12,178	30,729	4,323	2,022	*155,129*
	2040	318,656	93,214	204,702	69,264	181,844	24,600	14,967	*907,246*
	2050	869,773	222,862	458,630	179,737	491,338	64,843	52,306	*2,339,489*
Chicken: Eggs	**2025**	0	0	0	0	0	0	0	*0*
	2030	11,664	1,924	2,479	991	2,532	987	620	*21,196*
	2040	69,941	9,943	14,622	5,638	6,899	2,679	1,047	*110,769*
	2050	190,905	23,771	32,760	14,629	26,841	8,788	1,520	*299,214*

Note: based on simulations of the livestock production disease (LPD) model.

TABLE D.13 Simulated effects on livestock sector production outputs (scenario 4 *versus* reference) – differences in consumption equivalents (million people)

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	*0.0*
	2030	6.3	1.5	1.8	0.5	1.0	2.9	0.9	*14.9*
	2040	37.7	7.9	10.7	4.1	5.4	15.5	5.3	*86.5*
	2050	62.1	18.8	14.8	11.9	7.2	38.0	15.2	*167.9*
Cattle: Raw milk	**2025**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	*0.0*
	2030	1.3	1.3	0.2	0.3	0.5	0.7	0.6	*4.9*
	2040	7.6	6.6	1.3	2.1	2.4	3.9	3.5	*27.4*
	2050	12.0	15.1	1.8	5.7	3.1	9.8	10.0	*57.6*
Swine: Meat	**2025**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	*0.0*
	2030	1.2	0.4	0.4	0.1	0.3	1.2	0.4	*4.0*
	2040	7.1	2.0	2.6	0.4	1.8	6.1	2.4	*22.5*
	2050	19.3	4.9	6.1	1.0	4.3	14.8	7.5	*57.8*
Chicken: Meat	**2025**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	*0.0*
	2030	3.3	0.8	0.9	0.6	0.6	1.3	0.4	*7.8*
	2040	19.9	4.0	5.3	3.3	3.3	7.4	3.0	*46.2*
	2050	54.3	9.5	11.9	8.6	8.9	19.5	10.6	*123.4*
Chicken: Eggs	**2025**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	*0.0*
	2030	0.7	0.2	0.2	0.2	0.2	0.3	0.4	*2.0*
	2040	4.0	0.8	1.1	0.9	0.4	0.7	0.6	*8.6*
	2050	10.9	1.9	2.5	2.3	1.7	2.4	0.9	*22.6*

Notes: based on simulations of the livestock production disease (LPD) model. Entries report the projected production effects in tons from Table D.12 as consumption equivalents of millions of people by dividing estimated production losses by the average consumption of the modelled livestock sectors' products in kg per capita.

TABLE D.14 Simulated effects on livestock sector production outputs (scenario 4 *versus* reference) – differences in per cent

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	−2.82	−2.30	−2.03	−3.17	−2.56	−2.55	−1.73	*−2.38*
	2030	−2.85	−2.35	−2.11	−3.31	−2.56	−2.93	−2.59	*−2.54*
	2040	−2.97	−2.55	−2.46	−3.91	−2.56	−4.35	−5.57	*−3.20*
	2050	−3.17	−2.90	−3.05	−4.94	−2.56	−6.49	−9.35	*−4.29*
Cattle: Raw milk	**2025**	−2.85	−4.12	−1.12	−2.21	−3.25	−3.44	−2.02	*−3.21*
	2030	−2.86	−4.15	−1.13	−2.25	−3.25	−3.67	−2.41	*−3.27*
	2040	−2.91	−4.27	−1.19	−2.41	−3.25	−4.55	−3.76	*−3.55*
	2050	−2.98	−4.48	−1.29	−2.70	−3.25	−5.87	−5.47	*−4.06*
Swine: Meat	**2025**	−1.47	−1.17	−1.14	−1.42	−1.17	−1.77	−1.50	*−1.32*
	2030	−1.48	−1.18	−1.17	−1.43	−1.18	−1.93	−1.93	*−1.34*
	2040	−1.52	−1.23	−1.29	−1.47	−1.23	−2.54	−3.45	*−1.46*
	2050	−1.60	−1.31	−1.49	−1.52	−1.30	−3.46	−4.02	*−1.60*
Chicken: Meat	**2025**	−4.05	−3.63	−3.47	−4.32	−3.65	−3.75	−3.19	*−3.76*
	2030	−4.08	−3.66	−3.52	−4.36	−3.73	−4.07	−3.95	*−3.85*
	2040	−4.22	−3.79	−3.73	−4.53	−4.07	−5.31	−6.66	*−4.26*
	2050	−4.46	−4.00	−4.09	−4.81	−4.64	−7.23	−6.82	*−4.75*
Chicken: Eggs	**2025**	−0.93	−0.85	−0.81	−0.99	−0.80	−0.74	−0.62	*−0.87*
	2030	−0.93	−0.85	−0.82	−0.99	−0.81	−0.80	−0.75	*−0.88*
	2040	−0.96	−0.88	−0.86	−1.03	−0.87	−1.01	−1.22	*−0.95*
	2050	−1.01	−0.92	−0.93	−1.08	−0.98	−1.34	−1.24	*−1.04*

Note: based on simulations of the livestock production disease (LPD) model.

TABLE D.15 Simulated effects on livestock sector production outputs (scenario 4 *versus* reference) – differences in tons

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	−387,907	−278,393	−305,378	−51,743	−346,500	−163,650	−120,484	*−1,654,055*
	2030	−407,264	−299,704	−339,407	−59,510	−352,399	−198,068	−207,534	*−1,863,886*
	2040	−458,282	−361,921	−449,978	−84,949	−364,500	−325,773	−593,160	*−2,638,563*
	2050	−528,537	−456,496	−634,429	−129,232	−377,016	−538,624	−1,321,190	*−3,985,525*
Cattle: Raw milk	**2025**	−1,847,857	−10,717,599	−762,456	−736,264	−3,277,918	−2,578,829	−1,026,814	*−20,947,737*
	2030	−1,894,184	−11,144,551	−815,414	−807,475	−3,277,917	−2,939,341	−1,428,512	*−22,307,395*
	2040	−2,006,301	−12,226,490	−955,927	−1,005,914	−3,277,917	−4,142,086	−3,034,804	*−26,649,439*
	2050	−2,146,842	−13,655,999	−1,153,367	−1,302,330	−3,277,917	−6,081,791	−6,001,492	*−33,619,739*
Swine: Meat	**2025**	−626,738	−279,305	−89,238	−227	−174,975	−9,291	−33,531	*−1,213,306*
	2030	−655,112	−292,177	−97,621	−235	−181,951	−10,586	−51,565	*−1,289,247*
	2040	−726,579	−326,279	−122,518	−255	−200,537	−15,147	−131,501	*−1,522,814*
	2050	−820,843	−373,300	−161,392	−280	−226,149	−22,461	−219,113	*−1,823,539*
Chicken: Meat	**2025**	−1,197,441	−584,961	−710,692	−335,837	−722,966	−189,307	−115,935	*−3,857,138*
	2030	−1,259,994	−611,555	−758,352	−355,325	−793,434	−224,395	−183,224	*−4,186,279*
	2040	−1,418,701	−679,993	−888,861	−405,383	−996,508	−347,682	−503,984	*−5,241,111*
	2050	−1,630,417	−772,030	−1,076,741	−473,185	−1,308,017	−561,501	−839,736	*−6,661,626*
Chicken: Eggs	**2025**	−346,112	−83,202	−67,853	−35,974	−61,567	−48,186	−14,697	*−657,591*
	2030	−363,798	−86,881	−72,252	−38,016	−67,360	−56,538	−22,689	*−707,534*
	2040	−407,852	−96,150	−84,003	−43,163	−83,630	−85,213	−59,886	*−859,897*
	2050	−465,567	−108,366	−100,555	−50,010	−108,037	−134,282	−100,192	*−1,067,009*

Note: based on simulations of the livestock production disease (LPD) model.

TABLE D.16 Simulated effects on livestock sector production outputs (scenario 4 *versus* reference) – differences in consumption equivalents (million people)

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
Cattle: Meat	**2025**	−61.4	−18.4	−13.0	−7.6	−9.6	−64.7	−23.1	*−197.8*
	2030	−64.5	−19.8	−14.5	−8.7	−9.8	−78.3	−39.8	*−235.3*
	2040	−72.5	−23.9	−19.2	−12.5	−10.1	−128.8	−113.7	*−380.6*
	2050	−83.7	−30.1	−27.1	−19.0	−10.4	−212.9	−253.2	*−636.4*
Cattle: Raw milk	**2025**	−38.8	−55.3	−6.4	−11.2	−14.8	−35.1	−38.4	*−200.1*
	2030	−39.8	−57.5	−6.9	−12.3	−14.8	−40.0	−53.4	*−224.7*
	2040	−42.1	−63.1	−8.0	−15.3	−14.8	−56.4	−113.5	*−313.3*
	2050	−45.1	−70.5	−9.7	−19.9	−14.8	−82.8	−224.4	*−467.2*
Swine: Meat	**2025**	−23.0	−9.8	−6.7	−1.6	−6.1	−45.1	−17.7	*−110.0*
	2030	−24.0	−10.2	−7.3	−1.7	−6.4	−51.4	−27.2	*−128.3*
	2040	−26.7	−11.4	−9.2	−1.8	−7.0	−73.5	−69.5	*−199.1*
	2050	−30.1	−13.1	−12.1	−2.0	−7.9	−109.0	−115.7	*−290.0*
Chicken: Meat	**2025**	−74.8	−24.9	−18.5	−16.0	−13.1	−57.0	−23.4	*−227.8*
	2030	−78.7	−26.1	−19.7	−17.0	−14.4	−67.6	−37.0	*−260.4*
	2040	−88.6	−29.0	−23.1	−19.4	−18.1	−104.7	−101.8	*−384.6*
	2050	−101.9	−32.9	−28.0	−22.6	−23.7	−169.1	−169.6	*−547.8*
Chicken: Eggs	**2025**	−19.8	−6.5	−5.2	−5.5	−3.9	−13.3	−9.0	*−63.3*
	2030	−20.8	−6.8	−5.5	−5.9	−4.3	−15.6	−13.9	*−72.8*
	2040	−23.3	−7.5	−6.4	−6.7	−5.3	−23.6	−36.8	*−109.6*
	2050	−26.6	−8.5	−7.7	−7.7	−6.8	−37.2	−61.5	*−156.0*

Notes: based on simulations of the livestock production disease (LPD) model. Entries report the projected production effects in tons from Table D.15 as consumption equivalents of millions of people by dividing estimated production losses by the average consumption of the modelled livestock sectors' products in kg per capita.

GDP EFFECTS ATTRIBUTABLE TO AMR BY YEAR AND REGION

TABLE D.17 Predicted changes in cumulative real gross domestic product (GDP) by year, region and scenario (cumulative US$ at 2017 value compared to reference)

		East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa	*World*
A. Discount rate 0%									
Scenario 1	**2030**	48.7	14.5	14.6	7.9	17.5	10.2	4.7	*118.1*
	2040	161.1	46.1	43.6	26.8	61.8	34.7	15.1	*389.2*
	2050	307.5	85.7	77.8	53.4	124.6	68	30.6	*747.6*
Scenario 2	**2030**	−69.6	−28.8	−24.5	−12.9	−7.6	−23.5	−10.3	*−177.3*
	2040	−233.8	−92.4	−74.8	−46.6	−30.9	−87.5	−44	*−610.3*
	2050	−457.8	−175.8	−138.3	−98.6	−69.7	−197.4	−109.5	*−1,247.40*
Scenario 3	**2030**	2.8	1.1	1.4	0.4	1.5	0.5	0.3	*7.9*
	2040	19.7	7.5	8.7	2.8	11.1	3.8	2	*55.7*
	2050	56.8	21.1	23.3	8.8	34.9	11.6	5.9	*162.6*
Scenario 4	**2030**	2.5	0.6	1.1	0.3	1	0.2	0.1	*5.8*
	2040	29.2	6.2	11.9	3.8	12.9	3	0.8	*67.8*
	2050	120.6	23.2	38.4	17.7	49.6	12.8	2.9	*265.3*
Scenario 5	**2030**	−75.2	−54.5	−15.7	−8	−64.1	−11.8	−5.2	*−234.6*
	2040	−258.1	−164.4	−48.8	−28	−196.3	−42	−18	*−755.8*
	2050	−517.1	−298.1	−90	−58.1	−362	−86.7	−37.2	*−1,449.30*
Scenario 6	**2030**	−370.4	−247.4	−87.2	−45	−264.1	−70.7	−31	*−1,116.20*
	2040	−1,266.20	−751	−269.9	−159	−816.1	−255.8	−116.1	*−3,634.90*
	2050	−2,472.50	−1,331.10	−484.9	−324.5	−1,477.40	−534.5	−253.7	*−6,879.70*
B. Discount rate 3.5%									
Scenario 1	**2030**	37.5	11.2	11.2	6.1	13.5	7.9	3.6	*90.9*
	2040	103.2	29.7	28.2	17.1	39.3	22.2	9.7	*249.2*
	2050	164	46.1	42.5	28.1	65.3	36	16.1	*398.1*
Scenario 2	**2030**	−53.6	−22.2	−18.9	−9.9	−5.8	−18	−7.9	*−136.4*
	2040	−149.4	−59.4	−48.4	−29.5	−19.3	−55.2	−27.3	*−388.6*
	2050	−242.3	−94	−74.7	−51	−35.3	−100.4	−54.3	*−652.3*
Scenario 3	**2030**	2.1	0.9	1	0.3	1.1	0.4	0.2	*6*
	2040	11.8	4.5	5.3	1.7	6.6	2.3	1.2	*33.3*
	2050	27	10.1	11.3	4.1	16.4	5.5	2.8	*77.2*
Scenario 4	**2030**	1.8	0.5	0.8	0.2	0.8	0.2	0.1	*4.4*
	2040	16.9	3.6	6.9	2.2	7.4	1.7	0.4	*39.2*
	2050	54.2	10.5	17.9	7.8	22.5	5.7	1.3	*120*
Scenario 5	**2030**	−57.9	−42.1	−12.1	−6.1	−49.5	−9.1	−4	*−180.8*
	2040	−164.5	−106.5	−31.5	−17.8	−126.8	−26.7	−11.5	*−485.3*
	2050	−271.8	−162.1	−48.6	−30.2	−195.7	−45.2	−19.4	*−773.1*
Scenario 6	**2030**	−285.1	−190.9	−67.3	−34.6	−203.8	−54.4	−23.8	*−860.1*
	2040	−807.3	−485.9	−174.2	−100.9	−526.8	−162	−73.2	*−2,330.90*
	2050	−1,284.40	−710.7	−257.9	−166.6	−784.1	−272.9	−128.1	*−3,605.40*

The country-specific estimates in the relative changes in real GDP by year are based on using the projected percentage change between the modelled scenario and the reference scenario by year. These are then applied using the GDP projections by SSP2 (see Annex C) to calculate the absolute value change in real GDP for each country.

TABLE D.18 Predicted changes in real gross domestic product (GDP) (US$ at 2017 value in billions) by year (scenario 1 *versus* reference)

Country/Territory	2025	2030	2035	2040	2045	2050
Albania	0.005	0.006	0.008	0.009	0.01	0.011
Algeria	0.154	0.185	0.215	0.25	0.289	0.334
Angola	0.076	0.086	0.105	0.131	0.17	0.226
Antigua and Barbuda	0.001	0.001	0.001	0.001	0.001	0.001
Argentina	0.294	0.328	0.356	0.39	0.429	0.476
Armenia	0.005	0.007	0.009	0.011	0.013	0.014
Aruba	0.002	0.002	0.002	0.002	0.002	0.002
Australia	0.341	0.436	0.508	0.585	0.658	0.728
Austria	0.047	0.058	0.067	0.075	0.082	0.088
Azerbaijan	0.016	0.02	0.024	0.028	0.032	0.036
Bahamas	0.005	0.006	0.006	0.006	0.007	0.007
Bahrain	0.024	0.03	0.036	0.041	0.047	0.051
Bangladesh	0.463	0.638	0.898	1.123	1.36	1.605
Barbados	0.002	0.002	0.002	0.002	0.002	0.003
Belarus	0.018	0.021	0.024	0.027	0.029	0.031
Belgium	0.059	0.072	0.082	0.092	0.1	0.107
Belize	0.001	0.002	0.002	0.002	0.003	0.003
Benin	0.018	0.023	0.032	0.043	0.058	0.079
Bhutan	0.003	0.004	0.005	0.005	0.006	0.007
Bolivia	0.036	0.04	0.045	0.053	0.063	0.076
Bosnia and Herzegovina	0.006	0.007	0.009	0.01	0.011	0.011
Botswana	0.015	0.018	0.021	0.025	0.03	0.036
Brazil	1.165	1.247	1.384	1.573	1.806	2.077
Brunei	0.007	0.009	0.01	0.011	0.012	0.012
Bulgaria	0.018	0.024	0.028	0.032	0.035	0.038
Burkina Faso	0.019	0.024	0.034	0.046	0.064	0.089
Burundi	0.004	0.004	0.006	0.008	0.011	0.015
Cambodia	0.022	0.034	0.047	0.062	0.08	0.1
Cameroon	0.039	0.047	0.061	0.081	0.108	0.145
Canada	0.191	0.274	0.345	0.423	0.502	0.581
Cape Verde	0.002	0.002	0.002	0.003	0.004	0.004
Central African Republic	0.002	0.002	0.003	0.004	0.005	0.008
Chad	0.009	0.011	0.015	0.02	0.029	0.041
Chile	0.167	0.177	0.191	0.208	0.227	0.248
China (People’s Republic of)	7.434	10.02	11.898	13.454	14.762	15.848

TABLE D.18 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Chinese Taipei	0.359	0.451	0.494	0.508	0.498	0.474
Colombia	0.273	0.31	0.357	0.419	0.489	0.564
Comoros	0.001	0.001	0.001	0.002	0.003	0.004
Congo (Democratic Republic of the)	0.045	0.056	0.074	0.103	0.148	0.216
Congo (Republic of the)	0.008	0.009	0.011	0.014	0.018	0.023
Costa Rica	0.04	0.046	0.053	0.06	0.068	0.077
Cote d’Ivoire	0.063	0.081	0.108	0.142	0.186	0.244
Croatia	0.014	0.018	0.02	0.023	0.024	0.025
Cuba	0.028	0.035	0.043	0.054	0.069	0.085
Cyprus	0.004	0.005	0.007	0.008	0.009	0.01
Czechia (Czech Republic)	0.041	0.05	0.058	0.066	0.071	0.077
Denmark	0.033	0.04	0.046	0.051	0.056	0.061
Djibouti	0.002	0.003	0.004	0.005	0.006	0.008
Dominican Republic	0.084	0.106	0.128	0.149	0.17	0.192
Ecuador	0.07	0.079	0.089	0.101	0.114	0.13
Egypt	0.456	0.664	0.912	1.231	1.608	2.043
El Salvador	0.022	0.024	0.026	0.03	0.034	0.039
Equatorial Guinea	0.007	0.006	0.008	0.009	0.012	0.015
Eritrea	0.002	0.003	0.003	0.004	0.006	0.009
Estonia	0.005	0.006	0.007	0.008	0.009	0.009
Eswatini	0.004	0.004	0.005	0.006	0.008	0.009
Ethiopia	0.121	0.161	0.22	0.304	0.421	0.586
Fiji	0.003	0.004	0.005	0.006	0.007	0.009
Finland	0.026	0.031	0.036	0.04	0.043	0.046
France	0.295	0.357	0.409	0.462	0.504	0.545
French Guiana	0.005	0.006	0.007	0.008	0.009	0.01
French Polynesia	0.001	0.002	0.002	0.002	0.003	0.003
Gabon	0.012	0.013	0.016	0.019	0.023	0.029
Gambia	0.002	0.003	0.004	0.005	0.007	0.009
Georgia	0.007	0.011	0.014	0.017	0.02	0.021
Germany	0.417	0.492	0.556	0.625	0.68	0.732
Ghana	0.066	0.081	0.103	0.132	0.171	0.224
Greece	0.033	0.041	0.047	0.054	0.06	0.065
Grenada	0.001	0.001	0.001	0.001	0.001	0.001
Guam	0.002	0.002	0.003	0.003	0.004	0.004
Guatemala	0.06	0.072	0.085	0.101	0.12	0.142
Guinea	0.015	0.018	0.025	0.035	0.048	0.067
Guinea-Bissau	0.002	0.002	0.003	0.004	0.005	0.006
Guyana	0.02	0.042	0.062	0.081	0.092	0.093

TABLE D.18 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Haiti	0.011	0.012	0.015	0.019	0.024	0.03
Honduras	0.022	0.027	0.032	0.039	0.047	0.058
Hong Kong (Special Administrative Region of the People's Republic of China)	0.117	0.148	0.164	0.172	0.173	0.171
Hungary	0.034	0.043	0.051	0.058	0.063	0.067
Iceland	0.002	0.003	0.003	0.004	0.004	0.005
India	3.998	5.205	6.936	8.454	10.085	11.799
Indonesia	0.988	1.378	1.699	2.036	2.348	2.631
Iran	0.418	0.508	0.592	0.674	0.748	0.816
Iraq	0.126	0.161	0.218	0.333	0.478	0.641
Ireland	0.057	0.072	0.086	0.102	0.119	0.137
Israel	0.125	0.163	0.199	0.241	0.284	0.326
Italy	0.239	0.282	0.322	0.362	0.393	0.422
Jamaica	0.01	0.011	0.012	0.013	0.014	0.016
Japan	1.353	1.578	1.695	1.794	1.865	1.923
Jordan	0.032	0.041	0.05	0.063	0.077	0.094
Kazakhstan	0.057	0.073	0.09	0.107	0.121	0.134
Kenya	0.102	0.126	0.16	0.207	0.269	0.353
Kiribati	0	0	0	0	0	0
Korea (Democratic People's Republic of)	0.599	0.738	0.811	0.865	0.895	0.909
Korea (Republic of)	0.015	0.021	0.029	0.038	0.05	0.063
Kuwait	0.064	0.079	0.094	0.11	0.125	0.139
Kyrgyzstan	0.004	0.005	0.007	0.009	0.011	0.013
Laos	0.016	0.023	0.029	0.036	0.044	0.052
Latvia	0.006	0.007	0.008	0.009	0.01	0.01
Lebanon	0.02	0.024	0.029	0.034	0.041	0.048
Lesotho	0.002	0.002	0.002	0.003	0.004	0.005
Liberia	0.003	0.004	0.005	0.007	0.009	0.012
Libya	0.044	0.056	0.062	0.074	0.09	0.111
Lithuania	0.011	0.014	0.016	0.017	0.018	0.018
Luxembourg	0.007	0.01	0.011	0.012	0.013	0.014
Macao (Special Administrative Region of the People's Republic of China)	0.02	0.028	0.034	0.04	0.044	0.048
Madagascar	0.017	0.02	0.026	0.035	0.048	0.066
Malawi	0.011	0.013	0.017	0.024	0.033	0.048
Malaysia	0.269	0.367	0.444	0.513	0.569	0.615
Maldives	0.005	0.006	0.007	0.009	0.01	0.011
Mali	0.018	0.023	0.031	0.044	0.062	0.088
Malta	0.008	0.011	0.013	0.015	0.016	0.017
Mauritania	0.01	0.012	0.016	0.02	0.026	0.034

TABLE D.18 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Mauritius	0.011	0.012	0.014	0.016	0.019	0.022
Mayotte (French Department of)	0.003	0.004	0.005	0.007	0.009	0.012
Mexico	0.904	1.017	1.136	1.273	1.424	1.588
Micronesia (Federated States of)	0	0	0	0	0	0
Moldova	0.004	0.005	0.007	0.008	0.01	0.01
Mongolia	0.012	0.016	0.019	0.024	0.028	0.032
Montenegro	0.001	0.002	0.002	0.003	0.003	0.003
Morocco	0.095	0.124	0.154	0.189	0.229	0.274
Mozambique	0.016	0.025	0.039	0.058	0.084	0.121
Myanmar	0.059	0.077	0.094	0.113	0.133	0.154
Namibia	0.009	0.01	0.011	0.014	0.017	0.022
Nepal	0.046	0.058	0.078	0.098	0.122	0.149
Netherlands	0.099	0.121	0.139	0.157	0.17	0.182
New Caledonia	0.003	0.004	0.005	0.006	0.007	0.008
New Zealand	0.055	0.07	0.08	0.09	0.099	0.107
Nicaragua	0.015	0.018	0.021	0.026	0.031	0.038
Niger	0.014	0.018	0.026	0.038	0.055	0.082
Nigeria	0.395	0.448	0.564	0.727	0.947	1.259
North Macedonia (Republic of)	0.004	0.005	0.006	0.007	0.008	0.009
Norway	0.036	0.044	0.051	0.058	0.064	0.07
Oman	0.049	0.063	0.076	0.091	0.107	0.122
Pakistan	0.459	0.573	0.77	0.983	1.262	1.611
Panama	0.057	0.069	0.079	0.089	0.098	0.107
Papua New Guinea	0.009	0.012	0.016	0.02	0.026	0.033
Paraguay	0.035	0.041	0.048	0.054	0.062	0.07
Peru	0.162	0.185	0.21	0.239	0.27	0.306
Philippines	0.289	0.442	0.595	0.754	0.911	1.065
Poland	0.139	0.183	0.22	0.253	0.273	0.29
Portugal	0.036	0.045	0.053	0.061	0.067	0.074
Puerto Rico (Commonwealth of)	0.037	0.038	0.038	0.038	0.038	0.038
Qatar	0.081	0.105	0.121	0.136	0.148	0.159
Romania	0.059	0.075	0.089	0.1	0.108	0.113
Russia	0.383	0.462	0.544	0.63	0.702	0.773
Rwanda	0.013	0.018	0.024	0.032	0.042	0.057
Saint Lucia	0.001	0.001	0.001	0.001	0.001	0.001
Samoa	0	0	0	0.001	0.001	0.001
Sao Tome and Principe	0	0	0	0	0.001	0.001
Saudi Arabia	0.55	0.746	0.912	1.076	1.217	1.335
Senegal	0.026	0.032	0.043	0.057	0.075	0.099
Serbia	0.015	0.02	0.025	0.03	0.035	0.039

TABLE D.18 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Seychelles	0.001	0.001	0.002	0.002	0.002	0.003
Sierra Leone	0.005	0.006	0.008	0.011	0.015	0.021
Singapore	0.159	0.202	0.23	0.248	0.256	0.257
Slovakia	0.019	0.024	0.028	0.033	0.036	0.039
Slovenia	0.008	0.011	0.012	0.014	0.015	0.016
Solomon Islands	0	0	0.001	0.001	0.001	0.002
Somalia	0.008	0.011	0.015	0.022	0.033	0.047
South Africa	0.271	0.279	0.316	0.379	0.464	0.578
South Sudan (Republic of)	0.002	0.003	0.003	0.004	0.005	0.007
Spain	0.185	0.223	0.26	0.303	0.339	0.376
Sri Lanka	0.092	0.106	0.13	0.149	0.168	0.189
St. Vincent and the Grenadines	0.001	0.001	0.001	0.001	0.001	0.001
Sudan	0.043	0.059	0.074	0.093	0.113	0.136
Suriname	0.003	0.004	0.004	0.005	0.006	0.007
Sweden	0.056	0.071	0.084	0.097	0.106	0.116
Switzerland	0.062	0.073	0.083	0.092	0.099	0.105
Tajikistan	0.005	0.007	0.009	0.012	0.015	0.018
Tanzania	0.07	0.093	0.127	0.171	0.23	0.312
Thailand	0.338	0.44	0.515	0.585	0.644	0.693
Timor-Leste	0.001	0.001	0.002	0.002	0.003	0.004
Togo	0.008	0.009	0.013	0.017	0.022	0.03
Tonga	0	0	0	0	0	0
Trinidad and Tobago	0.013	0.014	0.014	0.015	0.016	0.017
Tunisia	0.039	0.048	0.058	0.069	0.082	0.096
Türkiye (Republic of)	0.302	0.41	0.516	0.621	0.71	0.793
Turkmenistan	0.01	0.013	0.016	0.018	0.021	0.023
Uganda	0.045	0.059	0.08	0.107	0.143	0.192
Ukraine	0.042	0.058	0.076	0.094	0.11	0.127
United Arab Emirates	0.225	0.305	0.375	0.436	0.483	0.516
United Kingdom	0.303	0.37	0.434	0.507	0.575	0.646
United States of America	2.308	3.265	3.995	4.709	5.381	6.024
United States Virgin Islands	0.001	0.001	0.001	0.001	0.001	0.001
Uruguay	0.031	0.034	0.036	0.039	0.041	0.043
Uzbekistan	0.033	0.048	0.066	0.085	0.104	0.124
Vanuatu	0	0	0	0.001	0.001	0.001
Vietnam	0.327	0.51	0.689	0.861	1.012	1.145
Western Sahara	0	0	0	0.001	0.001	0.001
Yemen	0.018	0.026	0.035	0.049	0.068	0.092
Zambia	0.025	0.03	0.039	0.05	0.065	0.085
Zimbabwe	0.013	0.015	0.018	0.021	0.026	0.032

TABLE D.19 Predicted changes in real gross domestic product (GDP) (US$ at 2017 value in billions) by year (scenario 3 *versus* reference)

Country/Territory	2025	2030	2035	2040	2045	2050
Albania	0	0.001	0.001	0.002	0.003	0.005
Algeria	0	0.013	0.027	0.043	0.063	0.086
Angola	0	0.008	0.017	0.028	0.042	0.062
Antigua and Barbuda	0	0	0	0	0.001	0.001
Argentina	0	0.047	0.087	0.131	0.18	0.235
Armenia	0	0.001	0.002	0.003	0.004	0.006
Aruba	0	0	0	0.001	0.001	0.001
Australia	0	0.037	0.072	0.115	0.163	0.216
Austria	0	0.007	0.013	0.02	0.028	0.036
Azerbaijan	0	0.002	0.005	0.007	0.011	0.014
Bahamas	0	0.001	0.001	0.002	0.003	0.003
Bahrain	0	0.002	0.004	0.007	0.01	0.013
Bangladesh	0	0.045	0.114	0.201	0.311	0.443
Barbados	0	0	0	0.001	0.001	0.001
Belarus	0	0.002	0.005	0.007	0.01	0.013
Belgium	0	0.008	0.016	0.024	0.034	0.043
Belize	0	0	0	0.001	0.001	0.002
Benin	0	0.002	0.005	0.009	0.014	0.022
Bhutan	0	0	0.001	0.001	0.001	0.002
Bolivia	0	0.006	0.011	0.018	0.026	0.037
Bosnia and Herzegovina	0	0.001	0.002	0.003	0.004	0.005
Botswana	0	0.002	0.003	0.005	0.007	0.01
Brazil	0	0.179	0.337	0.529	0.758	1.026
Brunei	0	0.001	0.001	0.002	0.003	0.004
Bulgaria	0	0.003	0.005	0.009	0.012	0.015
Burkina Faso	0	0.002	0.005	0.01	0.016	0.024
Burundi	0	0	0.001	0.002	0.003	0.004
Cambodia	0	0.003	0.007	0.012	0.02	0.03
Cameroon	0	0.005	0.01	0.017	0.027	0.04
Canada	0	0.033	0.07	0.12	0.184	0.26
Cape Verde	0	0	0	0.001	0.001	0.001
Central African Republic	0	0	0	0.001	0.001	0.002
Chad	0	0.001	0.002	0.004	0.007	0.011
Chile	0	0.026	0.047	0.07	0.095	0.122
China (People’s Republic of)	0	0.85	1.688	2.642	3.661	4.7
Chinese Taipei	0	0.038	0.07	0.1	0.124	0.141
Colombia	0	0.045	0.087	0.141	0.205	0.279
Comoros	0	0	0	0	0.001	0.001

TABLE D.19 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Congo (Democratic Republic of the)	0	0.005	0.012	0.022	0.037	0.059
Congo (Republic of the)	0	0.001	0.002	0.003	0.005	0.006
Costa Rica	0	0.007	0.013	0.02	0.029	0.038
Cote d'Ivoire	0	0.008	0.017	0.03	0.047	0.067
Croatia	0	0.002	0.004	0.006	0.008	0.01
Cuba	0	0.005	0.01	0.018	0.029	0.042
Cyprus	0	0.001	0.001	0.002	0.003	0.004
Czechia (Czech Republic)	0	0.006	0.011	0.017	0.024	0.031
Denmark	0	0.005	0.009	0.013	0.019	0.024
Djibouti	0	0	0	0.001	0.001	0.002
Dominican Republic	0	0.015	0.031	0.05	0.072	0.095
Ecuador	0	0.011	0.022	0.034	0.048	0.064
Egypt	0	0.047	0.113	0.212	0.349	0.523
El Salvador	0	0.003	0.006	0.01	0.014	0.019
Equatorial Guinea	0	0.001	0.001	0.002	0.003	0.004
Eritrea	0	0	0.001	0.001	0.002	0.002
Estonia	0	0.001	0.001	0.002	0.003	0.004
Eswatini	0	0	0.001	0.001	0.002	0.003
Ethiopia	0	0.015	0.035	0.064	0.105	0.161
Fiji	0	0	0.001	0.001	0.002	0.003
Finland	0	0.004	0.007	0.01	0.015	0.019
France	0	0.041	0.078	0.122	0.169	0.219
French Guiana	0	0.001	0.002	0.003	0.004	0.005
French Polynesia	0	0	0	0	0.001	0.001
Gabon	0	0.001	0.003	0.004	0.006	0.008
Gambia	0	0	0.001	0.001	0.002	0.002
Georgia	0	0.001	0.003	0.005	0.007	0.009
Germany	0	0.057	0.106	0.165	0.229	0.294
Ghana	0	0.008	0.016	0.028	0.043	0.061
Greece	0	0.005	0.009	0.014	0.02	0.026
Grenada	0	0	0	0	0	0.001
Guam	0	0	0	0.001	0.001	0.001
Guatemala	0	0.01	0.021	0.034	0.05	0.07
Guinea	0	0.002	0.004	0.007	0.012	0.018
Guinea-Bissau	0	0	0	0.001	0.001	0.002
Guyana	0	0.006	0.015	0.027	0.039	0.046
Haiti	0	0.002	0.004	0.006	0.01	0.015
Honduras	0	0.004	0.008	0.013	0.02	0.029

TABLE D.19 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Hong Kong (Special Administrative Region of the People's Republic of China)	0	0.013	0.023	0.034	0.043	0.051
Hungary	0	0.005	0.01	0.015	0.021	0.027
Iceland	0	0	0.001	0.001	0.001	0.002
India	0	0.365	0.883	1.515	2.306	3.253
Indonesia	0	0.117	0.241	0.4	0.582	0.78
Iran	0	0.036	0.074	0.116	0.162	0.209
Iraq	0	0.011	0.027	0.057	0.104	0.164
Ireland	0	0.008	0.016	0.027	0.04	0.055
Israel	0	0.012	0.025	0.042	0.062	0.084
Italy	0	0.033	0.062	0.095	0.132	0.17
Jamaica	0	0.002	0.003	0.004	0.006	0.008
Japan	0	0.134	0.241	0.352	0.463	0.57
Jordan	0	0.003	0.006	0.011	0.017	0.024
Kazakhstan	0	0.008	0.017	0.028	0.041	0.054
Kenya	0	0.012	0.026	0.044	0.067	0.097
Kiribati	0	0	0	0	0	0
Korea (Democratic People's Republic of)	0	0.063	0.115	0.17	0.222	0.27
Korea (Republic of)	0	0.002	0.004	0.008	0.012	0.019
Kuwait	0	0.006	0.012	0.019	0.027	0.036
Kyrgyzstan	0	0.001	0.001	0.002	0.004	0.005
Laos	0	0.002	0.004	0.007	0.011	0.016
Latvia	0	0.001	0.002	0.002	0.003	0.004
Lebanon	0	0.002	0.004	0.006	0.009	0.012
Lesotho	0	0	0	0.001	0.001	0.001
Liberia	0	0	0.001	0.001	0.002	0.003
Libya	0	0.004	0.008	0.013	0.02	0.028
Lithuania	0	0.002	0.003	0.004	0.006	0.007
Luxembourg	0	0.001	0.002	0.003	0.004	0.006
Macao (Special Administrative Region of the People's Republic of China)	0	0.002	0.005	0.008	0.011	0.014
Madagascar	0	0.002	0.004	0.007	0.012	0.018
Malawi	0	0.001	0.003	0.005	0.008	0.013
Malaysia	0	0.031	0.063	0.101	0.141	0.182
Maldives	0	0	0.001	0.002	0.002	0.003
Mali	0	0.002	0.005	0.009	0.015	0.024
Malta	0	0.001	0.002	0.003	0.004	0.004
Mauritania	0	0.001	0.002	0.004	0.007	0.009
Mauritius	0	0.001	0.002	0.003	0.005	0.006

TABLE D.19 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Mayotte (French Department of)	0	0	0.001	0.001	0.002	0.003
Mexico	0	0.146	0.277	0.428	0.598	0.785
Micronesia (Federated States of)	0	0	0	0	0	0
Moldova	0	0.001	0.001	0.002	0.003	0.004
Mongolia	0	0.001	0.003	0.005	0.007	0.01
Montenegro	0	0	0	0.001	0.001	0.001
Morocco	0	0.009	0.019	0.033	0.05	0.07
Mozambique	0	0.002	0.006	0.012	0.021	0.033
Myanmar	0	0.007	0.013	0.022	0.033	0.046
Namibia	0	0.001	0.002	0.003	0.004	0.006
Nepal	0	0.004	0.01	0.018	0.028	0.041
Netherlands	0	0.014	0.027	0.041	0.057	0.073
New Caledonia	0	0	0.001	0.001	0.002	0.002
New Zealand	0	0.006	0.011	0.018	0.024	0.032
Nicaragua	0	0.003	0.005	0.009	0.013	0.019
Niger	0	0.002	0.004	0.008	0.014	0.022
Nigeria	0	0.043	0.09	0.154	0.237	0.345
North Macedonia (Republic of)	0	0.001	0.001	0.002	0.003	0.004
Norway	0	0.005	0.01	0.015	0.022	0.028
Oman	0	0.004	0.009	0.016	0.023	0.031
Pakistan	0	0.04	0.098	0.176	0.289	0.444
Panama	0	0.01	0.019	0.03	0.041	0.053
Papua New Guinea	0	0.001	0.002	0.004	0.006	0.01
Paraguay	0	0.006	0.012	0.018	0.026	0.034
Peru	0	0.027	0.051	0.08	0.114	0.151
Philippines	0	0.037	0.084	0.148	0.226	0.316
Poland	0	0.021	0.042	0.067	0.092	0.116
Portugal	0	0.005	0.01	0.016	0.023	0.03
Puerto Rico (Commonwealth of)	0	0.005	0.009	0.013	0.016	0.019
Qatar	0	0.007	0.015	0.023	0.032	0.041
Romania	0	0.009	0.017	0.026	0.036	0.046
Russia	0	0.053	0.104	0.166	0.236	0.311
Rwanda	0	0.002	0.004	0.007	0.011	0.016
Saint Lucia	0	0	0	0	0.001	0.001
Samoa	0	0	0	0	0	0
Sao Tome and Principe	0	0	0	0	0	0
Saudi Arabia	0	0.053	0.113	0.186	0.264	0.342
Senegal	0	0.003	0.007	0.012	0.019	0.027
Serbia	0	0.002	0.005	0.008	0.012	0.015

TABLE D.19 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Seychelles	0	0	0	0	0.001	0.001
Sierra Leone	0	0.001	0.001	0.002	0.004	0.006
Singapore	0	0.017	0.033	0.049	0.064	0.076
Slovakia	0	0.003	0.005	0.009	0.012	0.016
Slovenia	0	0.001	0.002	0.004	0.005	0.006
Solomon Islands	0	0	0	0	0	0.001
Somalia	0	0.001	0.002	0.004	0.007	0.012
South Africa	0	0.027	0.051	0.08	0.116	0.158
South Sudan	0	0	0.001	0.001	0.001	0.002
Spain	0	0.026	0.05	0.08	0.114	0.151
Sri Lanka	0	0.007	0.017	0.027	0.038	0.052
St. Vincent and the Grenadines	0	0	0	0	0	0
Sudan	0	0.004	0.009	0.016	0.025	0.035
Suriname	0	0.001	0.001	0.002	0.002	0.003
Sweden	0	0.008	0.016	0.025	0.036	0.047
Switzerland	0	0.008	0.016	0.024	0.033	0.042
Tajikistan	0	0.001	0.002	0.003	0.005	0.007
Tanzania	0	0.009	0.02	0.036	0.057	0.085
Thailand	0	0.037	0.073	0.115	0.16	0.206
Timor-Leste	0	0	0	0	0.001	0.001
Togo	0	0.001	0.002	0.004	0.006	0.008
Tonga	0	0	0	0	0	0
Trinidad and Tobago	0	0.002	0.003	0.005	0.007	0.008
Tunisia	0	0.003	0.007	0.012	0.018	0.025
Türkiye (Republic of)	0	0.047	0.099	0.163	0.239	0.319
Turkmenistan	0	0.002	0.003	0.005	0.007	0.009
Uganda	0	0.006	0.013	0.023	0.036	0.053
Ukraine	0	0.007	0.014	0.025	0.037	0.051
United Arab Emirates	0	0.022	0.047	0.075	0.105	0.132
United Kingdom	0	0.043	0.083	0.133	0.193	0.26
United States of America	0	0.395	0.812	1.341	1.971	2.696
United States Virgin Islands	0	0	0	0	0.001	0.001
Uruguay	0	0.005	0.009	0.013	0.017	0.021
Uzbekistan	0	0.006	0.013	0.022	0.035	0.05
Vanuatu	0	0	0	0	0	0
Vietnam	0	0.043	0.098	0.169	0.251	0.34
Western Sahara	0	0	0	0	0	0
Yemen	0	0.002	0.004	0.008	0.015	0.023
Zambia	0	0.003	0.006	0.011	0.016	0.023
Zimbabwe	0	0.001	0.003	0.005	0.007	0.009

TABLE D.20 Predicted changes in real gross domestic product (GDP) (US$ at 2017 value in billions) by year (scenario 4 *versus* reference)

Country/Territory	2025	2030	2035	2040	2045	2050
Albania	0	0	0.001	0.003	0.004	0.006
Algeria	0	0.01	0.032	0.075	0.143	0.231
Angola	0	0.002	0.006	0.013	0.023	0.036
Antigua and Barbuda	0	0	0	0.001	0.001	0.001
Argentina	0	0.04	0.11	0.241	0.338	0.407
Armenia	0	0	0.001	0.003	0.005	0.008
Aruba	0	0	0.001	0.001	0.002	0.002
Australia	0	0.034	0.098	0.228	0.407	0.56
Austria	0	0.004	0.01	0.021	0.034	0.048
Azerbaijan	0	0.001	0.004	0.008	0.013	0.02
Bahamas	0	0.001	0.002	0.004	0.005	0.006
Bahrain	0	0.002	0.005	0.012	0.023	0.035
Bangladesh	0	0.021	0.085	0.202	0.382	0.611
Barbados	0	0	0.001	0.001	0.002	0.002
Belarus	0	0.001	0.004	0.007	0.012	0.017
Belgium	0	0.005	0.012	0.025	0.041	0.058
Belize	0	0	0.001	0.001	0.002	0.003
Benin	0	0.001	0.002	0.004	0.008	0.013
Bhutan	0	0	0	0.001	0.002	0.003
Bolivia	0	0.005	0.014	0.033	0.05	0.065
Bosnia and Herzegovina	0	0	0.001	0.003	0.005	0.006
Botswana	0	0	0.001	0.002	0.004	0.006
Brazil	0	0.152	0.426	0.973	1.422	1.772
Brunei	0	0.001	0.002	0.004	0.007	0.01
Bulgaria	0	0.002	0.004	0.009	0.015	0.021
Burkina Faso	0	0.001	0.002	0.005	0.009	0.014
Burundi	0	0	0	0.001	0.001	0.002
Cambodia	0	0.003	0.009	0.024	0.05	0.077
Cameroon	0	0.001	0.004	0.008	0.015	0.023
Canada	0	0.025	0.075	0.179	0.294	0.387
Cape Verde	0	0	0	0	0	0.001
Central African Republic	0	0	0	0	0.001	0.001
Chad	0	0	0.001	0.002	0.004	0.007
Chile	0	0.022	0.059	0.129	0.179	0.212
China (People’s Republic of)	0	0.78	2.293	5.25	9.124	12.182
Chinese Taipei	0	0.035	0.095	0.198	0.308	0.364
Colombia	0	0.038	0.11	0.259	0.385	0.482
Comoros	0	0	0	0	0	0.001

TABLE D.20 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Congo (Democratic Republic of the)	0	0.001	0.004	0.01	0.02	0.035
Congo (Republic of the)	0	0	0.001	0.001	0.002	0.004
Costa Rica	0	0.006	0.016	0.037	0.054	0.065
Cote d'Ivoire	0	0.002	0.006	0.014	0.025	0.039
Croatia	0	0.001	0.003	0.006	0.01	0.014
Cuba	0	0.004	0.013	0.034	0.054	0.073
Cyprus	0	0	0.001	0.002	0.004	0.005
Czechia (Czech Republic)	0	0.003	0.009	0.018	0.029	0.042
Denmark	0	0.003	0.007	0.014	0.023	0.033
Djibouti	0	0	0.001	0.002	0.003	0.005
Dominican Republic	0	0.013	0.039	0.092	0.134	0.164
Ecuador	0	0.01	0.027	0.062	0.09	0.111
Egypt	0	0.038	0.137	0.368	0.795	1.41
El Salvador	0	0.003	0.008	0.018	0.027	0.033
Equatorial Guinea	0	0	0	0.001	0.002	0.002
Eritrea	0	0	0	0	0.001	0.001
Estonia	0	0	0.001	0.002	0.004	0.005
Eswatini	0	0	0	0.001	0.001	0.001
Ethiopia	0	0.004	0.013	0.03	0.057	0.094
Fiji	0	0	0.001	0.002	0.005	0.007
Finland	0	0.002	0.005	0.011	0.018	0.025
France	0	0.023	0.061	0.126	0.208	0.296
French Guiana	0	0.001	0.002	0.005	0.007	0.008
French Polynesia	0	0	0	0.001	0.002	0.002
Gabon	0	0	0.001	0.002	0.003	0.005
Gambia	0	0	0	0	0.001	0.001
Georgia	0	0.001	0.002	0.005	0.008	0.012
Germany	0	0.032	0.084	0.171	0.281	0.397
Ghana	0	0.002	0.006	0.013	0.023	0.036
Greece	0	0.003	0.007	0.015	0.025	0.035
Grenada	0	0	0	0.001	0.001	0.001
Guam	0	0	0.001	0.001	0.002	0.003
Guatemala	0	0.009	0.026	0.062	0.094	0.121
Guinea	0	0	0.001	0.003	0.006	0.011
Guinea-Bissau	0	0	0	0	0.001	0.001
Guyana	0	0.005	0.019	0.05	0.072	0.079
Haiti	0	0.002	0.005	0.012	0.019	0.026
Honduras	0	0.003	0.01	0.024	0.037	0.049

TABLE D.20 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Hong Kong (Special Administrative Region of the People's Republic of China)	0	0.012	0.032	0.067	0.107	0.131
Hungary	0	0.003	0.008	0.016	0.026	0.036
Iceland	0	0	0	0.001	0.002	0.003
India	0	0.175	0.658	1.523	2.833	4.489
Indonesia	0	0.107	0.327	0.795	1.451	2.022
Iran	0	0.029	0.089	0.201	0.37	0.563
Iraq	0	0.009	0.033	0.099	0.236	0.442
Ireland	0	0.005	0.013	0.028	0.049	0.074
Israel	0	0.009	0.03	0.072	0.141	0.225
Italy	0	0.018	0.048	0.099	0.162	0.229
Jamaica	0	0.001	0.004	0.008	0.011	0.014
Japan	0	0.123	0.327	0.7	1.153	1.478
Jordan	0	0.002	0.008	0.019	0.038	0.065
Kazakhstan	0	0.005	0.014	0.029	0.05	0.072
Kenya	0	0.003	0.009	0.02	0.036	0.057
Kiribati	0	0	0	0	0	0
Korea (Democratic People's Republic of)	0	0.057	0.156	0.338	0.553	0.699
Korea (Republic of)	0	0.002	0.006	0.015	0.031	0.048
Kuwait	0	0.004	0.014	0.033	0.062	0.096
Kyrgyzstan	0	0	0.001	0.002	0.004	0.007
Laos	0	0.002	0.006	0.014	0.027	0.04
Latvia	0	0	0.001	0.003	0.004	0.006
Lebanon	0	0.001	0.004	0.01	0.02	0.033
Lesotho	0	0	0	0	0	0.001
Liberia	0	0	0	0.001	0.001	0.002
Libya	0	0.003	0.009	0.022	0.045	0.077
Lithuania	0	0.001	0.002	0.005	0.007	0.01
Luxembourg	0	0.001	0.002	0.003	0.005	0.007
Macao (Special Administrative Region of the People's Republic of China)	0	0.002	0.007	0.015	0.027	0.037
Madagascar	0	0	0.002	0.003	0.006	0.011
Malawi	0	0	0.001	0.002	0.004	0.008
Malaysia	0	0.029	0.086	0.2	0.351	0.473
Maldives	0	0	0.001	0.002	0.003	0.004
Mali	0	0.001	0.002	0.004	0.008	0.014
Malta	0	0.001	0.002	0.004	0.008	0.012
Mauritania	0	0	0.001	0.002	0.004	0.005
Mauritius	0	0	0.001	0.002	0.003	0.004

TABLE D.20 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Mayotte (French Department of)	0	0	0	0.001	0.001	0.002
Mexico	0	0.124	0.35	0.787	1.121	1.356
Micronesia (Federated States of)	0	0	0	0	0	0
Moldova	0	0	0.001	0.002	0.004	0.006
Mongolia	0	0.001	0.004	0.009	0.017	0.025
Montenegro	0	0	0	0.001	0.001	0.002
Morocco	0	0.007	0.023	0.057	0.113	0.189
Mozambique	0	0.001	0.002	0.006	0.011	0.019
Myanmar	0	0.006	0.018	0.044	0.082	0.118
Namibia	0	0	0.001	0.001	0.002	0.003
Nepal	0	0.002	0.007	0.018	0.034	0.057
Netherlands	0	0.008	0.021	0.043	0.07	0.099
New Caledonia	0	0	0.001	0.002	0.004	0.006
New Zealand	0	0.005	0.015	0.035	0.061	0.082
Nicaragua	0	0.002	0.007	0.016	0.025	0.033
Niger	0	0	0.002	0.004	0.007	0.013
Nigeria	0	0.01	0.033	0.072	0.128	0.201
North Macedonia (Republic of)	0	0	0.001	0.002	0.003	0.005
Norway	0	0.003	0.008	0.016	0.027	0.038
Oman	0	0.004	0.011	0.027	0.053	0.084
Pakistan	0	0.019	0.073	0.177	0.355	0.613
Panama	0	0.008	0.024	0.055	0.077	0.091
Papua New Guinea	0	0.001	0.003	0.008	0.016	0.026
Paraguay	0	0.005	0.015	0.034	0.049	0.059
Peru	0	0.023	0.065	0.148	0.213	0.261
Philippines	0	0.034	0.115	0.294	0.563	0.819
Poland	0	0.012	0.033	0.069	0.113	0.157
Portugal	0	0.003	0.008	0.017	0.028	0.04
Puerto Rico (Commonwealth of)	0	0.005	0.012	0.024	0.03	0.033
Qatar	0	0.006	0.018	0.041	0.073	0.11
Romania	0	0.005	0.013	0.027	0.045	0.062
Russia	0	0.03	0.082	0.172	0.29	0.419
Rwanda	0	0	0.001	0.003	0.006	0.009
Saint Lucia	0	0	0	0.001	0.001	0.001
Samoa	0	0	0	0	0	0.001
Sao Tome and Principe	0	0	0	0	0	0
Saudi Arabia	0	0.042	0.136	0.321	0.602	0.921
Senegal	0	0.001	0.002	0.006	0.01	0.016
Serbia	0	0.001	0.004	0.008	0.014	0.021

TABLE D.20 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Seychelles	0	0	0	0	0	0
Sierra Leone	0	0	0	0.001	0.002	0.003
Singapore	0	0.016	0.044	0.097	0.159	0.198
Slovakia	0	0.002	0.004	0.009	0.015	0.021
Slovenia	0	0.001	0.002	0.004	0.006	0.009
Solomon Islands	0	0	0	0	0.001	0.001
Somalia	0	0.001	0.002	0.007	0.016	0.032
South Africa	0	0.007	0.018	0.037	0.063	0.092
South Sudan	0	0	0	0	0.001	0.001
Spain	0	0.015	0.039	0.083	0.14	0.204
Sri Lanka	0	0.004	0.012	0.027	0.047	0.072
St. Vincent and the Grenadines	0	0	0	0.001	0.001	0.001
Sudan	0	0.003	0.011	0.028	0.056	0.094
Suriname	0	0	0.001	0.003	0.005	0.006
Sweden	0	0.005	0.013	0.026	0.044	0.063
Switzerland	0	0.005	0.012	0.025	0.041	0.057
Tajikistan	0	0	0.001	0.003	0.006	0.01
Tanzania	0	0.002	0.007	0.017	0.031	0.05
Thailand	0	0.034	0.099	0.228	0.398	0.533
Timor-Leste	0	0	0	0.001	0.002	0.003
Togo	0	0	0.001	0.002	0.003	0.005
Tonga	0	0	0	0	0	0
Trinidad and Tobago	0	0.002	0.004	0.009	0.012	0.014
Tunisia	0	0.003	0.009	0.021	0.041	0.066
Türkiye (Republic of)	0	0.027	0.077	0.17	0.294	0.43
Turkmenistan	0	0.001	0.002	0.005	0.009	0.012
Uganda	0	0.001	0.005	0.011	0.019	0.031
Ukraine	0	0.004	0.011	0.026	0.046	0.069
United Arab Emirates	0	0.017	0.056	0.13	0.239	0.356
United Kingdom	0	0.024	0.065	0.139	0.238	0.35
United States of America	0	0.292	0.867	1.991	3.152	4.009
United States Virgin Islands	0	0	0	0.001	0.001	0.001
Uruguay	0	0.004	0.011	0.024	0.032	0.037
Uzbekistan	0	0.003	0.01	0.023	0.043	0.067
Vanuatu	0	0	0	0	0	0.001
Vietnam	0	0.04	0.133	0.336	0.626	0.88
Western Sahara	0	0	0	0	0	0.001
Yemen	0	0.001	0.005	0.015	0.034	0.063
Zambia	0	0.001	0.002	0.005	0.009	0.014
Zimbabwe	0	0	0.001	0.002	0.004	0.005

TABLE D.21 Predicted changes in real gross domestic product (GDP) (US$ at 2017 value in billions) by year (scenario 2 *versus* reference)

Country/Territory	2025	2030	2035	2040	2045	2050
Albania	−0.009	−0.013	−0.016	−0.019	−0.022	−0.024
Algeria	−0.245	−0.311	−0.383	−0.461	−0.558	−0.682
Angola	−0.149	−0.21	−0.324	−0.506	−0.729	−0.97
Antigua and Barbuda	−0.001	−0.002	−0.002	−0.002	−0.002	−0.003
Argentina	−0.497	−0.552	−0.614	−0.693	−0.792	−0.913
Armenia	−0.01	−0.014	−0.019	−0.023	−0.027	−0.031
Aruba	−0.003	−0.003	−0.003	−0.003	−0.004	−0.004
Australia	−0.487	−0.624	−0.74	−0.868	−1.002	−1.14
Austria	−0.094	−0.116	−0.135	−0.154	−0.173	−0.191
Azerbaijan	−0.032	−0.04	−0.049	−0.057	−0.067	−0.078
Bahamas	−0.009	−0.009	−0.01	−0.011	−0.012	−0.013
Bahrain	−0.038	−0.05	−0.063	−0.076	−0.09	−0.105
Bangladesh	−0.989	−1.55	−2.267	−3.183	−4.384	−5.911
Barbados	−0.003	−0.003	−0.003	−0.004	−0.004	−0.005
Belarus	−0.036	−0.042	−0.048	−0.054	−0.061	−0.067
Belgium	−0.117	−0.142	−0.166	−0.188	−0.21	−0.23
Belize	−0.003	−0.003	−0.003	−0.004	−0.005	−0.006
Benin	−0.036	−0.057	−0.098	−0.165	−0.248	−0.338
Bhutan	−0.007	−0.009	−0.012	−0.016	−0.02	−0.026
Bolivia	−0.061	−0.068	−0.078	−0.094	−0.116	−0.145
Bosnia and Herzegovina	−0.011	−0.015	−0.018	−0.021	−0.023	−0.025
Botswana	−0.03	−0.043	−0.065	−0.097	−0.128	−0.153
Brazil	−1.968	−2.097	−2.384	−2.797	−3.329	−3.981
Brunei	−0.01	−0.013	−0.015	−0.017	−0.018	−0.02
Bulgaria	−0.036	−0.047	−0.057	−0.066	−0.074	−0.082
Burkina Faso	−0.038	−0.059	−0.104	−0.178	−0.273	−0.381
Burundi	−0.007	−0.011	−0.018	−0.03	−0.046	−0.065
Cambodia	−0.032	−0.049	−0.068	−0.093	−0.122	−0.157
Cameroon	−0.078	−0.115	−0.19	−0.312	−0.463	−0.624
Canada	−0.07	−0.132	−0.179	−0.237	−0.306	−0.385
Cape Verde	−0.003	−0.005	−0.008	−0.011	−0.015	−0.018
Central African Republic	−0.003	−0.005	−0.008	−0.014	−0.022	−0.033
Chad	−0.019	−0.026	−0.046	−0.079	−0.123	−0.176
Chile	−0.283	−0.298	−0.33	−0.37	−0.419	−0.475
China (People’s Republic of)	−10.602	−14.346	−17.319	−19.975	−22.482	−24.821
Chinese Taipei	−0.512	−0.646	−0.719	−0.755	−0.759	−0.743
Colombia	−0.46	−0.521	−0.616	−0.744	−0.901	−1.082
Comoros	−0.002	−0.003	−0.005	−0.008	−0.013	−0.019

TABLE D.21 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Congo (Democratic Republic of the)	−0.089	−0.136	−0.229	−0.398	−0.637	−0.928
Congo (Republic of the)	−0.016	−0.023	−0.035	−0.055	−0.077	−0.1
Costa Rica	−0.068	−0.077	−0.091	−0.107	−0.126	−0.147
Cote d’Ivoire	−0.123	−0.196	−0.334	−0.548	−0.798	−1.047
Croatia	−0.027	−0.035	−0.041	−0.046	−0.051	−0.054
Cuba	−0.048	−0.058	−0.074	−0.097	−0.126	−0.163
Cyprus	−0.008	−0.011	−0.013	−0.016	−0.019	−0.021
Czechia (Czech Republic)	−0.082	−0.1	−0.117	−0.134	−0.15	−0.165
Denmark	−0.066	−0.079	−0.092	−0.105	−0.118	−0.131
Djibouti	−0.003	−0.005	−0.007	−0.009	−0.012	−0.016
Dominican Republic	−0.143	−0.178	−0.22	−0.265	−0.314	−0.368
Ecuador	−0.119	−0.133	−0.153	−0.179	−0.211	−0.25
Egypt	−0.725	−1.114	−1.623	−2.267	−3.104	−4.169
El Salvador	−0.037	−0.04	−0.045	−0.053	−0.063	−0.075
Equatorial Guinea	−0.014	−0.016	−0.024	−0.036	−0.05	−0.065
Eritrea	−0.005	−0.006	−0.01	−0.017	−0.027	−0.038
Estonia	−0.009	−0.012	−0.015	−0.017	−0.019	−0.02
Eswatini	−0.008	−0.011	−0.016	−0.024	−0.033	−0.04
Ethiopia	−0.238	−0.391	−0.683	−1.17	−1.804	−2.513
Fiji	−0.005	−0.006	−0.008	−0.009	−0.011	−0.013
Finland	−0.051	−0.062	−0.071	−0.081	−0.091	−0.1
France	−0.584	−0.708	−0.823	−0.942	−1.058	−1.175
French Guiana	−0.009	−0.01	−0.012	−0.014	−0.016	−0.019
French Polynesia	−0.002	−0.002	−0.003	−0.004	−0.004	−0.005
Gabon	−0.024	−0.032	−0.049	−0.074	−0.101	−0.123
Gambia	−0.005	−0.007	−0.012	−0.019	−0.029	−0.039
Georgia	−0.014	−0.021	−0.028	−0.035	−0.041	−0.046
Germany	−0.827	−0.976	−1.119	−1.274	−1.429	−1.577
Ghana	−0.131	−0.197	−0.319	−0.509	−0.733	−0.96
Greece	−0.065	−0.081	−0.095	−0.111	−0.126	−0.141
Grenada	−0.001	−0.001	−0.002	−0.002	−0.002	−0.002
Guam	−0.002	−0.003	−0.004	−0.005	−0.006	−0.007
Guatemala	−0.102	−0.121	−0.146	−0.179	−0.221	−0.272
Guinea	−0.029	−0.045	−0.077	−0.133	−0.205	−0.286
Guinea-Bissau	−0.004	−0.005	−0.008	−0.014	−0.02	−0.026
Guyana	−0.034	−0.07	−0.107	−0.144	−0.17	−0.177
Haiti	−0.019	−0.021	−0.026	−0.033	−0.044	−0.058
Honduras	−0.038	−0.045	−0.055	−0.068	−0.087	−0.111

TABLE D.21 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Hong Kong (Special Administrative Region of the People's Republic of China)	−0.167	−0.212	−0.238	−0.255	−0.264	−0.268
Hungary	−0.067	−0.086	−0.102	−0.118	−0.132	−0.144
Iceland	−0.004	−0.005	−0.007	−0.008	−0.009	−0.01
India	−8.548	−12.644	−17.516	−23.951	−32.499	−43.443
Indonesia	−1.409	−1.973	−2.474	−3.023	−3.576	−4.12
Iran	−0.664	−0.853	−1.054	−1.241	−1.443	−1.664
Iraq	−0.201	−0.27	−0.387	−0.613	−0.922	−1.308
Ireland	−0.113	−0.143	−0.173	−0.208	−0.25	−0.295
Israel	−0.198	−0.274	−0.355	−0.444	−0.549	−0.666
Italy	−0.475	−0.56	−0.647	−0.737	−0.825	−0.909
Jamaica	−0.017	−0.018	−0.02	−0.023	−0.026	−0.03
Japan	−1.929	−2.259	−2.467	−2.663	−2.841	−3.012
Jordan	−0.051	−0.069	−0.09	−0.115	−0.149	−0.192
Kazakhstan	−0.113	−0.145	−0.181	−0.218	−0.254	−0.288
Kenya	−0.201	−0.307	−0.498	−0.797	−1.153	−1.515
Kiribati	0	0	0	0	0	0
Korea (Democratic People's Republic of)	−0.855	−1.057	−1.18	−1.284	−1.364	−1.424
Korea (Republic of)	−0.021	−0.03	−0.042	−0.057	−0.075	−0.098
Kuwait	−0.102	−0.133	−0.167	−0.203	−0.241	−0.284
Kyrgyzstan	−0.008	−0.01	−0.014	−0.018	−0.022	−0.028
Laos	−0.023	−0.032	−0.042	−0.054	−0.067	−0.082
Latvia	−0.012	−0.014	−0.017	−0.019	−0.02	−0.022
Lebanon	−0.031	−0.041	−0.051	−0.063	−0.078	−0.097
Lesotho	−0.004	−0.005	−0.008	−0.012	−0.016	−0.02
Liberia	−0.006	−0.009	−0.016	−0.026	−0.039	−0.053
Libya	−0.071	−0.093	−0.11	−0.136	−0.174	−0.227
Lithuania	−0.021	−0.027	−0.031	−0.035	−0.037	−0.039
Luxembourg	−0.015	−0.019	−0.022	−0.025	−0.028	−0.03
Macao (Special Administrative Region of the People's Republic of China)	−0.029	−0.04	−0.049	−0.059	−0.068	−0.075
Madagascar	−0.033	−0.05	−0.082	−0.135	−0.204	−0.282
Malawi	−0.022	−0.032	−0.053	−0.09	−0.143	−0.205
Malaysia	−0.383	−0.525	−0.647	−0.762	−0.866	−0.964
Maldives	−0.01	−0.014	−0.019	−0.025	−0.033	−0.042
Mali	−0.036	−0.056	−0.097	−0.168	−0.265	−0.378
Malta	−0.013	−0.018	−0.023	−0.027	−0.031	−0.035
Mauritania	−0.02	−0.03	−0.048	−0.077	−0.112	−0.146
Mauritius	−0.021	−0.029	−0.043	−0.062	−0.08	−0.094

TABLE D.21 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Mayotte (French Department of)	−0.006	−0.01	−0.016	−0.027	−0.039	−0.052
Mexico	−1.527	−1.711	−1.958	−2.263	−2.625	−3.045
Micronesia (Federated States of)	0	0	0	0	0	0
Moldova	−0.007	−0.01	−0.014	−0.017	−0.02	−0.023
Mongolia	−0.016	−0.022	−0.028	−0.035	−0.042	−0.05
Montenegro	−0.003	−0.004	−0.005	−0.005	−0.006	−0.007
Morocco	−0.152	−0.208	−0.273	−0.349	−0.442	−0.559
Mozambique	−0.032	−0.06	−0.12	−0.222	−0.359	−0.518
Myanmar	−0.084	−0.111	−0.137	−0.168	−0.202	−0.241
Namibia	−0.017	−0.023	−0.035	−0.053	−0.074	−0.093
Nepal	−0.098	−0.141	−0.197	−0.278	−0.392	−0.548
Netherlands	−0.196	−0.241	−0.28	−0.32	−0.358	−0.393
New Caledonia	−0.004	−0.006	−0.008	−0.009	−0.011	−0.012
New Zealand	−0.079	−0.1	−0.117	−0.133	−0.15	−0.167
Nicaragua	−0.026	−0.03	−0.036	−0.045	−0.057	−0.073
Niger	−0.027	−0.044	−0.08	−0.145	−0.236	−0.35
Nigeria	−0.778	−1.089	−1.749	−2.797	−4.064	−5.402
North Macedonia (Republic of)	−0.007	−0.01	−0.012	−0.015	−0.017	−0.02
Norway	−0.071	−0.086	−0.102	−0.118	−0.135	−0.152
Oman	−0.078	−0.105	−0.136	−0.168	−0.206	−0.249
Pakistan	−0.981	−1.391	−1.944	−2.785	−4.068	−5.933
Panama	−0.097	−0.116	−0.136	−0.158	−0.18	−0.205
Papua New Guinea	−0.013	−0.017	−0.023	−0.03	−0.04	−0.052
Paraguay	−0.06	−0.069	−0.082	−0.096	−0.114	−0.133
Peru	−0.274	−0.312	−0.362	−0.424	−0.498	−0.587
Philippines	−0.413	−0.633	−0.866	−1.12	−1.387	−1.668
Poland	−0.276	−0.364	−0.442	−0.515	−0.574	−0.624
Portugal	−0.072	−0.09	−0.106	−0.124	−0.142	−0.159
Puerto Rico (Commonwealth of)	−0.062	−0.064	−0.066	−0.068	−0.071	−0.074
Qatar	−0.128	−0.176	−0.216	−0.25	−0.285	−0.324
Romania	−0.117	−0.149	−0.178	−0.204	−0.226	−0.244
Russia	−0.76	−0.916	−1.094	−1.284	−1.475	−1.666
Rwanda	−0.026	−0.043	−0.073	−0.122	−0.182	−0.245
Saint Lucia	−0.002	−0.002	−0.002	−0.002	−0.002	−0.003
Samoa	0	−0.001	−0.001	−0.001	−0.001	−0.001
Sao Tome and Principe	−0.001	−0.001	−0.001	−0.002	−0.003	−0.003
Saudi Arabia	−0.875	−1.253	−1.621	−1.981	−2.35	−2.725
Senegal	−0.05	−0.078	−0.133	−0.218	−0.321	−0.426
Serbia	−0.029	−0.04	−0.051	−0.062	−0.073	−0.083

TABLE D.21 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Seychelles	−0.002	−0.003	−0.005	−0.007	−0.009	−0.011
Sierra Leone	−0.011	−0.016	−0.025	−0.042	−0.064	−0.089
Singapore	−0.226	−0.289	−0.335	−0.369	−0.391	−0.403
Slovakia	−0.038	−0.048	−0.057	−0.067	−0.076	−0.084
Slovenia	−0.017	−0.021	−0.025	−0.028	−0.031	−0.034
Solomon Islands	−0.001	−0.001	−0.001	−0.001	−0.002	−0.003
Somalia	−0.013	−0.018	−0.027	−0.041	−0.063	−0.096
South Africa	−0.534	−0.678	−0.98	−1.458	−1.991	−2.477
South Sudan	−0.004	−0.006	−0.01	−0.016	−0.023	−0.031
Spain	−0.367	−0.441	−0.524	−0.617	−0.713	−0.811
Sri Lanka	−0.197	−0.258	−0.329	−0.421	−0.542	−0.695
St. Vincent and the Grenadines	−0.001	−0.001	−0.001	−0.001	−0.002	−0.002
Sudan	−0.068	−0.099	−0.132	−0.171	−0.218	−0.277
Suriname	−0.006	−0.007	−0.008	−0.009	−0.011	−0.012
Sweden	−0.111	−0.142	−0.169	−0.197	−0.223	−0.249
Switzerland	−0.123	−0.145	−0.167	−0.188	−0.208	−0.227
Tajikistan	−0.009	−0.013	−0.018	−0.024	−0.031	−0.039
Tanzania	−0.138	−0.226	−0.393	−0.658	−0.986	−1.338
Thailand	−0.482	−0.63	−0.75	−0.869	−0.98	−1.085
Timor-Leste	−0.001	−0.002	−0.003	−0.003	−0.004	−0.006
Togo	−0.015	−0.023	−0.039	−0.064	−0.096	−0.13
Tonga	0	0	0	0	0	−0.001
Trinidad and Tobago	−0.022	−0.023	−0.024	−0.027	−0.029	−0.032
Tunisia	−0.062	−0.081	−0.103	−0.128	−0.159	−0.196
Türkiye (Republic of)	−0.599	−0.813	−1.037	−1.266	−1.492	−1.709
Turkmenistan	−0.021	−0.026	−0.032	−0.038	−0.043	−0.049
Uganda	−0.088	−0.144	−0.248	−0.412	−0.612	−0.824
Ukraine	−0.082	−0.115	−0.152	−0.192	−0.232	−0.273
United Arab Emirates	−0.357	−0.511	−0.666	−0.802	−0.932	−1.052
United Kingdom	−0.6	−0.734	−0.873	−1.034	−1.208	−1.392
United States of America	−0.843	−1.573	−2.068	−2.641	−3.279	−3.99
United States Virgin Islands	−0.002	−0.002	−0.002	−0.002	−0.002	−0.003
Uruguay	−0.052	−0.057	−0.063	−0.069	−0.076	−0.083
Uzbekistan	−0.065	−0.096	−0.132	−0.174	−0.219	−0.267
Vanuatu	0	0	−0.001	−0.001	−0.001	−0.002
Vietnam	−0.466	−0.73	−1.003	−1.279	−1.542	−1.794
Western Sahara	−0.001	−0.001	−0.001	−0.001	−0.001	−0.002
Yemen	−0.028	−0.043	−0.063	−0.091	−0.131	−0.187
Zambia	−0.049	−0.074	−0.12	−0.192	−0.277	−0.365
Zimbabwe	−0.026	−0.036	−0.055	−0.083	−0.112	−0.139

TABLE D.22 Predicted changes in real gross domestic product (GDP) (US$ at 2017 value in billions) by year (scenario 5 *versus* reference)

Country/Territory	2025	2030	2035	2040	2045	2050
Albania	−0.019	−0.023	−0.027	−0.031	−0.035	−0.038
Algeria	−0.155	−0.187	−0.229	−0.272	−0.324	−0.386
Angola	−0.079	−0.101	−0.129	−0.165	−0.211	−0.273
Antigua and Barbuda	−0.001	−0.001	−0.001	−0.001	−0.002	−0.002
Argentina	−0.313	−0.36	−0.406	−0.457	−0.516	−0.584
Armenia	−0.02	−0.026	−0.032	−0.038	−0.043	−0.048
Aruba	−0.002	−0.002	−0.002	−0.002	−0.002	−0.003
Australia	−0.529	−0.671	−0.823	−0.984	−1.157	−1.337
Austria	−0.185	−0.211	−0.234	−0.255	−0.277	−0.298
Azerbaijan	−0.063	−0.074	−0.085	−0.095	−0.107	−0.122
Bahamas	−0.006	−0.006	−0.007	−0.007	−0.008	−0.009
Bahrain	−0.024	−0.03	−0.038	−0.045	−0.052	−0.059
Bangladesh	−0.5	−0.775	−1.088	−1.436	−1.815	−2.227
Barbados	−0.002	−0.002	−0.002	−0.002	−0.003	−0.003
Belarus	−0.07	−0.076	−0.083	−0.09	−0.097	−0.105
Belgium	−0.231	−0.26	−0.288	−0.313	−0.337	−0.361
Belize	−0.002	−0.002	−0.002	−0.003	−0.003	−0.004
Benin	−0.019	−0.027	−0.039	−0.054	−0.072	−0.095
Bhutan	−0.004	−0.005	−0.006	−0.007	−0.008	−0.01
Bolivia	−0.039	−0.044	−0.052	−0.062	−0.076	−0.093
Bosnia and Herzegovina	−0.023	−0.027	−0.031	−0.035	−0.037	−0.038
Botswana	−0.016	−0.021	−0.026	−0.031	−0.037	−0.043
Brazil	−1.237	−1.366	−1.575	−1.844	−2.171	−2.546
Brunei	−0.011	−0.014	−0.017	−0.019	−0.021	−0.023
Bulgaria	−0.072	−0.085	−0.098	−0.109	−0.119	−0.129
Burkina Faso	−0.02	−0.029	−0.042	−0.058	−0.079	−0.107
Burundi	−0.004	−0.005	−0.007	−0.01	−0.013	−0.018
Cambodia	−0.035	−0.053	−0.076	−0.105	−0.141	−0.184
Cameroon	−0.041	−0.056	−0.076	−0.101	−0.134	−0.176
Canada	−0.79	−0.909	−1.039	−1.181	−1.33	−1.481
Cape Verde	−0.002	−0.002	−0.003	−0.004	−0.004	−0.005
Central African Republic	−0.002	−0.002	−0.003	−0.005	−0.006	−0.009
Chad	−0.01	−0.013	−0.018	−0.026	−0.036	−0.049
Chile	−0.178	−0.194	−0.218	−0.244	−0.273	−0.304
China (People’s Republic of)	−11.521	−15.425	−19.275	−22.659	−25.95	−29.092
Chinese Taipei	−0.557	−0.695	−0.8	−0.856	−0.876	−0.87
Colombia	−0.289	−0.339	−0.407	−0.491	−0.587	−0.692
Comoros	−0.001	−0.001	−0.002	−0.003	−0.004	−0.005

TABLE D.22 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Congo (Democratic Republic of the)	–0.048	–0.066	–0.091	–0.13	–0.185	–0.261
Congo (Republic of the)	–0.009	–0.011	–0.014	–0.018	–0.022	–0.028
Costa Rica	–0.043	–0.05	–0.06	–0.071	–0.082	–0.094
Cote d'Ivoire	–0.066	–0.095	–0.134	–0.178	–0.231	–0.295
Croatia	–0.054	–0.064	–0.071	–0.077	–0.081	–0.085
Cuba	–0.03	–0.038	–0.049	–0.064	–0.082	–0.104
Cyprus	–0.016	–0.02	–0.023	–0.026	–0.03	–0.033
Czechia (Czech Republic)	–0.162	–0.182	–0.202	–0.222	–0.241	–0.259
Denmark	–0.13	–0.145	–0.159	–0.174	–0.189	–0.205
Djibouti	–0.002	–0.003	–0.004	–0.005	–0.007	–0.009
Dominican Republic	–0.09	–0.116	–0.145	–0.175	–0.205	–0.236
Ecuador	–0.075	–0.087	–0.101	–0.118	–0.138	–0.16
Egypt	–0.46	–0.671	–0.97	–1.34	–1.801	–2.362
El Salvador	–0.023	–0.026	–0.03	–0.035	–0.041	–0.048
Equatorial Guinea	–0.007	–0.008	–0.009	–0.012	–0.015	–0.018
Eritrea	–0.002	–0.003	–0.004	–0.006	–0.008	–0.011
Estonia	–0.018	–0.022	–0.026	–0.028	–0.03	–0.031
Eswatini	–0.004	–0.005	–0.006	–0.008	–0.009	–0.011
Ethiopia	–0.127	–0.189	–0.273	–0.381	–0.523	–0.707
Fiji	–0.005	–0.007	–0.008	–0.011	–0.013	–0.016
Finland	–0.102	–0.113	–0.124	–0.135	–0.146	–0.157
France	–1.154	–1.294	–1.429	–1.563	–1.699	–1.839
French Guiana	–0.006	–0.007	–0.008	–0.009	–0.011	–0.012
French Polynesia	–0.002	–0.003	–0.003	–0.004	–0.005	–0.006
Gabon	–0.013	–0.016	–0.02	–0.024	–0.029	–0.035
Gambia	–0.002	–0.003	–0.005	–0.006	–0.008	–0.011
Georgia	–0.028	–0.038	–0.049	–0.059	–0.066	–0.072
Germany	–1.633	–1.784	–1.943	–2.116	–2.295	–2.468
Ghana	–0.07	–0.095	–0.127	–0.166	–0.213	–0.27
Greece	–0.129	–0.148	–0.165	–0.183	–0.202	–0.22
Grenada	–0.001	–0.001	–0.001	–0.001	–0.001	–0.002
Guam	–0.003	–0.004	–0.005	–0.006	–0.007	–0.008
Guatemala	–0.064	–0.079	–0.096	–0.118	–0.144	–0.174
Guinea	–0.016	–0.022	–0.031	–0.043	–0.06	–0.081
Guinea–Bissau	–0.002	–0.003	–0.003	–0.004	–0.006	–0.007
Guyana	–0.022	-0.046	–0.071	–0.095	–0.111	–0.113
Haiti	–0.012	–0.013	–0.017	–0.022	–0.028	–0.037
Honduras	–0.024	–0.029	–0.036	–0.045	–0.057	–0.071

TABLE D.22 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Hong Kong (Special Administrative Region of the People's Republic of China)	−0.181	−0.228	−0.265	−0.29	−0.305	−0.314
Hungary	−0.133	−0.156	−0.178	−0.196	−0.211	−0.225
Iceland	−0.008	−0.01	−0.012	−0.013	−0.015	−0.016
India	−4.318	−6.323	−8.411	−10.807	−13.458	−16.371
Indonesia	−1.531	−2.122	−2.753	−3.43	−4.127	−4.829
Iran	−0.422	−0.514	−0.63	−0.734	−0.838	−0.943
Iraq	−0.127	−0.163	−0.232	−0.362	−0.535	−0.741
Ireland	−0.223	−0.261	−0.3	−0.346	−0.401	−0.463
Israel	−0.126	−0.165	−0.212	−0.263	−0.319	−0.377
Italy	−0.938	−1.023	−1.123	−1.224	−1.325	−1.424
Jamaica	−0.011	−0.012	−0.013	−0.015	−0.017	−0.019
Japan	−2.096	−2.429	−2.746	−3.021	−3.279	−3.53
Jordan	−0.033	−0.042	−0.054	−0.068	−0.086	−0.108
Kazakhstan	−0.222	−0.265	−0.314	−0.363	−0.408	−0.451
Kenya	−0.107	−0.148	−0.199	−0.259	−0.334	−0.427
Kiribati	0	0	0	0	0	0
Korea (Democratic People's Republic of)	−0.929	−1.137	−1.313	−1.457	−1.574	−1.669
Korea (Republic of)	−0.022	−0.033	−0.046	−0.064	−0.087	−0.115
Kuwait	−0.065	−0.08	−0.1	−0.12	−0.14	−0.161
Kyrgyzstan	−0.015	−0.019	−0.024	−0.03	−0.036	−0.043
Laos	−0.025	−0.035	−0.047	−0.061	−0.077	−0.096
Latvia	−0.023	−0.026	−0.029	−0.031	−0.033	−0.034
Lebanon	−0.02	−0.025	−0.03	−0.037	−0.045	−0.055
Lesotho	−0.002	−0.002	−0.003	−0.004	−0.005	−0.006
Liberia	−0.003	−0.005	−0.006	−0.008	−0.011	−0.015
Libya	−0.045	−0.056	−0.066	−0.08	−0.101	−0.128
Lithuania	−0.042	−0.05	−0.055	−0.058	−0.06	−0.062
Luxembourg	−0.029	−0.035	−0.039	−0.042	−0.044	−0.046
Macao (Special Administrative Region of the People's Republic of China)	−0.032	−0.043	−0.055	−0.067	−0.078	−0.088
Madagascar	−0.018	−0.024	−0.033	−0.044	−0.059	−0.079
Malawi	−0.012	−0.015	−0.021	−0.029	−0.041	−0.058
Malaysia	−0.417	−0.565	−0.72	−0.864	−0.999	−1.129
Maldives	−0.005	−0.007	−0.009	−0.011	−0.014	−0.016
Mali	−0.019	−0.027	−0.039	−0.055	−0.077	−0.106
Malta	−0.008	−0.011	−0.014	−0.016	−0.018	−0.02
Mauritania	−0.011	−0.014	−0.019	−0.025	−0.032	−0.041
Mauritius	−0.011	−0.014	−0.017	−0.02	−0.023	−0.026
Mayotte (French Department of)	−0.003	−0.005	−0.007	−0.009	−0.011	−0.015

TABLE D.22 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Mexico	−0.959	−1.115	−1.294	−1.492	−1.711	−1.947
Micronesia (Federated States of)	0	0	0	0	0	0
Moldova	−0.014	−0.019	−0.024	−0.028	−0.032	−0.035
Mongolia	−0.018	−0.024	−0.031	−0.04	−0.049	−0.059
Montenegro	−0.006	−0.007	−0.008	−0.009	−0.01	−0.011
Morocco	−0.096	−0.125	−0.163	−0.206	−0.257	−0.317
Mozambique	−0.017	−0.029	−0.048	−0.072	−0.104	−0.146
Myanmar	−0.091	−0.119	−0.153	−0.191	−0.233	−0.282
Namibia	−0.009	−0.011	−0.014	−0.017	−0.021	−0.026
Nepal	−0.05	−0.07	−0.095	−0.125	−0.162	−0.207
Netherlands	−0.387	−0.44	−0.487	−0.531	−0.574	−0.615
New Caledonia	−0.005	−0.006	−0.008	−0.01	−0.012	−0.014
New Zealand	−0.085	−0.107	−0.13	−0.151	−0.174	−0.196
Nicaragua	−0.016	−0.02	−0.024	−0.03	−0.037	−0.047
Niger	−0.014	−0.021	−0.032	−0.047	−0.069	−0.099
Nigeria	−0.415	−0.526	−0.698	−0.91	−1.178	−1.52
North Macedonia (Republic of)	−0.015	−0.018	−0.021	−0.025	−0.028	−0.031
Norway	−0.14	−0.158	−0.177	−0.197	−0.217	−0.237
Oman	−0.05	−0.064	−0.081	−0.099	−0.12	−0.141
Pakistan	−0.496	−0.696	−0.933	−1.257	−1.684	−2.236
Panama	−0.061	−0.075	−0.09	−0.104	−0.118	−0.131
Papua New Guinea	−0.014	−0.019	−0.025	−0.034	−0.046	−0.061
Paraguay	−0.037	−0.045	−0.054	−0.064	−0.074	−0.085
Peru	−0.172	−0.203	−0.239	−0.28	−0.325	−0.375
Philippines	−0.448	−0.68	−0.964	−1.27	−1.601	−1.955
Poland	−0.545	−0.665	−0.767	−0.855	−0.922	−0.977
Portugal	−0.143	−0.164	−0.185	−0.206	−0.227	−0.248
Puerto Rico (Commonwealth of)	−0.039	−0.042	−0.044	−0.045	−0.046	−0.047
Qatar	−0.081	−0.106	−0.129	−0.148	−0.166	−0.184
Romania	−0.231	−0.272	−0.309	−0.339	−0.363	−0.383
Russia	−1.501	−1.674	−1.9	−2.131	−2.368	−2.608
Rwanda	−0.014	−0.021	−0.029	−0.04	−0.053	−0.069
Saint Lucia	−0.001	−0.001	−0.001	−0.001	−0.002	−0.002
Samoa	0	−0.001	−0.001	−0.001	−0.001	−0.001
Sao Tome and Principe	0	0	0	−0.001	−0.001	−0.001
Saudi Arabia	−0.556	−0.755	−0.969	−1.171	−1.364	−1.543
Senegal	−0.027	−0.038	−0.053	−0.071	−0.093	−0.12
Serbia	−0.058	−0.073	−0.089	−0.103	−0.117	−0.13
Seychelles	−0.001	−0.002	−0.002	−0.002	−0.003	−0.003

TABLE D.22 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Sierra Leone	–0.006	–0.007	–0.01	–0.014	–0.019	–0.025
Singapore	–0.246	–0.311	–0.372	–0.418	–0.451	–0.472
Slovakia	–0.076	–0.087	–0.099	–0.111	–0.121	–0.132
Slovenia	–0.033	–0.038	–0.043	–0.047	–0.05	–0.054
Solomon Islands	–0.001	–0.001	–0.001	–0.002	–0.002	–0.003
Somalia	–0.008	–0.011	–0.016	–0.024	–0.037	–0.054
South Africa	–0.285	–0.327	–0.391	–0.475	–0.577	–0.697
South Sudan	–0.002	–0.003	–0.004	–0.005	–0.007	–0.009
Spain	–0.726	–0.807	–0.909	–1.023	–1.144	–1.269
Sri Lanka	–0.1	–0.129	–0.158	–0.19	–0.225	–0.262
St. Vincent and the Grenadines	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001
Sudan	–0.043	–0.059	–0.079	–0.101	–0.127	–0.157
Suriname	–0.004	–0.004	–0.005	–0.006	–0.007	–0.008
Sweden	–0.22	–0.259	–0.294	–0.327	–0.359	–0.39
Switzerland	–0.243	–0.266	–0.29	–0.312	–0.334	–0.355
Tajikistan	–0.018	–0.024	–0.031	–0.039	–0.049	–0.061
Tanzania	–0.073	–0.109	–0.157	–0.214	–0.286	–0.377
Thailand	–0.524	–0.678	–0.835	–0.986	–1.131	–1.272
Timor–Leste	–0.002	–0.002	–0.003	–0.004	–0.005	–0.007
Togo	–0.008	–0.011	–0.016	–0.021	–0.028	–0.036
Tonga	0	0	0	0	–0.001	–0.001
Trinidad and Tobago	–0.014	–0.015	–0.016	–0.018	–0.019	–0.021
Tunisia	–0.039	–0.049	–0.061	–0.076	–0.092	–0.111
Türkiye (Republic of)	–1.183	–1.485	–1.801	–2.102	–2.395	–2.675
Turkmenistan	–0.041	–0.047	–0.055	–0.062	–0.07	–0.077
Uganda	–0.047	–0.069	–0.099	–0.134	–0.177	–0.232
Ukraine	–0.163	–0.211	–0.264	–0.318	–0.372	–0.428
United Arab Emirates	–0.227	–0.308	–0.398	–0.474	–0.541	–0.596
United Kingdom	–1.186	–1.34	–1.516	–1.716	–1.939	–2.178
United States of America	–9.525	–10.831	–12.022	–13.151	–14.254	–15.348
United States Virgin Islands	–0.001	–0.001	–0.001	–0.001	–0.002	–0.002
Uruguay	–0.033	–0.037	–0.041	–0.045	–0.049	–0.053
Uzbekistan	–0.129	–0.175	–0.229	–0.289	–0.351	–0.418
Vanuatu	0	0	–0.001	–0.001	–0.001	–0.002
Vietnam	–0.507	–0.785	–1.116	–1.45	–1.78	–2.102
Western Sahara	0	0	–0.001	–0.001	–0.001	–0.001
Yemen	–0.018	–0.026	–0.037	–0.054	–0.076	–0.106
Zambia	–0.026	–0.036	–0.048	–0.062	–0.08	–0.103
Zimbabwe	–0.014	–0.017	–0.022	–0.027	–0.033	–0.039

TABLE D.23 Predicted changes in real gross domestic product (GDP) (US$ at 2017 value in billions) by year (scenario 6 *versus* reference)

Country/Territory	2025	2030	2035	2040	2045	2050
Albania	−0.084	−0.104	−0.125	−0.144	−0.162	−0.178
Algeria	−0.872	−1.06	−1.301	−1.551	−1.853	−2.228
Angola	−0.466	−0.615	−0.842	−1.164	−1.573	−2.062
Antigua and Barbuda	−0.005	−0.005	−0.006	−0.007	−0.008	−0.01
Argentina	−1.742	−1.99	−2.236	−2.522	−2.856	−3.248
Armenia	−0.09	−0.118	−0.148	−0.176	−0.201	−0.223
Aruba	−0.009	−0.01	−0.011	−0.012	−0.013	−0.014
Australia	−2.599	−3.308	−4.032	−4.805	−5.629	−6.486
Austria	−0.837	−0.963	−1.07	−1.176	−1.282	−1.384
Azerbaijan	−0.285	−0.336	−0.387	−0.439	−0.497	−0.564
Bahamas	−0.031	−0.034	−0.037	−0.04	−0.044	−0.047
Bahrain	−0.135	−0.171	−0.215	−0.256	−0.299	−0.342
Bangladesh	−2.993	−4.656	−6.624	−8.928	−11.644	−14.816
Barbados	−0.01	−0.011	−0.012	−0.014	−0.015	−0.018
Belarus	−0.318	−0.346	−0.379	−0.413	−0.449	−0.488
Belgium	−1.045	−1.185	−1.317	−1.441	−1.558	−1.673
Belize	−0.009	−0.01	−0.012	−0.015	−0.018	−0.022
Benin	−0.112	−0.166	−0.255	−0.38	−0.536	−0.718
Bhutan	−0.021	−0.028	−0.035	−0.044	−0.053	−0.065
Bolivia	−0.215	−0.244	−0.284	−0.343	−0.42	−0.516
Bosnia and Herzegovina	−0.102	−0.124	−0.144	−0.159	−0.17	−0.179
Botswana	−0.095	−0.127	−0.17	−0.222	−0.276	−0.326
Brazil	−6.892	−7.562	−8.684	−10.174	−12.012	−14.161
Brunei	−0.052	−0.068	−0.082	−0.094	−0.103	−0.111
Bulgaria	−0.324	−0.389	−0.45	−0.504	−0.553	−0.599
Burkina Faso	−0.119	−0.174	−0.27	−0.409	−0.59	−0.809
Burundi	−0.022	−0.032	−0.047	−0.07	−0.1	−0.137
Cambodia	−0.17	−0.259	−0.372	−0.513	−0.685	−0.895
Cameroon	−0.243	−0.338	−0.494	−0.717	−0.999	−1.326
Canada	−3.229	−3.769	−4.334	−4.962	−5.628	−6.312
Cape Verde	−0.01	−0.015	−0.02	−0.026	−0.033	−0.039
Central African Republic	−0.01	−0.014	−0.021	−0.032	−0.048	−0.07
Chad	−0.058	−0.077	−0.118	−0.181	−0.266	−0.373
Chile	−0.99	−1.076	−1.201	−1.347	−1.511	−1.69
China (People’s Republic of)	−56.64	−76.058	−94.423	−110.606	−126.267	−141.167
Chinese Taipei	−2.737	−3.426	−3.921	−4.18	−4.261	−4.223
Colombia	−1.612	−1.879	−2.243	−2.708	−3.25	−3.849
Comoros	−0.006	−0.008	−0.012	−0.019	−0.028	−0.04

TABLE D.23 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Congo (Democratic Republic of the)	−0.279	−0.398	−0.594	−0.916	−1.375	−1.973
Congo (Republic of the)	−0.051	−0.067	−0.092	−0.126	−0.167	−0.214
Costa Rica	−0.239	−0.277	−0.33	−0.39	−0.455	−0.522
Cote d'Ivoire	−0.386	−0.575	−0.868	−1.261	−1.723	−2.226
Croatia	−0.244	−0.291	−0.328	−0.355	−0.377	−0.393
Cuba	−0.167	−0.21	−0.268	−0.351	−0.456	−0.58
Cyprus	−0.074	−0.089	−0.105	−0.121	−0.138	−0.154
Czechia (Czech Republic)	−0.732	−0.831	−0.928	−1.022	−1.113	−1.2
Denmark	−0.588	−0.658	−0.729	−0.8	−0.874	−0.952
Djibouti	−0.011	−0.015	−0.023	−0.031	−0.04	−0.051
Dominican Republic	−0.5	−0.644	−0.802	−0.964	−1.133	−1.311
Ecuador	−0.416	−0.479	−0.557	−0.651	−0.761	−0.89
Egypt	−2.583	−3.803	−5.507	−7.63	−10.309	−13.615
El Salvador	−0.128	−0.144	−0.165	−0.192	−0.226	−0.267
Equatorial Guinea	−0.043	−0.046	−0.061	−0.083	−0.109	−0.137
Eritrea	−0.014	−0.019	−0.027	−0.04	−0.058	−0.08
Estonia	−0.083	−0.102	−0.117	−0.129	−0.138	−0.146
Eswatini	−0.025	−0.031	−0.042	−0.055	−0.07	−0.085
Ethiopia	−0.746	−1.146	−1.775	−2.694	−3.896	−5.341
Fiji	−0.025	−0.033	−0.042	−0.052	−0.063	−0.076
Finland	−0.458	−0.516	−0.568	−0.621	−0.674	−0.728
France	−5.213	−5.893	−6.546	−7.2	−7.861	−8.536
French Guiana	−0.032	−0.038	−0.044	−0.051	−0.058	−0.067
French Polynesia	−0.01	−0.013	−0.016	−0.02	−0.023	−0.027
Gabon	−0.074	−0.095	−0.128	−0.171	−0.217	−0.262
Gambia	−0.014	−0.02	−0.03	−0.044	−0.062	−0.082
Georgia	−0.128	−0.174	−0.226	−0.271	−0.307	−0.335
Germany	−7.375	−8.124	−8.903	−9.746	−10.615	−11.457
Ghana	−0.409	−0.577	−0.828	−1.171	−1.583	−2.041
Greece	−0.581	−0.673	−0.756	−0.845	−0.934	−1.021
Grenada	−0.004	−0.005	−0.006	−0.006	−0.007	−0.009
Guam	−0.013	−0.018	−0.023	−0.028	−0.033	−0.038
Guatemala	−0.356	−0.435	−0.532	−0.652	−0.798	−0.968
Guinea	−0.091	−0.132	−0.201	−0.306	−0.444	−0.608
Guinea-Bissau	−0.011	−0.015	−0.022	−0.031	−0.043	−0.056
Guyana	−0.12	−0.252	−0.39	−0.523	−0.612	−0.631
Haiti	−0.066	−0.075	−0.094	−0.121	−0.157	−0.205
Honduras	−0.132	−0.161	−0.199	−0.249	−0.314	−0.395

TABLE D.23 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Hong Kong (Special Administrative Region of the People's Republic of China)	−0.892	−1.124	−1.299	−1.413	−1.483	−1.522
Hungary	−0.599	−0.712	−0.815	−0.903	−0.978	−1.046
Iceland	−0.038	−0.045	−0.053	−0.061	−0.068	−0.076
India	−25.864	−37.976	−51.19	−67.192	−86.321	−108.89
Indonesia	−7.525	−10.461	−13.486	−16.741	−20.083	−23.432
Iran	−2.367	−2.914	−3.576	−4.177	−4.794	−5.435
Iraq	−0.715	−0.922	−1.315	−2.062	−3.063	−4.272
Ireland	−1.008	−1.19	−1.375	−1.593	−1.855	−2.147
Israel	−0.706	−0.935	−1.204	−1.495	−1.823	−2.174
Italy	−4.236	−4.657	−5.147	−5.637	−6.129	−6.608
Jamaica	−0.061	−0.066	−0.073	−0.082	−0.094	−0.108
Japan	−10.307	−11.977	−13.452	−14.746	−15.955	−17.129
Jordan	−0.183	−0.236	−0.304	−0.388	−0.494	−0.625
Kazakhstan	−1.004	−1.207	−1.44	−1.671	−1.887	−2.092
Kenya	−0.631	−0.9	−1.293	−1.834	−2.49	−3.221
Kiribati	0	−0.001	−0.001	−0.001	−0.002	−0.002
Korea (Democratic People's Republic of)	−4.567	−5.605	−6.433	−7.111	−7.659	−8.1
Korea (Republic of)	−0.11	−0.161	−0.227	−0.314	−0.424	−0.557
Kuwait	−0.363	−0.454	−0.566	−0.682	−0.802	−0.926
Kyrgyzstan	−0.068	−0.087	−0.11	−0.137	−0.167	−0.202
Laos	−0.123	−0.172	−0.231	−0.299	−0.377	−0.467
Latvia	−0.105	−0.12	−0.133	−0.144	−0.152	−0.16
Lebanon	−0.112	−0.14	−0.173	−0.212	−0.26	−0.318
Lesotho	−0.012	−0.015	−0.02	−0.027	−0.034	−0.042
Liberia	−0.018	−0.027	−0.04	−0.059	−0.083	−0.112
Libya	−0.251	−0.318	−0.374	−0.458	−0.579	−0.74
Lithuania	−0.191	−0.227	−0.25	−0.267	−0.278	−0.286
Luxembourg	−0.131	−0.158	−0.177	−0.193	−0.204	−0.214
Macao (Special Administrative Region of the People's Republic of China)	−0.156	−0.211	−0.269	−0.326	−0.38	−0.428
Madagascar	−0.104	−0.145	−0.212	−0.311	−0.44	−0.599
Malawi	−0.068	−0.094	−0.137	−0.208	−0.309	−0.436
Malaysia	−2.048	−2.785	−3.526	−4.217	−4.863	−5.481
Maldives	−0.029	−0.042	−0.055	−0.071	−0.087	−0.106
Mali	−0.114	−0.164	−0.251	−0.387	−0.571	−0.803
Malta	−0.047	−0.062	−0.078	−0.091	−0.104	−0.116
Mauritania	−0.063	−0.087	−0.125	−0.178	−0.241	−0.311
Mauritius	−0.067	−0.086	−0.112	−0.143	−0.174	−0.2

TABLE D.23 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Mayotte (French Department of)	−0.02	−0.029	−0.042	−0.061	−0.084	−0.111
Mexico	−5.347	−6.171	−7.133	−8.233	−9.469	−10.832
Micronesia (Federated States of)	−0.001	−0.001	−0.001	−0.001	−0.002	−0.002
Moldova	−0.065	−0.087	−0.11	−0.131	−0.148	−0.164
Mongolia	−0.088	−0.118	−0.154	−0.193	−0.237	−0.287
Montenegro	−0.026	−0.032	−0.037	−0.041	−0.045	−0.049
Morocco	−0.54	−0.709	−0.927	−1.173	−1.469	−1.826
Mozambique	−0.099	−0.177	−0.312	−0.511	−0.775	−1.1
Myanmar	−0.449	−0.586	−0.749	−0.931	−1.136	−1.369
Namibia	−0.054	−0.068	−0.091	−0.122	−0.16	−0.199
Nepal	−0.297	−0.423	−0.577	−0.779	−1.04	−1.374
Netherlands	−1.749	−2.002	−2.229	−2.446	−2.656	−2.857
New Caledonia	−0.022	−0.032	−0.041	−0.051	−0.061	−0.07
New Zealand	−0.42	−0.53	−0.635	−0.739	−0.844	−0.951
Nicaragua	−0.09	−0.108	−0.133	−0.165	−0.207	−0.26
Niger	−0.085	−0.128	−0.209	−0.334	−0.511	−0.744
Nigeria	−2.434	−3.193	−4.543	−6.438	−8.776	−11.479
North Macedonia (Republic of)	−0.066	−0.082	−0.098	−0.113	−0.129	−0.145
Norway	−0.63	−0.72	−0.811	−0.905	−1.002	−1.102
Oman	−0.278	−0.36	−0.46	−0.566	−0.685	−0.814
Pakistan	−2.969	−4.178	−5.681	−7.814	−10.804	−14.87
Panama	−0.34	−0.417	−0.497	−0.574	−0.651	−0.729
Papua New Guinea	−0.069	−0.092	−0.123	−0.166	−0.222	−0.297
Paraguay	−0.209	−0.25	−0.298	−0.351	−0.41	−0.475
Peru	−0.959	−1.124	−1.318	−1.543	−1.798	−2.087
Philippines	−2.204	−3.355	−4.722	−6.2	−7.788	−9.487
Poland	−2.462	−3.027	−3.513	−3.94	−4.264	−4.536
Portugal	−0.646	−0.746	−0.846	−0.95	−1.052	−1.153
Puerto Rico (Commonwealth of)	−0.218	−0.23	−0.24	−0.249	−0.256	−0.262
Qatar	−0.456	−0.602	−0.733	−0.842	−0.948	−1.059
Romania	−1.045	−1.238	−1.416	−1.564	−1.681	−1.776
Russia	−6.778	−7.624	−8.703	−9.819	−10.956	−12.105
Rwanda	−0.081	−0.126	−0.191	−0.281	−0.392	−0.52
Saint Lucia	−0.006	−0.006	−0.007	−0.008	−0.009	−0.01
Samoa	−0.002	−0.003	−0.003	−0.004	−0.006	−0.007
Sao Tome and Principe	−0.002	−0.002	−0.003	−0.004	−0.006	−0.007
Saudi Arabia	−3.118	−4.277	−5.503	−6.667	−7.807	−8.898
Senegal	−0.158	−0.228	−0.345	−0.502	−0.692	−0.906
Serbia	−0.262	−0.333	−0.406	−0.474	−0.54	−0.603

TABLE D.23 *(Continued)*

Country/Territory	2025	2030	2035	2040	2045	2050
Seychelles	–0.008	–0.01	–0.013	–0.017	–0.02	–0.023
Sierra Leone	–0.033	–0.045	–0.066	–0.098	–0.139	–0.188
Singapore	–1.21	–1.534	–1.824	–2.042	–2.194	–2.289
Slovakia	–0.342	–0.396	–0.453	–0.51	–0.561	–0.61
Slovenia	–0.148	–0.175	–0.197	–0.217	–0.233	–0.248
Solomon Islands	–0.003	–0.004	–0.005	–0.008	–0.011	–0.016
Somalia	–0.045	–0.063	–0.092	–0.138	–0.209	–0.313
South Africa	–1.67	–1.988	–2.546	–3.356	–4.299	–5.265
South Sudan	–0.013	–0.019	–0.026	–0.036	–0.049	–0.065
Spain	–3.279	–3.673	–4.165	–4.715	–5.294	–5.891
Sri Lanka	–0.597	–0.775	–0.962	–1.182	–1.44	–1.742
St. Vincent and the Grenadines	–0.004	–0.004	–0.005	–0.005	–0.006	–0.007
Sudan	–0.243	–0.337	–0.449	–0.575	–0.725	–0.906
Suriname	–0.02	–0.023	–0.027	–0.032	–0.038	–0.044
Sweden	–0.992	–1.178	–1.348	–1.505	–1.659	–1.812
Switzerland	–1.095	–1.21	–1.328	–1.438	–1.544	–1.65
Tajikistan	–0.083	–0.108	–0.141	–0.18	–0.228	–0.284
Tanzania	–0.43	–0.664	–1.02	–1.515	–2.13	–2.843
Thailand	–2.577	–3.341	–4.089	–4.812	–5.505	–6.173
Timor–Leste	–0.008	–0.01	–0.014	–0.018	–0.025	–0.033
Togo	–0.047	–0.068	–0.101	–0.148	–0.207	–0.275
Tonga	–0.001	–0.001	–0.002	–0.002	–0.003	–0.003
Trinidad and Tobago	–0.076	–0.082	–0.089	–0.097	–0.105	–0.115
Tunisia	–0.22	–0.277	–0.348	–0.43	–0.527	–0.641
Türkiye (Republic of)	–5.343	–6.765	–8.251	–9.682	–11.08	–12.416
Turkmenistan	–0.185	–0.215	–0.252	–0.288	–0.322	–0.359
Uganda	–0.277	–0.421	–0.644	–0.948	–1.322	–1.75
Ukraine	–0.735	–0.96	–1.209	–1.467	–1.723	–1.985
United Arab Emirates	–1.272	–1.746	–2.261	–2.701	–3.095	–3.436
United Kingdom	–5.356	–6.105	–6.946	–7.904	–8.972	–10.111
United States of America	–38.933	–44.909	–50.167	–55.258	–60.308	–65.396
United States Virgin Islands	–0.007	–0.007	–0.008	–0.008	–0.009	–0.01
Uruguay	–0.181	–0.205	–0.228	–0.251	–0.273	–0.295
Uzbekistan	–0.583	–0.796	–1.051	–1.329	–1.625	–1.942
Vanuatu	–0.002	–0.002	–0.003	–0.004	–0.006	–0.009
Vietnam	–2.491	–3.869	–5.468	–7.079	–8.66	–10.201
Western Sahara	–0.002	–0.002	–0.003	–0.004	–0.005	–0.006
Yemen	–0.1	–0.147	–0.212	–0.305	–0.435	–0.611
Zambia	–0.153	–0.216	–0.311	–0.441	–0.599	–0.776
Zimbabwe	–0.08	–0.104	–0.142	–0.19	–0.242	–0.294

Annex E: Cost–benefit analysis of AI-based intervention for early disease detection

METHODOLOGY

Return-on-investment analysis

To estimate the return on investment (ROI) of the adoption of the AI-technology package on the farm, the following formula was used:

$$ROI = \frac{B_t - IC_t}{IC_t}$$

$$ROI = \frac{B_t}{IC_t} - 1$$

where B_t represents the benefit per pig attributable to the adoption of the technology package and IC_t represents the cost per pig of the technology package. The ROI assesses the amount of return that the technological investment has generated, that is, what the profitability of the AI-intervention on farms is, specifically focusing on the returns obtained per unit of investment in AI technology (AI-intervention fee). The ROI was calculated per pig and on a yearly basis over the study period of three years.

To compute the benefit attributable to AI, two steps were followed. First, the benefit gained by AI farms and conventional farms was computed using the following formula:

$$B_{f,t} = R_{f,t} - C_{f,t}$$

where $B_{f,t}$ is the benefit per pig gained by farm f at time t; $R_{f,t}$ is revenue per pig obtained from pork sales by farm f at year t; and $C_{f,t}$ represents the cost per pig, which includes feed and medical costs for both AI and conventional farms.

Second, to obtain the benefit attributable to the AI-intervention package, the difference in benefits between AI farms and conventional farms was computed as follows:

$$B_t = B_a - B_c$$

where B_t represents the benefit attributable to the adoption of the technology package. B_a represents the total benefit generated by AI farms and B_c represents the total benefit generated by conventional farms. This calculation of benefit attributable to AI assumes that, in the absence of AI, the two groups (conventional and AI farms) would be similar in their profitability margins; hence, the extra benefit realised by AI farms is attributed to investment in AI (AI intervention). Therefore, the benefit gained by AI and conventional farms was computed based on revenue and cost, excluding the AI-intervention cost. Then, using the benefits achieved by the two farm types, the benefit attributable to AI can be calculated. Finally, the ROI is calculated based on the benefit attributable to AI and the cost of the AI intervention on a yearly and per pig basis.

Annex F: Literature reviews

ACADEMIC LITERATURE REVIEW

The academic literature review used in this study employed the following inclusion and exclusion criteria when screening paper abstracts (see Table F.1).

Data was extracted on the following parameters:

- Settings (e.g. farms, aquaculture)
- Animal
- Geography
- Economic relevance
- Antimicrobial used and the purpose of use
- Qualitative and quantitative assessment of burden
- Impacts of AMR/AMU
- Interventions and their impacts
- Transmission across animal and human sectors at a high level

All the data extracted from the papers was synthesised thematically, based on the studies' key messages.

TABLE F.1 Inclusion and exclusion criteria

	Inclusion	Exclusion
Topic	Articles covering major economic pathways or wider societal impacts that can be monetised on the effects of AMU and interventions to tackle AMR in livestock sectors	Articles not covering the focus of interest, e.g. focusing solely on livestock sector perceptions, barriers to intervention implementation, government action plans or those focused on transmission to humans
Language	English language publications	Non-English language publications
Date	2013–2023	Articles published outside of this date range, unless found to be a seminal paper for context setting
Country settings	All countries	–
Population	Any animal population	Articles focusing on the impacts of AMR/AMU on human health
Accessibility	Full-text articles	Articles where the full text is not available or is only available behind a paywall
Article type	Published academic articles	–
Study design	Any study design, in particular: ■ Knowledge, Attitude and Practice (KAP) articles ■ Reviews ■ Evaluations ■ Perspectives and opinion pieces ■ Case studies ■ Conference proceedings	■ Abstracts ■ Marketing material

GREY LITERATURE REVIEW

The same inclusion and exclusion criteria were used for grey literature as per the academic literature review. The search involved first identifying potential sources (organisations) of grey literature. While those sources were reviewed, if additional sources were identified, these were then examined for potential resources.

The initial sources reviewed included:

- Quadripartite organisations: FAO, WHO, United Nations Environment Programme, WOAH
- Other relevant AMR bodies: OECD, World Bank, Wellcome Trust
- Implementing entities: ICARS, International Livestock Research Institute, ReACT
- Relevant Countries: the US, Canada, Denmark, Norway and Sweden

Initial review of the source organisations resulted in 48 pieces of grey literature to review for inclusion or exclusion. Three items were focused on economics, but not on animals. Thirty-six focused on AMR in animals, but not on economics. Six met the inclusion criteria but were only summary information from other published sources, and did not provide novel information. Three sources ultimately met all inclusion criteria, and full data extraction was conducted as per the parameters outlined above for the academic literature review.

Annex G: Bangladesh case study

BANGLADESH SURVEY DATA ANALYSIS

Two separate surveys were conducted in Bangladesh for livestock and fish farms. The questions were streamlined to accommodate differences in production environments and relevance to the respective sectors. The questionnaires included a variety of question types, including categorical, continuous and open-ended. These questions were then analysed accordingly.

First, the survey data were descriptively analysed to understand a selected theme of topics on farm practices that contribute to AMR, as well as their prevalence among the farms, farmer's awareness on AMR, animal disease and death impact, and to identify key players in AMU according to the farmers. For each team, relevant variables were selected and analysed descriptively. Where participants selected categorical option(s), the percentage of participants to select a given option was calculated. Percentages were calculated as a proportion of the total number of responses to that question. In instances where participants selected the category 'other' and then specified details in free-form text, the specified answers were reported when a substantial number (typically >1%) of respondents provided such details. Where participants responded with free-form text answers, the data was cleaned to pragmatically correct misspellings and to match words or phrases with similar meanings. A frequency table or word cloud was created to identify the most common responses.

Second, based on the findings from the descriptive analysis and broader research, further analysis was conducted to identify factors related to livestock and fish farmers' AMU, as measured by their annual spend on antimicrobials using regression modelling. Based on the hypothesis that antimicrobial spend relates to farm characteristics, specified uses of antimicrobials, broader practice and behaviours around antimicrobials, as well as experience of AMR, relevant variables were selected from the survey questions.

To examine drivers of spending on antimicrobials, measured in monetary value per year in the local currency of Bangladesh, the following model was specified:

$$y_{ij} = \alpha + \beta x_{ij} + v_j + \varepsilon$$

where y_{ij} represents annual spending on antimicrobials of farm i in sub-district j, which is log transformed to accommodate skewed distribution in the values. x_{ij} represents the independent variable of interest included in the model. This includes, among others, variables on farm characteristics, such as farm mangers' age and gender, type of farm ownership (family or commercial), and farm size (number of livestock for poultry, cattle, sheep and goats) or area for fish farms. v_j represents sub-district fixed effects, which capture location-specific factors that could affect spending. ε represents random error in the model.

The above model is estimated separately for fish and livestock farm survey data given that the practices are different, and questions are tailored to the specific sector rather than being generic. Different models with relevant variables were estimated using Ordinary Least Square estimation, and variables that are significant were reported in the final results. The dependent variable is log transformed; hence the Log-linear model is estimated, and the results include the estimated coefficients, standard errors of these esti-

TABLE G.1 Drivers of spending on antimicrobials among livestock farmers in Bangladesh: Linear regression model results

Dependent variable: Antimicrobial spending per year (log)				
Variables	**Coefficients**	**Std. err**	**Marginal effects**	**% Change**
Farm type	−0.595***	(0.094)	−0.813	−81.30
Number of cattle/buffalos owned	0.008***	(0.002)	0.008	0.80
Number of poultry owned (in thousands)	0.093***	(0.010)	0.097	9.70
Use of antimicrobials to treat bacterial disease	0.581***	(0.160)	0.788	78.80
Farm experienced drug failure	0.323***	(0.111)	0.381	38.10
Use of antimicrobials in feed formulations	0.413***	(0.127)	0.511	51.10
Farmer administered the antimicrobial the last time one was used	0.552***	(0.097)	0.737	73.70
Always go to a health professional to get the sick animal treated	−0.210**	(0.093)	−0.234	−23.4
Sub-district FE	Yes			
Observations	857			
Adjusted R2	0.420			

Notes: significance level is $^{**}p < 0.05$; $^{***}p < 0.01$.

mates, marginal effect and percentage change values to ease interpretation. In general, the interpretation of the result follows that for each unit increase (for continuous variables) or change in state (for binary variable), it is associated with the value of 'percentage change' that is provided in the result tables. Signs of the estimates indicate the direction of variable effect on the dependent variable (spending on antimicrobials).

Drivers of spending on antimicrobials among livestock farmers in Bangladesh

To identify the primary drivers of spending on antimicrobials, a simple linear regression model was estimated. Accordingly, Table G.1 presents the main drivers of spending on antimicrobials that were found to be significant in the model.

The analysis of potential factors that may impact spending on antimicrobials shows that antimicrobial expenditure is significantly driven by factors related to farm size and type, experience of drug failure and practices linked to treatment and feed. This result underscores the areas that require targeted policy interventions.

Annual antimicrobial expenditure was found to be 74% higher in cases where the farmer was the last person to administer antimicrobials to a sick animal, in comparison to where this was not the case. In contrast, spending is 23% lower in cases where farmers consistently seek a health professional to treat their sick animal.

Farmers who use antimicrobials in feed formulations spend 51% more on antimicrobials per year compared to those who do not.

Farm size is another significant driver of antimicrobial expenditure. Environmental factors contribute to the spread of disease and the need for antimicrobials, and thus may be more difficult to manage within larger operations compared to smaller ones. A further simple explanation is that having a larger number of animals means there are more animals that need treatment. Family farms spend 81% less on antimicrobials per year compared to commercial farms; family farms are likely smaller than commercial operations. Poultry farmers' annual expenditure on antimicrobials increases 10% for every 1,000 head increase. For cattle/buffalo farmers, spending increases by less than 1% for each single head increase. Poultry farms usually have a larger number of animals in comparison to cattle/buffalo farms.

Lastly, farmers who have experienced drug failure spend 38% more on antimicrobials per year compared to those who have not. This could be due to development of resistance and the need to use a second-line antimicrobial. Or this may be due to a fear that the treatment will not work again, leading farmers to use antimicrobials more frequently or in higher quantities, thus spending more.

Drivers of spending on antimicrobials among aquaculture farms in Bangladesh

The size of the aquaculture farm, measured in hectares, is positively related to antimicrobial expenditure. A one-hector increase in farm size is associated with an approximate 2% increase in spending on antimicrobials. Farmers that have experienced fish mass die-offs on their aquaculture farms in the past spend 78.2% more on antimicrobials annually than those who have not. This may suggest a heightened emphasis on preventing future similar events via AMU.

Farmers who reported using antimicrobials for only one purpose spend about 50% less on antimicrobials, indicating that occasional use results in significantly lower overall expenditure. This is likely due to reduced reliance on antimicrobials for managing fish health. Further investigation on this variable to compare spending among farms that specifically use antimicrobials for bacterial disease treatment and prevention reveals that farms using antimicrobials for preventive measures spend significantly more than those using them exclusively to treat bacterial diseases.

Administration of antimicrobials by fish health professionals leads to higher spending on antimicrobials. Farms where antimicrobials were last administered by fish health professionals are found to spend about 156% more than those who administer the antimicrobials themselves or via untrained service providers. This could be linked to the use of legitimate antimicrobials and professional services, which tend to be more expensive than untrained service providers. At the same time, aquaculture farms that sometimes employ untrained service providers to treat fish diseases spend 35.8% more on antimicrobials, which could reflect less effective treatment strategies necessitating higher AMU.

Farms that consistently seek professional health services for treating sick fish spend 41.2% less on antimicrobials than those who do not. This indicates that professional oversight may lead to more efficient and targeted use of antimicrobials, reducing overall expenditure.

These findings are presented in Table G.2 and highlight the diverse factors influencing antimicrobial spending

TABLE G.2 Drivers of spending on antimicrobials among aquaculture farmers in Bangladesh: Linear regression model results

Dependent variable: Antimicrobial spending per year (log)				
Variables	**Coefficients**	**Std. err**	**Marginal effects**	**% Change**
Farm manager's age	0.0003	(0.005)	0.0003	0.03
Female farm manager	−0.651	(0.348)	−0.917	−91.70
Aquaculture farm size (in hectare)	0.018***	(0.005)	0.018	1.80
Experience of fish mass die-off	0.578***	(0.135)	0.782	78.20
Single use of antimicrobials reported	−0.404**	(0.167)	−0.498	−49.80
Use of antimicrobials in feed formulation	−0.339	(0.192)	−0.404	−40.40
Antimicrobials administered by fish health professional	0.938***	(0.190)	1.555	155.50
Use of untrained service providers	0.306**	(0.147)	0.358	35.80
Always visit health professional to treat sick fish	−0.345**	(0.150)	−0.412	−41.20
Sub-district FE	Yes			
Observations	398			
Adjusted R2	0.332			

Notes: significance level is **$p < 0.05$; ***$p < 0.01$.

among aquaculture farmers. Farm size, past experiences of mass die-off, and the use of untrained service providers all tend to increase spending. On the other hand, the singular use of antimicrobials and regular professional oversight reduce costs. These insights can inform targeted interventions and policies to optimise AMU and enhance aquaculture farm management practices.

DETAILED BANGLADESH FARMER SURVEY RESULTS

Aquaculture farmers have low awareness of AMR and commonly use untrained service providers for advice and use of antimicrobials

When aquaculture farmers were asked whether excessive use of antibiotics in farming can make the medicines ineffective over time, 47% of farmers responded that they did not know, and 35% did not know if excessive use of antibiotics in aquaculture farming can also affect the health of humans. Over a quarter of respondents (27%), did not know if consuming aquaculture products from sick fish transmit disease to humans. Half of respondents (49%) did not know if vaccines can help avoid or reduce the use of antibiotics.

Forty percent of farmers rated professional services as unaffordable, and 40% rated antibiotics as being commonly available. Furthermore, 66% of aquaculture farmers avoid the use of laboratory services for disease diagnosis because of prohibitive costs. Most aquaculture farmers (73%) also report they sometimes use untrained service providers to treat fish disease on their farms.

About a quarter (26%) of respondents keep a stock of antibiotics in case their fish become sick. When these antibiotics expire, 7% of aquaculture farmers will use them anyway, and when aquaculture farmers have leftover antibiotics, 34% save them for later use. A total of 69% (n = 277) of farmers will sometimes buy the medication themselves when farmed fish are sick rather than seeking treatment from a fish health professional. Among this majority, 44% prefer to use untrained service providers, 34% report they are experienced themselves, and 20% report fish health professionals are expensive or not accessible.

Most aquaculture farmers (70%) reported they did not have a prescription the last time they purchased antibiotics. The last time antibiotics were used, most farmers (81%) either administered them personally or used untrained service providers. The majority (85%) of aquaculture farmers sourced the antibiotics from a pharmacy or veterinary health centre, while untrained service providers were reported as the source among 12% of respondents.

Over half (57%) of aquaculture farmers use antibiotics for disease prevention, and 14% report using antibiotics to treat viral disease. A high percentage (76%) of farmers do not complete the full antibiotic treatment when a sick fish appears to be free from disease; they will either dispose of the spare medication or save it for later use. Among farmers who have experienced treatment for a sick fish not working (n = 333), 68% reported that their next step was to administer a higher dose of the medicine, 33% initiated an emergency harvest to sell or consume the aquaculture, and 8% flash-out the fish and end the production cycle. Apart from the context of treatment failure, when asked if farmers wait before selling or consuming farmed fish after using antibiotics, 22% stated they do not wait or were unsure. When farmers were asked if they cook a dead animal after experiencing mass die-off, 14% responded yes. Moreover, wastewater practices raised concern for contamination by AMR organisms in the environment and future aquaculture production cycles. Over half (59%) of farmers reported not implementing wastewater treatment practices, and 46% of aquaculture farmers report discarding water into a neighbouring field after an aquaculture production cycle is complete, while 45% reuse it for the next production cycle.

Just under two-thirds (60%) of aquaculture farmers believe that using antibiotics brings them a better price for their fish. If they reduce or minimise the use of antibiotics, 85% of respondents believe there will be negative consequences, such as their fish growing more slowly, reduction in profits or lack of buyers for their fish. Almost all aquaculture farmers reported not using vaccines to prevent disease on their aquaculture farm; however, this is in alignment with industry practice in the Bangladesh fisheries sector where widespread use of vaccines for fisheries is not yet established, a fact that was shared during key informant interviews.

Aquaculture farmers trust peer farmers and untrained service providers for their information on antimicrobials and to treat sick animals

In terms of AMU in aquaculture farming, various professionals and institutions play pivotal roles, with differing levels of acceptance among farmers. Most aquaculture farmers (99%) do not belong to any association that guides antimicrobial use on their aquaculture farms. Farmers' engagement with fish health professionals is significantly weak. Advice on AMU for healthy fish primarily comes from non-professional sources. For advice on AMU on healthy fish, 88% ($n = 180$) primarily rely on peer farmers, pharmacies and drug sellers, as well as contract buyers. Only 13% ($n = 26$) sought help from fish health professionals. When it comes to trust in antibiotic use, most farmers (73.2%) trust peer farmers, untrained service providers, pharmacies and drug sellers, as well as contract buyers. The administration of antimicrobials on aquaculture farms shows varied practices: 52% administer the antimicrobials themselves, 29% rely on untrained service providers, and only 16% use a fish health professional.

This report is part of the EcoAMR series. As of September 2024, the series features these other publications:

- Forecasting the Fallout from AMR: Economic Impacts of Antimicrobial Resistance in Humans
- Forecasting the Fallout from AMR: Human Health Impacts of Antimicrobial Resistance
- Forecasting the Fallout from AMR: Averting the Health and Economic Impacts through One Health Policy and Investment

World Organisation for Animal Health

AID Animal Industry Data

CGD Center for Global Development

Institute for Health Metrics and Evaluation

RAND Europe

The World Bank IBRD • IDA | World Bank Group